

How Did China's WTO Entry Benefit U.S. Consumers?*

Mary Amiti

Federal Reserve Bank of New York

Robert C. Feenstra

University of California, Davis

Mi Dai

Beijing Normal Univesity

John Romalis

University of Sydney

May 27, 2017

Abstract

China's rapid rise in the global economy following its 2001 WTO entry has raised questions about its economic impact on the rest of the world. In this paper, we focus on the U.S. market and potential consumer benefits. We find that the China trade shock reduced the U.S. manufacturing price index by 7.6 percent between 2000 and 2006. In principle, this consumer welfare gain could be driven by two distinct policy changes that occurred with WTO entry. The first, which has received much attention in the literature, is the U.S. granting permanent normal trade relations (PNTR) to China, effectively removing the threat of China facing very high tariffs on its exports to the U.S. A second, new channel we identify is China reducing its own input tariffs. Our results show that China's lower input tariffs increased its imported inputs, boosting Chinese firms' productivity and their export values and varieties. Lower input tariffs also reduced Chinese export prices to the U.S. market. In contrast, PNTR had no effect on Chinese productivity nor export prices, but did increase Chinese entry into the U.S. export market. We find that at least two-thirds of the China WTO effect on the U.S. price index of manufactured goods was through China lowering its own tariffs on intermediate inputs.

*Amiti: Federal Reserve Bank of New York. 33 Liberty Street, New York, NY 10045 (email: mary.amiti@ny.frb.org); Dai: Business School, Beijing Normal University, Beijing 100875, China (email: daimi002@gmail.com); Feenstra: UC Davis (rfeenstra@ucdavis.edu); Romalis: University of Sydney (john.romalis@sydney.edu.au). We thank Pol Antras, Gordon Dahl, Gordon Hanson, Pablo Fajgelbaum, Kyle Handley, Dan Treffler, Maxim Pinkovski, and David Weinstein for insightful comments. We are grateful to Tyler Bodine-Smith and Preston Mui for excellent research assistance. Funding from the National Science Foundation is gratefully acknowledged. The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of New York or the Federal Reserve System.

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. Surprisingly, given the traditional focus of international trade theory, little analysis has been made of the potential gains to consumers 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, consumer 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, effectively removing the threat of China facing very high tariffs on its exports to the U.S. A second, new channel we identify through which China’s WTO entry lowered U.S. price indexes, is China reducing its own input tariffs. In this paper, we quantify how much U.S. consumer welfare improved due to China’s WTO entry; and we identify that the key mechanism by which China’s WTO entry reduced U.S. price indexes was through China lowering its own tariffs on intermediate inputs.

To measure China’s impact on U.S. consumers (by which we mean both households and firms importing from China), 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 this growth, and most of it is 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.¹ We find that the China import price index in the U.S. falls by 46 percent over the period 2000 to 2006 due to the growth in exported product varieties. But of course this number needs to be adjusted by China’s share in U.S. manufacturing industries to get a measure of U.S. consumer welfare. We supplement the Chinese data with U.S. reported trade data from other countries as well as U.S. domestic sales to construct overall U.S. manufacturing price indexes. With these data, we explicitly take into account that the China shock can affect prices of competitor firms as well as net entry in the U.S. market.

We model Chinese firm behavior by generalizing the Melitz (2003) model to allow firms to import intermediate inputs as in Blaum, Lelarge, and Peters (2015). We expect that the reduction in China’s

¹Broda 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 define a Chinese variety at the firm-product-destination level (rather than product-country).

tariffs on intermediate inputs has expanded the international sourcing of these inputs, as in Antràs, Fort, and Tintelnot (2017), Gopinath and Neiman (2014), and Halpern, Koren, and Szeidl (2015). Expanded sourcing of imported inputs raises Chinese firms' productivity, which makes it possible for them to increase their exports on both the intensive and extensive margins. Lower tariffs on Chinese imported inputs also lowers the marginal costs of Chinese firms producing goods, thus reducing export prices. We also extend the theory to allow the China shock to be driven by a reduction in uncertainty due to PNTR, which we model as a simplified version of Handley and Limão (2017).

Within this theoretical framework, we estimate an equation for Chinese firms' U.S. export participation and export prices, from which we construct fitted values due to WTO entry that we link to U.S. price indexes. We estimate these equations using highly disaggregated Chinese firm-product level international trade data, which we combine with tariff data and firm-level Chinese industrial data. A major challenge in the estimation is measuring marginal cost, which appears in the export price equation. In addition to material prices, our proxy for marginal costs is the inverse of Chinese firms' total factor productivity (TFP), for which we construct a novel instrument that targets the channel through which input tariffs affect TFP directly. More specifically, we estimate an importing equation of Chinese firms' inputs at the firm-product level and use the fitted import values from these estimates to construct theoretically consistent instruments of the intensive and extensive margins of importing. The results from the importing equations show that reductions in Chinese input tariffs lead to higher import values and more imported varieties. We show that lower input tariffs, by increasing imported intermediate inputs, boost firm-level productivity. Our specifications allow for exports to be influenced by input tariffs and the effect of PNTR, which we estimate by utilizing the "gap" between the U.S. column 2 tariff and the U.S. MFN tariff as in Pierce and Schott (2016) and Handley and Limão (2017).

Our results show that China's WTO entry drove down the U.S. price index of manufactured goods by 7.6 percent, averaging around 1 percent annually between 2000 and 2006, due to a lower conventional price index and increased variety. Lower tariffs on Chinese firms' imported inputs resulted in lower prices on their U.S. exports, both due to the direct effect of lower input tariffs and the indirect effect through TFP. In contrast, we find no effect at all from PNTR on China's export prices, as expected from the theory where Chinese firms set prices after the tariff is known. We find that PNTR has no effect on TFP but does have a significant effect on Chinese entry into U.S. exporting, with more entry in the higher gap industries post-WTO entry.

Interestingly, our results show that most of the effect of the China WTO shock on the U.S. price index of manufactured goods is due to China reducing its own input tariffs rather than the PNTR: we find that around two-thirds of China's WTO effect comes via China's conventional price index, which PNTR has no effect on. Our analysis explicitly takes into account how the China trade shock affects competitor prices and entry. We find that lower Chinese export prices due to China's WTO entry, constructed from the fitted values of our export price equation, reduced both the China price index and the prices of competitor firms in the U.S.; and led to exit of competitors in the U.S. These effects

could be due to less efficient firms exiting the U.S. market, lower marginal costs or lower markups. The China-WTO variety instrument, constructed from the fitted values of the export participation equation, works almost entirely through the China variety component with hardly any effect on competitor prices and varieties. Both PNTR and lower input tariffs contribute to the reduction in the U.S price index due to the Chinese variety component. However, since most of the effects work through the conventional price index it becomes clear that the overall WTO effect is primarily driven by lower Chinese input tariffs.

Our paper builds on a literature that finds lower input tariffs increase firms' TFP (see, for examples, Amiti and Konings (2007) for Indonesia; Goldberg, Khandelwal, Pavcnik, and Topalova (2010) for India; Yu (2015) and Brandt, Van Biesebroeck, Wang, and Zhang (2017) for China). Our results support the findings in Kee and Tang (2016) that show that lower input tariffs also benefit processing exporters by lowering the price of inputs sold by competing domestic producers, as well as increasing the number of domestic varieties. All of these studies only consider the effect of a country's own tariff reduction on firms in their own countries. In contrast, our focus is on how China's lower input tariffs generated gains to households and firms in another country — these are additional sources of gains from trade.²

The impact of China's enormous growth on the rest of the world is an increasingly active area of study. Focusing on the United States, Autor, Dorn, and Hanson (2013) find evidence that China's strong export growth has caused negative employment and wage effects in import-competing industries, and Acemoglu, Autor, Dorn, Hanson, and Price (2016) find that China's export growth reduced overall U.S. job growth.³ Pierce and Schott (2016) attribute the fall in U.S. manufacturing employment from 2001 to 2007 to the change in U.S. trade policy, whereby China was granted PNTR after its WTO entry. Feng, Li, and Swenson (2017) use firm-level data on Chinese exporters to show that the reduced policy uncertainty had a positive impact on the count of exporters, through simultaneous entry and exit. Handley and Limão (2017) argue that the granting of permanent MFN status to China is a reduction in U.S. policy uncertainty, which leads to greater entry and innovation by those exporters. They measure the positive effects on U.S. consumers, and attribute a 0.5 percent gain in U.S. consumer income due to the reduced policy uncertainty. Our focus is on a different channel — China's lower input tariffs — and we also take account of the PNTR policy for which we find a relatively small role.

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

²A number of papers have shown a connection between importing varieties and exporting. See Feng, Li, and Swenson (2016) on China, Bas (2012) on Argentina, and Bas and Strauss-Kahn (2014) on France.

³These type of channels have also been studied for other countries (for example, Bloom, Draca, and Van Reenen (2016) on European countries and Iacovone, Rauch, and Winters (2013) on Mexico).

to the rest of the world.⁴ More recently, Caliendo, Dvorkin, and Parro (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, Costinot, and Rodriguez-Clare (2012) (ACR) framework (i.e. a Pareto distribution for firm productivities). Our approach does not rely on a particular distribution of productivities, in contrast, and also differs from ACR in that we focus on the *channels* by which trade policy changes in one country (China) leads to consumer gains in another (the United States).

The rest of the paper is organized as follows. Section 2 develops the theoretical framework. Section 3 previews key features of the data, including estimates of variety, elasticities of substitution, and total factor productivity (TFP). Section 4 estimates export participation and export price equations for Chinese firms. Section 5 estimates the impact of China's WTO accession on U.S. manufacturing price indexes. Section 6 concludes.

2 Theoretical Framework

2.1 U.S. Consumers

In order to measure the impact of China's export growth on the U.S. price index of manufactured goods, we shall assume a nested CES utility function for the representative consumer (either a household or a firm). At the upper level, we can write utility from consuming goods $g \in G$ in the United States in period t as:

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

where g denotes an industry that will be defined at an HS 6-digit code, and G denotes the set of HS 6-digit codes; Q_{gt} is the aggregate consumption of good g in the U.S. in period t ; $\alpha_g > 0$ is a taste parameter for the aggregate good g in the U.S.; and κ is the elasticity of substitution across goods.

Consumption of g is comprised of varieties from each country i that the U.S. imports from within that HS6 code:

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

where Q_{gt}^i is the aggregate industry quantity in industry g sold by countries $i \in I_{gt}$ to the U.S. in period t , and σ_g denotes the elasticity of substitution across these aggregate country varieties in industry g .

⁴In a multi-country general equilibrium model, di Giovanni, Levchenko, and Zhang (2014) find that the welfare impact of China's integration is larger when its growth is biased toward its comparative disadvantage sectors.

We suppose that there are a number of disaggregate varieties N_{gt}^i sold in industry g by country i in year t . In practice, these varieties of products will be measured for China by firm-level data across all HS 8-digit level products within an HS 6-digit industry. Denoting consumption of these product varieties by $q_g^i(\omega)$, aggregate sales in industry g by country i to the U.S. are:

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

where $\alpha_g^i(\omega) > 0$ is a taste or quality parameter for the variety ω of good g sold by country i ; Ω_g^i is the set of varieties; and ρ_g denotes the elasticity of substitution across varieties in sector g . We can expect that the elasticity of substitution ρ_g at the firm-product level exceeds the elasticity σ_g across countries in sector g .

Our goal is to compute a price index that accurately reflects consumer utility given this nested CES structure, without knowledge of taste parameters α_g and $\alpha_g^i(\omega)$. We begin with the exports of a foreign country i (think of China). The CES price index that is dual to (3) is:

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

from which it follows that share of product variety ω within the exports of country i is,

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

Consider two equilibria with theoretical 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 $\bar{\Omega}_g^i = \Omega_{gt}^i \cap \Omega_{g0}^i$. We refer to the set $\bar{\Omega}_g^i$ as the “common” varieties, available in periods t and 0. Feenstra (1994) shows how the ratio of P_{gt}^i and P_{g0}^i can be measured, as:

$$\frac{P_{gt}^i}{P_{g0}^i} = \left[\prod_{\omega \in \bar{\Omega}_g^i} \left(\frac{p_{gt}^i(\omega)}{p_{g0}^i(\omega)} \right)^{w_{gt}^i(\omega)} \right] \left(\frac{\lambda_{gt}^i}{\lambda_{g0}^i} \right)^{\frac{1}{\rho_g-1}}, \quad i = \text{China}, \quad (6)$$

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

$$w_{gt}^i(\omega) \equiv \frac{\left(\bar{s}_{gt}^i(\omega) - \bar{s}_{g0}^i(\omega) \right) / \left(\ln \bar{s}_{gt}^i(\omega) - \ln \bar{s}_{g0}^i(\omega) \right)}{\sum_{\omega \in \bar{\Omega}_g^i} \left(\bar{s}_{gt}^i(\omega) - \bar{s}_{g0}^i(\omega) \right) / \left(\ln \bar{s}_{gt}^i(\omega) - \ln \bar{s}_{g0}^i(\omega) \right)}, \quad \bar{s}_{gt}^i(\omega) \equiv \frac{p_{gt}^i(\omega) q_{gt}^i(\omega)}{\sum_{\omega \in \bar{\Omega}_g^i} p_{gt}^i(\omega) q_{gt}^i(\omega)}, \quad (7)$$

and

$$\lambda_{gt}^i \equiv \frac{\sum_{\omega \in \bar{\Omega}_g^i} p_{gt}^i(\omega) q_{gt}^i(\omega)}{\sum_{\omega \in \Omega_{gt}^i} p_{gt}^i(\omega) q_{gt}^i(\omega)} = 1 - \frac{\sum_{\omega \in \Omega_{gt}^i \setminus \bar{\Omega}_g^i} p_{gt}^i(\omega) q_{gt}^i(\omega)}{\sum_{\omega \in \Omega_{gt}^i} p_{gt}^i(\omega) q_{gt}^i(\omega)}, \quad (8)$$

and likewise for $\bar{s}_{g0}^i(\omega)$ and λ_{g0}^i , 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 $\bar{\Omega}_g^i$, with log-change weights. The second component comes from Feenstra (1994) and takes into account net variety growth: λ_{gt}^i equals one minus the share of expenditure on new products, in the set Ω_{gt}^i but not in $\bar{\Omega}_g^i$, whereas λ_{g0}^i equals one minus the share of expenditure on disappearing products, in the set Ω_{g0}^i but not in $\bar{\Omega}_g^i$. A lower λ ratio implies more net variety, and hence a lower price index.

