Imported Inputs, Productivity, and the Impact of Import Liberalization: Evidence from Chinese Paint Manufacturers*

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Abstract

We develop and estimate a structural model of trade participation where firms are heterogeneous in productivity and access to intermediate inputs. Our model highlights the role importing can play in improving firms' access to materials—enabling firms to either reduce materials costs or raise materials quality—as a distinct incentive to import. This stands in contrast to the previous literature, which has assumed that firms face homogenous materials prices. We aim to distinguish the role of productivity, materials access, and market access to understand how changes in trade policies affect trade participation and firm performance. To do this, we apply our model using a dataset of the Chinese paint manufacturing industry from 2000 to 2006. Our analysis indicates that firms who engage in importing benefit from both improved access to materials and higher future productivity gains. Moreover, gains associated with importing are more than four times larger than those associated with exporting in terms of firm value. We illustrate how changing firms' incentive to import can affect both importing and exporting decisions in the long run. Specifically, we evaluate the effect of China's reduction in import tariffs upon joining WTO in 2001. We find that this policy increases average firm value by about 0.4 percent (2.1 million US dollars) through a direct effect on reducing input prices and an induced boost of trade participation and productivity.

Keywords: *Imported Inputs, Productivity, Import Liberalization, China, WTO*

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1 Introduction

When manufacturing firms engage in exporting output or importing materials they affect firm performance through multiple channels. Exporting allows firms' products to reach additional buyers; importing materials provides access to a wider variety of inputs which may be less expensive or a better fit for firms' production processes. Both importing and exporting have been associated with increasing firms' productivity (Aw et al., 2011; Kasahara and Lapham, 2013). Because trade participation affects firms in multiple ways—and because firms endogenously choose to engage in trade—disentangling the channels through which trade affects firms is difficult. In particular, most models of trade participation has assumed that materials prices are homogeneous, thus abstracting away the incentive of firms to engage in importing in order to gain access to lower input prices.[1] This is despite the fact that several studies have found significant heterogeneity in input prices across manufacturing firms (Ornaghi, 2006; Atalay, 2014). Accounting for this distinct incentive is especially important when evaluating import liberalization policies, since import tariffs directly effect the degree to which firms can improve their access to materials—either reducing materials costs, raising quality, or both—by engaging in importing.

In this paper, we propose a structural model to distinguish mechanisms by which trade participation affects firm performance: productivity, materials access, and market access. In our model, firms are heterogeneous in both productivity and access to intermediate materials (which is summarized by a quality adjusted price index). We use the optimization conditions of the firm to recover firm-specific productivity and input price indicies in each period. Firms are forward-looking and endogenously choose whether to engage in importing and exporting, knowing that trade participation can affect both productivity and its input price index according to a controlled Markov process.

We use the model to evaluate the separate impacts of importing and exporting on firm's productivity and materials access in the long run. Consistent with the previous literature regarding learning by exporting (Aw et al., 2011), we find that exporting increase firm productivity. We also find that importing has a much larger effect on productivity than exporting, which corroborates the findings of Kasahara and Lapham (2013). However, in contrast to Kasahara and Lapham (2013), our result controls for the fact that importing may affect heterogeneous materials prices directly, rather than affecting productivity only. In fact, we do find that engaging in importing

[1] Kasahara and Lapham (2013) have made important progress on this point by allowing imported and domestic materials inputs to be imperfect substitutes, but their model assumes homogeneity in input prices across firms.

improves materials access in addition to increasing productivity. In the Chinese paint manufacturing sector, we find that engaging in importing reduces quality adjusted materials prices by roughly 2 percent. Intuitively, we find no effect of engaging in exporting on material prices conditional on import status, which we interpret as a successful falsification test of our approach.

This result is important to understanding how import liberalization directly affects firm incentives to import materials from abroad. Our model of importing and exporting shows that, because of the complementarities between importing and exporting, import liberalization will endogenously increase both importing and exporting activities. Since both importing and exporting improve productivity, this will amplify the dynamic gains that result from an import tariff reduction: the direct gains due to improved materials endogenously affect incentives to import and export which both lead to increased benefits in firm productivity and market access in the long run.

We illustrate this amplification by examining the effect of China's accession to the WTO in the Paint manufacturing industry, which involved a significant import tariff cut from around 15% in 2000 to 7% in 2006. This import liberalization increased the materials access benefit (and thus incentive) to import. In the case of the Chinese paint industry, we find that the gap between input prices for importing firms relative to a non-importing firm increased by roughly 30% larger following WTO accession than before. We assess the impact of this change using a counterfactual analysis of our model. We find that in the absence of this increased benefit to importing, the proportion of importers in the Chinese paint industry would fall by 2.7 percentage points (a 22% decrease), and the proportion of exporters would fall by 1.3 percentage points (a 10% decrease) over 15 years. Consequently, this further leads to a 3.7 percent reduction in aggregate productivity and 2.6 percent increase in input prices over 15 years. All these channels together add up to a 0.4 percent loss in average firm value (2.1 million USD).

This paper contributes to an already large literature on trade and firm performance by illustrating the role of importing to improve materials access (though lower input prices or improved input quality) and how this incentive interacts with already-established mechanisms through which trade affects firms. Many papers have examined productivity gains from exporting or importing separately, such as Greenaway and Kneller (2007) and Aw et al. (2011) for exporting, and Kasahara and Rodrigue (2008), Goldberg et al. (2009, 2010) for importing.[2] However, comparing to

[2]There is a large literature on this point. In the import aspect, using recently available micro data it is shown that firms that actively participate in importing have relatively higher productivity than those which do not (Blalock and Veloso, 2007; Amiti and Konings, 2007; Kasahara and Rodrigue, 2008; Bernard et al., 2009; Halpern et al., 2011; Khandelwal and Topalova, 2011). Vogel and Wagner (2010) in contrast find that more productive firms are more likely to import material from abroad. In contrast, the empirical literature has quite mixed evidence on the impact of export on productivity. While some papers find a positive productivity effect of export participation

traditional emphasis of gains of importing via productivity, less attention has been paid to the potential input price gains from importing. Our work is motivated by recent findings that there is substantial heterogeneity in materials prices across firms. As shown in Ornaghi (2006) and Atalay (2014) using observed input price data and Grieco et al. (2015) using the estimated counterpart, the input prices, like productivity, have large dispersion across firms and is a key characteristics of individual firms. In this paper, we model input price variation as a persistent stochastic process and explicitly allow firms to affect input prices through their decision to import.

We estimate the model using a panel of 2,160 firms in the paint industry (a four-digit SIC industry) in China from 2000 to 2006. In this industry, intermediate input accounts for over ninety percent of total variable costs, implying the importance of input price gain. Moreover, there is a very strong linkage between input and output quality: for example, using volatile organic compounds produces toxic paint while organic resin increases durability of the paint. These firms produce (non-)water-based paint and coating chemicals, and are quite active in both exporting and importing. The major imported material inputs are resin, pigment, and additives. The data comes from two sources: the Chinese manufacturing survey collected by the Chinese National Bureau of Statistics and the custom transaction records collected by the Chinese Customs from 2000 to 2006. The former provides detailed input and output information at the firm level; the latter contains import and export information at the transaction level.

We face two major challenges in order to measure firm productivity and access to materials inputs as distinct, heterogeneous features of firms. The first challenge is that intermediate input prices are not observed in most firm-level datasets, including the one we use in this paper. To address this problem, the previous literature (e.g., Levinsohn and Petrin, 2003) uses the input expenditure deflated by an industry price index as the input quantity, assuming that all firms use homogeneous inputs and share the same input prices. However, ignoring input price heterogeneity across firms mechanically assumes away materials access gains from trade. Moreover, productivity estimates and other production parameters are biased if input prices are not taken into account, as shown by Grieco et al. (2015). A recent approach proposed by De Loecker et al. (2016) uses a control function for unobserved input price variation that utilizes observed output prices. Output prices contain information about input prices if under the reasonable assumption that input quality is correlated with output quality. In our study, we do not observe output prices, and we address the issue of unobserved input price heterogeneity by utilizing information from firms static input

at the firm level (Van Biesebroeck, 2005; De Loecker, 2007; Aw et al., 2011), other studies find small or even no productivity effect (Clerides et al., 1998; Bernard and Jensen, 1999; Vogel and Wagner, 2010).

demand to recover input prices. Specifically, we extend Grieco et al. (2015) to a trade setting.

