How Did China's WTO Entry Affect U.S. Prices?*

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Abstract

We analyze the effects of China's rapid export expansion following WTO entry on U.S. prices, exploiting cross-industry variation in trade liberalization. Lower input tariffs boosted Chinese firms' productivity, lowered costs, and, in conjunction with reduced U.S. tariff uncertainty, expanded export participation. We find that China's WTO entry significantly reduced variety-adjusted U.S. manufacturing price indexes between 2000 and 2006. For the Chinese components of these indexes, one third of the beneficial impact comes from Chinese exporters lowering their prices, while two-thirds of the beneficial impact comes from the entry of new Chinese exporters. China's WTO entry also led other countries exporting to the U.S. to lower their prices, which was partly offset by exit of these exporters. We find that this impact on competitor countries' prices is primarily explained by the reduction in China's own input tariffs, so that policy action becomes the largest source of welfare gain for the United States from China's WTO entry.

Key Words: trade liberalization, input tariffs, China, exports, variety

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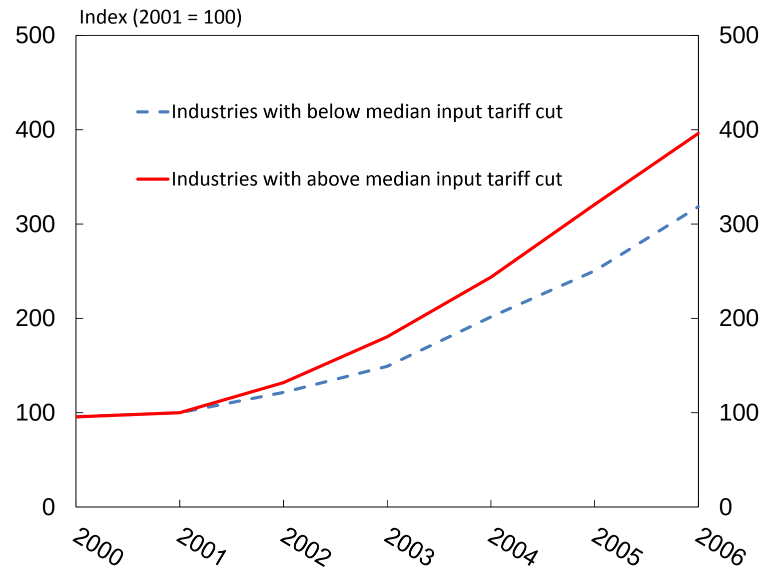
1 Introduction

China's manufacturing export growth in the last 20 years has produced a dramatic realignment of world trade, with China emerging as the world's largest exporter. China's export growth was especially rapid following its World Trade Organization (WTO) entry in 2001, with the 2001–2006 growth rate of 30 percent per annum being more than double the growth rate in the previous five years. This growth has been so spectacular that it has attracted increasing attention to the negative effects of the China "trade shock" on other countries, such as employment and wage losses in import-competing U.S. manufacturing industries (Autor et al. (2013), Acemoglu et al. (2016), and Pierce and Schott (2016)). Surprisingly, given the traditional focus of international trade theory, little analysis has been made of the potential gains to consumers of products, whether households or firms, in the rest of the world, who could benefit from access to cheaper Chinese imports and more imported varieties. Our focus is on potential benefits to consumers in the U.S., where China accounts for more than 20 percent of imports. In principle, gains could be driven by two distinct policy changes that occurred with China's WTO entry. The first, which has received much attention in the literature, is the U.S. granting permanent normal trade relations (PNTR) to China, reducing the threat of China facing very high tariffs on its exports to the U.S. A second channel we identify is China reducing its own input tariffs.[1] In this paper, we quantify how China's WTO entry affected U.S. manufacturing prices, and we find that an important cause of these effects was China lowering its own tariffs on intermediate inputs.

To motivate our analysis, in Figure 1 we plot Chinese exports to the U.S. in industries above and below the median input tariff cut of 4.6 percentage points. With exports of both bins indexed at 100 in 2001, we see substantially faster export growth in industries with larger reductions in their input tariffs. To understand where this faster growth might be coming from, in Table 1 we report a regression of the log-change in HS 6-digit unit values of China's exports to the U.S. between 2000 and 2006 on the corresponding change in Chinese input tariffs for that industry. Column 1 reports a simple OLS regression, and shows that Chinese input tariff reductions are strongly associated with reductions in their export prices. In column 2 we employ a simple IV regression strategy from Goldberg and Pavcnik (2005), exploiting the fact that the size of the tariff reduction is primarily determined by the pre-existing tariff level, so that the pre-existing input tariff is a valid instrument for the change in that tariff. The association between the fall in input tariffs and in export prices is slightly stronger in the IV results.

[1] We also consider the impact of other contemporaneous trade reforms when we check the robustness of our results in section 5.3. We use the term "WTO entry" as a shorthand for the specific trade reforms we study that occurred due to WTO entry.

Figure 1: China's U.S. Exports and China's Input Tariffs



Notes: The median input tariff cut over the sample period was 4.6 percentage points. The export industries with above-median input tariff cuts (from -4.6 to -11 percentage points) increased their export share from 67% of total to 72%. The export industries with below-median input tariff cuts experienced tariff reductions of -1.4 to -4.6 percentage points.

Table 1: Export Prices and Input Tariffs: 2000-2006

Dependent variable	$\triangle ln(price_g)$	
	OLS	IV
	(1)	(2)
$\triangle ln(Input\tau_{gt})$	3.224***	3.667***
	(0.749)	(0.793)
# obs.	2,954	2,954

Notes: The dependent variable is the log-change in the unit value of goods exported from China to the U.S. at the HS 6-digit level, calculated from Chinese reported data for 2000 and 2006. The explanatory variable is the change in Chinese tariffs on intermediate inputs, and the IV used in column (2) is the initial tariff level.

The goal of this paper is to exploit detailed firm-level Chinese data to perform a more structural analysis of the mechanisms behind the results illustrated in Figure 1 and Table 1. Specifically, we are interested in the impact of China's export growth following its WTO accession on U.S. prices. To measure China's impact, we utilize Chinese firm-product-destination level export data for the years 2000 to 2006, during which China's exports to the U.S. increased nearly four-fold. One striking feature is that the extensive margin of China's U.S. exports accounts for 85 percent of export growth, mostly due to new firms entering the export market (69 percent of total growth) rather than incumbents exporting new products (16 percent of total growth). To ensure we properly incorporate new varieties in measuring price indexes, we construct an exact CES price index, as in Feenstra (1994), which comprises a "price" and a "variety" component.[2] We find that the China import price index in the U.S. falls by 46 percent over the period 2000 to 2006 due to growth in export product variety. We supplement the Chinese data with U.S. reported trade data from other countries and U.S. domestic sales to construct overall U.S. price indexes for manufacturing industries. With these data, we explicitly take into account that the China shock affects competitors' prices and net entry into the U.S. market.

We find that China's WTO entry reduced U.S. manufacturing price indexes by 7.6% between 2000 and 2006. Focusing first on the U.S. imports of Chinese goods, about *one-third* of the beneficial impact on U.S. prices comes from Chinese exporters lowering their prices, which is entirely driven by the reduction in China's tariffs on intermediate inputs, while *two-thirds* of the beneficial impact comes through the entry of new Chinese exporters, with this addition to U.S. product variety caused by both China's input tariff reductions and the granting of PNTR. This direct impact from Chinese imports on the U.S. price indexes accounts for nearly 60 percent of the U.S. benefits from China's entry to the WTO, while the remaining 40 percent is through reductions in price indexes for goods sold by *other* competing countries. China's competitors react to lower prices of Chinese exports by cutting their own prices and, in some cases, by exiting altogether. This reduction in other countries' prices is explained entirely by the reduction in Chinese input tariffs, and not by the granting of PNTR. Incorporating the response of domestic and other countries' competitors in U.S. price indexes, we conclude that the reduction in China's own input tariffs becomes an important source of welfare gain for the United States.

Our paper draws on several lines of literature. Pierce and Schott (2016), Handley and Limão (2017) and Feng et al. (2017) study the effect of granting PNTR to China, but they do not study the input tariff reduction channel.[3] A second literature finds that that lower input tariffs increase firms' total factor productivity (e.g., Amiti and Konings (2007) for Indonesia; Kasahara and Rodrigue (2008) for Chile; Goldberg et al. (2010) for India; Halpern et al. (2015) for Hungary; Yu (2015) and Brandt et al. (2017) for China). While we are guided by that literature and we shall estimate the impact of lower input tariffs on productivity, our main interest is in going beyond the firm's domestic market to determine the impact on their prices abroad.[4] China's input tariff reductions lower firms' costs both directly (through lower prices of materials) and indirectly (through higher measured TFP), both of which contribute to their lower exports prices. We also find evidence consistent with Kee and Tang (2016) that lower input tariffs reduce the price of inputs sold by competing domestic producers and expand the range of domestic input varieties. Lower costs lead to lower export prices and more export participation.

[2]Broda and Weinstein (2006) built on this methodology to estimate the size of the gains from importing new varieties into the U.S. In contrast to that paper, we observe Chinese varieties within detailed trade categories at the firm level.

[3]Bai and Stumpner (2017) study total import penetration into the U.S. by industry, and show that increased import shares are associated with lower consumer prices in related AC Nielsen consumer goods categories. Their instrument for import penetration into the U.S. is Chinese product penetration into leading European markets; they are therefore agnostic on the underlying causes of rising import penetration.

[4]So we draw also on the literature connecting importing inputs and exporting: see Feng et al. (2016) on China, Bas (2012) on Argentina, and Bas and Strauss-Kahn (2014) on France.

A limitation of our study is that we consider only the potential consumer benefits, and do not attempt to evaluate the overall welfare gains to the U.S. from China's WTO entry. That broader question requires a computable model. For example, Hsieh and Ossa (2016) calibrate a multi-country model with aggregate industry data at the two-digit level, and find that China transmits small gains to the rest of the world.[5] More recently, Caliendo et al. (2015) combine a model of heterogeneous firms with a dynamic labor search model. Calibrating this to the United States, they find that China's export growth created a loss of about 1 million jobs, effectively neutralizing any short-run gains, but still increasing U.S. welfare by 6.7 percent in the long-run. Both of these papers rely on the assumption of the Arkolakis et al. (2012) (ACR) framework of a Pareto distribution for firm productivities. In contrast, our approach does not rely on a particular distribution of productivities, and also differs from ACR in that we focus on the *channels* through which trade policy changes in one country (China) leads to consumer gains in another (the United States).

Our paper is organized as follows. Section 2 presents our key assumptions about U.S. consumers. Section 3 examines the theoretical relationship between firm productivity and intermediate input use, and estimates how China's trade liberalization upon WTO entry has affected Chinese firms' intermediate input use and productivity. Section 4 studies how cost reductions from input tariff cuts and reduced policy uncertainty from PNTR affect export prices and export participation for Chinese firms. Section 5 constructs overall U.S. price indexes for manufacturing industries and trade-policy based instruments from the firm-level regressions in section 4, and then estimates the impact of China's WTO accession on U.S. prices. Section 6 concludes.

2 U.S. Consumption

2.1 Nested CES Utility

We use the term "consumer" to include consuming households and firms, since many traded goods are not final consumption goods. The representative consumer has a nested CES utility function. At the upper level, the utility from consuming goods $g \in G$ in the U.S. in period t is

$$U_t = \left(\sum_{g \in G} \alpha_g \left(Q_{gt} \right)^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}}, \tag{1}$$

where g denotes an Harmonized System (HS) 6-digit industry, G denotes the set of HS 6-digit codes; Q_{gt} is aggregate U.S. consumption of good g in period t; $\alpha_g > 0$ is the taste parameter for the aggregate good g; and κ is the elasticity of substitution across goods. Good g is a CES aggregate of HS6 goods from each country i:

[5] In a multi-country general equilibrium model, di Giovanni et al. (2014) find that the welfare impact of China's integration is larger when its growth is biased toward its comparative disadvantage sectors.

$$Q_{gt} = \left(\sum_{i \in I_{gt}} \left(Q_{gt}^i \right)^{\frac{\sigma_g - 1}{\sigma_g}} \right)^{\frac{\sigma_g}{\sigma_g - 1}}, \tag{2}$$

where Q_{gt}^i is aggregate U.S. consumption in industry g of varieties produced by country $i \in I_{gt}$, and $\sigma_g > 1$ is the elasticity of substitution between these aggregate country varieties.

Each country's aggregate variety is a CES aggregate of disaggregate varieties. Denoting consumption of the finest-classification of product varieties by $q_{gt}^i(\omega)$, aggregate U.S. consumption of country i output in industry g is

$$Q_{gt}^i = \left(\sum_{\omega \in \Omega_{gt}^i} \left(\alpha_g^i(\omega) q_{gt}^i(\omega) \right)^{\frac{\rho_g - 1}{\rho_g}} \right)^{\frac{\rho_g}{\rho_g - 1}}, \tag{3}$$

where $\alpha_g^i(\omega) > 0$ is a taste or quality parameter for variety ω of good g sold by country i; Ω_{gt}^i is the set of varieties; and ρ_g is the elasticity of substitution between varieties in sector g, with $\rho_g > \sigma_g > 1$. In practice, we can think of the finest classification of product varieties as individual products sold by firms, which in our Chinese data will be 8-digit Harmonized System products sold to the United States. The CES price index that is dual to (3) is

$$P_{gt}^i = \left(\sum_{\omega \in \Omega_{gt}^i} \left(p_{gt}^i(\omega) / \alpha_g^i(\omega) \right)^{1 - \rho_g} \right)^{\frac{1}{1 - \rho_g}}. \tag{4}$$

From equation (4) it follows that the share of product variety ω within the exports of country i is

$$s_{gt}^i(\omega) \equiv \left(\frac{p_{gt}^i(\omega) q_{gt}^i(\omega)}{\sum_{\omega \in \Omega_{gt}^i} p_{gt}^i(\omega) q_{gt}^i(\omega)} \right) = \left(\frac{p_{gt}^i(\omega) / \alpha_g^i(\omega)}{P_{gt}^i} \right)^{1 - \rho_g}. \tag{5}$$

These equations represent the U.S. demand for the products of Chinese firms, as well as exporters from other countries. Notice that as there are more products sold by Chinese firms (country *i*), then the set of products Ω_{gt}^i in (4) expands and with $\rho_g > 1$ and the CES price index P_{gt}^i falls. So expanding product variety from the entry of Chinese exporters, as well as lower prices from these firms, will lower the price index facing U.S. consumers. We describe the magnitude of this variety increase for Chinese exports in the next section.

2.2 Measuring the U.S. CES Price Index

Our goal is to compute a price index that accurately reflects the nested CES structure in section 2.1. We start with equation (4) and consider two equilibria with CES price indexes P_{gt}^i and P_{g0}^i, which reflect different prices $p_{gt}^i(\omega)$ and $p_{g0}^i(\omega)$ and also differing sets of varieties Ω_{gt}^i and Ω_{g0}^i. We assume that these two sets have a non-empty intersection of varieties, denoted by $\overline{\Omega}_g^i = \Omega_{gt}^i \bigcap \Omega_{g0}^i$. We refer to the set $\overline{\Omega}_g^i$ as the "common" varieties, available in periods t and 0. Feenstra (1994) shows that the ratio of P^i_{gt} and P^i_{g0} can be measured, as:

$$\frac{P^i_{gt}}{P^i_{g0}} = \left[\prod_{\omega\in\overline{\Omega}^i_g}\left(\frac{p^i_{gt}(\omega)}{p^i_{g0}(\omega)}\right)^{w^i_{gt}(\omega)}\right]\left(\frac{\lambda^i_{gt}}{\lambda^i_{g0}}\right)^{\frac{1}{\rho_g-1}}, \ \ i = China, \tag{6}$$

where $w^i_{gt}(\omega)$ are the Sato-Vartia weights at the variety level, defined using the shares $\bar{s}^i_{gt}(\omega)$ within the common set,

$$w^i_{gt}(\omega) \equiv \frac{\left(\bar{s}^i_{gt}(\omega)-\bar{s}^i_{g0}(\omega)\right)/\left(\ln\bar{s}^i_{gt}(\omega)-\ln\bar{s}^i_{g0}(\omega)\right)}{\sum\limits_{\omega\in\overline{\Omega}^i_g}\left(\bar{s}^i_{gt}(\omega)-\bar{s}^i_{g0}(\omega)\right)/\left(\ln\bar{s}^i_{gt}(\omega)-\ln\bar{s}^i_{g0}(\omega)\right)}, \ \bar{s}^i_{gt}(\omega) \equiv \frac{p^i_{gt}(\omega)q^i_{gt}(\omega)}{\sum\limits_{\omega\in\overline{\Omega}^i_g} p^i_{gt}(\omega)q^i_{gt}(\omega)}, \tag{7}$$

and

$$\lambda^i_{gt} \equiv \frac{\sum_{\omega\in\overline{\Omega}^i_g} p^i_{gt}(\omega)q^i_{gt}(\omega)}{\sum_{\omega\in\Omega^i_{gt}} p^i_{gt}(\omega)q^i_{gt}(\omega)} = 1 - \frac{\sum_{\omega\in\Omega^i_{gt}\setminus\overline{\Omega}^i_g} p^i_{gt}(\omega)q^i_{gt}(\omega)}{\sum_{\omega\in\Omega^i_{gt}} p^i_{gt}(\omega)q^i_{gt}(\omega)}, \tag{8}$$

and likewise for $\bar{s}^i_{g0}(\omega)$ and λ^i_{g0}, defined as above for $t = 0$.