Note that the quality of the products in the “common” set $\bar{\Omega}_g^i$, as reflected by their taste parameters $\alpha_g^i(\omega)$, is assumed to be constant over time, but products outside this set and appearing within the λ_{gt}^i terms can have changing quality. To achieve this in theory we can choose $\bar{\Omega}_g^i$ as any non-empty subset of $\Omega_{gt}^i \cap \Omega_{g0}^i$ 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 $\bar{\Omega}_g^i = \Omega_{gt}^i \cap \Omega_{g0}^i$ and then correct those prices in the common set for changing quality, using the empirical methods of Hallak and Schott (2011) and Khandelwal (2010); see section 4.

While (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 could be done in principle by using the exact price index for every other country, as we have done for China. But we will not be able to implement that approach because we do not have the firm-level export data for all other countries. So 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 can 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 (8). We also construct the Sato-Vartia index over the “common” unit-values $uv_{gt}^j(\omega)$ for 10-digit HS categories $\omega \in \bar{\Omega}_g^j$ 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,⁵

$$\frac{P_{gt}^j}{P_{g0}^j} = \left[\prod_{\omega \in \bar{\Omega}_g^j} \left(\frac{uv_{gt}^j(\omega)}{uv_{g0}^j(\omega)} \right)^{w_{gt}^j(\omega)} \right] \left(\frac{\lambda_{gt}^j}{\lambda_{g0}^j} \right)^{\frac{1}{\rho_g^j - 1}}, \quad j \neq i. \quad (9)$$

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 inter-

⁵In Appendix A 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.

section of countries selling to the U.S. in period t and period 0 by $\bar{I}_g = I_{gt} \cap I_{g0}$, which we call the “common” countries, the Sato-Vartia weights at the country-industry level are

$$W_{gt}^j = \frac{(\bar{S}_{gt}^j - \bar{S}_{g0}^j) / (\ln \bar{S}_{gt}^j - \ln \bar{S}_{g0}^j)}{\sum_{k \in \bar{I}_{gt}} (\bar{S}_{gt}^k - \bar{S}_{g0}^k) / (\ln \bar{S}_{gt}^k - \ln \bar{S}_{g0}^k)}, \text{ with } \bar{S}_{gt}^j \equiv \frac{P_{gt}^j Q_{gt}^j}{\sum_{k \in \bar{I}_{gt}} P_{gt}^k Q_{gt}^k}, j \in \bar{I}_{gt}. \quad (10)$$

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

$$\Lambda_{gt} \equiv \frac{\sum_{j \in \bar{I}_g} P_{gt}^j Q_{gt}^j}{\sum_{j \in I_{gt}} P_{gt}^j Q_{gt}^j}. \quad (11)$$

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

$$\frac{P_{gt}}{P_{g0}} = \left[\prod_{j \in \bar{I}_g} \left(\frac{P_{gt}^j}{P_{g0}^j} \right)^{W_{gt}^j} \right] \left(\frac{\Lambda_{gt}}{\Lambda_{g0}} \right)^{\frac{1}{\sigma_g - 1}}. \quad (12)$$

The term (11) 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 (12). 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 (12) 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,

$$\begin{aligned} \ln \frac{P_{gt}}{P_{g0}} = & \underbrace{\ln \left[\prod_{\omega \in \bar{\Omega}_g^i} \left(\frac{p_{gt}^i(\omega)}{p_{g0}^i(\omega)} \right)^{W_{gt}^i w_{gt}^i(\omega)} \right]}_{China P_g} + \underbrace{\ln \left[\prod_{j \in \bar{I}_g \setminus i} \prod_{\omega \in \bar{\Omega}_g^k} \left(\frac{uv_{gt}^j(\omega)}{uv_{g0}^j(\omega)} \right)^{W_{gt}^j w_{gt}^j(\omega)} \right]}_{Other P_g} \\ & + \underbrace{\ln \left(\frac{\lambda_{gt}^i}{\lambda_{g0}^i} \right)^{\frac{W_{gt}^i}{\rho_g - 1}}}_{China V_g} + \underbrace{\ln \left\{ \left[\prod_{j \in \bar{I}_g \setminus i} \left(\frac{\lambda_{gt}^j}{\lambda_{g0}^j} \right)^{\frac{W_{gt}^j}{\rho_g - 1}} \right] \left(\frac{\Lambda_{gt}}{\Lambda_{g0}} \right)^{\frac{1}{\sigma_g - 1}} \right\}}_{Other V_g}. \end{aligned} \quad (13)$$

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-Vartio 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.⁶

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

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

Then we can write the change in the overall U.S. price index of manufactured goods as,⁷

$$\frac{P_t}{P_0} = \prod_{g \in G} \left(\frac{P_{gt}}{P_{g0}} \right)^{W_{gt}}. \quad (14)$$

This completes our description of the consumer side of the model, but we still need to investigate the behavior of firms. If we find a substantial increase in the product variety of Chinese firms exporting to the U.S., it will be important to determine what amount of this increase is actually due to China's entry to the WTO, and whether this increase comes from reduced uncertainty over U.S. tariffs or from the reduction in Chinese tariffs. Introducing heterogeneous firms will allow us to develop structural equations to determine how variety in our model is related to U.S. and Chinese tariff changes.

2.2 Chinese Firms

We focus on Chinese firms exporting to the United States, so for simplicity we drop the superscript for country i and the subscript for industry g . Chinese firms randomly draw a productivity φ_{ft} . The production structure is as in Melitz (2003), but we also incorporate the imports of intermediate inputs by firms engaged in exporting. For convenience, we use the same production function used by Blaum, Lelarge, and Peters (2015):⁸

$$Y_{ft} = \varphi_{ft} L_{ft}^\gamma \left(\left(\alpha_D Q_{ft}^D \right)^{\frac{\sigma-1}{\sigma}} + \left(\alpha_M Q_{ft}^M \right)^{\frac{\sigma-1}{\sigma}} \right)^{(1-\gamma) \frac{\sigma}{\sigma-1}}, \quad (15)$$

where Y_{ft} is the output of firm f in year t with productivity φ_{ft} , using labor L_{ft} , the domestic intermediate input Q_{ft}^D , and the aggregate imported intermediate input Q_{ft}^M . We assume that the aggregate

⁶That 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.

⁷The U.S. price index that we construct in this way reflect the U.S. and import prices of all manufactured goods, whether these goods are used as intermediate inputs or as final goods. In our robustness analysis (section 5), we separate the final goods from intermediate inputs, obtaining what is closer to a U.S. CPI over final goods and a PPI over intermediate inputs, respectively.

⁸See also Antràs, Fort, and Tintelnot (2017), Gopinath and Neiman (2014), Halpern, Koren, and Szeidl (2015), Amiti, Itskhoki, and Konings (2014), Kasahara and Lapham (2013), Amiti and Davis (2011) for models of firm importing and exporting.

imported input is a CES aggregate of the various inputs $n \in \Sigma_{ft}$ that are purchased by the firm across different HS 8-digit categories:

$$Q_{ft}^M = \left(\sum_{n \in \Sigma_{ft}} (\alpha_n q_{fnt})^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}. \quad (16)$$

The unit-cost function dual to (16) is:

$$c_{ft}^M = c(\{p_{nt}\tau_{nt}\}, \Sigma_{ft}) = \left(\sum_{n \in \Sigma_{ft}} (p_{nt}\tau_{nt}/\alpha_n)^{1-\rho} \right)^{\frac{1}{1-\rho}}, \quad (17)$$

where τ_{nt} denotes one plus the *ad valorem* tariff that China charges on its imports of intermediate input n , with the net-of-tariff price p_{nt} , and $\{p_{nt}\tau_{nt}\}$ denotes the vector of tariff-inclusive prices.

Blaum, Lelarge, and Peters (2015) refer to $n \in \Sigma_{ft}$ as the *sourcing strategy* of the firm, and the goal of their analysis is to show how the productivity of the firm is enhanced as the range of imported inputs expands. To achieve this, let C_{ft} denote the unit-cost function for the production function in (15). Setting the wage equal to unity as the numeraire, then the unit-cost function dual to (15) is:

$$C_{ft} = C(P_t^D, c_{ft}^M, \varphi_{ft}) = \varphi_{ft}^{-1} \left((P_t^D/\alpha_D)^{1-\sigma} + (c_{ft}^M/\alpha_M)^{1-\sigma} \right)^{\frac{1-\gamma}{1-\sigma}}. \quad (18)$$

To express the ratio of costs in two periods independently of the parameters α_D and α_M , we can choose the domestic input as the “common” intermediate input that is sold in both periods 0 and t . Then the ratio of firm costs between period t and period 0 just depends on this price ratio and on the variety of intermediate inputs purchased, which is inversely related to the share of domestic inputs:⁹

$$\frac{C_{ft}}{C_{f0}} = \frac{\varphi_{f0}}{\varphi_{ft}} \left(\frac{P_t^D}{P_0^D} \right)^{1-\gamma} \left(\frac{S_{ft}^D}{S_{f0}^D} \right)^{\frac{1-\gamma}{\sigma-1}}, \quad (19)$$

where S_{ft}^D is the share of total expenditure on intermediate inputs that is devoted to *domestic* inputs in period t . Blaum, Lelarge, and Peters (2015) proceed by measuring the change in unit-costs using this domestic share variable, which endogenously reflects the sourcing strategy of the firm.¹⁰

There is another way to write the change in unit costs, however, that focuses more directly on the sourcing strategy. Using the unit-cost function over imported inputs denoted by c_{ft}^M in (17), let $\bar{\Sigma}_f \subseteq \Sigma_{ft} \cap \Sigma_{f0}$ denote a non-empty subset of the “common” imported inputs purchased in periods 0 and t . Then analogous to the consumer CES indexes discussed in section 2.1, the index of firm costs for imported inputs between period t and period 0 is

$$\frac{c_{ft}^M}{c_{f0}^M} = \left[\prod_{n \in \bar{\Sigma}_f} \left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}} \right)^{w_{nt}} \right] \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{\frac{1}{\rho-1}}, \quad (20)$$

⁹The result in (19) is derived by Blaum, Lelarge, and Peters (2015) and is also an immediate application of Theorem 2 in Feenstra (1994). That theorem 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 (19) which are also adjusted by the Cobb-Douglas share $1 - \gamma$ of intermediates.