The second challenge is that heterogeneous input prices, even when they are observed or recovered from a structural model, may partly reflect differences in input quality. Take the Chinese paint industry as an example, the quality of the inputs — resin, pigment, and additives — strongly influences the quality of paint (e.g. durability and environmental friendly compatibility). Its choice, however, is based on many firm characteristics such as productivity and capital stock. We address this challenge by explicitly modeling firms' choice of input quality. We assume firms face an input price menu that is increasing in the quality selected. We estimate the slope of this menu (the cost of quality) and allow firms to differ in a quality-adjusted materials access index. This approach allows us to estimate the quality-adjusted materials access index at the firm level and to further relate its variation to firm importing in order to investigate the role of material access on firm performance and trade participation. We find that productivity and input quality are complements. Firms with high productivity are self-selected to use inputs of higher quality which suggests a high unit price of material input. This corroborates the positive correlation between productivity and input prices in Kugler and Verhoogen (2012) and De Loecker et al. (2016).

Once we have recovered firm productivity and materials access, we relate them to the impact of trade. Specifically we assume both productivity and materials access evolve according to a controlled Markov process where firms choose future trade participation based on their current productivity, capital stock, materials prices and current trade status. Our results show that productivity and input prices demonstrate significant dispersion across firms and strong (but different) persistence over time. Importing provides much larger gains to productivity than exporting: importing and exporting on average increase firms' next-period productivity by 26.2% and 8.7% respectively, although both are substantial. Importing firms also enjoy lower (quality adjusted) input prices by about 2% compared with non-importing firms. Importantly, as discussed above, we find that this difference increased following China's accession to WTO in 2001 which included a significant import tariff reduction.

The final piece of the model is firms fixed and sunk costs of trade participation. We allow for a flexible specification of fixed and sunk cost for both importing and exporting based on current trade status. Due to the high dimensionality of firms' state space, we estimate the trade cost parameters using conditional choice probability (CCP) approach initially developed by Hotz and Miller (1993) and extended by Hotz et al. (1994) among others. The results show that sunk costs are substantially larger than fixed costs for both importing and exporting, consistent with the findings of earlier studies in other settings. Second and more interestingly, past importing experience reduces current export costs, and vice versa—although the magnitude of cost saving is smaller than that from experience of the same type. Moreover, importing and exporting also exhibit complementarity in terms of current sunk/fixed costs which corroborates the findings of Kasahara and Lapham (2013): the cost of importing and exporting in the same year is smaller than the sum of costs of importing or exporting separately. This may be due to familiarity in dealing with customs bureaucracy or other efficiencies in the management of trade-related tasks.

After documenting the impacts of trade on both productivity and materials access, we perform a separate series of counterfactuals to evaluate the relative importance of various mechanisms in determining the long term firm performance. First, we consider the relative impact of productivity and materials access by showing how shutting down each channels would affect firm valuations. We find that the productivity and material access channels are similar in magnitude, with the latter being relatively larger: eliminating dynamic productivity gains from trade would reduce firm valuations by 0.9 percent (5 million USD on average), while removing gains due to material access from importing would reduce gains by 1.2 percent (6.7 million USD on average). Second, we compare the joint effects of productivity and material access gains due to importing versus exporting. We find that gains due to the effects of importing (1.4 percent, 8 million USD) are roughly five times as large as the gains from exporting (0.3 percent, 1.6 million USD). This is not surprising since the impacts of importing on both productivity and materials access are larger than the impacts we measure of exporting. Finally, as discussed above, we use our model to illustrate how import liberalization associated with China's accession to the WTO served to affect importing, exporting, productivity and firm valuations in the long run.

The remainder of this paper is organized as follows. Section 2 introduces the background and data. Section 3 develops the model. Section 4 presents the estimation method. Section 5 reports the estimation result and evaluates how firms benefit from international trade via the channels of productivity and materials access. Section 6 presents the results of our several counterfactual experiments. We conclude in Section 7.

2 The Chinese Paint Industry: Background and Data

Four features drew us to the Chinese paint industry as an ideal setting to explore the role of input prices and import liberalization on trade participation. The first striking feature, which is also shared by many other Chinese industries, is that intermediate material inputs accounts for a large share in firms' total variable cost, over 90% on average. That is, on average expenditure on intermediate material inputs is more than 15 times than that on wage bill and is around 5 times of *book value* of capital stock. Thus, a small change of input prices could result in a radical change of profit. In particular, the average import tariff was reduced after the accession to WTO from 15% in 2000 to 7% in 2006 in this industry, as shown in the top of Figure 1, which naturally influenced the material prices faced by Chinese importers and consequently affected their performance in both domestic and export markets. As a result, it provides a natural field experiment to investigate how firms benefit from trade via the input prices channel after trade liberalization.

Second, this industry, as observed in many other Chinese industries, experienced a boom of both import and export volume after joining WTO. As shown in the bottom of Figure 1, conditional on importing, during 2000 to 2006 the firm-level import volume had grown from 22.9 to 40.9 million USD, and export volume had grown from 11.4 to 22.5 million USD for exporting firms. Overall, 12.9% of firms had exporting experience and 12.4% of firms had importing experience. The annual export revenue at the industry level is 606 million USD according to the manufacturing survey, accounting for 11.2% of the total output value. Meanwhile, the annual import expenditure at the industry level is 547 million USD, accounting for 8.9% of the total material expenditure. Conditional on exporting and importing firms, as shown in Table 1, export revenue accounts for about 34.8% of total revenues for exporters on average; material import accounts for about 42.2% of total intermediate input expenditure for importers on average.

However, 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.[3] Only 1.2% of export revenue and 2.1% of import is classified as processing trade with assembly and other types of trade. The remaining trade share is in the form of ordinary trade or processing trade with imported material. In constrast, many other Chinese industries significantly engage in processing trade with assembly, in which firms are less likely to independently make their own decisions on production, importing, and exporting to maximize profit. The feature of negligible assembly processing trade in the paint industry makes profit maximization and endogenous trade participation as reasonable assumptions in our model. In the empirical estimation, we define a firm engaged in export or import if and only if the trade is ordinary trade or processing trade with imported materials.

[3]See Appendix B for detailed description of trade types.

Finally, one more unique feature of this industry lies in the strong link between input quality and output quality. The major products of paint industry are various paint and coating materials: namely non-water-based paint (43.3%), water-based paint (7.5%), coating chemicals (6.8%), and other related products. The major imported material input includes resin (42.2%), pigment (22.5%), and additives (8.7%). The quality of material input largely determines the quality of paint. For example, use of heavy metals such as lead and other additives in the painting materials can be toxic to human health and have harmful influence on the environment, thus the resulting products are treated as of low quality. Instead, paint produced using environmentally friendly alternative materials have less negative impacts on the environment and human health, and they are considered as of high quality. Also, poor quality of paint can cause peeling, chalking, and cracking, which reduce the lifespan and durability of the paint. Firms can choose to produce high quality paint and sell for a higher price but the high quality input is also more costly. This suggests that, if price is a (rough) measure of quality, input quality and output quality are positively correlated. This naturally motivates us to explicitly take this input-output quality linkage into account and explore firms' endogenous choices on input quality, in order to recover input price and productivity net of input quality.

We take all these features into account by explicitly considering unobserved input price heterogeneity across firms, allowing the effect of WTO to play a role in firms' trade decision, and recognizing the input-output quality linkage in a framework of profit maximization and endogenous dynamic trade participation.

The data for our study are drawn from two sources. The first source is the firm-level manufacturing survey collected annually by National Bureau of Statistics in China. 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, book value of capital stock, but not the material prices nor quantities. The second source is the Chinese custom records of import and export from Chinese Customs, which covers every transaction of import and export associated with Chinese firms. This dataset provides information on the import and export values and other variables such as sources or destination countries, etc. We link these two datasets together to form an unbalanced panel containing both production information and import and export information at the firm level for a total of 2160 firms in the Chinese paint industry. The merged dataset consists of years from 2000-2006, i.e., covering two years prior to China's accession to WTO and the first few years after that. Table 1 describes the summary statistics of main variables in the

Chinese paint industry.

