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

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Abstract

We develop a dynamic structural model to analyze the impact of input tariff liberalization on input prices, trading decisions, productivity, and firm performance. While input tariff liberalization directly the affects input price benefits of importing, its impact on trade participation generates indirect benefits through additional channels, such as productivity improvements and complementarity between importing and exporting. To disentangle these effects, our model separately measures importing's effect on intermediate input prices and productivity. We apply the model to examine the reaction of Chinese paint manufacturers to China's accession to the World Trade Organization (WTO). We find a mild short-term effect of input tariff liberalization in the industry. The effect is amplified in the long run by induced trade participation, resulting in even higher aggregate productivity and lower input prices. Overall, this effect increases the average present firm value by 2.3 percent.

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

JEL: *D24, F14, L11*

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1 Introduction

Liberalizing input tariffs lowers prices on foreign-sourced intermediate inputs and encourages importing. If importing raises productivity, then tariff liberalization can improve firm performance both directly through reduced input prices and indirectly by promoting direct importing which increases firm efficiency. Kasahara and Rodrigue (2008) and Kasahara and Lapham (2013) have found importing improves performance using a dynamic model of endogenous importing, but have abstracted away from 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.[1] We examine how liberalization affects productivity and input prices over the short and long run by altering firms incentives to participate in importing. To do so, we must explicitly account for input prices and productivity as separate sources of firm heterogeneity within a dynamic model, since liberalization directly affects input prices (through tariff changes) but is unable to directly change productivity.

We introduce a methodology to explicitly model the input price effects of direct importing in a dynamic model. When input prices are not directly observed, 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 import on input prices and productivity that is essential to understanding the impact of input tariff liberalization. Because input prices are not observed in our data, we develop a method that uses the variation in input shares to jointly recover input prices and productivity accounting for firms' endogenous choice of input quality. This approach is embedded into a structural dynamic model that illustrates the mechanism through which input tariff liberalization improves the performance of importers via reduced input prices, increased trade participation, and improved productivity in the long run.

The 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, we find that direct importing has a causal impact on productivity through exposure to foreign firms. A 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

[1] The effect of liberalization on firm performance in these papers 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 paper, we will focus on productivity improvements resulting from incentives to import directly while controlling for changes in the domestic input market by using information from non-importing firms.

benefits of a tariff reduction. Therefore, if direct importing raises productivity, tariff liberalization can improve firm performance both directly though lower input prices and indirectly by promoting trade and increasing firm efficiency. Moreover, since trading firms tend to be more efficient (Melitz, 2003), liberalization will increase the correlation between output and efficiency, further raising aggregate efficiency.

However, sunk (or startup) costs to trade may inhibit firms from immediately reacting to these incentives after a policy change. The impact of a trade liberalization on trade participation and productivity may take many years to be fully realized. 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, longer run comparisons will have difficulty separately identifying policy impacts from other shocks to the industry. We overcome this challenge by proposing and estimating a dynamic structural model of trade participation that quantifies how reducing imported input prices affects import participation and firm performance over the long-run. To our knowledge, ours is the first dynamic model of trade participation to separately model input prices and productivity as distinct sources of firm heterogeneity. This is important, since the former is directly impacted by tariff liberalization, while the later is not.

To estimate the model, we must overcome the difficulty that our dataset—like many manufacturing datasets—does not include information on intermediate input prices or quality. Extending Grieco et al. (2016), we use firms' optimality conditions implied by our model together with variations in wages and input expenditures to infer materials input prices and total factor productivity. Our approach explicitly controls for firms' endogenous choice of input quality. Given productivity and current input prices, we are able to estimate the impact of trade participation decisions on future productivity and input prices. 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 (through importing) and productivity (through both) by comparing these benefits with the fixed/sunk costs of trade participation. We estimate a flexible specification of fixed and sunk cost of trade participation based on current trade status using the conditional choice probability (CCP) approach (Hotz and Miller, 1993; Hotz et al., 1994).

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 papers do not model the separate impact of tariff liberalization on input prices.[2] 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), as found in our paper. We extend this literature by documenting input price effects as a distinct and important source of gains from tariff liberalization. Our paper 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 on productivity and input prices. 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 2.1 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, an important falsification test of our structural model. 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 modeling input price dispersion and productivity jointly as a scalar Markov process is mis-specified. Third, we analyze the relationship between productivity, input prices and output over the data period. We find that the allocation of output 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

[2] Moreover, 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."

productivity and input price gains over the period were 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.

We illustrate how the model captures the long-run impact of tariff liberalization by examining the effect of China's accession to the WTO. Upon entry into the WTO, import tariffs for paint manufacturing materials fell from around 15 percent in 2000 to 7 percent in 2006. Assuming that middleman importers incompletely pass-through this tariff reduction, we would expect this change to increase the effect of direct importing on input prices. Our model identifies the impact of WTO accession on the wedge in input prices separately from other features of WTO accession. We estimate that the gap between input prices for importing relative to a non-importing firms increased from 1.8 percent to 2.4 percent following WTO accession. In counterfactual analysis, we consider the effect of this decline in input prices conditional on importing holding all other WTO-related effects constant.[3] Initially, the effect on trade participation is mild, after two years, the share of importers has increased only 0.5 percentage points (about 4 percent), however after 15 years, share of importers has increased by 3.0 percentage points (a 23 percent increase). In addition, the increased benefit to importing leads to a 1.4 percentage point (8 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 8.6 percent after 15 years (whereas the 2-year increase is only 1 percent). Interestingly, 73 percent of the increase in aggregate productivity is due to 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. Less productive firms, who are unlikely to undertake trade, are less affected by the policy. On average, long-run profits increased by 2.3 percent (about 2.4 million USD) in response to the policy change.

A key mechanism in our model is that trade liberalization incentivizes firms to initiate trade thereby amplifying the liberalizations direct effect. To get a further sense of the importance of the amplification effect of firms' endogenous trade response on productivity, we compute an alternative counterfactual where we increase the benefit of importing but hold firms' trade participation policies

[3]That is, we ignore possible effects of WTO accession on productivity of firms, or on the input price distribution of non-importers (which could be affected due to import competition). We do this in order to concentrate narrowly on the long run effect of lower imported input prices on trade and productivity.

fixed. Under this scenario, the increase in aggregate productivity is only 3.9 percent (compared to 8.6 percent when endogenous response is allowed). Therefore, more than half of the productivity increase is due to firms endogenous response to the change in import incentives.

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. Our work contributes to the literature on the measurement of productivity and materials access when input prices are not observed, and uses these measurements within a dynamic model of trade decisions. 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 input price variation that utilizes observed output prices, and measures the productivity and markup effects of tariff changes. In a related paper, Brandt et al. (2017) estimate the effect of import tariff liberalization on productivity and markups using industry-level input price deflators in Chinese manufacturing. However, these papers do not explicitly analyze the effect of tariff liberalization on input prices, nor do they distinguish whether tariff liberalization affects the productivity of importers and non-importers differently.[4] Since lower input prices potentially represent a direct incentive to import, we are motivated by these findings to explicitly recover input prices and incorporate them into a dynamic model of trade participation.

Finally, our paper allows for firms to endogenously choose the quality of their inputs, drawing 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.[5] Kugler and Verhoogen (2012) have documented a positive correlation

[4] Brandt 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.

[5] More 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. While both find that tariff reductions induce quality upgrading, they differ on whether high or low productivity traders benefit most from import tariff reduction. Our paper examines the impact of input tariff reduction on all firms, explicitly accounting for their

between between plant size and input prices in a dataset where input prices are observed. They propose a model whereby firms with high productivity endogenously use inputs of higher quality. We draw upon this model to control for unobserved input quality in our own setting.

The following section introduces the data and presents institutional background on Chinese paint manufacturing that guides our modeling 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 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 modeling. 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 direct importing on input prices.

2.1 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

dynamic decision to engage in trade.

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, while Post-WTO years is from 2002 to 2006.

[b] Import value does not include processing trade with assembly.

of 2,151 firms in the Chinese paint industry.

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 Chinese manufacturing, the 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 of input prices could result in a radical change of 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.[6] In contrast, processing trade with assembly is a important feature of

[6] Under 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

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.

2.2 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.[7] In contrast, a wide variety of materials which 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 Appendix A.2.

One key feature of this industry is the strong linkage between input quality and output quality. According to industry expert reports, three factors determine the quality of paint.[8] The first and most important determinant of paint quality is the quality of resin. For example, 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. Use of heavy metals such as lead and other additives can be toxic to human health and have 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

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imported intermediates is much more similar to ordinary trade than processing trade with assembly. In this paper, 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 Appendix A.1 for detailed description of trade types.

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

[8] For 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.

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 price is a (rough) measure of quality, input quality and output quality are positively correlated.[9] 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 fairly flexibly 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.

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. By contrast, the plurality of Chinese exports are sent to Hong Kong, where they are presumably re-exported to both developed and developing countries. 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 producers to find middlemen online to purchase material inputs,[10] besides the traditional local middlemen.

[9] Although 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.

[10] For example, middlemen offer paint inputs on many online platforms such as https://s.1688.com/kq/-BDF8BFDACDBFC1CFD4ADC1CF.html (accessed June 2, 2017).

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.

2.3 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. As shown in Figure 1, 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.[11] 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."[12] 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 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

[11] The 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.

[12] Translated 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).

Figure 1: Average Tariff for Paint Inputs, 2000-2006.

