

Input Prices, Productivity and Trade Dynamics: Long-run Effects of Liberalization on Chinese Paint Manufacturers*

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Abstract

We develop a dynamic model to analyze the impact of input tariff liberalization on input prices, trading decisions, and productivity. Although input tariffs directly affect input price benefits of importing, their impact on trade participation generates indirect benefits through productivity improvements and complementarity between importing and exporting. To disentangle these effects, we separately measure importing's effect on input prices and productivity and examine Chinese paint manufacturers' reaction to input tariff liberalization. We find that a mild short-term effect of tariff liberalization is amplified in the long run by induced trade participation, resulting in even higher productivity and lower input prices.

Keywords: *Imported Intermediate Inputs, Direct Importing, Productivity, Dynamics, China*

JEL: *D24, F14, L11*

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1 Introduction

Liberalizing input tariffs reduces input costs by lowering the price of using foreign-sourced intermediate inputs. In addition, lower input prices may encourage firms to initiate importing directly from foreign suppliers. Previous work by Kasahara and Rodrigue (2008) and Kasahara and Lapham (2013) has found that direct importing raises firms’ productivity.¹ Consequently, tariff liberalization improves firm profitability through two channels: directly through reduced input prices and indirectly by promoting direct importing. However, earlier studies on direct importing have not explicitly considered input price effects and do not study the impact of trade liberalization. On the other hand, Goldberg et al. (2010) and Topalova and Khandelwal (2011) have shown that trade liberalization can improve firm performance, but do not model trade participation.² This article combines these literatures to examine the precise channels through which liberalization affects input prices, trade participation and performance over the short and long run. To do so, we explicitly account for input prices and productivity as separate sources of firm heterogeneity within a dynamic model. This innovation is important because the policy that motivates our study—input tariff liberalization—directly affects input prices but only affects productivity through altering the incentive to engage in trade.

To capture the role of input tariffs as distinct drivers of trading decisions, we must overcome the common challenge that our dataset—like many manufacturing datasets—records data on total input expenditure but does not include information on input prices, quantities or quality. The literature often implicitly assumes input price differences across firms are captured as differences in productivity (Syverson, 2011). However, failure to separate input prices from productivity would mask the distinct effects of importing on input prices and productivity that is essential to understanding the impact of input tariff liberalization. To address this lack of data, we employ firms’ optimality conditions implied by profit maximization together with variation in wages and input expenditures to infer materials input prices and total factor productivity.³ Extending Grieco et al. (2016), we explicitly control for firms’ endogenous choice of input quality to account for higher productivity firms’ tendency to use high-quality inputs (Kugler and Verhoogen, 2012). This is crucial because otherwise, the inferred input prices would conflate a firm that uses high-quality inputs with a firm facing high prices conditional on quality, biasing the price effect of liberalization.

¹This would be the case if, for example, direct importers can gain expertise or know-how from foreign counterparts through product support or informal contacts which either improve product quality or lower production costs. In addition, promoting importing could enhance firm value through complementarities with exporting.

²The effect of liberalization on firm performance in these articles could arise from a variety of channels, including access to better inputs for non-importers resulting from import competition in the upstream market. In our article, we focus on improvements resulting from incentives to import directly while controlling for changes in the domestic input market by using information from non-importing firms.

³As will be made precise below, the notion of productivity we adopt in this article is revenue productivity, which can incorporate both technical efficiency and demand heterogeneity. We cannot separate cost and demand sources of revenue productivity because we do not observe the physical output quantities of firms.

Once productivity and input prices are recovered, we estimate a dynamic model of trade participation. Each period, forward-looking firms endogenously choose whether to engage in importing and exporting, knowing that trade participation will simultaneously affect market access (through exporting), materials access and input prices (through importing) and firm performance (through both) by comparing these benefits with the costs of trade participation. We estimate a flexible specification of fixed and sunk costs of trade based on current trade status.

The key mechanism of our model is straightforward. Firms have two incentives to engage in importing. First, they gain access to lower-priced, higher quality materials than they can acquire through the domestic market. Second, importing has a causal impact on productivity through exposure to foreign firms. Trade liberalization will increase the first incentive to import directly for lower materials prices as long as middlemen importers do not completely pass through the cost benefits of a tariff reduction. Therefore, if direct importing raises productivity, tariff liberalization can improve firm performance both directly through lower input prices and indirectly by promoting trade and increasing firm efficiency. Moreover, because trading firms tend to be more efficient (Melitz, 2003), liberalization will increase the correlation between output and efficiency, further raising aggregate efficiency.

However, the impact of trade liberalization on trade participation and productivity may take many years to be fully realized. Sunk (or startup) costs to trade inhibit firms from immediately reacting to these incentives after a policy change. The slow transition makes it challenging to evaluate the overall impact of trade liberalization on industry performance. On one hand, descriptive analyses that compare outcomes shortly before and after implementation will fail to capture long-run effects. On the other hand, long-run comparisons will have difficulty separately identifying policy impacts from other shocks to the industry. Our dynamic structural model is able to quantify the impact of input tariff liberalization on import participation and firm performance over the long run. To our knowledge, this article presents the first dynamic model of trade participation to separately model input prices and productivity as distinct sources of firm heterogeneity.

Previous work has shown that both importing and exporting activities increase firm efficiency or reduce variable costs (e.g., Greenaway and Kneller, 2007; Amiti and Konings, 2007; Bernard et al., 2009; Aw et al., 2011; Kasahara and Lapham, 2013; Halpern et al., 2015; Antras et al., 2017; Blaum et al., 2018), although these articles do not model the separate impact of tariff liberalization on input prices.⁴ Two recent studies have found that tariff liberalization can increase firm productivity after controlling for input price differences (De Loecker et al., 2016; Brandt et al., 2017). We extend this literature by documenting input price effects

⁴Moreover, this literature characterizes efficiency as a scalar, Hicks-neutral shifter that accounts for all unobservable firm characteristics, including differences in input prices and qualities. Syverson (2011) poignantly summarized the limitations of this approach, “TFP [Total Factor Productivity] is, at its heart, a residual. As with all residuals, it is in some ways a measure of our ignorance: it is the variation in output that cannot be explained based on observable inputs.”

as a distinct and important source of gains from tariff liberalization. Our article further highlights how the price effects of input tariff liberalization are amplified in the long run due to the interaction of input prices, trade participation, and productivity.

We apply the model using a panel dataset of Chinese paint manufacturers from 2000 to 2006. The Chinese paint sector is well-suited to studying the role of input tariffs and trade participation. First, many firms in the industry engage in trade. Over our sample, 12 percent of firms were importers, and 12 percent were exporters. Second, paint manufacturers produce paint and coating chemicals using a relatively simple production process and a limited set of intermediate inputs. The quality of inputs directly determines the quality of paint produced, which leads to a straightforward model of quality choice in which higher productivity firms *ceteris paribus* use higher quality, higher-priced inputs. Finally, China's accession to the WTO in November of 2001 included a significant import tariff liberalization for this industry's inputs.

Our analysis produces four novel findings regarding the role of input prices on dynamic trade decisions. First, we find that firms that import directly receive lower prices for inputs of the same quality. Engaging in importing reduces quality-adjusted materials prices of Chinese paint manufacturers by roughly 1.8 percent. This is consistent with importing either providing access to superior material inputs or enabling avoidance of markups charged by middlemen importers. This difference increased following China's accession to the WTO in 2001. Intuitively, we find no effect of exporting on input prices conditional on import status. We view this as an important falsification test of our empirical approach. Second, we find that input prices are more persistent over time than productivity. This is consistent with input prices being driven by relatively persistent unobserved firm features such as firm location-dependent transport costs and supplier relationships. It also suggests that modelling input price dispersion and productivity jointly as a scalar Markov process is misspecified. Third, we find that the allocation of output across firms is positively correlated with productivity and negatively correlated with input prices—more efficient firms with lower input prices produce more. Following WTO accession, the strength of these correlations increased. In fact, the bulk of aggregate productivity and input price gains over the period was due to an improvement in the allocation of output to efficient firms. Fourth, we find that liberalization of intermediate input tariffs results in an increase in trade participation. Because importing has a strong effect on productivity—as noted previously by Kasahara and Rodrigue (2008) and Kasahara and Lapham (2013), and corroborated by our study—this increase results in substantial aggregate productivity growth over time.

Using a counterfactual analysis, we compare the relative importance of input prices and productivity on the benefits of trading. We find that removing the effect of trade on input prices causes long-run profits to fall by 5.8 million US dollars on average, although removing the benefit of trade on productivity reduces long-run profits by only 3.5 million US dollars. Much of these declines result from a reduction in trade

participation when benefits are removed. For example, when we remove input price gains from importing, import participation falls by 9.2 percentage points and export participation falls by 4.4 percentage points after 15 years. Consequently, aggregate productivity declines by 24.7 percent and input price rises by 7.6 percent after 15 years, even though the direct benefit of importing on productivity remains unchanged.

We illustrate how the model captures the long-run impact of tariff liberalization by examining the impact of a one-third increase in the benefit of direct importing on input prices.⁵ This effect is equivalent to the change we estimate upon China’s accession to the WTO. Specifically, we find that the gap between input prices for importing relative to non-importing firms increased from 1.8 percent to 2.4 percent following WTO accession, when input tariffs fell by roughly 50 percent.⁶ Initially, the effect on trade participation is mild, after two years, the share of importers has increased only 0.6 percentage points (about 5 percent), however, after 15 years, the share of importers has increased by 3.4 percentage points (a 31 percent increase). In addition, the increased benefit to importing leads to a 1.7 percentage point (about 12 percent) increase in exporting. The increase in exporting is due to firms’ endogenous response to the higher benefits of importing and the effect of importing on productivity. Due in large part to the increase in trade participation, aggregate productivity increases by 9.3 percent after 15 years (whereas the 2-year increase is only 1.2 percent). Interestingly, 68 percent of the increase in aggregate productivity is due to a stronger correlation between high-output firms and high-productivity firms. This is intuitive, the policy encourages more productive firms to enter into trade, which both expands production and improves their efficiency further. On average, long-run profits increased by 2.2 percent (about 2.1 million USD) in response to the policy change. However, these benefits are not evenly distributed, less productive firms and those that face high input prices reap relatively smaller gains. Firms that are already engaged in trade, particularly importing, have relatively larger gains.

Relative to the empirical literature on trade and productivity, how trading decisions affect a firms’ material prices has received less attention. One reason for this is the lack of observable input prices in most data sets. The productivity literature has traditionally addressed the lack of input prices and quality by assuming that quality and prices are homogeneous within an industry (e.g., Levinsohn and Petrin, 2003). However, as shown in Ornaghi (2006) and Atalay (2014) using observed input price data, input prices can be very heterogeneous across firms and failure to control for this dispersion will bias estimates of the production function. A recent approach proposed by De Loecker et al. (2016) employs a control function for unobserved

⁵Although the tariff decline may affect prices of domestic-sourced goods as well, we would expect this change to increase the benefit of direct importing, assuming that middleman importers incompletely pass-through this tariff reduction.

⁶For paint manufacturing, input tariffs fell from around 15 percent to 7 percent following WTO accession. We do not consider this counterfactual policy to be an estimate of the impact of WTO accession for two reasons. First, we isolate one particular channel through which the WTO affected firms, but do not consider other potential impacts, such as import competition or the expansion of output markets. Second, although we estimate that, this estimate is statistically imprecise.

input price variation that utilizes observed output prices and measures the productivity and markup effects of tariff changes. Bøler et al. (2015) assume that the relative prices of input products are constant over time, and use the number of imported products as a proxy for a firm-level input price index. Brandt et al. (2017) estimate the effect of import tariff liberalization on productivity and markups using industry-level input price deflators in Chinese manufacturing.⁷

In contrast to the above work, this article recovers a quality-adjusted input price that varies across firms and over time on the basis of firms' expenditure decisions without relying on observable proxies. It incorporates the fact that firms endogenously choose the quality of their inputs, acknowledging insights from a related literature (e.g., Amiti and Khandelwal, 2013; Fieler et al., 2018) that has sought to understand the correlation between productivity, input quality, and trade. Vogel and Wagner (2010) find that more productive firms are more likely to import material from abroad. Fan et al. (2015) find that input tariff reduction in China induces incumbent importers and exporters to improve their output quality.⁸ Kugler and Verhoogen (2012) document a positive correlation between plant size and input prices and propose a model whereby firms with high productivity endogenously use inputs of higher quality. Our method of estimating quality-adjusted input prices and productivity draws upon this model to control for unobserved input quality. We use these insights to estimate a dynamic model that quantifies how input tariff liberalization affects quality-adjusted input prices, trading decisions, and productivity in the short and long run.

The following section introduces the data and presents the institutional background on Chinese paint manufacturing that guides our modelling decisions. Section 3 develops our model. Section 4 estimates the model in three stages and presents our estimates. Section 5 presents the results of counterfactual experiments that illustrate the effect of trade participation on productivity and input prices. Section 6 summarizes our findings.

2 The Chinese Paint Industry

The Chinese paint manufacturing industry has several features that lend it to the study of the relationship between input prices and trade. First, the paint industry is large, constituting roughly 5 percent of

⁷Brandt et al. (2017) argue that tariff liberalization had a limited role in increasing access to imported intermediates in Chinese manufacturing as a whole due to the fact that they observe a small increase in overall trade participation between 2000 and 2007. However, our analysis shows that the increase in trade participation builds gradually over a 15 year period, whereas they only consider five years after accession due to data constraints. Moreover, WTO accession was anticipated well before its implementation, which is likely to dampen the increase in trade participation immediately before versus after accession. Finally, we focus on the paint industry which has a relatively high proportion of non-state-owned firms; Brandt et al. (2017) note that the tariff response is highest among private firms.

⁸More recently, Fan et al. (2017) and Chevassus-Lozza et al. (2013) have examined how import tariff reductions affect the quality choice and performance of firms engaging in trade in a static setting. Although both find that tariff reductions induce quality upgrading, they differ on whether high or low productivity traders benefit most from import tariff reduction. Our article examines the impact of input tariff reduction on all firms, explicitly accounting for their dynamic decision to engage in trade.

the total Chinese chemicals, materials and products industry (SIC 26) and one-third of one percent of all Chinese manufacturing. Trade plays a substantial role in the industry, where high-quality inputs are typically imported. The paint production process, and particularly the role of input and output quality, are relatively straightforward and lend themselves to econometric modelling. Finally, the industry experienced a substantial reduction in import tariffs following China's accession to the WTO. This allows us to identify the importance of tariff policy on the price benefit of direct importing.

Data and Summary Statistics

The data for this study is drawn from two sources. The first is the firm-level Annual Survey of Industrial Firms (ASIF) collected annually by the National Bureau of Statistics in China from 2000 to 2006. It contains private firms with annual sales above five million RMB (or about six hundred thousand USD) and all state-owned firms. The survey records detailed information on total sales, export sales, number of workers, wage expenditure, material expenditure, and the book value of capital stock. However, like many manufacturing surveys, there is no information on either output or intermediate input prices. The second source is custom records of import and export transactions from Chinese Customs. This dataset provides information on the import and export values and other variables such as sources or destination countries. We link these two datasets together to form an unbalanced panel containing both production and trade information at the firm level for a total of 2,151 firms in the Chinese paint industry.

[Table 1 about here.]

Table 1 describes some aggregate statistics from the data. In addition to the annual industry totals, we split the sample into the years prior to WTO accession, 2000-2001, and those after accession, 2002-2006. Over the sample period, the Chinese paint industry generated roughly 6 billion USD in revenue per year. Like most of the Chinese manufacturing industries, this industry experienced substantial growth over our data period, as total revenues more than doubled. Part of this growth is due to a substantial net entry of firms. However, because of the revenue threshold for inclusion in the data, the extent to which this reflects true entry or simply the growth of firms is unclear. Over the entire sample, the industry is extremely materials intensive, which is a common feature of Chinese manufacturing. Expenditure on intermediate material inputs is more than 15 times the wage bill and is around 5 times the *book value* of capital stock. Thus, a small change in input prices could result in a radical change in profit. Trade plays a substantial role in the industry. The annual export revenue at the industry level is 675 million USD accounting for 11.2 percent of total industry revenue. Meanwhile, the annual import expenditure was 11.7 percent of total

material expenditure. The importance of importing has grown over time, going from 9.4 to 12.2 percent of total input expenditures.

One feature that makes the paint industry different from many other Chinese industries is that processing trade with assembly accounts for only a very small portion of international trade. Only 1.2 percent of export revenue and 2.1 percent of import expenditure is classified as processing trade with assembly. The remaining trade share is in the form of ordinary trade or processing trade with imported material.⁹ In contrast, processing trade with assembly is an important feature of many other Chinese industries. Firms conducting processing trade with assembly are less likely to independently make their own decisions on production, inputs, and trade participation to maximize profit. The lack of assembly processing trade in the paint industry supports our model assumptions that firms are profit-maximizing when considering production and trade decisions.

Industry Background

In China, the major products of the paint industry are water-based paint, solvent-based paint, coating chemicals, and other related paint and coating products. Labor is fairly homogeneous and low-skilled within the industry.¹⁰ In contrast, a wide variety of materials are used to make paint. The main material inputs include resin, pigment, chemical additive agents, and solvents. These can vary substantially in quality, as we discuss below. The paint production process is relatively standard across firms and is described in Online Appendix C.

One key feature of this industry is the strong link between input quality and output quality. According to industry expert reports, three factors determine the quality of paint.¹¹ The first and most important determinant of paint quality is the quality of resin. For example, the high-quality synthetic resin should have the following features: it should contain active functional groups; the difference between melting and decomposition temperature should be large; the melt viscosity should be low, with a high melting point and glass transition temperature; it should be non-toxic, and finally, it should have light color. The other material inputs, pigment and additives together with the curing agents, also affect the quality of paint. The

⁹Under processing trade with assembly, a foreign entity provides inputs to the domestic firm which must re-export its output to that firm. In contrast, under processing trade with imported inputs, the domestic firm transacts with a foreign entity, pays an import tariff, but may apply for a tariff rebate if the resulting output is exported (the foreign entities so need not be the same to qualify for the rebate). As such, the firm relationships under processing trade with imported intermediates is much more similar to ordinary trade than processing trade with assembly. In this article, we define a firm as engaged in trade if and only if the trade is “ordinary” trade or “processing trade with imported materials”, not “processing trade with assembly”. See Online Appendix C for detailed description of trade types.

¹⁰According to the 2004 Census, 52 percent of paint industry workers had not finished high school, and 96 percent had not achieved a college degree.

¹¹For background on Paint manufacturing see <http://www.madehow.com/Volume-1/Paint.html> (accessed May 29, 2017) for an example in developed countries, and <http://www.tlpfw.com/m/view.php?aid=4596> (accessed May 29, 2017, in Chinese) for a Chinese example specifically.

use of heavy metals such as lead and other additives can be toxic to human health and have a harmful influence on the environment, thus the resulting products are considered to be low quality. Alternatively, paint produced with relatively environmentally friendly materials that have less negative impacts—such as acrylic resins—are considered to be of higher quality.

The other two main determinants of paint quality are the firm’s formula and equipment used in production. A good formula is capable of efficiently using materials to make high quality paint. The formula is typically a trade secret of the firm. Production equipment impacts the stability of the formulation and hence the quality of the paint. Better equipment can produce paint faster, with less labor, and potentially fewer additives. The formula used by firms and to some extent the quality of machinery (if it is not captured by the capital stock value) will be key components of productivity in our model.

Firms that choose to produce high-quality paint can charge a higher price but must procure costly, high-quality inputs. This suggests that if the price is a (rough) measure of quality, input quality and output quality are positively correlated.¹² More productive firms, those who have more experienced labor, better machinery, and superior formulas, will be most motivated to produce high-quality paint. Our model will use the relationship between productivity and quality to explicitly account for endogenous input quality when recovering input price and productivity.

