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

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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 7.3 percent between 2000 and 2006. In principle, this consumer welfare gain could be driven by two distinct policy changes that occurred with WTO entry. One, 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. Two, a new channel we identify through which China's WTO entry lowered U.S. price indexes, is China reducing its own input tariffs. Our results show that China's lower input tariffs increased its imported inputs, boosting Chinese firm's productivity and their export values and varieties. Lower input tariffs also reduced Chinese export prices to the U.S. market. In contrast, PNTR only increased Chinese exports to the U.S. through its effect on new entry, but had no effect on Chinese productivity nor export prices. We find that at least two thirds of the China WTO effect on U.S. price indexes was through China lowering its own tariffs on intermediate inputs.

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1 Introduction

China's manufacturing export growth in the last 20 years has produced a dramatic realignment of world trade, with China emerging as the world's largest exporter. China's export growth was especially rapid following its World Trade Organization (WTO) entry in 2001, with the 2001–2006 growth rate of 30 percent per annum being more than double the growth rate in the previous five years. This growth has been so spectacular that it has attracted increasing attention to the negative effects of the China "trade shock" on other countries, such as employment and wage losses in import-competing U.S. manufacturing industries. 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. One, 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. Two, a 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 (70 percent of total growth) rather than incumbents exporting new products (15 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 44 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

[1] Broda and Weinstein (2006) built on this methodology to estimate the size of the gains from importing new varieties into the U.S. In contrast to that paper, we 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 Antras, Fort, and Tintelnot (2014), 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 (2013).

Within this theoretical framework, we estimate an equation for Chinese firms' U.S. export shares 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 costs, which appear in both the export share and export price equations. Our proxy for marginal costs is the inverse of a Chinese firm's 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, with proportionally bigger effects for large firms. In first-stage estimates of our export shares and export prices equations, we find that lower input tariffs, by increasing imported intermediate inputs, boost firm-level productivity. Our specifications allow for both export shares and export prices to be influenced by input tariffs and the effect of PNTR, which we estimate by utilizing the "gap" between the US column 2 tariff and the US MFN tariff as in Pierce and Schott (2016) and Handley and Limão (2013).

Our results show that China's WTO entry drove down the U.S. manufactured goods price index by 7.3 percent, an average of 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 exports to the U.S, mostly arising from the direct effect of lower input tariffs.[2] 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. In the export share equation, lower input tariffs increase TFP, which leads to higher export shares; lower input tariffs also increase export participation. 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 U.S. price

[2]The input tariff effect on export prices through TFP was difficult to identify, possibly due to a quality bias, which we address in section 4.3. In a related paper, Fan, Li, and Yeaple (2014) find that Chinese export prices are increasing in productivity and decreasing in tariffs due to quality upgrading. Also consistent with quality upgrading, Manova and Zhang (2012) show that Chinese firms charge higher prices to more distant richer countries. However, Khandelwal, Schott, and Wei (2013) find that the removal of quotas in China's textile industry led to lower export prices.

indexes is due to China reducing its own input tariffs rather than the PNTR: we find that two-thirds of China's WTO effect comes via China's conventional price index, which the 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 Chinese competitors and other 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 share 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 one-third 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 (2012) for China). 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.[3]

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 (2014) find that China's export growth reduced overall U.S. job growth.[4] 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 (2015) 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 (2013) 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 0.8 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

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

[4] These type of channels have also been studied for other countries (for example, Bloom, Draca, and Van Reenen (2011) on European countries and Iacovone, Rauch, and Winters (2013) on Mexico).

question requires a computable model. For example, Hsieh and Ossa (2011) calibrate a multi-country model with aggregate industry data at the two-digit level, and find that China transmits small gains to the rest of the world.[5] More recently, Caliendo, 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, and we shall argue that the sources of consumer gains from trade that we measure are *additional to* the gains from reducing iceberg trade costs in the ACR framework, and additional to the gains from reducing uncertainty over U.S. tariffs in Handley and Limão (2013).

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 share 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 Consumers

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

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

where g denotes an industry that will be defined at an HS 6-digit code or some other broad product grouping, and G denotes the set of HS 6-digit codes; Q_{gt}^j is the aggregate consumption of good g in country j and period t; $\alpha_g^j > 0$ is a taste parameter for the aggregate good g in country j; and η is the elasticity of substitution across goods.

Consumption of g is comprised of varieties from each country within that HS code:

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

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

[5] In 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.

industry g.

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

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

where $z_{gt}^{ij}(\omega) > 0$ is a *taste or quality* parameter for the variety ω of good g sold by country i to country j, which can vary over time to a limited extent (as explained below); Ω_g^{ij} is the set of varieties; and ρ_g denotes the elasticity of substitution across varieties in industry g. We can expect that the elasticity of substitution ρ_g at the firm-product level exceeds the elasticity σ_g across countries in industry g.[6]

Our goal is to compute a price index that accurately reflects consumer utility given this nested CES structure. We begin with the exports of a foreign country i (think of China) to country j (think of the U.S.). The CES price index that is dual to (3) is:

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

Consider two equilibria with theoretical price indexes P_{gt}^{ij} and P_{g0}^{ij}, which reflect different prices $p_{gt}^{ij}(\omega)$ and $p_{g0}^{ij}(\omega)$ and also differing sets of varieties Ω_{gt}^{ij} and Ω_{g0}^{ij}. We assume that these two sets have a non-empty intersection of varieties whose taste parameters are *constant* between the two periods, denoted by $\overline{\Omega}_g^{ij} \subseteq \Omega_{gt}^{ij} \bigcap \Omega_{g0}^{ij}$ with $z_{gt}^{ij}(\omega) = z_{g0}^{ij}(\omega)$ for $\omega \in \overline{\Omega}_g^{ij}$. We refer to the set $\overline{\Omega}_g^{ij}$ as the "common" varieties, available in periods t and 0 and with constant taste parameters. Feenstra (1994) shows how the ratio of P_{gt}^{ij} and P_{g0}^{ij} can be measured without knowledge of the underlying taste parameters, as:

$$\frac{P_{gt}^{ij}}{P_{g0}^{ij}} = \left[\prod_{\omega \in \overline{\Omega}_g^{ij}} \left(\frac{p_{gt}^{ij}(\omega)}{p_{g0}^{ij}(\omega)} \right)^{w_{gt}^{ij}(\omega)} \right] \left(\frac{\lambda_{gt}^{ij}}{\lambda_{g0}^{ij}} \right)^{\frac{1}{\rho_g - 1}}, \tag{5}$$

where $w_{gt}^{ij}(\omega)$ are the Sato-Vartia weights at the variety level, defined as

$$w_{gt}^{ij}(\omega) \equiv \frac{\frac{s_{gt}^{ij}(\omega) - s_{g0}^{ij}(\omega)}{\ln s_{gt}^{ij}(\omega) - \ln s_{g0}^{ij}(\omega)}}{\sum_{\omega \in \overline{\Omega}_g^{ij}} \left(\frac{s_{gt}^{ij}(\omega) - s_{g0}^{ij}(\omega)}{\ln s_{gt}^{ij}(\omega) - \ln s_{g0}^{ij}(\omega)} \right)}, \; s_{gt}^{ij}(\omega) \equiv \frac{p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)}{\sum_{\omega \in \overline{\Omega}_g^{ij}} p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)} \tag{6}$$

[6]Notice that we do not constrain the taste parameters $z_{gt}^{ij}(\omega)$ (beyond being positive), so they can be written as $z_{gt}^{ij}(\omega) = \beta_{gt}^{ij} \gamma_{gt}^{ij}(\omega)$ in which case β_{gt}^{ij} can be pulled outside of the summation and parentheses on the the right of (3). Then (3) could be re-defined as $\beta_{gt}^{ij} \widetilde{Q}_{gt}^{ij}$ and these terms would appear as country consumption on the right of (2). In other words, given that we allow for any (positive) taste parameters in (3), our assumption that the country aggregates appear *symmetrically* in (2) is without loss of generality.

and

$$\lambda_{gt}^{ij} \equiv \frac{\sum_{\omega \in \overline{\Omega}_g^{ij}} p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)}{\sum_{\omega \in \Omega_{gt}^{ij}} p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)} = 1 - \frac{\sum_{\omega \in \Omega_{gt}^{ij} \setminus \overline{\Omega}_g^{ij}} p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)}{\sum_{\omega \in \Omega_{gt}^{ij}} p_{gt}^{ij}(\omega) q_{gt}^{ij}(\omega)}, \tag{7}$$

and likewise for $s_{g0}^{ij}(\omega)$ and λ_{g0}^{ij}, defined as above for $t = 0$.

The first term in equation (5) is constructed in the same way as a conventional Sato-Vartia price index — it is a geometric weighted average of the price changes for the set of varieties $\overline{\Omega}_g^{ij}$, with log-change weights. The second component comes from Feenstra (1994) and takes into account net variety growth: λ_{gt}^{ij} equals one minus the share of expenditure on new products, in the set Ω_{gt}^{ij} but not in $\overline{\Omega}_g^{ij}$, whereas λ_{g0}^{ij} equals one minus the share of expenditure on disappearing products, in the set Ω_{g0}^{ij} but not in $\overline{\Omega}_g^{ij}$.[7]

While (5) provides us with an exact price index for varieties sold from country i to country j, we also want to incorporate all other countries selling good g. This can be done quite easily by using the Sato-Vartia price index over countries. Denoting the non-empty intersection of countries selling to j in period t and period 0 by $\overline{I}_g^j = I_{gt}^j \bigcap I_{g0}^j$, which we call the "common" countries, the Sato-Vartia weights at the country-industry level are

$$W_{gt}^{ij} = \frac{\frac{S_{gt}^{ij} - S_{g0}^{ij}}{\ln S_{gt}^{ij} - \ln S_{g0}^{ij}}}{\sum_{i \in \overline{I}_{gt}^j} \left(\frac{S_{gt}^{ij} - S_{g0}^{ij}}{\ln S_{gt}^{ij} - \ln S_{g0}^{ij}} \right)} \text{ with } S_{gt}^{ij} \equiv \frac{P_{gt}^{ij} Q_{gt}^{ij}}{\sum_{i \in \overline{I}_{gt}^j} P_{gt}^{ij} Q_{gt}^{ij}}. \tag{8}$$

The share of countries selling in both period t and period 0 is

$$\Lambda_{gt}^j \equiv \frac{\sum_{i \in \overline{I}_g^{ij}} P_{gt}^{ij} Q_{gt}^{ij}}{\sum_{i \in I_{gt}^{ij}} P_{gt}^{ij} Q_{gt}^{ij}}. \tag{9}$$

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

$$\frac{P_{gt}^j}{P_{g0}^j} = \left[\prod_{i \in \overline{I}_g^j} \left(\frac{P_{gt}^{ij}}{P_{g0}^{ij}} \right)^{W_{gt}^{ij}} \right] \left(\frac{\Lambda_{gt}^j}{\Lambda_{g0}^j} \right)^{\frac{1}{\sigma_g - 1}}. \tag{10}$$

In this equation, one of the exporting countries i denotes China, while the product above is taken over i and all other exporting countries k and also $i = j$ for the U.S. For China we will have firm-product-level data, from which we will construct the China import price index using equation (5). The Chinese price indexes incorporating variety will be constructed at the HS 6-digit level. For other importing countries we will not have firm level data, and will instead let ω in equation (5) refer to

[7] Varieties with changing quality parameters are excluded from the set $\overline{\Omega}_g^{ij}$, so they are essentially treated like a disappearing variety after period 0 and a new variety in period t.

the HS 10-digit goods within each HS 6-digit industry. Then for each HS 6-digit industry, we can construct the variety exported by those countries and the change in variety over time using (7). The Sato-Vartia index for each HS 6-digit industry and country is constructed using the unit-values over the "common" HS 10-digit products that are sold to the U.S. If exporting countries are selling in fewer HS 10-digit categories over time (due to competition from China), then that loss of variety will raise the price index in (5) above what is obtained from the conventional Sato-Vartia index, and contribute to a higher U.S. price index in (10).