¹⁰A solution to the sourcing strategy is illustrated by Antràs, Fort, and Tintelnot (2017).

where w_{nt} is the Sato-Vartia weight for input n , and λ_{ft} denotes the expenditure on imported inputs in the *common* set $\bar{\Sigma}_f$ relative to *total* expenditure on imported inputs in period t .¹¹ The first term on the right of (20) is the direct effect of tariffs on costs, or the Sato-Vartia index of input prices inclusive of tariffs.¹² 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 (20) back to the unit-costs of the production function C_{ft} . The ratio of unit-costs can be written as a Sato-Vartia index over the ratio of wages in period t relative to period 0, the ratio of the price of the domestic intermediate input, and the ratio of the price of imported intermediate inputs. Since we are treating the wage unchanged over time, we simply obtain:

$$\frac{C_{ft}}{C_{f0}} = \frac{\varphi_{f0}}{\varphi_{ft}} \left(\frac{P_t^D}{P_0^D} \right)^{W_{ft}^D(1-\gamma)} \left(\frac{c_{ft}^M}{c_{f0}^M} \right)^{W_{ft}^M(1-\gamma)}, \quad (21)$$

where W_{ft}^D (W_{ft}^M) is the Sato-Vartia weight of domestic (imported) inputs within total expenditure on intermediate inputs.¹³ We see that a reduction in the unit-cost of the import bundle in (20) corresponds directly to a reduction in overall unit costs in (21), by an amount that depends on the Sato-Vartia share of imported inputs. We expect that larger firms would have a greater share of expenditure on inputs, for example, and would therefore experience a greater efficiency gain from an expanded sourcing strategy.¹⁴

We can re-express the above equations in several different way to motivate our empirical work. First, substituting (20) into (21) and rearranging terms, we obtain:

$$\left(\frac{P_t^D}{P_0^D} \right)^{W_{ft}^D(1-\gamma)} \left[\prod_{n \in \bar{\Sigma}_f} \left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}} \right)^{w_{nt}} \right]^{W_{ft}^M(1-\gamma)} \left(\frac{C_{ft}}{C_{f0}} \right)^{-1} = \frac{\varphi_{ft}}{\varphi_{f0}} \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{-\frac{W_{ft}^M(1-\gamma)}{\rho-1}}. \quad (22)$$

The left-hand side of this equation is a measure of dual TFP, or the rise in prices of intermediate inputs (with wages normalized at unity) divided by the rise in marginal costs. On the right we see that dual TFP reflects the exogenous productivity term φ_{ft} and the endogenous change in import variety. Second, combining (19) with (22), we can readily solve for the change in the domestic share of intermediate inputs:

¹¹Goldberg, Khandelwal, Pavcnik, and Topalova (2010) adopt a similar approach to estimate the effect of trade liberalization of intermediate inputs on the number of domestic products produced in India.

¹²Holding the net-of-tariff input prices constant, this first term corresponds to the index of input tariffs that we denote in section 4 by $Input\tau_{gt}$. Because Chinese firms often produce multiple products and we cannot disentangle which of the firm's imports are used to produce each of its export goods, we cannot accurately measure the input weight w_{nt} for each input and output. So in practice, we construct the index of input tariffs as the industry level g , using the weights from an input-output table.

¹³Denoting the import share of intermediate input purchases by S_{ft}^M , then $W_{ft}^D = \left[(S_{ft}^D - S_{f0}^D) / (\ln S_{ft}^D - \ln S_{f0}^D) \right] / \left[(S_{ft}^D - S_{f0}^D) / (\ln S_{ft}^D - \ln S_{f0}^D) + (S_{ft}^M - S_{f0}^M) / (\ln S_{ft}^M - \ln S_{f0}^M) \right]$.

¹⁴Amiti, Itskhoki, and Konings (2014) find that large exporters have a greater share of imported intermediate inputs in their costs than small exporters. We find this same pattern for China.

$$\frac{S_{ft}^D}{S_{f0}^D} = \left[\prod_{n \in \Sigma_f} \left(\frac{p_{nt}\tau_{nt}}{p_{n0}\tau_{n0}} \right)^{w_{nt}} \right]^{W_{ft}^M(\sigma-1)} \left(\frac{P_t^D}{P_0^D} \right)^{-W_{ft}^M(\sigma-1)} \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{\frac{W_{ft}^M(\sigma-1)}{\rho-1}}. \quad (23)$$

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. Reflecting this, our approach will be to construct instruments that capture the right-hand side variables in (23), focusing on constructing instruments for λ_{ft} , while also including the change in tariffs. We experiment with using these instruments for the domestic share, which then affects total factor productivity (TFP) of firms, or simply using these instruments directly for TFP.

2.2.1 Tariffs

Given this structure of costs, the rest of model is similar to Melitz (2003), extended to allow for tariffs on the inputs and the outputs of the Chinese firms. We now 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 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 2.1. For simplicity, in this section and the next we ignore the taste parameters α_g and $\alpha_g^i(\omega)$ appearing in (2) and (4), and treat demand as symmetric, but these parameters will be re-introduced in section 4 to motivate errors in our empirical specification.

The firm's price is obtained as a markup over marginal costs:

$$p_{fht} = \frac{\rho_g}{(\rho_g - 1)} C(p_t^D, c_{ft}^M, \varphi_{ft}) \tau_{ht}, \quad (24)$$

where τ_{ht} is one plus the *ad valorem* U.S. tariff. We assume that firms make their pricing decision after the tariff is known, so that these tariffs should be treated at the U.S. MFN tariffs, while in the next section we allow for tariff uncertainty.

The quantity sold in the U.S. can be obtained from the CES demand function corresponding to (4),

$$q_{fht} = \left(\frac{p_{fht}}{P_{gt}} \right)^{-\rho_g} \frac{X_{gt}}{P_{gt}}, \quad (25)$$

where X_{gt} is the expenditure on all varieties that the U.S. imports from China in HS 8-digit industry g , and P_{gt} is the price index for these imports (corresponding to P_{gt}^i in (4) but now without the superscript $i = China$). Multiplying this equation by the p_{fht} and using (24), we can solve for firm exports as:

$$p_{fht} q_{fht} = X_{gt} \left(\frac{\rho_g C_{ft} \tau_{ht}}{(\rho_g - 1) P_{gt}} \right)^{1-\rho_g}. \quad (26)$$

The export revenue of the firm must be divided by τ_{ht} to reflect tariff payments, and then is further divided by the elasticity ρ_g to obtain firm profits. These profits must exceed the fixed labor costs of F_g of exporting, to give us the zero cut-off profit (ZCP) condition:

$$\frac{p_{fht}q_{fht}}{\tau_{ht}\rho_g} \geq F_g. \quad (27)$$

Provided that Chinese exporters make their pricing decisions *after* U.S. MFN tariff τ_{ht} is known, then because this tariff has changed very little over time, it will have minimal impact on the above equations. Before China's entry to the WTO, therefore, the risk that the U.S. tariff on China would revert to the column 2 level should not affect exporting firms prices, revenue or the ZCP condition, given their costs. But the risk of having the column 2 tariffs imposed will affect the free entry condition of Chinese firms (and the ZCP equation would become an exit condition), as we show in the next section.

2.2.2 Uncertainty in Tariffs

We now extend the model to incorporate tariff uncertainty, using a simplified version of Handley and Limão (2017).¹⁵ Suppose that the Chinese firm faces two possible values of the U.S. tariff $\tau_{ht} \in \{\tau_h^{MFN}, \bar{\tau}_h\}$, which are at either the MFN level or the alternative column 2 level denoted by $\bar{\tau}_h > \tau_h^{MFN}$. We suppose that some component of the fixed costs of exporting is sunk, which is common across firms in industry g and is denoted F_g^E , with the remaining per-period fixed costs of exporting denoted by F_g . Paying the sunk cost F_g^E allows the firm to draw its productivity φ_f , which we now treat as constant over time for simplicity. The firm's decision about its price is made after that tariff is known, while the decision about whether to participate in the export market or not is made before the tariff is known, so the tariff is the key variable that changes over time. Our goal is to solve for the forward-looking condition that ensures *entry* of Chinese firms into the export activity, or what we shall call *export participation*. This is more stringent than the ZCP condition in (27), which in the presence of sunk costs becomes the condition for a firm that already has its draw of productivity to *exit* from exporting.

The pricing decision is shown in (24). The revenue and variable profits for the firm are as before, and deducting the 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 (25) and we now treat marginal costs $C_f = C(P^D, c_f^M, \varphi_f)$ as constant over time.¹⁶ P_{gt} is the CES index as in (4) taken over the Chinese firms' prices in (24), 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,

¹⁵Our simplified treatment here draws on Feng, Li, and Swenson (2017).

¹⁶That 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 (33) that we could not measure empirically in any case.

$$v(\varphi_f, \tau_{ht}) = \frac{p_{fht}q_{fht}}{\tau_{ht}\rho_g} - F_g = \frac{X_{gt}}{\tau_{ht}\rho_g} \left(\frac{C_f}{C_g} \right)^{1-\rho_g} - F_g. \quad (28)$$

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. 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 \bar{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 the Chinese firm facing the MFN tariff is

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

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

$$\int_{\varphi} V(\varphi, \tau_h^{MFN}) dG = \int_{\varphi} \left\{ \frac{v(\varphi, \tau_h^{MFN})}{(1 - \delta\pi)} + \frac{\delta(1 - \pi)v(\varphi, \bar{\tau}_h)}{(1 - \delta)(1 - \delta\pi)} \right\} dG \geq F_g^E, \quad (29)$$

where $G(\varphi)$ is the distribution function of firm productivities. We can simplify this condition by using (28) to obtain,

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

Substituting this term into (29), we obtain the export participation condition written in terms of one-period profits:

$$\int_{\varphi} v(\varphi, \tau_h^{MFN}) dG \geq (T_h - 1)F_g + T_h(1 - \delta)F_g^E, \quad (30)$$

where,

$$T_h \equiv \left\{ \frac{(1 - \delta)}{(1 - \delta\pi)} + \frac{\delta(1 - \pi)}{(1 - \delta\pi)} \left(\frac{\bar{X}_g / \bar{\tau}_h}{X_g^{MFN} / \tau_h^{MFN}} \right) \right\}^{-1}. \quad (31)$$

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

$$\int_{\varphi} v(\varphi, \tau_h^{MFN}) dG \geq (1 - \delta)F_g^E. \quad (32)$$

The right-hand side of (32) differs from (30) 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, Li, and Swenson (2017), except that in (31) 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 $\delta \rightarrow 1$, then we have that,

$$\ln T_h \rightarrow \left(\ln \bar{\tau}_h - \ln \tau_h^{MFN} \right) - \left(\ln \bar{X}_g - \ln X_g^{MFN} \right). \quad (33)$$

The first term on the right of (33) 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, 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 (33) 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).

3 Data and Preliminary Estimates

To calculate the U.S. price index of manufactured goods in equation (13), 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 a number of different data sources. The first is from China Customs, providing 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 use these data to construct the China components of the overall U.S. price index as described in section 2.1.

Second, we supplement the China-reported trade data with U.S.-reported data in order 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 where we adjust equation (13), using the ratio of Herfindahl indexes in the second component, as described in Appendix A. These Herfindahls are from Feenstra and Weinstein (2017), built up using firm-HS10-digit data from PIERS.

Third, we construct measures of total factor productivity (TFP), as an inverse proxy for marginal cost, using the Annual Survey of Industrial Firms (ASIF) from the National Bureau of Statistics. This

is a survey of Chinese manufacturers, 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). 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 B1). Appendix B provides more details on the data construction.

3.1 China’s Export Variety

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 (see Table 1). Most important for our study is how much of this growth comes from new varieties. As noted in section 2, we measure Chinese products at the firm-HS 8-digit level. Denoting the value of Chinese exports to the U.S. by X_{fht} for firm f and product h in year t , we decompose China’s aggregate export growth to the U.S. as follows:

$$\frac{\sum_{fh}(X_{fht} - X_{fh0})}{\sum_{fh} X_{fh0}} = \frac{\sum_{fh \in \bar{\Omega}} X_{fht} - \sum_{fh \in \bar{\Omega}} X_{fh0}}{\sum_{fh} X_{fh0}} + \frac{\sum_{fh \in \Omega_t \setminus \bar{\Omega}} X_{fht} - \sum_{fh \in \Omega_0 \setminus \bar{\Omega}} X_{fh0}}{\sum_{fh} X_{fh0}}, \quad (34)$$

where $\bar{\Omega} = \Omega_t \cap \Omega_0$ is the set of varieties (at the firm-product level) that were exported in t and $t = 0$, $\Omega_t \setminus \bar{\Omega}$ is the set of varieties exported in t but not in 0 and $\Omega_0 \setminus \bar{\Omega}$ is the set of varieties exported in t_0 but not in t . This equation 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 1. Surprisingly, most of this growth arises from new 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). In many countries, it is often the case that new entrants do not account for a large share of their export growth because new firms typically start off small. But for Chinese exporters, even in the year-to-year changes the extensive margin accounts for around 40 percent of export 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 and the other 16 percent is by incumbent firms exporting new products (columns 4 and 5 sum to the total extensive margin in column 3).

The results in Table 1 clearly show that most of the growth in China’s exports to the U.S. was

Table 1: Decomposition of China's Export Growth to the U.S.

Proportion of export growth due to different margins:							
Year	Total Export Growth %	Variety at the HS8-firm level				Equivalent Price Change	
		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 (13), both weighted using the Sato-Vartia weights in equation (14).

due to new entrants into the U.S. export market. 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 over time. This affects 5 percent of the firms and hardly changes the size of the extensive margin (see Table D1 in the Appendix).¹⁷ Even if our algorithm for tracking reclassifications has missed some identifier changes for incumbent firms due to, say, mergers and acquisitions, our approach to measuring the gains from China's entry into the U.S. market using equation (6) is largely unaffected by reclassifications of product codes or firm codes, as the new entry would be offset by the exit.