We will assume that firms can adjust the quality of their inputs by adjusting their input purchases. This assumption is reasonable for the paint industry. The same equipment can be used to produce paints of different types and qualities. To alter the output, the firm simply stops production, cleans the whole production line, and then begins producing the new product with different inputs.

[Table 2 about here.]

Due to technology limitations in domestic upstream chemical industries, many high-quality material inputs could not be produced efficiently in China during our sample period. As a result, high-quality Chinese paint producers relied on imports of these materials from economies with a more developed chemicals industry. Table 2 lists the main countries from which Chinese paint producers import materials, together with the share from each country. The major imported material inputs include resin (42.2%), pigment (22.5%), and additives (8.7%). Imported material can be acquired either by importing directly or through middleman traders. These middlemen charge a markup to manufacturers to facilitate their services. Thus, manufacturing firms face a tradeoff between paying a higher price for imported inputs purchased from a middleman, or paying a fixed/sunk cost to import materials directly. It is fairly easy for Chinese paint

¹²Although prices are not observed in our full data set, export output prices and import input prices available from the customs data are positively associated (in logs) with a slope of 0.45.

producers to find middlemen to purchase material inputs.¹³

On the export side, China’s primary destination markets for paint are industrialized Asian economies. Exports to Hong Kong, Korea, Japan, and Taiwan account for over two thirds of the Chinese paint exports. The high rate of exports to Hong Kong may contain some trans-shipments to other destinations. However, according to the industry-level bilateral trade data (World Bank, 2020), Hong Kong imports much more paint than it exports, so it appears much is consumed domestically.¹⁴ Moreover, 87 percent of Hong Kong’s exports of paint (excluding that to Mainland China) are to Asia from 2000 to 2006 on average, including 44 percent exported to Korea, Japan and Taiwan which are also the major export destinations for Chinese paint (besides Hong Kong itself). Based on this evidence, we think it is reasonable to follow the bulk of the literature and abstract away from modelling the choice of export market destinations in favor of focusing on the decision to initiate exporting generally.

WTO Accession and the Paint Industry

China’s accession to the WTO in November of 2001 had a dramatic impact on the entire manufacturing sector. For the paint industry, expert reports suggested that the largest impact of WTO accession would come from the tariff reduction on intermediate inputs. The average import tariff was reduced after the accession to the WTO from 15 percent in 2000 to 7 percent in 2006, with the bulk of the change occurring in 2002.¹⁵ The large tariff reduction after joining WTO directly reduced the prices of imported materials and increased access to high-quality inputs. According to an article published by the China National Association of Engineering Consultants (CNAEC) in 2003, “...this [tariff reduction on imported materials] ensures Chinese paint producers have access to a full set of low priced, high-quality material inputs, together with good after-sale service from foreign providers. This can help Chinese paint producers to improve their product quality and competitiveness in the product markets.”¹⁶ The emphasis on after-sale service is particularly interesting given the possibility of “learning by importing” that is open to firms when they import directly rather than purchase imported material through middlemen. In addition, it is possible that WTO accession created import competition for Chinese firms, which spurred them to improve efficiency.

[Table 3 about here.]

¹³For example, middlemen offer paint inputs on many online platforms such as <https://s.1688.com/kq/-BDF8BFDACDBFC1CFD4ADC1CF.html> (accessed June 2, 2017). Traditional local middlemen are also active in the industry.

¹⁴Hong Kong imported \$389 million worth of paint annually from 2000–2006 and exported only \$51.8 million, suggesting significant domestic consumption.

¹⁵The average import tariff is defined as the geometric mean of product-specific tariff rate at HSID 6-digit level, weighted by the import share of each product category in the paint industry for each year.

¹⁶Translated from Chinese. The original article in Chinese is available at <http://www.cnaec.com.cn/Info/Show.asp?ID=168646&Code=REZLZJ> (accessed May 28, 2017).

Table 3 provides a first look at the trade participation of paint manufactures before and after accession. Overall, the importance of both imports and exports has grown over the period, as seen by the industry level export and import shares respectively. However, we find little change in the firm-level average intensive or extensive margins. On the intensive margin, the average share of imports (exports) relative to total expenditure (revenue) conditional on importing (exporting) has actually declined. On the extensive margin, the proportion of firms participating in trade following WTO accession is almost unchanged. This result for imports in the paint industry echoes the findings of Brandt et al. (2017), who argue that this is evidence that better access to materials inputs could not have had large effects. However, at least in the paint industry, this direct comparison masks a substantial increase in the relative output of importers and exporters, which explains the increase in the industry level ratios. This becomes apparent when we weight trade participation by revenues.¹⁷ The industry experiences a 10 percent increase in weighted import participation and a 31 percent increase in weighted export participation. The bulk of this increase is attributable to faster growth among traders over non-traders during the period.

Of course, many other factors besides WTO accession may affect the rate of importing over time. For example, there has been a steady improvement in domestic upstream technology which may reduce importing because firms can use improved domestic inputs to produce higher quality paints. Rather than examining aggregates from the industry, our model will focus on the experience of individual firms to identify how importing and exporting affects firm performance. We will then isolate the effect of lower import tariffs on the paint industry in our counterfactual analysis while holding all other factors constant.

Preliminary Evidence on Trade and Productivity

[Table 4 about here.]

Our model posits that trade liberalization has the potential to increase aggregate productivity in the long run through increased trade participation. There is an active literature on trade’s causal effect on productivity with some researchers finding significant effects (e.g., De Loecker, 2007) although others finding none (e.g., Bernard and Jensen, 1999). The heart of this debate lies in the potential endogeneity of trade participation—higher productivity firms are more likely to engage in trade.¹⁸ Before introducing our model of the industry, this section performs preliminary analysis of the impact of trade on productivity in Chinese paint manufacturing. The goal of this analysis is not to settle the question of trade and productivity, but simply to provide some preliminary evidence and illustrate the importance of controlling for productivity when measuring the impact of trade.

¹⁷Weighting trade participation by expenditures produces very similar results.

¹⁸Although much of this literature has focused on the effects of exporting, a similar argument can be made for importing.

Table 4 presents a series of regressions of (logged) labor productivity on indicators for importing and exporting. These regressions are in the spirit of Bernard and Jensen (1999) but add controls for importing as well as exporting. Although the OLS regressions demonstrate a strong correlation between both importing and exporting and productivity, they are confounded by an upward bias due to the endogeneity of trade participation. Estimates using the Arellano and Bond (1991) estimator, which controls for fixed effects and a lagged dependent variable, produce substantially different results. The estimated effect of exporting is essentially zero and precisely estimated, in line with previous studies. However, the impact of importing remains economically large, although it is imprecisely estimated and statistically insignificant.¹⁹

We draw the following lessons from this preliminary analysis. First, as is well established, controlling for endogeneity is important when attempting to assess the causal effect of exporting on productivity, and the same is true for importing. Second, if anything, the evidence for a link between importing and productivity is *stronger* in Table 4 than the link between exporting and productivity. Motivated by these preliminary findings, the following sections will employ a structural model to measure and control for total factor productivity with these issues in mind. The model will explicitly control for variation in input prices and output quality across firms at the cost of additional assumptions on firm behavior.

3 Model

We propose a dynamic model of profit-maximizing firms. Firms' trade decisions will endogenously affect their intermediate input prices, access to foreign markets, and productivity. To keep the model tractable, we abstract away from endogenous capital investment or entry and exit.²⁰ At the beginning of each period, firms are described by a state variable containing their current import and export status, capital stock, wage, input price index, and productivity.

The firm makes two sets of choices: First, given its state, the firm chooses homogeneous labor quantity and materials quality and quantity to maximize its current-period profits. We assume that labor and material choices are fully flexible from period to period and therefore these choices have no dynamic implications.²¹ We use the first-order conditions implied by these choices to infer materials quality and quantity from revenue and expenditure data. Our approach generalizes Grieco et al. (2016) to allow for separate domestic and export markets and allow for an endogenous quality choice to recover firm-level input prices and productivity

¹⁹Qualitatively similar results can be found using fixed effects and Blundell and Bond (2000) estimators.

²⁰Because we have a relatively short panel, the variation in capital stock over time is small relative to the cross-sectional differences, which we control for in our empirical application. Moreover, firms on the margin between trading and not are unlikely to also be on the margin between exit and remaining in the market.

²¹The assumption of static labor choices is quite plausible in the context of China for several practical reasons. First, the high volume of labor supply in China tends to favor firms. Second, China lacks effectively-enforced labor laws and regulations to protect workers. Third, labor unions in China are very weak, and in most cases are controlled by the employing firms. These factors together result in low hiring and firing costs for Chinese firms compared with developed countries.

controlling for input quality.

Second, the firm chooses whether to engage in importing and exporting in the following period. If it chooses to export, it must pay a sunk or fixed cost but will have access to the export market. Exporting may also affect firms' future productivity. If the firm chooses to import, it must also pay a fixed or sunk cost. In return, the expected future input prices will be lower, reflecting the price benefit the firm can gain from direct importing. In addition, importing may also affect firms' future productivity. This may be due to technical expertise gained from after-sale services and interacting directly with sophisticated upstream sellers of inputs. Firms make their trading decisions by maximizing the present discounted value of future profits.

The remainder of this section presents the model in detail. For expositional convenience, we first present the firms' static profit maximization decision, and then introduce the additional elements of state transition processes and sunk and fixed costs that drive firms dynamic trade participation decisions.

Period Profits

Demand and Supply

In each period t , a firm j produces output, Q_{jt} , and sells this quantity in the domestic market and, if it is an exporter, to an export market, $Q_{jt} = Q_{jt}^D + Q_{jt}^X$. Consumers in both markets, $m \in \{D, X\}$, purchase from the set of available goods J_t^m (which includes an outside good) to maximize utility subject to their budget constraint. We assume a representative consumer in each market with a constant elasticity of substitution (CES) utility function,

$$U(Q_t^m) = \left[\sum_{j \in J_t^m} (\Phi_{jt}^* Q_{jt}^m)^{\frac{1+\eta_m}{\eta_m}} \right]^{\frac{\eta_m}{1+\eta_m}}. \quad (1)$$

Consumers' taste for good j is affected by a demand shifter Φ_{jt}^* which we informally refer to as output quality. This quality is good specific but does not vary across markets. Of course, demand for good j will be determined by its quality relative to that of other goods available in the market, J_t^m , which does vary across markets. A product's quality is heterogeneous to reflect both idiosyncratic and endogenous differences across firms. As explained below, differences in Φ_{jt}^* may reflect firms' choice of input quality, which we model explicitly, as well as persistent elements such as brand affinity or marketing expertise, which we assume to be exogenously determined.

We assume the market structure is monopolistic competition. Appendix A derives the inverse demand

for firm j in each of the two markets,

$$P_{jt}^D = \Phi_{jt}^{\frac{1+\eta_D}{\eta_D}} (Q_{jt}^D)^{\frac{1}{\eta_D}}, \quad (2)$$

$$P_{jt}^X = \kappa_t \Phi_{jt}^{\frac{1+\eta_X}{\eta_X}} (Q_{jt}^X)^{\frac{1}{\eta_X}}, \quad (3)$$

where Φ_{jt} is a function of the firm-specific demand shock Φ_{jt}^* and domestic market conditions (e.g., income and the aggregate price index), and κ_t is constant across firms but depends on the relative conditions across the two markets. Because all firms in our data sell domestically, Φ_{jt} is a monotonic transformation of Φ_{jt}^* . Thus, Φ_{jt} can be also thought as an index of output quality.

Turning to the supply side, firms produce according to a (normalized) CES production function:²²

$$Q_{jt} = Q_{jt}^D + Q_{jt}^X = A_{jt} [\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}}, \quad (4)$$

where $\alpha_L, \alpha_M, \alpha_K$ are the distribution parameters for labor, material, and capital respectively, which sum up to one. This production function normalizes returns to scale to be one. As we show in Online Appendix D, returns to scale is not generally identified separately from the demand elasticities when only revenue is observed. However, variation between returns to scale and demand elasticities do not affect the estimates of productivity and input prices as well as the period profit (see Online Appendix D for a full discussion). The elasticity of substitution among inputs, σ , is determined by γ , where $\gamma = \frac{\sigma-1}{\sigma}$. Firms are heterogeneous in their technical efficiency, which is captured by A_{jt} . Like demand heterogeneity, technical efficiency may vary either for exogenous reasons or due to the firm's endogenous choice of input quality, modelled below.

Quality Adjusted Output and Firm Capability

We observe domestic and export revenue, however, we do not directly observe either physical output, output quality, or output prices. This is a common problem in production datasets and we address it by following Klette and Grilches (1996) in estimating the demand and production parameters jointly via the revenue equation. As discussed by Foster et al. (2008) and Atkin et al. (2019), this approach has some drawbacks because we will recover *revenue productivity*, which is a combination of demand heterogeneity, Φ_{jt} , and technical efficiency, A_{jt} . However, revenue productivity represents an index of firm profitability (conditional on input prices and observables), and as such, it is an important determinant of firm actions, such as trade

²²We normalize the CES production function according to the geometric mean. Specifically, the inputs (labor, material, and capital) are normalized by their corresponding geometric mean, $\sqrt[\gamma]{\Pi X_{jt}}$. The implication is that the geometric means of input variables (L_{jt}, M_{jt}, K_{jt}) in (5) are $\bar{L} = \bar{M} = \bar{K} = 1$. A branch of the literature has analyzed the importance and the method of normalization (de La Grandville, 1989; Klump and de La Grandville, 2000; Klump and Preissler, 2000; de La Grandville and Solow, 2006; León-Ledesma et al., 2010). Refer to Grieco et al. (2016) for more details.

participation.

To illustrate our approach, define *quality-inclusive* output as $\tilde{Q}_{jt} = \Phi_{jt}Q_{jt}$, and *quality-inclusive revenue productivity*, as $\tilde{\Omega}_{jt} = \Phi_{jt}A_{jt}$ reflecting a combination of demand heterogeneity and technical efficiency. Then the production of quality-inclusive output is simply,

$$\tilde{Q}_{jt} = \Phi_{jt}Q_{jt} = \tilde{\Omega}_{jt} [\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^\frac{1}{\gamma}, \quad (5)$$

In short, a firm with higher $\tilde{\Omega}_{jt}$ may either produce more of the same good (higher A_{jt}), or produce the same amount of a good at a higher quality (higher Φ_{jt}) or some combination of both, and our model takes no stance on which choice it makes but acknowledges that both lead to an increase in \tilde{Q}_{jt} .

The firm chooses output quantities to maximize profits. However, this is equivalent to choosing quality-inclusive output. To see this, note that revenues in both markets can be written as a function of quality-inclusive output instead of Q_{jt} and Φ_{jt} separately,

$$R_{jt}^D = P_{jt}^D Q_{jt}^D = \Phi_{jt}^\frac{1+\eta_D}{\eta_D} (Q_{jt}^D)^\frac{1}{\eta_D} Q_{jt}^D = (Q_{jt}^D \Phi_{jt})^\frac{1+\eta_D}{\eta_D} = \left(\tilde{Q}_{jt}^D\right)^\frac{1+\eta_D}{\eta_D}, \quad (6)$$

$$R_{jt}^X = P_{jt}^X Q_{jt}^X = \kappa_t \Phi_{jt}^\frac{1+\eta_X}{\eta_X} (Q_{jt}^X)^\frac{1}{\eta_X} Q_{jt}^X = \kappa_t (Q_{jt}^X \Phi_{jt})^\frac{1+\eta_X}{\eta_X} = \kappa_t \left(\tilde{Q}_{jt}^X\right)^\frac{1+\eta_X}{\eta_X}. \quad (7)$$

Previous work has treated quality inclusive productivity as a feature of the firm which is taken as given in the firm's static profit maximization problem. Our goal, however, is to separate the effect of input prices from other sources of revenue productivity while accounting for the fact that firms may choose high-priced, high-quality inputs in order to raise either output quality or physical efficiency.²³ To do this, the following subsection distinguishes variation in endogenously chosen input quality from other components that affect quality-inclusive productivity, $\tilde{\Omega}_{jt}$.

Productivity and Input Quality

Kugler and Verhoogen (2009, 2012) and others have found that higher productivity firms tend to use higher quality inputs, which cost more on a per-unit basis. De Loecker et al. (2016) have posited the same relationship between productivity, input quality, and output quality to motivate the use of output prices as proxies for input prices. Suppose a firm experiences a reduction in input prices, it may continue to purchase the same quality of input at a lower price or may choose to upgrade the quality of their inputs and hence

²³In Foster et al. (2008), the effect of input prices is a component of technical efficiency which they do not separate from "technological fundamentals" (see their footnote 12). One reason they are able to separate revenue productivity, "TFPR" from technical efficiency "TFPQ" without observing input prices is that they assume inputs are homogeneous. Our model will allow inputs to vary in quality and separate the role of factor prices from other sources of demand heterogeneity and technical efficiency.

improve its quality-inclusive productivity. In light of this, we assume that $\tilde{\Omega}_{jt}$ is a function of the firm's underlying *fundamental productivity*, Ω_{jt} , and its endogenous choice of input quality, H_{jt} .²⁴ We adopt the following functional form which allows fundamental productivity and input quality to be either substitutes or complements,

$$\tilde{\Omega}_{jt} = (\Omega_{jt}^\theta + H_{jt}^\theta)^{\frac{1}{\theta}}. \quad (8)$$

This approach follows Kugler and Verhoogen (2009, 2012) in assuming that input quality augments the productivity of all inputs, rather than augmenting materials only.²⁵ We believe this assumption fits paint manufacturers well, because higher-quality additives and resins will produce higher quality paint even though the basic mixing and canning process will remain unchanged. If $\theta < 0$ then productivity and input quality are gross complements to each other, and the magnitude expresses the degree of complementarity. We expect productivity and quality to be complementary in the paint industry because more productive workers and capital can carry out production wasting a smaller proportion of inputs (resins and additives) in the mixing process. Less wasteful firms should be more willing to use higher quality inputs.

By modelling the effect of input quality on quality-inclusive productivity, $\tilde{\Omega}_{jt}$, rather than its components demand heterogeneity Φ_{jt} or technical efficiency A_{jt} , our model is agnostic as to whether higher-quality inputs enable the firm to produce a higher quality output or to produce more output for the same units of input. Either effect or a combination of the two may explain the ability of the firm to produce more revenue for a given level of inputs when they upgrade input quality. By contrast, we will use the model to separately identify fundamental productivity, Ω_{jt} , and input quality, H_{jt} .

Input Price Menu

Firms pay a *quality-inclusive input price*, \tilde{P}_{Mjt} , for physical units of material inputs. This price reflects two sources of heterogeneity: the vertically differentiated input quality due to the firm's choice of H_{jt} , and a *fundamental input price* index faced by the firm, P_{Mjt} , which is part of the firm's state. Specifically, firms can choose any quality of materials according to the following simple price menu,

$$\tilde{P}_{Mjt} = P_{Mjt} H_{jt}^\phi, \quad (9)$$

²⁴For expositional ease, we will refer to the fundamental productivity simply as productivity where its meaning is clear from context.

²⁵Note that M_{jt} is the quantity of material inputs in physical units. Although it is plausible to consider that high-quality input is more efficient in a non-Hicks-neutral way, say allowing for $H_{jt}M_{jt}$ in the production function, we restrain ourselves from this seemingly more general case, because we can show that it is empirically equivalent to our model where such non-Hicks-neutral production efficiency is adjusted in the input prices. Moreover, in the paint industry, the major impact of high-quality inputs is to improve the quality of output, as discussed in Section 2.

where $\phi > 0$, reflecting the fact that higher-quality inputs are more costly.²⁶ Firm heterogeneity in fundamental input prices arises from observed and unobserved characteristics, including the firm’s current status as an importer. In addition, unobserved characteristics such as proximity to transportation networks or the firm’s network of supplier connections may create differences in fundamental input prices. As with fundamental productivity, we refer to fundamental input price simply as input price when the meaning is clear from the context.