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. In particular, firms may sell in two monopolistically competitive output markets: a domestic market and an export market. They can choose to use domestic material exclusively, or to use (partly) import material inputs from abroad. Firms are forward-looking and recognize the influence of trade participation on productivity and input prices, and they make their export and import decisions to maximize their discounted total future net profit. At the beginning of each period, firms are fully 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. We assume that labor and material are fully flexible from period to period and therefore these choices have no dynamic implications. In the static model of production decisions, we show that the approach developed in Grieco et al. (2015) can be generalized to the multiple-market case with endogenous quality choice to recover firm-level input prices and productivity. Second, the firm chooses whether to engage in importing and exporting in the following period.[4] If it chooses to trade, it must pay a sunk or fixed cost, but will have access to the export market in the following period if it exports, and may reduce its materials price index if it imports. Both importing and exporting may dynamically affect the firms future productivity. The dynamic model of trade participation is then used to evaluate the dynamic gains from trade through channels of productivity and input prices in the long run, and especially, to evaluate the impact of WTO accession on Chinese Paint manufacturers via both productivity and input price channels.

[4]To keep the model tractable, we do not directly model firms' investment decisions, and treat investment as exogenous. Since we have only a 6 year panel, the variation in capital stock over time is small relative to the cross sectional differences, which we control for in our empirical application.

3.1 Static Decisions

3.1.1 Production and Demand

In each period t, every firm produces a single product with a constant elasticity production function.[5] Specifically, in each period t, a firm j produces quality-adjusted output, Q_{jt}, using homogeneous labor input, L_{jt}, intermediate material inputs, M_{jt}, and capital K_{jt}.[6] We further allow the material inputs to be heterogeneous in quality. In addition, following Kugler and Verhoogen (2009, 2012), we allow productivity (ω_{jt}) and input quality (ν_{jt}) to influence output quality and that firms can choose input quality endogenously. We use a function $h(\omega_{jt}, \nu_{jt})$ to capture the productivity-input quality combination in producing output quality. Specifically, the (parametric) production function we consider is[7]

$$Q_{jt} = h(\omega_{jt}, \nu_{jt})F(L_{jt}, M_{jt}, K_{jt}) = h(\omega_{jt}, \nu_{jt}) \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}\right]^{\frac{1}{\gamma}}, \tag{1}$$

where $\alpha_L, \alpha_M, \alpha_K$ are the distribution parameters which sum up to one by normalization. The elasticity of substitution among inputs (σ) is determined by γ, where $\gamma = \frac{\sigma-1}{\sigma}$.

The function $h(\omega_{jt}, \nu_{jt})$, which depends on both productivity and input quality, is observationally equivalent to total factor productivity of a homogenous output. As a common issue in the literature, we cannot separate the firm-level demand heterogeneity from physical productivity without additional data on output price. So in this paper the recovered $h(\omega_{jt}, \nu_{jt})$, and the associated productivity measure ω_{jt} are revenue-based and contain both physical productivity and firm-level demand shifters. In addition, we are unable to separate the effect of higher quality inputs ν increasing either the quality of output or the quantity of output. Therefore, we model Q_{jt} as a quality adjusted output reflecting both effects. We hence forth call $h(\omega_{jt}, \nu_{jt})$ firm capability —although it is a mixture of physical productivity, output quality, and other demand shifters—and assume the following structure to capture the productivity-input quality linkage

[5] This approach can be straightforwardly applied to more flexible parametric production functions, as in discussed in Grieco et al. (2015).

[6] We do not observe physical output but instead only total revenue. Q_{jt} is quality adjusted output in that we include an adjustment for output quality due to the use of high-quality inputs as part of Q_{jt} rather than having output quality included as part of the output price, which we will model according to Dixit-Stiglitz demand.

[7] Note that M_{jt} is the quantity of material inputs in its purchase unit. Although it is plausible to consider that high quality input is more efficient in a non-Hicks-neutral way, say allowing for $\nu_{jt} M_{jt}$ in the production function, 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 in this model. Refer to Appendix A for details.

following Kugler and Verhoogen (2012):

$$h(\omega_{jt},\nu_{jt}) = \left[\frac{1}{2}\left(exp(\omega_{jt})\right)^{\theta} + \frac{1}{2}\left(\nu_{jt}\right)^{\theta}\right]^{\frac{1}{\theta}}, \theta \neq 0. \tag{2}$$

If $\theta < 1$ then productivity and input quality are gross complements to each other. Within each period, the productivity ω_{jt} is fixed, but input quality ν_{jt} is an endogenous choice of the firms.

Material inputs are vertically differentiated in input quality ν_{jt}. The variation of unit price of material inputs across firms, as a result, reflects two sources of heterogeneity: a quality-adjusted materials access index/price (p_{jt})—which is part of the firms state—and an endogenous choice of input quality (ν_{jt}). The heterogeneity of the input 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 and transportation costs may create differences in input prices; importing firms may enjoy a lower price compared with non-importing firms due to the expanded choice set of inputs and suppliers. As a result, even when firms choose the same level of input quality, the unit prices they face may be still different. Given p_{jt}, firm j can endogenously choose the quality level of inputs, ν_{jt} from a continuum of material qualities. The higher the quality, the higher the unit price. So the firm faces a menu of quality-specific material input prices denoted as $P_{Mjt}(p_{jt},\nu_{jt})$. It is natural to assume that the price menu is strictly increasing in quality $\frac{\partial P_{Mjt}}{\partial \nu_{jt}} > 0$. We assume that the input price menu takes a simple form:

$$P_{Mjt} = p_{jt}\nu_{jt}^{\phi}, \tag{3}$$

where $\phi > 0$. Note that, while it is intuitive that higher quality inputs cost more, the scale of the price increase is due to the arbitrary scale of quality, which is fixed by $h(\cdot)$. Therefore, the parameter ϕ measures the combined effect of the price of increasing quality, and the the impact raising quality has on increasing quality-adjusted output Q_{jt}.

In our model, importing does not affect the materials access conditional on p_{jt}. Instead, the distribution of p_{jt} 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. However, input prices may differ for reasons other than import status—such as firm geography or supply contacts—and this is allowed in our framework. Moreover, this does not suggest that the 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, P_{Mjt} the quality-inclusive unit input price may be higher for on average for importers than non-importers.

On the demand side, there are two markets: a domestic market and an export market. Firms are monopolistically competitive and face different demand functions in the domestic and export markets, which we assume are Dixit-Stiglitz,

$$P_{jt}^{D} = \left(Q_{jt}^{D}\right)^{1/\eta^{D}}, \tag{4}$$

$$P_{jt}^{X} = \left(Q_{jt}^{X}\right)^{1/\eta^{X}}, \tag{5}$$

where P_{jt}^D and P_{jt}^X are output prices, Q_{jt}^D and Q_{jt}^X are the quantities demanded, and η^D and η^X are demand elasticities for domestic and export markets, respectively. Note that, due to the lack of output price data, demand heterogeneity in the two markets are not identifiable from physical productivity. The implication of adopting this simple demand function is that demand heterogeneity across firms is captured in the revenue-based firm capability $h(\cdot)$, while the firm-level difference between domestic and foreign demand is ignored. In particular, in the estimation, aggregate demand shifters that potentially change over time will also captured $h(\cdot)$. We test a range of flexible specifications, such as controlling for year effect, in Section 5.2 (Table 3) to make sure that the variation of aggregate demand shifters are not driving our main findings regarding the evolution of productivity and input prices.

3.1.2 Static Decisions of Labor, Material, and Input Quality

At the beginning of each period, a firm observes its own state variables including trade status, capital stock, productivity, quality-adjusted input prices, and wage rate, which are fixed within the period. 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. That is:

$$\begin{aligned} \pi(\omega_{jt}, p_{jt}, K_{jt}, P_{Ljt}, e_{jt}) = \max_{L_{jt}, M_{jt}, Q_{jt}^D, Q_{jt}^X, \nu_{jt}} \quad & P_{jt}^D Q_{jt}^D + e_{jt} P_{jt}^X Q_{jt}^X - P_{L_{jt}} L_{jt} - P_{Mjt} M_{jt}, \\ \text{subject to:} \quad & Q_{jt}^D + e_{jt} Q_{jt}^X = h(\omega_{jt}, \nu_{jt}) F(L_{jt}, M_{jt}, K_{jt}), \\ & P_{jt}^D = \left(Q_{jt}^D\right)^{\frac{1}{\eta_D}}, \quad P_{jt}^X = \left(Q_{jt}^X\right)^{\frac{1}{\eta_X}}, \quad P_{Mjt} = p_{jt} \nu_{jt}^{\phi}, \end{aligned} \tag{6}$$

where P_{Ljt} is the wage rate, and export status, e_{jt}, has been determined in the beginning of this period before the firm maximize the period profit: $e_{jt} = 0$ if the firm only sells in the domestic market, and $e_{jt} = 1$ if the firm also exports. Note that we assume the firm always sells in the domestic market. The resulting period-profit π_{jt} is the maximum total profit in period t and it is a function of the above state variables: $\pi(\omega_{jt}, p_{jt}, K_{jt}, P_{Ljt}, e_{jt})$.