The first term in equation (6) is constructed in the same way as a conventional Sato-Vartia price index –it is a geometric weighted average of the price changes for the set of varieties $\overline{\Omega}^i_g$, with log-change weights. The second component comes from Feenstra (1994) and takes into account net variety growth: λ^i_{gt} equals one minus the share of expenditure on new products, in the set Ω^i_{gt} but not in $\overline{\Omega}^i_g$, whereas λ^i_{g0} equals one minus the share of expenditure on disappearing products, in the set Ω^i_{g0} but not in $\overline{\Omega}^i_g$. A lower λ ratio implies more net variety, and hence a lower price index.[6]

We now construct the variety component of the U.S. price index for Chinese imports. As shown in Table 2, China's manufacturing exports to the U.S. grew a spectacular 290 percent over the sample period, with growth rates of around 30 percent every year except in 2001. Determining how much of this growth comes from new varieties is very important for our study. We measure Chinese products at the HS 8-digit level for Chinese exporting firms, so that the index ω denotes a HS8-firm variety. The value of Chinese exports to the U.S. for this firm is $X^i_{gt}(\omega)\equiv p^i_{gt}(\omega)q^i_{gt}(\omega)$ in year t, and we decompose China's aggregate export growth to the U.S. as follows:

$$\frac{\sum_\omega[X^i_{gt}(\omega)-X^i_{g0}(\omega)]}{\sum_\omega X^i_{g0}(\omega)} = \frac{\sum_{\omega\in\overline{\Omega}}[X^i_{gt}(\omega)-X^i_{g0}(\omega)]}{\sum_\omega X^i_{g0}(\omega)} + \frac{\sum_{\omega\in\Omega_t\setminus\overline{\Omega}} X^i_{gt}(\omega)-\sum_{\omega\in\Omega_0\setminus\overline{\Omega}} X^i_{g0}(\omega)}{\sum_\omega X^i_{g0}(\omega)}, \tag{9}$$

[6]Note that the quality of products in the "common" set $\overline{\Omega}^i_g$, as reflected by their taste parameters $\alpha^i_g(\omega)$, is assumed to be constant over time, but products outside this set and appearing within the λ^i_{gt} terms can have changing quality. To achieve this in theory we can choose $\overline{\Omega}^i_g$ as any non-empty *subset* of $\Omega^i_{gt}\bigcap\Omega^i_{g0}$ for which the products have constant quality, and the price index formulas above continue to hold true (see Feenstra (1994)). In practice, however, it is hard to know which products have constant quality, so we shall simply use $\overline{\Omega}^i_g = \Omega^i_{gt}\bigcap\Omega^i_{g0}$.

Table 2: Decomposition of China's Export Growth to the U.S.

		Proportion of export growth due to different margins:					
		Variety at the HS8-firm level				Equivalent Price Change	
Year	Total Export Growth %	Intensive Margin	Extensive Margin	Extensive Margin new firms	Extensive Margin incumbents	Due to Chinese Variety	Weighted by China Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2001	4.2	0.09	0.91	0.75	0.17	-0.018	-0.001
2002	29.8	0.56	0.44	0.21	0.22	-0.040	-0.004
2003	32.2	0.61	0.39	0.23	0.16	-0.081	-0.004
2004	35.1	0.65	0.35	0.23	0.12	-0.026	-0.004
2005	29.4	0.57	0.43	0.22	0.21	-0.079	-0.005
2006	25.6	0.65	0.35	0.20	0.15	0.010	-0.003
2000-2006	290.0	0.15	0.85	0.69	0.16	-0.460	-0.031

Notes: All these margins are calculated using manufacturing data concorded to HS 8-digit codes at the beginning of the sample. The sum of the intensive margin (column 2) and the extensive margin (column 3) equal 100 percent. The sum of the extensive margin of new firms (column 4) and the extensive margin of incumbent firms (column 5) equals the total extensive margin (column 3). Column 6 converts the variety gain in column 3 to the equivalent change in the price index i.e. the second term on the right of equation (6) and column 7 computes the third term on the right of equation (30), both weighted using the Sato-Vartia weights in equation (32).

where $\overline{\Omega} = \Omega_t \cap \Omega_0$ is the set of varieties (at the firm-product level) that were exported in t and $t = 0$, $\Omega_t \setminus \overline{\Omega}$ is the set of varieties exported in t but not in 0, and $\Omega_0 \setminus \overline{\Omega}$ is the set of varieties exported in t_0 but not in t. For convenience, we are summing over *all* HS8-firm varieties in these sets, without distinguishing the HS6-digit industries g. Equation (9) is an identity that decomposes the total export growth into the intensive margin (the first term on the right) and the extensive margin (the last term), which we report in Table 2.

Surprisingly, most of the growth in Chinese exports for the U.S. arises from net variety growth. From the bottom of column 3, we see that the extensive margin accounts for 85 percent of export growth to the U.S. over the whole sample period (columns 2 and 3 sum to 100 percent of the total growth). We can further break down the extensive margin to see if it is driven by incumbent exporters shipping new products or new firms exporting to the U.S. We see from columns 4 and 5 that the extensive margin is almost entirely driven by new exporters —69 percent of the total export growth over the sample period comes from new firms while 16 percent is by incumbent firms exporting new products (columns 4 and 5 sum to the total extensive margin in column 3).

Table 2 clearly shows that most of the growth in China's exports was due to new entrants into the U.S. export market, and this result is robust.[7] Rapid export variety growth leads to a large reduction

[7]Given that some firms change their identifier over time due to changes of firm type or legal person representatives, we tracked firms over time (using information on the firm name, zip code and telephone number) to ensure that the firm maintains the same identifier. This affects 5 percent of firms and hardly changes the size of the extensive margin. Even if our algorithm for tracking reclassifications has missed some identifier changes for incumbent firms due to, for example, mergers and acquisitions, our approach to measuring the gains from Chinese firm entry into the U.S. market is driven

in Chinese export prices due to the extensive margin, as reported in column 6, where we compute the year-to-year variety adjustment in the China price index and the variety gain over the whole sample period, 2000-2006, i.e. the second term in equation (6). The lambda ratios are raised to a power that includes the elasticity of substitution ρ_g, and then weighted across industries using appropriate weights.[8] So column 6 reports the effective drop in the U.S. import price index from China due to the new varieties, which amounts to -46 percent over 2000-2006. Notice that this total change at the bottom of column 6 is not the same as summing the year-to-year changes in the earlier rows, because the calculation for 2000-2006 is performed using the exports that are "common" to those two years. If there is a new variety exported from China in 2001, for example, then its growth in exports up to 2006 is attributed to variety growth; whereas in the earlier rows, only its initial growth of exports from 2001-2002 is attributed to variety growth.[9]

To see the contribution of China's export variety growth on the overall U.S. manufacturing sector price index, however, we also need to adjust the values of the variety index in column 6 by China's weight in the entire U.S. market (not just the import shares) in each industry g.[10] Making that adjustment, column 7 shows that the US manufacturing sector price index drop due to variety gain from China is 3.1 percent, so that U.S. consumers (i.e. households and importing firms) experience a welfare gain of 3.1 percent due to the expansion of import variety from China. This is a number that we will carry forward into our later calculations. While it is a large welfare gain (measured relative to total U.S. expenditure on manufactured goods), we do not know what amount of it can be explained by China's accession to the WTO in 2001. We also do not know the effect of WTO accession on the prices charged by Chinese exporters to the U.S., or on the prices and variety of other exporting countries. To begin to answer these questions, in the next section we discuss the productivity, pricing, and entry decisions of Chinese exporting firms.

3 Intermediate Inputs and Chinese Firm Productivity

3.1 Cost Function

We build on the methodology of Feenstra (1994) and Broda and Weinstein (2006) for measuring the consumer gains from new imported varieties to measure reductions in producer costs from new varieties of imported inputs. For convenience we omit the indexes ω for varieties, g for industries and i for countries, but add an index f for Chinese firms. The unit-cost function for *imported inputs* is a CES aggregate of all imported inputs $n \in \Sigma_{ft}$ purchased by the firm:

by net entry, which is largely unaffected by reclassifications of product codes or firm codes, as the new entry due to reclassifications would be offset by the exit.

[8] We use the industry-level Sato-Vartia weights, defined later in equation (31). The estimation of the elasticities of substitution ρ_g is described in Appendix A.

[9] This method of using a "long difference" to measure variety growth is consistent with the theory outlined in section 2.1, as it allows for increases in the U.S. taste parameter for that Chinese export variety in the intervening years as it penetrates the U.S. market; see note 6.

[10] We do this using the Sato-Vartia weights at the country-industry level shown later in equation (27), as used in the third term in equation (30), before weighting across industries g as in equation (32).

$$c_{ft}^M = \left(\sum_{n \in \Sigma_{ft}} (p_{nt}\tau_{nt}/\alpha_n)^{1-\rho} \right)^{\frac{1}{1-\rho}}, \tag{10}$$

where p_{nt} denotes the net-of-tariff price that firm f pays for imports of intermediate input n, τ_{nt} denotes one plus the *ad valorem* tariff, and $\alpha_n > 0$, $\rho > 1$ are parameters. Denote the overall unit-costs by C_{ft} , which also includes labor with a share of γ, and domestic combined with imported intermediate inputs, with share $(1-\gamma)$:

$$C_{ft} = C(P_t^D, c_{ft}^M, \varphi_{ft}) = \varphi_{ft}^{-1} \left((P_t^D/\alpha_D)^{1-\sigma} + (c_{ft}^M/\alpha_M)^{1-\sigma} \right)^{\frac{1-\gamma}{1-\sigma}}. \tag{11}$$

where φ_{ft} is firm productivity, P_t^D is the price of domestic intermediate inputs, the wage is normalized at unity, and $\alpha_D,\ \alpha_M > 0$, $\sigma > 1$ are parameters.

An alternative way to write the change in unit costs focuses more directly on the sourcing strategy. Using the unit-cost function over imported inputs c_{ft}^M in (10), let $\overline{\Sigma}_f \subseteq \Sigma_{ft} \cap \Sigma_{f0}$ be a non-empty subset of the "common" imported inputs purchased in periods 0 and t. Then analogous to consumer CES indexes developed by Feenstra (1994) and presented in section 2.2, the index of firm costs for imported inputs between period t and period 0 is:

$$\frac{c_{ft}^M}{c_{f0}^M} = \left[\prod_{n \in \overline{\Sigma}_f} \left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}} \right)^{w_{nt}} \right] \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{\frac{1}{\rho-1}}, \tag{12}$$

where λ_{ft} is the expenditure on imported inputs in the *common* set $\overline{\Sigma}_f$ relative to *total* expenditure on imported inputs in period t,[11] and w_{nt} is the Sato-Vartia weight for input n, defined as:

$$w_{nt} \equiv \frac{(s_{nt} - s_{n0}) / (\ln s_{nt} - \ln s_{n0})}{\sum_{n \in \overline{\Sigma}_f} (s_{nt} - s_{n0}) / (\ln s_{nt} - \ln s_{n0})}, \tag{13}$$

where s_{nt} is expenditure on input n divided by expenditure on all imported inputs in the common set $\overline{\Sigma}_f$. The first term on the right of (12) captures the direct effect of tariffs on costs, or the Sato-Vartia index of input prices inclusive of tariffs. The second term is the efficiency gain from expanding the range of inputs, resulting in $\lambda_{ft} < \lambda_{f0} \leq 1$.

We can easily relate the efficiency gain in (12) to the overall productivity of the firm, and we show in Appendix B that:

$$\left(\frac{P_t^D}{P_0^D} \right)^{W_{ft}^D(1-\gamma)} \bigg/ \left(\frac{C_{ft}}{C_{f0}} \right) = \frac{\varphi_{ft}}{\varphi_{f0}} \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{-\frac{W_{ft}^M(1-\gamma)}{\rho-1}} \left[\prod_{n \in \overline{\Sigma}_f} \left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}} \right)^{w_{nt}} \right]^{W_{ft}^M(1-\gamma)}. \tag{14}$$

The left-hand side of this equation is a measure of the dual total factor productivity (TFP), or the rise in prices of intermediate inputs (with wages normalized at unity) divided by the rise in marginal

[11] Goldberg et al. (2010) adopt a similar approach to estimate the effect of trade liberalization of intermediate inputs on the number of domestic products produced in India.

costs. On the right we see that dual TFP reflects the exogenous productivity term φ_{ft}, the endogenous change in import variety, and possibly an index of the change in imported input prices for the firm.[12]

Since the change in import variety is endogenous, in the following section we will estimate the *exogenous* change in firm-level import variety that is due to changes in Chinese input tariffs. That exogenous change will be used as an instrument for TFP. A different approach, taken by Blaum et al. (2016), would be to relate TFP to the share of spending on domestic inputs, S_{ft}^D, which falls as the variety of imported inputs rises since $\sigma > 1$ is assumed. However, the share of spending on domestic inputs is also endogenous, and as we show in Appendix B, it is likewise determined by variables including firm-level import variety. So the instrument that we develop for TFP in the next section can also be used as an instrument for S_{ft}^D, which is then used to determine TFP. In Appendix B we show that these two approaches give similar results, and can be interpreted as a reduced form versus a structural approach to explaining TFP. We prefer to focus directly on the relationship between firm-level import variety and TFP (the reduced form approach), as we shall do for the rest of the paper.

3.2 Trade Liberalization upon China's WTO Entry

China joined the WTO in December 2001 and committed to bind all import tariffs at an average of 9 percent.[13] Although China had previously reduced tariffs, average tariffs in 2000 were still high at 15 percent, with a large standard deviation of 10 percent. Our objective is to determine the impact of China's lower imported intermediate input tariffs on Chinese firms' TFP. Identifying what is an input is not straightforward in the data, so we approach this in two ways. Our first approach exploits detailed data on Chinese tariffs τ_{nt} and individual Chinese firms to estimate equations for each firm's imports of inputs. We then use these regressions to estimate the effect of China's tariff reductions on each firm's imports of inputs, from which we construct instruments for the observed expansion of each firm's inputs λ_{ft} when we estimate firm-level TFP.

Our second approach follows Amiti and Konings (2007) by constructing tariffs on intermediate inputs, $Input\tau_{gt}$, using China's 2002 input-output (IO) tables. The most disaggregated IO table available is for 122 sectors, with 72 of these in manufacturing.[14] We take the HS 8-digit Chinese import tariff data, which are MFN ad valorem rates, and calculate the simple average of these at the IO industry level. The input tariff for each industry g is the weighted average of these IO industry tariffs, using the cost shares in China's IO table as weights.[15] Average tariffs for each year are reported in

[12]If the prices of intermediate inputs appearing on the left of (14) also incorporate *imported* intermediates, then there would be no need to include $Input\tau_{gt}$ on the right. As described in Appendix E, we construct TFP using a double-deflation method that uses the prices of materials from the IO table, and we believe that these are unlikely to accurately reflect import prices. So it is possible that $Input\tau_{gt}$ influences firm TFP. For reasons described in the next paragraph, however, we only construct $Input\tau_{gt}$ at the industry level g, which may limit its explanatory power for firm-level TFP in section 3.4. Regardless of this limitation, we can expect that $Input\tau_{gt}$ will be an important determinant of firm prices, since it is a component of imported input prices in (12) and therefore impacts overall unit costs in (11). Thus, $Input\tau_{gt}$ will be used in the pricing equation for firms estimated in section 4.

[13]See wto.org for more details.

[14]This is preferable to constructing firm-level tariffs, which can only be constructed using import shares rather than overall cost shares of each input and would induce an endogeneity bias.

[15]We thank Rudai Yang from Peking university for the mapping from IO to HS codes, which he constructed manually

Table 3: Average Tariffs

Year	China's tariffs on intermediate inputs				Gap	
	HS8 digit		IO category			
	Average	Std Dev	Average	Std Dev	Average	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
2000	0.15	0.10	0.13	0.05	0.24	0.15
2001	0.14	0.09	0.12	0.05	0.24	0.15
2002	0.11	0.08	0.09	0.03	0	0
2003	0.10	0.07	0.08	0.03	0	0
2004	0.10	0.07	0.08	0.03	0	0
2005	0.09	0.06	0.07	0.03	0	0
2006	0.09	0.06	0.07	0.02	0	0

Notes: All tariffs are defined as the log of 1 plus the ad valorem tariff so a 5 percent tariff is $ln(1.05)$. The first column presents the simple average of China's import tariffs on HS 8-digit industries. Column 3 presents the simple mean of the cost-weighted average of China's input tariffs within an IO industry code, using weights from China's 2002 input-output table. Column 5 presents the simple average of the "gap" defined as the difference between the U.S. column 2 tariff and the U.S. MFN tariff in 2000.

Table 3. Tariff levels fell on average by 40% (6 percentage points) over this period and their dispersion also declined. In general, the largest declines in tariffs were in products with the highest initial tariffs. The correlation between the 2000-2006 change in tariffs and the 2000 level is -0.7. China implemented other reforms to its export barriers, import barriers, and foreign direct investment (FDI) restrictions during the period encompassing China's WTO entry, and these reforms may also have affected firm productivity and exports and therefore need to be included in our empirical analysis. We describe these policy changes in Appendix C, and incorporate variables to reflect them in our analysis below.

Upon China's WTO entry, China benefited from trade liberalization by other countries. One benefit was the U.S. Congress granting Permanent Normal Trade Relations (PNTR). It is important to realize that PNTR did not actually change the tariffs that China faced on its exports to the U.S. The U.S. had applied MFN tariffs on its Chinese imports since 1980, but they were subject to annual renewal, with the risk of tariffs reverting to the much higher non-NTR tariff rates assigned to some non-market economies. These non-NTR tariffs are set at the 1930 Smoot-Hawley Tariff Act levels and can be found in "column 2" of the U.S. tariff schedule. Studies by Pierce and Schott (2016) and Handley and Limão (2017) find that the removal of the uncertainty surrounding these tariff rates helped boost China's exports to the U.S. economy. Following this literature, we refer to this measure as the "gap" and define it as the difference between the column 2 tariff and the U.S. MFN tariff rate in 2000. We see from the last two columns in Table 3 that the average gap was very high at 24 percent, with a large standard deviation. We will exploit this cross-industry variation to analyze its effect on China's U.S. exports.

based on industry descriptions. We include both manufacturing and nonmanufacturing inputs and drop "waste and scrapping".

3.3 Trade Liberalization and Chinese Firms' Imported Inputs

Our immediate goal is to estimate the effect of China's tariff reductions on each firm's imports of inputs, from which we construct the exogenous change in firm-level import variety, denoted by $\hat{\lambda}_{ft}$. Specifically, we estimate the following import value and import participation equations using firm-level data from China Customs and disaggregated import tariff data:

$$\ln M_{fnt} = \gamma_1 \ln \tau^i_{nt} + \gamma_2 \ln \tau^i_{nt} \times Process_f + \gamma_f + \gamma_t + \epsilon_{1fnt}, \tag{15}$$

$$I^M_{fnt} = \theta_1 \ln \tau^i_{nt} + \theta_2 \ln \tau^i_{nt} \times Process_f + \theta_3 \ln ShareEligible_{gt} + \theta_4 \ln ShareEligible_{gt} \times Foreign_f + \theta_f + \theta_t + \epsilon_{2fnt}, \tag{16}$$

where $\ln M_{fnt}$ is the log value of Chinese firm f's imports in HS 8-digit category n at time t, τ^i_{nt} is the Chinese MFN import tariff, $Process_f$ is an indicator variable that equals 1 if more than 99 percent of the firm's imports were for processing and re-export, and γ_f and γ_t are full sets of firm and year fixed effects.