Importing does not affect the materials access conditional on P_{Mjt} . Instead, as discussed below in Section 3, the level of P_{Mjt} will be influenced by the decision to participate in importing, which was taken in the previous period. This is a convenient way of modelling the difference between importers and non-importers: non-importers on average face higher fundamental input prices than importers. This is consistent with the existence of middleman importers who are willing to re-sell imported materials to domestic firms but take an additional markup over the prices that are offered to direct importers. However, it also captures the fact that input prices may differ for reasons other than import status—such as firm geography or supply contacts. Consequently, it does not suggest that the quality-inclusive input prices paid by importers are necessarily lower than those paid by non-importers. If importers tend to have higher productivity, they may find it optimal to choose higher-quality inputs on average and hence the quality-inclusive input price, \tilde{P}_{Mjt} , may be higher.

Static Decisions: Outputs, Inputs, and Input Quality

At the beginning of each period, a firm observes the state variable vector that includes the firm’s fundamental productivity, fundamental input price, wage, export and import status, and capital stock, as summarized in $(\Omega_{jt}, P_{Mjt}, P_{Ljt}, e_{jt}, i_{jt}, K_{jt})$.²⁷ The firm’s objective is to maximize its period profit in period t given its state, by optimally choosing labor quantity, material input quantity, material input quality, and the quality-inclusive quantity of product sold in each market.²⁸

²⁶Although it is intuitive that higher-quality inputs cost more, the scale of the price increase is due to the arbitrary scale of quality. Therefore, the parameter ϕ measures the combined effect of the price of increasing quality, and the impact raising quality has on increasing quality-inclusive output \tilde{Q}_{jt} .

²⁷For ease of exposition, the remainder of the article will drop the word “fundamental” from the state variables for productivity and input prices where it is clear from the context.

²⁸As shown in Appendix A, the firms’ static profit maximization problem can be equivalently represented using either physical output or quality-adjusted output. However because we do not observe output prices, we can only recover quality-inclusive output in the empirical application.

Specifically, the firm solves:²⁹

$$\begin{aligned} \pi(\Omega_{jt}, P_{Mjt}, P_{Ljt}, e_{jt}, K_{jt}) &= \max_{L_{jt}, M_{jt}, \tilde{Q}_{jt}^D, \tilde{Q}_{jt}^X, H_{jt}} R_{jt}^D + e_{jt}R_{jt}^X - P_{Ljt}L_{jt} - \tilde{P}_{Mjt}M_{jt}, \\ &\text{subject to: (5), (6), (7), (8), (9), and } \tilde{Q}_{jt}^D + e_{jt}\tilde{Q}_{jt}^X = \tilde{Q}_{jt}, \end{aligned} \quad (10)$$

where P_{Ljt} is the wage rate, and export status, e_{jt} , is an indicator for whether the firm has paid the fixed cost in the previous period to enable exporting.³⁰ The resulting period-profit π_{jt} is the total profit in period t as a function of the state variables: $\pi(\Omega_{jt}, P_{Mjt}, P_{Ljt}, e_{jt}, K_{jt})$. Given our assumptions, there is a unique solution to (10) which can be calculated numerically.

Long-Run Profits

In addition to static profit maximization, firms must also determine whether or not to import and/or export in the following period. The decisions are dynamic for two reasons. First, there are sunk and fixed costs of exporting and importing; second, the current trade participation will change the future paths of productivity and input prices. There are four possible trade statuses, denoted as $ie_{jt} = (i_{jt}, e_{jt}) \in \{(0, 0), (1, 0), (0, 1), (1, 1)\}$, with the first argument as import participation and the second export participation.

State Transition Processes

Both exporting and importing may have an impact on future productivity (Aw et al., 2011; Kasahara and Lapham, 2013). In both cases trade may enhance productivity through technical support from trading partners, exposure to new techniques, and experience gained from operating in foreign markets. This is colloquially referred to as “learning by exporting/importing” and is distinct from gains from trade through market or materials access. To capture this, we assume the logarithm of productivity evolves according to an AR(1) process that is a function of the firms’ trade participation decisions,³¹

$$\begin{aligned} \omega_{jt+1} &= f(\omega_{jt}, e_{jt}, i_{jt}, \tau_{t+1}) + \epsilon_{jt+1}^\omega \\ &= f_0 + f_\omega \omega_{jt} + f_e e_{jt} + f_i i_{jt} + f_{wto} \tau_{t+1} + \epsilon_{jt+1}^\omega, \end{aligned} \quad (11)$$

²⁹Note that import status, i_{jt} , does not enter the static maximization problem but only affects the firms dynamic problem of trade participation discussed in Section 3.

³⁰The model assumes that firms always sell in the domestic market. In the data, 99.6 percent of firms serve the domestic market. We drop the 0.4 percent who export exclusively from our analysis.

³¹We follow the literature in denoting the logarithm of upper case variables as lower case.

where τ_{t+1} represents a dummy for WTO accession to account for changes in aggregate productivity: the accession to the WTO may have impacted firm productivity due to its liberalization and openness to new technologies, inward foreign direct investment (FDI), and other investment opportunities.³² Finally, ϵ_{jt+1}^ω is a shock to firm productivity that is assumed to be uncorrelated with the firm's information set in period t .

We now turn to the evolution of the input prices. Compared to the evolution of productivity in which the effects of trade participation are lagged, we assume that importing affects the fundamental input price in the current period.³³ This assumption is consistent with De Loecker et al. (2016) and captures the idea that although it takes time for firms to adopt and digest the new technologies acquired from international trade, the imported material inputs are used immediately. Additionally, the accession to the WTO played an important role in influencing the benefits of importing. As import tariffs were reduced substantially, the input prices faced by *all* firms were potentially lower due to more price competition in the input market. For importers, this benefit could be even larger because they are the firms that directly face the tariff. For example, if firms can acquire imported materials through middleman importers, then as long as these middlemen do not completely pass through the cost reduction from a tariff decrease,³⁴ the gap between input prices for importers and non-importers will grow after a tariff cut. We therefore allow the effect of importing on input prices changes before and after WTO accession to have separate effects on importers and non-importers.³⁵ Specifically, the evolution process of the fundamental input price is:

$$\begin{aligned} p_{Mjt+1} &= g(p_{Mjt}, i_{jt+1}, \tau_{t+1}) + \epsilon_{jt+1}^p \\ &= g_0 + g_p p_{Mjt} + g_{i0} i_{jt+1} (1 - \tau_{t+1}) + g_{i1} i_{jt+1} \tau_{t+1} + g_{wto} \tau_{t+1} + \epsilon_{jt+1}^p, \end{aligned} \quad (12)$$

where ϵ_{jt+1}^p is an unanticipated shock to input prices. Thus, g_{i0} and g_{i1} measures the input price benefit from importing before and after China's accession to the WTO. If $g_{i1} < g_{i0} < 0$, then WTO accession leads to a larger difference in input price between importers and non-importers. We include the level term so that g_{wto} will account for a general decrease in prices for all firms, regardless of individual import status, following WTO accession. Such a decrease is likely because non-importers may be purchasing indirect imports through middlemen or from domestic suppliers who reduce their prices as a result of import competition.

Finally, we allow the wage rate faced by the firm and its capital stock to evolve exogenously. The wage

³²We assume WTO accession was anticipated from 2000, the first year of our data. In the empirical exercise, we have also experimented with using a more flexible specification with individual year dummies, instead of the WTO dummy.

³³We also tested for different timing assumptions and other potential specifications, and also considered Markov processes of a higher order. Our results are robust to these alternative specifications.

³⁴In the presence of local distribution costs or search costs in the importing country, Burstein et al. (2003), Corsetti and Dedola (2005) and Alessandria and Kaboski (2011) show that there will be incomplete pass-through of exchange rate fluctuations. This insight carries over to the case of import middlemen in China in response to tariff changes.

³⁵Ideally, one could measure the effect tariff rates on input prices; however, because variation tariff rates is very small aside from the drop upon WTO accession, we instead use an indicator variable to measure the effect of WTO accession on input prices of importers.

rate follows a simple AR(1) process,

$$pL_{jt+1} = \zeta_0 + \zeta_\ell pL_{jt} + \epsilon_{jt+1}^\ell. \quad (13)$$

where ϵ_{jt+1}^ℓ is a shock to wages. We discretize the capital stock by quintiles and estimate separate first-order Markov transition matrices before and after WTO accession.³⁶ The firms use these processes to form rational expectations over their future wage rates and capital stock.

Fixed and Sunk Costs

Importing and exporting also incur fixed costs that vary across firms and time. We model trade costs in a flexible way, allowing them to depend on not only current trade status, but also lagged trade status as in Das et al. (2007). For example, a new exporter may need to pay a higher cost (referred to as sunk cost or startup cost) to start exporting compared with continuing exporters who have established distribution networks in the past. In addition, we observe a high correlation between import and export participation in the data, and our flexible cost specification rationalizes this fact by allowing two types of complementarity between import and export costs. First, having export (import) experience in the previous period can reduce the firm's import (export) costs in the current period. Second, if a firm imports and exports simultaneously, it may gain some cost advantage over importing and exporting separately. Thus, the trade cost for trade participation ie_{jt+1} is specified as,

$$\begin{aligned} C(ie_{jt+1}; ie_{jt}, \xi_{jt}) &= C(ie_{jt+1}, ie_{jt}; \lambda) - \lambda_\xi \xi_{jt}^{ie_{jt+1}} \\ &= \lambda_{ie_{jt+1}, ie_{jt}} - \lambda_\xi \xi_{jt}^{ie_{jt+1}}. \end{aligned} \quad (14)$$

The first term incorporates 16 parameters, $(\lambda_{(0,0),(0,0)}, \dots, \lambda_{(1,1),(1,1)})$, one for each combination of current and future importing and exporting status. We normalize the mean cost of neither importing nor exporting (regardless of the previous status) to zero, $\lambda_{00,ie} = 0$, leaving 12 parameters to estimate. The last term, $\xi_{jt}^{ie_{jt+1}}$, captures idiosyncratic shocks to trade costs. It is assumed to be a Type-1 extreme value draw that is independent across four possible choices ie_{jt+1} and over time. The scale of this shock is estimated by λ_ξ , which is identified because we are able to estimate the scale of period profits. Hence, λ denotes the vector of 13 parameters that index the sunk and fixed costs of trade.

³⁶The estimated Markov transition matrices are presented in Online Appendix F.

Dynamic Decisions: Trade Participation

At the beginning of each period t , all shocks—including trade cost shocks and all innovations in the Markov processes of productivity, input price, and wage rate—are realized. Each firm observes its own dynamic state $s_{jt} = (\Omega_{jt}, P_{Mjt}, P_{Ljt}, ie_{jt}, K_{jt}, \tau_t)$ and trade cost shocks ξ_{jt} . Given the large state space, in the empirical implementation, we assume the relative aggregate demand shifter in the domestic and export market is constant over time $\kappa_t \equiv \kappa$.³⁷ Denote the beginning-of-period firm value as

$$V_t(s_{jt}, \xi_{jt}) = \max_{ie_{jt+1}} \{ \pi(s_{jt}) - C(ie_{jt+1}; ie_{jt}, \xi_{jt}) + \delta E[V_{t+1}(s_{jt+1}, \xi_{jt+1}) | s_{jt}, ie_{jt+1}] \} \quad (15)$$

subject to: (11), (12), and (13),

where period profits are determined by (10). The expectation is taken over all future shocks, including future trade cost shocks, productivity shocks, input price shocks, wage rate shocks, and exogenous changes in the capital stock.

The value function, $V_t(s_{jt}, \xi_{jt})$, is indexed by t to capture the idea firms anticipate joining the WTO in 2002. We assume the problem is stationary after WTO accession takes place. This assumption is motivated by the fact that China’s accession was widely anticipated following the bilateral agreement between the United States and China in support of China’s application to the WTO in 1999. Section 4 describes how we account for possible anticipation of the WTO in our estimation. Firms’ anticipation of WTO accession along with the substantial sunk costs of initiating trade are important explanations for why we may not see a sharp immediate rise in productivity or trade participation following WTO accession. This also justifies why we must use a dynamic model to fully measure these effects. Section 4 describes how we account for possible anticipation of the WTO in our estimation.

4 Estimation and Model Parameters

In this section, we estimate the model parameters given data on firm revenues, input expenditures, and trade participation decisions. The procedure is divided into three stages. First, we estimate the demand and production functions, recovering the quality-inclusive productivity and input price measures. Second, we estimate the quality parameters (θ, ϕ) and the transition processes of fundamental productivity and input prices. Finally, the third stage estimates the sunk and fixed costs using the static profit and state variables recovered from the previous stages together with the firms’ observed trade participation decisions.

³⁷As a robustness check in Online Appendix F, we estimated a more flexible model with κ_t varying over time and we find that κ_t is statistically equal before and after WTO.

Demand and Production Functions

The parameters of the demand and production functions, (2), (3) and (5), are estimated from firm revenues R_{jt}^D and R_{jt}^X , materials and labor expenditure, E_{Mjt} , E_{Ljt} , labor quantity L_{jt} and capital stock K_{jt} . With a little abuse of notation, domestic and export revenue are measured as,

$$R_{jt}^D = \exp(u_{jt}^D) P_{jt}^D Q_{jt}^D = \exp(u_{jt}^D) \left(\tilde{Q}_{jt}^D \right)^{\frac{1+\eta^D}{\eta^D}}, \quad (16)$$

$$R_{jt}^X = \exp(u_{jt}^X) e_{jt} P_{jt}^X Q_{jt}^X = \kappa \exp(u_{jt}^X) e_{jt} \left(\tilde{Q}_{jt}^X \right)^{\frac{1+\eta^X}{\eta^X}}, \quad (17)$$

where (u_{jt}^D, u_{jt}^X) are measurement errors and e_{jt} is the export-status indicator. The researcher observes expenditures for the static inputs,

$$E_{Mjt} = \tilde{P}_{Mjt} M_{jt}, \quad E_{Ljt} = P_{Ljt} L_{jt}.$$

We follow Aw et al. (2011) in using domestic producers to estimate the production and domestic demand parameters, and then use export revenue to estimate export demand. This approach addresses the fact that both domestic and export revenue are measured with error.³⁸

For firms that sell domestically only, revenue as a function of the other observables can be derived by following Grieco et al. (2016). We briefly review the procedure here and refer to Grieco et al. (2016, Appendix A) for a detailed derivation. The method exploits the input demand first-order conditions implied by static profit maximization, as characterized in Appendix A. Taking the ratio of the first-order conditions of labor and material leads to a closed-form solution for materials quantity as a function of observables and production function parameters:

$$M_{jt} = \left[\frac{\alpha_L E_{Mjt}}{\alpha_M E_{Ljt}} \right]^{\frac{1}{\gamma}} L_{jt}. \quad (18)$$

Consequently, we obtain $\tilde{P}_{Mjt} = E_{Mjt}/M_{jt} = \left[\frac{\alpha_L}{\alpha_M} \right]^{-\frac{1}{\gamma}} \left[\frac{E_{Mjt}}{E_{Ljt}} \right]^{1-\frac{1}{\gamma}} P_{Ljt}$. This shows that as long as $\gamma \neq 0$ —the special case of Cobb-Douglas, where the expenditure ratio does not vary across firms—variation in the expenditure ratio, together with the firm-specific wage rate, provides information about the input prices.

Substituting this expression back into the first-order condition for labor, we can solve out the closed-form solution of quality-inclusive productivity of non-exporting firms, $\tilde{\Omega}_{jt}$, as in (7) in Grieco et al. (2016). By substituting the recovered material quantity (M_{jt}) and quality-inclusive productivity ($\tilde{\Omega}_{jt}$) into the the

³⁸We have also experimented with an approach where a single source of measurement error is applied to the sum of domestic and export revenue and the results are similar.

production function, domestic revenue (in logarithm) for non-exporters is,

$$r_{jt}^D = \log\left(\frac{\eta^D}{1 + \eta^D}\right) + \log\left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^\gamma\right)\right] + u_{jt}^D. \quad (19)$$

Note that because the quality-inclusive productivity ($\tilde{\Omega}_{jt}$) is substituted out by observed variables and parameters to be estimated, estimation based on this equation is not subject to a simultaneity problem. Following Grieco et al. (2016), the production function parameters and η^D are identified with two additional constraints implied by the model. The first constraint is the normalization assumption on the distribution parameters,

$$\alpha_L + \alpha_M + \alpha_K = 1. \quad (20)$$

The second constraint arises from the aggregate implication of (18). Taking its geometric mean over all firms and years leads to:

$$\frac{\bar{E}_L}{\bar{E}_M} = \frac{\alpha_L}{\alpha_M}, \quad (21)$$

where \bar{E}_L and \bar{E}_M are the geometric mean of labor expenditure and material expenditure across firms and years, respectively.³⁹ We estimate (19) using non-linear least square (NLLS) with constraints (20) and (21) using data from firms that sell only domestically.⁴⁰

Next, we turn to the estimation of the export demand parameters, (κ, η^X) . When a firm sells in both domestic and export markets, the first-order conditions with respect to (quality-inclusive) output quantities in these two markets—as characterized by (A.7) and (A.8) in Appendix A—imply that export quantity can be written as an increasing function of domestic quantity. To see this, take the ratio of these two first order conditions and solve for exports,

$$\tilde{Q}_{jt}^X = \left(\frac{1}{\kappa} \frac{\eta^X}{\eta^D} \frac{1 + \eta^D}{1 + \eta^X}\right)^{\eta^X} (\tilde{Q}_{jt}^D)^{\eta^X / \eta^D}. \quad (22)$$

Using this relationship and (16) we can express export (log) revenue in terms of domestic revenue.⁴¹ Taking

³⁹This equation can be derived by taking the geometric mean of (18) over all observations. Given the normalization of our production function discussed in Footnote 22, the geometric mean of L_{jt} and that of M_{jt} both equal to one.

⁴⁰As an anonymous referee pointed out, recovering material price in (18) and the consistent estimation in (19) require the precise measurement of labor inputs. The number of workers is a reasonable approximate for labor inputs in this industry, for two reasons. First, labor is fairly homogeneous and low-skilled in this industry, as shown in Footnote 10. Second, although working hours per worker is not reported in our dataset, it seems that there was no substantial change in working hours in this industry during our data period (especially across importers and non-importers). According to the “China Labor Statistical Yearbook 2005”, the average working hours of urban workers are 44.9, 45.2, 45.4, and 45.5 hours per week from 2001 to 2004, showing no obvious change of trend after WTO.

⁴¹Here we implicitly drop e_{ij} because it equals 1 for all exporters by definition.

logarithms, and using our estimate of $\hat{\eta}^D$ from (19), we arrive at the estimating equation,

$$r_{jt}^X = -\eta^X \ln \kappa + (1 + \eta^X) \log \left(\frac{\eta^X}{\hat{\eta}^D} \frac{1 + \hat{\eta}^D}{1 + \eta^X} \right) + \frac{1 + \eta^X}{1 + \hat{\eta}^D} r_{jt}^D + u_{jt}. \quad (23)$$

where $u_{jt} = (u_{jt}^X - \frac{1+\eta^X}{1+\hat{\eta}^D} u_{jt}^D)$ is the composite error term. Because u_{jt} is correlated with r_{jt}^D through u_{jt}^D , we estimate (23) via generalized method of moments (GMM) using logarithm of $(K_{jt}, L_{jt}, E_{Mjt}, E_{Ljt})$ as instruments for r_{jt}^D . This procedure is consistent because the instruments are uncorrelated with the contemporaneous measurement error.