3.2 Dynamic Decisions

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.

We start with specifying the law of motion of the state variables of the model, beginning with firm productivity. Both export and import may have an impact on future productivity as suggested by Aw et al. (2011) and Halpern et al. (2011). We follow the literature and assume productivity evolves according to an AR(1) process that is a function of trade participation,

$$\begin{aligned} \omega_{jt+1} &= f(\omega_{jt}, e_{jt}, i_{jt}, \tau_{t+1}) + \epsilon^{\omega}_{jt+1} \\ &= f_0 + f_\omega \omega_{jt} + f_e e_{jt} + f_i i_{jt} + f_{wto}\tau_{t+1} + \epsilon^{\omega}_{jt+1}. \end{aligned} \tag{7}$$

We let τ_{t+1} represent a dummy of WTO to account for changes in aggregate productivity following WTO accession: the accession to WTO may had impacted firm productivity due to its liberalization and openness to new technologies, inward FDI, and investment opportunities. We have also experimented with using a specification with individual time dummies and the result is robust. Finally, ϵ^{ω}_{jt+1} is an i.i.d. shock to firm productivity.

We now turn to the evolution of the quality-adjusted materials price index. If a firm imports inputs from abroad, it may also enjoy a lower material price menu due to expanded choice set of inputs, compared with non-importers. Additionally, in the circumstance of China, the accession to WTO may play an importance role in influencing the benefits from trade. As import tariff was reduced substantially after the accession to WTO, the input prices faced by *all* firms were potentially lower due to more price competition. For importers, this benefit could be even larger because they are the firms who directly face the tariff.[8] To capture these effects, we assume the firm's input price index evolves over time according to a first order Markov processes, which can be shifted by firms' import participation. However, compared to the evolution of productivity in which the effects of trade participation are lagged, we assume that import affects the material input price index immediately in the same period of importing.[9] This assumption is consistent with the one in De Loecker et al. (2016), and it 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 is used in the period of importing so they affect the input prices in the same period. Specifically, the evolution process of the input price index is:

$$\begin{aligned} \ln(p_{jt+1}) &= g(\ln(p_{jt}), i_{jt+1}, \tau_{t+1}) + \epsilon^p_{jt+1} \\ &= g_0 + g_p \ln(p_{jt}) + g_{i0} i_{jt+1}(1-\tau_{t+1}) + g_{i1} i_{jt+1}\tau_{t+1} + g_{wto}\tau_{t+1} + \epsilon^p_{jt+1}, \end{aligned} \tag{8}$$

where ϵ^p_{jt+1} are i.i.d. shocks to input prices. Thus, g_{i0} and g_{i1} measures the input price benefit from importing before and after China's accession to WTO. If $g_{i1} < g_{i0} < 0$, then this means WTO leads to a larger difference of input price between importers and non-importers, due to the tariff cut. 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. We test a set of more flexible specifications in Section 5 to check the robustness of the effects that this specification captures.

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

$$\log(P_{L_{jt+1}}) = \zeta_0 + \zeta_\ell \log(P_{L_{jt}}) + \epsilon^\ell_{jt+1}, \tag{9}$$

with ϵ^ℓ_{jt+1} as an i.i.d. shock.

Importing and exporting also incur fixed costs that varies across firms and time. We model the trade cost in a very flexible way, by allowing it to depend on not only its current trade status, but also its lagged trade status as in Das et al. (2007). For example, a new exporter may need to pay a higher cost (referred as sunk cost) to start exporting compared with continuing exporters who have established distribution networks in the past. In addition, we observe high

[8] Ideally, one could measure the exact effect of tariff cut on input prices; however, due to we only have tariff rates at the industrial level which had the most significant drop in 2002 – the first year after China's accession to WTO, we use a dummy and interact it with import participation in order to measure the direct effect of WTO on input prices of importers, after taking the general WTO effect on all firms into account.

[9] 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.

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 experience of export (import) in the last period can reduce the firms' cost of import (export) in the current period. Second, if a firm imports and exports simultaneously, it may gain some cost advantage over importing and exporting separately. Thus, the trade cost for trade participation ie_{jt+1} is specified as,[10]

$$\begin{aligned} C(ie_{jt+1}; ie_{jt}, \xi_{jt}^{ie_{jt+1}}) &= C(ie_{jt+1}, ie_{jt}; \lambda) - \lambda_\epsilon \xi_{jt}^{ie_{jt+1}} \\ &= \sum_{ie_{jt+1}, ie_{jt}} \lambda_{ie_{jt+1}, ie_{jt}} I_{ie_{jt+1}, ie_{jt}} - \lambda_\epsilon \xi_{jt}^{ie_{jt+1}} \end{aligned} \tag{10}$$

This specification not only captures the conventional fixed and sunk costs of import and export, but also embody the idea of import-export complementarity in terms of saving trade costs as discussed above. The first term gives us 16 parameters $\lambda_{ie_{jt+1}, ie_{jt}}$, 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 the 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.[11] The scale of this shock is estimated by λ_ξ, which is identified because we are able to estimate the scale of flow profits. Note that we assume that firms make trade participation decisions for period $t+1$ in the end of period t when the trade cost shocks are realized. Specifically, the timing is specified as follows:

1. At the beginning of each period t, all shocks—including trade cost shocks and all i.i.d. shocks in the Markov processes of productivity, input price, and wage rate—are realized. Each firm observes its own state (s_{jt}, ξ_{jt}), where econometricians observe $s_{jt} = (\omega_{jt}, K_{jt}, p_{jt}, P_{L_{jt}}, ie_{jt})$ but not the trade cost shocks $\xi_{jt} = (\xi_{jt}^{(0,0)}, \xi_{jt}^{(0,1)}, \xi_{jt}^{(1,0)}, \xi_{jt}^{(1,1)})$. Denote the beginning-of-period firm value as $V^\xi(s_{jt}, \xi_{jt})$. The expected firm value before observing trade shocks ξ_{jt} is $V(s_{jt}) = E_\xi[V^\xi(s_{jt}, \xi_{jt})]$.

2. The firm chooses labor quantity, and material quantity together with its quality to maximize the period profit.

[10] In order to check the possibility that the access to WTO might also change the sunk and fixed costs of trade, we also estimated a version of dynamic model by adding time dummies in Eq. (10). The estimated time dummies are insignificant. So we assume that the sunk and fixed costs of international trade are time-invariant.

[11] We make this technical assumption to reduce the computation burden when estimating these cost parameters. Note that this distribution assumption implies that when the firm does not engage in trade, it still needs to pay the i.i.d. cost shock, which can be interpreted as a daily operational cost in the domestic market.