For $i = j$ we will also need to measure the change in variety for U.S. firms. Once again we do not have the U.S. firm-level data, but we can follow Feenstra and Weinstein (2015) in using publicly available data on the share of sales in each industry accounted for by the largest firms. Specifically, suppose that from one year to the next, the identity of the top firms remains the same. Then we can use the share of sales by those firms to measure λ_{g0}^{ij} and λ_{gt}^{ij}. The Sato-Vartia component of the price index will be constructed using the U.S. producer price index for each industry. Feenstra and Weinstein (2015) found that there was rising concentration in U.S. industries on average, indicating a rising value for λ_{gt}^{ij}, which will raise the price indexes in (5) and (10).

We see that these methods will account for exiting foreign and U.S. firms, potentially due to competition from China. If a country k 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 (10). 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 (10) accounts for all these offsetting effects, and will be the basis for our calculations of U.S. consumer welfare.

Using all the above equations, and denoting China by country i, we can decompose this industry g price index as,

$$\ln \frac{P_{gt}^{j}}{P_{g0}^{j}} = \ln \left[\prod_{\omega \in \overline{\Omega}_g^{ij}} \left(\frac{p_{gt}^{ij}(\omega)}{p_{g0}^{ij}(\omega)} \right)^{W_{gt}^{ij} w_{gt}^{ij}(\omega)} \right] + \ln \left[\prod_{k \in \overline{I}_g^{j} \setminus i} \prod_{\omega \in \overline{\Omega}_g^{kj}} \left(\frac{p_{gt}^{kj}(\omega)}{p_{g0}^{kj}(\omega)} \right)^{W_{gt}^{kj} w_{gt}^{kj}(\omega)} \right]$$
$$+ \ln \left(\frac{\lambda_{gt}^{ij}}{\lambda_{g0}^{ij}} \right)^{\frac{W_{gt}^{ij}}{\rho_g - 1}} + \ln \left\{ \left[\prod_{k \in \overline{I}_g^{j} \setminus i} \left(\frac{\lambda_{gt}^{kj}}{\lambda_{g0}^{kj}} \right)^{\frac{W_{gt}^{kj}}{\rho_g - 1}} \right] \left(\frac{\Lambda_{gt}^{j}}{\Lambda_{g0}^{j}} \right)^{\frac{1}{\sigma_g - 1}} \right\}. \tag{11}$$

The first term on the right is a conventional Sato-Vartia price index for Chinese imports, constructed over common goods in industry g available both years. The second term is the Sato-Vartia price index for common goods in industry g for all other countries, including 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 from other exporters k and the U.S. itself, and also from the changing set of exporters.

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

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

Then we can write the change in the overall U.S. price index as

$$\frac{P_t^j}{P_0^j} = \prod_{g \in G} \left(\frac{P_{gt}^j}{P_{g0}^j} \right)^{W_{gt}^j}. \tag{12}$$

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 and instruments to determine how variety in our model is related to U.S. and Chinese tariff changes. This investigation will also clarify the various sources of gains from trade in our model and, in particular, how these sources are related to the gains from trade in ACR (2012).

2.2 Firms

We focus on Chinese firms (country i) exporting to the United States (country j). Within each industry g, firms randomly draw a productivity φ. The production structure is somewhat more complicated than in Melitz (2003), however, because we want to incorporate the imports of intermediate inputs by firms engaged in exporting. That generalization is particularly important as China's accession to the WTO reduced its own import tariffs. In our specification of costs in China, we are influenced by Amiti, Itskhoki, and Konings (2014), who find that large exporters have a greater share of imported intermediate inputs in their costs than do small exporters; in other words, there appears to be a non-homothetic feature to the production structure, as we shall also find for China.

To model this, we generalize the Melitz model to allow firms to import intermediate inputs. A firm with productivity φ might not use all possible imported inputs, however, since there could be fixed costs required to import from different sources. We follow Blaum, Lelarge, and Peters (2015) in denoting the *sourcing strategy* of the Chinese firm with productivity φ in industry g by Σ_g^i, by which we mean the complete list of input industries n and countries j that this firm sources from.[8] The sourcing strategy is endogenous and determining it requires the solution of a complex problem

[8] In principle, the sourcing strategy could also include the list of varieties ω for each industry and country that the firm sources from.

for the firm, as illustrated by Antras, Fort, and Tintelnot (2014), Gopinath and Neiman (2014) and Halpern, Koren, and Szeidl (2015). We do not attempt to solve that problem here.

With some assumptions,[9] Blaum, Lelarge, and Peters (2015) show that the sourcing strategy will depend on the productivity φ of the firm, and it would also naturally depend on the tariffs the firm faces on its output(s) and on its intermediate inputs. We let τ_t^i denote the vector of one plus the *ad valorem* tariffs τ_{nt}^i that China charges on its imports of intermediate input n. In principle, all these tariffs potentially influence the sourcing strategy $\Sigma_g^i(\tau_t^i, \varphi)$ of a Chinese firm.[10] Then the marginal cost of a Chinese firm with productivity φ in industry g is written as

$$mc_g^i(\tau_t^i, \varphi) \equiv \frac{c_g^i(\tau_t^i, \Sigma_g^i(\tau_t^i, \varphi))}{\varphi}, \quad \frac{\partial mc_g^i}{\partial \varphi} < 0. \tag{13}$$

The function $c_g^i(\tau_t^i, \Sigma_g^i(\tau_t^i, \varphi))$ denotes an *input price index* for the firm. We divide this price index by productivity φ in (13) to obtain marginal costs $mc_g^i(\tau_t^i, \varphi)$. The reliance of $c_g^i(\tau_t^i, \Sigma_g^i(\tau_t^i, \varphi))$ on φ captures the non-homothetic nature of the sourcing strategy: we expect that more productive and therefore larger firms will source from more suppliers, leading to a greater share of intermediate inputs in costs. We impose the restriction $\partial \ln c_g^i / \partial \ln \varphi < 1$ so that $\partial \ln mc_g^i / \partial \ln \varphi < 0$, that is, marginal costs are declining in productivity.

Given this structure of costs, the rest of model is very much like Melitz (2003), but with the addition of *ad valorem* tariffs and also allowing for a simple treatment of quality, which we have denoted by $z_g^{ij}(\varphi)$. Specifically, we shall suppose that each productivity level corresponds to a quality $z_g^{ij}(\varphi)$, and that the marginal costs in (13) are needed to produce one unit of the *quality-adjusted quantity* $z_g^{ij}(\varphi) q_{gt}^{ij}(\varphi)$. For the moment we ignore any uncertainty about the U.S. tariff that is applied to China, so that the U.S. tariff τ_{gt}^{ij} does not change. For simplicity we do not consider the entry of firms into each industry, but normalize the mass of potential entrants at unity. The *quality-adjusted prices* $p_{gt}^{ij}(\varphi)/z_g^{ij}(\varphi)$ of an individual product variety are inclusive of tariffs, and are obtained as a markup over marginal costs:

$$\frac{p_{gt}^{ij}(\varphi)}{z_g^{ij}(\varphi)} = \frac{\rho_g}{(\rho_g - 1)} mc_g^i(\tau_t^i, \varphi) \tau_{gt}^{ij}. \tag{14}$$

The revenue of the firm must be divided by τ_{gt}^{ij} to reflect tariff payments, and then is further divided by the elasticity of substitution ρ_g to obtain firm profits. These profits are set equal to the fixed costs of f_g^{ij} to give us the zero-profit-cutoff (ZPC) condition[11]

[9] To obtain this specification they assume: a CES production function over intermediate inputs; the quality of inputs purchased from different countries has a Pareto distribution; and a symmetric fixed costs of adding a new supplier.

[10] The sourcing strategy and the firm's costs will also depend on the local wage and on the net-of-tariff prices of imports, and on the U.S. tariffs on imports from China. These local wage and the net-of-tariff prices of imports will not appear in our empirical specification and we hold them fixed in the model, so they are suppressed in the notation. In our empirical work we did not find that the U.S. tariff, or the "gap" between the U.S. MFN and column 2 tariffs, impacted the sourcing strategy of Chinese firms, so the U.S. tariff is also suppressed in the notation $\Sigma_g^i(\tau_t^i, \varphi)$ for the sourcing strategy.