Since $\ln M_{fnt}$ is not defined for zero import values, we need to control for potential selection bias. We do so by estimating an import selection equation (16), where the dependent variable, I^M_{fnt}, equals one if the firm imports an intermediate input in category n and zero otherwise. It comprises all of the explanatory variables in the import value equation plus an additional variable $ShareEligible_{gt}$ measuring the share of firms with sufficient capital to be allowed to trade. Since that capital requirement depends on the industry the firm produces in, we merge data on this variable developed by Bai et al. (2017) using the firm's largest export industry g. We also interact $ShareEligible_{gt}$ with a foreign firm indicator, as foreign firms are likely to have better access to capital.

We estimate the import participation equation using a linear probability model (LPM) instead of a probit model. This enables us to include the same fixed effects as in the import value equation and avoids the incidental parameter problem inherent in nonlinear models that gives rise to biased estimates. One potential drawback of using a LPM is that some of the predictions might lie outside the 0 to 1 range, although in practice there are very few of these observations. We control for selection bias in equation (15) by including a fourth order polynomial series of the predicted probabilities from equation (16). In an alternative specification we adopt a more flexible approach by including additional explanatory variables in (16) comprising interactions and polynomial series of all the variables in that equation, and then including a fourth order polynomial series of predicted probabilities in the import value equation.[16]

We report results in Table 4. In column 1, we see that the probability of importing inputs increases when tariffs are lowered, but only for non-processing firms. Processing imports already enjoyed duty-free access so a lower tariff on those imports would not reduce the cost of importing and thus

[16] See Das et al. (2003) and Dahl (2002).

Table 4: Chinese Input Imports

Dependent variable	I^M_{fnt} =1 if M_{fnt} >0	$ln(M_{fnt})$		
	(1)	(2)	(3)	(4)
$ln(\tau_{nt})$	-0.200***	-5.466***	-5.378***	-5.121***
	(0.026)	(0.662)	(0.660)	(0.665)
$ln(\tau_{nt}) \times Process_f$	0.536***	5.531***	5.100***	4.619***
	(0.051)	(0.780)	(0.778)	(0.811)
$ln(ShareEligible_{gt})$	-0.075***			
	(0.005)			
$ln(ShareEligible_{gt}) \times Foreign_f$	0.186***			
	(0.005)			
$Selection\ Control$		no	yes	yes
$Year\ FE$	yes	yes	yes	yes
$Firm\ FE$	yes	yes	yes	yes
# obs.	25,599,921	7,027,916	7,027,916	7,027,916
R^2	0.048	0.152	0.152	0.153

Notes: All observations are at the HS8-firm-year level. The sample includes all Chinese importers that exported at least once to the U.S. during the sample period. All columns include firm fixed effects and year fixed effects. The dependent variable in column 1 equals 1 for positive import values and zero otherwise, 27.5% of the observations equal 1. For columns 2 to 4, the dependent variable is the log of a Chinese firm's import value at the HS 8-digit level at time t. Both columns 3 and 4 control for selection, with the more flexible approach in column 4. We cluster standard errors at the HS 8-digit level. The *Process* dummy equals 1 if more than 99% of the firm's imports were processing over the sample, and the *Foreign* dummy equals 1 if the firm in China was classified as foreign at any time during the sample in the import customs data. We use the predictions from column 4 to construct instruments for firm-level TFP as described in the text.

should not have a direct impact on imports. Lower tariffs actually appear to reduce the probability of importing for processing firms, which may be due to it being less worthwhile to comply with processing-trade requirements.[17]

The import value regressions show that lower tariffs cause Chinese firms to increase imports on the intensive margin. In column 2 of Table 4, the coefficient on tariffs is negative and significant, $\gamma_1 = -5.5$, showing that trade liberalization increased imports for non-processing firms. In contrast, the coefficient on the tariff interacted with a processing dummy is positive, $\gamma_2 = 5.5$. The sum of γ_1 and γ_2 is not significantly different from zero, suggesting that the intensive margin for processing imports is not affected by lower tariffs. These results are robust to the two different sets of selection controls in columns 3 and 4, with the tariff coefficients very close to those in column 2.

Thus, Chinese tariff reductions caused Chinese firms to expand imports of inputs on both the

[17]This result is consistent with Kee and Tang (2016). We also experimented with including the "gap" variable used by Pierce and Schott (2016), Handley and Limão (2017), interacted with the WTO dummy in equation (16), but the coefficient was insignificant. Including the gap variable had no effect on the coefficients on the tariff variables.

extensive and intensive margins. This should also produce an increase in dual TFP according to equation (14). We now use the predicted values from column 4 of Table 4 (estimating equation (15)) to construct estimates of key components of λ_{ft}, which will become instruments in subsequent regression analysis of TFP and Chinese firm exports. The first instrument is the firm's fitted *total* imports at time t —we take the exponential of the fitted import values $\ln \hat{M}_{tot,ft}$, summed across all of the firm's imports n in each year to get the firm's total and then take the log. That instrument corresponds to the denominator of λ_{ft}. The numerator of λ_{ft} is the expenditure on inputs that are common in period t and period 0, or any non-empty subset of these common inputs. In practice, we found that many firms did not have common imported inputs over the entire sample period, so we could not construct predicted values for the numerator of λ_{ft}. Instead, we use the predicted import value of the firm's largest HS 8-digit category import each year, and denote the fitted value of those imports by $\ln \hat{M}_{max,ft}$. Then the difference between these two instruments, $\ln \hat{\lambda}_{ft} \equiv \ln \hat{M}_{max,ft} - \ln \hat{M}_{tot,ft}$, should be negatively related to the number of imported inputs, and therefore capture the expansion of imported inputs on the extensive margin. Note that the two instruments are very non-linear functions of thousands of underlying tariffs τ_{nt}^{i} applied to each firm's specific imports, and can be used as instruments even in specifications where the industry-level input tariffs $Input\tau_{gt}$ enter linearly as regressors.

3.4 Imported Inputs and Total Factor Productivity

We estimate TFP using data on all manufacturing firms from the Annual Survey of Industrial Firms (ASIF) from 1998 to 2007, produced by the National Bureau of Statistics. We follow Olley and Pakes (1996) by taking account of the simultaneity between input choices and productivity shocks using firm investment. We modify the procedure to incorporate the firm's decision to enter the international market, via importing and/or exporting as in Amiti and Konings (2007).[18] Further details on the estimation of TFP are provided in Appendix E.

We find that average TFP growth of Chinese exporters has been very high. For the average exporter in the full sample it has grown 10 percent per year, with similar growth of 11 percent per year in the *matched* sample where firms appear in both the ASIF and in Chinese Customs data. We interpret our primal TFP results as similar to dual TFP on the left of (14), so that the variables on the right of (14) will be determinants of TFP.[19] In particular, from the previous section we obtain an instrument for firm TFP, representing the first term on the right of (14), and the index of imported input tariffs $Input\tau_{gt}$ representing the second term. The results from regressing TFP on these variables are shown in Table 5.

[18] As a robustness check we also estimate TFP measures using the methodology in De Loecker (2013), which allows for learning by exporting. Our results are robust to these alternative measures.

[19] A difference between primal and dual TFP arises when firms have markups, as explained by Roeger (1995). Brandt et al. (2017) also stress the primal TFP is difficult to separate from the markup of the firm. We are not that concerned with this issue, because we are not trying to identify marginal costs in order to measure markups. Rather, we will be using our measure of TFP (which might be conflated with markups to some extent) as an explanatory variable for firm prices, in section 4. For an examination of the markups of Chinese exporters, see Corsetti and Crowley (2018).

Table 5: Chinese Firm TFP and Importing

Dependent variable	$ln(TFP_{ft})$			
	(1)	(2)	(3)	(4)
$ln(\hat{M}_{max,ft})$	-0.041***		-0.041***	-0.042***
	(0.012)		(0.012)	(0.013)
$ln(\hat{M}_{tot,ft})$	0.052***		0.051***	0.052***
	(0.005)		(0.005)	(0.005)
$ln(\hat{\lambda}_{ft})$		-0.053***		
		(0.005)		
$ln(Input\tau_{gt})$			0.275	0.243
			(0.435)	(0.442)
$ln(Gap_g) \times WTO_t$				0.027
				(0.062)
$Year\,FE$	yes	yes	yes	yes
$Firm\,FE$	yes	yes	yes	yes
# obs.	82,203	82,203	80,043	79,276
R^2	0.692	0.691	0.692	0.691

Notes: The observations are at the firm-year level. The sample includes all firms that could be matched from the customs data with the ASIF survey, from which we estimate TFP. The dependent variable in the first 6 columns is ln(TFP) estimated using Olley-Pakes methodology as described in section 3.3. The $\hat{M}$ variables are constructed from column 4 in Table 4, as described in the text, with ln$\hat{\lambda}_{ft}$ =ln$\hat{M}_{max,ft}$−ln$\hat{M}_{tot,ft}$. In column 3, we add in the input tariff. Because the observations are at the firm-year level, we merged the input tariff and the gap that corresponded to the firm's largest HS 6-digit total (world) export, which we denote as g. All columns are estimated using OLS. All columns control for selection into importing nonparametrically. As the sample includes nonexporters, we do not need to control for export selection bias. All standard errors are clustered at the firm level.

In column 1 of Table 5, we regress ln(TFP_{ft}) on the two instruments $\ln \hat{M}_{max,ft}$ and $\ln \hat{M}_{tot,ft}$, and see that they both have the expected signs, with a coefficient of -0.04 on $\ln \hat{M}_{max,ft}$ and +0.05 on $\ln \hat{M}_{tot,ft}$. In column 2, we include the difference between the two instruments $\ln \hat{\lambda}_{ft} = \ln \hat{M}_{max,ft} - \ln \hat{M}_{tot,ft}$ to proxy for lnλ_{ft}, and we see that the coefficient of -0.05 has the expected negative sign. These results indicate that more imported varieties, due to lower tariffs, leads to higher firm-level TFP. In column 3, we also include the input tariff $Input\tau_{gt}$ that is associated with the firm's largest HS 6-digit export industry (to the world). For example, if the firm's largest export is apparel, then the input tariff is the weighted average of all of the intermediate inputs used to produce apparel. We find that the coefficient on input tariffs is insignificantly different from zero, so we cannot reject the hypothesis that all TFP gains from lower input tariffs accrue through the firm importing more inputs.

In column 4, we include the "gap" variable used by Pierce and Schott (2016) and Handley and Limão (2017), interacted with a dummy variable for China's entry to the WTO. This variable measures the gap between the column 2 tariffs that the United States applied to communist countries, and the MFN rate that China enjoyed by an annual vote in Congress even before its accession to the

WTO. When China joined the WTO it received permanent normal trade relations, meaning that it received the MFN rate without that annual vote, so that particular source of uncertainty about its U.S. tariff was removed. Handley and Limão (2017) argue that this removal of uncertainty would stimulate investment and entry by Chinese exporters. In column 4, we do not find any evidence of an impact on TFP, but in the next section we will find that the "gap" variable is important in stimulating entry by new exporters. We now have several alternatives for constructing predicted values of TFP following WTO entry. We proceed by using column 1 to construct $\ln(\hat{TFP}_{ft}) = -0.04 \times \ln \hat{M}_{max,ft}$ + $0.05 \times \ln \hat{M}_{tot,ft}$, which we shall use in the next section.

4 WTO Entry, Export Participation and Export Prices

We established in section 3 that lower tariffs on imported inputs caused an expansion in the variety of imported inputs and an increase in Chinese firms' TFP. In this section we will estimate the effect of China's WTO entry on Chinese firms' participation in exporting to the U.S. market and on their export prices.

4.1 Tariffs and the Entry of Exporters

We now return to the theoretical analysis of Chinese exporters, and re-introduce the subscript for industry g, which represents an HS 6-digit category. Within industry g, Chinese firms f sell more disaggregate goods $h \in H_g$ at the HS 8-digit level, so that p_{fht} is the price of a product exported to the United States measured inclusive of U.S. tariffs. Under this notation, the firm-product pair fh plays the role of the product index ω used in section 2. We drop the country superscript i used earlier, since we are focusing on Chinese exporting firms. In this notation, the share $s_g^i(\omega)$ appearing in equation (5) is re-written as s_{fht} for $h \in H_g$.

We suppose that Chinese firms act as Bertrand oligopolists in the U.S. market and recognize that a change in their prices can have an impact on the price index in (4). In that case, the elasticity of demand for a firm selling variety h is $\eta_{fht} = \sigma_g s_{fht} + (1 - s_{fht})\rho_g$ for $h \in H_g$. The firm's price is obtained as a markup over marginal costs:

$$p_{fht} = \frac{\eta_{fht}}{(\eta_{fht} - 1)} C(P_t^D, c_{ft}^M, \varphi_{ft}) \tau_{ht}, \tag{17}$$

where τ_{ht} is one plus the *ad valorem* U.S. tariff. As the share of the firm rises then the elasticity will fall (since $\sigma_g < \rho_g$), so that the markup over marginal costs will rise.

The quantity sold in the U.S. can be obtained from the CES demand function:

$$q_{fht} = \left(\frac{p_{fht}}{P_{gt}} \right)^{-\rho_g} \frac{X_{gt}}{P_{gt}}, \tag{18}$$

where X_{gt} is the expenditure on all varieties that the U.S. imports from China in HS 6-digit industry g, and P_{gt} is the price index for these imports (corresponding to P_{gt}^i in (4) but without the superscript $i = China$). Multiplying this equation by the p_{fht} and using (17) , we solve for firm exports:

$$p_{fht}q_{fht} = X_{gt}\left(\frac{\eta_{fht}C_{ft}\tau_{ht}}{(\eta_{fht}-1)P_{gt}}\right)^{1-\rho_g}, \tag{19}$$

where $C_{ft} = C(P_t^D, c_{ft}^M, \varphi_{ft})$ is the unit costs given in (11).

The export revenue of the firm must be divided by τ_{gt} to reflect tariff payments, and then further divided by the elasticity η_{fht} to obtain firm variable profits. After deducting the per-period fixed costs of exporting denoted by F_g, the one-period value of the firm is:

$$v(\varphi_{ft}, \tau_{ht}) \equiv \frac{p_{fht}q_{fht}}{\tau_{ht}\eta_{fht}} - F_g = \frac{X_{gt}}{\tau_{ht}\eta_{fht}}\left(\frac{\eta_{fht}C_{ft}\tau_{ht}}{(\eta_{fht}-1)P_{gt}}\right)^{1-\rho_g} - F_g \geq 0.$$

This expression is bounded below by zero because a firm with very low productivity will exit and not pay the fixed costs of F_g. If there were no uncertainty about tariffs, then we can use the per-period profits to solve for the free entry condition of an exporter as:

$$\int_\varphi v(\varphi, \tau_h)dG \geq F_g^E, \tag{20}$$

where $G(\varphi)$ is the distribution function of firm productivities, and paying the sunk cost of F_g^E allows the firm to draw its productivity φ_f, which for simplicity we now assume does not change over time.

The free entry condition (20) is very similar to Melitz (2003) except that we have allowed for variable markups charged by the firm. The form of the free entry condition changes, however, when there is uncertainty about tariffs, which we can incorporate using a simplified version of Handley and Limão (2017).[20] Suppose that the Chinese firm faces two possible values of the U.S. tariff $\tau_{ht} \in \left\{\tau_h^{MFN}, \overline{\tau}_h\right\}$, which are at either the MFN level or the alternative column 2 level $\overline{\tau}_h > \tau_h^{MFN}$. The firm's decision about its price is made after the tariff is known, while the decision about whether to participate in the export market is made before the tariff is known, so the tariff is the key variable that changes over time.

We suppose for simplicity that if the tariff starts at its MFN level then it remains there in the next period with probability π, and with probability $(1-\pi)$ the tariff moves to its column 2 level; whereas if the tariff starts at its column 2 level then it stays there forever. With a discount rate $\delta < 1$, the present discounted value of a Chinese firm facing MFN tariffs is

$$V(\varphi_f, \tau_h^{MFN}) = v(\varphi_f, \tau_h^{MFN}) + \delta\left[\pi V(\varphi_f, \tau_h^{MFN}) + (1-\pi)V(\varphi_f, \overline{\tau}_h)\right].$$

Since $V(\varphi_f, \overline{\tau}_h) = v(\varphi_f, \overline{\tau}_h)/(1-\delta)$ by our assumption that the column 2 tariff is an absorbing state, we obtain the *entry condition* for a Chinese firm facing MFN tariffs,

$$\int_\varphi V(\varphi, \tau_h^{MFN})dG = \int_\varphi \left\{\frac{v(\varphi, \tau_h^{MFN})}{(1-\delta\pi)} + \frac{\delta(1-\pi)v(\varphi, \overline{\tau}_h)}{(1-\delta)(1-\delta\pi)}\right\} dG \geq F_g^E. \tag{21}$$

[20] Our simplified treatment does not allow firms to upgrade their technology, as in Handley and Limão (2017), and draws on Feng et al. (2017).

This form of the free entry condition for Chinese firms is quite different from that in (20), because the column 2 tariff $\overline{\tau}_h$ enters on the right. In Appendix F we solve condition (21) and show that entry depends on the "gap" between the MFN and column 2 tariffs, defined by $Gap_h \equiv \left(\ln \overline{\tau}_h - \ln \tau_h^{MFN}\right)$. To match U.S. and Chinese data we construct this gap at the HS 6-digit rather than 8-digit level, which we refer to Gap_g. Provided that Chinese exporters make their pricing decisions *after* U.S. MFN tariff is known, then the gap should not affect their pricing decisions, but it will have an impact on the entry of exports, as we show in the next section.