3. The firm chooses its trade status for next period, ie_{jt+1}, which depends on (s_{jt}, ξ_{jt}).

Given $\pi(s_{jt})$ is the maximized period profit at period t, a firm's long-term firm value after observing the current period cost shocks is

$$V^{\xi}(s_{jt}, \xi_{jt}) = \max_{\{ie_{jt+\tau}\}_{\tau=1}^{\tau=+\infty}} \left\{ \pi(s_{jt}) + E \sum_{\tau=1}^{+\infty} \delta^{\tau} \left[\pi(s_{jt+\tau}, ie_{jt+\tau}) - C(ie_{jt+\tau}; ie_{jt+\tau-1}, \xi_{jt+\tau-1}) \right] \right\}. \quad (11)$$

The firm's objective is to find the optimal dynamic trade path $\{ie_{j\tau}\}_{\tau=t}^{\infty}$ to maximize the above long-term value function. The expectation is taken over all shocks, including all trade cost shocks, productivity shocks, input price shocks, and wage rate shocks. The associated Bellman equation, defined from researchers' perspective without observing trade cost shocks, ξ_{jt}, is

$$\begin{aligned} V(s_{jt}) \quad &= \quad E_{\xi}[V^{\xi}(s_{jt}, \xi_{jt})] = E_{\xi} \max_{ie_{jt+1}} \left\{ \pi(s_{jt}) - C(ie_{jt+1}; ie_{jt}, \xi_{jt}^{ie_{jt+1}}) + \delta E_{\epsilon^{m\ell\omega}}[V(s_{jt+1}|s_{jt}, ie_{jt+1})] \right\} \\ & \quad \text{subject to: } \quad (7), (8), \text{ and } (9) \end{aligned} \quad (12)$$

The first expectation after the second equality is taken over the trade cost shocks in period t. The second expectation is taken over all future shocks, which are unknown to the firm when it makes its trade participation decision.[12] Considering that the schedule of China accession to WTO was pre-announced, we treat the WTO effect as an exogenous variable commonly known to all firms and there is no uncertainty about it.

4 Identification and Estimation Strategy

The challenge of identification comes from the fact that we do not observe neither productivity nor material associated variables: input quantity, its price or quality. We need to recover them from observables: labor employment, wage expenditure, material expenditure, capital stock, domestic and export revenues and model parameters. The identification strategy consists two steps by utilizing the firm's static profit maximization problem. The first step is to identify firm capability, $h(\cdot)$ (the combined effect of productivity and input quality), and unit price of material input using the same insight as Grieco et al. (2015): a change of unit price of material input affect the optimal ratio of labor and material input, while a change of firm capability, which is Hicks-neutral, does not have such effect. Thus, the observed variation in labor input quantities, together with labor and materials expenditures, allows us to identify the variation of the unit

[12] To simplify the dynamic estimation, we treat capital stock as exogenous firm type in the model so that we do not have to consider the dynamic investment choices of capital stock. This is reasonable in our case as we are considering a relatively short panel.

material price from firm capability across firms. The second step is to identify quality-adjusted materials access price index and firm productivity from the recovered unit price of input and firm capability. De Loecker et al. (2016) use output price variation (which is analogous to variation in firm capability in our model) to control for input quality variation in Indian manufacturing data. In our data set, we do not observe output prices. Instead we exploit the optimal choice of input quality implied by our model to derive a relation between input quality and firm capability that helps us to identify the cost of materials quality, ϕ, and hence the materials access index.

Notice that firm capability is a function of two components: productivity and input quality. The former is fixed for the purpose of the materials input choice while the latter is endogenously chosen. The optimization of input quality implies a one-to-one mapping from firm capability to input quality given other observables. Thus, conditional on input quality (or equivalently firm capability and other observables), the variation of unit price of input allows us to identify the variation of quality-adjusted price of input. With input quality identified, productivity can be identified from the variation of firm capability.

The identification strategy suggests an estimation procedure of three stages. In the first stage, we focus on the firm's static decisions about input and output given its state variables, and estimate production functions to recover firm capability and unit input price in the scenario that firms can sell in two markets. To do this, we extend Grieco et al. (2015) to the two-market case, and estimate the production function to recover the unobserved unit input prices and firm capability by utilizing the structure implied by the firms' optimal labor and material choices. In the second stage, with the firm-time specific firm capability and unit input price measures recovered, we estimate productivity and quality-adjusted input prices by utilizing their evolution processes as well as firms' optimal choice of input quality. The evolution processes reflect the gains from international trade, which consequently serves as a building block in the third stage estimation of the dynamic model: it takes the output from the second stage, including profit function, productivity and quality-adjusted input price measures together with their evolution processes, to the Bellman equation (12) to estimate the distribution of trade costs.

4.1 Production Function Estimation

For expositional purpose, we focus on firms selling in both domestic and export markets. The estimation method degenerates to the exact procedure in Grieco et al. (2015) when firms selling in the domestic market only.

When a firm sells in both domestic and exporting markets, the period profit maximization problem defined in (6) implies the following four first order conditions for labor quantity, material quantity, output quantity sold in each of the markets. We substitute P_{jt}^D and P_{jt}^X by the demand functions, and use μ_{jt} to denote the Lagrange multiplier of the production constraint. The first order conditions with respect to Q_{jt}^D and Q_{jt}^X are,

$$\frac{\partial \mathcal{L}}{\partial Q_{jt}^D} = \frac{1+\eta^D}{\eta^D}(Q_{jt}^D)^{1/\eta^D} - \mu_{jt} = 0, \tag{13}$$

$$\frac{\partial \mathcal{L}}{\partial Q_{jt}^X} = \frac{1+\eta^X}{\eta^X}(Q_{jt}^X)^{1/\eta^X} - \mu_{jt} = 0, \tag{14}$$

The first order conditions with respect to labor and material quantities are,

$$\frac{\partial \mathcal{L}}{\partial L_{jt}} = -P_{L_{jt}} + \mu_{jt} h(\omega_{jt}, \nu_{jt}) \frac{\partial F}{\partial L_{jt}} = 0, \tag{15}$$

$$\frac{\partial \mathcal{L}}{\partial M_{jt}} = -P_{M_{jt}} + \mu_{jt} h(\omega_{jt}, \nu_{jt}) \frac{\partial F}{\partial M_{jt}} = 0. \tag{16}$$

As a result, multiplying Equation (15) and (16) by L_{jt} and M_{jt} respectively, we have

$$\mu_{jt} h(\omega_{jt}, \nu_{jt}) \frac{\partial F}{\partial L_{jt}} L_{jt} = E_{Ljt}, \tag{17}$$

$$\mu_{jt} h(\omega_{jt}, \nu_{jt}) \frac{\partial F}{\partial M_{jt}} M_{jt} = E_{Mjt}. \tag{18}$$

Where $E_{Ljt} = P_{Ljt} L_{jt}$ and $E_{Mjt} = P_{Mjt} M_{jt}$ represent the expenditure on labor and material, respectively. Dividing these two equations yields

$$\frac{\frac{\partial F}{\partial L_{jt}} L_{jt}}{\frac{\partial F}{\partial M_{jt}} M_{jt}} = \frac{E_{Ljt}}{E_{Mjt}}. \tag{19}$$

We can recover the unobserved material quantity M_{jt} as a function of observed variables from equation (19) upto a set of parameters to be estiamted, as in Grieco et al. (2015). In the case of CES production function, it is straightforward to show that the recovered material quantity and the unit input price admit a simple closed-form solution:

$$M_{jt} = \left[\frac{\alpha_L E_{Mjt}}{\alpha_M E_{Ljt}}\right]^{\frac{1}{\gamma}} L_{jt}, \tag{20}$$

$$P_{Mjt} = \left[\frac{\alpha_L E_{Mjt}}{\alpha_M E_{Ljt}}\right]^{1-\frac{1}{\gamma}} P_{Ljt}. \tag{21}$$

That is, they can be written as functions of observed variables in the data up to unknown parameters to be estimated.

Next, we show that $h(\omega_{jt}, \nu_{jt})$ can also be written as a function of observed variables. To see this, take the ratio of (13) and (14) and solve for the relationship between the output sold domestically and abroad:

$$Q_{jt}^X = z \cdot (Q_{jt}^D)^{\eta^X/\eta^D}, \tag{22}$$

where $z = (\frac{\eta^X}{\eta^D}\frac{1+\eta^D}{1+\eta^X})^{\eta^X}$ is an constant. Substitute it into the production function (with material quantity replaced by (20)), we have

$$z \cdot (Q_{jt}^D)^{\eta^X/\eta^D} + Q_{jt}^D = h(\omega_{jt}, \nu_{jt}) \left[\alpha_L L_{jt}^\gamma \left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}}\right) + \alpha_K K_{jt}^\gamma\right]^{\frac{1}{\gamma}}. \tag{23}$$

Note that this provides us with one equation relating the two unknown variables $(Q_{jt}^D, h(\omega_{jt}, \nu_{jt}))$, while the labor first order condition provides us another: substitute the first order condition associated with Q_{jt}^D (13) into that for labor (15), we get

$$\frac{1+\eta^D}{\eta^D}(Q_{jt}^D)^{1/\eta_D} \alpha_L L_{jt}^{\gamma-1} h(\omega_{jt}, \nu_{jt}) \left[\alpha_L L_{jt}^\gamma \left(1 + \frac{E_{M_{jt}}}{E_{L_{jt}}}\right) + \alpha_K K_{jt}^\gamma\right]^{\frac{1}{\gamma}-1} = P_{L_{jt}}. \tag{24}$$

It is straightforward to show that (23) and (24) admit a unique solution of $(Q_{jt}^D, h(\omega_{jt}, \nu_{jt}))$ as long as $\eta^D, \eta^X < -1$. That is, (23) and (24) imply an one-to-one mapping from the observable variables to $(Q_{jt}^D, h(\omega_{jt}, \nu_{jt}))$ given model parameters, which consequently can be written as a unique implicit function of observables given model parameters. The counterpart of (23) and (24) is Equation (7) in Grieco et al. (2015). Finally, Q_{jt}^X is also recovered from (22) as a function of observables. Therefore, we have shown that we are able to recover $(M_{jt}, P_{M_{jt}}, Q_{jt}^D, Q_{jt}^X, h(\omega_{jt}, \nu_{jt}))$ uniquely from the observable data $(E_{Ljt}, E_{Mjt}, L_{jt}, K_{jt}, R_{jt}^D, R_{jt}^X)$ up to parameters to be estimated.