[11] If there are fixed costs associated with the sourcing of inputs, then we treat these as sunk costs.

$$\frac{p_{gt}^{ij}(\varphi_{gt}^{ij})q_{gt}^{ij}(\varphi_{gt}^{ij})}{\tau_{gt}^{ij}\rho_g} \geq f_g^{ij}. \tag{15}$$

To solve for the cutoff productivity, we can combine the above two equations with the CES demand equation for product varieties from country i,

$$z_g^{ij}(\varphi)q_{gt}^{ij}(\varphi) = \left(\frac{p_{gt}^{ij}(\varphi)/z_g^{ij}(\varphi)}{P_{gt}^{ij}}\right)^{-\rho_g} \frac{X_{gt}^{ij}}{P_{gt}^{ij}}, \tag{16}$$

where X_{gt}^{ij} is the expenditure on all varieties sold from country i to j in industry g. Multiplying this equation by the quality-adjusted price $p_{gt}^{ij}(\varphi)/z_g^{ij}(\varphi)$ and using (14) and (15), we can solve for firm exports as:

$$p_{gt}^{ij}(\varphi)q_{gt}^{ij}(\varphi) = X_{gt}^{ij}\left(\frac{\rho_g mc_g^i(\tau_t^i,\varphi)}{(\rho_g-1)P_{gt}^{ij}}\frac{\tau_{gt}^{ij}}{z_g^{ij}(\varphi)}\right)^{1-\rho_g}, \tag{17}$$

with the ZPC condition,

$$p_{gt}^{ij}(\varphi)q_{gt}^{ij}(\varphi) \geq \tau_{gt}^{ij}\rho_g f_g^{ij}. \tag{18}$$

Note that the U.S. tariff on Chinese firms, τ_{gt}^{ij}, enters in two places in the above equations. First, it enters into the value of exports on the right of (17), which also then appears on the left of (18). A reduction in U.S. tariffs *only* as they appear on the right of (17) and on the left of (18) would have the same impact on U.S. welfare as a reduction in iceberg trade costs in ACR (2012). Namely, if the marginal costs defined in (13) are distributed as Pareto, then the gains to the U.S. from a reduction in its tariff on Chinese imports would be inversely proportional to the fall in the U.S. share of expenditure on home varieties. As we explain below, however, the tariff that appears on the right of (17) and on the left of (18) is the MFN tariff; since this tariff changed very little over the period, this source of gains from trade for the U.S. is correspondingly small.

A second place that the U.S. tariff enters is on the right of (18), where it multiplies the fixed costs. The tariff enters there because we have modeled the *ad valorem* tariffs as applying to the import revenue, so the revenue on the left of (15) must be divided by τ_{gt}^{ij} to obtain the net-of-tariff revenue remaining for the Chinese firm. This means that a reduction in tariffs *only* on the right of (18) will have the same impact on the selection of Chinese firms into exporting as a reduction in the *fixed costs* of exporting. This welfare gain for the U.S. does not rely on any distributional assumption for firm productivity and is *distinct from* a reduction in iceberg trade costs in the ACR framework. Indeed, as illustrated in a two-sector, two-country model by Caliendo, Feenstra, Romalis, and Taylor (2015), when *ad valorem* tariffs are reduced there is a welfare gain due to the reduction in the home share of varieties (the ACR gain), and in addition, another potential gain due to the entry of firms and expansion in varieties (reflecting the fall in τ_{gt}^{ij} on the right of (18) as well as the change in tariff

revenue).[12] As we explain below, the tariff that appears on the right of (18) is actually the "gap" between the U.S. column 2 and MFN tariff, which was eliminated once China joined the WTO. This is the source of the gains from trade identified in Handley and Limão (2013), and is distinct from the gains in ACR (2012).

Of course, there is a third way that tariffs enter the above equations, and that is through the Chinese tariffs on intermediate inputs, τ_t^i. We have followed Blaum, Lelarge, and Peters (2015) in our specification of this sourcing strategy $\Sigma_g^i(\tau_t^i, \varphi)$, which depends on firm productivity. The productivity gains to the firm from expanding suppliers are exactly as we have described in the previous section, i.e. the gains depend on the share of expenditure on new suppliers, just as in Feenstra (1994) and ACR (2012). These gains will translate into lower Chinese prices and also more Chinese exporters due to the term $mc_g^i(\tau_t^i, \varphi)$ appearing in (17) and on the left of (18). Furthermore, we can expect that the resulting drop in Chinese prices will lead to the exit of some domestic U.S. producers, as well as the exit of firms exporting to the U.S. from other countries. These various effects will lead to gains for the U.S. that are similar in spirit to those in ACR (2012), but could only crudely be captured by a drop in iceberg trade costs because the drop in Chinese marginal costs should be proportionately larger for more productive firms (who expand their sourcing more). So from the U.S. point of view, these potentially large gains are also *additional to* the drop in iceberg trade costs in ACR (2012).

Let us now extend the model to incorporate tariff uncertainty, using a simplified version of Handley and Limão (2013).[13] Suppose that the Chinese firm faces two possible values of the U.S. tariff $\tau_{gt}^{ij} \in \left\{\tau_g^{MFN}, \bar{\tau}_g\right\}$, which are at either the MFN level or the alternative column 2 level denoted by $\bar{\tau}_g > \tau_g^{MFN}$. We require that some component of the fixed costs of exporting is sunk, which we denote by F_g^{ij}, with the remaining per-period fixed costs of exporting denoted by f_g^{ij}. 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. The pricing decision is then identical to that shown by (14). 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

$$v(\varphi, \tau_{gt}^{ij}) = \frac{p_{gt}^{ij}(\varphi) q_{gt}^{ij}(\varphi)}{\tau_{gt}^{ij} \rho_g} - f_g^{ij}. \tag{19}$$

We suppose for simplicity that if the tariff starts at its MFN level then it remains there in the next period with probability κ, and with probability $(1-\kappa)$ 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 further suppose that Chinese firms treat the U.S. expenditure on Chinese imports in each industry, which is X_{gt}^{ij} in (17), as fixed over time.[14] Because of the impact of

[12] The additional impact on welfare from the potential entry of firms appears in Costinot and Rodriguez-Clare (2014) and their appendix, who treat it separately from the change in the home share in their welfare expressions. In our simple model here we have ignored entry, but there will still be extra potential gains due to the selection of Chinese firms into exporting.

[13] Our simplified treatment here draws on Feng, Li, and Swenson (2015).

[14] This strong assumption is only used to present a very simplified version of the Handley and Limão (2013) model with

tariffs on the entry and exit of Chinese firms, we need to keep track of what happens to the Chinese import price index P_{gt}^{ij}, and we let $\overline{P}_g$ (P_g^{MFN}) denote that price index when all tariffs are at their column 2 (MFN) level. By using (3) with the simplifying condition $z_g^{ij}(\omega) = 1$, along with the pricing equation (14), the Chinese price index can be written as $P_{gt}^{ij} = \frac{\rho_g}{(\rho_g - 1)} \tau_{gt}^{ij} MC_{gt}^{ij}$, where

$$MC_{gt}^{ij} \equiv \left(\sum_{\omega \in \Omega_{gt}^{ij}} mc_g^i(\tau_{gt}^{ij}, \tau_t^i, \varphi)^{1-\rho_g} \right)^{\frac{1}{1-\rho_g}}. \tag{20}$$

That is, MC_{gt}^{ij} is a CES index of Chinese marginal costs, and we let $\overline{MC}_g$ (MC_g^{MFN}) denote the marginal cost index when all U.S. tariffs are at their column 2 (MFN) level. It follows that $\overline{P}_g / P_g^{MFN} = (\overline{\tau}_g / \tau_g^{MFN})(\overline{MC}_g / MC_g^{MFN})$, as we shall use below.

With a discount rate $\delta < 1$, the present discounted value of the Chinese firm facing the MFN tariff is[15]

$$V(\varphi, \tau_g^{MFN}) = v(\varphi, \tau_g^{MFN}) + \delta \left[\kappa V(\varphi, \tau_g^{MFN}) + (1-\kappa) V(\varphi, \overline{\tau}_g) \right].$$

Since $V(\varphi, \overline{\tau}_g) = v(\varphi, \overline{\tau}_g)/(1-\delta)$ 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,

$$V(\varphi, \tau_g^{MFN}) = \frac{v(\varphi, \tau_g^{MFN})}{(1-\delta\kappa)} + \frac{\delta(1-\kappa) v(\varphi, \overline{\tau}_g)}{(1-\delta)(1-\delta\kappa)} \geq F_g^{ij}. \tag{21}$$

We can simplify this condition by using (17), (19) and $\overline{P}_g / P_g^{MFN} = (\overline{\tau}_g / \tau_g^{MFN})(\overline{MC}_g / MC_g^{MFN})$ to obtain

$$v(\varphi, \overline{\tau}_g) + f_g^{ij} = \left[v(\varphi, \tau_g^{MFN}) + f_g^{ij} \right] \left(\frac{\overline{\tau}_g}{\tau_g^{MFN}} \right)^{-1} \left(\frac{\overline{MC}_g}{MC_g^{MFN}} \right)^{\rho_g - 1}.$$

Substituting this into (21), we obtain the export participation condition written in terms of one-period profits:

$$v(\varphi, \tau_g^{MFN}) \geq (T_g - 1) f_g^{ij} + T_g (1-\delta) F_g^{ij}, \tag{22}$$

where,

$$T_g \equiv \left\{ \frac{(1-\delta)}{(1-\delta\kappa)} + \frac{\delta(1-\kappa)}{(1-\delta\kappa)} \left(\frac{\overline{\tau}_g}{\tau_g^{MFN}} \right)^{-1} \left(\frac{\overline{MC}_g}{MC_g^{MFN}} \right)^{\rho_g - 1} \right\}^{-1}. \tag{23}$$

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

uncertainty, and is not used in the general model that we use to motivate our estimating equations.

[15] The value of the firm as written is independent of time because of our assumption that Chinese exporters treat X_{gt}^{ij} as fixed, which would occur when $\eta = \sigma_g = 1$ and there is no redistribution of tariff revenue. We are not allowing WTO entry to be anticipated – it comes as a surprise – so we also treat the Chinese tariffs τ_t^i on intermediate inputs as fixed from the firms' point of view.

becomes $v(\varphi, \tau_g^{MFN}) \geq (1-\delta)F_g^{ij}$. The right-hand side of that condition differs from (22) by the term $(T_g - 1)[f_g^{ij} + (1-\delta)F_g^{ij}]$, which we interpret as the "effective" tariff term $(T_g - 1)$ multiplied by fixed and sunk costs. The effective tariff we have obtained is similar to the results in Handley and Limão (2013) and Feng, Li, and Swenson (2015), except that in (23) we also keep track of industry entry and exit. If the fixed costs are small so that $f_g^{ij} \to 0$ and also discounting is small so that $\delta \to 1$, then we see that

$$lnT_g \to \left(ln\overline{\tau}_g - ln\tau_g^{MFN}\right) - (\rho_g - 1)\left(ln\overline{MC}_g - lnMC_g^{MFN}\right). \tag{24}$$

The first term on the right of (24) is the "gap" between the column 2 and MFN *ad valorem* tariffs, as first used by Pierce and Schott (2016). The second term reflects the exit of less productive Chinese firms under Column 2 tariffs as compared to MFN tariffs. The CES index of marginal costs would be higher under column 2 tariffs due to exit, so that $\overline{MC}_g > MC_g^{MFN}$, and this second term *offsets* the "gap" in (24). The intuition for this result is that if U.S. tariffs ever reverted to their column 2 level, then demand for the most productive firms would not fall by the full amount of the tariff increase because the less-productive firms would exit. It can be argued that (24) remains positive in equilibrium, so that $T_g > 1$.[16] In practice, the second term cannot be measured, and because it is correlated with the "gap" between the column 2 and MFN *ad valorem* tariffs, we will be taking that correlation into account by using only the "gap" itself.