4.2 Empirical Analysis of Export Participation

We now estimate an export participation equation for Chinese exporters to the U.S. that is the empirical counterpart to the free entry condition (21):

$$\begin{aligned} I_{fht}^X = {} & \delta_1 lnT\hat{F}P_{ft} + \delta_2 \ln Input\tau_{gt} + \delta_3 \ln Input\tau_{gt} \times Process_{fh} + \delta_4 \ln P_{gt}^D + \delta_5 \text{ln} Gap_g \times WTO_t \\ & + \delta_6 \text{ln} ShareEligible_{gt} + \delta_7 \text{ln} ShareEligible_{gt} \times Foreign_f + \delta_f + \delta_h + \delta_t + \epsilon_{3fht}. \end{aligned} \tag{22}$$

We estimate the export participation equation (22) using all firm-industry observations for the period 2000 to 2006 for the set of firms that have at least one non-zero U.S. export observation. The binary dependent variable I_{fht}^X equals 1 if the Chinese firm f had positive export value in product h, defined at the HS 8-digit level, at time t, and zero for all fht observations where the firm did not export in those HS 8-digit categories. We include: year fixed effects to control for macro factors that affect overall entry and exit; firm fixed effects to account for unobserved firm heterogeneity; and industry effects since firms can span many products.

The level of firm marginal costs are critical to satisfying the entry condition (21). We control for marginal costs by including: i) predicted TFP; ii) the industry-level index of input tariffs $Input\tau_{gt}$; and iii) an index of the domestic prices of intermediate inputs in each industry g, P_{gt}^D.[21] We include the fitted TFP variable, $(T\hat{F}P_{ft})$, directly in the export selection equation instead of instrumenting for measured TFP so that we can use the full sample of exporting firms, otherwise we would be limited to using the much smaller matched sample. We also need to control for Gap_g, which is interacted with a dummy variable WTO_t that equals unity after China joins the WTO in 2001. As additional controls we include $ShareEligible_{gt}$, measuring the share of firms that met China's capital requirements to engage in international trade, and its interaction with $Foreign_f$, an indicator variable that equals 1 if firm f was ever classified as foreign, since foreign firms may have systematically different capital levels to domestic firms. The Gap_g and $ShareEligible_{gt}$ variables affect the export participation decision but in our model do not affect the intensive margin of exporting; these variables will therefore provide exclusion restrictions when we need to control for selection in our export price equations in section 4.3.

[21] These are the domestic intermediate input price indexes, constructed by aggregating industry output deflators from Brandt et al. (2017) using the same Chinese IO table described in section C.

Table 6: Chinese Firms U.S. Exports

Dependent variable	I^X_{fht} =1 if X_{fht} >0	$ln(s_{fht})/(1-\bar{\rho})$		$ln(price_{fht})$		
		IV	IV			
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(\widehat{TFP}_{ft})$	1.918***			-1.000†	-1.000†	-1.000†
	(0.033)					
$ln(TFP_{ft})$		-0.938***	-1.062***			
		(0.149)	(0.292)			
$ln(Input\tau_{gt})$	-1.948***			3.101***	3.645**	3.632**
	(0.452)			(1.167)	(1.583)	(1.594)
$ln(Input\tau_{gt}) \times Process_{fh}$	-0.198			-1.689***	-1.165**	-1.157**
	(0.153)			(0.572)	(0.516)	(0.518)
$Process_{fh}$	0.020			0.172**	0.113*	0.113*
	(0.012)			(0.066)	(0.064)	(0.064)
$ln(P^D_{gt})$	0.024			0.466**	0.470**	0.469**
	(0.096)			(0.188)	(0.187)	(0.187)
$ln(Gap_g) \times WTO_t$	0.070*					-0.034
	(0.036)					(0.111)
$ln(ShareEligible_{gt})$	-0.012					
	(0.024)					
$ln(ShareEligible_{gt}) \times Foreign_f$	0.251***					
	(0.017)					
$HS6\ Industry \times Year\ FE$	no	yes	yes	no	no	no
$HS8\ Industry\ FE$	yes	no	no	yes	yes	yes
$Year\ FE$	yes	no	no	yes	yes	yes
$Firm\ FE$	yes	yes	yes	yes	yes	yes
$Selection\ Control$		no	no	no	yes	yes
# obs.	3,983,952	158,473	23,155	1,332,574	1,315,157	1,315,157
R^2	0.129			0.951	0.951	0.951

† The coefficient, β_1, is constrained to equal -1.

Notes: All observations are HS8-firm-year. In column 1, the sample includes all Chinese firms that exported at least once to the U.S. during the sample period. The dependent variable in column 1 equals 1 for positive export values (35.1%) and zero otherwise. ln($T\hat{F}P_{ft}$) are the fitted values constructed from column 4 in Table 4. $Input\tau_{gt}$ is the input tariff constructed using China's input-output table at the IO level, mapped to HS 6-digit industry codes. $Process_{fh}$ is a processing dummy equal to 1 if more than 99% of a Chinese firm's U.S. exports in HS8 industry h are processing. Gap_g is the difference between HS 6-digit column 2 and MFN tariffs, while $ShareEligible_{gt}$ is the share of firms eligible to export in HS 6-digit industry g. The *Foreign* dummy equals one if the firm in China was classified as foreign at any time during the sample in the customs data. In columns 2 and 3, the dependent variable is a Chinese firm's exports to the U.S. in HS 8-digit industry h as a share of total Chinese U.S. exports in the corresponding HS6 category, divided by $1-\bar{\rho}$, where $\bar{\rho}$ is the median estimated elasticity of substitution ($= 4.57$, see section A for more detail). Columns 2 and 3 are estimated using IV and include industry×year fixed effects as well as firm fixed effects. The dependent variable in columns 4 to 6 is the log of the unit value of Chinese firms exports to the U.S, estimated using weighted least squares (WLS) with export value weights. Column 6 controls for selection into importing and exporting. All standard errors are clustered at the IO industry level, except in columns 2 and 3 where they are clustered at the firm level.

We present the results in column 1 of Table 6. We find that the coefficient on predicted lnTFP_{ft} is positive and significant, indicating a higher probability of exporting for firms with higher predicted TFP arising from more imported inputs. The coefficient on China's input tariff suggests that lower Chinese import tariffs on intermediate inputs increase the probability of exporting. This input tariff variable is interacted with an export processing dummy at the firm-HS8 level, defined as equal to unity if the Chinese firm's exports to the U.S. in the HS8 product were more than 99% processing over the sample period. The coefficient on this interaction term is insignificant, suggesting that there is no significant differential effect of lower input tariffs on the export probabilities of processing and ordinary export firms. This is somewhat surprising, but could reflect spillover benefits for all firms. For example, lower input tariffs could also lower prices of domestically produced inputs, as we discuss in section 4.3 below. Alternatively, this result may simply reflect our definition of "processing", which in Table 6 is based on exports of the specific HS8 product to the U.S. The exporting firm may only be getting tariff relief on some inputs, so that a reduction in input tariffs may still improve that firm's access to imported inputs, thereby increasing TFP and lowering costs.

We also find that the probability of exporting to the U.S. increases in the post-WTO period in industries where Gap_g is high, consistent with the literature (see Pierce and Schott (2016)). Once China entered the WTO, the threat of raising U.S. import tariffs to the high column 2 tariffs was removed, increasing the expected profitability of exporting in those industries. The positive coefficient on the interactive $ShareEligible$ variable with the foreign dummy is consistent with the idea that foreign firms are in a better position to meet capital requirements for entering export markets.

An important implication of these results is that China's WTO accession caused an exogenous expansion in the number of firms exporting from China to the U.S. This will be invaluable for identifying the effect of expanded Chinese trade on the U.S. price index.

4.3 WTO Entry and Chinese Firms' U.S. Export Prices

China's WTO entry not only affects export participation, but also China's export prices. To study this, we return to the firm pricing equation (17), and remind the reader that we have allowed for taste parameters $\alpha_g^i(\omega)$ in the CES price index (4), which we interpret as *product quality.* We drop the superscript *i* for China and rewrite these quality parameters as α_{fht}, where as in section 4.1, the firm-product pair *fh* plays the role of ω. We now suppose that the specification of firms' marginal costs in section 4.1 refers to the cost of producing one unit of a *quality-adjusted* quantity $\alpha_{fht}q_{fht}$, which would sell at the *quality-adjusted* price p_{fht}/α_{fht}. Then (17) is re-written as

$$\frac{p_{fht}}{\alpha_{fht}} = \frac{\eta_{fht}}{(\eta_{fht}-1)} C(P_t^D, c_{ft}^M, \varphi_{ft})\tau_{ht}. \tag{23}$$

The estimation of a pricing equation in a variable markup model is discussed by Amiti et al. (2016), who show that in a nested CES framework, firm's prices can be estimated as a log-linear function of marginal costs and competitor's prices. We will incorporate firms' own marginal costs by using their TFP, which will be treated as endogenous. Competitors' prices are also endogenous, so instead we incorporate variables that affect their marginal costs. Those variables include the index of input tariffs $Input\tau_{gt}$, and the index of domestic prices of intermediate inputs in each industry g, P^D_{gt}. The tariff variable τ_{ht} is the U.S. MFN tariff on China's exports to the U.S., which differs hardly at all over our sample period and is absorbed into firm, industry, and year fixed effects β_f, β_h and β_t. This gives us the pricing equation:

$$\ln p_{fht} = \beta_1 \ln TFP_{ft} + \beta_2 \ln Input\tau_{gt} + \beta_3 \ln P^D_{gt} + \beta_f + \beta_h + \beta_t + \epsilon_{4fht}, \tag{24}$$

where unobserved quality α_{fht} from the left of (23) is absorbed into the error term in (24), $\epsilon_{4fht} \equiv \ln \alpha_{fht}$.[22]

Product quality will likely be correlated with the firm's TFP, which means that we would not obtain an unbiased estimate of β_1 even when attempting to instrument for TFP. We can correct for the quality bias by substituting the pricing equation (24) into the log share equation for Chinese firms in (5) to obtain:

$$\frac{\ln s_{fht}}{(1-\bar{\rho})} = \ln\left(\frac{p_{fht}}{\alpha_{fht}}\right) - \ln P_{gt} = \beta_f + \beta_{gt} + \beta_1 \ln TFP_{ft} + (\epsilon_{4fht} - \ln \alpha_{fht}), \tag{25}$$

where $\beta_{gt} \equiv \beta_t - \ln P_{gt} - \beta_2 \ln Input\tau_{gt} - \beta_3 \ln P^D_{gt}$ are introduced as year$\times$ HS 6-digit industry fixed effects, which absorb all industry g variables. Given the error term in the pricing equation (24) is $\epsilon_{4fht} \equiv \ln \alpha_{fht}$, the error in (25) cancels out, which will allow us to obtain an unbiased estimate of β_1 from this share equation.

We should really think of the dependent variable in (25) as reflecting the *quality-adjusted price* of each firm (relative to the industry price index), analogous to Hallak and Schott (2011) and Khandelwal (2010). The dependent variable is the value of a Chinese firm's exports in product h to the U.S. relative to total Chinese exports to the U.S. in g divided by one minus the median estimated elasticity $\bar{\rho}$ in industry g (equal to 4.57).[23] Imposing this unbiased estimate of β_1 in the pricing equation 24, we can estimate the remaining parameters of that equation and construct predicted export prices. We also include firm fixed effects to control for unobserved firm heterogeneity. We estimate equation (25) using the two $\hat{M}$ variables capturing predicted imported input expansion from section 3.1 as instruments for measured lnTFP.

We report the results in columns 2 and 3 of Table 6. In the untabulated first stage results, the coefficient on ln$\hat{M}_{max,ft}$ is -0.06 and the coefficient on ln$\hat{M}_{tot,ft}$ is $+0.05$, both significant at the 1 percent level and similar in magnitude to those in the firm-level regressions in column 3 of Table 4. Both pass the over-identification and weak instrument tests.[24] In column 2, we include all possi-

[22] The error will also incorporate terms reflecting the fact that the pass-through coefficient β_1 differs across firms, as discussed in Amiti et al. (2016). As analyzed by Murtazashvili and Wooldridge (2008), pooling across firms to obtain a single coefficient means that additional terms are introduced into the error.

[23] We discuss estimation of elasticities in Appendix A below.

[24] We do not report the first stages to save space and because the coefficients on the two instruments are so close to the regression results in Table 4. The Cragg-Donald Wald F-stat in column 2 is 172.29 and the p-value for the overid test is 0.10. In column 3, the F-stat is 32.8 and the overid p-value is 0.43.

ble observations from the matched sample and find that we cannot reject that the coefficient β_1 on lnTFP_{ft} equals -1. To check whether sample selection is affecting the magnitude of this coefficient, we re-estimate equation (25) using a balanced sample in column 3, that is only including the observations for which the Chinese firm exports the same HS8 product to the U.S. in all years.[25] The β_1 estimate in both columns is close to -1. We impose this result in the subsequent columns reporting export price regressions.

In columns 4-6 the dependent variable, ln$price_{fht}$, is the log unit value of each Chinese exporting firm f in each product h, inclusive of freight, insurance, and duties.[26] We regress the export prices on input tariffs and constrain the coefficient $\hat{\beta}_1$ on lnTFP_{ft} to be -1. The observations are weighted using export values, so that observations where exports are higher (and unit values may be measured with more precision) are given more weight. The results in columns 4-6 show that lower input tariffs cause lower export prices, and the coefficient on input tariffs is surprisingly high, ranging between 3.1 and 3.6, depending on the specification. The coefficient on the input tariff interacted with a processing dummy is negative and significant, but the sum of the two coefficients is still positive, indicating that processing export prices are also lower when there are lower input tariffs. These results are similar to what we found in column 1, which focused on the probability of exporting, and suggest that lower input tariffs have a beneficial impact on *all* Chinese firms using these inputs.

An alternative explanation for these findings is that the reduction in input tariffs also lowers the price of domestic firms producing the same inputs. However, we already control for lnP^D_{gt} in Table 6, which has a significant positive coefficient of 0.47, indicating that lower prices of domestically purchased intermediate inputs also lowers export prices. Although the inclusion of lnP^D_{gt} in the equation results in a lower coefficient on input tariffs it still remains large.[27] Indeed, the variable $Input\tau_{gt}$ has roughly the same size of coefficient (about 3.5) as in our motivating regressions in Table 1.

An explanation we propose for these findings is that lower input tariffs actually lead to *greater entry and product variety* of domestic input-producing firms. The result that lower tariffs *enhance* entry into the domestic industry is found to hold under weak conditions by Caliendo et al. (2015), in a model with heterogeneous firms.[28] Indeed, Kee and Tang (2016) found increased purchases of domestic Chinese intermediate inputs since its WTO entry, especially among processing exporters. They attribute that increase to China's trade and investment liberalization, which they argue led to a greater variety of domestic materials becoming available at lower prices. We have not been able to include the *variety* of domestic inputs in our analysis, and to the extent that it is positively correlated with the tariff reductions on imported intermediate inputs, that can help explain the large coefficients

[25] We cannot use the propensity scores from the participation equations here because of the presence of industry $\times$ year fixed effects, which would invalidate our exclusion restrictions.

[26] The results are unchanged for firm unit values that exclude duties because the U.S. MFN import tariffs are very low and have hardly changed over the sample period. For this reason, the MFN tariff is not included on the right of (24).

[27] The coefficient on $Input\tau_{gt}$ in a specification like column 5 but without lnP^D_{gt} is 4.1.

[28] According to Theorem 1 of Caliendo et al. (2015), this result follows if there is a non-traded sector in the economy, and that tariff revenue is distributed to consumers who spend it on the traded and non-traded sectors. From Lerner symmetry, an import tariff in this setting is equivalent to an export tax, which reduces entry in the differentiated sector, so that a reduction in tariffs (near free trade) raises entry.

on $\ln Input\tau_{gt}$ found in Table 6. As mentioned in section 4.2, another explanation may be that exports are classed as "processing" even if the firm is only getting tariff relief on a subset of imported inputs.

We see that these results in the pricing equation are robust to controlling for selection bias in column 5, with selection into exporting modeled using the predicted probabilities from column 1 in Table 6 and for importing from column 1 in Table 4. Finally, in column 6, we show that Gap_g has a small coefficient, insignificantly different from zero, while the positive coefficient on input tariffs continues to be large and significant.

To summarize results so far, lower Chinese input tariffs increase Chinese firms' imports of intermediate inputs, both on the intensive and extensive margins, and thus increase their TFP. This, in turn, increases their probability of entry into the U.S. market. Lower input tariffs also reduce Chinese firms' export prices in the U.S. market. The effect from PNTR is more limited, with no direct effect on export prices, but an effect through new entry into exporting. We now turn to evaluate how these effects feed into U.S. prices.