The estimation equation is constructed by plugging all these recovered variables into the revenue equations in the domestic and export markets which have not been used yet:

$$R_{jt}^D = \left(Q_{jt}^D\right)^{1/\eta^D+1}, \quad R_{jt}^X = \left(Q_{jt}^X\right)^{1/\eta^X+1}. \tag{25}$$

After the same algebra in Grieco et al. (2015), we arrive the following equation:

$$\frac{1+\eta^D}{\eta^D}R^D_{jt} + \frac{1+\eta^X}{\eta^X}R^X_{jt} = \left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right]. \tag{26}$$

It is worth noting that this equation is a natural extension of Equation (8) in Grieco et al. (2015) to the two-market case. When the firm does not sell in the export market (i.e., $R^X_{jt} = 0$), the above equation becomes the one in Grieco et al. (2015). As a result, if we denote $R^X_{jt} = 0$ when the firm does not sell in the export market, (26) also holds when the firm only sells in the domestic market. Of course, it is also straightforward to extend (26) to more than two markets.

The estimation procedure of associated model parameters, $\beta \equiv (\alpha_L, \alpha_M, \alpha_K, \eta^D, \eta^X, \gamma)$, consists of two steps. In the first step, a subset of the parameters, $\beta^D \equiv (\alpha_L, \alpha_M, \alpha_K, \eta^D, \gamma)$, is estimated with the information on non-exporters only following the same procedure in Grieco et al. (2015). By allowing multiplicative measurement errors u^D_{jt} to the observed domestic revenue, equation (26) for non-exporters implies an empirical estimation equation:

$$\log(R^D_{jt}) = \log(\frac{\eta^D}{1+\eta^D}) + \log\left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right] + u^D_{jt}. \tag{27}$$

Note that the measurement error in revenue does not influence the derivation of the equations above, because the whole derivation process, except the final estimation equation (26), does not utilize the revenue data. Following Grieco et al. (2015), the model parameters in β^D are identified with two additional constraints naturally implied by the model. The first additional constraint is the normalization assumption:

$$\alpha_L + \alpha_M + \alpha_K = 1. \tag{28}$$

The second is the ratio of input expenditure aggregation equation resulted directly from taking the geometric mean of first order conditions for labor and material quantities of all firms:

$$\frac{\overline{E}_L}{\overline{E}_M} = \frac{\alpha_L}{\alpha_M}, \tag{29}$$

where $\overline{E}_L$ and $\overline{E}_M$ are the geometric mean of labor expenditure and material expenditure for all firms, respectively. They can be computed directly from the data. We estimate (27) using non-linear least square (NLLS) for non-exporters with constraints (28) and (29),

$$\begin{aligned}\hat{\beta}^D &= \operatorname{argmin}_{\beta^D} \sum_{jt} \left\{ \log(R_{jt}^D) - \log(\frac{\eta^D}{1+\eta^D}) - \log\left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^\gamma\right)\right]\right\}^2 \\ &\quad \text{subject to (28) and (29).} \end{aligned} \tag{30}$$

With $\hat{\beta}^D$, the estimation of η^X is straightforward: as the second step, we take the ratio of export and domestic revenues utilizing equation (22) and (25), we get:

$$R^X = \left(\frac{\eta^X}{\hat{\eta}^D}\frac{1+\hat{\eta}^D}{1+\eta^X}\right)^{1+\eta^X} R^{D\,\frac{1+\eta^X}{1+\hat{\eta}^D}}. \tag{31}$$

We allow for similar multiplicative measurement errors u_{jt}^X to the observed export revenue, thus we obtain an estimating equation:

$$\log(R_{jt}^X) = (1+\eta^X)\log\left(\frac{\eta^X}{\hat{\eta}^D}\frac{1+\hat{\eta}^D}{1+\eta^X}\right) + \frac{1+\eta^X}{1+\hat{\eta}^D}\log(R_{jt}^D) + u_{jt}, \tag{32}$$

where $u_{jt} = (u_{jt}^X + \frac{1+\eta^X}{1+\hat{\eta}^D}u_{jt}^D)$. Notice that u_{jt} is correlated with R_{jt}^D through u_{jt}^D. Therefore, we estimate this equation for η^X via GMM using (K_{jt}, L_{jt}) as instruments.

It is important to notice that the estimation procedure discussed so far has not used any restriction on how input quality is chosen. Thus, this method applies no matter whether there is input quality difference across firms or not, or whether input quality is endogenous or exogenous, or how the firm capability function (2) or the input price menu (3) are specified. However, the measures of firm capability and unit input prices, $\widehat{h}(\omega_{jt}, \nu_{jt})$ and $\widehat{P}_{Mjt}$, respectively, both contain input quality ν_{jt}: $\widehat{h}(\omega_{jt}, \nu_{jt})$ contains input quality as it echoes the linkage between input quality and output quality as suggested by Kugler and Verhoogen (2009, 2012); $\widehat{P}_{Mjt}$, by definition, is $p_{jt}\nu_{jt}^{\phi}$, thus it also contains input quality. The next step is to recover productivity ω_{jt} and quality-adjusted price p_{jt} from firm capability and unit input prices.

4.2 Input Price Index and Productivity Processes

In this section, we make use of the optimization of firms' endogenous input quality choice to recover the productivity and input prices from the firm capability measure $\widehat{h}(\omega_{jt}, \nu_{jt})$ and unit price of material input $\widehat{P}_{Mjt}$. Specifically, the first order condition of endogenous input quality choice is

$$\frac{\partial P_{Mjt}(p_{jt},\nu_{jt})}{\partial \nu_{jt}} M_{jt} = \mu_{jt} F(L_{jt}, M_{jt}, K_{jt}) \frac{\partial h(\nu_{jt},\omega_{jt})}{\partial \nu_{jt}} \tag{33}$$

Solve μ_{jt} from (18) and plug it into (33), and after some algebra we can derive a closed-form relation between endogenous input quality choice and productivity:

$$\ln \nu_{jt} = \frac{1}{\theta} \ln \frac{\phi \sigma_{Mjt}}{1 - \phi \sigma_{Mjt}} + \omega_{jt}, \tag{34}$$

where $\sigma_{Mjt} = \frac{\partial F}{\partial M_{jt}} \frac{M_{jt}}{F(\cdot)}$ is the output elasticity of material. This equation indicates that 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) given that $\theta < 0$. Notice that σ_{Mjt} can be directly computed according to the estimated production function and material input quantity from the previous step. For this reason, we employ $\widehat{\sigma}_{Mjt}$ as a consistent estimate of σ_{Mjt} from now on.