Identification. This stage of the estimation process recovers the parameters $(\eta^D, \eta^X, \kappa, \gamma, \alpha_M, \alpha_L, \alpha_K)$. Identification of $(\eta^D, \gamma, \alpha_M, \alpha_L, \alpha_K)$ follows directly from Grieco et al. (2016). Briefly, variation in revenues, input expenditures and the capital-to-labor ratio are employed in (19) to identify domestic demand elasticity η^D , the substitution parameter γ and the ratio of distribution parameters $\frac{\alpha_K}{\alpha_L}$. The individual distribution parameters are then identified by matching the aggregate expenditure ratios (21) and satisfying the adding up constraint (20). These restrictions can all be cast in terms of a generalized method of moments estimator and estimated jointly following Grieco et al. (2016). With these parameters identified, the relationship between export revenue and domestic revenue identifies (κ, η^X) from (23). The overall size of the export market can be established based on aggregate revenues while the extent to which export revenue grows with domestic revenue is indicative of relative demand elasticities under the assumption the same good is sold to both markets.

Once the above parameters have been estimated, the quality-inclusive productivity and input price variables $(\tilde{P}_{Mjt}, \tilde{\Omega}_{jt})$ can be recovered by solving a set of nonlinear equations implied by the first-order conditions of labor and input quantity. The details of this procedure are provided in Appendix A. Intuitively, the quality-inclusive productivity $\tilde{\Omega}_{jt}$ enters both the labor and materials first-order conditions multiplicatively and so cancels out of their ratio, whereas the unobserved materials quantity does not. The variation between the wage rate and the expenditure ratio of labor to materials, together with the model parameters, allow us to impute the materials quantity that is needed to satisfy the input demand first-order conditions in conjunction with the observed labor quantity, as in (18). Once this materials quantity is known, quality-inclusive materials price \tilde{P}_{Mjt} can be recovered from data on materials expenditure. Finally, $\tilde{\Omega}$ can be recovered from the production function.

Parameter Estimates. The production and demand estimates are reported in Table 5. The estimate of the distribution parameter for material inputs, α_M , is 0.883, which is close to the level of material share

used in production for Chinese paint manufacturers, as shown in Table 1. The estimates of capital and labor distribution parameters, α_K and α_L , echo the labor and capital intensity. The implied labor share relative to the total expenditure on labor and capital (but excluding material) equals 46.2%. The magnitude is similar to those estimated in the literature on other industries using other methods and data. The estimate of γ is 0.201, implying that the elasticity of substitution across inputs is 1.251. Although macro-economic estimates of the elasticity of substitution tend to be below unity, we are focusing on a single industry whose characteristics may not reflect the “aggregate” production process.⁴² Within the paint industry, the role of labor and mixers in promoting the effective use of materials may indicate higher than typical elasticities of substitution. Also, our estimates explicitly control for unobserved price heterogeneity at the firm level. Grieco et al. (2016) have shown in Monte Carlo experiments that failure to control for input price heterogeneity tends to bias the elasticity of substitution downward. On the other hand, Doraszelski and Jaumandreu (2017) have found that assuming labor is flexible in the face of adjustment costs may bias the elasticity of substitution upward. That said, Chinese labor laws in this period were very weak, leading to high labor flexibility relative to other countries (see Footnote 21).

[Table 5 about here.]

On the demand side, we find that the foreign market is slightly more elastic than the domestic market, but the difference is statistically insignificant. Although in both markets we expect markups between 10 and 20 percent, which are common in the literature.⁴³

After all production and demand parameters have been estimated, we solve the quality-inclusive input price and productivity ($\tilde{P}_{Mjt}, \tilde{\Omega}_{jt}$) following Appendix A. Although we do not have a direct measure of input prices, we can compare the recovered \tilde{P}_{Mjt} to the share weighted unit value of imports for importing firms. We find a positive and strongly significant relationship (coefficient: 0.693, p-value: 0.00) when regressing $\log(\tilde{P}_{Mjt})$ against unit value of imports in logarithm. Although the coefficient is less than one, this is consistent with the fact that the majority of materials used in paint manufacturing are sourced domestically (Table 3). Note that this result is not mechanical because the unit price of imports is not used to construct \tilde{P}_{Mjt} , which instead relies on wages and labor and materials input expenditure. We provide a more detailed discussion of these results in Online Appendix E.

⁴²Oberfield and Raval (2019) cite a range of estimates for the aggregate elasticity of substitution ranging from 0.5 to 1.6. Their own estimate, developed by aggregating up micro-level estimated elasticities to account for the change in allocation across plants, is 0.5-0.7. They build upon the approach developed by Raval (2019) to estimate plant-level elasticities of substitution between labor and capital using cross-sectional variation in wages with industry fixed effects. Using US data, (Raval, 2019, Figure 4) finds substantial heterogeneity in micro elasticities of substitution at the two-digit SIC level, although all estimates are below 1. SIC 2-digit industries are much more aggregated and hence not comparable to the Chinese paint industry we consider here.

⁴³It is possible that WTO accession itself changed demand conditions in either the export or domestic market. To investigate this possibility, we estimated a specification that allows the demand parameters (η^D, η^X, κ) to vary before versus after WTO accession. For all three parameters, the differences are small and statistically insignificant.

Quality Parameters and Processes for Productivity and Input Prices

The second stage of estimation makes use of the optimization conditions of firms' input *quality* choice to estimate the quality parameters, (θ, ϕ) , and the transition processes for fundamental input prices and productivity that are purged of firms' endogenous quality choice.

The key to this step is a one-to-one mapping between the quality-inclusive productivity and quality inclusive input prices recovered in the previous step, $(\tilde{\omega}_{jt}, \tilde{p}_{jt})$, and the fundamental productivity and input prices that are the model primitives (and firms' state variables), (ω_{jt}, p_{jt}) . Combining the first order conditions of material choice and quality choice, as shown in Appendix A, we can derive a closed-form relation between input quality and fundamental productivity:

$$h_{jt} = \frac{1}{\theta} \ln \frac{\phi \sigma_{Mjt}}{1 - \phi \sigma_{Mjt}} + \omega_{jt}, \quad (24)$$

where $\sigma_{Mjt} = \frac{\partial F(\cdot)}{\partial M_{jt}} \frac{M_{jt}}{F(\cdot)}$ is the (firm-specific) output elasticity of materials. This equation indicates that—if, as expected, $\theta < 0$ —the endogenous quality choice positively relates to the productivity level, but negatively relates to the output elasticity of material (which is also affected by productivity). For each observation, we can directly compute an estimate of σ_{Mjt} using the estimated production function and material input quantity recovered from the previous step.

Substitute (24) into (8) and take logarithms to find the relationship between quality-inclusive productivity and fundamental productivity,

$$\omega_{jt} = \tilde{\omega}_{jt} + \frac{1}{\theta} \ln(1 - \phi \sigma_{Mjt}). \quad (25)$$

The fundamental price index can be found by utilizing the price menu function (9) directly,

$$p_{Mjt} = \tilde{p}_{Mjt} - \phi h_{jt} = \tilde{p}_{Mjt} - \phi \left[\tilde{\omega}_{jt} + \frac{1}{\theta} \ln(\phi \sigma_{Mjt}) \right], \quad (26)$$

where the final equality comes from substituting (25) into (24). This shows that we can express productivity and the price index as a function of the two unknown quality parameters (θ, ϕ) and functions of objects that have already been estimated: $\tilde{\omega}_{jt}$, \tilde{p}_{Mjt} and σ_{Mjt} . We use the Markov specification of the transition processes of productivity and the price index to identify the quality parameters. This specification implies that lagged input price does not directly affect current productivity and that lagged productivity does not directly affect the current input price index. Given this assumption, correlation between the recovered quality-inclusive $\tilde{\omega}_{jt}$ and \tilde{p}_{Mjt} is attributed to firms' endogenous quality choice and serves as identifying variation for the quality parameters.

We estimate (θ, ϕ) together with $(f_0, f_{wto}, f_\omega, f_i, f_e, g_0, g_{wto}, g_p, g_{i0}, g_{i1})$ associated with (11) and (12) via GMM:

$$E[Z_{jt} \otimes (\epsilon_{jt+1}^\omega, \epsilon_{jt+1}^p)] = 0, \quad (27)$$

where $\epsilon_{jt+1}^\omega = \omega_{jt+1} - f(\omega_{jt}, e_{jt}, i_{jt}, \tau_{t+1})$ and $\epsilon_{jt+1}^p = p_{Mjt+1} - g(p_{Mjt}, i_{jt+1}, \tau_{t+1})$. Valid instruments for this estimation are any variable that is in the information set of firm j in time t . In our specification we use $Z_{jt} = (X_{jt}, \sigma_{M_{jt}}, ie_{jt}, \tau_t, ie_{jt}\tau_t)$ where X_{jt} contains the logarithm of $K_{jt}, E_{M_{jt}}, E_{L_{jt}}$ up to second-order interactions.⁴⁴

Identification. Identification of the quality parameters and the transition processes relies on the time series elements of the data. Recall that $(\tilde{p}_{jt}, \tilde{\omega}_{jt})$ were recovered using only current period data and a cross-sectional estimation. Thus, the time series of these variables reflect the over-time movements in the firm state variables and static choices (e.g., wages, labor expenditure and materials expenditure). Intuitively, comovement of the quality-inclusive variables $\tilde{\omega}_{jt}$ and \tilde{p}_{jt} indicates that productive firms pay more for the same quantity of inputs. Our model explains this correlation through the firms' endogenous quality choice, which is a function of the complementarity between fundamental productivity, ω_{jt} and input quality h_{jt} . Firms choose quality to maximize profits according to the first-order condition (24), which balances the marginal benefit of input quality in raising firms' productive capability with the marginal cost of quality due to higher input prices. This implies a one to one mapping from $(\tilde{p}_{jt}, \tilde{\omega}_{jt})$ to (p, ω) . Therefore, for any candidate quality parameters (θ, ϕ) , the time series of $(\tilde{p}_{jt}, \tilde{\omega}_{jt})$ recovered in Section 4 can be inverted into a candidate time series of (p, ω) . Using the transition processes (11) and (12) we recover innovations in the firms' fundamental shocks $(\epsilon_{jt+1}^\omega, \epsilon_{jt+1}^p)$ as functions of candidate quality and transition process parameters. Following Olley and Pakes (1996), the parameters are identified by moment conditions restricting these innovations to be uncorrelated with the firm's information set in time t . We augment the standard instrument set for this estimation with the output elasticity of labor, $\sigma_{M_{jt}}$ because of the important role it plays in the inversion of quality-inclusive to fundamental productivity and input price, as is clear from (25) and (26).

Parameter Estimates. Table 6 presents the estimation results for several alternative specifications of the transition processes.⁴⁵ Our main specification is listed in column I. The estimate of θ is consistently near -0.25 across all specifications, which implies an elasticity of substitution of 0.8: productivity and input quality are indeed complements in production. We find that the estimate of ϕ is close to unity in all

⁴⁴We have experimented with a subset of these instruments (e.g., excluding $\sigma_{M_{jt}}$ or using lags of ie_{jt}) and have found that our results are quantitatively similar.

⁴⁵The evolution process of wage rate, (13) is estimated independently. We find that $\hat{\zeta}_0 = 2.523$ with a standard error of 0.108 and $\hat{\zeta}_\ell = 0.640$ with a standard error of 0.017.

specifications, confirming that firms pay more for inputs of higher quality.

[Table 6 about here.]

The second panel of Table 6 reports our estimates of the productivity transition processes. The effect of exporting on productivity is positive, as expected. Across the specifications, exporting increases the firm’s next-period productivity by 8 to 10 percent, although this effect is not statistically significant in all specifications. The effect of importing on productivity is higher and statistically significant for all specifications. Importing increases next-period productivity by 26 percent. As pointed out by Kasahara and Rodrigue (2008), Halpern et al. (2015), and Zhang (2017) among others, this may arise from learning by importing or technical support from foreign suppliers. The substantial productivity boost when a firm begins importing is plausible in the paint industry, where importers gain access both to a larger variety of inputs and are likely to interact with foreign firms—usually from developed countries as seen in Table 2 (Section 2)—that have substantial chemical expertise.

Comparing the results from the structural model to those of the preliminary regressions on labor productivity in Table 4, we see that our model finds a smaller impact of importing in magnitude, although the structural estimate is much more precise and is now statistically significant. The effect of exporting is not significant in either the panel data regression or the structural model. Both estimates are much smaller than the OLS regressions that fail to account for the endogeneity of trade participation.

The WTO coefficient, f_{wto} , is positive and significant. This may be due to either a boost of productivity resulting from China’s accession to the WTO or a positive trend of productivity growth in this industry. We do not interpret this parameter causally, but instead use it as a control for changes in market conditions after the WTO accession.⁴⁶

The third panel of Table 6 reports our estimates of the transition process for fundamental input prices. The estimation results show significant gains from trade through lower input prices. Column II indicates that on average importers expect to pay 2.1 percent lower input prices than do similar non-importers, conditioning on last period’s input price index. This effect is both economically and statistically significant.⁴⁷ The specification in Column I is based on (11) and (12) and captures the change in the input price benefit of importing pre- and post-WTO accession status. Combined with the WTO accession dummy, this specification

⁴⁶For example, output market condition might be changed if output tariff cut resulted in intensified competition from foreign sellers. Such impact, if common to all firms, can be captured by the impact of WTO on productivity measure (f_{wto}), which is revenue-based. Of course, if foreign paint products are mainly of high quality, then such competition might affect importers more than non-importers, because importers are more likely to produce high-quality products. In an unreported specification, we examined this possibility by investigating whether WTO accession affected the productivity process of importers and non-importers differently. We found that the difference was not economically or statistically significant, and more importantly, the estimates of other parameters in the productivity process were not changed.

⁴⁷As a back of the envelope calculation, reducing the input prices by 2.1 percent will raise variable profits by about 1.9, even if the firm does not adjust their input usage.

forms a difference-in-difference design that captures the causal impact of WTO accession on the input price gap (pre-WTO v.s. post-WTO years and importer v.s. non-importer). The result indicates that after WTO accession, the input price gap between importers and non-importers grew from 1.8 to 2.4 percent. Although the change is not statistically significant (p -value = 0.328) it does represent a one-third increase in the price gap. In the long run, this effect is even larger because of the persistence of input prices: according to the evolution process, a persistent importing firm would enjoy a 29.5 percent lower input price compared with a non-importing firm in the long run steady state prior to accession. After China’s accession to the WTO, this advantage increases to 39.3 percent. In Columns II, III, and V, we find that the effect of exporting on input prices, g_e , is neither statistically nor economically significant, which is intuitive given that exporting should not directly affect the available set of inputs. We interpret this result as a falsification test to show that our input price index is in fact capturing input prices rather than other forms of firm heterogeneity. For the remainder of the article, we use our preferred specification of the transition processes from Column I.

To put our estimates of price impacts into perspective, the average importer imports 30 percent of their materials, and WTO accession led to a 7 percent drop in the tariff rate, so a back of envelope calculation suggests importers’ prices would fall by 2.1 percent.⁴⁸ Our estimation suggests a drop of 2.6 percent in the input prices of importers following accession. However, this back of the envelope calculation has several caveats. For example, it assumes perfect passthrough, ignores non-tariffs impacts of WTO, and assumes no effect through import competition. Still, it is comforting that our estimates are broadly consistent with the magnitude suggested by this intuition.

In previous dynamic models of trade, input price differences are implicitly included as part of productivity, whereas we separate input prices from productivity. To gauge the importance of this generalization, we compare the persistence of the productivity and input price processes to each other and to the previous literature. The persistence parameter for productivity is 0.623 and is robust across all specifications. This is at the lower end of the persistence estimates documented in the literature including Foster et al. (2008) and Ábrahám and White (2006), which find that the productivity persistence coefficient is on the order of 0.6 to 0.8. The input price process is much more persistent, 0.939, and is also robust across specifications. This is higher than that found in Atalay (2014) where firm-level input prices and quantities are observed and Grieco et al. (2016) where input prices are estimated. This may be due to the fact that the input price measures in these two articles contain input quality which is likely to be more volatile because it is an endogenous firm choice and a function of productivity. In contrast, the fundamental input price p_{Mjt} is purged of quality effects and captures only firm characteristics such as geographic location and importing status, which are likely to be more persistent. Overall, our results indicate that input prices are more persistent than other

⁴⁸We thank an anonymous referee for offering this comparison.

sources of heterogeneity captured in the productivity process.

Productivity and Input Price Distributions. We recover fundamental productivity and input prices from (25) and (26). The distribution of productivity, ω_{jt} , is plotted in solid line in Figure 1. It shows substantial heterogeneity of fundamental productivity across firms. The inter-quartile range is 1.15, implying a productivity ratio of $e^{1.15} = 3.158$, which is within the range documented in other empirical studies, such as Fox and Smeets (2011). This is also close to the results in Hsieh and Klenow (2009), who use manufacturing data from China and India with average 90th-10th productivity ratios over 5:1, but higher than that found in Syverson (2004), which reports an average 75th-25th productivity ratio of 1.56 within four-digit SIC industries in US manufacturing sector.

[Figure 1 about here.]

[Figure 2 about here.]

For comparison, we plot the distribution of $\tilde{\omega}_{jt}$ as the dashed line in Figure 1. Its dispersion is much larger than that of productivity, with an inter-quartile range of 4.14. This is intuitive given the complementarity between productivity and input quality: more productive firms endogenously purchase inputs of higher quality, which expands the dispersion of $\tilde{\omega}_{jt}$ compared with ω_{jt} . This suggests that failure to account for quality will bias the dispersion of productivity upwards. The dispersion of $\tilde{\omega}$ is much larger than the comparable non-quality adjusted estimates in the literature cited above. However, the distribution of $\tilde{\omega}$ in our article accounts for input price heterogeneity while ignoring quality variation, whereas both are typically abstracted away in the literature.

The distribution of (log) fundamental input prices, p_{Mjt} , is reported in the solid line in Figure 2. The inter-quartile range is 0.25, which implies that the input price (conditional on quality) paid by the 75th percentile firm in the distribution is about 28.4% ($e^{0.25} - 1 \approx 0.284$) higher than that faced by the 25th percentile firm. In contrast, the distribution of quality-inclusive input prices, \tilde{p}_{Mjt} (dashed line in Figure 2) is much more dispersed, with an interquartile range of 4.65. Purging quality from the input prices reduces the dispersion substantially.

We find a very weak correlation between fundamental productivity and fundamental input prices, $\text{corr}(\omega_{jt}, p_{Mjt}) = 0.050$. This contrasts with the literature which finds a strong positive correlation between productivity and unit input price (Kugler and Verhoogen, 2012; Grieco et al., 2016). However, the literature uses observed or inferred unit input prices that include the effect of input quality. If more productive firms tend to choose high-quality inputs, then the quality-inclusive input price will be positively correlated with

productivity. This conjecture is supported by the strong positive correlation between productivity and our measure of quality-inclusive input prices, $\text{corr}(\omega_{jt}, \tilde{p}_{Mjt}) = 0.734$.

[Table 7 about here.]

Finally, we examine how productivity and input prices have changed over time at the industry level. In particular, it is interesting to see whether WTO accession is associated with changes in productivity or input prices.⁴⁹ We define aggregate productivity and input price as the revenue share-weighted average of firm-level productivity and input price levels:

$$\Omega_t = \sum_j w_{jt} \Omega_{jt}, \quad P_{Mt} = \sum_j w_{jt} P_{Mjt},$$

where $w_{jt} = R_{jt} / \sum_k R_{kt}$. In addition to the industry average, we examine whether larger firms (in revenue terms) are higher performing, as we would expect more productive firms to account for a larger share of output. Olley and Pakes (1996) show that a simple decomposition of aggregate productivity can determine whether output is allocated to high-productivity firms,

$$\Omega_t = \bar{\Omega}_t + \sum_j (w_{jt} - \bar{w}_t)(\Omega_{jt} - \bar{\Omega}_t) = \bar{\Omega}_t + \sum_j \Delta w_{jt} \Delta \Omega_{jt},$$

Where the bar denotes the *unweighted* mean of the variable across firms. The final term in this decomposition is the covariance between revenue and productivity, or the degree to which the most productive firms in the industry produce more. Over time, this decomposition allows us to see whether aggregate productivity growth is due to an increase in the unweighted firm average or due to an improvement in the allocation of sales to productive firms. We can construct the analogous decomposition for aggregate input prices. In this case, a more efficient allocation of sales would come from a more negative covariance term because firms with access to lower fundamental input prices can produce more efficiently.