Those measures also support the finding of a large extensive margin, as we see from column 6, where we report 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 , which we describe in the next subsection, and then weighted as in equation (14). 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 what is obtained by summing the year-to-year changes in the earlier rows, because the calculation for 2000-2006 is

¹⁷In the Appendix Table D1, we also show that the very high extensive margin is present when we use alternative ways to define a variety, including HS6-firm, HS4-firm, and HS2-firm, provided we keep the firm dimension. Furthermore, this large extensive margin is present in various subsamples of the data, including nonprocessing trade, consumer goods, nontraders and private firms.

done on 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 value of exports in 2001 is attributed to variety growth. This method of using a “long difference” to measure variety growth is consistent with the theory outlined in section 2, as it allows for increases in the U.S. taste parameter for that Chinese export in the intervening years, as it penetrates the U.S. market.

To see China’s effect on the overall U.S. manufacturing sector price index, we need to adjust the values of the variety index in column 6 by China’s share in each industry g , which averaged 7 percent in 2006 and 3 percent in 2000. (These are the weights in the entire U.S. market, and not just the import shares.) We do this using the Sato-Vartia weights as in the third term in equation (13), before weighting across industries g as in equation (14). Column 7 shows that the effective price drop due to variety gain from China is reduced to 3.1 percent — this will be the starting point in our consumer welfare calculations, in section 5.¹⁸

3.2 Elasticities

We estimate the elasticity of substitution between varieties following Feenstra (1994), Broda and Weinstein (2006), and Soderbery (2015).¹⁹ 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 .²⁰ This parameter enters in the variety adjustment in the price index — the second term in equation (6) and the third term in equation (13). The median ρ_g , reported in Table 2, is 4.57. We see that there is a big range in the elasticities, with some very large numbers. Variety growth in industries with low elasticities will generate the largest gains whereas variety growth in industries with high elasticities will have a negligible effect on the U.S. price index.

For countries other than China, we do not have data at the firm-product level so we estimate elasticities of substitution across varieties defined at the HS 10-digit level within an HS 6-digit industry for each country. The methodology is otherwise the same as for China, except that we constrain the elasticities to be the same for all these other countries within an industry g .²¹ We see that the median elasticity for “other countries” is lower at 2.9. This is to be expected because a variety is defined at a more aggregate level. Finally, we estimate σ_g , which is the elasticity of substitution between varieties in industry g produced in different countries — this elasticity appears in the last term of equation (13). We estimate it in two steps. First, we calculate an exact price index for each country-HS6 pair as in equation 9 using 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

¹⁸The common goods price index for China — the first component in equation (6) — increased 1.76 percent per year on average.

¹⁹This methodology is also used in Ossa (2015).

²⁰We 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.

²¹We estimate the elasticities using U.S. import data for the top 40 countries which account for 95 percent of U.S. manufacturing imports. See Appendix C for more details on the estimation of the elasticities.

Table 2: 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. The summary stats are reported for the 1,599 HS6 industries in Table 8.

of σ_g is also around 3.

3.3 Total Factor Productivity

We estimate total factor productivity (TFP) using data on all manufacturing firms in the ASIF sample for the period 1998 to 2007. We follow Olley and Pakes (1996), by taking account of the simultaneity between input choices and productivity shocks using firm investment.²² To estimate the production coefficients, 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, Wang, and Wei (2012)). Real value added is constructed as deflated production less deflated materials. We use industry level deflators from Brandt, Van Biesebroeck, Wang, and Zhang (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.²³ 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 periods’ 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 D2 in the Appendix, are used to calculate each firm’s log TFP as follows:²⁴

²²As 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.

²³see <http://www.econ.kuleuven.be/public/N07057/CHINA/appendix>

²⁴For the TFP estimation, we clean the ASIF data on the top and bottom one percentile changes in real value added, output, materials, and investment rates.

Table 3: China's Productivity Growth

Year	Total factor productivity			Real value added per worker		
	All exporters	Matched sample		All exporters	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).

$$\ln(TFP_{ft}) = \ln(VA_{ft}) - \gamma_l \ln L_{ft} - \gamma_k \ln K_{ft} \quad (35)$$

We interpret this measure as similar to the dual TFP on the left of (22), and import variety on the right of (22) will be one if its determinants. The TFP measures are all normalized relative to the firm's main 2-digit CIC industry. From Table 3, 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 and only slightly more, at 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.

3.4 Trade Liberalization

China joined the WTO in December 2001, when it gave a commitment to bind all import tariffs at an average of 9 percent.²⁵ Although China had already begun the process of reducing tariffs long before then, average tariffs in 2000 were still high at 15 percent, with a large standard deviation of 10 percent. Our main interest is in how China's lower import tariffs on intermediate inputs affected Chinese firms' TFP. Identifying what is an input is not straightforward in the data so we approach this in two ways. Our first approach utilizes the more disaggregated HS 8-digit raw tariff data directly where possible and targets the main channel through which we expect input tariffs to affect TFP. We do this by estimating Chinese exporters fitted imported inputs that are due to lower import tariffs at the HS8 level. These fitted import values will form the basis for our main instruments for firm-level TFP.

Second, we follow Amiti and Konings (2007) in the way we construct tariffs on intermediate inputs using China's 2002 input-output (IO) tables. The most disaggregated IO table available is for 122 sectors, with only 72 of these in manufacturing. We take the 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

²⁵See wto.org for more details.

Table 4: Average Tariffs

Year	China's tariffs on intermediate inputs				$\ln(Gap)$	
	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 the ad valorem tariff so a 5 percent tariff appears as $\ln(1.05)$. The first column presents the simple average of China's import tariffs on HS 8-digit industries. Column 3 represents 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 represents 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.

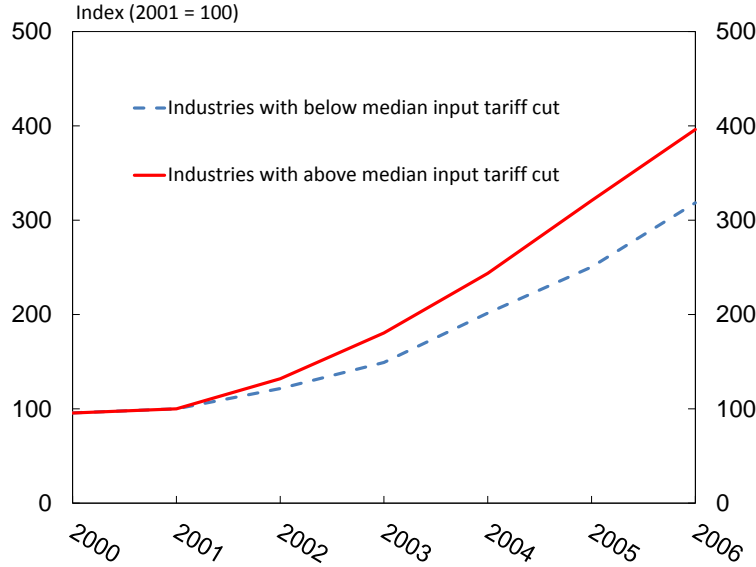
level. The input tariff for each industry g is the weighted average of these IO industry tariffs, using the cost shares in China's IO table as weights.²⁶ Average tariffs for each year are reported in Table 4. Tariffs levels fell on average by 40% (6 percentage points) over this period and their dispersion also declined. In general, the largest declines in tariffs were in products with the highest initial tariffs. The correlation between the 6-year change in tariffs and the 6-year lag level is -0.7 .

We expect relatively higher export growth from Chinese industries that experienced the largest drops in their input tariffs. To preview the data, we plot Chinese exports to the U.S. in industries above and below the median input tariff cut of 4.6 percentage points in Figure 1. With exports of both bins indexed at 100 in 2001, we see a substantially larger export growth of industries with large reductions in their input tariffs.

Upon China's WTO entry, China benefited from another form of trade liberalization with the U.S. Congress granting Permanent Normal Trade Relations (PNTR). It is important to realize that the PNTR did not actually change the tariffs that China faced on its exports to the U.S. The U.S. had applied the low 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 4 that the average gap was very high at 24 percent

²⁶We thank Rudai Yang from Peking university for the mapping from IO to HS codes, which he constructed manually based on industry descriptions. We include both manufacturing and nonmanufacturing inputs and drop "waste and scrapping".

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



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

with a large standard deviation. We will exploit this cross-industry variation to analyze its effect on China's U.S. exports by interacting the gap with a WTO dummy that equals one post-2001. This variable will form our key exclusion restriction in the export participation equation since it affects the entry condition but not the export prices as shown in section 2.2.2, and we verify in the empirical section below.

3.5 Other Reforms in China

During this period and the time leading up to China's WTO entry, China implemented many other reforms that may have affected its productivity and exports. Bai, Krishna, and Ma (2017) focus on the lifting of restrictions on Chinese firms being allowed to export. In the early part of the sample period, Chinese firms faced restrictions on exporting and importing, based on capital requirements, which were removed gradually in the beginning of the sample period and were completely removed by 2004.²⁷ This variable will act as an additional exclusion restriction in our export participation equation and import participation equation. We also interact this variable with a foreign firm indicator, as foreign firms are likely to have better access to capital markets to be able to enter the global market.

Other noteworthy reforms that we will take into account in the robustness section include FDI liberalization, eliminating quotas under the Multi-Fiber Agreement (MFA), and lifting requirements for import licenses. China still had a number of restrictions on inward foreign direct investment when

²⁷We thank Xue Bai, Ma Hong and Kala Krishna for providing these data, which indicate the share of firms that were allowed to export within a CIC 4-digit industry, which we mapped to HS6 industries.

it joined the WTO and in certain industries FDI was completely prohibited. 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. Many restrictions were removed following China's WTO accession. The data listing which industries were subject to FDI restrictions are from the Catalogue for the Guidance of Industries for Foreign Investment issued by the Ministry of Commerce of China. The Catalogue lists the industries in which FDI to China is "restricted" or "prohibited" and this list is amended every 3 to 5 years. For our sample, we use the list issued in 1997, 2002 and 2004. Based on the industry descriptions listed in the Catalogue, we map them to the 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 Multi-fiber Arrangement (MFA), and its successor, Agreement on Textile 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, Schott, and Wei (2013)). Our data for MFA quotas are drawn from Brambilla, Khandelwal, and Schott (2010), which provides the list of HS10 products under quota restrictions, and period the quota was removed for each product. With these data we construct a dummy variable $MFA2002$ which equals 1 if the quota was removed in 2002, and $MFA2005$ which equals 1 if the quota was removed in 2005 at HS 6-digit level.

China also imposed restrictions on its imports through an import license system. The China Customs announced a list of products for which imports were only allowed with 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 an indicator 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.

4 Estimation

To analyze how China's WTO entry benefited U.S. consumers, we estimate how much the U.S. price index (the left side of equation (13)) moved due to China's WTO entry. The price index comprises the four components on the right side of (13), including both the common goods price index and variety components for China and all other countries. Since all of these prices are likely to be correlated and jointly determined, we need an exogenous instrument related to China's WTO entry. That is, we need to construct the variation in China's common goods component (the first term in (13)) and the variation in China's variety component (the third term in (13)) solely due to China's WTO entry, which we will denote as $\hat{China}P_g$ and $\hat{China}V_g$, respectively. We discuss how these instruments are obtained.

First, for the $\hat{China}P_g$ instrument, we need to predict the change in China's export prices between 2000 and 2006 due to its WTO entry. We start with the log of the firm pricing equation (24), but we now extend our earlier treatment to allow 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 we write these quality parameters instead as α_{fht} , where as in section 3, the firm-product fht plays the role of ω . We suppose that the specification of firms' marginal costs in section 3 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 (24) is re-written as

$$\frac{p_{fht}}{\alpha_{fht}} = \frac{\rho_g}{(\rho_g - 1)} C(p_t^D, c_{ft}^M, \varphi_{ft}) \tau_{ht}. \quad (36)$$

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 . We measure the marginal costs in (36) by: i) TFP, which will be treated as endogenous; ii) an index of input tariffs $Input\tau_{gt}$, which is an industry-level measure of the tariffs on imported intermediate inputs faced by the Chinese firms in industry g ; ²⁸ and iii) an index of the domestic prices of intermediate inputs in each industry g , P_{gt}^D .²⁹ Then we shall estimate:

$$\ln p_{fht} = \beta_f + \beta_h + \beta_t + \beta_1 \ln TFP_{ft} + \beta_2 \ln Input\tau_{gt} + \beta_3 \ln P_{gt}^D + \epsilon_{1fht}, \quad (37)$$

where unobserved quality α_{fht} from the left of (36) is absorbed into the error term in (37), $\epsilon_{1fht} \equiv \ln \alpha_{fht}$.³⁰ Since the TFP of the Chinese firms is an inverse measure of marginal costs, we expect a coefficient of $\beta_1 = -1$.³¹ This quality will likely be correlated with the firm's TFP, however, 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 (37) into the log share equation for Chinese firms in (5) to obtain:

$$\frac{\ln s_{fht}}{(1 - \bar{\rho})} = \ln \left(\frac{p_{fht}}{\alpha_{fht}} \right) - \ln P_{gt} = \beta_f + \beta_{gt} + \beta_1 \ln TFP_{ft} + (\epsilon_{1fht} - \ln \alpha_{fht}), \quad (38)$$

where $\beta_{gt} \equiv \beta_t - \ln P_{gt} - \beta_2 \ln Input\tau_{gt} - \beta_3 \ln P_{gt}^D$ 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 (37) is

²⁸We obtain $Input\tau_{gt}$ by using the input-output table for China to construct the average input tariff that each firm producing in industry g faces, as described in section 3.