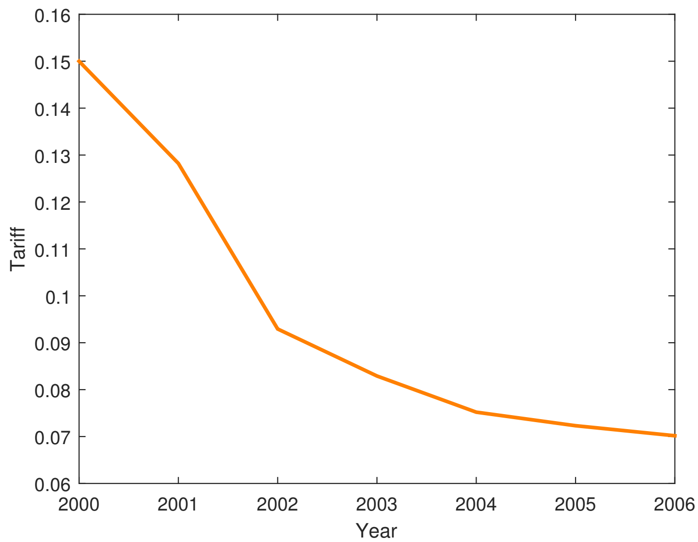


Table 3: Trade before and after WTO Accession (percent).

	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.
[b] Shares conditional on participation.
[c] Firms weighted by revenue.

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 an 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.[13] 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.

[13]Weighting trade participation by expenditures produces very similar results.

For example, there has been a steady improvement in domestic upstream technology which may reduce importing since 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.

2.4 Preliminary Evidence on Trade and Productivity

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 the causal effect on productivity with some researchers finding significant causal effects (e.g., De Loecker, 2007) while others finding none (e.g., Bernard and Jensen, 1999). The heart of this debate lies in potential endogeneity of trade participation—higher productivity firms are more likely to engage in trade.[14] 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.

Table 4 presents a series of regressions of (logged) labor productivity on indicators for importing and exporting. While 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. In contrast, estimates using the Arellano and Bond (1991) estimator, which controls for fixed effects and a lagged dependent variable, produces substantially smaller estimates of the impact of trade and productivity. Indeed, the estimated effect of exporting is essentially zero. The effect of importing, while still economically large, is statistically insignificant. Qualitatively similar results can be found using a fixed effects and Blundell and Bond (2000) estimators.

In contrast to the dynamic panel methods applied to labor productivity in this section, the following sections will employ a structural model to measure and control for total factor productivity. The model will explicitly control for variation in input prices and output quality across firms at the cost of additional assumptions on firm behavior.

[14] While much of this literature has focused on the effects of exporting, a similar argument can be made for importing.

Table 4: Labor productivity and trade

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

3 Model

In this section, we develop a model of firms' decision-making on input, output, import and export, with productivity and input price as two endogenous processes which are influenced by trade participation. To keep the model tractable, we abstract away from endogenous capital investment or entry and exit.[15] 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 labor and material inputs to maximize its current-period profit. As part of this choice, the firm selects an input quality that affects the quality their final product. We assume that labor and material choices are fully flexible from period to period and therefore these choices have no dynamic implications.[16] 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 quality-adjusted input prices and productivity.

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.

[15] Since 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.

[16] The assumption of static labor choices, besides material decisions, 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.

Exporting may affect firms future productivity. Importing also has two distinct effects. If the firm imports in the following period, 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 which drive firms dynamic trade participation decisions.

3.1 Period Profits

3.1.1 Demand and Production Funcitons

In each period t, a firm j produces output, Q_{jt}, which is of some output quality Φ_{jt}. The output quality can depend on the firms' intrinsic ability and their choice of input quality. We assume that goods of higher quality boost demand and so quality-inclusive output is $\tilde{Q}_{jt} = \Phi_{jt} Q_{jt}$.[17] Firms sell their output domestically and, if they are exporters, in a foreign market as well. So the total output equals the sum of domestic and exported quantity , $Q_{jt} = Q^D_{jt} + Q^X_{jt}$. We assume that firms face constant elasticity of demand in both markets, but allow for different demand elasticities and market size in these two markets,

$$\begin{aligned} P^D_{jt} &= (\Phi_{jt} Q^D_{jt})^{1/\eta^D} = (\tilde{Q}^D_{jt})^{1/\eta^D}, \\ P^X_{jt} &= \kappa(\Phi_{jt} Q^X_{jt})^{1/\eta^X} = \kappa(\tilde{Q}^X_{jt})^{1/\eta^X}, \end{aligned} \tag{1}$$

where κ measures the difference in the size of the foreign market compared with the domestic market. We observe domestic and export revenue separately however we do not directly observe output quality. Therefore, we model the production of quality adjusted output while acknowledging that the underlying productivity and input qualities we recover may be either raising physical output Q_{jt} or output quality Φ_{jt}. That is, a more productive firm may either produce more of the same good, or produce the same amount of a good at a higher quality, and our model takes no stance on which

[17] Throughout, we will use a ˜ to denote variables that incorporate the firms endogenous choice of quality.

choice it makes but acknowledges that both lead to an increase in $\tilde{Q}_{jt}$. As a result, the productivity measures we recover in this paper should be understood as revenue-productivity or TFPR as discussed in Foster et al. (2008) and therefore may be interpreted as a combination of demand and cost heterogeneity.[18] The quality-inclusive output is produced according to a (normalized) production function with constant elasticity of substitution (CES):[19]

$$\tilde{Q}_{jt} = \tilde{\Omega}_{jt} F(L_{jt}, M_{jt}, K_{jt}) = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}\right]^{\frac{1}{\gamma}}, \tag{2}$$

where $\alpha_L, \alpha_M, \alpha_K$ are the distribution parameters for labor, material, and capital respectively, which sum up to one by normalization.[20] The elasticity of substitution among inputs, σ, is determined by γ, where $\gamma = \frac{\sigma-1}{\sigma}$. The Hicks-neutral shifter $\tilde{\Omega}_{jt}$ captures output-productivity and output-quality heterogeneity at the firm level, as we explain in the following subsection.

3.1.2 Productivity and Input Quality

A primary goal of this paper is to separate the impact of input price and quality dispersion from other potential sources of productivity differences across firms. Our approach acknowledges the finding of Kugler and Verhoogen (2009, 2012) and others that higher productivity firms tend to use higher quality inputs. 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. In light of this, we assume that $\tilde{\Omega}_{jt}$ is a function of the firm's underlying productivity, Ω_{jt}, and its endogenous choice of input quality, H_{jt}. We adopt the following functional form which allows productivity and input quality to be either substitutes or complements:

$$\tilde{\Omega}_{jt} = \left(\Omega_{jt}^{\theta} + H_{jt}^{\theta}\right)^{\frac{1}{\theta}} \tag{3}$$

This approach follows Kugler and Verhoogen (2009, 2012) in assuming that input quality augments the productivity of all inputs, rather than only augmenting material itself.[21] We believe this

[18] For expositional simplicity, we have chosen to present this heterogeneity as a supply side object, but it does account for firm-level heterogeneity in demand as well.

[19] We normalize the CES production function according to the geometric mean. Specifically, the inputs (labor, material, and capital) are normalized by their corresponding geometric mean, $\sqrt[n]{\Pi X_{jt}}$. The implication is that the geometric means of input variables (L_{jt}, M_{jt}, K_{jt}) in (2) are $\overline{L} = \overline{M} = \overline{K} = 1$. 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.

[20] This production function normalizes returns to scale to be constant. This normalization is needed because we observe only revenue and returns to scale are not separately identified from the demand elasticities.

[21] Note 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,

assumption fits paint manufacturers well, since 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.

3.1.3 Input Price Menu

The variation of unit prices of physical material inputs across firms reflects two sources of heterogeneity: the vertically differentiated in input quality due to the firm's choice of H_{jt}, and a quality-adjusted materials price faced by the firm (P_{Mjt})—which is part of the firm's state. The heterogeneity of the quality-adjusted price index arises from firm characteristics, including the firms current status as an importer, which are determined in the previous period. For example, geographic locations, transportation costs, or the firms network of supplier connections may create differences in input prices. As a result, even when firms choose the same level of input quality, the unit prices they face may still be different. We assume that firms can choose any quality of materials according to the following simple price menu,

$$\tilde{P}_{Mjt} = P_{Mjt} H_{jt}^{\phi}, \tag{4}$$

where $\phi > 0$, reflecting the fact that higher quality inputs are more costly.[22]

Importing does not affect the materials access conditional on P_{Mjt}. Instead, the distribution of P_{Mjt} will be shifted by the decision to participate in importing. This is a convenient way of modeling the the difference between importers and non-importers: non-importers draw from a distribution of quality-adjusted input price indices that is higher in expectation than that of importers. It 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

we restrain ourselves from this more general case, because we can show that this more general case 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.

[22]While 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-adjusted output Q_{jt}.

quality-inclusive unit 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, $\tilde{P}_{Mjt}$ the quality-inclusive unit input price, may be higher.

3.1.4 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 productivity, materials and labor input prices, import and export status, and capital stock. 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. Specifically, the firm solves:

$$\pi(\Omega_{jt}, P_{Mjt}, P_{Ljt}, e_{jt}, K_{jt}) = \tag{5}$$

$$\max_{L_{jt}, M_{jt}, \tilde{Q}_{jt}^D, \tilde{Q}_{jt}^X, H_{jt}} \quad P_{jt}^D \tilde{Q}_{jt}^D + e_{jt} P_{jt}^X \tilde{Q}_{jt}^X - P_{L_{jt}} L_{jt} - \tilde{P}_{Mjt} M_{jt},$$

$$\text{subject to: (1)-(4)}, \tilde{Q}_{jt}^D + e_{jt} \tilde{Q}_{jt}^X = \tilde{Q}_{jt},$$

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.[23] 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 (5) which can be calculated numerically.

3.2 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 material 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.

[23] The 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.