We will implement the export share equation in (17) and the export participation equation in (22) for Chinese firm-level exports to the U.S. using a 2-stage Heckman procedure. In principle, MFN tariffs on Chinese firms $\tau_g^{ij} = \tau_g^{MFN}$ would enter both equations, since they affect both (17) and the left side of (22). Using$P_{gt}^{ij} = \frac{\rho_g}{(\rho_g - 1)}\tau_{gt}^{ij}MC_{gt}^{ij}$, however, we see that the MFN tariff and also the iceberg costs cancel in (17) when we measure the exports of each Chinese firm relative to overall Chinese exports in that industry,

$$ln\left[\frac{p_{gt}^{ij}(\varphi)q_{gt}^{ij}(\varphi)}{X_{gt}^{ij}}\right] = (1-\rho_g)ln\left(\frac{mc_g^i(\tau_t^i, \varphi)}{MC_g^{ij}}\right).$$

We rewrite this equation slightly by noting that the CES marginal cost index in (20) is not a true average of marginal costs, because it depends on the number of varieties N_{gt}^{ij} within the set Ω_{gt}^{ij}. We can convert the CES index into an average by defining,

$$\widetilde{MC}_{gt}^{ij} \equiv \left(\frac{1}{N_{gt}^{ij}}\sum_{\omega \in \Omega_{gt}^{ij}} mc_g^i(\tau_t^i, \varphi)^{1-\rho_g}\right)^{\frac{1}{1-\rho_g}},$$

from which it follows that $MC_{gt}^{ij} = (N_{gt}^{ij})^{\frac{1}{1-\rho_g}}\widetilde{MC}_{gt}^{ij}$. Substituting this above, we obtain

[16]Because F_g^{ij} are sunk costs, the exit condition for Chinese firms in the presence of column 2 tariffs is $v(\varphi, \tau_{gt}^{ij}) < 0$, so the borderline firms exiting satisfies $v(\overline{\varphi}, \overline{\tau}_g) = 0$. That firm would have been profitable under MFN tariffs, so that $v(\overline{\varphi}, \tau_g^{MFN}) > 0$. Using (17), (19), and the assumptions in the previous footnote, we can then show that (24) remains positive.

$$ln\left[\frac{p_{gt}^{ij}(\varphi)q_{gt}^{ij}(\varphi)}{X_{gt}^{ij}}\right] = (1-\rho_g)ln\left(\frac{mc_g^i(\tau_t^i,\varphi)}{\widetilde{MC}_g^{ij}}\right) - lnN_{gt}^{ij}. \tag{25}$$

This is the export share equation that we shall estimate. The variables are the marginal cost of each Chinese firm relative to the industry average marginal costs — or what we call relative marginal costs — and the number of Chinese exporters. The relative marginal costs will be measured inversely by relative total factor productivity of Chinese exporters. The challenge will be to find suitable instruments for the relative TFP and the number of exporters, both of which are endogenous.

The participation equation (22) depends on the same variables as the exporter equation, but since they are endogenous, only their instruments are included in the participation equation. In addition, (22) depends on the "effective" tariff $(T_g - 1)$, which will be measured by the logarithmic "gap" between the column 2 and MFN tariffs before China's WTO entry as in (24), which we interact with a WTO dummy that equals one post 2001. We see from (25) that the "gap" variable does not enter the export share equation, and we shall test this exclusion restriction. It is desirable to have additional variables in the participation equation reflecting these fixed costs that also do not appear in the export equation. For this purpose we will also include the age of the firm, using the argument that more experienced firms are better able to penetrate foreign markets than are new firms. The choice of the age variable is also based on Hopenhayn (1992), who shows that the rate of survival of firms is higher for older firms. We also include a dummy variable indicating whether the firm is foreign owned, using the argument that foreign-owned firms will have lower fixed costs of exporting. We provide a more detailed discussion of the Heckman equations in section 4.

3 Data and Preliminary Estimates

The key variables required for our analysis are China's export prices, measures of variety, estimates of elasticities of substitution, and total factor productivity. 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 price indexes 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 or 8 U.S. firms, also available from U.S. Census, for the variety component of the price index.

Third, to construct measures of total factor productivity (TFP), we draw on the Annual Survey of Industrial Firms (ASIF) from the National Bureau of Statistics. This is a survey of 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. To combine the customs and industrial data sets, we relied on information on firm names, addresses, and zip codes because the firm codes are not consistent across the two data sets. For the merged data sets, we end up with industrial data for a third of exporting firms, which account for 50 percent of China's total U.S. exports over this period. We keep the set of firms that exported to the U.S. at any point between 2000 to 2006 and that appear in the industrial data for at least one overlapping year. We will refer to this as our "overlapping sample" and we will make comparisons with the complete data set whenever possible. The data show that the number of U.S. exporters more than tripled over the sample period. See Appendix A for more details on the data construction.

3.1 China's Export Variety

China's exports to the U.S. grew a spectacular 286 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. Denoting the value of Chinese exports to the U.S. by X_{fgt} for firm f and product g in year t, where the products are now defined at the Chinese HS 8-digit level, and dropping the earlier superscripts ij, we can decompose China's export growth to the U.S. as follows:

$$\frac{\sum_{fg}(X_{fgt} - X_{fg0})}{\sum_{fg} X_{fg0}} = \frac{\sum_{fg\in\overline{\Omega}} X_{fgt} - \sum_{fg\in\bar{\Omega}} X_{fg0}}{\sum_{fg} X_{fg0}} + \frac{\sum_{fg\in\Omega_t\setminus\bar{\Omega}} X_{fht} - \sum_{fg\in\Omega_0\setminus\overline{\Omega}} X_{fg0}}{\sum_{fg} X_{fg0}}, \tag{26}$$

where $\overline{\Omega} = \Omega_t \cap \Omega_0$ is the set of varieties (at the firm-product level) that were exported in t and $t = 0$, $\Omega_t \setminus \overline{\Omega}$ is the set of varieties exported in t but not in 0 and $\Omega_0 \setminus \overline{\Omega}$ is the set of varieties exported in t_0 but not in t. 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). It is often the case in many other countries 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 — 70 percent of the total export growth over the sample

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

		Proportion of export growth due to different margins:					
		Variety at the HS8-firm level				Equivalent Price Change	
Year	Total Export Growth %	Intensive Margin	Extensive Margin	Extensive Margin new firms	Extensive Margin incumbents	Due to Chinese Variety	Weighted by China Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2001	4.2	0.09	0.91	0.75	0.17	-0.025	-0.010
2002	29.8	0.56	0.44	0.21	0.22	-0.036	-0.014
2003	32.2	0.61	0.39	0.23	0.16	-0.076	-0.019
2004	35.1	0.65	0.35	0.23	0.12	-0.019	-0.009
2005	29.4	0.57	0.43	0.22	0.21	-0.066	-0.011
2006	25.6	0.65	0.35	0.20	0.15	0.000	-0.003
2000-2006	286.3	0.15	0.85	0.70	0.15	-0.441	-0.034

Notes: All these margins are calculated using 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 (5) and column 7 computes the third term on the right of equation (11), both weighted using the Sato-Vartia weights in equation (12).

period comes from new firms and the other 15 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. is 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 C1 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 (5) 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 (5). 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 (12). So column 6 reports the effective drop in the U.S.

[17] In the Appendix Table C1, 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.

import price index from China due to the new varieties, which amounts to -44 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 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 index, we need to adjust the values of the variety index in column 6 by China's share in each industry g, which averaged 6 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 (11), before weighting across industries g as in equation (12). Column 7 shows that the effective price drop due to variety gain from China is reduced to 3.4 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 as in Feenstra (1994), Broda and Weinstein (2006), and Soderbery (2015). 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.[19] This parameter enters in the variety adjustment in the price index — the second term in equation (5) and the third term in equation (11). The median ρ_g, reported in Table 2, is 4.2. 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.[20] We see that the median elasticity for "other countries" is lower at 3.0. 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 (11), and its median estimate is also around 3.

[18] The common goods price index for China — the first component in equation (5) — increased 1.7 percent per year on average.

[19] We trim the top and bottom 1 percentiles. 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.

[20] For the baseline specifications, we estimate the elasticities using U.S. import data for the top 40 countries which account for 98 percent of U.S. manufacturing imports.

Table 2: Distribution of Elasticities of Substitution

	China ρ_g	Other countries ρ_g	σ_g
Percentile 5	1.55	1.40	1.51
Percentile 25	2.61	2.21	2.21
Percentile 50	4.21	2.98	3.08
Percentile 75	8.26	5.08	4.31
Percentile 95	31.72	28.76	15.83
Mean	10.98	9.27	5.42
Standard Deviation	32.49	53.70	11.29

Notes:

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. 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, Biesebroeck, and Zhang (2012), where output deflators draw on "reference prices" from China's Statistical Yearbooks and the input deflators are constructed using China's 2002 national input-output table.[21] 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 C2 in the Appendix, are used to calculate each firm's log TFP as follows:[22]

$$ln(TFP_{ft}) = ln(VA_{ft}) - \beta_l ln(L_{ft}) - \beta_k ln(K_{ft})$$

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 9 percent per year and only slightly more, at 10 percent per year, in the overlapping sample. For comparison, we also report the average growth in real value

[21] see http://www.econ.kuleuven.be/public/N07057/CHINA/appendix

[22] For 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; and drop any firm with less than 10 employees.

Table 3: Productivity Growth

Year	Total factor productivity			Real value added per worker		
	All exporters	Overlapping sample		All exporters	Overlapping sample	
	Simple av	Simple av	Weighted av	Simple av	Simple av	Weighted av
2001	-0.01	0.00	0.02	0.01	0.00	-0.03
2002	0.07	0.09	0.11	0.10	0.11	0.12
2003	0.12	0.13	0.11	0.16	0.16	0.10
2004	0.09	0.11	0.13	0.12	0.13	0.15
2005	0.16	0.16	0.11	0.21	0.20	0.19
2006	0.10	0.10	0.10	0.15	0.14	0.15
Average	0.09	0.10	0.10	0.13	0.12	0.11

Notes:

added per worker, which shows a similar pattern to TFP growth though at slightly higher average rates of between 11 and 13 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.[23] 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. First, 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 raw Chinese import tariff data, which are MFN ad valorem rates at the HS 8-digit level, and calculate the simple average of these at the IO industry level. The input tariff for industry g is the weighted average of these IO industry tariffs, using the cost shares in China's IO table as weights.[24] Average tariffs for each year are reported in Table 4.

Our second 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. In this case we identify an input as any HS 8-digit import that the firm does not also export. These fitted import values will form the basis for our main instruments for firm-level TFP.