Substitute (34) into firm capability function (2) to solve for productivity, and utilize the price menu function (3) directly for quality-adjusted prices, we obtain:

$$\omega_{jt} = \ln \widehat{h}(\omega_{jt}, \nu_{jt}) - \frac{1}{\theta} \ln \left[\frac{1/2}{1 - \phi \widehat{\sigma}_{Mjt}} \right]. \tag{35}$$

$$\ln p_{jt} = \ln \widehat{P}_{Mjt} - \phi \ln \nu_{jt}. \tag{36}$$

By substituting (35) into (34) we have:

$$\ln \nu_{jt} = \ln \widehat{h}(\omega_{jt}, \nu_{jt}) + \frac{1}{\theta} \ln(2\phi \widehat{\sigma}_{Mjt}). \tag{37}$$

This equation contains the key of the identification: from researchers' perspective, conditional on the output elasticity of material input $\widehat{\sigma}_{Mjt}$ (which is chosen by the firm), the firm capability reflects the input quality choice of the firm; consequently, the variation of unit input price $\ln \widehat{P}_{Mjt}$, after input quality is controlled, identifies the quality-adjusted input prices according to (36).

To estimate the related parameters, notice that Equation (35) and (36) express the productivity and quality-adjusted input prices as functions of recovered variables up to unknown parameters (θ, ϕ). These parameters can be estimated by using the Markov processes of productivity and quality-adjusted input prices: (7) and (8). Specifically, 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 (7) and (8) via Generalized Method of Moments with a set of moment conditions:

$$E[Z_{jt} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1})] = 0, \tag{38}$$

where $\epsilon^{\omega}_{jt+1} = \omega_{jt+1} - f(\omega_{jt}, e_{jt}, i_{jt})$ and $\epsilon^{p}_{jt+1} = \ln(p_{jt+1}) - g(\ln(p_{jt}), i_{jt+1}, \tau_{t+1})$.[13]

Formally,

$$\hat{\vartheta} \;=\; \underset{\vartheta}{\operatorname{argmin}} \left[\sum_{jt} Z_{jt} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1})\right]' W \left[\sum_{jt} Z_{jt} \otimes (\epsilon^{\omega}_{jt+1}, \epsilon^{p}_{jt+1})\right], \tag{39}$$

where $\vartheta = (\theta, \phi, f_0, f_{wto}, f_\omega, f_i, f_e, g_0, g_{wto}, g_p, g_{i0}, g_{i1})$ and W is a weighting matrix.

4.3 Sunk and Fixed Costs of Trade Participation

In the dynamic estimation, we take the output from the previous stages, including productivity, input prices, their evolution processes, and production and demand functions, to the Bellman equation, and estimate the sunk and fixed costs distributions associated with import and export defined in (10). Because of the high-dimensional continuous state space, it takes a long time to solve the dynamic model once given one set of trade cost parameters. As a result, it is almost impossible to directly estimate the model using nested fixed point algorithm. We instead use the Conditional Choice Probability (CCP) approach developed in Hotz and Miller (1993) and Hotz et al. (1994), which avoids solving the model in the estimation stage and make it possible to estimate the model parameters with high-dimensional state space more efficiently. Refer to Appendix C for a detailed discussion of how we implement the CCP approach, while here we describe the key steps.

Specifically, we estimate the dynamic model in two steps. In the first step, we estimate a bivariate probit model for CCP of import and export jointly as functions of state variables

[13] The instrumental set used in the estimation of this paper is

$$Z_{jt} = (K_{jt}, E_{Mjt}, E_{Ljt}, L_{jt}K_{jt}E_{Mjt}, K_{jt}E_{Ljt}, K_{jt}L_{jt}, E_{Mjt}L_{jt}, \widehat{\sigma}_{M_{jt}}, ie_{jt}, \tau_t, ie_{jt}\tau_t).$$

$s_{jt} = (\omega_{jt}, K_{jt}, p_{jt}, P_{L_{jt}}, ie_{jt})$ as follows:

$$i_{jt+1} = \mathbf{1}[\psi_0^i + \psi_e^i e_{jt} + \psi_i^i i_{jt} + \psi_\omega^i \omega_{jt} + \psi_p^i \ln p_{jt} + \psi_k^i \ln K_{jt} + \psi_\ell^i \ln P_{L_{jt}} + v_{jt}^i > 0], \tag{40}$$

$$e_{jt+1} = \mathbf{1}[\psi_0^e + \psi_e^e e_{jt} + \psi_i^e i_{jt} + \psi_\omega^e \omega_{jt} + \psi_p^e \ln p_{jt} + \psi_k^e \ln K_{jt} + \psi_\ell^e \ln P_{L_{jt}} + v_{jt}^e > 0], \tag{41}$$

where (v_{jt}^i, v_{jt}^e) are jointly standard normally distributed with correlation parameter ρ. 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). We refer to (40) and (41) as the offline CCP.

In the second step, we compute the CCP predicted by the Bellman equation and match it to the offline CCP to estimate the trade cost parameters. Specifically, given the state (s_{jt}, ξ_{jt}) for firm j at period t, we denote the choice-specific firm value for any action ie_{jt+1} (not necessarily optimal) as

$$\begin{aligned} V^\xi(s_{jt}, \xi_{jt}|ie_{jt+1}) &= \pi_{jt}(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}} + \delta E_{\epsilon^{m\ell\omega}}[V(s_{jt+1}|s_{jt}, ie_{jt+1}; \lambda)] \\ &= \pi_{jt}(s_{jt}) - C(ie_{jt+1}, ie_{jt}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}} \\ &\quad + \delta \int_{\epsilon^{m\ell\omega}} V(s_{jt+1}|s_{jt}, ie_{jt+1}; \lambda) dF(s_{jt+1}|s_{jt}, ie_{jt+1}) \\ &\equiv \widetilde{V}^\xi(s_{jt}|ie_{jt+1}; \lambda) + \lambda_\xi \xi_{jt}^{ie_{jt+1}}, \end{aligned} \tag{42}$$

where $\widetilde{V}^\xi(s_{jt}|ie_{jt+1})$ is the choice-specific value net of current period fixed costs shocks. The three-dimensional integration in Equation (42) will substantially slow down the estimation. So we compute the value function using a simulation-based CCP approach as described in Hotz et al. (1994). Because $\widetilde{V}^\xi(s_{jt}|ie_{jt+1})$ is linear in all trade cost parameters, we only need to simulate the component of the value function once throughout the dynamic estimation stage. This feature makes the CCP approach much less computationally intensive. More specifically, we approximate the expectation of the choice specific value $\widetilde{V}^\xi(s_{jt}|ie_{jt+1})$ by simulating the model for 40 periods. We simulate the 40-period path of each firm for 3000 times and average over the sum of discounted net profit (total profit minus trade cost) as an approximation for $\widetilde{V}^\xi(s_{jt}|ie_{jt+1})$ which clearly depends on trade cost parameter λ. Use $\overline{V}^\xi(s_{jt}|ie_{jt+1})$ to denote the mean of $\widetilde{V}^\xi(s_{jt}|ie_{jt+1})$ in the 3000 simulations, and it is an approximate of the expected choice-specific firm value.

Given the expectation of the choice-specific value function $\overline{V}^\xi(s_{jt}|ie_{jt+1})$ and the type I extreme distribution assumption on the trade cost shocks, we can construct the model-predicted choice probability as follows:

$$\Pr\{ie_{jt+1}|s_{jt}\} = \frac{\exp(\overline{V}^{\xi}(s_{jt}|ie_{jt+1};\lambda)/\lambda_{\xi})}{\sum_{ie}\exp(\overline{V}^{\xi}(s_{jt}|ie;\lambda)/\lambda_{\xi}))}. \tag{43}$$

This choice probability implies the following relationship between expected choice-specific firm value and choice probability for any choices ie_{jt+1} and ie'

$$[\overline{V}^{\xi}(s_{jt}|ie_{jt+1};\lambda) - \overline{V}^{\xi}(s_{jt}|ie';\lambda)]/\lambda_{\xi} = \ln \Pr(ie_{jt+1}|s_{jt}) - \ln \Pr(ie'|s_{jt}). \tag{44}$$

Since the CCP on the right hand side is estimated from (40) and (41) already, we estimate the trade cost parameters by matching the two sides of (44). The estimator is defined as,

$$\widehat{\lambda} = \underset{\lambda}{\operatorname{argmin}} \frac{1}{N}\sum_{j,t}\sum_{ie'\neq ie_{jt+1}}\left\{\frac{1}{\lambda_{\xi}}\left[\overline{V}^{\xi}(s_{jt}|ie_{jt+1};\lambda) - \overline{V}^{\xi}(s_{jt}|ie';\lambda)\right] - \left[\ln \Pr(ie_{jt+1}|s_{jt}) - \ln \Pr(ie'|s_{jt})\right]\right\}^2, \tag{45}$$

where N is the number of observations in the data.