3.2.1 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 though 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,[24]

$$\begin{aligned} \omega_{jt+1} &= f(\omega_{jt}, e_{jt}, i_{jt}, \tau_{t+1}) + \epsilon^{\omega}_{jt+1} \\ &= f_0 + f_{\omega}\omega_{jt} + f_e e_{jt} + f_i i_{jt} + f_{wto}\tau_{t+1} + \epsilon^{\omega}_{jt+1}. \end{aligned} \tag{6}$$

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.[25] Finally, ϵ^{ω}_{jt+1} 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 quality-adjusted materials price index. Compared to the evolution of productivity in which the effects of trade participation are lagged, we assume that importing affects the (quality-adjusted) material input price index in the current period.[26] This assumption is consistent with De Loecker et al. (2016), and captures the idea that while 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 play 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 who 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,[27] the gap between input prices for importers and non-importers will grow after a tariff cut.

[24] We follow the literature in denoting the logarithm of upper case variables as lower case.

[25] We 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.

[26] We 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.

[27] In the presence of local distribution costs or search costs in the importing country, Burstein et al. (2003), Corsetti

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.[28] Specifically, the evolution process of the input price index is:

$$\begin{aligned} p_{Mjt+1} &= g(p_{Mjt}, i_{jt+1}, \tau_{t+1}) + \epsilon^{p}_{jt+1} \\ &= g_0 + g_p p_{Mjt} + g_{i0} i_{jt+1}(1-\tau_{t+1}) + g_{i1} i_{jt+1}\tau_{t+1} + g_{wto}\tau_{t+1} + \epsilon^{p}_{jt+1}, \end{aligned} \tag{7}$$

where ϵ^{p}_{jt+1} 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.

Finally, we allow the wage rate faced by the firm to evolve exogenously as a simple AR(1) process,

$$p_{L_{jt+1}} = \zeta_0 + \zeta_\ell p_{L_{jt}} + \epsilon^{\ell}_{jt+1}. \tag{8}$$

where ϵ^{ℓ}_{jt+1} is a shock to wages.

3.2.2 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 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

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 middleman in China in response to tariff changes.

[28]Ideally, 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 a indicator variable to measure the effect of WTO accession on input prices of importers.

ie_{jt+1} is specified as,

$$C(ie_{jt+1}; ie_{jt}, \xi_{jt}) = C(ie_{jt+1}, ie_{jt}; \lambda) - \lambda_{\epsilon}\xi_{jt}^{ie_{jt+1}} \tag{9}$$
$$= \lambda_{ie_{jt+1}, ie_{jt}} - \lambda_{\epsilon}\xi_{jt}^{ie_{jt+1}}$$

The first term incorporates 16 parameters, $(\lambda_{(0,0),(0,0)}, \ldots, \lambda_{(1,1),(1,1)})$, one for each combination of current and future importing and exporting status. We normalize the mean cost of neither importing nor exporting (regardless of previous status) to zero, $\lambda_{00,ie} = 0$, leaving 12 parameters to estimate. The last term, $\xi_{jt}^{ie_{jt+1}}$, captures idiosynchratic 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.

3.2.3 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 $s_{jt} = (\Omega_{jt}, P_{Mjt}, P_{Ljt}, ie_{jt}, K_{jt})$ and trade cost shocks ξ_{jt}. Denote the beginning-of-period firm value as,

$$\begin{aligned} V_t(s_{jt}, \xi_{jt}) \quad = \quad & \max_{ie_{jt+1}} \{\pi(s_{jt}) - C(ie_{jt+1}; ie_{jt}, \xi_{jt}) + \delta E[V_{t+1}(s_{jt+1}, \xi_{jt+1}) | s_{jt}, ie_{jt+1}]\} \\ & \text{subject to: (6), (7), and (8).} \end{aligned} \tag{10}$$

Where period profits are determined by (5). The expectation is taken over all future shocks, including future trade cost shocks, productivity shocks, input price shocks, and wage rate shocks.

After WTO accession takes place, we assume the problem is stationary. However, for 2000-2001, the years prior to WTO accession, we assume that all firms anticipate that tariff liberalization will occur. 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.

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 parameters of the demand and production functions, recovering the quality-inclusive productivity and input price measures. In this stage, we use firms' labor and materials quantity demand equations to control for unobserved productivity and input prices. Second, we estimate the quality parameters (θ, ϕ) and the transition processes of quality-adjusted productivity and input prices. The key inputs for this stage are the quality-inclusive productivity and input prices from the initial stage. Firms' optimal demand for quality implied by profit maximization leads to a one-to-one relationship between quality-inclusive and quality-adjusted variables. 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.

4.1 Demand and Production Functions

The parameters of the demand and production functions, (1) and (2), are estimated from firm revenues R^D_{jt} and R^X_{jt}, materials and labor expenditure, E_{Mjt}, E_{Ljt}, labor quantity L_{jt} and capital stock K_{jt}. Domestic and export revenue are measured as,

$$\begin{aligned} R^D_{jt} &= \exp(u^D_{jt}) P^D_{jt} \tilde{Q}^D_{jt} = \exp(u^D_{jt}) \left(\tilde{Q}^D_{jt}\right)^{\frac{1+\eta^D}{\eta^D}}, \\ R^X_{jt} &= \exp(u^X_{jt}) e_{jt} P^X_{jt} \tilde{Q}^X_{jt} = \kappa \exp(u^X_{jt}) e_{jt} \left(\tilde{Q}^X_{jt}\right)^{\frac{1+\eta^X}{\eta^X}}, \end{aligned} \tag{11}$$

where (u^D_{jt}, u^X_{jt}) are measurement error and e_{jt} is the export-status indicator. Whereas expenditures are assumed to be perfectly observed,

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

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.[29]

For firms that sell domestically only, revenue as a function of the other observables can be derived

[29] We 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.

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 B. 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:

$$M_{jt} = \left[\frac{\alpha_L E_{Mjt}}{\alpha_M E_{Ljt}}\right]^{\frac{1}{\gamma}} L_{jt}. \tag{12}$$

This equation 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 production function, domestic revenue (in logarithm) for firms that sell only to the domestic market is,

$$r^D_{jt} = \log\left(\frac{\eta^D}{1+\eta^D}\right) + \log\left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right] + u^D_{jt}. \tag{13}$$

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,

$$\alpha_L + \alpha_M + \alpha_K = 1. \tag{14}$$

The second constraint arises from the aggregate implication of (12). Taking its geometric mean over all firms and years leads to:

$$\frac{\overline{E}_L}{\overline{E}_M} = \frac{\alpha_L}{\alpha_M}, \tag{15}$$

where $\overline{E}_L$ and $\overline{E}_M$ are the geometric mean of labor expenditure and material expenditure across firms and years, respectively.[30] We estimate (13) using non-linear least square (NLLS) with constraints (14) and (15) using data from firms that sell only domestically.

Next, we turn to 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 (B.3) and (B.4) in Appendix B—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,

$$\tilde{Q}^X_{jt} = \left(\frac{1}{\kappa}\frac{\eta^X}{\eta^D}\frac{1+\eta^D}{1+\eta^X}\right)^{\eta^X} (\tilde{Q}^D_{jt})^{\eta^X/\eta^D}. \tag{16}$$

[30] This equation can be derived by taking the geometric mean of (12) over all observations. Given the normalization of our production function discussed in Footnote 19, the geometric mean of L_{jt} and that of M_{jt} both equal to one.

Using this relationship and (11) we can express export (log) revenue in terms of their domestic revenue.[31] Taking logarithms, and using our estimate of $\hat{\eta}^D$ from (13), we arrive at the estimating equation,

$$r_{jt}^X = -\eta^X \ln \kappa + (1+\eta^X)\log\left(\frac{\eta^X}{\hat{\eta}^D}\frac{1+\hat{\eta}^D}{1+\eta^X}\right) + \frac{1+\eta^X}{1+\hat{\eta}^D} r_{jt}^D + u_{jt}. \tag{17}$$

where $u_{jt} = (u_{jt}^X - \frac{1+\eta^X}{1+\hat{\eta}^D} u_{jt}^D)$ is the composite error term. Since u_{jt} is correlated with r_{jt}^D through u_{jt}^D, we estimate (17) 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 contemporaneous measurement error.

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. While 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. Within the paint industry, the role of labor and mixers in promoting 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 16).

On the demand side, we find that the foreign market is slightly more elastic than the domestic market. Although in both markets we expect markups between 10 and 20 percent, which are common in the literature. We have investigated whether the elasticity of demand in the export market has changed following WTO accession, but have found little difference between the pre- and

[31] Here we implicitly drop e_{ij} since it equals 1 for all exporters by definition.

Table 5: Production and demand function parameter estimates

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

Note: Bootstrap standard errors in parenthesis.

post-WTO period.[32]

After all production and demand 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.[33] While 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. As suggested by our model, we find a positive and strongly significant relationship ($\rho = 0.111$, p-value = .001).[34] While the correlation is not extremely strong, 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 since the unit price of imports is not used to construct $\tilde{P}_{Mjt}$, which instead relies on wages and labor and materials input expenditure.

4.2 Quality Parameters and Processes for Productivity and Input Prices

We make use of the optimization conditions of firms' input *quality* choice to estimate the quality parameters, (θ, ϕ), and the transition processes for quality adjusted productivity and input prices. This enables us to recover the underlying productivity and input price indices that are purged of firms' endogenous quality choice.

The key to this estimation step is establishing a one-to-one mapping between the quality-inclusive productivity and input prices recovered in the previous step and the quality-adjusted productivity and input prices that are the firms' state variables. Combining the first order conditions of material

[32]Specifically, when we split the sample into pre and post WTO periods, the estimate of export elasticity in the pre-WTO period is -6.817 with the standard deviation as 2.190 while the post-WTO estimate is -6.869 with the standard deviation as 1.049.

[33]The details of solving for $(\tilde{P}_{Mjt}, \tilde{\Omega}_{jt})$ are provided in Appendix B.