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.

[23] See wto.org for more details.

[24] We 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".

Table 4: Average Tariffs

	Tariffs on intermediate inputs					
	HS8 digit		IO category		$ln(Gap)$	
Year	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.

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 (2013) argue 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 gap was very high 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.

4 Estimation

In this section, we estimate the export share equation (25) and the price equation (14) for Chinese firms exporting to the U.S. We will use the predicted values from these equations to calculate how much China's WTO entry changed the U.S. manufacturing price index in the following section. We expect that China's lower import tariffs on intermediate inputs increased productivity, with amplified effects for larger firms due to the non-homothetic sourcing strategy (equation (13)). This in turn leads to higher Chinese exports to the U.S. We also expect a direct price effect from lower input tariffs.

4.1 TFP Instrument

In both of the export share and price equations the marginal costs of the firm appear on the right (in (25) these costs are measured relative to the industry average). We shall measure marginal costs

inversely by the TFP of each firm, which is influenced by its sourcing strategy. To develop instruments for TFP, we rely on the discussion of the sourcing strategy in Halpern, Koren, and Szeidl (2015) and Blaum, Lelarge, and Peters (2015). Suppose that the firm uses imported intermediate inputs that are weakly separable from other domestic inputs. The portion of the production and cost function devoted to imported inputs is CES, with elasticity of substitution $\varepsilon > 1$. We let $c_{ft} \equiv c_f(\tau_t, \Sigma_f(\tau_t))$ denote that portion of the cost function, which is defined over the prices of inputs $n \in \Sigma_f(\tau_t)$ purchased in period t.[25] Let $\overline{\Sigma}_f \subseteq \Sigma_f(\tau_0) \cap \Sigma_f(\tau_t)$ denote a non-empty subset of the "common" inputs purchased in periods 0 and t. Then like the CES indexes in section 2, the index of firm costs between period t and period 0 is

$$\frac{c_{ft}}{c_{f0}} = \left[\prod_{n \in \overline{\Sigma}_f} \left(\frac{\tau_{nt}}{\tau_{n0}} \right)^{w_{nt}} \right] \left(\frac{\lambda_{ft}}{\lambda_{f0}} \right)^{\frac{1}{\varepsilon - 1}}, \tag{27}$$

where w_{nt} is the Sato-Vartia weight for input n, and λ_{ft} denotes the expenditure on imported inputs in the *common* set $\overline{\Sigma}_f$ relative to *total* expenditure on imported inputs in period t. The first term on the right of (27) is the direct effect of tariffs on costs, or the Sato-Vartia index of input tariffs.[26] The second term is the efficiency gain from expanding the range of inputs, resulting in $\lambda_{ft} < \lambda_{f0} \leq 1$. This second term corresponds to TFP growth for the firm.

We construct instruments for λ_{ft} by exploiting the highly disaggregated raw tariffs and directly target the channel through which these operate. We regress Chinese firms' imports on China's import tariffs at the HS 8-digit level — the most disaggregated level available — and use those fitted values to construct our instruments. More specifically, we estimate the following equation with OLS:

$$\begin{aligned} ln(M_{fnt}) = \delta_f + \delta_t + \delta_1 ln(\tau^i_{nt}) + \delta_2 Process_f \times ln(\tau^i_{nt}) \\ + \delta_3 ln(L_f) \times ln(\tau^i_{nt}) + \delta_4 IMR(M_{fnt}) + \epsilon_{1fnt}. \end{aligned} \tag{28}$$

The dependent variable is the value of firm f imports in HS 8-digit category n, and the Chinese tariffs τ_{nt} are those that apply to those imports. In order to ensure that these imports are actually intermediate inputs and not final goods, we exclude any import of an HS 8-digit good that the firm exports to any country in that year. We also interact the tariff with a processing dummy to indicate whether the input is imported under processing trade, and with the average firm size, measured by employment. 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 the quantity imported.[27] We expect that firms with some portion of ordinary trade to benefit from trade liberalization. We

[25] As in section 3, we are holding constant the net-of-tariff prices of imported inputs, so these prices are suppressed in the notation.

[26] In principle, this first term corresponds to the index of input tariffs that we denoted 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.

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

also include year fixed effects and firm fixed effects. Given that the dependent in equation (28) is undefined for zero imports, we address the potential selection bias by including an inverse mills ratio $IMR(M_{fnt})$. The variable is calculated as the ratio of the probability density function to the cumulative distribution function, from the following import participation equation:

$$prob(M_{fnt} > 0|X_{ft} = 1) = \theta_g + \theta_t + \theta_1 ln(\tau^i_{nt}) + \theta_2 Process_f \times ln(\tau^i_{nt}) + \theta_3 Process_f \\ + \theta_4 ln(L_f) \times ln(\tau^i_{nt}) + \theta_5 ln(L_f) + \theta_6 Age_{ft} + \theta_7 Foreign_f + \epsilon_{2ft}. \tag{29}$$

The dependent variable equation equals one if the firm imports an intermediate input in HS 6-digit category n, and zero otherwise.[28] In addition to the variables included in equation (28), we also include the firm's age and a foreign ownership indicator to proxy for the firm's ability to cover the fixed costs of importing, as in the export participation equation — these will provide our exclusion restrictions.

We present the results from estimating the import participation equation in Table 5 and the results from estimating the import value equation in Table 6.[29] In the import participation equation, we also introduce industry effects to take account that some industries may be high-growth industries due to factors such as technological progress, however, in a probit we need to be mindful of the incidental parameters problem induced by too many fixed effects. In Table 5, the first 4 columns are estimated using probit, with no industry fixed effects in column 1, HS 4-digit industry fixed effects in column 2, and HS 6-digit industry random effects in columns 3 and 4. In the first three columns we interact tariffs with the firm's log mean number of workers and in column 4 we use a dummy indicator equal to one if the firm has more than 1,000 employees. We find that lower tariffs reduce the probability of importing for processing firms[30] and they increase that probability for large nonprocessing firms. The magnitude of the effect of lower tariffs for large nonprocessing firms is equal to $\theta_1 + \theta_4 \times ln(L_f)$, which is negative above the threshold of 790 employees — the median number in the sample is 590. In column 4, we include a "Large" indicator and we see that the coefficient for firms with more than 1,000 workers is equal to -0.25 (summing $\theta_1$and θ_4), which suggests that large exporting firms are more likely to import their inputs. We would expect larger firms to be more likely to be able to cover the fixed costs of importing as they probably have better access to capital markets to finance fixed costs and working capital. As expected, we find foreign firms are more likely to import their inputs; however older exporters are less likely to import their inputs. This might appear surprising but we need to bear in mind that this result is conditional on exporting. We use this equation to construct the inverse mills ratio for importing, $IMR(M_{fnt})$, in the import value equation.

All of the specifications from estimating the import value equation (28) include firm fixed effects and year fixed effects. In column 1 of Table 6, we include China's import tariffs and the tariffs inter-

[28]The dimensionality became too large to estimate at the more disaggregated HS 8-digit level.

[29]We experimented with including the gap variable and its interaction with the WTO dummy in equation (29); however it had an insignificant coefficient with the wrong sign.

[30]This is consistent with Kee and Tang (2016).

Table 5: Import Participation

Dependent variable Y_{fnt} =1 if Imports>0	probit				OLS
	(1)	(2)	(3)	(4)	(5)
$ln(\tau_{nt})$	-0.248	-0.037	0.549***	0.050*	0.324***
	(0.244)	(0.246)	(0.063)	(0.029)	(0.101)
$ln(\tau_{nt}) \times Process_f$	1.387***	1.161***	1.088***	1.085***	0.396***
	(0.177)	(0.132)	(0.034)	(0.034)	(0.046)
$ln(\tau_{nt}) \times ln(L_f)$	-0.105***	-0.076**	-0.092***		-0.037***
	(0.030)	(0.030)	(0.009)		(0.011)
$ln(L_f)$	0.071***	0.077***	0.083***		0.030***
	(0.004)	(0.004)	(0.001)		(0.001)
$ln(\tau_{nt}) \times Large_f$				-0.300***	
				(0.023)	
$Large_f$				0.198***	
				(0.003)	
Age_{ft}	-0.007***	-0.007***	-0.007***	-0.006***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Foreign_f$	-0.013	0.017***	0.033***	0.030***	0.012***
	(0.008)	(0.006)	(0.001)	(0.001)	(0.002)
$Process_f$	0.084***	0.007	-0.002	-0.006	-0.000
	(0.024)	(0.018)	(0.004)	(0.004)	(0.006)
industry effects	no	HS4 fe	HS6 re	HS6 re	HS6 fe
N	5,685,934	5,685,928	5,685,934	5,685,934	5,685,934

Notes: Observations are at the HS6-firm-year level. The sample includes all firms that import an input at any time during the sample and appear in the ASIF sample at least once and export at least once. Standard errors clustered at HS6 level. Process dummy equals one if more than 99% of the firm's imports were processing over the sample. The dependent variable equals one in 36.1% of the observations.

acted with a processing dummy. We find that the the coefficient on tariffs is negative and significant, $\delta_1 = -5.72$, showing that trade liberalization results in higher imports for firms that import under ordinary trade. In contrast, the coefficient on the interacted processing term is positive, $\delta_2 = 4.88$. The sum of δ_1 and δ_2 is not significantly different from zero, suggesting that processing imports are not greatly affected by lower tariffs. In column 2, we include the interacted employment variable and in column 3 we use the large-firm dummy instead. Both specifications show there is a non-homothetic effect of sourcing imported inputs, with the effects significantly bigger for large firms. In column 4, where we include $IMR(M_{fnt})$, we show that the results are robust to selection bias — the coefficients in column 4 are close to those in column 2.

We use the results from estimating (28) to construct two instruments for λ_{ft} and therefore for TFP. The first 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

Table 6: Import Value

Dep. Var: $ln(M_{fnt})$	(1)	(2)	(3)	(4)
$ln(\tau_{nt})$	-5.715***	-2.310*	-5.537***	-2.590*
	(0.790)	(1.204)	(0.796)	(1.480)
$ln(\tau_{nt}) \times Process_f$	4.879***	4.626***	4.808***	4.102***
	(0.878)	(0.887)	(0.881)	(1.365)
$ln(\tau_{nt}) \times ln(L_f)$		-0.512***		-0.466**
		(0.145)		(0.199)
$ln(\tau_{nt}) \times Large_f$			-0.568*	
			(0.297)	
$IMR(M_{ft})$				-0.700
				(1.799)
N	1,908,374	1,908,374	1,908,374	1,908,374
R^2	0.142	0.142	0.142	0.142

Notes: Observations are at the firm-HS8-year level. All columns include firm fixed effects and year fixed effects. Standard errors are clustered at the HS8 level. Process dummy equals one if more than 99% of imports are processing. Large dummy equals one if average firm employment is greater than 1000.