5 Impact on U.S. Prices

5.1 Measuring the Aggregate U.S. CES Price Index

While equation (6) provides us with an exact price index for varieties sold from country i (China) to the U.S., we also want to incorporate all other countries selling good g. This can be done in principle by using the exact price index for every other country, as we have done for China. But we are not able to implement that approach because we do not have the firm-level export data for all other countries. Instead, for countries exporting to the U.S. other than China we will use their unit-values at the HS 10-digit level, and we will measure the product variety of these HS 10-digit products *within* each HS 6-digit industry. That is, for each HS 6-digit industry, we construct the variety terms λ_{gt}^{j} for the HS 10-digit products exported by each country to the U.S. and the change in variety using equation (8). We also construct the Sato-Vartia index over the "common" unit-values $uv_{gt}^{j}(\omega)$ for 10-digit HS categories $\omega \in \overline{\Omega}_g^j$ within each HS 6-digit industry, exported by each country other than China in the periods t and 0. For these other exporters, we therefore measure,[29]

$$\frac{P_{gt}^{j}}{P_{g0}^{j}} = \left[\prod_{\omega \in \overline{\Omega}_g^j} \left(\frac{uv_{gt}^{j}(\omega)}{uv_{g0}^{j}(\omega)} \right)^{w_{gt}^{j}(\omega)} \right] \left(\frac{\lambda_{gt}^{j}}{\lambda_{g0}^{j}} \right)^{\frac{1}{\rho_g - 1}}, \quad j \neq i. \tag{26}$$

We will aggregate over these U.S. import price indexes from all source countries j, including the U.S. itself, using Sato-Vartia price weights defined over countries. Denoting the non-empty intersection of countries selling in industry g to the U.S. in period t and period 0 by $\overline{I}_g = I_{gt} \bigcap I_{g0}$, which we call the "common" countries, the Sato-Vartia weights at the country-industry level are

[29] In Appendix G we show how the Sato-Vartia indexes over unit-values for exporting countries other than China can be improved to become a Sato-Vartia index over prices by using the Herfindahl index of exporting firms from these countries to the U.S. This adjustment will be made in the robustness exercise.

$$W_{gt}^{j} = \frac{\left(\overline{S}_{gt}^{j} - \overline{S}_{g0}^{j}\right) / \left(\ln \overline{S}_{gt}^{j} - \ln \overline{S}_{g0}^{j}\right)}{\sum\limits_{k \in \overline{I}_{gt}} \left(\overline{S}_{gt}^{k} - \overline{S}_{g0}^{k}\right) / \left(\ln \overline{S}_{gt}^{k} - \ln \overline{S}_{g0}^{k}\right)}, \text{ with } \overline{S}_{gt}^{j} \equiv \frac{P_{gt}^{j} Q_{gt}^{j}}{\sum\limits_{k \in \overline{I}_{gt}} P_{gt}^{k} Q_{gt}^{k}}, \;\; j \in \overline{I}_{gt}. \tag{27}$$

The share of countries selling to the U.S. in both period t and period 0 is,

$$\Lambda_{gt} \equiv \frac{\sum_{j \in \overline{I}_{g}} P_{gt}^{j} Q_{gt}^{j}}{\sum_{j \in I_{gt}} P_{gt}^{j} Q_{gt}^{j}}. \tag{28}$$

Then we can write the change in the overall U.S. price index for industry g as,

$$\frac{P_{gt}}{P_{g0}} = \left[\prod_{j \in \overline{I}_{g}^{j}} \left(\frac{P_{gt}^{j}}{P_{g0}^{j}} \right)^{W_{gt}^{j}} \right] \left(\frac{\Lambda_{gt}}{\Lambda_{g0}} \right)^{\frac{1}{\sigma_g - 1}}. \tag{29}$$

The second term on the right of (29) accounts for countries that begin exporting to the U.S. in industry g during the 2000-2006 period, or who drop out due to competition from China, for example if a country j selling to the U.S. in the base period drops out entirely and no longer sells in period t, then that will lower Λ_{g0}^{j} and raise the price index in (29). Provided that the loss in variety from exiting firms and exiting countries is not greater than the gain in variety due to entering Chinese firms, then there will still be consumer variety gains due to the expansion of Chinese trade following its WTO entry. The overall price index (29) accounts for all these offsetting effects, and it will be the basis for our calculations of U.S. consumer welfare.

Using all the above equations, we can decompose this industry g price index as,

$$\begin{aligned} \ln \frac{P_{gt}}{P_{g0}} = & \underbrace{\ln \left[\prod_{\omega \in \overline{\Omega}_{g}^{i}} \left(\frac{p_{gt}^{i}(\omega)}{p_{g0}^{i}(\omega)} \right)^{W_{gt}^{i} w_{gt}^{i}(\omega)} \right]}_{ChinaP_g} + \underbrace{\ln \left[\prod_{j \in \overline{I}_{g} \setminus i} \prod_{\omega \in \overline{\Omega}_{g}^{k}} \left(\frac{uv_{gt}^{j}(\omega)}{uv_{g0}^{j}(\omega)} \right)^{W_{gt}^{j} w_{gt}^{j}(\omega)} \right]}_{OtherP_g} \\ & + \underbrace{\ln \left(\frac{\lambda_{gt}^{i}}{\lambda_{g0}^{i}} \right)^{\frac{W_{gt}^{i}}{\rho_g - 1}}}_{ChinaV_g} + \underbrace{\ln \left\{ \left[\prod_{j \in \overline{I}_{g} \setminus i} \left(\frac{\lambda_{gt}^{j}}{\lambda_{g0}^{j}} \right)^{\frac{W_{gt}^{j}}{\rho_g - 1}} \right] \left(\frac{\Lambda_{gt}}{\Lambda_{g0}} \right)^{\frac{1}{\sigma_g - 1}} \right\}}_{OtherV_g}. \end{aligned} \tag{30}$$

The first term on the right is a conventional Sato-Vartia price index for Chinese imports, constructed over common goods in industry g available both years. The second term is the Sato-Vartia index constructed over the unit-values $uv_{gt}^{j}(\omega)$ in industry g for all other exporting countries, where ω measures the HS 10-digit products within each HS 6-digit industry, but using the PPI for the U.S. The third term is the gain from increased varieties from China, constructed using Chinese firm-level export data. The fourth term is the combined welfare effect (potentially a loss) of changing variety at the HS 6-digit level from other countries *j* and from the U.S. itself.[30]

To aggregate over goods, we follow Broda and Weinstein (2006) and again use the Sato-Vartia weights, now defined at the industry level as:

$$W_{gt} = \frac{(S_{gt} - S_{g0}) / (\ln S_{gt} - \ln S_{g0})}{\sum\limits_{g \in G} (S_{gt} - S_{g0}) / (\ln S_{gt} - \ln S_{g0})}, \text{ with } S_{gt} \equiv \frac{P_g Q_g}{\sum\limits_{g \in G} P_g Q_g}. \tag{31}$$

Then we can write the change in the overall U.S. price index of manufactured goods as,

$$\frac{P_t}{P_0} = \prod_{g \in G} \left(\frac{P_{gt}}{P_{g0}} \right)^{W_{gt}}. \tag{32}$$

The U.S. price index that we construct in this way reflects the U.S. prices of all manufactured goods, whether these goods are used as intermediate inputs or as final goods. We envisage that measured price changes are passed through to the ultimate purchasers of these goods, as happens in many models with CES demand. In our robustness analysis (section 5.3), we separate final goods from intermediate inputs, obtaining what is closer to a U.S. CPI over final goods and a PPI over intermediate inputs, respectively. This completes our description of how we will construct the U.S. price index of manufactured goods (see Appendix C for details on the data sources).

In section 2.2, we reported the results for China's export variety growth, which is just one of the components of the change in the U.S. CES price index for manufactured goods, appearing as the third term "$ChinaV_g$" on the right of equation (30). Its weighted growth of -3.1 percent appears at the top of column 5 in Table 7. We also calculate the other three components at an industry-level and then aggregate them across industries. Each of these components and their sum are reported in the top row of Table 7. The U.S. import price index of common Chinese goods (the first term on the right in equation (6))(30) calculated using the firm-product-destination level China Customs data, rose by an average of 1.76 percent per year, causing "$ChinaP_g$" to add 1.3 percent to the U.S. manufacturing price index between 2000-2006 (see column 3, Table (7)). The price index for other common goods (including from the U.S.) "$OtherP_g$", contributed 4.9 percent; while the variety component "$OtherV_g$" for other countries (including the U.S.), calculated from HS 10-digit U.S. import data for foreign countries while U.S. variety growth is calculated using U.S. census data on the share accounted for by the largest four firms, contributed 0.0 percent. These four components together sum to a 3.1 percent increase in the U.S. manufacturing price index between 2000 and 2006.

[30] That is, for the United States itself, where we will use the Producer Price Index (PPI) in each industry to measure the Sato-Vartia index. For the U.S. variety term in each industry we follow Feenstra and Weinstein (2017) and use the share of sales accounted for by the largest four firms, which is a valid measure of λ_{gt}^{j} if these are the same firms over time in each industry.

5.2 Estimating the Impact of China's WTO Entry on U.S. Prices

To analyze how China's WTO entry benefited U.S. consumers, we estimate how much the U.S. manufacturing price index moved due to China's WTO entry. The price index comprises the four components on the right side of (30), including both the common goods price index and variety components for China and all other countries. These four price index components are likely to be jointly determined, but we know that the Chinese price index components, and perhaps the other components, also directly depend on China's WTO entry. We will capture this latter dependency by constructing exogenous variables that measure the key causal effects of China's WTO entry. That is, we construct the predicted variation in China's common goods component (the first term in (30)) and the predicted variation in China's variety component (the third term in (30)) solely due to China's WTO entry, which we will denote as $Chi\hat{n}aP_g$ and $Chi\hat{n}aV_g$, respectively. We discuss how these exogenous variables are obtained from our earlier regressions shortly.

We can capture the joint determination of prices by collecting our four price index components into an $(N \times 4)$ matrix P, our two WTO entry exogenous variables plus the constant term into an $(N \times 3)$ matrix X, and write down a standard linear simultaneous equations system:

$$P\Gamma + XB + E = 0,$$

where $\mathit{\Gamma}$ and B are respectively (4×4) and (3×4) matrices of the structural parameters of the system and E is an $(N \times 4)$ matrix of random error terms. We can include any other exogenous variables in the matrix X. We are not going to attempt to identify the structural parameters of this system. Instead, post-multiply the terms in this system by Γ^{-1} and rearrange to yield

$$P = -XB\Gamma^{-1} - E\Gamma^{-1},$$

which can be rewritten using standard notation for reduced-form regressions:

$$P = X\Pi + V.$$

The reduced-form coefficients on our exogenous variables in X are identified. We can estimate this system using four single-equation regressions, where each of our four price index components is regressed on a constant and our two exogenous variables. Each reduced-form regression reveals how China's WTO entry has affected the particular price index component by industry, up to a constant term. From (30) we know that the overall price index is simply the sum of the four components, so the overall predicted WTO entry effect by industry is simply the sum of the predictions for each of the price index components. The identical overall predicted effect can be directly obtained by regressing the left side of (30) on the two WTO entry variables:

$$ln\left(\frac{P_{gt}}{P_{g0}}\right) = \alpha_0 + \alpha_1 Chi\hat{n}aP_g + \alpha_2 Chi\hat{n}aV_g. \tag{33}$$

The first China WTO entry variable on the right, $Chi\hat{n}aP_g$, is the predicted change in Chinese exporter prices constructed using predicted values of TFP from equation (24) , with β_1 being imposed at unity based on estimates from the quality adjusted equation (25). We employ results from column 5 in Table 6 to construct predicted prices as:

$$\hat{p}^i_{fht} = exp\left[-1 \times \ln T\hat{F}P_{ft} + 3.645 \times \ln Input\tau_{gt} - 1.165 \times Process_{fh} \times \ln Input\tau_{gt}\right],$$

where for clarity we have included the superscript $i = China$. This captures both the direct and indirect effects of lowering input tariffs on Chinese firms' U.S. export prices. Letting the year 2000 represent the base period 0, we predict prices in 2006 relative to 2000. Then we construct the variable as follows:

$$Chi\hat{n}aP_g \equiv W^i_{gt} \ln\left[\prod_{fh\in\overline{\Omega}_g}\left(\frac{\hat{p}^i_{fht}}{\hat{p}^i_{fh0}}\right)^{w_{fht}}\right], \tag{34}$$

where $\overline{\Omega}_g = \Omega_{gt} \cap \Omega_{g0}$ is the set of varieties (at the firm-product level, fh) that were exported in industry g during both 2000 and 2006, and w_{fht} are the Sato-Vartia weights over these varieties. Note that this instrument uses only the predicted export prices for Chinese firms due to China's WTO entry, and does not include any prices from other exporters to the U.S. nor prices of U.S. domestic producers. When we aggregate this industry-level instrument using the industry-level Sato-Vartia weights from (31), we find that it is substantial, equivalent to a -1.4 percent contribution to the U.S. manufacturing price index, which we report in column 1 of Table 7.

The second WTO entry variable captures exogenous variation in Chinese firms' export participation using fitted values from the export participation equation (22), with predicted probability of a positive outcome $pr\hat{o}b_{fht}$. These predictions only include the tariff and gap terms, and do not include any of the fixed effects. We sum the predicted probability of exporting from the participation equation (22), using results from column 1 in Table 6:

$$Chi\hat{n}aV_g \equiv \frac{W^i_{gt}}{\hat{\rho}_g - 1}\left[\ln\left(\frac{\sum_{fh\in\overline{\Omega}_g}\widehat{prob}_{fht}}{\sum_{fh\in\Omega_{gt}}\widehat{prob}_{fht}}\right) - \ln\left(\frac{\sum_{fh\in\overline{\Omega}_g}\widehat{prob}_{fh0}}{\sum_{fh\in\Omega_{g0}}\widehat{prob}_{fh0}}\right)\right]. \tag{35}$$

The terms in the brackets are constructed to reflect the terms $\left[\ln(\lambda^i_{gt}) - \ln(\lambda^i_{g0})\right]$ that appear in (30).[31] That term is raised to a power, W^i_{gt}, reflecting China's importance in overall U.S. expenditure in industry g, and then divided by the estimated industry elasticity $\hat{\rho}_g - 1$. When we aggregate this instrument using the industry-level Sato-Vartia weights from (31), we also find that it is substantial, equivalent to a -1.6 percent contribution to the U.S. manufacturing price index, which we report in column 1 of Table 7. When added to the $Chi\hat{n}aP_g$ term, the predicted direct effect of WTO entry on U.S. prices that we compute from our firm-level regressions is -3.0 percent, but this calculation ignores feedback effects on other prices.

[31]The estimated probabilities of exporting from (22) are meant to reflect estimated export shares of Chinese firms.

Table 7: Decomposition of WTO Effect on U.S. Manufacturing Price Index

Dependent Variable	(1)	US Price Index (2)	$ChinaP_g$ (3)	$OtherP_g$ (4)	$ChinaV_g$ (5)	$OtherV_g$ (6)
	Growth 2000-2006	0.031	0.013	0.049	-0.031	0.000
$\hat{ChinaP_g}$	-0.014	3.535***	1.266***	3.210***	-0.055	-0.885***
	(aggregate)	(0.815)	(0.124)	(0.686)	(0.194)	(0.337)
growth x regression coefficient		-0.049	-0.018	-0.045	0.001	0.012
contribution		*65.2%*	*23.3%*	*59.2%*	*-1.0%*	*-16.3%*
$\hat{ChinaV_g}$	-0.016	1.607***	-0.086***	-0.003	1.744***	-0.049
	(aggregate)	(0.157)	(0.024)	(0.132)	(0.037)	(0.065)
growth x regression coefficient		-0.026	0.001	0.000	-0.029	0.001
contribution		*34.8%*	*-1.9%*	*-0.1%*	*37.8%*	*-1.1%*
Total WTO effect		-0.076	-0.016	-0.045	-0.028	0.013
N		1,599	1,599	1,599	1,599	1,599
R^2		0.096	0.327	0.037	0.649	0.006

Notes: The first row reports aggregate growth rates of the U.S. price index and each of its four components in equation (30) using the Sato-Vartia weights from equation (31). The first column growth rates are the aggregate value of each instrument in equations (34) and (35), using the same Sato-Vartia weights. The total WTO effect in the last row is the sum of the China WTO price and variety effects on the U.S. price index, with each effect calculated as the aggregate value of the instrument times the regression coefficient: the price component is 3.535 x $-0.014 = -0.049$; the variety component is 1.607 x$-0.016 = -0.026$. The remainder of the last row contains similar calculations for each component of the U.S. price index.

We estimate (33) with weighted least-squares using the industry-level Sato Vartia weights W_{gt} from equation (32), and report the results in column 2 of Table 7. We see that lower Chinese export prices caused by China's WTO entry (lower $\hat{ChinaP_g}$) reduce the U.S. price index, and more Chinese export variety due to WTO entry (lower $\hat{ChinaV_g}$) also lowers the U.S. price index, so U.S. consumers gain due to both lower Chinese export prices and more varieties. To get a sense of economic significance, we multiply the coefficients by the aggregate growth in the two WTO entry variables (reported in column 1), which gives an identical result to performing this multiplication at an industry-level and then aggregating the results. Lower Chinese export prices due to WTO entry reduce the U.S. manufacturing price index by 4.9 percent, while greater Chinese export variety reduce the index by 2.6 percent. The sum of these two values indicates that the total WTO effect on the U.S. price index is -0.076, that is the U.S. manufacturing price index was 7.6 percent lower in 2006 relative to 2000 due to China joining the WTO. Note that this fall is after correcting for any overall inflation in domestic and import prices that is common across industries in the constructed U.S. price index, since these common trends would be absorbed by the constant term in (33).[32] So we interpret this 7.6 percent

[32] As with any regression analysis, we are unable to determine the effect of China's WTO entry on the constant term i.e. on the overall inflation in manufacturing prices.

fall in prices as the *real* impact on U.S. *manufacturing* prices relative to inflation. Since manufacturing is only a fraction of the U.S. economy, this seemingly large effect is notably smaller than the *aggregate* 6.7 percent long-run U.S. welfare increase that Caliendo et al. (2015) estimate from the 2000-2007 China trade shock.[33]

To examine which components of the U.S. price index are most affected, we regress each of the four price index components on the right of (30) on the two WTO entry variables in the subsequent columns of Table 7. By construction, summing coefficients obtained on each variable across the four regressions will give the same results to when we regressed the left-hand side of (30) on these two variables. We call the first term on the right of (30) the U.S. import price index of common Chinese goods, or $ChinaP_g$; the second term is the common goods price index from all other countries (including the U.S.), or $OtherP_g$; the third term is the Chinese variety component of imports, or $ChinaV_g$; and the fourth term is the variety component from other countries (including the U.S.), or $OtherV_g$.

Our regression results reveal how each of our WTO-entry variables affected each of the components of the U.S. price index. The largest effect is coming through $Chi\hat{n}aP_g$. As expected, the lower China price instrument lowers the China common goods price index (column 3), and this channel reduces U.S. prices by 1.6 percent. Interestingly, it also has a very big effect on competitor prices in column 4, which contribute a 4.5 percent reduction in U.S. manufacturing prices. A large coefficient on competitor price index terms is not unexpected, since these terms incorporate the fact that competitors' prices carry six times the weight of Chinese prices in the U.S. price index, which we explore further below. We also note that it would likely take substantial effects on competitors' prices to generate the widespread labor-market effects that Autor et al. (2013) attributed to Chinese trade. This strong price effect may reflect the exit of inefficient competitor firms, lower marginal costs or lower markups.[34] Further, a lower $Chi\hat{n}aP_g$ has an insignificant effect on net entry of Chinese competitor firms (column 5), but causes net exit among other competitors (column 6).