[34]In practice, we run this correlation in logarithms to be consistent with how prices are employed within the dynamic model.

choice and quality choice, as shown in Appendix C, we can derive a closed-form relation between input quality and (quality-adjusted) productivity:

$$h_{jt} \quad = \quad \frac{1}{\theta} \ln \frac{\phi\sigma_{Mjt}}{1-\phi\sigma_{Mjt}} + \omega_{jt}, \tag{18}$$

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 (18) into (3) and take logarithms to find the relationship between quality-inclusive productivity and quality-adjusted productivity,

$$\omega_{jt} = \tilde{\omega}_{jt} + \frac{1}{\theta} \ln(1 - \phi\sigma_{Mjt}). \tag{19}$$

The quality adjusted price index can be found by utilizing the price menu function (4) directly,

$$\begin{aligned} p_{Mjt} \quad &= \quad \tilde{p}_{Mjt} - \phi h_{jt} \\ &= \quad \tilde{p}_{Mjt} - \phi \cdot \left[\tilde{\omega}_{jt} + \frac{1}{\theta} \ln(\phi\sigma_{Mjt})\right]. \end{aligned} \tag{20}$$

Where the final equality comes from substituting (19) into (18). 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 parameters that have already been estimated: $\tilde{\omega}_{jt}, \tilde{p}_{Mjt}$ and σ_{Mjt}. We rely on 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 (6) and (7) via GMM:

$$E[Z_{jt} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1})] = 0, \tag{21}$$

where $\epsilon^{\omega}_{jt+1} = \omega_{jt+1} - f(\omega_{jt}, e_{jt}, i_{jt}, \tau_{t+1})$ and $\epsilon^{p}_{jt+1} = p_{Mjt+1} - g(p_{Mjt}, i_{jt+1}, \tau_{t+1})$. 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 $Z_{jt} = (\log(K_{jt}), X_{jt-1}, \sigma_{M_{jt-1}}, ie_{jt}, \tau_t, ie_{jt}\tau_t)$ where X_{jt-1} contains the logarithm of $K_{jt-1}, E_{Mjt-1}, E_{Ljt-1}$ up to second-order interactions.[35]

Parameter Estimates. Table 6 presents the estimation results for several alternative specifications of the transition processes.[36] 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 specifications, confirming that firms pay more for inputs of higher quality.

The second panel of Table 6 reports our estimates of the productivity transition processes. The results indicate that the effect of exporting on productivity is positive and significant. Exporting increases the firm's next-period productivity by 8.6 percent, although this effect is not statistically significant. The effect of importing on productivity is higher and significant. Importing increases next-period productivity by 26.4 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.[37]

[35] We have experimented with a subset of these instruments (e.g., excluding $\sigma_{M_{jt-1}}$ or using lags of ie_{jt}) and have found that our results are quantitatively similar.

[36] The evolution process of wage rate, Equation (8) 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.

[37] For 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

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

Parameter	I	II	III	IV	V
θ	-0.249	-0.244	-0.250	-0.247	-0.248
	(0.090)	(0.080)	(0.084)	(0.085)	(0.082)
ϕ	0.985	0.982	0.986	0.985	0.985
	(0.008)	(0.010)	(0.009)	(0.009)	(0.009)
f_0	2.343	2.507	2.343	2.655	2.654
	(1.948)	(0.992)	(1.198)	(2.520)	(1.370)
f_e	0.087	0.077	0.087	0.102	0.102
	(0.050)	(0.060)	(0.059)	(0.045)	(0.050)
f_i	0.264	0.268	0.263	0.265	0.265
	(0.055)	(0.058)	(0.059)	(0.055)	(0.053)
f_{wto}	0.185		0.185		
	(0.048)		(0.057)		
f_ω	0.640	0.641	0.640	0.638	0.638
	(0.038)	(0.041)	(0.052)	(0.071)	(0.053)
g_0	0.623	0.655	0.645	0.558	0.578
	(0.146)	(0.110)	(0.104)	(0.115)	(0.104)
g_e		-0.006	-0.006		-0.006
		(0.005)	(0.005)		(0.005)
g_i		-0.021			
		(0.005)			
g_{i0}	-0.018		-0.017	-0.015	-0.014
	(0.010)		(0.010)	(0.014)	(0.012)
g_{i1}	-0.024		-0.022	-0.025	-0.023
	(0.005)		(0.005)	(0.005)	(0.005)
g_{wto}	-0.020		-0.020		
	(0.007)		(0.007)		
g_p	0.939	0.934	0.937	0.943	0.941
	(0.010)	(0.010)	(0.009)	(0.010)	(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.

The third panel of Table 6 reports our estimates of the transition process for (quality-adjusted) 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.[38] Our preferred specification in Column I is based on Equation (6)

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.

[38] As 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.

and (7). The interaction between importing and pre- and post-WTO accession status, combined with the WTO accession dummy, form 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. While the change is not statistically significant (p-value = 0.328) it does represent an over 30 percent 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 effect 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 paper, 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.[39] 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 though 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

[39] We thank an anonymous referee for offering this comparison.

two papers contain input quality which is likely to be more volatile because it is an endogenous firm choice and a function of productivity. In contrast, our quality-adjusted price measure 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 sources of heterogeneity captured in the productivity process.

Productivity and Input Price Distributions. We recover productivity and quality-adjusted prices from (19) and (20). The distribution of productivity, ω_{jt}, is plotted in solid line in Figure 2. It shows substantial heterogeneity of 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.

For comparison, we plot the distribution of $\tilde{\omega}_{jt}$ as the dashed line in Figure 2. 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 $\tilde{\omega}$ accounts for input price heterogeneity while ignoring quality variation, whereas both are typically abstracted away in the literature.

The distribution of (log) quality-adjusted input prices, p_{Mjt}, is reported in solid line in Figure 3. 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 3) 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 productivity and (quality-adjusted) 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

Figure 2: Densities of quality-inclusive productivity, $\tilde{\omega}$ and quality adjusted productivity, ω

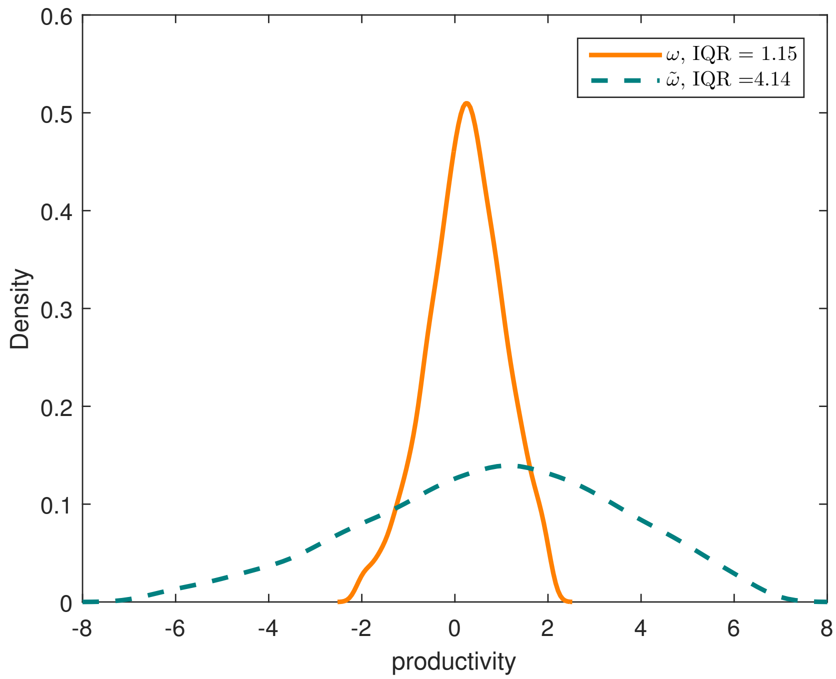
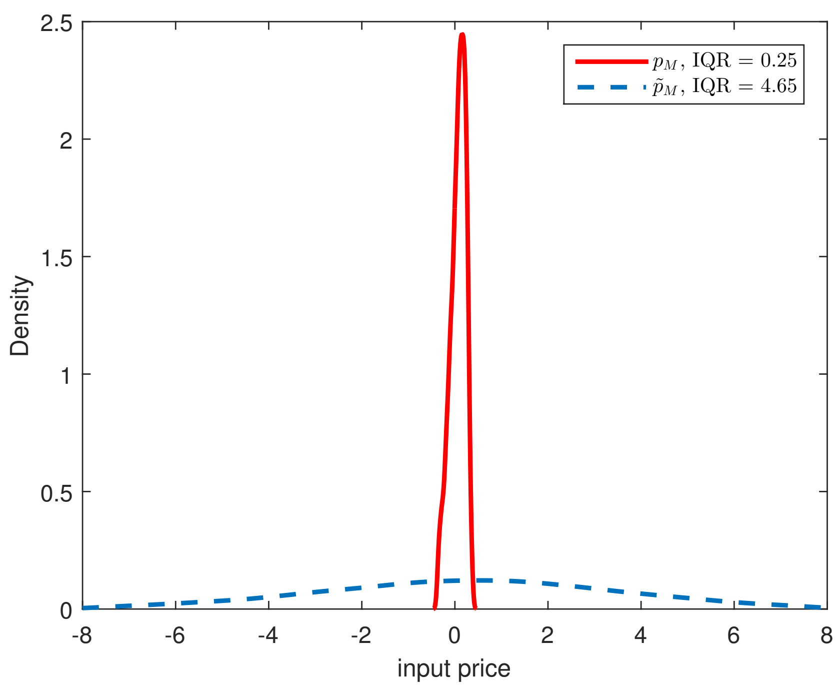


Figure 3: Densities of quality-inclusive prices, $\tilde{p}_M$ and quality adjusted input prices, p_M



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, $\text{corr}(\omega_{jt}, \tilde{p}_{Mjt}) = 0.734$.