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, such as the imports in the median HS category.[31] In practice, we found that many firms did not have common imported inputs over the entire sample period, so the median HS category over the entire sample could not be constructed. We have instead used imports in the median HS 8-digit category on a year-by-year basis, and denote the fitted value of those median imports by $ln(\hat{M}_{med,ft})$. Then the difference between these two instruments, $ln(\hat{M}_{tot,ft}) - ln(\hat{M}_{med,ft})$, is meant to capture the expansion of imported inputs on the extensive margin. One limitation of these instruments is that they are only defined for firms that import their inputs, which means that we can only estimate the export share equation for the set of exporters that also import their inputs. This could potentially induce an additional selection bias if exporters that are nonimporters behave differently from exporters that also import. We address this by including the inverse mills ratios constructed from the import selection equation (29).

4.2 Selection into Exporting

Another issue we need to address in estimating the Chinese firm export share equation (25) and the price equation (14) is the potential bias due to selection into exporting since the dependent

[31] The use of a non-empty subset of common goods rather than the entire set was shown to be valid by Feenstra (1994) when constructing the λ terms, and it also applies to the variety results in section 2, though we did not use it there.

variables are undefined for zero export values. To address this, we include the inverse mills ratio $IMR(X_{fgt})$,which we construct from estimating the following export participation equation:

$$prob(X_{fgt} > 0) = \alpha_g + \alpha_t + \alpha_1 ln(Input\tau_{gt}) + \alpha_2 Gap_g + \alpha_3 Gap_g \times WTO_t + \alpha_4 Age_{ft} + \alpha_5 Foreign_f + \epsilon_{3fgt}. \tag{30}$$

For the baseline estimation, we include all firm-HS6 observations for the period 2000 to 2006 for the set of firms that have at least one nonzero U.S. export observation and that can be mapped to the industrial ASIF data in at least one year. The dependent variable is binary, equal to 1 if the firm had positive export value in industry g, defined at the HS 6-digit level, and zero for all fgt observations where the firm did not export in those HS 6-digit categories.

The explanatory variables include industry fixed effects α_g, time fixed effects α_t, and a full set of tariff variables. We use the input-output table for China to construct the average input tariff that each firm *producing* in industry g faces, denoted by $Input\tau_{gt}$. The input tariffs affect marginal costs and the value of exports in (17), which influences export participation via equations (19) and (22).[32] We also include the "gap" between the column 2 U.S. tariff and the MFN tariffs and also its interaction with a WTO dummy that takes the value of one after 2001. As explained in section 3, the "gap" proxies for the "effective" tariff $(T_g - 1)$ that is approximated in (24). In addition to these tariff variables, we include the age of the firm — so long as the firm's age is reported for at least one year we can include it for all of the sample years. As discussed earlier, this variable is used to represent the fixed costs of exporting, using the argument that more experienced exporters will have lower fixed costs. We also include an indicator variable for whether the firm is foreign owned, since we expect that such firms will have lower fixed costs and a higher probability of exporting.

We present the results in Table 7, with columns 1 through 4 presenting estimates from probit models with different sets of industry effects. All of the equations have year fixed effects to take account of macro factors that affect overall entry and exit. In column 1, with no industry effects, we find that all of the coefficients have the expected signs. The coefficient on China's input tariffs on imported inputs — our main variable of interest — suggests that lower Chinese import tariffs on intermediate inputs increase the probability of exporting. We also find that the probability of entry into the U.S. export market is high 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 coefficients on the foreign firm indicator and the firm's age are consistent with the idea that older firms and foreign firms are in a better position to cover the fixed costs of entering export markets.

[32]Marginal costs are measured inversely in the export share equation (17) using firms' total factor productivity. That variable is not included in the participation equation, however, because it is endogenous. See note 26 for further discussion of $Input\tau_{gt}$.

Table 7: Export Participation

Dependent variable Y_{fgt} =1 if exports>0	probit				OLS
	(1)	(2)	(3)	(4)	(5)
$ln(Input\tau_{gt})$	-2.325***	-7.242***	-7.242***	-6.651***	-1.934***
	(0.475)	(0.868)	(2.299)	(0.127)	(0.195)
$ln(Gap_g)$	-0.381**	-0.208	-0.208		
	(0.190)	(0.129)	(0.239)		
$ln(Gap_g) \times WTO_t$	0.388***	0.298**	0.298	0.329***	0.052**
	(0.127)	(0.119)	(0.244)	(0.022)	(0.026)
$Foreign_f$	0.028***	0.041***	0.041***	0.047***	0.015***
	(0.006)	(0.005)	(0.009)	(0.003)	(0.002)
Age_{ft}	0.002***	0.003***	0.003***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
industry effects	no	HS4 fe	HS4 fe	HS6 re	HS6 fe
clustering	HS6	HS6	IO	no	HS6
# obs.	1,370,885	1,370,885	1,370,885	1,370,885	1,370,885

Notes: Standard errors are clustered at the HS6 industry level in all columns except column 3 where they are clustered at the more aggregate IO industry level. The dependent variable equals one in 31% of the observations.

In the next three columns, we also introduce industry effects to take account that some industries may be high-growth industries due to factors such as technological progress or increased world demand: columns 2 and 3 include industry fixed effects at the more aggregated HS 4-digit level; and column 4 includes random industry effects at the HS 6-digit level. We see that the signs on all of the coefficients remain the same as in column 1, which has no industry effects, but some of the point estimates are different. In particular, the magnitude of the negative coefficient on the input tariff becomes much larger with industry effects, and of similar size in the fixed effects and random effects estimations. For comparison, we present OLS estimates with HS 6-digit level fixed effects in column 5, and again find the same signs on all of the coefficients.[33]

4.3 Main Results

We now have all the variables we need to estimate the export price equation, (14), and the export share equation, (25), which we rewrite as follows.

$$lnp_{fgt} = \beta_f + \beta_t + \beta_1 ln(TFP_{ft}) + \beta_2 ln(Input\tau_{gt}) + \beta_3 IMR(X_{fgt}) + \epsilon_{4fgt}, \tag{31}$$

[33]We show that these results are robust to expanding the sample to include the universe of exporters (rather than just those in the overlapping sample) in Table C3 in Appendix C. Although the age variable is unavailable for the full sample, we find that the coefficients on all of the other variables are the same as in the overlapping sample.

and

$$ln(X_{fgt}/X_{gt}) = \gamma_f + \gamma_t + \gamma_1 ln(TFP_{ft}) + \gamma_2 ln(N_{gt}) + \gamma_3 IMR(X_{fgt}) + \epsilon_{5fgt}. \tag{32}$$

The dependent variable in the pricing equation is the log unit value, inclusive of freight, insurance, and duties.[34] The pricing equation (31) includes the average tariff on inputs at the industry level, $Input\tau_{gt}$, but that variable does not appear in the export share equation (32) because it is common to all Chinese exporters in the industry (and hence cancels out). Further, because the dependent variable is a share variable, the TFP on the right side of equation (32) is TFP relative to the industry average. If all firms had equal productivity, they would set the same prices and shares, so the export share for every firm would be $1/N$, which is why the export share equation includes the log number of Chinese exporters, $ln(N_{gt})$, as shown in (25), with a coefficient of -1. Then from the relative TFP term, firms with higher than average productivity will have higher than average export shares. Both the TFP and the N terms are treated as endogenous. We instrument for TFP using the two instruments we constructed from the fitted import values above. We instrument for the number of Chinese firms exporting to the U.S. in each industry with the number of Chinese firms exporting to EU countries. We also experiment with an alternative instrument constructed from the predicted number of exporters obtained by summing the predicted probability of exporting from the participation equation (30).

Our model implies the coefficients $\gamma_1 = \beta_1(1-\rho_g)$, $\beta_2 = 1$, $\gamma_2 = -1$. Given that we do not allow the coefficients to differ across industries g, a better way to capture this cross-equation restriction is with $\gamma_1 = \beta_1(1-\rho_{med})$, using a median estimate ρ_{med}. We will not find coefficients satisfying these cross-equation constraints, however, and a model-based reason for this finding is that the error terms in both equations include the unobserved *quality* of the export product. To see how unobserved quality can influence the coefficient estimates, notice that from (31) the error term in the pricing equation, ϵ_{4fgt}, includes log quality, which we now denote by lnz_{fgt} instead of $lnz_g^{ij}(\varphi)$. Suppose that quality is linearly related to TFP according to $lnz_{fgt} = \zeta ln(TFP_{ft}) + u_{fgt}$, for an error term u_{fgt} that is uncorrelated with the other variables on the right of (31) or (32). In the price regression, then, the coefficient estimates on TFP in (31) becomes the biased estimate $\widetilde{\beta}_1 = \hat{\beta}_1 + \hat{\zeta}$. In the export share equation (32), log quality enters the error term with the coefficient $\rho_g - 1$, as shown by (25). Replacing this with a median estimate $\hat{\rho}_{med} - 1$, the coefficient estimates on TFP in (32) becomes $\widetilde{\gamma}_1 = \hat{\gamma}_1 + (\hat{\rho}_{med} - 1)\hat{\zeta}$, which is alternatively written as $\widetilde{\gamma}_1 = (\hat{\rho}_{med} - 1)(\hat{\zeta} - \hat{\beta}_1)$ using the cross-equation restriction $\hat{\gamma}_1 = \hat{\beta}_1(1-\hat{\rho}_{med})$. Using these two biased estimates, we therefore solve for the unbiased estimates $\hat{\beta}_1 = 0.5[\widetilde{\beta}_1 - \widetilde{\gamma}_1/(\hat{\rho}_{med} - 1)]$ and $\hat{\gamma}_1 = 0.5[(1-\hat{\rho}_{med})\widetilde{\beta}_1 + \widetilde{\gamma}_1]$, as we shall compute.[35]

The results from estimating equation (31) and (32) are summarized in Table (8) and Table (9). All

[34] The results are unchanged for unit values that exclude duties because the U.S. MFN import tariffs are very low and have hardly changed over the sample period. For this reason, the MFN tariff is not included on the right of (31).