To interpret the effect of $Chi\hat{n}aP_g$ appearing in Table 7, consider the impact on $OtherP_g$ in column 4, which is the the second term on the right of (30). To be explicit, the coefficients appearing in column 4 are obtained from the regression (ignoring the included constant term):

$$OtherP_g = \sum_{j \in \overline{I}_g^j \setminus i} W_{gt}^j \ln\left(\frac{P_{gt}^j}{P_{g0}^j}\right) = 3.210 Chi\hat{n}aP_g - 0.003 Chi\hat{n}aV_g. \tag{36}$$

Notice that the dependent variable in this regression has the weights W_{gt}^j on each country, but that these weights sum to *less than unity* over the countries $j \in \overline{I}_g^j \setminus i$. Specifically, $\sum_{j \in \overline{I}_g^j \setminus i} W_{gt}^j = 1 - W_{gt}^i$, where W_{gt}^i is the Chinese share in U.S. consumption within industry g. On the other hand, the instruments $Chi\hat{n}aP_g$ and $Chi\hat{n}aV_g$ defined in (34) and (35) have the weights W_{gt}^i, which are just the

[33]Their much smaller short-term welfare effects include labor market adjustment costs and are therefore less comparable to our estimates.

[34]Atkin et al. (2017) find that one quarter of the price index impact of entry of global retailers in Mexico is due to pro-competitive effects on the prices charged by domestic stores.

Chinese share. The coefficient estimates obtained in column 4 are certainly influenced by having weights on the left and the right of (36) that differ from unity.

To illustrate, suppose that we divide $Chi\hat{n}aP_g$ and $Chi\hat{n}aV_g$ by $\overline{W}_t^i$, by which we mean the average over industries g of the Chinese shares W_{gt}^i. That will ensure that the weights $W_{gt}^i/\overline{W}_t^i$ average to unity over the industries used in the regression (36). Analogously, we divide the dependent variable in (36) by the weight $1-\overline{W}_t^i$, so that the industry weights $W_{gt}^j/(1-\overline{W}_t^i)$ average to unity. With this re-normalization of the left and right-side variables in (36), the regression becomes,

$$\frac{OtherP_g}{1-\overline{W}_t^i} = 0.538\frac{Chi\hat{n}aP_g}{\overline{W}_t^i} - 0.000\frac{Chi\hat{n}aV_g}{\overline{W}_t^i}, \tag{37}$$

which is obtained directly from (36) because the average Chinese share of U.S. consumption over 2000-2006 across manufacturing industries is $\overline{W}_t^i = 0.144$, so that $0.538 = 3.210(0.144/0.856)$; and similarly for the second term. With this re-normalization of weights, we see that the actual impact of the Chinese price instrument on the prices of other country's exporters and U.S. firms selling in the U.S. market is a pass-through coefficient of 0.5. That is still a very sizable impact of Chinese prices on other prices in the U.S. market, when we consider that the Chinese share is only 0.144 on average. Still, this re-normalization helps us to properly interpret the rather large coefficient of 3.21 appearing in column 4 of Table 7.[35]

Turning to the variety instrument in the lower half of the table, we see that increased Chinese variety due to WTO entry increases the China variety component in column 5 with a coefficient of 1.744. The contribution of this channel to U.S. prices is -2.8 percent at the bottom of column 5, very close to the measured welfare impact of -3.1 percent at the top of column 5 (and coming from our calculations in section 2.2). The coefficient on other competitors (column 6) is negative, suggesting that there could be some exit, however it is insignificant. We find that a lower $Chi\hat{n}aV_g$ leads to a very small increase in Chinese prices in column 3, possibly due to some quality bias, but it has no effect on competitor prices in column 4.

The bottom row of Table 7 reports the contribution of each of the four components of the U.S. price index, and enables a decomposition of the total effect into contributions from each of the price index components. The two Chinese components combine to contribute a 4.4 percent reduction in this index. Of this reduction, *one-third* (-1.6 percent in column 3) is explained by the fall in Chinese prices, which is due to China's liberalization of its own tariffs on inputs, while *two-thirds* (or -2.8 percent in column 5) is explained by the entry of exporters in China and the accompanying rise in U.S. import variety. The entry of exporters is partly due to China's lower input tariffs and partly due to the United States granting PNTR to China on its accession to the WTO. The contribution of these Chinese price and variety components is about 60 percent of the overall reduction in prices (7.6 percent in column 1).

[35]The coefficient reported in column (5) can be re-interpreted in the same way, i.e. by multiplying them by $(0.144/0.856) = 0.168$, which gives a coefficient of -0.148. The coefficients reported in column (2) and (4) do not need any re-interpretation, however, since if we divide the dependent variables and the instruments by the appropriate weight $\overline{W}_t^{ij} = 0.144$, the coefficient estimates do not change.

The story changes, however, when we also incorporate the prices and variety of other countries exporting to the U.S., which is the other 40 percent of the overall reduction in prices. The contribution of these components for all other producers is a further 3.2 percent reduction, which is composed *primarily* of a predicted fall in the prices from other countries (of -4.5 percent in column 4), offset somewhat by a reduction in the variety from these other countries (leading to an effective price rise of 1.3 percent in column 6). When we put together all these various sources of change to the overall U.S. price index, the reduction in China's input tariffs becomes a very important contribution, as seen from column 2,

Column 2 in Table 7 decomposes the total WTO entry effect into the contributions from each of our instruments; and shows that two-thirds of the China WTO effect on the U.S. price index comes through the China common goods export price instrument. The finding that most of the gains come through a lower $\hat{China}P_g$ rather than a lower $\hat{China}V_g$ is because a large portion of the consumer gain comes from China's impact on competitor prices. The source of all of the variation of the $\hat{China}P_g$ instrument is China lowering its own input tariffs, since the "gap" does not affect $\hat{China}P_g$ at all (the point estimate on the "gap" in column 6 of Table 6 is essentially zero), nor does it significantly affect Chinese firms' TFP or export prices, as shown in Tables 4 and 6. Column 1 of Table 6 reveals that China's export participation growth owed much more to its input tariff reduction than to the reduction in the uncertainty of the U.S. tariffs its exporters faced; this comes from the direct coefficient on the input tariff, and more importantly on the dominant role of predicted TFP, which itself overwhelmingly depends on input tariffs. Therefore, we can conclude that the bulk of the aggregate WTO effect on U.S. manufacturing prices was due to China lowering its import tariffs on intermediate inputs.

5.3 Robustness

In this section we check the robustness of our results by estimating alternative specifications of our key equations. We first address concerns that arise from the fact that we only have firm-product level data for Chinese exports while we have to rely on more aggregated data for exports from other countries (i.e. HS 10-digit U.S. import data). In Appendix G we demonstrate that, under conditions of symmetric CES demand for a country's products, we can improve the observed unit values for that country into a true price index by multiplying the unit value by a slightly generalized Herfindahl index. We obtain Herfindahl indexes from a combination of PIERS firm-product level trade data,[36] U.S. Census data, and national sources for Canada and Mexico. These data also give us more detailed information on variety growth within a country-HS category pair. We re-estimate equation (33) after replacing the dependent variable with a U.S. price index that incorporates this Herfindahl index adjustment and report the results in column 1 of Table 8. These results are very similar to our baseline results in column 1 of Table 7. This was expected, as for most countries measures of concentration change slowly over time.

[36] The PIERS data does not include reliable firm-level unit-value data, otherwise we would directly use that.

Table 8: WTO Effect on U.S. Price Index: Robustness

Dependent Variable	US Price Index					
	HHI (1)	TFP (2)	Final Goods (3)	Inputs (4)	HS4 (5)	Other Reforms (6)
$Chi\hat{n}aP_g$	3.406***	3.412***	1.461**	1.978	3.800**	4.286***
	(0.815)	(0.836)	(0.633)	(1.790)	(1.554)	(0.887)
growth x regression coefficient	-0.048	-0.048	-0.037	-0.014	-0.047	-0.056
contribution	*64.1%*	*64.9%*	*41.4%*	*60.8%*	*81.1%*	*66.7%*
$Chi\hat{n}aV_g$	1.623***	1.599***	1.787***	1.057***	0.768**	1.724***
	(0.158)	(0.157)	(0.137)	(0.238)	(0.315)	(0.161)
growth x regression coefficient	-0.027	-0.026	-0.052	-0.009	-0.011	-0.028
contribution	*35.9%*	*36.1%*	*58.6%*	*39.2%*	*18.9%*	*33.3%*
Total WTO effect	-0.075	-0.073	-0.090	-0.023	-0.058	-0.084
N	1,599	1,602	489	850	539	1,597
R^2	0.104	0.095	0.310	0.089	0.116	0.103

Notes: Each column re-estimates column 1 in Table 8 with the following differences. Column 1 adjusts the US price index by the ratio of Herfindahl indexes. Column 2 uses an alternative measure of TFP. Column 3 restricts the set of industries to “final” goods (BEC categories 112, 122, 522, 51, 6). Column 4 restricts the set of industries to “inputs” (BEC categories 111, 121, 21, 22, 42, 53). Column 5 constructs the price index and the instruments at the HS 4-digit level. Column 6 uses predicted values to construct instruments from regressions that control for additional reforms.

Another concern we address relates to the construction of the TFP variable. For our baseline estimates, we use the Olley and Pakes (1996) approach. To check the sensitivity of our results, we re-estimate TFP using the De Loecker (2013) approach, which builds on Olley and Pakes (1996) and Ackerberg et al. (2015) by allowing exporting to affect learning. With these new TFP estimates, we re-estimate all of the specifications in Tables 5 and 6, and use those results to reconstruct the instruments $Chi\hat{n}aPg$ and $Chi\hat{n}aVg$. We re-estimate equation (33) with these reconstructed instruments and report the results in column 2 of Table 8. Once again, our results are insensitive to this change, with a 7.3 percent total WTO entry effect, of which two-thirds is still due to the common goods price index instrument $Chi\hat{n}aPg$.

If tariff reductions on imported inputs are an important mechanism through which China’s WTO entry affects U.S. prices, then it is likely that the WTO entry effect will be stronger for final goods than for goods that are themselves inputs. This is because final goods are likely to incorporate more intermediate inputs, creating greater scope for input tariff reductions to increase productivity. We categorize HS 6-digit industries as either “Final Goods” or “Inputs” using the Broad Economic Categories (BEC) classification, and construct new U.S. price indexes for these two categories by recalculating the industry-level Sato-Vartia weights in equation (31). Columns 3 and 4 contain regression results for equation (33) for these two sets of goods. The largest gains are in the final goods industries, with a total WTO effect of -9 percent. For final goods, almost 60 percent of the gains are attributed to the variety instrument $Chi\hat{n}aVg$. Intermediate input industries show a smaller total WTO effect of -2.3

percent. We also note that final goods prices may feed more directly into consumer prices than do intermediate input prices.

We next address the concern that our analysis at the HS 6-digit level covers only a subsample of U.S. manufacturing. The 1,599 industries in our baseline analysis account for more than 60 percent of U.S. manufacturing consumption and 85 percent of China's manufacturing exports to the U.S. The remaining industries were dropped due to missing components needed to construct the variables in equation (33); for example, in some industries we could not define a λ ratio. If our results only held for those industries and if China's WTO entry had zero effect in the omitted industries, then our results still suggest a 4.5 percent reduction in the U.S. price index. To cover a larger share of the U.S. manufacturing sector we construct the U.S. price index and the two instruments at the HS 4-digit level, which raises the covered consumption share close to 80 percent and the covered China export share to 90 percent. With more than 1200 codes, HS 4 is still a reasonably fine classification, and using this classification has the advantage of capturing the effect of China's entry into one HS 6-digit industry in other industries within the HS 4-digit code. But, if HS 6-digit industries within an HS 4-digit code are unrelated, then regressing a 4-digit U.S. price index on instruments derived from a subset of those industries could attenuate the estimated effects. We re-estimate all of the elasticities at the HS 4-digit level and redo our entire analysis with industries defined at that level. Column 5 contains these estimates of equation (33). The estimated WTO entry effect is a bit lower than the baseline but remains sizable at -5.8 percent.

Finally, we address the concern that we have omitted some contemporaneous reforms that might be correlated with our input tariff and "gap" measures, and therefore may be incorrectly attributing gains from omitted reforms to our WTO entry instruments. We have already included the liberalization of export eligibility restrictions. We now incorporate additional reforms: the MFA; reform to import license controls; FDI liberalization; and tariffs on final goods. Some of these reforms might be considered as part of the WTO entry process; China's output tariffs certainly fall into this category, and it is arguable as to whether other countries would have removed quotas on China's textile and clothing exports if it had not joined the WTO. We prefer to confine our baseline results to incorporating the key mechanisms identified in the theory: productivity growth driven by WTO-mandated reductions to imported intermediate input tariffs causing increased export participation and lower export prices; and increased export participation driven by the reduced threat of non-MFN tariffs. We re-estimate our key TFP, export participation, and export price equations after including the additional reform variables (see Appendix Table H6). Our conclusions are little changed. The estimated total WTO effect is -8.4 percent, with two-thirds of the gain due to the export-price instrument $Chi\hat{n}aP_g$.

6 Conclusion

The value of China's exports to the U.S. grew by 290 percent within six years of joining the WTO, with the bulk of this growth coming from new exporters. This extraordinary growth suggests the strong likelihood of a substantial impact on U.S. prices, which we quantify. Theoretical analysis of the channels through which China's WTO entry can affect U.S. prices demonstrates how China's substantial input tariff cuts produce productivity improvements that lead to lower prices from existing exporters and more firms exporting to the U.S. This firm-entry effect is enhanced by the reduction in tariff uncertainty following the U.S. granting China PNTR status.

Building on this analysis, we construct and estimate empirical models of Chinese trade using highly disaggregated Chinese firm-product data for the period 2000 to 2006. We aggregate model estimates to construct predictions of the changes in prices of existing exporters and the growth of the number of exporters that stem solely from WTO entry. Regressions of exact CES price indexes for all U.S. manufacturing sales on these predicted changes in Chinese prices and export participation reveal that China's WTO entry reduced the U.S. price index of manufactured goods by 7.6 percent over this period. Intuitively, the China component of the U.S. price index is impacted the most, accounting for 60% of the variation. We find that about one-third of the reduction in the effective price of Chinese exports to the U.S. comes from Chinese exporters lowering their prices, while two-thirds of the beneficial impact comes from the entry of new Chinese exporters, adding to U.S. product variety.

Importantly, our analysis explicitly takes account of China's trade shock on competitor prices and entry. The reduction in China's tariffs on intermediate inputs also led *other* countries exporting to the U.S. to lower their prices (which is offset somewhat by exit from these exporters). China's competitors react to lower prices of Chinese exports by cutting their own prices and, in some cases, by exiting altogether. This reduction in other countries prices is explained entirely by the reduction in Chinese inputs tariffs, and not by the granting of PNTR.

Our paper is the first to show that the key mechanism underlying the China WTO effect on U.S. prices is China lowering its own import tariffs on intermediate inputs. Lower Chinese tariffs on intermediate inputs not only directly reduced Chinese firms' costs, but increased the value and range of its firms' imports of intermediate inputs, boosting their productivity. Lower marginal costs caused increased entry into the U.S. market and lower Chinese export prices. We also study how the granting of PNTR upon WTO entry affected Chinese exports —a channel that has received a lot of attention —and consistent with the literature we show that PNTR does result in higher entry into exporting. However, we find no effect of PNTR on Chinese firms TFP or export prices. By incorporating the response of domestic and other countries' U.S. prices to China's lower prices, we conclude that the reduction in China's own tariffs becomes an important source of welfare gain for the United States.

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Appendix

A Estimating Elasticities of Substitution

We estimate the elasticity of substitution between varieties following Feenstra (1994), Broda and Weinstein (2006), and Soderbery (2015).[37] We follow the methodology described and coded in Appendix 2.1 of Feenstra (2010) to estimate three sets of elasticities of substitution, all at the HS6 industry level: (i) Elasticities of substitution between firm-HS8 Chinese varieties exported to the U.S. (China ρ_g); (ii) Elasticities of substitution between varieties sold in the U.S. by all non-Chinese exporters (Other ρ_g); and (iii) Elasticities of substitution across HS 6-digit varieties (σ_g). For each set of elasticities, we filled in any missing HS 6-digit elasticity with the median estimate within the same HS4 code. All data is cleaned by dropping price ratios (the unit value in t relative to $t-1$) less than $1/10$ or greater than 10.

For China's exports to the U.S., we estimate the elasticities of substitution across varieties, defined at the firm-HS 8-digit level and within an HS 6-digit industry, ρ_g.[38] This parameter enters in the variety adjustment for Chinese goods in the price index —the second term in equation (6) . The median ρ_g, reported in Table A1, is 4.57. We estimate a wide range in the elasticities. Variety growth in industries with low elasticities will generate the largest gains whereas variety growth in industries with high elasticities will have a smaller effect on the U.S. price index.

We do not have access to firm-level data for non-Chinese exporters, so we use the most disaggregated data available to us, which is U.S. reported import data at the country-HS 10-digit level. We estimate "Other ρ_g" as the elasticity of substitution across HS10 varieties produced by the same country. We do this by pooling the top 40 exporting countries to the U.S. (which account for 95% of total U.S. manufacturing imports) and constrain Other$\rho_g$to be the same for all exporting countries other than China. There were too few observations for some countries to estimate country-specific elasticities. We assume that Other ρ_g also applies to U.S. produced varieties. We see that the median elasticity for "other countries" is lower at 2.9. This was expected because a variety is defined at a more aggregate level.

Finally, we estimate σ_g, the elasticity of substitution between varieties in industry g produced in different countries that appears in the last term of equation (30). We estimate σ_g in two steps. First, we calculate an exact price index for each country-HS6 pair using equation (26) and the within-country elasticity of substitution ρ_g, and then we estimate the between-country elasticity, σ_g, using the same procedure as with the ρ_g's. The median estimate of σ_g is 3.4.[39] We ensure there are a minimum of 3 country varieties within each HS 6-digit estimation, and drop the top and bottom 1 percentiles of the λ ratios and exact price indexes.

[37] This methodology is also used in Ossa (2015).

[38] We trim outliers by dropping any price ratios greater than 10 or less than $1/10$. If there were insufficient observations to estimate an elasticity for an HS 6-digit industry, we used the median in the next level of aggregation.