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.[40] We define aggregate productivity and input price as the revenue share-weighted average of firm-level productivity and input price levels:

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

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 output 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 output to productive firms. We can construct the analogous decomposition for aggregate input prices. In this case, a more efficient allocation of output would come from a more negative covariance term, since firms with access to lower quality-adjusted input prices can produce more efficently.

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.[41] While 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 output. In addition, the growth in output over time—especially up to 2005—is mostly due to an improvement in the allocation of output to productive firms, rather

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

[41] We normalize the aggregate levels by the first year of our sample, 2000.

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

	Productivity			Input Price		
Year	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

than an increase in the unweighted mean.

The right hand panel performs the analogous exercise for input prices. While 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.

While 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.

4.3 Sunk and Fixed Costs of Trade Participation

Finally, we take the output from the previous stages to the Bellman equation to estimate the sunk and fixed costs of trade defined in (9). Because of the high-dimensional continuous state space, solving of 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 D provides more technical details on the procedure.

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 $s_{jt} = (\omega_{jt}, k_{jt}, p_{Mjt}, p_{Ljt}, ie_{jt})$:[42]

$$\begin{aligned} i_{jt+1} &= \mathbf{1}[\psi_0^i + \psi_e^i e_{jt} + \psi_i^i i_{jt} + \psi_{ie}^i e_{jt} i_{jt} + \psi_\omega^i \omega_{jt} + \psi_p^i p_{Mjt} + \psi_k^i k_{jt} + \psi_{wage}^i + v_{jt}^i > 0], \\ e_{jt+1} &= \mathbf{1}[\psi_0^e + \psi_e^e e_{jt} + \psi_i^e i_{jt} + \psi_{ie}^e e_{jt} i_{jt} + \psi_\omega^e \omega_{jt} + \psi_p^e p_{Mjt} + \psi_k^e k_{jt} + \psi_{wage}^e + v_{jt}^e > 0], \end{aligned} \tag{22}$$

where (v_{jt}^i, v_{jt}^e) are jointly standard normally distributed with correlation parameter ρ. The final parameter reflects the terciles of the wage distribution across firms, $wage \in \{low, med, high\}$ with med serving as the reference group. This approach captures the idea that firms' import and export decisions may be affected by some common unobserved factors (including complementarity in sunk and fixed costs).

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 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,[43]

$$\begin{aligned} V(s_{jt}, \xi_{jt} | ie_{jt+1}; \lambda) &= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}} + \delta E[V(s_{jt+1}, \xi_{jt+1}) | s_{jt}, ie_{jt+1}] \\ &= \pi(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}} \\ &\quad + \delta \int_{\xi_{jt+1}} \int_{s_{jt+1}} V(s_{jt+1}, \xi_{jt+1}) dF(s_{jt+1} | s_{jt}, ie_{jt+1}) dG(\xi_{jt+1}) \\ &\equiv V^\xi(s_{jt} | ie_{jt+1}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}}, \end{aligned} \tag{23}$$

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. 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 (23). 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

[42] For expositional clarity, denote the state using the logarithm of continuous state variables this section.

[43] Formally, our problem is stationary only after China's WTO accession. While we assume China's entry into the WTO is anticipated prior to 2002, we drop the time subscript from the value function in this section for notational conveinience.

(1991, 1993).[44] This procedure solves $\pi(\cdot)$ for a subset of points and uses these points to approximate the function over the entire state space. To choose this subset of points we rely on 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 D. The second challenge is computing the integral in (23) 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 D.

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,

$$\Pr(ie_{jt+1}|s_{jt}) = \frac{\exp(V^{\xi}(s_{jt}|ie_{jt+1};\lambda)/\lambda_{\xi})}{\sum_{ie}\exp(V^{\xi}(s_{jt}|ie;\lambda)/\lambda_{\xi}))}. \tag{24}$$

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

$$\frac{V^{\xi}(s_{jt}|ie;\lambda) - V^{\xi}(s_{jt}|ie';\lambda)}{\lambda_{\xi}} = \ln \Pr(ie|s_{jt}) - \ln \Pr(ie'|s_{jt}). \tag{25}$$

Since the right hand side is estimated from (22), we estimate the trade cost parameters by matching the two sides of (25). The estimator is defined as,

$$\widehat{\lambda} = \underset{\lambda}{\operatorname{argmin}} \sum_{j,t}\sum_{ie'}\left\{\frac{1}{\lambda_{\xi}}\left[V^{\xi}(s_{jt}|ie_{jt+1};\lambda) - V^{\xi}(s_{jt}|ie';\lambda)\right] - \left[\ln\widehat{\Pr}(ie_{jt+1}|s_{jt}) - \ln\widehat{\Pr}(ie'|s_{jt})\right]\right\}^2. \tag{26}$$

CCP Estimates. The results of the first-stage CCP estimation are reported in Table 8.[45] 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 year substantially (86.9 percent), and also

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

[45]In 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.

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 (9).

Table 8 also illustrates firms' endogenous selection into importing and exporting based on productivity and input prices. The estimate $\psi^e_\omega = 0.081$ 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 export probability by 2.0 percentage points (a 16.7 percent increase). Similarly, lower input prices also increase the export probability. Lowering input prices by one standard deviation can increase export probability by 3.2 percentage points (a 26.5 percent increase). In contrast, the selection into importing based on productivity and input prices is much weaker. The coefficient $\psi^i_\omega = 0.002$, translates to a 0.2 percentage point (1.7 percent) increase in the import probability on average when productivity increases by one standard deviation. The impact of input prices on the import probability is negative but insignificant.

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.[46] Consistent with the findings in the literature, sunk costs are much larger than 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, 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 see 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.

To check the possibility that WTO accession might have changed the sunk and fixed costs of trade, we also estimated a version the model that adds time dummies in (9). The estimated time dummies are insignificant, indicating that WTO accession had at most a small impact on fixed/sunk costs.

With all model parameters estimated, we can solve for optimal trade policies. We check the fit of

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

Table 8: Conditional choice of export and import probability estimates

Import		Export	
ψ_0^i	0.594	ψ_0^e	4.161
	(2.930)		(2.575)
ψ_e^i	0.599	ψ_e^e	2.553
	(0.166)		(0.116)
ψ_i^i	3.298	ψ_i^e	0.778
	(0.127)		(0.112)
ψ_{ie}^i	0.004	ψ_{ie}^e	-0.446
	(0.252)		(0.189)
ψ_ω^i	0.018	ψ_ω^e	0.081
	(0.053)		(0.052)
ψ_p^i	-0.312	ψ_p^e	-0.660
	(0.279)		(0.234)
ψ_k^i	0.091	ψ_k^e	0.075
	(0.035)		(0.026)
ψ_{low}^i	-0.018	ψ_{low}^e	-0.019
	(0.125)		(0.093)
ψ_{high}^i	0.230	ψ_{high}^e	-0.082
	(0.120)		(0.092)
ρ	0.205		
	(0.071)		

Note: Bootstrap standard errors in parenthesis.

our model by comparing transition probabilities from the raw data, our CCP estimation, and the policy function of the dynamic model in Appendix E.

5 Counterfactual Analysis

Understanding and measuring the mechanisms through which trade participation influences firm performance—and how these mechanisms play out over time—is of particular interest to policy makers as a tool to evaluate the potential gains from trade liberalization. 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 did the cut in import tariffs associated with WTO accession affect Chinese paint manufacturers' propensity to import and export, and how did these changes impact firm performance in terms of productivity, input prices, and firm value?

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
$\ln p$	-0.042	-0.166

Note: Marginal effects of productivity and input prices are averaged over firms actually participating in trade.

Table 10: Estimate of trade cost distribution parameters

Parameter	Estimate	Parameter	Estimate
$\lambda_{00,01}$	5.519	$\lambda_{01,01}$	0.084
	(0.721)		(0.087)
$\lambda_{00,10}$	7.141	$\lambda_{01,10}$	5.928
	(0.992)		(0.994)
$\lambda_{00,11}$	11.518	$\lambda_{01,11}$	5.857
	(1.606)		(0.939)
$\lambda_{10,01}$	4.012	$\lambda_{11,01}$	0.966
	(0.626)		(0.324)
$\lambda_{10,10}$	0.152	$\lambda_{11,10}$	0.319
	(0.101)		(0.325)
$\lambda_{10,11}$	4.138	$\lambda_{11,11}$	0.068
	(0.652)		(0.087)
λ_{ξ}	4.808		
	(3.028)		

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

5.1 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 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.[47] To evaluate how the change affects the industry, we compare expected outcomes of all firms in the data starting from 2006 and going forward up to 15 years. To calculate expected outcomes we simulate the transition paths for each firm 30 times and take the average over these

[47] Recall 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).

simulated paths.

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, average firm value will drop by 4.2 percent, equivalent to 5.2 million USD.[48] This loss is in part due to a substantial decline in aggregate productivity of 39.7 percent. The loss of productivity benefits from trade reduces trade participation for two reasons. First, productivity is lower under the counterfactual, and since there is 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.[49] The combined effect of removing the productivity benefits of trade is a reduction in the export probability by 3.3 percentage points (17.4 percent) after 15 years. The effect on import participation is even stronger, 5.4 percentage points (33.6 percent). However, these declines accrue slowly after the policy change since 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 quality-adjusted 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.

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 6.4 percent, equivalent to about 7.2 million USD. After 15 years, we find that quality-adjusted input prices are 8.2 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 25.4 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 elimination of the input price benefit, which is further amplified by a reduction in exporting. The 4.0 percentage point drop in the proportion of exporters 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

[48] Firm value is calculated as present discounted value using a discount factor of .95.