²⁹These are the domestic intermediate input price indexes, constructed from running the industry output deflators from Brandt, Van Biesebroeck, Wang, and Zhang (2017) through an IO table, as described in the section 3.

³⁰The error will also incorporate terms reflecting the fact that the pass-through coefficient β_1 differs across firms, as discussed in the next footnote. As analyzed by Murtazashvili and Wooldridge (2008), pooling across firms to obtain a single coefficient means that additional terms are introduced into the error.

³¹Amiti, Itskhoki, and Konings (2016) show that in the nested CES framework we are using, if the market shares of firms are not infinitesimally small then a pass-through of less than unity (in absolute value) that differs across firms is obtained. We allow for any magnitude of β_1 in our empirical analysis, but we find that $\beta_1 = -1$ is not rejected.

$\epsilon_{1fht} \equiv \ln \alpha_{fht}$, the error in (38) 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 (38) 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 $\bar{\rho}$ in industry g (equal to 4.57). Substituting this unbiased estimate of β_1 into the pricing equation, we can estimate the rest of that equation to predict the fitted export prices and then construct $\hat{China}P_g$.

Second, for the $\hat{China}V_g$ variable, we need to predict the export variety component due to China's WTO entry, which we do by estimating an export participation equation for Chinese exporters to the U.S.:

$$I_{fht}^X = \delta_1 \ln TFP_{ft} + \delta_2 \ln Input \tau_{gt} + \delta_3 \ln P_{gt}^D + \delta_4 \ln Gap_g \times WTO_t + \delta_5 \ln ShareEligible_{gt} + \delta_5 \ln ShareEligible_{gt} \times Foreign_f + \delta_f + \delta_h + \delta_t + \epsilon_{2fht} \quad (39)$$

The dependent variable, I_{fht}^X , is binary, equal to 1 if the Chinese firm f had a positive U.S. export value in product h at time t , and zero otherwise. We view this export participation equation as the empirical counterpart of the entry conditions (30) and (32). In particular, the probability of export participation is increased as the effective fixed/sunk costs fall between (30) and (32) when China joins the WTO. The fall in those fixed/sunk costs is captured by the "gap" between the column 2 U.S. tariff and the MFN tariffs, in (33). This participation equation includes all of the variables from equation (37), as well as exclusion restrictions, which are variables that affect the entry into exporting decision but not the intensive margin of exporting. These variables comprise the "gap" interacted with a WTO dummy that takes the value of one after 2001. An additional exclusion variable we include is $ShareEligible_{gt}$, which reflects the share of firms that met China's capital requirements to engage in international trade. This equation provides the predicted probabilities to construct the fitted λ terms in $\hat{China}V_g$.

4.1 Chinese Firms Importing and Tariffs

To estimate the exporting equations (37), (38) and (39), we first need to address the endogeneity of TFP , which is our inverse proxy for a component of marginal cost. We construct an instrument for TFP following equation (23), where the firm's marginal cost is influenced by its import sourcing strategy with the firm's productivity increasing with the range of imported inputs. To focus on this channel, we exploit the variation in China's highly disaggregated raw import tariff data. More specifically, we estimate the following import value and import participation equations:

$$\ln M_{fnt} = \gamma_1 \ln \tau_{nt}^i + \gamma_2 \ln \tau_{nt}^i \times Process_f + \gamma_f + \gamma_t + \epsilon_{3fnt}. \quad (40)$$

$$I_{fnt}^M = \theta_1 \ln \tau_{nt}^i + \theta_2 \ln \tau_{nt}^i \times Process_f + \theta_3 \ln ShareEligible_{gt} + \theta_4 \ln ShareEligible_{gt} \times Foreign_f + \theta_f + \theta_t + \epsilon_{4ft} \quad (41)$$

The dependent variable in equation (40) is the log of the value of a Chinese firm f 's imports from the rest of the world in an HS 8-digit category n at time t . Because this dependent variable is not defined for zero import values, we need to control for potential selection bias. We do so by estimating an import selection equation (41), where the dependent variable, I_{fnt}^M , 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 as well as an exclusion restriction, defined as the share of firms with sufficient capital to be allowed to trade. Because the measure is based on the industry the firm produces output rather than which inputs are imported, we merge this variable based on the firm's largest export industry g .

We estimate the import participation equation using a linear probability model (LPM) instead of a probit. This enables us to include all of the same fixed effects as in the import value equation and avoids the incidental parameter problem inherent in probits that give 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; however, in practice there are very few of these observations. We control for selection bias in equation (40) by including a fourth order polynomial series of the predicted probabilities from equation (41). Alternatively, we can use a more flexible approach by using the predicted probabilities from reestimating (41) with additional explanatory variables comprising interactions and polynomial series of all the variables in that equation, and then include a forth order polynomial series of those predicted probabilities in the import value equation.³² Both approaches produces the same results.

Our main interest in the import value equation is to construct a *TFP* instrument for the export equations. In addition, the results from these equations serve to illustrate the mechanisms by which China's WTO entry affects Chinese exporting firms. The key variable of interest is the tariff τ_{nt} applied to China's imported intermediate inputs n at the HS 8-digit level, the most disaggregated level available. We interact this tariff variable with a processing dummy that indicates whether the input is imported under processing trade. Processing imports already enjoyed duty-free access so a lower tariff on those imports would not reduce the cost of importing and thus should not have a direct impact on imports.³³ We expect that firms with some portion of ordinary trade to benefit from lower tariffs.

We present the results in Table 5. In the import participation equation, we include all of the variables in the import value equation (40), and additional variables that affect entry into importing but not the intensive margin and estimate it using OLS. In column 1, we see that the probability of importing inputs is higher in industries with lower tariffs, but this is not so for processing imports. Lower tariffs reduce the probability of importing for processing firms.³⁴ And the probability of ex-

³²See Das, Newey, and Vella (2003) and Dahl (2002).

³³We classify a firm as processing if it imports more than 99% of its total intermediate inputs under processing trade over the sample period.

³⁴This is consistent with Kee and Tang (2016).

porting to the U.S. is higher in industries with fewer restrictions only for Chinese firms with some foreign ownership.³⁵

Table 5: Chinese Imports

Dependent variable	$I_{fnt}^M = 1 \text{ if } M_{fnt} > 0$	$\ln(M_{fnt})$		
	(1)	(2)	(3)	(4)
$\ln(\tau_{nt})$	-0.200*** (0.026)	-5.466*** (0.662)	-5.378*** (0.660)	-5.121*** (0.665)
$\ln(\tau_{nt}) \times \text{Process}_f$	0.536*** (0.051)	5.531*** (0.780)	5.100*** (0.778)	4.619*** (0.811)
$\ln(\text{ShareEligible}_{gt})$	-0.075*** (0.005)			
$\ln(\text{ShareEligible}_{gt}) \times \text{Foreign}_f$	0.186*** (0.005)			
<i>Selection Control</i>		no	yes	yes
<i>Year FE</i>	yes	yes	yes	yes
<i>Firm FE</i>	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 to 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 measure in column 4. Standard errors clustered at HS 8-digit level. The *Process* dummy equals one if more than 99% of the firm's imports were processing over the sample, and the *Foreign* dummy equals one 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 instrument for firm-level TFP as described in the text.

The import value regressions also show that Chinese firms increased imports in industries with lower import tariffs on the intensive margin. In column 2 of Table 5, we find that the coefficient on tariffs is negative and significant, $\theta_1 = -5.5$, showing that trade liberalization increased imports for firms that import under ordinary trade. In contrast, the coefficient on the tariff interacted with a processing dummy is positive, $\theta_2 = 5.5$. The sum of θ_1 and θ_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 coefficients on tariffs very close to those in column 2.

³⁵We also experimented with including the gap variable and its interaction with the WTO dummy in equation (41); however the coefficient was insignificant and had the wrong sign. Including the gap variable had no effect on the coefficients on the tariff variables.

We use the fitted values from the predicted values in column 4 of Table 5 (estimating equation (40)) to construct instruments for TFP , which correspond to the terms in the third component in equation (23). 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 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 the total values of the common sets over the entire sample could not be constructed. Instead, we used the predicted import value of the firm's largest HS 8-digit category each year, and denote the fitted value of those imports by $\ln \hat{M}_{max,ft}$. Then the difference between these two instruments, $\ln \hat{M}_{max,ft} - \ln \hat{M}_{tot,ft}$, is a proxy for λ_{ft} , and is meant to capture the expansion of imported inputs on the extensive margin.

We can see the effect of these two instruments on Chinese firms' TFP in Table 6. In column 1, 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 the first instrument and +0.05 on the second. In column 2, we include the difference between the two instruments to proxy for $\ln \lambda_{ft}$, and we also see it has the expected negative sign (also equal to -0.05). 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 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 are insignificantly different from zero, so we cannot reject that all of the TFP gains from lower input tariffs accrue through the firm importing more inputs. In addition, in column 4, we include the gap variable interacted with WTO to see if eliminating the tariff uncertainty that Chinese firms faced in the U.S. export market boosted their TFP but we find an insignificant coefficient close to zero.

Following our earlier discussion in section 2.2, an alternative to using these two instruments to predict TFP is to instead use these instruments to predict the share of domestic inputs S_{ft}^D in a first stage, and then regress $\ln TFP_{ft}$ on S_{ft}^D in a second stage. This approach is closer to that of Blaum, Lelarge, and Peters (2015), though as we argued in section 2.2, it is import variety that we expect to be most important in any case. In column 5, we first use OLS to regress $\ln TFP_{ft}$ on S_{ft}^D (equal to (total expenditure on domestic materials)/(total material costs + wagebill)), and find a small negative effect of -0.04 on firm-level TFP. However, when we instrument for S_{ft}^D , with λ_{ft} , the magnitude of the coefficient on $\ln TFP$ increases to 0.7. We find that the instrument has the expected sign in the first stage regression in column 7, and if we were to include the two \hat{M} instruments separately they are similar in magnitude to the coefficients in column 1, where we regress $\ln(TFP)$ on the instruments. Given the endogeneity of S_{ft}^D , we proceed by constructing predicted values of TFP from column 1, as $\ln(\hat{TFP}_{ft}) = -0.04 \times \ln \hat{M}_{max,ft} + 0.05 \times \ln \hat{M}_{tot,ft}$, which we use in the estimation of the exporting equations below.

Table 6: Chinese Firm TFP and Importing

Dependent variable	$\ln(TFP_{ft})$					First Stage: $\ln(S_{ft}^D)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(S_{ft}^D)$					-0.036*** (0.009)	-0.655*** (0.063)	
$\ln(\hat{M}_{max,ft})$	-0.041*** (0.012)		-0.041*** (0.012)	-0.042*** (0.013)			
$\ln(\hat{M}_{tot,ft})$	0.052*** (0.005)		0.051*** (0.005)	0.052*** (0.005)			
$\ln(\hat{\lambda}_{ft})$		-0.053*** (0.005)					0.084*** (0.003)
$\ln(Input\tau_{gt})$			0.275 (0.435)	0.243 (0.442)			
$\ln(Gap_g) \times WTO_t$				0.027 (0.062)			
Year FE	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes
# obs.	82,203	82,203	80,043	79,276	76,603	76,603	76,603
R ²	0.692	0.691	0.692	0.691	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 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 5, 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 on 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, except column 6 where we instrument for the share of domestic inputs in total costs, $\ln(S_{ft}^D)$, with $\hat{\lambda}_{ft}$, as shown in column 7. Alternatively, we could include the \hat{M} variables separately - this produces the same results, and passes the overidentification test and the first stage weak instrument test. 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.

4.2 Chinese Firms' U.S. Exports and Tariffs

To estimate the export participation equation (39), we include all firm-industry observations for the period 2000 to 2006 for the set of firms that have at least one nonzero U.S. export observation. The dependent variable is equal to 1 if the firm had positive export value in product h , defined at the HS 8-digit level, and zero for all fht observations where the firm did not export in those HS 8-digit categories. All of the equations have year fixed effects to control for macro factors that affect overall entry and exit. We include firm fixed effects to take account of unobserved firm heterogeneity. In addition, we also include industry effects since the firms span across many products. We include the fitted TFP variable, (\hat{TFP}_{ft}) , directly in the export selection equation instead of instrumenting for the measured TFP so that we can use the full sample of exporting, otherwise we would only be limited to using the much smaller matched sample.