The left panel of Table 7 reports the results of aggregate productivity and the terms of the OP decomposition over the years of our data.⁵⁰ Although aggregate productivity is somewhat volatile, it clearly increases over the sample period, particularly following WTO accession in late 2001. Turning to the decomposition, the correlation between output and productivity is positive in all years, so more productive firms have higher sales. In addition, the growth in aggregate productivity over time—especially up to 2005—is mostly due to an improvement in the allocation of sales to productive firms, rather than an increase in the unweighted mean.

⁴⁹China acceded to the WTO in November of 2001, so we take 2002 as the first year after WTO accession.

⁵⁰We normalize the aggregate levels by the first year of our sample, 2000.

The right-hand panel performs the analogous exercise for input prices. Although the movements are much smaller, we do observe a decline in input prices following WTO accession. The covariance between input prices and revenue share is negative. Again, this is consistent with higher-performing firms producing more output. This relationship is more stable over the time period, although again, a substantial proportion of the improvement in aggregate input prices is due to the allocation term of the decomposition.

Although Table 7 reports how productivity and input prices have evolved over time, it does not establish any causal relationship between trade policy, productivity and input prices. The Chinese economy is extremely dynamic and this exercise does not separate WTO accession from other shocks to the paint industry over time. However, one might expect that trade liberalization may improve the allocation of output if the benefits of liberalization flow towards those firms that engage in trade (which tend to be larger, and higher performing than average). We examine this possibility in the context of our counterfactual analysis in Section 5.

Sunk and Fixed Costs of Trade Participation

The final estimation stage takes the output from the previous stages to the Bellman equation to estimate the sunk and fixed costs of trade defined in (14). Because of the high-dimensional continuous state space, solving the dynamic model is computationally intensive. Hence, it is impractical to directly estimate the model using a nested fixed-point algorithm. To circumvent this issue, we instead use the conditional choice probability (CCP) approach developed by Hotz and Miller (1993) and Hotz et al. (1994). This avoids solving the model during estimation. Here, we describe the key steps of the estimation procedure, and Appendix B provides more technical details.

We estimate the dynamic model in two steps. In the first step, we estimate a bivariate probit model of import and export decisions conditional on the state variables $s_{jt} = (\omega_{jt}, k_{jt}, p_{Mjt}, p_{Ljt}, i_{e_{jt}}, \tau_t)$:⁵¹

$$i_{jt+1} = \mathbb{I}(\psi_0^i + \psi_e^i e_{jt} + \psi_i^i i_{jt} + \psi_{ie}^i e_{jt} i_{jt} + \psi_\omega^i \omega_{jt} + \psi_p^i p_{Mjt} + \psi_k^i k_{jt} + \psi_{wage}^i + \psi_{wto}^i (1 - \tau_t) + v_{jt}^i > 0), \quad (28)$$

$$e_{jt+1} = \mathbb{I}(\psi_0^e + \psi_e^e e_{jt} + \psi_i^e i_{jt} + \psi_{ie}^e e_{jt} i_{jt} + \psi_\omega^e \omega_{jt} + \psi_p^e p_{Mjt} + \psi_k^e k_{jt} + \psi_{wage}^e + \psi_{wto}^e (1 - \tau_t) + v_{jt}^e > 0), \quad (29)$$

where $\mathbb{I}(\cdot)$ is an indicator function. Each of parameters ψ_{wage}^i and ψ_{wage}^e reflects the terciles of the wage distribution across firms, $wage \in \{low, med, high\}$ with *med* serving as the reference group. The dummy variable τ_t controls for the changes in firm strategies prior to WTO accession when the model is non-stationary.⁵² The error terms (v_{jt}^i, v_{jt}^e) are jointly standard normally distributed with correlation parameter

⁵¹For expositional clarity, denote the state using the logarithm of continuous state variables this section.

⁵²Note that in estimating the CCP, there is only have one year (2001) before WTO because the year 2000 is used to create the lagged state variables. If we had additional years prior to the WTO, these would ideally be estimated individually to account for

ρ . This approach captures the idea that firms' import and export decisions may be affected by some common unobserved factors.

In the second step, we use the estimated conditional choice probabilities to evaluate the choice-specific value function of the firm. These are used to estimate the fixed costs parameters λ that rationalize the observed choice probabilities. Specifically, given the state (s_{jt}, ξ_{jt}) we denote the choice-specific firm value for any action ie_{jt+1} (not necessarily optimal) as,⁵³

$$\begin{aligned}
V(s_{jt}, \xi_{jt} | ie_{jt+1}; \lambda) &= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_{\xi} \xi_{jt}^{ie_{jt+1}} + \delta E[V(s_{jt+1}, \xi_{jt+1}) | s_{jt}, ie_{jt+1}] \\
&= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_{\xi} \xi_{jt}^{ie_{jt+1}} \\
&\quad + \delta \int_{\xi_{jt+1}} \int_{s_{jt+1}} V(s_{jt+1}, \xi_{jt+1}) dF(s_{jt+1} | s_{jt}, ie_{jt+1}) dG(\xi_{jt+1}) \\
&\equiv V^{\xi}(s_{jt} | ie_{jt+1}; \lambda) + \lambda_{\xi} \xi_{jt}^{ie_{jt+1}}, \tag{30}
\end{aligned}$$

where $F(\cdot)$ is the distribution of s_{t+1} given the current state and the firms' current period choice of next-period trade status, ie_{jt+1} and $G(\cdot)$ is the distribution of next period's fixed cost shocks. As is common in the literature, we fix the discount factor δ to 0.95. For our implementation, we assume the shocks to productivity, input prices and wages are jointly normal with a variance-covariance matrix estimated from the residuals of the GMM estimates. As discussed above, the cost shocks are assumed to be distributed according to the Type-I extreme value distribution. For notational convenience, define $V^{\xi}(s_{jt} | ie_{jt+1}; \lambda)$ as the choice-specific value net of current period fixed cost shocks.

There are two computational challenges to the efficient computation of (30). First, $\pi(\cdot)$ does not have a closed-form, and must be solved numerically for every state vector. To address this, we approximate $\pi(\cdot)$ using multivariate adaptive regression splines (MARS) proposed by Friedman (1991, 1993).⁵⁴ This procedure solves $\pi(\cdot)$ for a subset of points and uses these points to approximate the function over the entire state space. To balance the computational burden and accuracy of the approximation, we choose this subset of points by using the epsilon distinguishable set (EDS) technique developed by Judd et al. (2012) and Maliar and Maliar (2015). The details of the approximation of $\pi(\cdot)$ are provided in Appendix B. The second challenge is computing the integral in (30) over all future state transitions. We approximate this integral following the forward-simulation approach introduced by Hotz et al. (1994), which is described in Appendix B.

anticipation of WTO accession. We have experimented with a fully flexible estimation of the CCP (with WTO-accession-specific parameters) prior to accession, the results were qualitatively similar but, not surprisingly, much less precise.

⁵³Formally, our problem is stationary only after China's WTO accession. We assume China's entry into the WTO is anticipated prior to 2002 and we used a dummy to control for this in the CCP estimation. When forward simulating the state space to estimate the dynamic parameters, we account for the fact that firms are aware that WTO accession will occur in 2002 with certainty. Incorporating this sort of deterministic state transition is another advantage of the Hotz and Miller (1993)-style approach to dynamic estimation over solving a stationary model as part of the estimation procedure.

⁵⁴The MARS approximation was introduced into the economics literature by Barwick and Pathak (2015).

Given that the trade cost shocks are distributed according to the Type-I extreme value distribution, the model-predicted choice probabilities can be computed from the choice-specific value functions,

$$\Pr(ie_{jt+1}|s_{jt}) = \frac{\exp(V^\xi(s_{jt}|ie_{jt+1}; \lambda)/\lambda_\xi)}{\sum_{ie} \exp(V^\xi(s_{jt}|ie; \lambda)/\lambda_\xi)}. \quad (31)$$

This implies the following relationship between choice-specific firm value and observed conditional choice probabilities for any pair of choices ie and ie' ,

$$\frac{V^\xi(s_{jt}|ie; \lambda) - V^\xi(s_{jt}|ie'; \lambda)}{\lambda_\xi} = \ln \Pr(ie|s_{jt}) - \ln \Pr(ie'|s_{jt}). \quad (32)$$

Because the right hand side is estimated from (28), we estimate the trade cost parameters by matching the two sides of (32). The estimator is defined as,

$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmin}} \sum_{j,t} \sum_{ie'} \left\{ \frac{1}{\lambda_\xi} [V^\xi(s_{jt}|ie_{jt+1}; \lambda) - V^\xi(s_{jt}|ie'; \lambda)] - [\ln \widehat{\Pr}(ie_{jt+1}|s_{jt}) - \ln \widehat{\Pr}(ie'|s_{jt})] \right\}^2. \quad (33)$$

Identification. Identification of the sunk and fixed cost parameters follows Hotz and Miller (1993). The CCPs are directly identified from the data because all state variables are either directly observed or are a function of observed data and previously identified parameters. Equation (32) inverts the CCPs identify differences in choice-specific value functions. Choice specific valuations can be calculated up to the sunk and fixed cost parameters. Our assumption that choosing to neither import nor export is costless provides the location normalization to identify the remaining sunk and fixed cost parameters.

[Table 8 about here.]

CCP Estimates. The results of the first-stage CCP estimation are reported in Table 8.⁵⁵ As expected, current export and import status have a substantial impact on future trade participation. An importer (exporter) is more likely to continue importing (exporting), which is consistent with the well-documented fact that trade participation is persistent. Interestingly, we also find that a current exporter (importer) is more likely to import (export) in the following period, which is indicative of some complementarity between importing and exporting. Table 9 presents the average marginal effects of state variables on trade participation. Previous export experience increases the probability of importing by 6.3 percent and of exporting by 70.3 percent. Similarly, we find that import experience increases the probability of import this

⁵⁵In the empirical estimation, we categorize the firms into three groups according to their wage rate percentile: high wage firms with wage rate above 66 percentile; low wage firms with wage rate below 33 percentile; and the remaining as middle-wage firms.

year substantially (86.9 percent), and also increases the probability of export by 10.0 percent. This suggests the presence of complementarity between importing and exporting in terms of trade costs that is explicitly accounted for in our flexible trade cost specification (14).

Table 8 also illustrates firms' endogenous selection into importing and exporting based on productivity and input prices. The estimate $\psi_{\omega}^e = 0.083$ suggests that more productive firms are more likely to export, reprising a well-known result in the literature. Accordingly, as calculated in Table 9, a one-standard-deviation improvement of productivity increases the export probability by 2.0 percentage points. Similarly, lower input prices also increase the export probability. Lowering input prices by one standard deviation can increase the export probability by 16.6 percentage points. In contrast, the selection into importing based on productivity and input prices is much weaker. The coefficient $\psi_{\omega}^i = 0.017$ translates to a 0.2 percentage point increase in the import probability on average when productivity increases by one standard deviation. The impact of input price increase on the import probability is negative but is less significant than that on the export probability.

[Table 9 about here.]

Fixed and Sunk Cost Estimates The final step in the estimation is the recovery of the trade cost parameters. The estimates are reported in Table 10.⁵⁶ Consistent with the findings in the literature, sunk costs are much larger than the fixed cost for both importing and exporting. In addition, the estimates exhibit some complementarity between importing and exporting. This is captured by, for example, $\hat{\lambda}_{00;01} > \hat{\lambda}_{10;01}$ and $\hat{\lambda}_{00;10} > \hat{\lambda}_{01;10}$. Intuitively, importing from foreign markets in the past period helps the firm to get familiar with the customs regulations and market conditions, makes it easier to search for a business partner, or establishes distribution networks in the coming year, all of which reduce the cost of exporting. Similarly, the export experience can make it easier for firms to initiate importing. We also find some evidence of contemporaneous complementarity between importing and exporting. This can be seen from, for example, $\hat{\lambda}_{00;01} + \hat{\lambda}_{00;10} > \hat{\lambda}_{00;11}$ for sunk cost and $\hat{\lambda}_{11;01} + \hat{\lambda}_{11;10} > \hat{\lambda}_{11;11}$ for fixed cost. This is intuitive because when the firm is engaging in both importing and exporting, information and knowledge, as well as managerial communication and travel costs, can be shared across both activities, reducing the total trade cost.

[Table 10 about here.]

To check the possibility that WTO accession might have changed the sunk and fixed costs of trade, we also estimated a version of the model that adds time dummies in (14). The estimated time dummies are insignificant, indicating that WTO accession had at most a small impact on fixed/sunk costs.

⁵⁶For the dynamic estimation, we assume the annual discount factor is $\delta = .95$. Our results are qualitatively robust to other choices of the discount factor.

With all model parameters estimated, we can solve for optimal trade policies. We check the fit of our model by comparing transition probabilities from the raw data, our CCP estimation, and the policy function of the dynamic model in Online Appendix F.

5 Counterfactual Analysis

Understanding and measuring the mechanisms through which tariff policy and trade participation interact to influence firm performance—and how these mechanisms play out over time—is of particular interest to policymakers. In this section, we conduct a series of counterfactual experiments based on our dynamic model to answer the following two questions: First, how important are the productivity and input price channels in terms of overall gains from trade? Second, how does a change in the input price benefit of importing (e.g. due to trade liberalization) affect manufacturers’ propensity to import and export, and what is the overall impact on firm performance in terms of productivity and firm value?

Long-term Gains: Productivity, Input Prices, Importing and Exporting

Our first counterfactual exercise is a thought experiment meant to evaluate the importance of the distinct productivity and input price effects of trade. To do this, we compare our baseline model to a counterfactual case where trade participation has no effect on productivity or input prices, respectively. We remove the impact of the trade from the productivity transition process by setting $f_e = f_i = 0$ and re-solving the model. Analogously, setting $g_i = 0$ removes the impact of trade on input prices.⁵⁷ To evaluate how the change affects the industry, we compare the expected outcomes of all firms in the data starting from 2006 and going forward 15 years. To calculate expected outcomes we simulate the transition paths 30 times for each of the 1,331 firms in the data in 2006 and take the average over these simulated paths.⁵⁸

[Table 11 about here.]

The first panel of Table 11 compares the expected outcomes between the baseline and counterfactual model removing the productivity effect of trade. The bottom row reports the overall effect on firm valuations: if the productivity effects of trade are removed, the average firm value will drop by 3.5 percent, equivalent to 3.5 million USD. This loss is in part due to a substantial decline in aggregate productivity of 34.1 percent.

⁵⁷Recall that our preferred specification of the model does not include an effect of exporting on input prices. When this effect is included, it is economically small and statistically insignificant (Table 6).

⁵⁸Because we do not model entry into the industry, our counterfactuals should be understood as the impact on incumbent firms in the industry in 2006. It is possible that our counterfactual changes could affect both entry rates and the productivity distribution of entrants. However, because relatively few entrants (8.4% for entrants v.s. 13.3% for incumbents) immediately engage in direct trade, we believe these effects will be less important than the effects on incumbents. Moreover, because capital is exogenous in our model, the counterfactuals do not account for the impact of the changes on investment policies.

The loss of productivity benefits from trade reduces trade participation for two reasons. First, productivity is lower under the counterfactual, and because there is a positive selection of productivity into trade, fewer firms will have productivity levels high enough to justify trading. Second, because the benefits of trade have decreased, firms react by increasing the threshold productivity levels at which they engage in trade.⁵⁹ The combined effect of removing the productivity benefits of trade is a reduction in the export probability by 3.1 percentage points (20 percent) after 15 years. This effect emerges slowly because the substantial sunk and fixed costs create hysteresis in firms trading decisions over time. The effect on import participation is even stronger, 5.2 percentage points (36 percent). Again, these declines accrue slowly after the policy change because the sunk and fixed costs maintain significant persistence in trade participation. The decline in importing reduces materials access and therefore has an indirect effect on input prices. After 15 years, the difference in the average fundamental input price is 2.1 percent. As this effect follows entirely from the reduction in import participation, it accrues much more slowly than the direct effect on productivity, which is immediately influenced by the counterfactual change.

In the second panel of Table 11, we report the impact of the removal of input price benefits of trade. The mean loss of present discounted value is 6.0 percent, equivalent to about 5.8 million USD. After 15 years, we find that input prices are 7.6 percent higher when we remove the input price benefit of trade. However, the loss in firm value is not simply due to higher input prices. In fact, productivity declines by a substantial 24.7 percent, almost two thirds the reduction we saw when we removed the productivity benefit itself. This loss is due to a large reduction in importing in response to the elimination of the input price benefit, which is further amplified by a reduction in exporting. The 4.4 percentage point drop in the proportion of exporters (28 percent) is particularly striking given that there is no direct impact of exporting on input prices. However, when facing higher input prices, many firms are no longer able to maintain a scale to justify paying the fixed costs of exporting. This strong reaction to a change in the input price process with regard to trade (and particularly importing) is in part driven by the high persistence of input prices relative to productivity. Because of this persistence, even modestly higher input prices have a substantial impact on firms' expectations of future profitability, drastically reducing incentives to initiate trade.

Input Tariffs and Price Incentives to Import

We have found that input price incentives play a large role in trade participation and firm performance. Moreover, changes in the effect of importing on input pricing can generate large changes in trade participation, aggregate productivity and profitability that grow over time. Therefore, policy shocks that affect input prices,

⁵⁹Note that even though we eliminate the direct benefit of trade on productivity, there will still be positive selection into the trade because the benefits of market access and materials access are increasing in productivity.

such as an import tariff cut, not only impact input prices but also indirectly affect productivity through trade participation. This effect of tariff liberalization on productivity through trade decisions is inherently dynamic and will not be accounted for in static analyses of gains from trade (e.g., Arkolakis et al., 2012).⁶⁰

The goal of this subsection is to measure the potential magnitude of these effects from a plausible reduction in input tariffs. To do so, we use the magnitude of the impact of China’s accession to the WTO in 2001 as a guidepost. As we discussed in Section 2, China’s accession to the WTO roughly halved import tariffs for the inputs of paint materials from 15 to 7 percent. Although imported intermediates can be purchased domestically from middlemen, if those middlemen incompletely pass through the reduction in costs due to tariffs, we would expect the effect of direct importing on input prices to increase after WTO accession. In fact, we find a small but economically significant increase in the gap between input prices of importers and non-importers following accession, with the benefit increasing from $g_{0i} = 1.8$ to $g_{1i} = 2.4$ percent (Table 6). Although the change is not statistically significant, we take the point estimate as a guideline and conduct a counterfactual to quantify the impact of tariff liberalization through an increase in the input price benefit of importing. That is, we re-solve the model with $g'_{i1} = 0.75 \times g_{i1}$ (as in $1.8 = 0.75 \times 2.4$) and all other parameters are held fixed. Comparing these two scenarios, we calculate a potential benefit of tariff liberalization through lower input prices for direct importers as $\frac{\Xi(g_{i1}) - \Xi(g'_{i1})}{\Xi(g'_{i1})}$, where $\Xi(\cdot)$ is the counterfactual outcome of interest. Our goal is *not* to produce a counterfactual analysis of WTO accession itself, which could have had many other potential effects, such as changes in fixed or sunk costs, a change in the demand elasticity in the export market or a substantial change in the domestic input market in reaction to increased import competition.⁶¹ Instead, the counterfactual is narrowly focused on measuring the potential gains in terms of productivity, trade participation and firm value from altering firms’ incentive to import via tariff liberalization.