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

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

Year	2	5	10	15
Eliminate Productivity Benefit				
Aggregate productivity (percent)	-26.4	-34.9	-39.6	-39.7
Aggregate input price (percent)	0.6	1.1	1.6	2.1
Proportion of exporters (percentage points)	-0.6	-1.4	-2.4	-3.3
Proportion of importers (percentage points)	-1.0	-2.2	-4.0	-5.4
Firm value (percent and million USD)		-4.2 (-5.2)		
Eliminate Input Price Benefit				
Aggregate productivity (percent)	-4.1	-10.7	-21.4	-25.4
Aggregate input price (percent)	2.6	5.3	7.4	8.2
Proportion of exporters (percentage points)	-0.6	-1.7	-3.0	-4.0
Proportion of importers (percentage points)	-1.8	-3.9	-6.8	-9.0
Firm value (percent and million USD)		-6.4 (-7.2)		

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.

impact on firms' expectations of future profitability.

5.2 WTO Tariff Reduction and Price Incentives to Import

We have found that import price incentives can 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. The effect of tariff liberalization on productivity though trade decisions is inherently dynamic and will not be accounted for in static analyses of gains from trade (e.g., Arkolakis et al., 2012). We use China's accession to the WTO in 2001 to assess the importance of the trade participation response to firms' overall gains. As we discussed in Section 2, China's accession to the WTO caused a substantial decline in import tariffs for the inputs of paint materials. While imported intermediates can be purchased domestically from importers, if those importers 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 (Table 6).[50]

We now illustrate the impact of this change in the incentive to import on firm performance in the Chinese paint industry. The difference between g_{i0} and g_{i1} reflects the increased effect of importing

[50] While the change is not statistically significant at the five percent level, we can still use this change to illustrate how a realistic change in the input price gap will affect firm outcomes.

Table 12: Effect of WTO Price-Incentive to Import

Year	2	5	10	15
Full Effect (firms re-optimize trade policy)				
Aggregate Productivity (percent)	1.0	3.1	7.0	8.6
Aggregate Input price (percent)	-0.7	-1.6	-2.4	-2.8
Exporters (percentage point)	0.2	0.5	1.0	1.4
Importers (percentage point)	0.5	1.2	2.2	3.0
Valuation (percent and million USD)		2.3 (2.4)		
Direct Effect (firms do not update trade policy)				
Average productivity (percent)	0.8	1.7	3.3	3.9
Average input price (percent)	-0.6	-1.3	-1.9	-2.1
Exporters (percentage)	0.0	0.0	0.2	0.2
Importers (percentage)	0.0	0.1	0.3	0.5
Valuation (Percent, million USD)		2.1 (2.2)		

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.

on quality-adjusted input prices because of the WTO accession. By setting $g_{i1} = g_{i0}$ we remove this effect. This change does *not* remove the effect of WTO accession on the overall input price level, g_{wto} or the change in productivity associated with accession, f_{wto}.[51] Therefore, the counterfactual is narrowly focused on gains from altering firms' incentive to import via input prices.

The top panel of Table 12 reports the outcomes from this exercise. The WTO effect on the input price gap increases average firm value by 2.3 percent (2.4 million US dollars). This gain in firm value is due to the input price incentive, but operates through multiple channels. While in the first few years, the effect is mild, after 15 years, the average input price is about 2.8 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 3.0 percentage points and export probability by 1.4 percentage points. 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 8.6 percent increase in aggregate productivity due to the input price incentive. This result compliments Yu (2014) who has documented that lower tariffs following China's accession to the WTO had a positive impact on firm productivity.

[51] Other potential effects of the WTO, such as changes in fixed or sunk costs or a change in the demand elasticity in the export market are also held constant. In robustness checks, we found little difference in trade costs and the demand elasticity across the pre and post WTO period.

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

	Weighted	Unweighted	Cov.
Productivity	8.6	2.3	6.3
Input Price	-2.8	-1.4	-1.4

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 due to WTO accession with the indirect effect of firms' endogenous responses to those incentive changes. In the bottom panel, we re-calculate the effects 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.[52] Over 80 percent of the growth in import and export participation following WTO accession is due to firms' endogenous response to trade incentives.[53] 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 45 percent of the full impact, while input prices declines are only 75 percent of the full impact. The difference in firm values is smaller, with the direct effect achieving 91.7 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. Since trading firms tend to be larger and more productivity 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 producivity and the decrease in input prices following Olley and Pakes (1996), and finds that this is the case. Allocation improvement accounts for 73 percent of aggregate productivity growth and half of the input price decline. 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 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

[52] The increase that we do observe is due to the selection into trade participation and liberalization's associated impacts on input prices.

[53] It is calculated as $(1.4 - 0.2)/1.4 \approx 86\%$ for exporting and $(3 - 0.5)/3 \approx 80\%$ for importing. Other numbers in this paragraph are similarly computed.

Table 14: Effect of WTO Accession Price-Incentive to Import by Firm Type

	Overall	Low ω	High ω	Neither	Export Only	Import Only	Both
Aggregate productivity (percent)	5.0	3.6	5.5	3.1	8.1	5.9	5.8
Aggregate input price (percent)	-2.6	-1.6	-3.0	-0.8	-2.6	-5.1	-5.7
Proportion of exporters (percentage points)	1.4	1.1	1.7	0.9	2.8	4.9	5.0
Proportion of importers (percentage points)	3.0	2.6	3.3	2.0	4.9	9.1	8.8
Firm value (Million USD)	2.3	1.9	2.8	1.3	3.3	8.0	10.8

Notes: The groups of firms are defined by their status in the first year of the simulation. For example, "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.

productivity firms to command a larger market share, leading to aggregate productivity increases.

We investigate the allocative impact of the WTO accession's input price effect by considering different firm types. 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 initial revenue shares for all years. The results are reported in Table 14. This again highlights the importance of reallocation in raising aggregate productivity, as overall growth under this calculation is only 5.0 percent versus 8.6 accounting for reallocation by weighting based on current shares. The next two columns confirm our intuition that high productivity firms reap larger gains from the policy change. Also, gains are larger for firms who are already engaged in trade, and therefore do not need to pay a sunk cost to realize the benefits of the policy.

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 that import materials directly face lower quality-adjusted input prices, and also experience significant productivity growth consistent with "learning by importing". The price-incentive to import is increased following liberalization of input tariffs. As a result, domestic firms increase trade participation and boost productivity following a trade liberalization, although this transition is gradual to 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, who 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 modeled 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 stronger effect from the input price channel.

Several features of the Chinese paint manufacturing industry fit our modeling 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 paper 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 which 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.

References

Ábrahám, Á. and K. White (2006). The dynamics of plant-level productivity in us manufacturing. *Center for Economic Studies Working Paper 6*, 20.

Alessandria, G. and J. P. Kaboski (2011). Pricing-to-market and the failure of absolute ppp. *American Economic Journal: Macroeconomics 3*(1), 91–127.

Amiti, M. and A. K. Khandelwal (2013). Import competition and quality upgrading. *Review of Economics and Statistics 95*(2), 476–490.

Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review 97*(5), 1611–1638.

Antras, P., T. C. Fort, and F. Tintelnot (2017). The margins of global sourcing: theory and evidence from us firms. *American Economic Review 107*(9), 2514–64.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012). New trade models, same old gains? *American Economic Review 102*(1), 94–130.

Atalay, E. (2014, June). Materials prices and productivity. *Journal of the European Economic Association 12*(3), 575–611.

Aw, B. Y., M. Roberts, and D. Y. Xu (2011). R&d investment, exporting, and productivity dynamics. *American Economic Review 101*, 1312–1344.

Banerjee, A. V. and E. Duflo (2005). Growth theory through the lens of development economics. *Handbook of Economic Growth 1*, 473–552.

Barwick, P. J. and P. Pathak (2015, January). The costs of free entry: An empirical study of real estate agents in greater Boston. *The RAND Journal of Economics 46*(1), 103–145.

Bernard, A. B. and J. B. Jensen (1999). Exceptional exporter performance: Cause, effect, or both? *Journal of International Economics 47*, 1–25.

Bernard, A. B., J. B. Jensen, and P. K. Schott (2009). Importers, exporters and multinationals: A portrait of firms in the U.S. that trade goods. In T. Dunne, J. B. Jensen, and M. J. Roberts (Eds.), *Producer Dynamics: New Evidence from Micro Data*, pp. 513 – 552. Chicago: University of Chicago Press.

Blaum, J., C. Lelarge, and M. Peters (2018). The gains from input trade with heterogeneous importers. *American Economic Journal: Macroeconomics 10*(4), 77–127.

Blundell, R. and S. Bond (2000). Gmm estimation with persistent panel data: an application to production functions. *Econometric Reviews 19*, 321–340.

Brandt, L., J. V. Biesebroeck, L. Wang, and Y. Zhang (2017). WTO accession and performance of Chinese manufacturing firms. University of Toronto, KU Leuven, Xiamen University.

Burstein, A. T., J. C. Neves, and S. Rebelo (2003). Distribution costs and real exchange rate dynamics during exchange-rate-based stabilizations. *Journal of monetary Economics 50*(6), 1189–1214.

Chevassus-Lozza, E., C. Gaigné, and L. L. Mener (2013). Does input trade liberalization boost downstream firms' exports? Theory and firm-level evidence. *Journal of International Economics 90*, 391–402.

Corsetti, G. and L. Dedola (2005). A macroeconomic model of international price discrimination. *Journal of International Economics 67*(1), 129–155.

Das, S., M. J. Roberts, and J. R. Tybout (2007, May). Market entry costs, producer heterogeneity and export dynamics. *Econometrica 75*(3), 837–873.

de La Grandville, O. (1989). In quest of the Slutsky diamond. *American Economic Review 79*(3), 468–481.

de La Grandville, O. and R. M. Solow (2006). A conjecture on general means. *Journal of Inequalities in Pure and Applied Mathematics 7*(1).

De Loecker, J. (2007). Do exports generate higher productivity? evidence from Slovenia. *Journal of International Economics 73*, 69–98.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445–510.

Doraszelski, U. and J. Jaumandreu (2017). Measuring the bias of technological change. *Journal of Political Economy*, forthcoming.