Table 7: Chinese Firms U.S. Exports

Dependent variable	$I_{fht}^X = 1 \text{ if } X_{fht} > 0$	$\ln(s_{fht}) / (1 - \bar{\rho})$		$\ln(\text{price}_{fht})$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(TFP_{ft})$	1.918*** (0.033)	-0.938*** (0.149)	-1.062*** (0.292)	-1.000 [†]	-1.000 [†]	-1.000 [†]
$\ln(\text{Input}\tau_{gt})$	-1.948*** (0.452)			3.101*** (1.167)	3.645** (1.583)	3.632** (1.594)
$\ln(\text{Input}\tau_{gt}) \times \text{Process}_{fh}$	-0.198 (0.153)			-1.689*** (0.572)	-1.165** (0.516)	-1.157** (0.518)
Process_{fh}	0.020 (0.012)			0.172** (0.066)	0.113* (0.064)	0.113* (0.064)
$\ln(P_{gt}^D)$	0.024 (0.096)			0.466** (0.188)	0.470** (0.187)	0.469** (0.187)
$\ln(\text{Gap}_g) \times \text{WTO}_t$	0.070* (0.036)					-0.034 (0.111)
$\ln(\text{ShareEligible}_{gt})$	-0.012 (0.024)					
$\ln(\text{ShareEligible}_{gt}) \times \text{Foreign}_f$	0.251*** (0.017)					
<i>HS6 Industry</i> \times <i>Year FE</i>	no	yes	yes	no	no	no
<i>HS8 Industry FE</i>	yes	no	no	yes	yes	yes
<i>Year FE</i>	yes	no	no	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes
<i>Selection Control</i>		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 at 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. $\ln(TFP_{ft})$ are the fitted values constructed from column 4 in Table 5. $\text{Input}\tau_{gt}$ is the input tariff constructed using China's input-output table at the IO level, mapped to HS 6-digit industry codes. The Process_{fh} is a processing dummy equal to 1 if more than 99% of a Chinese firm's U.S. exports in HS8 industry are processing. The Gap is the difference between column 2 and MFN tariffs at HS 6-digit, while $\text{ShareEligible}_{gt}$ is the share of firms eligible to export in HS 6-digit industry. The Foreign dummy equals one if the firm in China was classified as foreign at any time during the sample in the export 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 as a share of total Chinese U.S. exports in HS6, divided by $1 - \bar{\rho}$, where $\bar{\rho}$ is the median (= 4.57) estimated elasticity of substitution. Columns 2 and 3 are estimated using IV and include industry \times 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 U.S. exports, 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 they are clustered at the firm level.

We present the results in Table 7. We find that the coefficient on the predicted $\ln TFP_{ft}$ in column 1 is positive and significant, showing a higher probability of exporting for firms with a higher TFP arising from more imports. We also include the input tariff, $\ln \text{Input}\tau_{gt}$, which was constructed from the IO tables and mapped to the HS 6-digit industry level, g , because lower input tariffs can

reduce the prices of inputs and thus make it more profitable to export, independently from the TFP channel. Indeed, 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 1 if the Chinese firm's exports to the U.S. in HS8 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 between processing and ordinary exports from lower input tariffs raising the probability of exporting to the U.S. 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 below.

We also find that the probability of exporting to the U.S. in industries where the gap between the U.S. column 2 tariffs and MFN tariffs is high in the post-WTO period, 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 cover their fixed costs of entering export markets.

To investigate the effect of China's lower input tariffs on U.S. export prices, we first estimate equation (38), in order to identify an unbiased β_1 coefficient on $\ln(TFP_{ft})$. The dependent variable, $\frac{\ln s_{fht}}{(1-\bar{\rho})}$, is defined as a Chinese firm's exports to the U.S. in HS 8-digit industry as a share of total Chinese U.S. exports in HS6, divided by $1 - \bar{\rho}$, where $\bar{\rho}$ is the median ($= 4.57$) estimated elasticity of substitution. We include HS6-industry \times year fixed effects to proxy for the price index in industry g , as well as firm fixed effects to control for unobserved firm heterogeneity. We estimate columns 2 and 3 with instrumental variables, using the two \hat{M} instruments for measured $\ln TFP$. In the 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 6. Both pass the overidentification and weak instrument tests.³⁶ In column 2, we include all possible observations from the matched sample and find that we cannot reject that the coefficient β_1 on $\ln TFP_{ft}$ equals -1 . To check whether sample selection is affecting the magnitude of this coefficient, we reestimate the column 2 equation 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.³⁷ The coefficient in both columns are almost identical at around -1 . We use this result in the subsequent columns.

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.³⁸ We regress the export prices

³⁶We don't report the first stages to save space and because the coefficients on the two instruments are so close to the regression results in Table 6. 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.

³⁷We can not 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.

³⁸The results are unchanged for firm unit values that exclude duties because the U.S. MFN import tariffs are very low

on input tariffs and constrain the coefficient $\hat{\beta}_1$ on $\ln TFP_{ft}$ 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 column 4 show that export prices are lower in industries with lower input tariffs, and the coefficient on the inputs 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 in industries with 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, even those engaged in processing exports who did not face the input tariff.

One 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 $\ln P_{gt}^D$ in Table 7, 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 $\ln P_{gt}^D$ in the equation results in a lower coefficient on input tariffs it still remains large.³⁹ Another explanation we propose for these findings is that the lower input tariffs actually leads 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, Feenstra, Romalis, and Taylor (2015), in a model with heterogeneous firms.⁴⁰ Indeed, Kee and Tang (2016) find that there has been a rise in 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 on $\ln Input\tau_{gt}$ found in Table 7.

We see that these results in the pricing equation are robust to controlling for selection bias in column 5, with selection into exporting using the predicted probabilities from column 1 in Table 7 and for importing from column 1 in Table 5. Finally, in column 6, we show that the gap variable has a small coefficient, insignificantly different from zero, confirming the validity of this variable as an exclusion variable in the export participation equation. The positive coefficient on input tariffs continues to be large and significant.

To summarize this section, the results show that 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

and have hardly changed over the sample period. For this reason, the MFN tariff is not included on the right of (37).

³⁹The coefficient on input tariff in a specification like column 5 but without $\ln P_{gt}^D$ is 4.1.

⁴⁰According to Theorem 1 of Caliendo, Feenstra, Romalis, and Taylor (2015), all that is needed is that there is an additional non-traded sector in the economy, and that the tariff revenue is distributed to the consumer who spends it on both 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.

also reduce Chinese firms' export prices in the U.S. market. The effect from PNTR is more limited. There is no direct effect on export prices — the only effect we detected was through new entry into exporting. We now turn to evaluate how these effects feed into the U.S. price index.

5 The Impact of China's WTO Entry

With our regression results in hand, we turn to estimating the impact of China's WTO entry on U.S. consumer welfare (treating U.S. importing households and firms as “consumers”) by regressing the U.S. price index, constructed as in equation (13) on two instruments, to obtain the *overall* impact of China's entry to the WTO on the U.S. price index of manufactured goods:

$$\ln \left(\frac{P_{gt}}{P_{g0}} \right) = \eta_0 + \eta_1 \hat{China}P_g + \eta_2 \hat{China}V_g. \quad (42)$$

The first China WTO instrument on the right, $\hat{China}P_g$, is the change in Chinese exporter prices predicted from equation (37), with β_1 from the quality adjusted equation (38), using results from columns 2, 3, and 6 in Table (7): $\hat{p}_{fht}^i = \exp \left[-1 \times \ln T\hat{F}P_{ft} + 3.645 \times \ln Input\tau_{gt} - 1.165 \times Process_{fh} \right]$, where for clarity we have added back the superscript $i = \text{China}$ on these prices. 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 instrument as follows:

$$\hat{China}P_g \equiv W_{gt}^i \ln \left[\prod_{fh \in \bar{\Omega}_g} \left(\frac{\hat{p}_{fht}^i}{\hat{p}_{fh0}^i} \right)^{w_{fht}} \right], \quad (43)$$

where $\bar{\Omega}_g = \Omega_{gt} \cap \Omega_{g0}$ is the set of varieties (at the firm-product level, fh) that were exported in industry g during both years 2006 and 2000, 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.

The second WTO instrument uses the fitted values from the China firm export participation equation (39), with predicted probability of a positive outcome \hat{prob}_{fht} . These predictions only include the tariff and gap terms, and do not include any of the fixed effects. We instrument for the Chinese variety term λ_{gt} with the predicted number of exporters obtained by summing the predicted probability of exporting from the participation equation (39), with the results from column 1 in Table 7. The instrument for the China variety component in (13) is given by:

$$\hat{China}V_g \equiv \frac{W_{gt}^i}{\hat{\rho}_g - 1} \left[\ln \left(\frac{\sum_{fh \in \bar{\Omega}_g} \hat{prob}_{fht}}{\sum_{fh \in \Omega_{gt}} \hat{prob}_{fht}} \right) - \ln \left(\frac{\sum_{fh \in \bar{\Omega}_g} \hat{prob}_{fh0}}{\sum_{fh \in \Omega_{g0}} \hat{prob}_{fh0}} \right) \right]. \quad (44)$$

Table 8: Decomposition of WTO Effect on U.S. Price Index

Dependent Variable		US Price Index (1)	$ChinaP_g$ (2)	$OtherP_g$ (3)	$ChinaV_g$ (4)	$OtherV_g$ (5)
Growth 2000-2006		0.031	0.013	0.049	-0.031	0.000
\hat{ChinaP}_g	-0.014	3.535*** (0.815)	1.266*** (0.124)	3.210*** (0.686)	-0.055 (0.194)	-0.885*** (0.337)
growth x regression coefficient contribution		-0.049 65.2%	-0.018 23.3%	-0.045 59.2%	0.001 -1.0%	0.012 -16.3%
\hat{ChinaV}_g	-0.016	1.607*** (0.157)	-0.086*** (0.024)	-0.003 (0.132)	1.744*** (0.037)	-0.049 (0.065)
growth x regression coefficient contribution		-0.026 34.8%	0.001 -1.9%	0.000 -0.1%	-0.029 37.8%	0.001 -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 growth rates are the weighted averages of the U.S. price index and each of its four components in equation (13) with the Sato-Vartia weights in equation (14). The first column growth rates are the weighted average of each instrument in equations (43) and (44), using the same Sato-Vartia weights from equation (14). 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 growth rate times the regression coefficient: the price component is $3.535 \times -0.014 = -0.049$; the variety component is $1.607 \times -0.016 = -0.026$.

The terms in the square brackets are meant to reflect the terms $[\ln(\lambda_{gt}^{ij}) - \ln(\lambda_{g0}^{ij})]$ that appear in (13).⁴¹ That term is raised to a power, W_{gt}^{ij} , reflecting China's share of overall U.S. expenditure in industry g , and then dividing by the estimated industry elasticity $\hat{\rho}_g - 1$.

We include a constant term in this regression, which absorbs any price inflation that is common across industries g in either the U.S. manufacturing price index on the left, or the China price instrument on the right.⁴² We estimate this equation with weighted least-squares using the industry-level Sato weights W_{gt} from equation (14).

From column 1 in Table 8, we see that a lower China price index due to China's WTO entry (lower \hat{ChinaP}_g) reduces 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 convert these regression coefficients into aggregate effects, we multiply them by the aggregate growth in the two instruments (reported on the left of column 1). The sum of these two values indicates that the total WTO effect on the U.S. price index is -0.076 i.e. the

⁴¹The estimated probabilities of exporting from (39) are meant to reflect estimated export shares of Chinese firms.

⁴²In the regression we also include the Sato-Vartia weight on China in each industry g , W_{gt}^i , because it appears as an interaction term in (43) and (44).

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 (42). So we interpret this 7.6 percent fall in prices as the *real* impact on U.S. manufacturing prices.

In the subsequent columns of Table 8, we regress each of the four terms on the right of (13) on these two instruments. By construction, summing coefficients obtained on each instrument across the four regression will give the same results as if we regressed the left-hand side of (13) on these two instrument as in column 1. We call the first term on the right of (13) 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.; 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 $OtherV_g$. We shall regress each of these terms on two instruments that we construct, based on China's entry to the WTO.

Now, let's consider how each of these instruments affected each of the components of the U.S. price index. The largest effect is coming through \hat{ChinaP}_g . As expected, the lower China price instrument lowers the China common goods price index (column 2). Interestingly, it also has a very big effect on competitor prices in column 3, which may reflect exit of inefficient competitor firms, lower marginal costs or lower markups.⁴³ Further, a lower \hat{ChinaP}_g causes exit of some other competitor firms (column 5), and an insignificant effect on Chinese competitor firms (column 4).