[Table 12 about here.]

[Table 13 about here.]

The top panel of Table 12 reports the outcomes from this exercise. The higher input price benefit increases average firm value by 2.2 percent (2.1 million US dollars). This gain in firm value is due to the input price incentive but operates through multiple channels. Although in the first few years, the effect is mild, after 15 years, the average input price is about 2.9 percent lower due to both the direct effect of the price gap and firms being incentivized to engage in importing. The import probability increases by 3.4

⁶⁰So although this experiment could be carried out as part of section 5.1, given the stark changes in firms’ optimal policy (as to be shown in this section), we believe that the effect of change in the benefit of importing measured from an actual policy change is more illustrative of our point.

⁶¹That said, in robustness checks, we found little difference in trade costs and the demand elasticity across the pre and post WTO period.

percentage points (31 percent) and export probability by 1.7 percentage points (12 percent). The difference in export and import participation is very gradual, with less than half of the impact realized after five years. This suggests that even though directly imported intermediates may be an important source of gains from trade liberalization there may not be a substantial change in import participation immediately following liberalization (cf., Brandt et al., 2017). Finally, we see a substantial 9.3 percent increase in aggregate productivity due to the input price incentive. This result complements Yu (2014) who has documented that lower tariffs following China’s accession to the WTO had a positive impact on firm productivity.

The effects reported in the top panel of Table 12 combine the direct effect of the change in input prices between importers and non-importers with the indirect effect of firms’ endogenous responses to those incentive changes. To further understand the dynamic effects of trade policy, the bottom panel separates these two effects by re-running the simulation holding firms’ trade participation policies fixed. That is, these results correspond to the reduction of input prices for importers alone, without allowing firms to respond to the increased incentive to import. Intuitively, if firms do not re-optimize, the increase in trade participation is much more muted.⁶² Over 80 percent of the growth in import and export participation is due to firms’ endogenous response to trade incentives.⁶³ This highlights the role of increased trade participation in supporting productivity growth and input price declines. Without endogenous responses, long-run aggregate productivity gains are only 47 percent of the full impact, and input prices declines are only 69 percent of the full impact. The difference in firm values is smaller, with the direct effect achieving 90 percent of the full effect. This is because an increase in trade participation incurs more fixed costs of trade, which partially offset the gains due to larger output markets, higher productivity and lower input prices.

The importance of firms’ endogenous response to input price incentives to trade suggests that much of the gains in aggregate productivity and lower input prices flow to firms on the margin between trading and not trading. Because trading firms tend to be larger and more productive than non-trading firms, we would expect that tariff liberalization will improve the allocation of output to more productive, lower input price firms. Table 13 decomposes the increase in productivity and the decrease in input prices following Olley and Pakes (1996) and finds that this is the case. Allocation improvement accounts for 68 percent of aggregate productivity growth and almost half of the input price decline over a period of 15 years. Tariff liberalization and trade promotion appear to be one mechanism through which policymakers can reduce misallocation of output to low performing firms. Recently, there has been significant interest in how institutions and policies affect resource (mis)allocation and aggregate total factor productivity (Banerjee and Duflo, 2005; Restuccia

⁶²The increase that we do observe is due to the selection into trade participation and liberalization’s associated impacts on input prices.

⁶³It is calculated as $(1.7 - 0.3)/1.7 \approx 82\%$ for exporting and $(3.4 - 0.5)/3.4 \approx 85\%$ for importing. Other numbers in this paragraph are similarly computed.

and Rogerson, 2008; Hsieh and Klenow, 2009). Our results provide some evidence that intermediate import tariff liberalization reduces the production cost of importers (which are usually more productive firms) and enables high productivity firms to command a larger market share, leading to aggregate productivity increases.

Firm Heterogeneity in Tariff Response

The previous subsection illustrated how import tariff liberalization resulted in a reduction in input prices, an increase in productivity, and an increase in trade participation. In this section, we investigate the allocative impact of liberalization. For this exercise, we divide firms into groups based on productivity level (above or below median) or trade status at the start of the policy change. We then compute the same set of impacts for each firm type. To emphasize the effect on individual firms, we share-weight using revenue shares for the *initial* year of the simulation. That is, a firm's categorization and weight are constant over time based on its year 2006 state.

We focus on the effects of the tariff reduction five years after implementation. Fifteen year effects are available in Online Appendix F. Tables 14 and 15 report the overall impact of the import tariff reduction on firms categorized by productivity, input price, and trade status in the year the reduction is implemented.

[Table 14 about here.]

[Table 15 about here.]

First, we note how these results again highlight the importance of reallocation in driving the aggregate effects reported in Table 12. For example, 5-year productivity growth is only 1.5 percent when firm shares are held constant (Table 14) although it is 3.4 percent when accounting for reallocation by weighting based on current shares (Table 12).

Turning to the heterogeneity of impacts, Table 14 shows that the firms in a more advantaged position when the tariff reduction is implemented tend to reap larger benefits from the policy change. Although all groups experience productivity increases and price decreases due to the policy, high productivity firms' benefits in terms of productivity increases and price decreases are more than 50 percent larger than these of low productivity firms. The differences are even starker when we classify firms by input price. Next, we consider the effect on trade participation. Starting with importing, we see that a large number of firms with high productivity and low input price are induced to import five years later as a result of the policy change, although the impact is slightly smaller in terms of percentage changes in import participation compared

to firms with low productivity and high input price.⁶⁴ Turning to export participation, although a similar number of high and low productivity firms are induced to export in response to the change,⁶⁵ low input price firms are induced to export at higher rates than high input price firms. One reason for this is because low input price firms are more likely to already be importers, reducing their sunk cost to initiate exporting. The final row of Table 14 summarizes these findings by reporting the overall effect of the import tariff reduction on the present discounted value of firms in the year of implementation. As expected, we see that the more advantaged firms benefit more: 41 percent higher gains for high productivity firms and more than 100 percent higher gains for low input price firms.

Table 15 considers heterogeneity in liberalization impact based on initial trade status. Again, the largest benefits flow to the most advantaged firms, in this case, those firms who are already engaged in both importing and exporting. Between solo importers and solo exporters, importers experience larger gains in terms of firm value. This is intuitive because they are able to receive the direct benefit of the tariff liberalization immediately, whereas solo exporting firms must initiate importing to take advantage of the tariff reduction. Although clearly the policy primarily benefits trading firms, it is notable that even those firms who are neither importing nor exporting at the time of liberalization do see a substantial increase in their present discounted value as a result of the policy change.

As time passes, the firm's expected state will converge toward the stationary distribution. Therefore, the differences between the groups delineated in Tables 14 and 15 will decline over longer time horizons as the effects for all groups will be the difference between stationary distributions with and without tariff liberalization. To evaluate the speed of convergence, Online Appendix F presents the same statistics for 15 years after liberalization rather than 5 years. Although there is a clear trend towards convergence, there are still substantial differences across categories. Thus, our model implies a great deal of persistence in a firm's initial state, implying that the effects of tariff liberalization will increase the dispersion in firm productivity and prices over the medium to long run.⁶⁶

6 Conclusion

We propose and estimate a dynamic structural model that measures the distinct effects of trade liberalization on input prices and productivity, as well as incentives for firms to participate in trade. We find that firms

⁶⁴Note that in Table 14, firms are classified based on the median level of productivity (or input price), so the percentage point columns are directly comparable.

⁶⁵Of course, because high productivity firms select into exporting, the similar size of the effect in percentage point terms means a larger increase for low productivity firms in percentage terms.

⁶⁶As mentioned above, our counterfactual simulations do not incorporate firm entry or exit. Because exiting firms are likely to have low capability (i.e., low productivity and high input prices), doing so would be likely to increase the difference in benefits between high and low capability firms.

that import materials directly face lower input prices, and also experience significant productivity growth consistent with “learning by importing”. The price incentive to import is increased following the liberalization of input tariffs. As a result, domestic firms increase trade participation and boost productivity following trade liberalization, although this transition is gradual due to high sunk costs of trade participation. In the counterfactual analysis, we show how these joint effects of importing can amplify gains from import tariff liberalization: there is a direct effect due to lower input prices, and an indirect effect due to an increase in trade participation and consequent productivity gains. Interestingly, these gains flow primarily to the most efficient firms, which are most likely to trade. Therefore, trade liberalization also enhances aggregate productivity by endogenously re-allocating production to more efficient firms.

The mechanism of our model is based on input liberalization increasing the input price benefit of direct importing, which to our knowledge has not been explicitly modelled in previous work. One reason that input prices have received less attention in the literature as an incentive to import is that they are rarely directly measured. We surmount this obstacle by proposing an approach to recover the firm-level productivity and input prices that extends the methodology developed in Grieco et al. (2016) to the multiple-market case with endogenous input quality choice. We find that the recovered input prices and productivity are indeed impacted by trade participation decisions. In order to evaluate the long-term gains from trade participation, we then estimate a model of dynamic import and export decisions. Using a dataset of Chinese paint manufacturers from 2000 to 2006, we find that firms gain from trade through both increased productivity and reduced input prices. The gains from both channels are of similar orders of magnitude, with a stronger effect from the input price channel.

Several features of the Chinese paint manufacturing industry fit our modelling choices well. In particular, it is an industry with significant trade, a straightforward production process, and a clear link between input quality and output quality. That said, many of the insights from this article are likely to extend to other Chinese and developing world manufacturers. Many industries are like the paint industry in that materials inputs account for a large proportion of costs, inputs are typically sourced from high-technology countries and can be imported directly or through middlemen, and firms face significant fixed and sunk costs to participate in trade directly. These are the essential features that underlie our results that an import tariff liberalization, by increasing firms’ incentive to trade, can lead to a compounding effect on firm and aggregate efficiency. This sort of amplification represents a dynamic gain from trade that cannot be captured by static trade models.

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Appendices

A Derivations

Deriving the Demand Function from Consumer Utility

This appendix derives the demand function, (2) and (3). Consider the utility maximization problem of the representative consumer in market $m \in \{X, D\}$,

$$\begin{aligned} \max_{Q_{0t}^m, Q_{1t}^m, \dots, Q_{J_t^m}^m} & \left[\sum_{j=0}^{J_t^m} (\Phi_{jt}^* Q_{jt}^m)^{\frac{1+\eta_m}{\eta_m}} \right]^{\frac{\eta_m}{1+\eta_m}} \\ \text{subject to:} & \sum_{j=0}^{J_t^m} P_{jt}^m Q_{jt}^m = Y_t^m, \end{aligned} \quad (\text{A.1})$$

where Y_t^m is the income of the consumer in market m , and we use $j = 0$ to represent the outside good. The first order condition with respect to good j in market m is,

$$(Q_{jt}^m)^{\frac{1}{\eta_m}} (\Phi_{jt}^*)^{\frac{1+\eta_m}{\eta_m}} \left[\sum_{j=0}^{J_t^m} (\Phi_{jt}^* Q_{jt}^m)^{\frac{1+\eta_m}{\eta_m}} \right]^{\frac{\eta_m}{1+\eta_m} - 1} = \lambda^m P_{jt}^m, \text{ for all } j \in \{0, 1, \dots, J_t^m\}. \quad (\text{A.2})$$

where λ^m is the Lagrange multiplier associated with the budget constraint. Dividing the FOC for product j over that for the outside good 0 yields,

$$Q_{jt}^m = \frac{(P_{jt}^m)^{\eta_m}}{(\Phi_{jt}^*)^{1+\eta_m}} \frac{(\Phi_{0t}^*)^{1+\eta_m}}{(P_{0t}^m)^{\eta_m}} Q_{0t}^m. \quad (\text{A.3})$$

Multiplying both sides of the above equation by P_{jt}^m and summing across all products $j \in \{0, 1, \dots, J_t^m\}$ yields total expenditure,

$$Y_t^m = \sum_{j=0}^{J_t^m} P_{jt}^m Q_{jt}^m = \frac{(\Phi_{0t}^*)^{1+\eta_m}}{(P_{0t}^m)^{\eta_m}} Q_{0t}^m \sum_{j=0}^{J_t^m} \left(\frac{P_{jt}^m}{\Phi_{jt}^*} \right)^{1+\eta_m}.$$

This equation can be solved for demand for the outside good,

$$Q_{0t}^m = \frac{(P_{0t}^m)^{\eta_m}}{(\Phi_{0t}^*)^{1+\eta_m}} \frac{Y_t^m}{\sum_{j=0}^{J_t^m} \left(\frac{P_{jt}^m}{\Phi_{jt}^*} \right)^{1+\eta_m}} = \frac{(P_{0t}^m)^{\eta_m}}{(\Phi_{0t}^*)^{1+\eta_m}} (C_t^m)^{-\eta_m},$$

where $C_t^m \equiv \left[Y_t^m / \sum_{j=0}^{J_t^m} \left(\frac{P_{jt}^m}{\Phi_{jt}^*} \right)^{1+\eta_m} \right]^{-1/\eta_m}$ is a constant that depends on aggregate expenditure and price index in the market. Plugging the above equation into Eq. (A.3) yields the inverse demand,

$$P_{jt}^m = \Phi_{jt}^* \frac{1+\eta_m}{\eta_m} (Q_{jt}^m)^{\frac{1}{\eta_m}} C_t^m, \quad (\text{A.4})$$

Define $\Phi_{jt} \equiv \Phi_{jt}^* (C_t^D)^{\frac{\eta_D}{1+\eta_D}}$ and $\kappa_t \equiv C_t^X / (C_t^D)^{\frac{\eta_D}{1+\eta_D} \frac{1+\eta_X}{\eta_X}}$, we can rewrite the above inverse demand functions for the domestic and export markets as,

$$P_{jt}^D = \Phi_{jt} \frac{1+\eta_D}{\eta_D} (Q_{jt}^D)^{\frac{1}{\eta_D}}, \quad P_{jt}^X = \kappa_t \Phi_{jt} \frac{1+\eta_X}{\eta_X} (Q_{jt}^X)^{\frac{1}{\eta_X}},$$

which corresponds to (2) and (3) in Section 3.

Profit Maximization: Equivalent Quality-Inclusive Representation

This subsection shows that the profit maximization problem defined in (10) in Section 3 in which firms choose quality-inclusive output is an equivalent representation of firms' original profit maximization problem in which firms choose physical output quantity.

At the beginning of each period, firm j observes its state that includes its productivity, materials and labor input prices, export status, and capital stock, as summarized in $(\Omega_{jt}, P_{Mjt}, P_{Ljt}, e_{jt}, K_{jt})$. The firm's objective is to maximize its period profit in period t given its state, by optimally choosing labor quantity, material input quantity, material input quality, and the quantity of product sold in each market. So the firm's profit maximization problem in its original form is defined as follows,

$$\begin{aligned} & \max_{L_{jt}, M_{jt}, H_{jt}, Q_{jt}^D, Q_{jt}^X, A_{jt}, \Phi_{jt}} P_{jt}^D Q_{jt}^D + e_{jt} P_{jt}^X Q_{jt}^X - P_{Ljt} L_{jt} - \tilde{P}_{Mjt} M_{jt}, \\ & \text{subject to: } P_{jt}^D = \Phi_{jt}^{\frac{1+\eta_D}{\eta_D}} (Q_{jt}^D)^{\frac{1}{\eta_D}}, \\ & P_{jt}^X = \kappa_t \Phi_{jt}^{\frac{1+\eta_X}{\eta_X}} (Q_{jt}^X)^{\frac{1}{\eta_X}}, \\ & Q_{jt}^D + Q_{jt}^X = A_{jt} [\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}}, \\ & A_{jt} \Phi_{jt} = (\Omega_{jt}^\theta + H_{jt}^\theta)^{\frac{1}{\theta}}, \\ & \tilde{P}_{Mjt} = P_{Mjt} H_{jt}^\phi. \end{aligned}$$

Note that the original profit maximization problem is based on the original demand function, (2) and (3), and the original production function (4). The firm chooses its physical quantity of output sold in the domestic and export markets, Q_{jt}^D and Q_{jt}^X , together with inputs to maximize short-term profit. The firm chooses input quality and then may choose how to divide its capability between A_{jt} and Φ_{jt} , following (8) and the definition $\tilde{\Omega} = A_{jt} \Phi_{jt}$. Although formally A_{jt} and Φ_{jt} are choice variables, all combinations of A_{jt} and Φ_{jt} that satisfy the constraints will yield the same level of profit.

To re-write the objective function using the quality-inclusive variables, note that the demand functions (2) and (3) directly imply the revenue functions (6) and (7), and that the original production function (4) is equivalent to the quality-inclusive production function (5). Therefore, making use of the definitions $\tilde{Q}_{jt}^D = \Phi_{jt} Q_{jt}^D$, $\tilde{Q}_{jt}^X = \Phi_{jt} Q_{jt}^X$, and $\tilde{\Omega} = \Phi_{jt} A_{jt}$, we can re-write the problem as:

$$\begin{aligned} & \max_{L_{jt}, M_{jt}, \tilde{Q}_{jt}^D, \tilde{Q}_{jt}^X, H_{jt}} R_{jt}^D + e_{jt} R_{jt}^X - P_{Ljt} L_{jt} - \tilde{P}_{Mjt} M_{jt}, \\ & \text{subject to: } R_{jt}^D = \left(\tilde{Q}_{jt}^D \right)^{\frac{1+\eta_D}{\eta_D}}, \\ & R_{jt}^X = \kappa_t \left(\tilde{Q}_{jt}^X \right)^{\frac{1+\eta_X}{\eta_X}}, \\ & \tilde{Q}_{jt}^D + \tilde{Q}_{jt}^X = \tilde{\Omega}_{jt} [\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}}, \\ & \tilde{\Omega} = (\Omega_{jt}^\theta + H_{jt}^\theta)^{\frac{1}{\theta}}, \\ & \tilde{P}_{Mjt} = P_{Mjt} H_{jt}^\phi. \end{aligned}$$

This is the profit maximization problem defined in (10) in Section 3. Note that we do not include $\tilde{\Omega}_{jt}$ as a choice variable as it is completely determined by the choice of H_{jt} .

Recovering $(\tilde{\Omega}_{jt}, \tilde{P}_{Mjt})$ from Production and Demand Estimates

This appendix recovers the quality-inclusive productivity and input prices, given that the production and demand parameters are estimated.

The static profit maximization problem, as defined in (10), implies five first-order conditions. Specifically, the first order conditions for the firms demanded quantity of labor and materials imply:

$$\mu_{jt} \tilde{\Omega}_{jt} \frac{\partial F}{\partial L_{jt}} L_{jt} = E_{L_{jt}}, \quad (\text{A.5})$$

$$\mu_{jt} \tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt} = E_{M_{jt}}. \quad (\text{A.6})$$

Where μ_{jt} represents the Lagrange multiplier on the production constraint. When a firm sells in both domestic and exporting markets,⁶⁷ the first order conditions with respect to (quality-inclusive) output quantities are,

$$\frac{1 + \eta^D}{\eta^D} (\tilde{Q}_{jt}^D)^{1/\eta^D} - \mu_{jt} = 0, \quad (\text{A.7})$$

$$\kappa_t \frac{1 + \eta^X}{\eta^X} (\tilde{Q}_{jt}^X)^{1/\eta^X} - \mu_{jt} = 0, \quad (\text{A.8})$$

Similarly, the first order condition associated with firms' optimal input quality choice is

$$\frac{\partial \tilde{P}_{M_{jt}}(P_{M_{jt}}, H_{jt})}{\partial H_{jt}} M_{jt} = \mu_{jt} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}. \quad (\text{A.9})$$

Under our assumptions, the system of first order conditions admit a unique solution to firms' optimal static choice $(L_{jt}, M_{jt}, \tilde{Q}_{jt}^D, \tilde{Q}_{jt}^X, H_{jt})$.