Fan, H., Y. A. Li, and S. R. Yeaple (2015). Trade liberalization, quality, and export prices. *The Review of Economics and Statistics 97*(5), 1033–1051.

Fan, H., Y. A. Li, and S. R. Yeaple (2017). On the relationship between quality and productivity: Evidence from China's accession to the WTO. NBER Working Paper 23690.

Fieler, A. C., M. Eslava, and D. Y. Xu (2018). Trade, quality upgrading, and input linkages: Theory and evidence from colombia. *American Economic Review 108*(1), 109–46.

Foster, L., J. Haltiwanger, and C. Syverson (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review 98*(1), 394–425.

Fox, J. and V. Smeets (2011). Does input quality drive measured productivity differences in firm productivity. *International Economic Review 52*(4), 961–989.

Friedman, J. H. (1991). Multivariate adaptive regression splines. *The Annals of Statistics 19*(1), 1–67.

Friedman, J. H. (1993). Fast MARS. Dept. of Statistics, Stanford University Technical Report.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010). Imported intermediate inputs and domestic product growth: Evidence from India. *The Quarterly Journal of Economics 125 (4)*, pp. 1727–1767.

Greenaway, D. and R. Kneller (2007, February). Firm heterogeneity, exporting and foreign direct investment. *Economic Journal 117*, F134–F161.

Grieco, P., S. Li, and H. Zhang (2016). Production function estimation with unobserved input price dispersion. *International Economic Review 57*(2), 665–690.

Halpern, L., M. Koren, and A. Szeidl (2015, December). Imported inputs and productivity. *American Economic Review 105*(12), 3660–3703.

Hotz, V. J. and R. A. Miller (1993, July). Conditional choice probabilities and the estimation of dynamic models. *Review of Economic Studies 60*(3), 497–529.

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994, April). A simulation estimator for dynamic models of discrete choice. *The Review of Economic Studies 61*(2), 265–289.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448.

Judd, K. L., L. Maliar, and S. Maliar (2012). Merging simulation and projection aproaches to solve high-dimensional problems. NBER Working Paper 18501.

Kasahara, H. and B. Lapham (2013). Productivity and the decision to import and export: Theory and evidence. *Journal of International Economics Vol. 89*, pp. 297–316.

Kasahara, H. and J. Rodrigue (2008). Does the use of imported intermediates increase productivity? Plant-level evidence. *Journal of Development Economics 87*(1), 106 – 118.

Klump, R. and O. de La Grandville (2000). Economic growth and the elasticity of subsitituion: Two theorems and some suggestions. *American Economic Review 90*(1), 282–291.

Klump, R. and H. Preissler (2000). CES production functions and economic growth. *Scandanavian Journal of Economics 102*(1), 41–56.

Kugler, M. and E. Verhoogen (2009). Plants and imported inputs: New facts and an interpretation. *American Economic Review 99*(2), 501–07.

Kugler, M. and E. Verhoogen (2012). Prices, plant size, and product quality. *Review of Economic Studies 79*(1), 307–339.

León-Ledesma, M. A., P. McAdam, and A. Willman (2010). Identifying the elasticity of substitition with biased technical change. *American Economic Review 100(4)*(4), 1330–1357.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies 70*(2), 317–341.

Maliar, L. and S. Maliar (2015). Merging simulation and projection aproaches to solve high-dimensional problems with an application to a New Keynesian model. *Quantitative Economics 6*(1), 1–47.

Melitz, M. J. (2003, November). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*(6), 1263–1297.

Ornaghi, C. (2006). Assessing the effects of measurement errors on the estimation of production functions. *Journal of Applied Econometrics 21*(6), 879–891.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics 11*(4), 707–720.

Syverson, C. (2004). Product substitutability and productivity dispersion. *Review of Economics and Statistics 86*(2), 534–550.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature 49*(2), 326–65.

Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: The case of India. *The Review of Economics and Statistics 93 (3)*, 995–1009.

Vogel, A. and J. Wagner (2010). Higher productivity in importing German manufacturing firms: Self-selection, learning from importing, or both? *Review of World Economics vol. 145(4)*, pp. 641–665.

Yu, M. (2014, June). Processing trade, tariff reductions and firm productivity: Evidence from Chinese firms. *The Economic Journal 125*(585), 943–988.

Zhang, H. (2017). Static and dynamic gains from costly importing of intermediate inputs: Evidence from Colombia. *European Economic Review 91*, 118–145.

Appendices

A Additional Institutional Details

A.1 Trade Types in Chinese Manufacturing

This appendix summarizes the definition and shares of different trade types in the Chinese paint Industry. There are three major types of international trade in this industry.

Ordinary trade
In ordinary trade, firms purchase inputs either from domestic or foreign markets freely and have full control of the production and selling decisions. They can choose price and quantity to maximize their profits, facing the demand function.

Processing trade with imported material
In processing export with imported material, firms still maximize profits by choosing inputs and outputs freely. 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 paper, 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".

Processing trade with assembly
Under processing trade with assembly, a foreign entity provides inputs to the domestic firm which must re-export its output to that firm. There is no transaction of inputs or outputs between the producer and foreign supplier(s). The producer has no control over what material inputs to be used in the production, nor how much to produce. The producer charges a fee for producing the products.

In the Chinese paint industry, ordinary trade and processing trade with imported material account for about 98.8% of the total export revenue and 97.9% of import expenditure. Processing trade with assembly together with other trade types accounts for only 1.2% of export revenue and 2.1% of import expenditure.

A.2 Chinese Paint Manufacturing Process

Paint manufacturing is typically divided into four basic steps:

- **Step 1: Premixing.** The pigment, resin, solvents, and additives are weighed and premixed to produce a mill base (or paste) in a mixer.
- **Step 2: Milling and dispersing.** The mill base is then sent to a sand mill (for most industrial and some consumer paints) or a high-speed dispersion tank (for most water-based latex paints) to grind the pigment particles and disperse them throughout the mixture. The mixture is then filtered to remove the sand particles if using a sand mill. In addition, the color phase is adjusted with color materials in this stage.
- **Step 3: Thinning.** The paste is thinned to produce the final product and transferred to

large tanks. It is agitated with the proper amount of solvent for the type of paint desired.

- **Step 4: Filtering and Packaging.** The finished paint product is then packed into a container, labeled and prepared for shipment.

There is substantial scope for substitution among inputs in the production process. Poorly mixed batches of paint are unsuitable for sale, so inadequate equipment or labor can produce waste. Conversely, advanced equipment can also save material and labor. For example, a high-speed mixer can mix the inputs very well in a short period of time, so a small amount of pigment can produce good color phase, reducing the usage of (usually expensive) pigments.

Firms typically produce a homogeneous product. Within exporters, the median export share of the largest 6-digit Harmonized System (HS) category is 93 percent.[54] However, the quality of product can vary substantially across firms. Paint quality can vary across several dimensions including density, fineness of grind, dispersion, viscosity, scrub-ability, bleed resistance, adhesion, rate of drying, texture, and color. Poor quality of paint can cause peeling, chalking, and cracking, which reduce the lifespan and durability of the paint.

B Recovering Firm Heterogeneity ($\tilde{\Omega}_{jt}, \tilde{P}_{Mjt}$) 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 Eq. (5), implies five first order conditions. Specifically, the first order conditions for the firms demanded quantity of labor and materials imply:

$$\mu_{jt}\tilde{\Omega}_{jt}\frac{\partial F}{\partial L_{jt}}L_{jt} = E_{Ljt}, \tag{B.1}$$

$$\mu_{jt}\tilde{\Omega}_{jt}\frac{\partial F}{\partial M_{jt}}M_{jt} = E_{Mjt}. \tag{B.2}$$

Where μ_{jt} represents the Lagrange multiplier on the production constraint. When a firm sells in both domestic and exporting markets,[55] the first order conditions with respect to (quality-inclusive) output quantities are,

$$\frac{1+\eta^D}{\eta^D}(\tilde{Q}^D_{jt})^{1/\eta^D} - \mu_{jt} = 0, \tag{B.3}$$

$$\kappa\frac{1+\eta^X}{\eta^X}(\tilde{Q}^X_{jt})^{1/\eta^X} - \mu_{jt} = 0, \tag{B.4}$$

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

$$\frac{\partial \tilde{P}_{Mjt}(P_{Mjt}, H_{jt})}{\partial H_{jt}}M_{jt} = \mu_{jt}F(L_{jt}, M_{jt}, K_{jt})\frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}. \tag{B.5}$$

Under our assumptions, the system of first order conditions admit a unique solution to firms' optimal

[54] Unfortunately, we do not have product level data on domestic sales. However, we would expect that non-exporting firms are less likely to be multi-product firms compared with exporters. The lower quartile of largest export share still derives 70 percent of total export revenue from a single product.

[55] When 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 (B.4).

static choice $(L_{jt}, M_{jt}, \tilde{Q}^D_{jt}, \tilde{Q}^X_{jt}, H_{jt})$.

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

Given the CES production function, take the ratio of the first order conditions for labor and materials, Eq. (B.1) and (B.2) and after some rearrangement, we get a closed form solution for material quantity as a function of observables and production parameters, as captured by Eq. (12).