To interpret the effect of \hat{ChinaP}_g appearing in Table 8, consider the impact on $OtherP_g$ in column 3, which is the the second term on the right of (13). To be explicit, the coefficients appearing in column 3 are obtained from the regression (ignoring the constant term which is also used):

$$OtherP_g = \sum_{j \in \bar{I}_g^j \setminus i} W_{gt}^j \ln \left(\frac{P_{gt}^j}{P_{g0}^j} \right) = 3.210 \hat{ChinaP}_g - 0.003 \hat{ChinaV}_g. \quad (45)$$

Notice that the dependent variable in this regression has the weights W_{gt}^{kj} on each country, but that these weights sum to *less than unity* over the countries $j \in \bar{I}_g^j \setminus i$. Specifically, $\sum_{j \in \bar{I}_g^j \setminus i} W_{gt}^j = 1 - W_{gt}^i$, where W_{gt}^i is the Chinese share in U.S. consumption within industry g . On the other hand, the instruments \hat{ChinaP}_g and \hat{ChinaV}_g defined in (43) and (44) have the weights W_{gt}^i , which are just the Chinese share. The coefficient estimates obtained in column (3) are certainly influenced by having weights on the left and the right of (45) that differ from unity.

To illustrate, suppose that we divide \hat{ChinaP}_g and \hat{ChinaV}_g by \bar{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 / \bar{W}_t^i average to unity over the industries used in the regression (45). Analogously, we divide the dependent variable in (45) by the weight $1 - \bar{W}_t^i$, so that the industry weights $W_{gt}^j / (1 - \bar{W}_t^i)$ average to unity. With this

⁴³ Atkin, Faber, and Gonzalez-Navarro (2017) also find strong effects on competitor prices from entry of foreign retail in Mexico.

re-normalization of the left and right-side variables in (45), the regression becomes,

$$\frac{OtherP_g}{1 - \bar{W}_t^i} = 0.538 \frac{\hat{China}P_g}{\bar{W}_t^i} - 0.000 \frac{\hat{China}V_g}{\bar{W}_t^i}, \quad (46)$$

which is obtained directly from (45) because the average Chinese share of U.S. consumption over 2000-2006 across manufacturing industries is $\bar{W}_t^i = 0.144$, 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 3.210 appearing in column (3) of Table 8.⁴⁴

Turning to the variety instrument in the lower half of the table, we see that increased Chinese variety due to WTO increases the China variety component in column 4 with a coefficient of 1.744. The coefficient on other competitors (column 5) is negative, suggesting there could be some exit, however it is insignificant. We also find that a lower $\hat{China}V_g$ leads to a very small increase in Chinese prices in column 2, probably due to some quality bias, and it has no effect on competitor prices in column 3.

The decomposition in Table 8 shows that 65 percent or two-thirds of the China WTO effect on the U.S. price index comes through China's 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 somewhat surprising given the large extensive margin of exporting we documented above. In fact, a large portion of the consumer gain comes from China's impact on competitor prices. All of this effect is due to China lowering their own input tariffs since the gap does not affect $\hat{China}P_g$ at all, nor does it affect Chinese firms' *TFP* or export prices, as shown in Table 6 and 7. In contrast, we did find that the gap increased the probability of export participation as did China's lower input tariffs, so the 35 percent contribution from the variety gain is due to both the elimination of the tariff uncertainty and lower input tariffs. Therefore, we can conclude that more than 65 percent of the aggregate WTO effect on U.S. manufacturing prices was indeed due to China lowering its import tariffs on intermediate inputs.

5.1 Robustness

In this section we explore some alternative specifications in order to check the robustness of our results. First, we reestimate equation (42), by replacing the dependent variable with a U.S. price index that is adjusted for the fact that we only had firm-product level data for the China exports and we had to rely on more aggregated data for the imports from other countries (i.e. HS 10-digit U.S.

⁴⁴The 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 all by the appropriate weight $\bar{W}_t^{ij} = 0.144$, then the coefficient estimates do not change at all.

Table 9: 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)
$\hat{China}P_g$	3.406*** (0.815)	3.412*** (0.836)	1.461** (0.633)	1.978 (1.790)	3.800** (1.554)	4.286*** (0.887)
growth x regression coefficient contribution	-0.048 64.1%	-0.048 64.9%	-0.037 41.4%	-0.014 60.8%	-0.047 81.1%	-0.056 66.7%
$\hat{China}V_g$	1.623*** (0.158)	1.599*** (0.157)	1.787*** (0.137)	1.057*** (0.238)	0.768** (0.315)	1.724*** (0.161)
growth x regression coefficient contribution	-0.027 35.9%	-0.026 36.1%	-0.052 58.6%	-0.009 39.2%	-0.011 18.9%	-0.028 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 reestimates 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 HS 4-digit level. Column 6 uses predicted values to construct instruments from regressions that control for additional reforms.

imports). As we show in Appendix A, we can correct for this by adjusting the unit values that appear in the second component of equation (13) with their product with Herfindahl indexes of exporters from each country. In practice, this makes very little difference to the results because these measures of concentration change very slowly over time, and so most of the ratios of these indexes are close to one. We can see this in column 1 of Table 9 where the results with the adjusted price index are almost the same as our baseline results in column 1 of Table 8.

Another potential measurement issue 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 reestimate TFP using the De Loecker (2013) approach, which builds on Olley and Pakes (1996) and Akerberg, Caves, and Frazer (2015), by allowing exporting to affect learning. With these new TFP estimates, we reestimate all of the specifications in Tables 6 and 7, and use those results to reconstruct the instruments $\hat{China}P_g$ and $\hat{China}V_g$. Column 2 of Table 9 presents the results from reestimating equation (42) with these instruments based on the De Loecker (2013) TFP measures and again we see the results are very close to our baseline, with a 7.3 percent total WTO effect and 65 percent of that due to $\hat{China}P_g$.

In the next two columns, we split the HS 6-digit industries into “final” and “inputs” use the Broad Economic Categories (BEC). As expected, the largest gains are in the final goods industries, with a total WTO effect of 9 percent. The U.S. price index in these industries could fall not only due to exit of inefficient producers and lower markups, but also due to access to cheaper and more varieties of

intermediate inputs. For these categories, a larger share (58.6 percent) is due to the variety channel. Consistent with this finding, the industries that are in the “input” category have a lower total WTO effect of 2.3 percent.

The sample of industries in our baseline table comprise only a subsample of all U.S. manufacturing as some industries had to be dropped due to missing components of elements needed to construct each variable in equation (42), for example in some industries we could not define a λ ratio. The aggregate value of the 1,599 industries account for more than 60% of U.S. manufacturing consumption (and 85 percent of China’s manufacturing exports to the U.S.) One way to cover a larger share of the U.S. manufacturing sector is to construct the U.S. price index and the two instruments in equation (42) at the HS 4-digit level, which raises the share close to 80 percent (and the China export share to 90 percent). For example, suppose there were three HS 6-digit industries that map to one HS 4-digit industry and we can only construct the instruments for one of those HS 6-digit categories. In our baseline, the other two HS 6-industries would be dropped but at the HS 4-digit all three of those industries would be included. The advantage of including those industries is that China’s entry into one HS 6-digit industry could also have effects on the other two industries within the HS 4-digit. (Note for the HS 4-digit specification, we reestimated all of the elasticities at the HS 4-digit level.) However, if the HS 6-digit industries within an HS 4-digit industry are unrelated then regressing a 4-digit U.S. price index on instruments that only contain a subset of those industries could dilute the effects. In column 5, we do see that the WTO effect is a bit lower than the baseline but there still remains a sizable effect at 5.8 percent covering this larger manufacturing share.

Finally, we consider other reforms during this period that could be correlated with our input tariff and gap measures, which if omitted would then incorrectly attribute gains from these reforms. We have already included the reforms that lifted restrictions on which firms were eligible to export. We now also incorporate additional reforms, namely MFA, import licenses, FDI liberalization, and tariffs on final goods. We present the results in the Appendix Table D3 for the TFP, export participation, and export price equations with these additional reform variables. We see in column 1 that including the additional reforms did not affect the coefficients on the two \hat{M} instruments, and only two of the additional reform variables are significant. The coefficient on the output tariff is negative, showing that lower output tariffs increased productivity in addition to the effect coming through increased imported inputs. The import license restrictions are entered as the log of the share of a firm’s imports that are *not* subject to import restrictions, $\ln(\text{Unrestricted Import Share}_{it})$. The coefficient on this variable is positive and significant indicating that firms that import a large share of inputs that are unrestricted by import licenses have higher *TFP*.

As with the TFP equation, we find that the additional reform variables do not have much of an effect on the size of the coefficients on *TFP* and input tariffs in the export participation equation in column 2 and export prices in column 3. The coefficient on input tariffs falls marginally to 3.4 in column 3 of Table D3 (from 3.6 in column 5 of Table 7). Also, the coefficient on the gap variable is hardly affected in the export participation equation. In these specifications the output tariff is

insignificant and of the wrong sign in the price equation. However, all of the other additional reform variables are significant and of the expected signs. In the industries where quotas were lifted, in both phases represented by the MFA variables, the probability of entering the export market increased and the export prices fell. In the industries where FDI was restricted, the probability of entry was lower and export prices were higher. Firms importing a large share of imports under import licenses have a lower probability of exporting, but its coefficient in the export price equation is insignificant. We show that accounting for these additional reforms does not change our conclusions — the total WTO effect is around 8 percent with two-thirds of the gain due to $\hat{China}P_g$ in the last column of Table D3. Even though many of these additional reforms impacted Chinese firms' productivity and exporting, they do not affect our main conclusions on the contribution of input tariffs and the gap to the overall U.S. manufacturing price index.

6 Conclusion

In this paper, we quantify the effect of China's WTO entry on U.S. consumers. We construct U.S. manufacturing price indexes by combining highly disaggregated Chinese firm-product data for the period 2000 to 2006, with U.S. import data from other countries and U.S. domestic sales. To take account of new product varieties, we construct exact CES price indexes, which comprise both a price and variety component. We find that China's WTO entry reduced the U.S. price index of manufactured goods by 7.6 percent over this period, with 65 percent of this effect coming through the conventional price index component, despite there being a huge extensive margin of exporting. Importantly, our analysis explicitly takes account of China's trade shock on competitor prices and entry. Our results indicate that lower Chinese export prices due to WTO entry reduced both the China price index and the prices of competitor firms in the U.S., which also led to exit of Chinese firms' competitors in the U.S. These effects could be due to less efficient firms exiting the U.S. market, lower marginal costs or lower markups.

Our paper is the first to show that the key mechanism underlying the China WTO effect on U.S. price indexes is China lowering its own import tariffs on intermediate inputs. Indeed, we find that lower Chinese tariffs on its intermediate inputs increased its import values and varieties, which in turn boosted Chinese firms productivity. This higher productivity meant that new firms could enter the U.S. market. In addition, lower input tariffs have a direct effect on Chinese export prices. We also allow for China's access to PNTR under WTO to affect 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. As such, most of the WTO effect on U.S. price indexes comes through China's lower input tariffs, accounting for more than two-thirds of the overall effect.

References

- ACEMOGLU, D., D. AUTOR, D. DORN, G. H. HANSON, AND B. PRICE (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34(S1), 141–198.
- ACKERBERG, D. A., K. CAVES, AND G. FRAZER (2015): "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83(6), 2411–2451.
- AMITI, M., AND D. R. DAVIS (2011): "Trade, Firms, and Wages: Theory and Evidence," *Review of Economics Studies*, 79, 1–36.
- AMITI, M., O. ITSKHOKI, AND J. KONINGS (2014): "Importers, Exporters, and Exchange Rate Disconnect," *American Economic Review*, 104(7), 1942–78.
- (2016): "International Shocks and Domestic Prices: How Large Are Strategic Complementarities?," Working Paper 22119, National Bureau of Economic Research.
- AMITI, M., AND J. KONINGS (2007): "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review*, 97(5), 1611–1638.
- ANTRÀS, P., T. C. FORT, AND F. TINTELNOT (2017): "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," *American Economic Review*, forthcoming.
- ARKOLAKIS, C., A. COSTINOT, AND A. RODRIGUEZ-CLARE (2012): "New Trade Models, Same Old Gains?," *American Economic Review*, 102(1), 94–130.
- ATKIN, D., B. FABER, AND M. GONZALEZ-NAVARRO (2017): "Retail Globalization and Household Welfare: Evidence from Mexico," *Journal of Political Economy*, forthcoming.
- AUTOR, D. H., D. DORN, AND G. H. HANSON (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6), 2121–68.
- BAI, X., K. KRISHNA, AND H. MA (2017): "How You Export Matters: Export Mode, Learning, and Productivity in China," *Journal of International Economics*, forthcoming.
- BAS, M. (2012): "Input-trade Liberalization and Firm Export Decisions: Evidence from Argentina," *Journal of Development Economics*, 97(2), 481–493.
- BAS, M., AND V. STRAUSS-KAHN (2014): "Does Importing More Inputs Raise Exports? Firm-level Evidence from France," *Review of World Economics (Weltwirtschaftliches Archiv)*, 150(2), 241–275.
- BLAUM, J., C. LELARGE, AND M. PETERS (2015): "The Gains From Input Trade in Firm-Based Models of Importing," .
- BLOOM, N., M. DRACA, AND J. VAN REENEN (2016): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *The Review of Economic Studies*, 83(1), 87.