Recovering Quality-inclusive Input Prices ($\tilde{P}_{M_{jt}}$)

Given the CES production function, take the ratio of the first-order conditions for labor and materials, (A.5) and (A.6) and after some rearrangement, we get a closed-form solution for material quantity as a function of observables and production parameters, as captured by (18).

Then we can directly compute the quality-inclusive material quantity from (18). Then by following the expenditure identity $E_{M_{jt}} = \tilde{P}_{M_{jt}} M_{jt}$, we can solve the quality inclusive material input prices as

$$\tilde{P}_{M_{jt}} = \frac{E_{M_{jt}}}{M_{jt}}.$$

Recovering Quality-inclusive Productivity ($\tilde{\Omega}_{jt}$)

Next, we show that quality-inclusive productivity $\tilde{\Omega}_{jt}$ can be written as a function of observed variables. By definition, the production function is $\tilde{Q}_{jt} = \tilde{Q}_{jt}^X + \tilde{Q}_{jt}^D = \tilde{\Omega}_{jt} F(L_{jt}, M_{jt}, K_{jt})$. Substitute \tilde{Q}_{jt}^X calculated in (22) into the production function (with material quantity replaced by (18)), and we have,

$$\left(\frac{1}{\kappa_t} \frac{\eta^X}{\eta^D} \frac{1 + \eta^D}{1 + \eta^X} \right)^{\eta^X} \times (\tilde{Q}_{jt}^D)^{\eta^X/\eta^D} + \tilde{Q}_{jt}^D = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^\gamma \left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}} \right) + \alpha_K K_{jt}^\gamma \right]^{\frac{1}{\gamma}}. \quad (\text{A.10})$$

This provides us with one equation relating the two unknown variables $(\tilde{Q}_{jt}^D, \tilde{\Omega}_{jt})$. The first order condition of optimal labor choice provides us another. Substituting the first order condition associated with Q_{jt}^D defined in (A.7) into that for labor, yields,

$$\frac{1 + \eta^D}{\eta^D} (\tilde{Q}_{jt}^D)^{1/\eta^D} \alpha_L L_{jt}^{\gamma-1} \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^\gamma \left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}} \right) + \alpha_K K_{jt}^\gamma \right]^{\frac{1}{\gamma}-1} = P_{L_{jt}}. \quad (\text{A.11})$$

It is straightforward to show that (A.10) and (A.11) admit a unique solution of $(\tilde{Q}_{jt}^D, \tilde{\Omega}_{jt})$ as long as $\eta^D, \eta^X < -1$. That is, (A.10) and (A.11) imply an one-to-one mapping from the observable variables

⁶⁷When a firm sells only domestically, the case degenerates to the one-market case discussed in Grieco et al. (2016), and the only difference is that we do not have equation (A.8).

to $(\tilde{Q}_{jt}^D, \tilde{\Omega}_{jt})$ given model parameters, which consequently can be written as a unique implicit function of observables given model parameters. The counterpart of (A.10) and (A.11) is (7) in Grieco et al. (2016). Finally, \tilde{Q}_{jt}^X is also recovered from (22) as a function of observables. Therefore, we have shown that we are able to recover $(\tilde{M}_{jt}, \tilde{P}_{M_{jt}}, \tilde{Q}_{jt}^D, \tilde{Q}_{jt}^X, \tilde{\Omega}_{jt})$ uniquely from the observable data $(E_{L_{jt}}, E_{M_{jt}}, L_{jt}, K_{jt}, R_{jt}^D, R_{jt}^X)$ up to parameters to be estimated.

Deriving Optimal Quality (h_{jt})

This appendix section derives the solution for optimal quality choice. Specifically we solve for μ_{jt} from the material choice first order condition (A.6),

$$\mu_{jt} = \frac{E_{M_{jt}}}{\tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt}}.$$

To begin, substitute into the quality choice first order condition (A.9) to replace μ_{jt} , we have

$$\frac{\partial \tilde{P}_{M_{jt}}(P_{M_{jt}}, H_{jt})}{\partial H_{jt}} M_{jt} = \frac{E_{M_{jt}}}{\tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt}} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}. \quad (\text{A.12})$$

Given the CES production function, $\tilde{P}_{M_{jt}} = P_{M_{jt}} H_{jt}^\phi$, and $\tilde{\Omega}_{jt} = (\Omega_{jt}^\theta + H_{jt}^\theta)^{\frac{1}{\theta}}$, we have

$$\phi P_{M_{jt}} H_{jt}^{\phi-1} M_{jt} = \frac{E_{M_{jt}}}{\tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt}} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}.$$

Multiplying both sides by H_{jt} yields,

$$\phi \tilde{P}_{M_{jt}} M_{jt} = \frac{E_{M_{jt}}}{\tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt}} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}.$$

Using the definition $E_{M_{jt}} = \tilde{P}_{M_{jt}} M_{jt}$ and cancel $E_{M_{jt}}$ on both sides we have

$$\phi \sigma_{M_{jt}} = \frac{H_{jt}}{\tilde{\Omega}_{jt}} \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}} = \frac{H_{jt}^\theta}{\Omega_{jt}^\theta + H_{jt}^\theta} \quad (\text{A.13})$$

where $\sigma_{M_{jt}} = \frac{\partial F}{\partial M_{jt}} \frac{M_{jt}}{F(\cdot)}$ is the output elasticity of material, and the second equality holds given the functional form of $\tilde{\Omega}_{jt}$ defined in (8). After some algebra based on (A.13), we can derive a closed-form relation between endogenous input quality choice and productivity in (24).

B Forward-simulation-based Dynamic Estimation

This appendix explains the details of how we implement a forward-simulation-based CCP approach in the dynamic estimation, in order to solve the high-dimension state-space problem.

Approximation of Period Profits

The firm's period-profit maximization problem does not have a close form solution. This poses a computational challenge for the forward simulation process in the dynamic estimation procedure, which must compute period profits for many potential values of the high-dimensional dynamic state. To address this, we approximate the profit function using multivariate adaptive regression splines (MARS) proposed by Friedman (1991, 1993). This procedure solves the profit function for a subset of points and uses these points to approximate the function over the entire state space. To balance the computational burden and accuracy of the approximation, we choose this subset of points by using the epsilon distinguishable set (EDS)

technique developed by Judd et al. (2012) and Maliar and Maliar (2015). The EDS is constructed from the pre-simulated paths of the state. Whereas Judd et al. (2012) and Maliar and Maliar (2015) use the EDS technique for approximating the ergodic state set and computing the value function on the ergodic set, we employ the EDS technique to efficiently reduce the size of the training points in the approximation of the period profit function. This function returns an approximated profit for any possible states in the forward simulation paths (rather than the states in the EDS only). This appendix describes our approximation procedure.

Construction of EDS

The epsilon distinguishable set (EDS) method was initially developed to combine the advantages of both stochastic simulation and projection for approximating dynamic programming problems.⁶⁸ The basic idea is to construct the EDS based on the simulated path of data and solve the value function exactly on the points in EDS. Its major advantage lies in that its grid set is based on the simulated path and excluding those points never potentially been visited in the simulation. At the same time, the EDS points are roughly evenly distributed. As a result, it largely saves computation time, especially when the dimension is high.

Because we are estimating the dynamic parameters using forward simulation, we do not use EDS to solve the value function on the EDS set; instead, our purpose is simply to approximate the period profit function economically so that we can compute period profits for any possible state in the forward simulation paths. For this purpose, we construct the EDS as follows:

1. Massively simulate N paths of state variables starting from the data points, using the CCP function estimated from the data. Denote the set of the simulated states as A . A can be thought of as an approximation of the ergodic set for these state variables in this problem. In our implementation, set A contains about 25 million points in the state space.
2. Normalize and orthogonalize the simulated states set A using principal component transformation, so that the measurement unit and correlation among state variables do not affect the measurement of Euclidean distance between points in set A .
3. Construct an appropriate domain of state-space upon which we approximate the period profit function. In order to achieve a high level of approximation accuracy (given computational power), we trim the points near the edge of set A (which are less likely to be visited by simulated paths) to obtain the domain. Specifically, we compute the Euclidean distance between each point of A and the center of A and drop the points that are further than the ι quantile of distance from the center. We call the resulting set A^ι .⁶⁹
4. Because the points in A^ι is still too dense to implement MARS, we construct a subset $P^\epsilon \subset A^\iota$, to further reduce the computational burden. P^ϵ is an EDS because the distance of any pair of points is larger than or equal to ϵ . We construct P^ϵ from the domain A^ι as follows
 - (a) Starting with $P^\epsilon = \emptyset$.
 - (b) Select one point $x_i \in A^\iota$. Compute its distance to all other points $x_j \in A^\iota$, denoted the distance as $D(x_i, x_j)$.
 - (c) Eliminate all x_j such that $D(x_i, x_j) < \epsilon$ from the domain A^ι , and use this smaller set to replace A^ι .
 - (d) Add x_i into P^ϵ .
 - (e) Iterate between (b)-(d) until all points are eliminated from A^ι .
5. Remove the effect of normalization and orthogonalization using the inverse of the Principal Component transformation in step 2, to recover the EDS to the initial measurement units in the data.

⁶⁸For details, see Judd et al. (2012).

⁶⁹An alternative strategy is to estimate the kernel density function of points in A and drop those points that are with a low density (according to the estimated density function). However, given MARS uses continuous splines for approximation (specifically, the MATLAB package ‘‘ARESLab’’ that we adopt uses piecewise-linear and piecewise-cubic splines), we prefer the distance-based trimming to keep the domain convex.

In our implementation, we set ι to be 0.8 such that the domain of A^ι covers an average of 94% of the states in any given simulation path. We set ϵ to be 0.028, which yields a P^ϵ of 15,852 training points on which to apply the MARS approximation. We found that increasing ι or decreasing ϵ substantially increased the number of points in P^ϵ (and consequently approximation time) without substantially improving performance as measured by out-of-sample R^2 of the MARS approximation discussed below, which is already reasonably high (0.89) for the given value of (ι, ϵ) .

Approximation using MARS

Once the EDS P^ϵ is obtained, we solve the period profit maximization problem to obtain the associated period profit on each point in P^ϵ . In particular, we solve the maximization problem with multiple initial guesses to make sure the profit is solved accurately.

The profit and the EDS form a training pair, $(P^\epsilon, \pi(P^\epsilon))$, that we can use to approximate the profit function. Among many possible approximation methods, we adopt the MARS method developed by Friedman (1991, 1993). A recent empirical implementation is Barwick and Pathak (2015), in which the author uses MARS to find an appropriate set of basis functions for value function approximation. In our article, we utilize it to approximate the period profit function. Essentially, MARS is a form of stepwise linear regression that is designed to take a high-dimensional state as the input and can deal with non-linearities. The methodology of MARS is to repeatedly split the state space with added spline terms in order to improve the fitness according to some criterion function until the marginal improvement of the fit is below a threshold.

In our implementation, we use the MATLAB package “ARESLab”, which is a Matlab/Octave toolbox developed by Gints Jekabsons for building piecewise-linear and piecewise-cubic regression models using the MARS method. We have a total of 15,852 training points on a 5-dimensional state space. We end up with a MARS model with 31 splines (i.e., base functions), which approximates the profit function on the training points with a R^2 of 0.99. We also test the out-of-sample fit using simulated paths of the states, and we find that the approximation reaches a R^2 of 0.89.

Forward Simulation of the Value Function

The observed state space includes four continuous variables and two binary choice variables of import and export decisions. Because the profit function can be estimated beforehand using static information, the rest of the task is to estimate the parameters in the trade cost function, vector λ .

We summarize the estimation procedure briefly as follows:

1. Inputs to the dynamic model include:
 - (a) Estimate the conditional probability (CCP) (28) using a flexible bivariate probit model, as an approximate to the policy functions of import and export. CCP will be one input to the dynamic model.
 - (b) Estimate the state transition probability function (density function): $f(s_{jt+1}|s_{jt}, ie_{jt})$. This can be done by estimating the transition function of state variables first, and then compute the density function.
 - (c) Profit function.
 - (d) Data: $(\omega_{jt}, k_{jt}, P_{Mjt}, P_{Ljt}, ie_{jt}, ie_{jt+1}, \text{WTO dummy})$.

2. Forward simulation based on the estimated CCP.

In order to forward-simulate the choice-specific value function, we need to know the exact choice of firms after observing their cost shock and state. There is a one-to-one mapping between the states and choices by assumption. Given each state, we “draw” the endogenous choice action from the CCP estimated above, and then compute the conditional cost shock to simulate a path of optimal choice for each firm.

Specifically, we estimate the choice-specific value $V^\xi(s_{jt}|ie_{jt+1}; \lambda)$ net of fixed/sunk costs for any choice ie_{jt+1} (optimal or not), which is defined in (30) as $V^\xi(s_{jt}|ie_{jt+1}; \lambda) \equiv V^\xi(s_{jt}, \xi_{jt}|ie_{jt+1}; \lambda) - \lambda_\xi \xi_{jt}$. It is the choice-specific value, net of current period fixed costs shocks, ξ_{jt} .

Given our additively-separable assumption of cost shocks in the net payoff function, the net choice-specific function can be written as

$$\begin{aligned}
V^\xi(s_{jt}|ie_{jt+1}; \lambda) &= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) \\
&+ \delta E_{s_{jt+1}|s_{jt}, ie_{jt+1}} E_{ie_{jt+2}|s_{jt+1}} E_{\xi_{jt+1}|s_{jt+1}, ie_{jt+2}} \left\{ \pi(s_{jt+1}) - C(ie_{jt+2}, ie_{jt+1}; \lambda) + \lambda_\xi \xi_{jt+1} \right. \\
&+ \delta E_{s_{jt+2}|s_{jt+1}, ie_{jt+2}} E_{ie_{jt+3}|s_{jt+1}} E_{\xi_{jt+2}|s_{jt+2}, ie_{jt+3}} \left[\pi(s_{jt+2}) - C(ie_{jt+3}, ie_{jt+2}; \lambda) + \lambda_\xi \xi_{jt+2} \right. \\
&\left. \left. \left. + \dots \right] \right\} \tag{B.1}
\end{aligned}$$

The three integrations can be easily taken care of under our assumption. The first is the evolution of state, and the second is the CCP. The third conditional expected cost has closed form solution due to the logit assumption of the cost shocks ξ_{ie} , with

$$E(\xi_{jt}|s_{jt}, ie_{jt+1}) = \gamma - \ln(\Pr(ie_{jt+1}|s_{jt})). \tag{B.2}$$

Given any starting state and choice (s_{jt}, ie_{jt+1}) , we can simulate a path of T periods to approximate the above net-choice-specific value function. Specifically, we proceed as follows:

- Draw the innovations for the state variables, $(\epsilon_{jt+1}^\omega, \epsilon_{jt+1}^{PM}, \epsilon_{jt+1}^{PL})$. (Note: we can draw it for all T periods once for all j , because they are independent over time and across firms).
 - Update to state s_{jt+1} (taking care of the first integration $E_{s_{jt+1}|s_t, ie_{jt+1}}$).
 - Compute the net period payoff (excluding cost shock) $\pi(s_{jt}, ie_{jt+1}) - C(ie_{jt+1}, ie_{jt}; \lambda)$.
- Given the state s_{jt+1} , draw an action ie_{jt+2} from the estimated CCP (taking care of the second integration $E_{ie_{jt+1}|s_{jt+1}}$).
- Use the drawn action ie_{jt+2} and updated state s_{jt+1} to compute the conditional expectation of trade costs, given that ie_{jt+2} is chosen. It is already shown that $E(\xi_{jt+1}|s_{jt+1}, ie_{jt+2}) = \gamma - \ln(\Pr(ie_{jt+2}|s_{jt+1}))$ (taking care of the third integration).
- Update state to s_{jt+2} using the drawn (1) ie_{jt+2} , (2) associated s_{jt+1} , and (3) $(\epsilon_{jt+2}^\omega, \epsilon_{jt+2}^{PM}, \epsilon_{jt+2}^{PL})$. Continue the above procedure until T periods.

The generated approximate of net-choice-specific value function for this particular path n conditional on model parameter λ is

$$\begin{aligned}
V^\xi(s_{jt}|ie_{jt+1}; \lambda) &= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) \\
&+ \delta \left[\pi(s_{jt+1}) - C(ie_{jt+2}, ie_{jt+1}; \lambda) + \lambda_\xi (\gamma - \ln(\Pr(ie_{jt+2}|s_{jt+1}))) \right] + \\
&+ \delta \left[\pi(s_{jt+2}) - C(ie_{jt+3}, ie_{jt+2}; \lambda) + \lambda_\xi (\gamma - \ln(\Pr(ie_{jt+3}|s_{jt+2}))) \right] + \dots \\
&+ \delta \left[\pi(s_{jt+T}) - C(ie_{jt+T+1}, ie_{jt+T}; \lambda) + \lambda_\xi (\gamma - \ln(\Pr(ie_{jt+T+1}|s_{jt+T}))) \right] \Big] \Big] \\
&= \sum_{\tau=0}^T \delta^\tau \pi(s_{jt+\tau}) - \sum_{\tau=0}^T \delta^\tau \left[C(ie_{jt+\tau+1}, ie_{jt+\tau}; \lambda) \right] \\
&\quad + \lambda_\xi \sum_{\tau=1}^T \delta^\tau \left[\gamma - \ln(\Pr(ie_{jt+\tau}|s_{jt+\tau})) \right] \tag{B.3}
\end{aligned}$$

The first term summarizes the component of firm value from profit; the second term refers to the deterministic part of the trade cost; the last term is due to the trade cost shocks conditional on

the path of trade status. The parameters of interest in the dynamic estimation include λ , which are buried in the cost function. Under the linear-in-parameter assumption in the cost function, we can split the cost function, and henceforth the net choice-specific value function, into a parameter term and a term free of parameters. As a result, we only need to simulate once—when we iterate over parameters, we do not have to simulate the model again. Specifically, plugging the cost function defined in Eq. (14) we can rearrange the above net choice-specific value, by separating parameters and simulated data, as follows,

$$V^\xi(s_{jt}|ie_{jt+1}; \lambda) = \sum_{\tau=0}^T \delta^\tau \pi(s_{jt+\tau}) + \Pi' \lambda, \quad (\text{B.4})$$

where λ is the column vector of parameters of interest, and the column vector Π can be computed from the simulation directly,

$$\Pi = \left(\sum_{\tau=0}^T \delta^\tau CIE_{jt+\tau}, - \sum_{\tau=1}^T \delta^\tau [\gamma - \ln(\Pr(i_{e_{jt+\tau}}|s_{jt+\tau}))] \right)'. \quad (\text{B.5})$$

The collection of trade status $CIE_{jt+\tau}$ is:

$$CIE_{jt+\tau} = \left[I_{00,01}, I_{00,10}, I_{00,11}, I_{10,01}, I_{10,10}, I_{10,11}, I_{01,01}, I_{01,10}, I_{01,11}, I_{11,01}, I_{11,10}, I_{11,11} \right]$$

which determines what trade costs the firm should pay.

We simulate the model for N paths for each firm following the above procedure, use n to represent each simulation, and use $V_n^\xi(s_{jt}|ie_{jt+1}; \lambda)$ to record the value in each simulation. The generated approximated net-choice-specific value function can be formed as follows

$$\begin{aligned} \bar{V}^\xi(s_{jt}|ie_{jt+1}; \lambda) &= \frac{1}{N} \sum_{n=1}^N V_n^\xi(s_{jt}|ie_{jt+1}; \lambda) \\ &= \frac{1}{N} \sum_{n=1}^N \left(\sum_{\tau=0}^T \delta^\tau \pi(s_{jt+\tau}) + \Pi' \lambda \right) \\ &= \frac{1}{N} \sum_{n=1}^N \left(\sum_{\tau=0}^T \delta^\tau \pi(s_{jt+\tau}) \right) + \left(\frac{1}{N} \sum_{n=1}^N \Pi \right)' \lambda \end{aligned} \quad (\text{B.6})$$

3. Construct the likelihood function. Given $\bar{V}^\xi(s_{jt}|ie_{jt+1})$, and the assumption that the cost shocks are drawn from a Type I extreme distribution, we can construct the model-predicted choice probability as shown in (31), which implies (32). The model parameters, λ can then be estimated via (33).