Then we can directly compute the quality-inclusive material quantity from Eq. (12). Then by following the expenditure identity $E_{Mjt} = \tilde{P}_{Mjt} Mjt$, we can solve the quality inclusive material input prices as

$$\tilde{P}_{Mjt} = \frac{E_{Mjt}}{Mjt}.$$

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 $\tilde{Q}_{jt} = \tilde{Q}^X_{jt} + \tilde{Q}^D_{jt} = \tilde{\Omega}_{jt} F(L_{jt}, M_{jt}, K_{jt})$. Substitute $\tilde{Q}^X_{jt}$ calculated in Eq. (16) into the production function (with material quantity replaced by (12)), and we have,

$$\left(\frac{1}{\kappa}\frac{\eta^X}{\eta^D}\frac{1+\eta^D}{1+\eta^X}\right)^{\eta^X} \cdot (\tilde{Q}^D_{jt})^{\eta^X/\eta^D} + \tilde{Q}^D_{jt} = \tilde{\Omega}_{jt}\left[\alpha_L L^{\gamma}_{jt}\left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}}\right) + \alpha_K K^{\gamma}_{jt}\right]^{\frac{1}{\gamma}}. \tag{B.6}$$

This provides us with one equation relating the two unknown variables $(\tilde{Q}^D_{jt}, \tilde{\Omega}_{jt})$. The first order condition of optimal labor choice provides us another. Substituting the first order condition associated with Q^D_{jt} defined in Eq. (B.3) into that for labor, yields,

$$\frac{1+\eta^D}{\eta^D}(\tilde{Q}^D_{jt})^{1/\eta_D}\alpha_L L^{\gamma-1}_{jt}\tilde{\Omega}_{jt}\left[\alpha_L L^{\gamma}_{jt}\left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}}\right) + \alpha_K K^{\gamma}_{jt}\right]^{\frac{1}{\gamma}-1} = P_{L_{jt}}. \tag{B.7}$$

It is straightforward to show that (B.6) and (B.7) admit a unique solution of $(\tilde{Q}^D_{jt}, \tilde{\Omega}_{jt})$ as long as $\eta^D, \eta^X < -1$. That is, (B.6) and (B.7) imply an one-to-one mapping from the observable variables to $(\tilde{Q}^D_{jt}, \tilde{\Omega}_{jt})$ given model parameters, which consequently can be written as a unique implicit function of observables given model parameters. The counterpart of (B.6) and (B.7) is Equation (7) in Grieco et al. (2016). Finally, $\tilde{Q}^X_{jt}$ is also recovered from (16) as a function of observables. Therefore, we have shown that we are able to recover $(\tilde{M}_{jt}, \tilde{P}_{M_{jt}}, \tilde{Q}^D_{jt}, \tilde{Q}^X_{jt}, \tilde{\Omega}_{jt})$ uniquely from the observable data $(E_{Ljt}, E_{Mjt}, L_{jt}, K_{jt}, R^D_{jt}, R^X_{jt})$ up to parameters to be estimated.

C Deriving Optimal Quality (h_{jt})

The optimal quality choice can be solved out from the first order conditions of quality choice. Specifically, we can solve for μ_{jt} from the material choice first order condition (B.2),

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

Substitute into the quality choice first order condition (B.5) to replace μ_{jt}, we have

$$\frac{\partial \tilde{P}_{Mjt}(P_{Mjt}, H_{jt})}{\partial H_{jt}} M_{jt} = \frac{E_{Mjt}}{\tilde{\Omega}_{jt} \frac{\partial F}{\partial M_{jt}} M_{jt}} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}}. \tag{C.1}$$

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

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

Multiplying both sides by H_{jt} yields,

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

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

$$\phi \sigma_{Mjt} = \frac{H_{jt}}{\tilde{\Omega}_{jt}} \frac{\partial \tilde{\Omega}_{jt}(\Omega_{jt}, H_{jt})}{\partial H_{jt}} = \frac{H_{jt}^{\theta}}{\Omega_{jt}^{\theta} + H_{jt}^{\theta}} \tag{C.2}$$

where $\sigma_{Mjt} = \frac{\partial F}{\partial M_{jt}} \frac{M_{jt}}{F(\cdot)}$ is the output elasticity of material, and the second equality holds given the functional form of $\tilde{\Omega}_{jt}$ defined in Eq. (3). After some algebra based on Eq. (C.2), we can derive a closed-form relation between endogenous input quality choice and productivity in Eq. (18).

D Dynamic Estimation: forward-simulation-based CCP Approach

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

D.1 Approximation of Period Profits

In our model, the firm's profit maximization problem does not have a close form solution. This proposes a computational challenge in the forward simulation process in the dynamic estimation procedure. To address this issue, we approximate the profit function on a Epsilon Distinguishable Set (EDS) based on Multivariate Adaptive Regression Spline (MARS). This methodology has a few advantages. First, the approximation provides an easy way to compute the associated profit on any possible state in the forward simulation pass. Second, the EDS constructed from the pre-simulated paths of state allows us to approximate the profit function more economically. Finally, due to the large state space the profit function, MARS is a flexible and efficient way for approximation. The details of the implementation are described as follows.

D.1.1 Construction of EDS

Epsilon Distinguishable Set (EDS) method combines the advantages of both stochastic simulation approach and projection approach.[56] The basic idea is to construct the EDS based on the simulated path of data, and solve the model 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.

In our paper, we use EDS for the purpose of approximating the profit function. The idea of the procedure for constructing EDS is as follows:

1. Simulate N paths of state variables starting from the data points, using the CCP function estimated from the data. Denote the set simulated state as A. A can be thought of an approximation of the ergodic set for these state variables in this problem.
2. Normalize and orthogonalize the simulated data using Principal Component transformation, so that the measurement unit and correlation among state variables do not affect the measurement of distance.
3. Construct the essentially ergodic set, A^η, by dropping all points with a density below η.
4. Constructing EDS, P^ϵ. A set P^ϵ is called EDS, if the distance of any pair of points is larger than or equal to ϵ. We construct P^ϵ from the essentially ergodic set, A^η as follows
   (a) Starting with $P^\epsilon = \emptyset$.
   (b) Select one point $x_i \in A^\eta$. Compute its distance to all other points $x_j \in A^\eta$, denoted the distance as $D(x_i, x_j)$.
   (c) Eliminate all x_j such that $D(x_i, x_j) < \epsilon$ from the essentially ergodic set A^η, and use this smaller set to replace A^η.
   (d) Add x_i into P^ϵ.
   (e) Iterate between (b)-(d) until all points are eliminated from A^η.
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.

D.1.2 Approximation using MARS

Once the EDS P^ϵ is obtained, we solve the profit maximization problem to obtain the associated profit on each point in P^ϵ. In particular, we solve for 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 method, we adopt MARS method developed by Friedman (1991, 1993). A recent empirical implementation is Barwick and Pathak (2015), in which the author use MARS to find an appropriate set of basis functions for value function approximation.

[56] For details, see Judd et al. (2012).

In our paper, we utilize it to approximate the profit function. Essentially, MARS is a form of stepwise linear regression that is designed to take high dimensional state as the input and can deal with non-linearities. The methodology of MARS is to repeatedly splits 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 this paper, 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. In our implemetation, we have a total of 20,356 training points on a 5-dimensional state space. We end up with a MARS model with 51 splines, which approximates the profit function on the training points with a R^2 of 99.9%.

D.2 Forward Simulation of the Value Function

The observed state space includes four continuous variables and two binary choice variables of import and export decisions. As the profit function can be estimated beforehand using static information, we only need 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) (22) 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: $(\omega_{jt}, k_{jt}, P_{Mjt}, P_{Ljt}, ie_{jt}, ie_{jt+1}$, 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 (23) 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

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

The three integration 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

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

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, $(\epsilon^{\omega}_{jt+1}, \epsilon^{PM}_{jt+1}, \epsilon^{PL}_{jt+1})$. (Note: we can draw it for all T periods once for all, 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) $(\epsilon^{\omega}_{jt+2}, \epsilon^{PM}_{jt+2}, \epsilon^{PL}_{jt+2})$. 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

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

  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 $C(ie_{jt+\tau+1}; ie_{jt+\tau})$ except

λ_ξ. 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. (9) we can rearrange the above net choice-specific value, by separating parameters and simulated data, as follows,

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

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

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

Where the collection of trade status

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

which determines what trade costs the firm should pay.

We simulate 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

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

3. Construct the likelihood function. Given $\overline{V}^{\xi}(s_{jt}|ie_{jt+1})$, 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 Equation (24), which implies Eq. (25). The model parameters, λ can then be estimated by matching (25).

E Model Fit: Conditional Choice Probability Comparison

The results reported in Table 15 show they are matched reasonably well. As expected, the transition probabilities are consistent with the estimates of trade cost parameters. For example, around 97% of non-trading firms stay as non-trading suggests a significant sunk cost of entry. Also, the probability from "Neither" to "Export Only" is higher than that from "Neither" to "Import Only' means the sunk cost of importing is higher than that of exporting. Further, the probability from "Import Only" to "Both" is larger than "Export Only" to "Both" corroborates that past importing is more useful in facilitating engagement in both activities than the effect from previous exporting experience:

Table 15: Transition probabilities: data, offline CCP predicted, and model predicted

Actual Data	Neither	Export Only	Import Only	Both
Neither	0.969	0.022	0.008	0.001
Export Only	0.248	0.701	0.013	0.037
Import Only	0.127	0.016	0.730	0.127
Both	0.013	0.033	0.134	0.883
Overall	0.821	0.057	0.059	0.063
Offline CCP Predicted	Neither	Export Only	Import Only	Both
Neither	0.969	0.022	0.008	0.001
Export Only	0.242	0.702	0.006	0.049
Import Only	0.123	0.010	0.722	0.145
Both	0.012	0.030	0.129	0.829
Overall	0.817	0.056	0.062	0.064
Model Predicted	Neither	Export Only	Import Only	Both
Neither	0.972	0.020	0.008	0.001
Export Only	0.151	0.799	0.006	0.045
Import Only	0.073	0.007	0.815	0.104
Both	0.011	0.023	0.098	0.868
Overall	0.812	0.059	0.066	0.064

$\hat{\lambda}_{10,11} < \hat{\lambda}_{01,11}$. These trade cost parameters, together with the benefits from trade, determines the endogenous trade participation at the firm level. We will use them as the basic components to evaluate the multi-dimensional gains from international trade at the firm level in the long run in Section 5.