[39] It is not a surprise that the median σ_g is slightly higher than the "other-countries" ρ_g. While we estimate ρ_g across

Table A1: Distribution of Elasticities of Substitution

	China ρ_g	Other countries ρ_g	σ_g
Percentile 5	1.68	1.47	1.54
Percentile 25	3.02	2.28	2.41
Percentile 50	4.57	2.94	3.42
Percentile 75	9.14	4.61	4.64
Percentile 95	33.77	17.27	15.83
Mean	11.45	6.47	6.79
Standard Deviation	32.05	21.93	36.93

Notes: The China ρ_g are estimated using Chinese firm-HS8 level US export data for each HS 6-digit industry g. The "Other countries" ρ_g are estimated using U.S. import data at the HS 10-digit country level. And the σ_g are elasticities of substitution across different countries' HS6 digit goods exported to the U.S.

B Relating the Variety of Imported Intermediate Inputs to the Share of Spending on Domestic Inputs

To express the ratio of costs in two periods independently of the parameters α_D and α_M, Blaum et al. (2016) show that the ratio of firm costs between period t and period 0 can be expressed as:[40]

$$\frac{C_{ft}}{C_{f0}} = \frac{\varphi_{f0}}{\varphi_{ft}} \left(\frac{P_t^D}{P_0^D}\right)^{1-\gamma} \left(\frac{S_{ft}^D}{S_{f0}^D}\right)^{\frac{1-\gamma}{\sigma-1}}, \tag{38}$$

where S_{ft}^D is the share of total expenditure on intermediate inputs that is devoted to *domestic* inputs in period t. Thus, when $\sigma > 1$, having more imported intermediate inputs means that the share spent on domestic inputs is reduced, and that corresponds to a reduction in unit costs. Blaum et al. (2016) proceed by measuring the change in unit-costs using this domestic share variable, which endogenously reflects the sourcing strategy of the firm.[41]

An alternative way to express the ratio of unit costs is as a Sato-Vartia index over the ratio of the price of the domestic intermediate input, and the ratio of the price of imported intermediate inputs (this is the Sato-Vartia result discussed in equation (3) of Feenstra (1994)). So we simply obtain:

$$\frac{C_{ft}}{C_{f0}} = \frac{\varphi_{f0}}{\varphi_{ft}} \left(\frac{P_t^D}{P_0^D}\right)^{W_{ft}^D(1-\gamma)} \left(\frac{c_{ft}^M}{c_{f0}^M}\right)^{W_{ft}^M(1-\gamma)}, \tag{39}$$

where W_{ft}^D (W_{ft}^M) is the Sato-Vartia weight of domestic (imported) inputs within total expenditure

different HS 10-digit varieties, we estimate σ_g using price indexes that incorporate the same HS 10-digit categories.

[40]The result in (38) is an immediate application of Proposition 1 in Feenstra (1994). That result states that the ratio of unit-costs for a CES function is the Sato-Vartia price index over "common" goods available in both periods (in this case we have only one common domestic input), times the ratio of expenditure on the common goods in the two periods (i.e. the domestic input), raised to the inverse of the elasticity of substitution minus one as shown by the final term in (38), which is also adjusted by the Cobb-Douglas share $1-\gamma$ of intermediates.

[41]A solution to the sourcing strategy is illustrated by Antràs et al. (2017).

on intermediate inputs, with $W_{ft}^D + W_{ft}^M = 1$.[42] We see that a reduction in the unit-cost of the import bundle in (12) corresponds directly to a reduction in overall unit costs in (39), by an amount that depends on the Sato-Vartia share of imported inputs.

Substituting (12) into (39) we can readily solve for the change in the domestic share of intermediate inputs, as:

$$\frac{S_{ft}^D}{S_{f0}^D} = \left[\prod_{n\in\overline{\Sigma}_f}\left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}}\right)^{w_{nt}}\right]^{W_{ft}^M(\sigma-1)}\left(\frac{P_t^D}{P_0^D}\right)^{-W_{ft}^M(\sigma-1)}\left(\frac{\lambda_{ft}}{\lambda_{f0}}\right)^{\frac{W_{ft}^M(\sigma-1)}{\rho-1}}. \tag{40}$$

This equation emphasizes that the change in the domestic share is endogenous to the sourcing strategy of the firm and to the tariffs that it faces. Substituting (40) into (38) and re-arranging terms, we obtain (14) in the main text.

In Table B2, we extend the results from Table 5 in the main text to include the share of spending on domestic inputs, S_{ft}^D, as an endogenous control for TFP. This follows the approach of Blaum et al. (2016) as summarized in equation (38) in the main text. In column 1 of Table B2, we first use OLS to regress lnTFP_{ft} on S_{ft}^D, which is constructed as (total expenditure on domestic materials)/(total material costs + wage costs), and estimate a fairly small negative coefficient of -0.04. However, when we instrument for S_{ft}^D with $\hat{\lambda}_{ft}$, in column 2, we obtain a much more negative coefficient of -0.66. We find that the instrument has the expected sign in the first stage regression in column 3. When we include the two $\hat{M}$ instruments separately, we get very similar results. The results in columns 2 and 3 can be interpreted as structural equations for the reduced form estimation in column 2 of Table 5. Notice that if we multiply the two coefficients in columns 2 and 3 we obtain $-0.055 = -0.655 \cdot 0.084$, which is nearly the same as the reduced form coefficient -0.053 in column 2 of Table 5. We conclude that making use of the share of spending on domestic inputs, S_{ft}^D, as a variable does not add much information as compared with proceeding with the reduced form analysis, as we do in the main text.

[42]Denoting the import share of intermediate input purchases by S_{ft}^M, then $W_{ft}^D = \left[(S_{ft}^D - S_{f0}^D)/(\ln S_{ft}^D - \ln S_{f0}^D)\right] / \left[(S_{ft}^D - S_{f0}^D)/(\ln S_{ft}^D - \ln S_{f0}^D) + (S_{ft}^M - S_{f0}^M)/(\ln S_{ft}^M - \ln S_{f0}^M)\right]$.

Table B2: Chinese Firm TFP and Importing

Dependent variable	$ln(TFP_{ft})$	$ln(TFP_{ft})$	First Stage: $ln(S^D_{ft})$
	(1)	(2)	(3)
$ln(S^D_{ft})$	-0.036***	-0.655***	
	(0.009)	(0.063)	
$ln(\hat{\lambda}_{ft})$			0.084***
			(0.003)
$Year\ FE$	yes	yes	yes
$Firm\ FE$	yes	yes	yes
# obs.	76,603	76,603	76,603
R^2	0.703	0.657	0.726

Notes: The observations are at the firm-year level. The sample includes all firms that could be matched from the customs data with the ASIF survey, from which we estimate TFP. The dependent variable in the first 2 columns is $\ln(TFP)$ estimated using Olley-Pakes methodology as described in section 3.3. The $\hat{M}$ variables are constructed from column 4 in Table 4, as described in the text, with $\ln\hat{\lambda}_{ft} = \ln\hat{M}_{max,ft} - \ln\hat{M}_{tot,ft}$. Column 1 is estimated using OLS, and column 2 is estimated using IV, where we instrument for the share of domestic inputs in total costs, $\ln(S^D_{ft})$, with $\hat{\lambda}_{ft}$. Alternatively, we could include the $\hat{M}$ variables separately - this produces the same results, and passes the over-identification test and the first stage weak instrument test. All estimations control for selection into importing nonparametrically. As the sample includes nonexporters, we do not need to control for export selection bias. All standard errors are clustered at the firm level.

C Chinese Tariffs, Quotas and FDI Restrictions

In addition to lowering its own import tariffs, China implemented other reforms to export barriers, import barriers, and foreign direct investment (FDI) restrictions during the period encompassing China's WTO entry, and these reforms may also have affected firm productivity and exports and therefore need to be included in our empirical analysis. Chinese firms faced restrictions on exporting and importing based on capital requirements, which were progressively removed during the sample period and were completely removed by 2004. Bai et al. (2017) studied the effect of relaxing export restrictions on Chinese firms' export activity and productivity, and generously provided us with export-restriction data indicating the share of firms allowed to export within a CIC 4-digit industry, which we mapped to HS6 industries for our analysis. China Customs announced a list of products requiring an import license. Because the total number of licenses is subject to government control, the license essentially serves as a quota. Drawing on annual circulars of the Ministry of Foreign Trade and Economic Cooperation and the Ministry of Commerce, we collect the list of HS 8-digit products to create a measure of the share of a firm's imports that were subject to import license control. Around 5% of products were subject to license control in 2000, and this number dropped to 1% in 2006.

China maintained restrictions on inward FDI when it joined the WTO, including complete prohibitions in certain industries. These restrictions took various forms, such as: higher initial capital requirements; less favorable tax treatment; more complicated business registry and approval procedures; and in the case of joint ventures, requirements of majority shareholding by a Chinese party.

China removed many restrictions following WTO accession. The Catalog for the Guidance of Industries for Foreign Investment issued by the Ministry of Commerce of China lists the industries where FDI to China is "restricted" or "prohibited". This list is amended every 3 to 5 years, and we use the lists issued in 1997, 2002 and 2004, mapping the Catalog's industry descriptions to HS8 digit codes. We categorize an industry as subject to an FDI restriction if it is either "restricted" or "prohibited".

Another important trade reform for China was the elimination of quotas for textile exports. Before WTO accession, China's textile exports were subject to quota restrictions governed by the Multifiber Arrangement (MFA), and its successor, the Agreement on Textiles and Clothing (ATC). These restrictions were phased out in 2002 and 2005, leading to a surge in textile exports to the United States and Europe (Khandelwal et al. (2013)). Our data for MFA quotas are drawn from Brambilla et al. (2010), which provides the list of HS10 products under quota restrictions, and the period the quota was removed for each product. We use these data to construct dummy variables MFA2002 and MFA2005 which equal 1 if the quota was removed in 2002 and 2005 respectively.

D Data Construction

To estimate the effect of this liberalization on Chinese firms, we need detailed information on the trade and production activity of those firms. China Customs provides annual trade data on values and quantities at the HS 8-digit level by firm-destination for the period 2000 to 2006. This covers the universe of Chinese exporters. We restrict the sample to manufacturing products, which we identify using a mapping to SITC 1-digit codes in the range 5 to 8. We source production and input data from the Annual Survey of Industrial Firms (ASIF) produced by the National Bureau of Statistics. This survey of Chinese manufacturers is available for the same period as the customs data. It contains firm-level information on output, materials cost, employment, capital and wages. Each firm's main industry is recorded at the 4-digit Chinese Industrial Classification (CIC) level. We keep all manufacturing industries, being CIC 2-digit industry codes 13 to 44. For some specifications, we need to combine the customs and industrial data sets. Since there are no unique firm identifiers across these two data sets, we relied on information on firm names, addresses, and zip codes to construct a "matched sample". This comprises a third of exporting firms in the industrial data, which account for 50 percent of China's total U.S. exports over this period. We use this matched sample of firms only when it is not possible to use the universe. The customs data show that the number of U.S. exporters more than tripled over the sample period (see Table C4). Further details on data construction are as follows.

ASIF data: Chinese firm-level data comes from the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics of China for 1998 to 2007. The survey includes all state-owned enterprises and private enterprises with annual sales of RMB five million (about $800,000) or more. The data set includes information from balance sheets of profit and loss and cash flow statements of firms, and provides detailed information on firms' identity, ownership, export status, employment, capital stock, and revenue. There is a large entry spike of 43 percent in 2004 (more than double in other years). This has been attributed to improvements in the business registry in the industrial census in 2004 so more privately owned firms were included in the survey.

The ASIF data records each firm's main industrial activity at the CIC 4-digit level, which comprise over 500 industrial codes. The ASIF has a firm indicator called "id". Some firms change their id because of changes in name, location, or ownership type, yet they are still the same firm; these have been mapped to a consistent "panelid" so that each firm maintains a unique identifier. The mapping is done through a two-step procedure. We first link firms by name. For those not linked by name, we then link by zip code, telephone number, and legal person representatives (i.e. two observations are linked if they have the same zip code, telephone number and legal person representative). The number of firms shrinks by 7 percent after the mapping.

Customs data: The customs data includes the universe of firms, reporting import and export values and quantities at the HS 8-digit level. Each firm has a firm identifier called "partyid", different from the one assigned in the ASIF data. Some firms change their partyid because of changes in location, firm type, or trade mode. Thus, we also link firms in the customs data to create a firm identifier that is unique over time, as a robustness check. The linking procedure is similar to the one for the ASIF data, except that with the customs data we link firms using the monthly trade data. The number of firms shrinks by 5 percent due to this mapping.

Matching firm id's in customs and ASIF data: Although both the customs data and the ASIF report firm codes, they come from different administrative systems and have no common elements. Thus we construct a concordance between the two data sets using information on the firm name as the main matching variable and the zip code and telephone number as a supplement, as in Yu (2015). Using this methodology, we were able to match 32-36 percent of firms in the customs data, which account for 46 percent of the value of exports to the world and 51 percent of the value of U.S. exports. The details of the matching procedure are as follows. When the firm name is identical in the two data sets the match is straightforward. If not, we use information on zip codes and telephone numbers to aid in the matching process, given that the telephone number is unique within a region.

The total number of exporters is reported in Table C4. The striking pattern to emerge from Table C4 is the massive net entry into exporting. First, note that the number of firms in the ASIF data doubled over the sample period, with 278,000 firms by 2006. But since only firms with at least 5 million RMB are included in the sample, some of this increase in firm numbers in the sample is due to firms crossing this threshold. These data comprise a large portion of the manufacturing sector. Comparing the ASIF data with the 2004 census, we find these data cover 91 percent of the manufacturing sector in terms of output, 71 percent in terms of employment, and 98 percent in terms of export value (see Brandt et al. (2017) for more details.) Of more relevance for our study is the pattern for exporters. In the customs data, we see that the number of U.S. exporters more than tripled over the sample period. This represents actual net entry into the market since the customs data represents the universe of exporters. This pattern is also mirrored for exporting to the world, and in the overlapping sample.

Table D3: Number of Firms

year	# firms in ASIF	# exporters in ASIF	# exporters in customs	# US exporters in customs	share of US export value in matched sample
2000	138,431	38,854	62,746	23,437	0.41
2001	151,017	43,978	68,487	26,172	0.44
2002	162,780	49,824	78,613	31,835	0.47
2003	179,151	56,737	95,690	39,556	0.50
2004	252,540	81,435	120,590	49,878	0.55
2005	250,909	84,251	144,031	63,193	0.53
2006	277,863	89,329	171,205	76,081	0.53

Product concordances: We make the China HS 8-digit codes consistent over time, using a concordance from China Customs. We map all HS8 codes to their earliest code in the sample. The Chinese Industrial Classifications (CIC) were revised in 2003, so we used a concordance from the China National Bureau of Statistics (NBS) to bridge the two sets of codes, which we mapped to the new codes. As usual with concordances, we found that some of these mappings were not one-to-one so this required some groupings of the codes. The manufacturing codes comprise those CIC codes that begin with 13 to 44: there are 502 distinct CIC manufacturing codes in the pre-2003 revision and 432 after we group some industry codes to account for the many-to-many mappings.

We mapped the HS8 codes to CIC codes using a partial concordance from NBS, and completed the rest manually. This required some additional groupings of the CIC codes. The mapping between HS8 and IO codes uses the HS2002 version so we converted that to HS 2000 codes. We built on a concordance from HS6 2002 to IO from one constructed manually by Rudai Yang, Peking University, using a mapping from HS to SITC to IO. The mappings from IO_2002 to CIC_2003 and IO_2002-CIC_2002 were downloaded from Brandt et al. (2012)
(http://www.econ.kuleuven.be/public/n07057/China/).

We made the U.S. reported HTS 10 codes time consistent using the concordance from Pierce and Schott (2012). Once we had both the China reported HS codes and the U.S. reported codes mapped back to 2000, we could match them to a consistent HS 6-digit 1996 revision.

U.S. domestic sales: We employ a concordance from HS 10-digit to NAICS 6-digit to convert U.S. production data from NAICS 6-digit to HS 6-digit. We follow Feenstra and Weinstein (2017) (p45 of their Appendix) and assume that the domestic share ($share_k$) in total consumption is the same in each HS 10-digit category as it is in the corresponding NAICS 6-digit category. Denoting a NAICS industry by k, and U.S. domestic sales as $domestic_k \equiv production_k - exports_k$, then domestic sales at the HS 10-digit level is obtained as,

$$domestic_h = \left(\frac{share_k}{1 - share_k}\right) * Imports_h.$$

Once we have U.S. domestic sales at HS10, we can easily aggregate to HS 6-digit and combine with the import data to get total sales in the U.S. market.

Herfindahl Indexes: The Herfindahl indexes used to adjust unit values in Appendix G are from Feenstra and Weinstein (2017). These were constructed using PIERS firm-product level data from bills of lading for all sea shipments and U.S. Census data to adjust for land and air shipments. For Canada and Mexico, they were provided directly from their respective countries. Originally at the HS4-country level, we convert these Herfindahls to our HS1996 grouped codes by assuming that each 6-digit code has the same Herfindahl as its overlying 4-digit code within each country. When concording back to HS1996 6-digit codes, there are some many-to-many correspondences for which we assume that the value for each HS6 code is a simple average of the values for the related HS4 codes.

The Herfindahls are typically available for two years. For Canada, the Herfindahls are available in 1996 and 2005. For Mexico, they are available for 1993 and 2003. For other countries, they available for 1992 and 2005. We use linear interpolation and linear extrapolation to estimate the Herfindahls for 2000 and 2006. In cases where a country-HS6 Herfindahl does not exist for one or both years, we drop that Herfindahl from our sample.

Price Indexes: To calculate the U.S. price index of manufactured goods in equation (30), we need measures of China's export prices, other foreign export prices, U.S. domestic prices, measures of variety, and estimates of elasticities of substitution. For these, we utilize several data sources. The first is from China Customs. We use these data to construct the China components of the overall U.S. price index. We supplement the China-reported trade data with U.S.-reported data to incorporate all other foreign countries and domestic U.S. firms in the construction of the U.S. price index for manufacturing industries. For U.S. imported goods from countries other than China, we use customs data at the HS 10-digit-country level from the U.S. Census; for domestic sales by U.S. producers we use the U.S. producer price indexes (PPI) for the common goods component of the price index, and domestic sales shares of the top 4 U.S. firms, also available from U.S. Census, for the variety component of the price index. Both of these are at the NAICS 6-digit level, which we map to HS10. Because we don't have firm-product level data for the non-China components of the U.S. price index, we also present a robustness check where we adjust equation (30) using Herfindahl indexes in the second component, as described in Appendix G. These Herfindahls are from Feenstra and Weinstein (2017), built up using firm-HS10-digit data from PIERS bills of lading sourced data and complementary sources .