Figure 1: Densities of quality-inclusive productivity, $\tilde{\omega}$ and fundamental productivity, ω

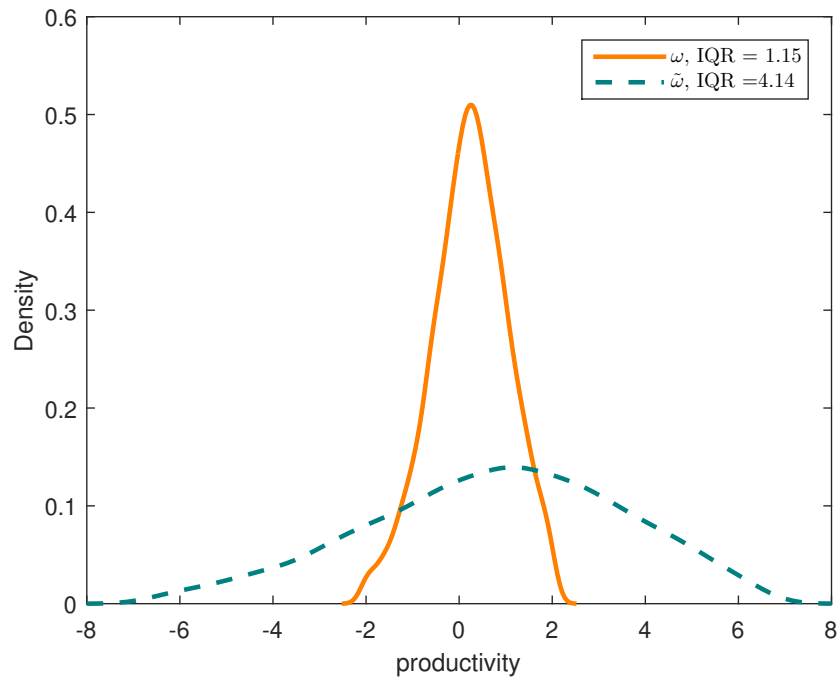


Figure 2: Densities of quality-inclusive prices, \tilde{p}_M and fundamental input prices, p_M

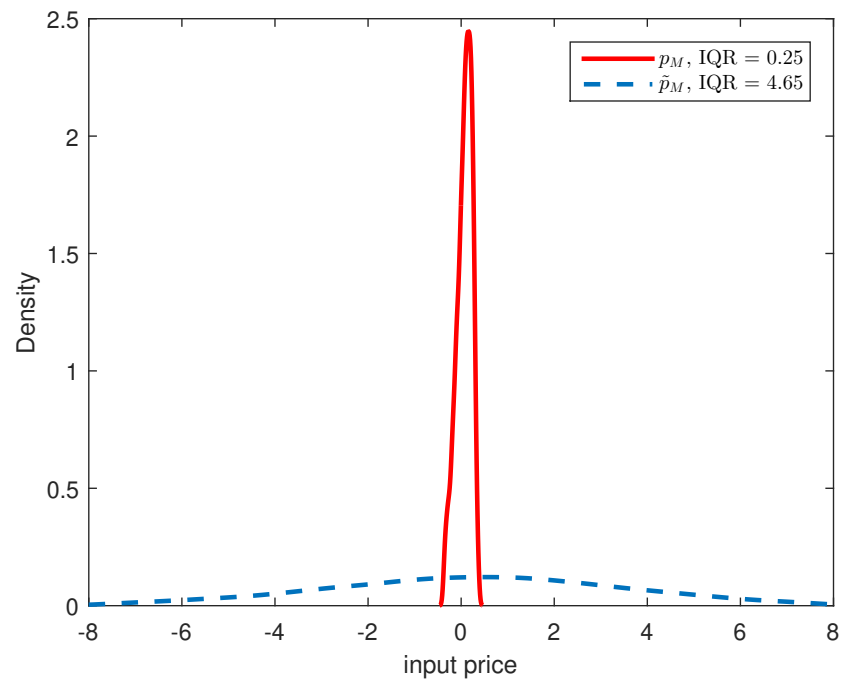


Table 1: Annual Aggregate Statistics (million 2000 USD).

	Overall	Pre-WTO ^a	Post-WTO ^a
Total Sales	5,979	3,203	7,090
Material Expenditure	4,600	2,478	5,449
Wage Expenditure	289	182	332
Capital Stock	1,304	930	1,454
Export Revenue	675	311	820
Import Value ^b	542	232	666
Number of Firms	2,151	837	2,082

^a Pre-WTO years are 2000 and 2001, whereas Post-WTO years is from 2002 to 2006.

^b Import value does not include processing trade with assembly.

Table 2: Largest Import Origins and Export Destinations.

Origins			Destinations		
Country	Value	Share	Country	Value	Share
Taiwan	96	15.7	Hong Kong	112	47.7
Japan	93	15.1	Korea	23	9.9
USA	86	14.1	Japan	11	4.8
Germany	70	11.5	Taiwan	9	3.9
Korea	69	11.2	Vietnam	7	3.2

Note: The value is average by year, in million USD. Share is in percent.

Table 3: Trade before and after WTO Accession (percent).

	Pre-WTO	Post-WTO
Industry Export Share	9.7	11.6
Firm-level Export Share ^{a,b}	34.4	31.8
Export Participation ^a	12.5	12.1
Weighted Export Participation ^c	27.9	36.6
Industry Import Share	9.4	12.2
Firm-level Import Share ^{a,b}	30.5	28.6
Import Participation ^a	12.3	12.3
Weighted Import Participation ^c	32.8	36.0

^a Firms weighted equally. Export shares and export participation are defined based on the firm-reported export activities in the Annual Survey of Industrial Firms. Following Bai et al. (2017), they include both direct exporting and indirect exporting.

^b Shares conditional on participation.

^c Firms weighted by revenue.

Table 4: Labor productivity and trade

	OLS	A-B ^a	OLS	A-B ^a	OLS	A-B ^a
Import ^b	0.773 (0.054)	0.332 (0.220)			0.710 (0.058)	0.352 (0.227)
Export ^b			0.442 (0.053)	-0.090 (0.083)	0.128 (0.055)	-0.095 (0.083)
Lag Labor Prod.		0.136 (0.037)		0.134 (0.037)		0.135 (0.037)
Obs	5029	2880	5029	2880	5029	2880

^a Arellano and Bond (1991) dynamic panel estimator, includes firm fixed effect.

^b Import and export indicators lagged one year.

Dependent variable is log labor productivity. All regressions include year fixed effects. Robust standard errors in parentheses.

Table 5: Production and demand function parameter estimates

parameter	estimate	parameter	estimate
η^D	-7.106 (0.383)	α_M	0.883 (0.001)
η^X	-7.243 (1.322)	α_L	0.054 (0.008)
γ	0.201 (0.057)	α_K	0.063 (0.009)
κ	0.773 (0.376)		

Note: Bootstrap standard errors in parenthesis.

Table 6: Estimates of quality parameters and evolution for ω and p_M

Parameter	I	II	III	IV	V
θ	-0.249 (0.090)	-0.244 (0.080)	-0.250 (0.084)	-0.247 (0.085)	-0.248 (0.082)
ϕ	0.985 (0.008)	0.982 (0.010)	0.986 (0.009)	0.985 (0.009)	0.985 (0.009)
f_0	2.343 (1.948)	2.507 (0.992)	2.343 (1.198)	2.655 (2.520)	2.654 (1.370)
f_e	0.087 (0.050)	0.077 (0.060)	0.087 (0.059)	0.102 (0.045)	0.102 (0.050)
f_i	0.264 (0.055)	0.268 (0.058)	0.263 (0.059)	0.265 (0.055)	0.265 (0.053)
f_{wto}	0.185 (0.048)		0.185 (0.057)		
f_ω	0.640 (0.038)	0.641 (0.041)	0.640 (0.052)	0.638 (0.071)	0.638 (0.053)
g_0	0.623 (0.146)	0.655 (0.110)	0.645 (0.104)	0.558 (0.115)	0.578 (0.104)
g_e		-0.006 (0.005)	-0.006 (0.005)		-0.006 (0.005)
g_i		-0.021 (0.005)			
g_{i0}	-0.018 (0.010)		-0.017 (0.010)	-0.015 (0.014)	-0.014 (0.012)
g_{i1}	-0.024 (0.005)		-0.022 (0.005)	-0.025 (0.005)	-0.023 (0.005)
g_{wto}	-0.020 (0.007)		-0.020 (0.007)		
g_p	0.939 (0.010)	0.934 (0.010)	0.937 (0.009)	0.943 (0.010)	0.941 (0.009)
Year dummies	No	No	No	Yes	Yes

Note: Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Table 5.

Table 7: Olley-Pakes Decomposition of Aggregate Productivity and Input Price Level by Year

Year	Productivity			Input Price		
	Weighted	Unweighted	Cov.	Weighted	Unweighted	Cov.
2000	1.00	0.82	0.18	1.00	1.29	-0.29
2001	0.92	0.64	0.28	1.01	1.32	-0.31
2002	1.00	0.69	0.31	1.02	1.30	-0.28
2003	1.19	0.72	0.47	0.97	1.28	-0.31
2004	1.45	0.73	0.73	0.99	1.30	-0.31
2005	1.30	0.80	0.49	0.96	1.29	-0.32
2006	1.64	1.04	0.60	0.92	1.25	-0.33

Table 8: Conditional choice of export and import probability estimates

	Import		Export
ψ_0^i	0.637 (2.433)	ψ_0^e	4.137 (2.281)
ψ_e^i	0.598 (0.160)	ψ_e^e	2.558 (0.119)
ψ_i^i	3.299 (0.141)	ψ_i^e	0.780 (0.112)
ψ_{ie}^i	0.006 (0.271)	ψ_{ie}^e	-0.451 (0.234)
ψ_ω^i	0.017 (0.061)	ψ_ω^e	0.083 (0.063)
ψ_p^i	-0.317 (0.252)	ψ_p^e	-0.658 (0.224)
ψ_k^i	0.090 (0.058)	ψ_k^e	0.079 (0.065)
ψ_{low}^i	-0.021 (0.126)	ψ_{low}^e	-0.008 (0.103)
ψ_{high}^i	0.230 (0.138)	ψ_{high}^e	-0.081 (0.105)
ψ_{wto}^i	0.082 (0.135)	ψ_{wto}^e	-0.230 (0.106)
ρ	0.207 (0.101)		

Note: Bootstrap standard errors in parenthesis.

Table 9: Mean marginal effects on future trade probability

Next period:	Import	Export
Export	0.063	0.703
Import	0.869	0.100
ω	0.002	0.020
$\ln p_M$	-0.042	-0.166

Note: Marginal effects of productivity and input prices reflect the changes of export and import probabilities after a one-standard-deviation improvement of productivity and input prices, respectively. The effects are averaged over firms actually participating in trade.

Table 10: Estimate of trade cost distribution parameters

Parameter	Estimate	Parameter	Estimate
$\lambda_{00,01}$	5.504 (0.461)	$\lambda_{01,01}$	0.122 (0.114)
$\lambda_{00,10}$	7.113 (0.605)	$\lambda_{01,10}$	5.929 (0.786)
$\lambda_{00,11}$	11.573 (1.017)	$\lambda_{01,11}$	5.927 (0.696)
$\lambda_{10,01}$	4.057 (0.855)	$\lambda_{11,01}$	0.900 (0.427)
$\lambda_{10,10}$	0.161 (0.103)	$\lambda_{11,10}$	0.271 (0.288)
$\lambda_{10,11}$	4.220 (0.567)	$\lambda_{11,11}$	0.079 (0.061)
λ_{ξ}	4.348 (3.699)		

Note: Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6 and 8.

Table 11: Effect of Trade Participation on Productivity and Input Prices

Year	2	5	10	15
Eliminate Productivity Benefit				
Aggregate productivity (percent)	-23.3 (4.7)	-31.4 (6.0)	-32.8 (5.7)	-34.1 (5.5)
Aggregate input price (percent)	0.6 (0.3)	1.1 (0.3)	1.7 (0.4)	2.1 (0.4)
Exporters				
Percentage points	-0.6 (0.3)	-1.3 (0.6)	-2.4 (1.0)	-3.1 (1.3)
Percent	-4.6 (2.0)	-9.5 (3.9)	-15.6 (5.8)	-19.7 (6.9)
Importers				
Percentage points	-0.9 (0.4)	-2.1 (0.9)	-3.8 (1.6)	-5.2 (2.1)
Percent	-7.8 (2.6)	-17.5 (5.1)	-28.4 (7.3)	-35.6 (8.5)
Firm value				
Million USD		-3.5 (0.6)		
Percent		-3.5 (1.2)		
Eliminate Input Price Benefit				
Aggregate productivity (percent)	-4.8 (1.1)	-12.0 (2.4)	-20.0 (3.2)	-24.7 (4.0)
Aggregate input price (percent)	2.5 (0.6)	5.0 (1.4)	7.0 (1.7)	7.6 (1.8)
Exporters				
Percentage points	-0.7 (0.3)	-1.6 (0.7)	-3.2 (1.3)	-4.4 (1.9)
Percent	-5.5 (2.1)	-11.7 (4.5)	-21.3 (7.2)	-27.6 (8.9)
Importers				
Percentage points	-1.8 (0.6)	-4.0 (1.4)	-6.9 (2.7)	-9.2 (3.7)
Percent	-15.6 (3.9)	-33.4 (7.2)	-51.9 (10.3)	-62.8 (12.1)
Firm value				
Million USD		-5.8 (1.6)		
Percent		-6.0 (2.3)		

Notes: Aggregate productivity and input price rows report the differences in revenue-weighted values between baseline and counterfactual simulations. Exporters and Importers rows report the percentage point difference in trade participation. Valuation is the average difference in firms' present discounted value. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6, 8 and 10.

Table 12: Effect of Liberalization: Reduction in Price-Incentive to Import

Year	2	5	10	15
Full Effect (firms re-optimize decision policy function)				
Aggregate productivity (percent)	1.2 (0.3)	3.4 (0.7)	6.9 (1.1)	9.3 (1.5)
Aggregate input price (percent)	-0.7 (0.2)	-1.5 (0.4)	-2.4 (0.5)	-2.9 (0.5)
Export Participation				
Percentage points	0.2 (0.1)	0.5 (0.2)	1.2 (0.4)	1.7 (0.6)
Percent	1.3 (0.7)	3.9 (1.6)	8.3 (2.9)	11.7 (3.8)
Import Participation				
Percentage points	0.6 (0.2)	1.4 (0.5)	2.5 (0.9)	3.4 (1.3)
Percent	5.3 (1.5)	13.1 (3.2)	23.0 (5.1)	30.7 (6.2)
Firm value				
Million USD		2.1 (0.4)		
Percent		2.2 (0.9)		
Direct Effect (firms do not update decision policy function)				
Aggregate productivity (percent)	1.1 (0.3)	2.2 (0.6)	3.8 (0.7)	4.4 (0.7)
Aggregate input price (percent)	-0.6 (0.2)	-1.3 (0.4)	-1.8 (0.4)	-2.0 (0.4)
Export Participaton				
Percentage points	0.0 (0.0)	0.0 (0.0)	0.1 (0.0)	0.3 (0.1)
Percent	0.0 (0.1)	0.2 (0.2)	0.9 (0.2)	2.0 (0.3)
Import Participation				
Percentage points	0.1 (0.0)	0.2 (0.0)	0.4 (0.1)	0.5 (0.1)
Percent	0.7 (0.2)	1.7 (0.3)	3.3 (0.4)	4.5 (0.5)
Firm value				
Million USD		1.9 (0.4)		
Percent		2.0 (0.8)		

Notes: See Table 11 for output variable descriptions. The first panel reports the overall impact of the change in the incentive to import due to WTO accession. The second panel reports the direct effect of the incentive change by simulating the model where firms' to not re-optimize policy functions in response to the incentive change. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6, 8 and 10.

Table 13: Decomposition of Change of Productivity and Input Price Level

	5 Years			15 Years		
	Weighted	Unweighted	Cov.	Weighted	Unweighted	Cov.
Productivity	3.4 (0.7)	0.6 (0.2)	2.8 (0.6)	9.3 (1.5)	3.0 (0.9)	6.3 (0.8)
Input Price	-1.5 (0.4)	-0.4 (0.1)	-1.1 (0.3)	-2.9 (0.5)	-1.5 (0.5)	-1.4 (0.3)

Notes: Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6, 8 and 10.

Table 14: Effect of WTO Accession Price-Incentive to Import (by Firm Type of Productivity and Input Prices, 5 Years)

	Overall	Low ω	High ω	Low p_M	High p_M
Aggregate productivity (percent)	1.5 (0.3)	1.0 (0.3)	1.6 (0.3)	1.6 (0.3)	0.5 (0.3)
Aggregate input price (percent)	-1.0 (0.2)	-0.5 (0.1)	-1.2 (0.2)	-1.1 (0.2)	-0.2 (0.1)
Export Participation					
Percentage points	0.5 (0.2)	0.5 (0.2)	0.6 (0.2)	0.7 (0.3)	0.4 (0.2)
Percent	3.9 (1.6)	4.1 (2.1)	3.8 (1.5)	4.0 (1.5)	3.7 (2.2)
Import Participation					
Percentage points	1.4 (0.5)	1.2 (0.5)	1.6 (0.5)	2.0 (0.6)	0.8 (0.5)
Percent	13.1 (3.2)	16.6 (4.3)	11.4 (2.6)	12.8 (2.6)	13.8 (4.8)
Firm value (Million USD)	2.1 (0.4)	1.7 (0.4)	2.4 (0.4)	2.8 (0.4)	1.3 (0.4)

Notes: The groups of firms are defined by their status in the first year of the simulation. For example, the “High ω ” group is the firms with ω higher than the median in the initial year. The numbers reflect the changes compared to the counterfactual where the WTO accession effect on price is removed. Each number is calculated using the with-in-group market share in the first year as the weight within each group. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6, 8 and 10.

Table 15: Effect of WTO Accession Price-Incentive to Import (by Firm Type of Trade, 5 Years)

	Overall	Neither	Export	Import	Both
Aggregate productivity (percent)	1.5 (0.3)	0.6 (0.3)	3.1 (0.8)	2.3 (0.5)	1.5 (0.2)
Aggregate input price (percent)	-1.0 (0.2)	-0.1 (0.1)	-0.6 (0.2)	-2.5 (0.4)	-2.6 (0.4)
Export Participation					
Percentage points	0.5 (0.2)	0.4 (0.2)	1.3 (0.8)	0.5 (0.9)	1.9 (0.5)
Percent	3.9 (1.6)	4.8 (2.8)	3.1 (2.5)	2.1 (2.4)	3.4 (0.7)
Import Participation					
Percentage points	1.4 (0.5)	0.7 (0.5)	3.0 (1.2)	6.0 (1.3)	5.2 (0.7)
Percent	13.1 (3.2)	24.7 (8.0)	31.5 (7.1)	10.0 (1.9)	7.0 (0.8)
Firm value (Million USD)	2.1 (0.4)	1.2 (0.3)	2.2 (0.4)	6.9 (0.7)	9.0 (0.6)

Notes: The groups of firms are defined by their status in the first year of the simulation. The numbers reflect the changes compared to the counterfactual where the WTO accession effect on price is removed. Each number is calculated using the with-in-group market share in the first year as the weight within each group. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters in Tables 5, 6, 8 and 10.