[35] Adjusting the estimated coefficients in this way did not affect our conclusions in the final decomposition below.

of the equations include firm fixed effects and year fixed effects.[36] In column 1, we present the results using OLS as a benchmark for all exporters in the overlapping sample. The coefficient on the log number of exporters in an HS6 industry is negative one as indicated by the theory. Our main interest is in the coefficient on the log TFP, constructed at the firm level. As expected, we find that firms with higher TFP export more. However, we are concerned that the magnitude is biased due to the issues we raised above. To address endogeneity, we instrument for both $ln(TFP_{fgt})$ and $ln(N_{gt})$ in all of the subsequent columns with the following instrument set: the fitted import values from equation (28) for the *total* and *median* imported input expenditure; the log gap interacted with the WTO dummy equal to 1 post-2001; and the number of Chinese firms exporting to the EU, which pass the weak instrument test and the overidentification tests. With the instrumental variables estimation, we see that the coefficient on TFP jumps to 1.2 in column 2 — much larger than the OLS coefficient of 0.1 in column 1. In column 3, we control for potential selection bias by including the IMR(X) constructed from the export participation equation, since the dependent variable is undefined for zero export shares; and we include the IMR(M) to take account of the fact that our fitted import instruments are undefined for nonimporters. The coefficients on both the IMR's turn out to be insignificant and leave the TFP coefficient unchanged.

Another potential issue is that the dependent variable is at the firm-industry level whereas the TFP is at the firm level. Ideally, we would have a measure of TFP for each product that a firm produces but that is not possible. This could be problematic because our average firm-level TFP measure is unlikely to be representative of the smaller export share products, which would result in a downward bias. So in column 4, we exclude any observation for which the Chinese firm's exports within its total U.S. exports that year were less than 5 percent. We see that this makes an enormous difference with the coefficient on TFP more than tripling.[37] We also experimented with alternative cutoffs, with all giving similar results, and in column 4 we report the case where we only include the firm's largest value HS 6-digit U.S. export, and the TFP coefficient is 4.5. The coefficient on the log number of firms remains close to -1 in all of the specifications. These magnitudes are consistent with that implied by equation (25), where the coefficient on log TFP is equal to $\rho_g - 1$; recall that the median ρ_g we estimated is equal to 4.2.

Turning to the first-stage results, reported in the bottom panel of Table 8, the coefficients on the instruments have the expected signs, with higher total imports boosting TFP. However, the gap variable is only significant in the column 3 specification which has the full sample of firms. It becomes insignificant as soon as we exclude the smallest export shares (see the first stage results for columns 4 and 5 specifications). We also checked whether it might be significant in the second stage equation (column 6) and there we find it is insignificant and of the wrong sign. These results suggest that elimination of the gap did not result in a higher intensive margin. However, we do find there were

[36] Because firms produce multiple products and sometimes switch product categories, the full set of firm fixed effects does not quite span the space of industry fixed effects. So we also include industry fixed effects α_g when estimating these equations, though most of these fixed effects are dropped due to multicollinearity.

[37] Similarly, if we reestimate the OLS column 1 for the limited sample we find that its coefficient triples.

Table 8: Export Share

	OLS	IV				
Sample	All	All	All	>0.05 share	Major	>0.05 share
Dep var: $ln(xshare_{fgt})$	(1)	(2)	(3)	(4)	(5)	(6)
$ln(TFP_{ft})$	0.100***	1.185***	1.174***	3.679***	4.546***	3.776***
	(0.010)	(0.307)	(0.348)	(0.449)	(0.864)	(0.445)
$ln(N_{gt})$	-0.970***	-0.962***	-0.958***	-1.005***	-0.859***	-1.007***
	(0.033)	(0.054)	(0.054)	(0.098)	(0.217)	(0.099)
$IMR(X_{fgt})$			-1.001	1.525	2.548	1.735
			(0.908)	(1.423)	(2.840)	(1.415)
$IMR(M_{ft})$			0.720	4.127**	5.597	3.758**
			(1.006)	(1.654)	(3.443)	(1.729)
$ln(Gap_g) \times WTO_t$						-0.333
						(0.376)
Overid. J-test		1.131	1.508	0.936	0.097	0.009
[p-value]		[0.568]	0.470	0.626	0.953	0.923
Weak instrument F-test		89.443	74.651	41.460	15.876	53.854
# obs.	295,600	215,476	209,693	97,323	49,010	97,323

First Stage

	Column 3		Column 4		Column 5	
Dependent Variable:	$ln(TFP_{ft})$	$ln(N_{gt})$	$ln(TFP_{ft})$	$ln(N_{gt})$	$ln(TFP_{ft})$	$ln(N_{gt})$
	(i)	(ii)	(i)	(ii)	(i)	(ii)
$ln(\hat{M}_{tot,ft})$	0.038***	0.007***	0.045***	0.005***	0.043***	0.005*
	(0.003)	(0.001)	(0.005)	(0.002)	(0.007)	(0.002)
$ln(\hat{M}_{med,ft})$	0.017	0.048***	-0.046*	0.029*	-0.045	0.027
	(0.014)	(0.011)	(0.024)	(0.016)	(0.038)	(0.022)
$ln(Gap_g) \times WTO_t$	0.128**	0.267***	0.122	0.278***	0.126	0.226*
	(0.055)	(0.072)	(0.097)	(0.098)	(0.155)	(0.128)
$ln(N_{gt}^{EU})$	0.028***	0.769***	0.060***	0.738***	0.080***	0.705***
	(0.009)	(0.017)	(0.015)	(0.022)	(0.028)	(0.032)
# obs.	209,693	209,693	97,323	97,323	49,010	49,010

Notes: The observations are at the firm-HS6-year level, and include all exporters that could be mapped to the industrial data (ASIF). All regressions include firm fixed effects and year fixed effects. Standard errors are clustered at the firm level. The major subsample is defined as the HS 6 code the firm has the largest export over the sample period. The instrument set is the firm's fitted weighted average imports (see text for description). The variable IMR(X_{fgt}) is the inverse mills ratio from the export participation equation, and the variable IMR(M_{ft}) is the inverse mills ratio from the import participation equation.

Table 9: Export Price

Sample Dep var: $ln(price_{fgt})$	All (1)	>0.05 share (2)	Major (3)	>0.05 share (4)
$ln(TFP_{ft})$	0.167	-0.117	-0.107	-0.118
	(0.161)	(0.130)	(0.139)	(0.131)
$ln(Input\tau_{gt})$	4.890***	4.285**	4.688***	4.353**
	(1.305)	(1.809)	(1.619)	(2.050)
$IMR(X_{fgt})$	-0.360	-0.831**	-0.596	-0.826*
	(0.324)	(0.399)	(0.521)	(0.414)
$IMR(M_{ft})$	-2.438**	-2.937**	-3.846***	-2.998**
	(1.009)	(1.255)	(1.145)	(1.389)
$ln(Gap_g) \times WTO_t$				-0.011
				(0.112)
Overid. J-test	5.989	0.012	0.153	0.000
[p-value]	[0.050]	[0.994]	[0.927]	[0.992]
Weak instrument F-test	91.816	53.822	20.107	80.548
First Stage: Dep var: $ln(TFP_{ft})$				
$ln(\hat{M}_{tot,ft})$	0.038***	0.046***	0.043***	0.046***
	(0.005)	(0.008)	(0.010)	(0.008)
$ln(\hat{M}_{med,ft})$	0.011	-0.045	-0.059	-0.045
	(0.023)	(0.030)	(0.043)	(0.030)
$ln(Gap_g) \times WTO_t$	0.028	-0.022	0.065	-0.022
	(0.175)	(0.276)	(0.410)	(0.276)
# obs.	197,292	90,789	45,709	90,789

Notes: Standard errors are clustered at the IO level. The first stage also includes all second stage variables, not reported to save space.

more firms in industries with a high gap post–WTO — there is a positive and significant coefficient on the interactive gap variable in the first stage log N equation (see lower panel of Table 8). This is consistent with the export participation results in Table 7. That is, the higher Chinese exports to the U.S. in high gap industries increased after China joined the WTO through new entry rather than the intensive margin.

Finally, we present the results from estimating the export price equation (31) in Table 9, where we instrument for TFP as in the export share equation and control for potential selection bias in importing and exporting. However, unlike the export equation, the price equation does not include the number of firms but it does include the input tariff directly. The first thing to note is that the coefficient on input tariffs is positive and significant — lower input tariffs lead to lower export prices as we would expect. This is one of the main channels through which input tariffs affect the U.S. price index. Another channel we would expect input tariffs to affect prices is by increasing TFP. We

find this channel is more difficult to detect in the price regression. It is insignificant in all of the specifications, but does switch from being positive in the full sample in column 1 to the expected negative sign as soon as we omit firms' tiny export shares. We suspect that this is due to the quality bias and we can correct for this as described above. In the first stage results in the lower panel of Table (9) we see that the total fitted import values have a positive effect on TFP but the gap variable is again insignificant (and close to zero) and switches signs across specifications. We further experiment with including the gap term in the second stage equation in the upper panel of column 4 and find it is insignificant and close to zero. These results suggest that the gap variable does not affect prices consistent with our theory, as prices are chosen after the tariff is known.

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 export shares relative to the average firm, as well as increasing the probability of entry into the U.S. market. Lower input tariffs also lower Chinese firms export prices in the U.S. market. The effect from PNTR is more limited. There is no direct effect on export prices nor on export shares — 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"). Our starting point is equation (11). We call the first term on the right of (11) 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.

The first China WTO instrument is the change in Chinese exporter prices predicted from equation (31). Letting the year 2000 represent the base period 0, we predict prices in 2006 relative to 2000. Then we construct the instrument as follows:

$$\hat{ChinaP}_g \equiv \ln \frac{\hat{P}_{gt}}{\hat{P}_{g0}} = W_{gt}^{ij} \ln \left[\prod_{fh \in \overline{\Omega}_g} \left(\frac{\hat{p}_{fht}}{\hat{p}_{fh0}} \right)^{w_{fht}} \right], \tag{33}$$

where $\overline{\Omega}_g = \Omega_{gt} \cap \Omega_{g0}$ is the set of varieties (at the firm-product level, fh) that were exported in industry g during both year 2006 and 2000, and w_{fht} are the Sato-Vartia weights over these varieties. Note that this instrument uses only the predicted export prices from Chinese firms, 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 fitted values from the China firm export share equation (32). For convenience let $x_{fgt} \equiv X_{fgt}/X_{gt}$ denote the exporter share on the left of (32), with predicted

Table 10: Decomposition of WTO Effect on U.S. Price Index

Independent Variable		US Price Index (1)	$ChinaP_g$ (2)	$OtherP_g$ (3)	$ChinaV_g$ (4)	$OtherV_g$ (5)
Growth, 2000-2006		0.053	0.015	0.057	-0.034	0.015
$\hat{ChinaP_g}$	-0.024	2.058*	0.888***	3.371***	-1.140***	-1.062**
		(0.916)	(0.145)	(0.715)	(0.291)	(0.372)
growth x regression coefficient		-0.049	-0.021	-0.080	0.027	0.025
contribution		*66.1%*	*28.6%*	*108.4%*	*-36.6%*	*-34.1%*
$\hat{ChinaV_g}$	-0.051	0.491***	-0.057***	-0.086	0.635***	-0.001
		(0.067)	(0.011)	(0.052)	(0.021)	(0.027)
growth x regression coefficient		-0.025	0.003	0.004	-0.032	0.000
contribution		*33.9%*	*-3.9%*	*-5.9%*	*43.8%*	*-0.1%*
Total WTO effect		-0.073	-0.018	-0.075	-0.005	0.025
N		889	889	889	889	889
R^2		0.117	0.331	0.067	0.590	0.010