E Total Factor Productivity

To estimate the production coefficients for Chinese firms, we use real value added rather than gross output as the dependent variable because of the large number of processing firms present in China. These processing firms import a large share of their intermediate inputs and have very low domestic value added (Koopman et al. (2012)). Real value added is constructed as deflated production less deflated materials. We use industry level deflators from Brandt et al. (2017), where output deflators use China firm-level unit values and the input deflators are constructed by weighting these output deflators using cost shares from China's 2002 national input-output table.[43] For the firm's investment measure, we construct a capital series using the perpetual inventory method, with real investment calculated as the time difference in the firm's capital stock deflated by an annual capital stock deflator. The firm's real capital stock is the fixed capital asset at original prices deflated by capital deflators. We begin with the firm's initial real capital stock and construct subsequent period's real capital stock as $K_{ft} = (1-\delta)K_{f,t-1} + I_{ft}$, where δ is the firm's actual reported depreciation rate. The production coefficients for each 2-digit CIC industry, reported in Table E4 , are used to calculate each firm's log TFP as follows:[44]

$$\ln(TFP_{ft}) = \ln(VA_{ft}) - \gamma_l \ln L_{ft} - \gamma_k \ln K_{ft} \tag{41}$$

The TFP measures are all normalized relative to the firm's main 2-digit CIC industry.

From Table E5, we see that average TFP growth of Chinese exporters has been very high. For the average exporter in the full sample it has grown 10 percent per year, with similar growth of 11 percent per year in the matched sample. For comparison, we also report the average growth in real value added per worker, which shows a similar pattern to TFP growth, though at slightly higher average rates of between 11 and 12 percent per annum. These TFP results are also similar to the benchmark results for Chinese manufacturers in Brandt et al. (2012).

[43]See http://www.econ.kuleuven.be/public/N07057/CHINA/appendix

[44]For TFP estimation, we clean the ASIF data by dropping observations in the top and bottom percentile for changes in real value added, output, materials, and investment rates.

Table E4: Production Coefficients for Chinese Plants: 1998-2006

	Chinese Industrial Classification	Olley-Pakes Labor β_l	Olley-Pakes Capital β_k
13	Processing of Foods	0.39	0.40
14	Manufacture of Foods	0.43	0.46
15	Manufacture of Beverages	0.39	0.63
17	Manufacture of Textile	0.37	0.37
18	Manufacture of Apparel, Footwear & Caps	0.51	0.35
19	Manufacture of Leather, Fur, Feather & Related Products	0.48	0.30
20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm & Straw Products	0.36	0.43
21	Manufacture of Furniture	0.56	0.39
22	Manufacture of Paper & Paper Products	0.27	0.44
23	Printing, Reproduction of Recorded Media	0.27	0.49
24	Manufacture of Articles For Culture, Education, & Sport Activities	0.44	0.33
25	Processing of Petroleum, Coking, & Nuclear Fuel	0.22	0.61
26	Manufacture of Raw Chemical Materials	0.28	0.49
27	Manufacture of Medicines	0.32	0.42
28	Manufacture of Chemical Fibers	0.36	0.54
29	Manufacture of Rubber	0.31	0.40
30	Manufacture of Plastics	0.33	0.39
31	Manufacture of Non-metallic Mineral Products	0.19	0.53
32	Smelting & Processing of Ferrous Metals	0.38	0.49
33	Smelting & Processing of Non-ferrous Metals	0.33	0.48
34	Manufacture of Metal Products	0.40	0.40
35	Manufacture of General Purpose Machinery	0.32	0.44
36	Manufacture of Special Purpose Machinery	0.29	0.58
37	Manufacture of Transport Equipment	0.40	0.50
39	Electrical Machinery & Equipment	0.43	0.41
40	Computers & Other Electronic Equipment	0.49	0.39
41	Manufacture of Measuring Instruments & Machinery for Cultural Activity & Office Work	0.31	0.51
42	Manufacture of Artwork & Other Manufacturing	0.42	0.28
	Average: all manufacturing	0.37	0.45

Notes: We estimate the production coefficients following Olley and Pakes (1996).

Table E5: China's Productivity Growth

Year	Total factor productivity: All exporters			Real value added per worker: All exporters		
		Matched sample			Matched sample	
	Simple av	Simple av	Weighted av	Simple av	Simple av	Weighted av
2001	0.00	0.01	0.05	0.00	0.00	0.07
2002	0.08	0.11	0.10	0.10	0.11	0.09
2003	0.13	0.14	0.13	0.15	0.15	0.15
2004	0.10	0.12	0.11	0.11	0.12	0.13
2005	0.18	0.17	0.13	0.21	0.20	0.14
2006	0.11	0.11	0.07	0.15	0.13	0.10
Average	0.10	0.11	0.10	0.12	0.12	0.11

Notes: Total factor productivity is estimated at the firm level as in Olley and Pakes (1996).

F Uncertainty in Tariffs and Export Participation

For simplicity, consider the case where the shares sold by each Chinese firms are small enough that they treat their elasticity of demand ρ_g is constant. The pricing decision, revenue and variable profits for the firm are still governed by equations (17), (19) , but with η_{fht} replaced by ρ_g. After deducting the per-period fixed costs of exporting, the one-period value of the firm is

$$v(\varphi_f, \tau_{ht}) = \frac{p_{fht}q_{fht}}{\tau_{ht}\rho_g} - F_g = \frac{X_{gt}}{\tau_{ht}\rho_g}\left(\frac{\rho_g C_f \tau_{ht}}{(\rho_g - 1)P_{gt}}\right)^{1-\rho_g} - F_g,$$

where we have substituted for export revenue from (19) and we now treat marginal costs $C_f = C(P^D, c_f^M, \varphi_f)$ as constant over time.[45] P_{gt} is the CES index as in (4) taken over the Chinese firms' prices in (17) , from which it follows that $P_{gt} = \rho_g C_g \tau_{gt}/(\rho_g - 1)$, where C_g denotes the CES index as in (4) but now taken over the Chinese firms' marginal costs C_f. Substituting above, we obtain a slightly simpler equation for the one-period profits,

$$v(\varphi_f, \tau_{ht}) = \frac{p_{fht}q_{fht}}{\tau_{ht}\rho_g} - F_g = \frac{X_{gt}}{\tau_{ht}\rho_g}\left(\frac{C_f}{C_g}\right)^{1-\rho_g} - F_g. \tag{42}$$

As explained in the main text, we suppose that if the tariff starts at its MFN level then it remains there in the next period with probability π, and with probability $(1-\pi)$ the tariff moves to its column 2 level; whereas if the tariff starts at its column 2 level then it stays there forever. This Markov process applies to all industries simultaneously. We need to keep track of what happens to overall Chinese exports under the differing tariffs, so let $\overline{X}_g$ (X_g^{MFN}) denote the value of Chinese exports X_{gt} when all tariffs are at their column 2 (MFN) level.

With a discount rate $\delta < 1$, the present discounted value of a Chinese firm facing MFN tariffs is

$$V(\varphi_f, \tau_h^{MFN}) = v(\varphi_f, \tau_h^{MFN}) + \delta\left[\pi V(\varphi_f, \tau_h^{MFN}) + (1-\pi)V(\varphi_f, \overline{\tau}_h)\right].$$

Since $V(\varphi_f, \overline{\tau}_h) = v(\varphi_f, \overline{\tau}_h)/(1-\delta)$ by our assumption that the column 2 tariff is an absorbing state, we obtain the *entry condition* for a Chinese firm facing MFN tariffs,

$$\int_\varphi V(\varphi, \tau_h^{MFN})dG = \int_\varphi \left\{\frac{v(\varphi, \tau_h^{MFN})}{(1-\delta\pi)} + \frac{\delta(1-\pi)v(\varphi, \overline{\tau}_h)}{(1-\delta)(1-\delta\pi)}\right\} dG \geq F_g^E, \tag{43}$$

where $G(\varphi)$ is the distribution function of firm productivities. We can simplify this condition by using (42) to obtain

$$v(\varphi_f, \overline{\tau}_h) + F_g = \left[v(\varphi_f, \tau_h^{MFN}) + F_g\right]\left(\frac{\overline{X}_g/\overline{\tau}_h}{X_g^{MFN}/\tau_h^{MFN}}\right).$$

[45] That is, in addition to assuming that productivity φ_f is constant over time, we suppose that there is no change to the prices or tariffs on Chinese domestic or imported inputs, and therefore no changes to the sourcing strategy, even if column 2 tariffs are imposed. This assumption can be weakened by allowing C_f and C_g to vary depending on whether MFN or column 2 tariffs are applied, but doing so would just lead to extra terms in (47) that we could not measure empirically in any case.

Substituting this term into (43), we obtain the export participation condition written in terms of one-period profits:

$$\int_{\varphi} v(\varphi, \tau_h^{MFN}) dG \geq (T_h - 1)F_g + T_h(1-\delta)F_g^E, \tag{44}$$

where,

$$T_h \equiv \left\{ \frac{(1-\delta)}{(1-\delta\pi)} + \frac{\delta(1-\pi)}{(1-\delta\pi)} \left(\frac{\overline{X}_g/\overline{\tau}_h}{X_g^{MFN}/\tau_h^{MFN}} \right) \right\}^{-1}. \tag{45}$$

These conditions hold in the presence of tariff uncertainty. After China's entry to the WTO, U.S. tariffs are permanently at their MFN level, and the export participation condition for Chinese firms becomes

$$\int_{\varphi} v(\varphi, \tau_h^{MFN}) dG \geq (1-\delta)F_g^E. \tag{46}$$

The right-hand side of (46) differs from (44) by the term $(T_h - 1)[F_g + (1-\delta)F_g^E]$, which we interpret as the "effective" tariff term $(T_h - 1)$ multiplied by fixed costs and amortized sunk costs. The effective tariff we have obtained is similar to the results in Handley and Limão (2017) and Feng et al. (2017), except that in (45) we also keep track of what happens to overall Chinese exports to the U.S. Measuring the effective tariff $(T_h - 1)$ by the first-order approximation $(T_h - 1) \approx \ln T_h$, if discounting is small so that $\delta \to 1$, we have that

$$\ln T_h \to \left(\ln \overline{\tau}_h - \ln \tau_h^{MFN}\right) - \left(\ln \overline{X}_g - \ln X_g^{MFN}\right). \tag{47}$$

The first term on the right of (47) is the "gap" between the column 2 and MFN *ad valorem* tariffs, as first used by Pierce and Schott (2016). That variable acts as an effective drop in the fixed costs of entry facing Chinese exporters following WTO accession, which will lead to greater entry of those firms. We will therefore incorporate the "gap" into the specification of our export participation equation. The second term on the right of (47) keeps track of what happens to the value of Chinese exports to the U.S. market. We will not attempt to measure this additional term, and in any case, it will be controlled for by including industry g fixed effects in the export participation equation, which will also control for differences in the fixed and sunk costs F_g and F_g^E.

G Using Herfindahl Indexes to Improve Unit Value Indexes

For exporting countries other than China, we use HS-10 digit U.S. import data to construct unit-values for each country. Denoting exporting firms by the subscript *f*, the observed unit value is:

$$uv_{gt}^j \equiv \left(\frac{\sum_f p_{fgt}^j q_{fgt}^j}{\sum_f q_{fgt}^j} \right). \tag{48}$$

The following result shows how these unit values are related to the CES index defined analogously to equation (4), but assuming symmetry over products,

$$P^j_{gt} = \left(\sum_f \left(p^j_{fgt} \right)^{1-\rho_g} \right)^{\frac{1}{1-\rho_g}}. \tag{49}$$

LEMMA 1. With symmetry over products, the CES index is related to unit values by $P^j_{gt} = uv^j_{gt} H^j_{gt}$, where $H^j_{gt} \equiv \sum_f \left(s^j_{fgt} \right)^{\frac{\rho_g}{\rho_g - 1}}$.

PROOF:

Making use of the symmetric CES demand in (18) and adding the country superscript j, we can rewrite the unit value as,

$$uv^j_{gt} = \left(\frac{\sum_f (p^j_{fgt})^{1-\rho_g}}{\sum_f (p^j_{fgt})^{-\rho_g}} \right). \tag{50}$$

Again using symmetric demand in (18), it follows that,

$$s^j_{fgt} \equiv \frac{p^j_{fgt} q^j_{fgt}}{X^j_{gt}} = \left(\frac{p^j_{fgt}}{P^j_{gt}} \right)^{1-\rho_g} \Leftrightarrow p^j_{fgt} = P^j_{gt} \left(s^j_{fgt} \right)^{\frac{1}{1-\rho_g}} \Leftrightarrow \sum_f (p^j_{fgt})^{-\rho_g} = (P^j_{gt})^{-\rho_g} \sum_f \left(s^j_{fgt} \right)^{\frac{\rho_g}{\rho_g - 1}}.$$

Substituting into (50) and using (49), we readily obtain,

$$uv^j_{gt} = \left(\frac{\sum_f (p^j_{fgt})^{1-\rho_g}}{(P^j_{gt})^{-\rho_g} \sum_f \left(s^j_{fgt} \right)^{\frac{\rho_g}{\rho_g - 1}}} \right) = P^j_{gt} \left(\frac{\sum_f (p^j_{fgt})^{1-\rho_g}}{(P^j_{gt})^{1-\rho_g} \sum_f \left(s^j_{fgt} \right)^{\frac{\rho_g}{\rho_g - 1}}} \right) = \frac{P^j_{gt}}{H^j_{gt}},$$

so it follows that $P^j_{gt} = uv^j_{gt} H^j_{gt}$. QED

To interpret this result, H^j_{gt} is a modified Herfindahl index depending on the elasticity ρ_g, and if $\rho_g = 2$ then it is the usual Herfindahl index, as we will use empirically. For countries exporting to the U.S. other than China we use their unit-values at the HS 10-digit level. In a slight abuse of notation, let ω in (6) refer to the HS 10-digit goods within each HS 6-digit industry, and let $p^j_{gt}(\omega)$ in (6) denote the CES price indexes at the HS 10-digit level. Applying the Lemma, we will replace the CES indexes $p^j_{gt}(\omega)$ by $uv^j_{gt}(\omega) H^{ij}_{gt}$, where $uv^j_{gt}(\omega)$ are the unit values at the HS 10-digit level. So the unit values times the Herfindahls should appear in the second term of (30) for all exporters other than China. In principle we should be using the Herfindahl indexes of exporters at the HS 10-digit level, but in practice due to data limitations we use these indexes at the HS 6-digit level (see Appendix G). For each HS 6-digit industry, we can construct the variety terms λ^j_{gt} for the products exported by those countries and the change in variety using (8). We also construct the Sato-Vartia index for each HS 6-digit industry g and country using the unit-values times their Herfindahls, $uv^j_{gt}(\omega) H^j_{gt}$.

H Additional Tables

Adding the additional reform variables to our TFP, export participation and export price equations of Table H6 does not greatly affect any of our previous coefficient estimates. In our TFP equation shown in column 1, the coefficients on our two predicted import instruments are essentially unaffected, while two of the additional reform variables are significant. The coefficient on the output tariff is negative, showing that lower tariffs on competing imports also increase productivity, consistent with Brandt et al. (2017). Import license reforms that increase the share of a firm's imports that are not subject to import restrictions, ln($Unrestricted\ Import\ Share_{ft}$), also boost productivity. In columns 2 and 3, the additional reform variables usually enter significantly with the expected signs. The probability of entering the export market increased and export prices fell in industries where MFA quotas were lifted. Export entry increased and export prices fell in industries where FDI restrictions were abolished. Import license liberalization also led to more export entry of firms with increased access to imports. We then reconstruct our WTO entry instruments using these regression results, re-estimate equation (33), and report the results in column 6 of Table 8.

Table H6: Including Additional Reforms

Dependent variable	$ln(TFP_{ft})$	I^X_{fht} =1 if X_{fht} >0	$ln(price_{fht})$
	(1)	(2)	(3)
$ln(\hat{M}_{max,ft})$	-0.042***		
	(0.013)		
$ln(\hat{M}_{tot,ft})$	0.051***		
	(0.005)		
$ln(\widehat{TFP}_{ft})$		1.944***	-1.000†
		(0.032)	
$ln(Input\tau_{gt})$	0.493	-1.638***	3.344**
	(0.451)	(0.423)	(1.472)
$ln(Input\tau_{gt}) \times Process_{fh}$		-0.190	-0.987*
		(0.148)	(0.518)
$Process_{fh}$		0.019	0.097
		(0.012)	(0.063)
$ln(P^D_{gt})$		0.023	0.489**
		(0.084)	(0.189)
$MFA\,2002_{g,t-1}$	-0.010	0.051***	-0.045*
	(0.032)	(0.006)	(0.023)
$MFA\,2005_{g,t-1}$	-0.008	0.083***	-0.121***
	(0.016)	(0.010)	(0.033)
$FDI_{h,t-1}$	0.040	-0.023**	0.090**
	(0.027)	(0.010)	(0.045)
$ln(Output\tau_{ht})$	-0.288*	0.017	-0.268
	(0.156)	(0.095)	(0.230)
$ln(Unrestricted\ Import\ Share_{ft})$	0.029**	0.008**	0.012
	(0.014)	(0.004)	(0.041)
$ln(Gap_g) \times WTO_t$		0.068*	
		(0.035)	
$ln(ShareEligible_{gt})$		-0.021	
		(0.024)	
$ln(ShareEligible_{gt}) \times Foreign_f$		0.252***	
		(0.017)	
$HS8\ Industry\ FE$	no	yes	yes
$Year\ FE$	yes	yes	yes
$Firm\ FE$	yes	yes	yes
# obs.	79,602	3,971,038	1,313,431
R^2	0.692	0.130	0.951

Notes: Column 1 is parallel to column 3 in Table 4; column 2 relates to column 1 in Table 6; and column 3 is analogous to column 5 in Table 6. The MFA variables are dummy variables equal to 1 for HS 6-digit products where the quota has been lifted. FDI is an indicator variable equal to 1 if there was a restriction on that industry at the HS 8-digit level. Output$\tau_{ht}$is the HS 8-digit Chinese import tariff on that industry. Import licenses are at the firm-year level, calculated as the share of imports that are subject to import licenses.