- BRAMBILLA, I., A. K. KHANDELWAL, AND P. K. SCHOTT (2010): "China's Experience under the Multi-Fiber Arrangement (MFA) and the Agreement on Textiles and Clothing (ATC)," in *China's Growing Role in World Trade*, NBER Chapters, pp. 345–387.
- BRANDT, L., J. V. BIESEBROECK, AND Y. ZHANG (2012): "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97, 339–351.
- BRANDT, L., J. VAN BIESEBROECK, L. WANG, AND Y. ZHANG (2017): "WTO Accession and Performance of Chinese Manufacturing Firms," *American Economic Review*, forthcoming.
- BRODA, C., AND D. E. WEINSTEIN (2006): "Globalization and the Gains from Variety," *The Quarterly Journal of Economics*, 121(2), 541–585.
- CALIENDO, L., M. DVORKIN, AND F. PARRO (2015): "The Impact of Trade on Labor Market Dynamics," NBER Working Paper 21149.
- CALIENDO, L., R. C. FEENSTRA, J. ROMALIS, AND A. M. TAYLOR (2015): "Tariff Reductions, Entry and Welfare: Theory and Evidence from the last Two Decades," NBER Working Paper 21768 (revised April 2017).
- DAHL, G. B. (2002): "Mobility and the Return to Education: Testing a Roy Model with Multiple Markets," *Econometrica*, 70(6), 2367–2420.
- DAS, M., W. K. NEWKEY, AND F. VELLA (2003): "Nonparametric Estimation of Sample Selection Models," *Review of Economic Studies*, 70, 33–58.
- DE LOECKER, J. (2013): "Detecting Learning By Exporting," *American Economic Journal: Microeconomics*, 5(3), 1–21.
- DI GIOVANNI, J., A. A. LEVCHENKO, AND J. ZHANG (2014): "The Global Welfare Impact of China: Trade Integration and Technological Change," *American Economic Journal: Macroeconomics*, 6(3), 153–83.
- FEENSTRA, R. C. (1994): "New Product Varieties and the Measurement of International Prices," *American Economic Review*, 84(1), 157–77.
- FEENSTRA, R. C. (2010): *Product Variety and the Gains from International Trade*. MIT Press.
- FEENSTRA, R. C., AND D. E. WEINSTEIN (2017): "Globalization, Markups and U.S. Welfare," *Journal of Political Economy*, forthcoming.
- FENG, L., Z. LI, AND D. L. SWENSON (2016): "The Connection Between Imported Intermediate Inputs and Exports: Evidence from Chinese firms," *Journal of International Economics*, 101, 86 – 101.

- FENG, L., Z. LI, AND D. L. SWENSON (2017): "Trade Policy Uncertainty and Exports: Evidence from China's WTO Accession," *Journal of International Economics*, 106, 20–36.
- GOLDBERG, P. K., A. K. KHANDELWAL, N. PAVCNIK, AND P. TOPALOVA (2010): "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *The Quarterly Journal of Economics*, 125(4), 1727–1767.
- GOPINATH, G., AND B. NEIMAN (2014): "Trade Adjustment and Productivity in Large Crises," *American Economic Review*, 104(3), 793–831.
- HALLAK, J. C., AND P. K. SCHOTT (2011): "Estimating Cross-Country Differences in Product Quality," *Quarterly Journal of Economics*, 126(1), 417–474.
- HALPERN, L., M. KOREN, AND A. SZEIDL (2015): "Imported Inputs and Productivity," *American Economic Review*, 105(12), 3660–3703.
- HANDLEY, K., AND N. LIMÃO (2017): "Policy Uncertainty, Trade and Welfare: Theory and Evidence for China and the U.S," *American Economic Review*, forthcoming.
- HSIEH, C.-T., AND R. OSSA (2016): "A Global View of Productivity Growth in China," *Journal of International Economics*, 102, 209 – 224.
- IACOVONE, L., F. RAUCH, AND L. A. WINTERS (2013): "Trade as an engine of creative destruction: Mexican experience with Chinese competition," *Journal of International Economics*, 89(2), 379–392.
- KASAHARA, H., AND B. LAPHAM (2013): "Productivity and the Decision to Import and Export: Theory and Evidence," *Journal of International Economics*, 89(2), 297–316.
- KEE, H. L., AND H. TANG (2016): "Domestic Value Added in Exports: Theory and Firm Evidence from China," *American Economic Review*, 106(6), 1402–36.
- KHANDELWAL, A. (2010): "The Long and Short (of) Quality Ladders," *Review of Economics Studies*, 77, 1450–1476.
- KHANDELWAL, A. K., P. K. SCHOTT, AND S.-J. WEI (2013): "Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters," *American Economic Review*, 103(6), 2169–95.
- KOOPMAN, R., Z. WANG, AND S.-J. WEI (2012): "Estimating Domestic Content in Exports When Processing is Pervasive," *Journal of Development Economics*, 99, 178–189.
- MELITZ, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.
- MURTAZASHVILI, I., AND J. M. WOOLDRIDGE (2008): "Fixed Effects Instrumental Variables Estimation in Correlated Random Coefficient Panel Data Models," *Journal of Econometrics*, 142(1), 539–552.

- OLLEY, S. G., AND A. PAKES (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.
- OSSA, R. (2015): "Why Trade Matters After All," *Journal of International Economics*, 97(2), 266–277.
- PIERCE, J. R., AND P. K. SCHOTT (2012): "A Concordance Between Ten-digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries," Discussion paper.
- (2016): "The Surprisingly Swift Decline of U.S. Manufacturing Employment," *American Economic Review*, 106(7), 1632–1662.
- SODERBERY, A. (2015): "Estimating Import Supply and Demand Elasticities: Analysis and Implications," *Journal of International Economics*, 96(1), 1–17.
- YU, M. (2015): "Processing Trade, Tariff Reductions, and Firm Productivity: Evidence from Chinese Firms," *Economic Journal*, 125, 943–988.

Appendix

A Introducing Herfindahl Indexes to improve Unit Value Indexes

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

$$uv_{gt}^j \equiv \left(\frac{\sum_f p_{fgt}^j q_{fgt}^j}{\sum_f q_{fgt}^j} \right). \quad (47)$$

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

$$P_{gt}^j = \left(\sum_f (p_{fgt}^j)^{1-\rho_g} \right)^{\frac{1}{1-\rho_g}}. \quad (48)$$

LEMMA 1. With symmetry over products, then the CES index is related to the unit values by $P_{gt}^j = uv_{gt}^j H_{gt}^j$, where $H_{gt}^j \equiv \sum_f (s_{fgt}^j)^{\frac{\rho_g}{\rho_g-1}}$.

PROOF:

Making use of the symmetric CES demand in (25), while adding the country superscript j , we can rewrite the unit value as,

$$uv_{gt}^j = \left(\frac{\sum_f (p_{fgt}^j)^{1-\rho_g}}{\sum_f (p_{fgt}^j)^{-\rho_g}} \right). \quad (49)$$

Again using symmetric demand in (25), it follows that,

$$s_{fgt}^j \equiv \frac{p_{fgt}^j q_{fgt}^j}{X_{gt}^j} = \left(\frac{p_{fgt}^j}{P_{gt}^j} \right)^{1-\rho_g} \Leftrightarrow p_{fgt}^j = P_{gt}^j (s_{fgt}^j)^{\frac{1}{1-\rho_g}} \Leftrightarrow \sum_f (p_{fgt}^j)^{-\rho_g} = (P_{gt}^j)^{-\rho_g} \sum_f (s_{fgt}^j)^{\frac{\rho_g}{\rho_g-1}}.$$

Substituting into (49) and using (48), we readily obtain,

$$uv_{gt}^j = \left(\frac{\sum_f (p_{fgt}^j)^{1-\rho_g}}{(P_{gt}^j)^{-\rho_g} \sum_f (s_{fgt}^j)^{\frac{\rho_g}{\rho_g-1}}} \right) = P_{gt}^j \left(\frac{\sum_f (p_{fgt}^j)^{1-\rho_g}}{(P_{gt}^j)^{1-\rho_g} \sum_f (s_{fgt}^j)^{\frac{\rho_g}{\rho_g-1}}} \right) = \frac{P_{gt}^j}{H_{gt}^j},$$

so it follows that $P_{gt}^j = uv_{gt}^j H_{gt}^j$. QED

To interpret this result, H_{gt}^j 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. To apply this Lemma to our data, for countries exporting to the U.S. other than China we will 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 $p_{gt}^{ij}(\omega)$ in (6) denote the CES price indexes at the HS 10-digit level. Applying

the Lemma, we will replace the CES indexes $p_{gt}^{ij}(\omega)$ by $uv_{gt}^{ij}(\omega)H_{gt}^{ij}$, where $uv_{gt}^{ij}(\omega)$ denotes the unit values at the HS 10-digit level. So the unit values times the Herfindahls should appear in the second term of (13), for all exporters other than China. In principle we should be using the Herfindahl indexes of exporters at the HS 10-digit level, too, but in practice due to data limitations we use these indexes at the HS 6-digit level (see Appendix B). For each HS 6-digit industry, we can construct the variety terms λ_{gt}^{ij} 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, $uv_{gt}^{ij}(\omega)H_{gt}^{ij}$.

B Data construction

ASIF data: The firm-level data in this paper comes from 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 (or equivalently, 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 the 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. As such, 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

Table B1: 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

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 B1. The striking pattern to emerge from Table B1 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. It does, however, 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, Van Biesebroeck, Wang, and Zhang (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.

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 take 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, Biesebroeck, and Zhang (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.

C Variables

Elasticities of Substitution: To estimate the elasticities of substitution we follow the methodology described and coded in Appendix 2.1 of Feenstra (2010). We estimate three sets of elasticities, all at the HS6 industry level: (i) Elasticities of substitution between Chinese varieties exported to the U.S. (China ρ_g). The variety is defined at the firm-HS8 level. (ii) Elasticities of substitution between varieties sold in the U.S. by all non-Chinese exporters (Other ρ_g). As we do not have access to firm-level data for other exporters, 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 an elasticity of substitution across varieties within each 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 the coefficient for each HS 6-digit elasticity to be the same for all countries (omitting China in “other ρ_g ”). There were too few observations for some countries to estimate country-specific elasticities. We assume the elasticity across domestically produced varieties within each HS6 is also the same. (iii) Elasticities of substitution across HS 6-digit varieties (σ_g). We construct exact price indices for each HS6-country, using the ρ'_g s to construct the exact price index for each country as in equations (6) and (9), to estimate elasticities of substitution across each of these country-HS6 digit varieties. 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. For each set of elasticities, we filled in any missing HS 6-digit elasticity with the median of the next level up. 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 .

U.S. domestic sales: To convert U.S. production data from NAICS 6-digit to HS 6-digit, we follow Feenstra and Weinstein (2017) (p45 Appendix), which assume that the domestic share (*share*) in total consumption is the same in HS 10-digit as it is in NAICS 6-digit. 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 by

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

Once we have U.S. domestic sales at HS10, we can easily map 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 the unit values indexes (described in A) are taken from Feenstra and Weinstein (2017). These were constructed using PIERS firm-product level data on 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 con-
cording back to HS1996 6-digit codes, there are some many-to-many issues for which we assume each HS6 is a simple average of its 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 then use a linear interpolation and a 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.

D Additional Results

Table D1: Export Decompositions

Sample	Type of trade	Total export growth	EM proportion	Share in total US	Share of total US growth
Full sample	Variety defined at HS6-firm	2.90	0.83		
	Variety defined at HS4-firm	2.90	0.79		
	Variety defined at HS2-firm	2.90	0.73		
Sub-samples	Nonprocessing trade	3.56	0.90	0.36	0.38
	Consumer goods	1.73	0.89	0.38	0.33
	Nontraders	3.71	0.85	0.85	0.90
	Private firms	4.36	0.87	0.84	0.92
	Foreign firms	4.05	0.85	0.68	0.74
	ASIF overlap	3.29	0.80	0.56	0.57

Notes: Private firms exclude SOE. The matched sample comprises the observations that we could map from ASIF to customs data.

Table D2: Production Coefficients for Chinese Plants: 1998-2006

Chinese Industrial Classification		Olley-Pakes	
		Labor	Capital
		β_l	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 & Cap	0.51	0.35
19	Manufacture of Leather, Fur, & Feather	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 Product	0.27	0.44
23	Printing, Reproduction of Recording Media	0.27	0.49
24	Manufacture of Articles For Culture, Education, & Sport Activities	0.44	0.33
25	Processing of Petroleum, Coking, & 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 goods	0.19	0.53
32	Smelting & Pressing of Ferrous Metals	0.38	0.49
33	Smelting & Pressing 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	0.42	0.28
Average: all manufacturing		0.37	0.45

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

Table D3: Additional Reforms

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

Notes: Column 1 is in parallel with column 3 in Table 6. Column 2 compares with column 1 in Table 7. Column 3 is analogous to column 5 in Table 7. The MFA variables are dummy variables equal to 1 for the HS 6-digit product 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 import that are subject to import licenses.