Notes: The first row growth rates are the weighted averages of the U.S. price index and each of its four components in equation (11) with the Sato-Vartia weights in equation (12). The first column growth rates are the weighted average of each instrument in equations (33) and (34), using the same Sato-Vartia weights from equation (12). 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 2.058 x $-0.024 = -0.049$; the variety component is 0.491 x$-0.051 = -0.025$.

value $\hat{x}_{fgt}$, then the instrument for the China variety component in (11) is given by:

$$\hat{ChinaV_g} \equiv \frac{W_{gt}^{ij}}{\hat{\rho}_g - 1}\left[ln\left(\sum_{fh\in\overline{\Omega}_g}\widehat{x}_{fht}\right) - ln\left(\sum_{fh\in\overline{\Omega}_g}\widehat{x}_{fh0}\right)\right]. \tag{34}$$

The terms in the square brackets are the fitted values of the analogous term $(\lambda_{gt}^{ij}/\lambda_{g0}^{ij})$ that appears in (11). 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 regress each of the four terms on the right of (11) 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 (11) on these two instruments. In this way, we obtain the *overall* impact of China's entry to the WTO on the U.S. manufacturing price index. We report the results in Table 10. From column 1, 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 -0.073 i.e. the U.S. manufacturing price index was 7.3 percent lower in 2006 relative to 2000 due to China joining 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. Further, a lower $\hat{ChinaP_g}$ causes exit of some competitor Chinese firms (column 4) and other competitor firms (column 5). 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, though this is somewhat muted with a coefficient of 0.6, and it has no effect on other competitors (column 5). We also find that a lower $\hat{ChinaV_g}$ leads to higher Chinese prices in column 2 and competitor prices in column 3, though these are both very small effects, and we suspect that the negative coefficients are due to a quality bias.

The decomposition in Table 10 shows that 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 $\hat{ChinaP_g}$ rather than a lower $\hat{ChinaV_g}$ is somewhat surprising given the large extensive margin of exporting we documented above. In fact, most of the consumer gain comes from China's impact on competitor prices. Given that the gap does not affect $\hat{ChinaP_g}$ at all, since it had no effect on Chinese export prices, as shown in Table 9, we can conclude that at least two-thirds of the WTO effect was indeed due to lower Chinese tariffs on intermediate inputs.

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. manufactured goods price index by 7.3 percent. Two thirds of this effect arose 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 competitors and other 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 and increase their market shares. 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, export prices, or the intensive margin of exporting. As such, most of the WTO effect on U.S. price indexes comes through China's lower input tariffs; accounting for at least two thirds of the overall effect. These gains are additional to the standard gains from trade that arise from reducing iceberg trade costs and in addition to the gains from reducing uncertainty.

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A 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 non-state-owned 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 we construct a concordance between the two data sets using information on 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. However, sometimes firm names recorded in the two data sets can be slightly different, and in each data set, the name for the same firm might change slightly over time. This may arise because of typos, inaccurate recordings by the administrative staff, and

other reasons. For example, a firm may report its name in the customs data as "Beijing ABC Steel Company" in year 2001 and "Beijing ABC Steel Co. Ltd" in year 2002, while in the ASIF, they report the opposite. In this case, no observations will be matched if the matching is based solely on firm name and year.

To address this issue, we match firms based on all names ever used in the two data sets. More precisely, an id_customs will be matched to an id_asif if one of the names ever used by the id_customs is also ever used by the id_asif. In our previous example, since "Beijing ABC Steel Company" appeared in the customs data in year 2001 and in ASIF in year 2002, firm codes pertaining to this name will be matched. In other words, we exhaust all combinations of id_customs and id_asif if their names are identical at least once in the sample period.

We further use information on zip codes and telephone numbers to aid in the matching process, given that the telephone number is unique within a region. We match two firm codes if they have identical zip codes and the last seven digits of the telephone number. Using the last seven digits of the telephone number is based on several considerations. First, telephone numbers are reported in different formats in the two data sets. Area codes are included at the beginning of each telephone number in the customs data, but not in ASIF. Taking the last seven digits makes the formats in the two data sets comparable. Second, during the sample period, some large cities changed their telephone numbers from seven to eight digits by adding one digit before the original seven-digit number. As a result, the reported telephone number for the same firm may change over time. Taking the last seven digits solves this problem. We dropped the zip codes and telephone numbers that are inconsistent with China's regulations (e.g. ones that only have one digit, or contain non-numerical symbols). Finally, similar to the matching by name, we also exhaust all combinations of codes if they have the same zip code and telephone numbers at least once in the sample period.

The total number of exporters is reported in Table A1. The striking pattern to emerge from Table A1 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, Biesebroeck, and Zhang (2012) 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

Table A1: Number of Firms

year	# firms in ASIF	# exporters in ASIF	# exporters in customs	# US exporters in customs	share of US export value in overlapping 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

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. Our concordance is consistent with Brandt, Biesebroeck, and Zhang (2012). 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 care of the many-to-many mappings.

We mapped the HS8 codes to CIC codes using a partial concordance from NBS, and completed the rest manually. 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/).

B U.S. Consumption

To construct China's share in total U.S. consumption in equations (10) and (11), at the HS 6-digit level, we combine production, import and export data, and define S_{gt}^{ij}= (China's imports to U.S. / (production – exports + imports). However, the production data is only available in NAICS 6-digit (from NBER database) and the trade data is at HS10 level. There is a concordance that maps HS10 to NAICS, but it is more difficult to go from NAICS to HS6 because of the usual many-to-many issue. To overcome this problem, we follow Feenstra and Weinstein (2015) (p45 Appendix) as follows. First, denote a NAICS industry by k, we define

$$share^k = \left(\frac{supply^k}{supply^k + imports^k} \right)$$

which can easily be constructed at NAICS (with supply defined as production less exports).

Second, we assume that the share in NAICS equals the share in HS10. Imposing that equality, and rearranging we get

$$supply^{HS10} = \left(\frac{share^k}{1 - share^k}\right) * Imports^{HS10}.$$

Once we have U.S. supply at HS10, we can then construct China's share in U.S. consumption at any level of HS. Note that in some cases there were some negative supply values at the NAICS levels (15 out of 447), in which case we replaced those negative values with zeros. Once we have supply at the HS10 level, it is straightforward to construct China's share, which equals imports from China into the U.S./(U.S. supply + total imports).

C Additional Results

Table C1: 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	2.86	0.83		
	Variety defined at HS4-firm	2.86	0.79		
	Variety defined at HS2-firm	2.86	0.74		
	Time consistent id (unconcorded hs8)	2.86	0.87		
	Time consistent id (concorded hs8)	2.86	0.84		
Sub-samples	Nonprocessing trade	3.39	0.91	0.37	0.39
	Consumer goods	4.00	0.86	0.39	0.33
	Nontraders	3.66	0.88	0.85	0.90
	Private firms	4.32	0.89	0.84	0.92
	Foreign firms	4.00	0.87	0.67	0.73
	ASIF overlap	3.30	0.83	0.53	0.57

Notes: Private firms exclude SOE. ASIF overlap is the set of exporters for which we could match in the industrial data

Table C2: Production Coefficients for Chinese Plants: 1998-2006

	Chinese Industrial Classification	Olley-Pakes	
		Labor β_l	Capital β_k
13	Processing of Foods	0.38	0.37
14	Manufacture of Foods	0.46	0.44
15	Manufacture of Beverages	0.46	0.48
17	Manufacture of Textile	0.44	0.36
18	Manufacture of Apparel, Footwear & Cap	0.52	0.31
19	Manufacture of Leather, Fur, & Feather	0.47	0.33
20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm & Straw Products	0.40	0.37
21	Manufacture of Furnitur	0.55	0.32
22	Manufacture of Paper & Paper Product	0.41	0.37
23	Printing, Reproduction of Recording Medi	0.42	0.44
24	Manufacture of Articles For Culture, Education, & Sport Activities	0.48	0.32
25	Processing of Petroleum, Coking, & Fue	0.23	0.47
26	Manufacture of Raw Chemical Materials	0.33	0.44
27	Manufacture of Medicines	0.44	0.39
28	Manufacture of Chemical Fibers	0.41	0.55
29	Manufacture of Rubber	0.40	0.52
30	Manufacture of Plastics	0.38	0.38
31	Manufacture of Non-metallic Mineral goods	0.33	0.46
32	Smelting & Pressing of Ferrous Metals	0.45	0.37
33	Smelting & Pressing of Non-ferrous Metals	0.34	0.34
34	Manufacture of Metal Products	0.41	0.38
35	Manufacture of General Purpose Machiner	0.41	0.40
36	Manufacture of Special Purpose Machinery	0.42	0.42
37	Manufacture of Transport Equipment	0.46	0.42
39	Electrical Machinery & Equipment	0.41	0.43
40	Computers & Other Electronic Equipment	0.49	0.41
41	Manufacture of Measuring Instruments & Machinery for Cultural Activity & Office Work	0.37	0.38
42	Manufacture of Artwork	0.44	0.31
	Average: all manufacturing	0.42	0.40

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

Table C3: Export Participation- Full Sample

Dependent variable fgt=1 if exports>0	probit				OLS
	(1)	(2)	(3)	(4)	(5)
$ln(Input\tau_{gt})$	-1.266***	-5.669***	-5.600***	-5.792***	-1.626***
	(0.236)	(0.675)	(0.061)	(0.064)	(0.163)
$ln(Gap_g)$	-0.353***	-0.252***			
	(0.108)	(0.087)			
$ln(Gap_g) \times WTO_t$	0.417***	0.306***	0.309***	0.314***	0.057***
	(0.096)	(0.094)	(0.010)	(0.010)	(0.019)
$Foreign_f$	0.196***	0.197***	0.197***	0.197***	0.063***
	(0.008)	(0.008)	(0.002)	(0.002)	(0.003)
$ln(Output\tau_{gt})$				0.227***	
				(0.022)	
industryeffects	no	HS4 fe	HS6 re	HS6 re	HS6 fe
#obs.	7,366,709	7,366,709	7,366,709	7,365,585	7,366,709

Notes: This includes the universe of Chinese exporters to the U.S.. All equations include year fixed effects. Standard errors are clustered at the firm level.