5 Estimation Results

5.1 Production and Demand Parameters

The production and demand parameters are estimated using nonlinear least square (NLLS) based on (30). The results are reported in Table 2. The output elasticity of material inputs, $\hat{\alpha}_M$, 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 elasticity, $\hat{\alpha}_K$ and $\hat{\alpha}_L$, echo the labor and capital intensity. The implied labor share relative to the total expenditure on labor and capital (but excluding material) equals 52.5% in the industry. The estimated elasticity of substitution in the CES production function, $\hat{\sigma}$, is larger than 1, which is consistent with Grieco et al. (2015) using Colombian plant level data in a variety of industries.

On the demand side, the export market is somewhat less elastic than the domestic market, showing that firms face very different market conditions at home versus abroad. This highlights the importance of allowing for separate demand elasticities in the domestic and foreign markets, because otherwise the single-market model will generate a systematically biased estimator of recovered productivity and material input prices. Given these estimates, we recover the unit price of material inputs, $\widehat{P}_{Mjt}$, from Equation (21) and firm capability, $\widehat{h}(\omega_{jt}, \nu_{jt})$, from (23) and

(24) numerically.

5.2 Productivity, Input Price, and Quality Parameters

With the production function and demand parameters in hand, we estimate the firm capability function, (2), and the Markov processes of productivity and input prices, (7) and (8) following (39).[14] The estimate of this main specification is presented in column II of Table 3, although the result is robust across the other specifications we consider. The result suggests the elasticity of substitution between productivity and input quality is $\frac{1}{1-\theta} = 0.8$. This implies that productivity and input quality are indeed complements for firm capabiliy $h(\omega_{jt}, \nu_{jt})$. As a result, firms with higher productivity will endogenously choose to use inputs of higher quality. Nonetheless, the high quality of inputs also comes at a cost: the estimate of the price menu parameter $\hat{\phi} > 0$ implies that firms need to pay more for inputs with higher quality. This, together with the complementarity, suggests that firms with higher productivity are associated with higher unit input prices. This corroborates the finding of positive correlation between firm productivity and input prices in Kugler and Verhoogen (2012).

Panel two and three ofTable 3 reports our estimates results of the transition processes of productivity and quality-adjusted prices, respectively. Again, column II contains our preferred specification. This specification is based on Equation (7) and (8): we use a WTO dummy with 2001 as the cutoff year, to allow for possible structure changes of the evolution processes. This, together with the interaction between the WTO dummy and import particiation in Equation (8), forms a difference-in-difference approach (pre-WTO v.s. post-WTO years and importer v.s. non-importer), which helps to identify the WTO effect on importers' input price gains. This WTO effect is captured by the difference between the pre-WTO gain g_{i0} and post-WTO gain g_{i1}. From the estimates, we first observe substantial gains in productivity when a firm engages in trade. The effect of exporting on productivity is positive and significant, meaning that being an exporter increases the firm's next-period productivity by 8.7% on average. This corraberates the "learning by exporting" effect in Aw et al. (2011) and others, but in a broader scenario where the gains through input prices are taken into account separately. The effect of import on productivity is even higher. The coefficient of import parcitipation on productivity suggests that being an importer in the Chinese paint industry increases its next-period productivity by 26.2% on average. As pointed out by Kasahara and Rodrigue (2008), Halpern et al. (2011), and

[14] The evolution process of wage rate, Equation (9) is estimated independently as $\hat{\zeta}_0 = 2.523$ and $\hat{\zeta}_\ell = 0.640$.

Zhang (2014) 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 firms that have substantial chemical expertise. The positive and significant coefficient of WTO dummy (f_{wto}) in the productivity evolution process may be due to a boost of productivity after China's accession to WTO or a positive trend of productivity growth for both importers and non-importers.

The estimation result also shows substantial gains from trade through the input price channel. Both the estimates of import participation on input prices pre-WTO (g_{i0}) and post-WTO (g_{i1}) are negative, and this suggests that firms indeed benefit from importing in terms of input prices. More importantly, because we control both pre-and post- WTO eras by the WTO dummy, the difference between g_{i0} and g_{i1} reveal a causal effect from WTO to the change of input price gains from importing: $|g_{i1}| > |g_{i0}|$ implies an increase of input price gain from importing after China joined WTO, potentially due to the significant decrease of tariff rate after WTO. Specifically, before China joined WTO, importing reduces a firm's input prices by 1.9%; after China's accession to WTO, the benefit is enlarged to 2.3%. Considering the material expenditure accounts for over 90% of the total expenditure in the production process, this change of input price gain is significant for the Chinese firms: reducing the input prices by 1.9% is equivalent to increase the profit by about 1.7% (even if the firm does not adjust their inputs usage to cheaper inputs), which intuitively can increase profit substantially. 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 31.1% lower input price compared with a non-importing firm in the long run steady state. After China's accession to WTO, this advantage boosts to 40.1% in the long run. Adding this to the productivity gain from importing strongly suggests that importing dominates exporting as the main source of gains from trade in the Chinese paint industry. Our counterfactuals in the next section will illustrate this further.

We also find that both productivity and input prices are persistent. The persistence parameter for productivity is 0.640, meaning that 64% of productivity can be carried over to next period. This is within the order of persistence documented in the literature including Foster et al. (2008) and Ábrahám and White (2006), which document that the one-year-lag productivity persistence coefficient is on the order of 0.6 to 0.8. The input price is even more persistent, with about 93.8% of the price level being carried over to next period. This is higher than that found in Atalay (2014) where firm-level input prices and quantities are observed and Grieco et al. (2015) where input prices are estimated. This may be due to the fact that the input price measures in these two papers contain input quality which is likely to be more volatile because it is an endogenous firm choice; in contrast, our quality-adjusted price measure p is quality exclusive and its variation captures firm characteristics (other than input quality) such as geographic location and importing status, which are more persistent.

Finally, we estimate a range of alternative specifications of the Markov processes to make sure these key results— the positive productivity gains from import and export and the negative effect of import on input prices—are robust. The results are presented in Column I, III, IV, and V of Table 3. Specification I considers a more restricted specification with all WTO effect removed. Specification III allows export participation to affect input prices, in order to test if export has a direct impact on input prices after controlling for other variables. In specification IV and V are similar to specification II and III except that the WTO dummy is replaced by a set of year dummies. We find that all key parameters are robust to different specifications, both qualitatively and quantitatively. In particular, both import and export have positive effects on productivity, with stronger effect from import. Import reduces input prices, with WTO strengthening this effect. The effect of export on input prices, whenever considered, is always insignificant.

We conclude by noting that, when estimating the production model in Section 5.1 which is the productivity and input price measures are based on, we did not use any information about firms' import status. The finding that input prices are negatively related to the trade status while productivity is positively related to the trade status provides assurance that the recovered measures reflect important dimensions of firm heterogeneity that is affected by trade.

5.3 Productivity and Input Price Distributions

Given all parameters that have been estimated, we recover the productivity and quality-adjusted prices from Equation (35) and (36). The distribution of productivity (from the kernel density estimation), ω_{jt}, is plotted in Figure 3. 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 of the result documented in other empirical studies such as Fox and Smeets (2011). This suggests that the 75th percentile firm in the productivity distribution is about 3.158 times as productive the 25th percentile firm. This is also close to the results in Hsieh and Klenow (2009) using 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 purpose, we plot in Figure 3 the distribution of $\widehat{h}(\omega_{jt}, \nu_{jt})$, which contains the combined heterogeneity in productivity and endogenous input quality. Its dispersion is much larger than that of productivity, with an inter-quartile range of 4.14. This is intuitive giving the complementarity between productivity and input quality: more productive firms endogenously purchase inputs of higher quality, which expands the dispersion of $\widehat{h}(\omega_{jt}, \nu_{jt})$ compared with ω_{jt}. This means that not accounting for quality upgrading exaggerates the dispersion of productivity (TFP).

The distribution of the quality-adjusted input prices in logarithm, $\log(p_{jt})$, is reported in Figure 4. Recall that it is quality-exclusive and it measures the heterogeneity that drives the difference of unit input prices other than quality. Its dispersion is large economically. The inter-quartile range is 0.25, which implies that the input price (given the level of input quality) paid by the 75th percentile firm in the distribution is about 28.4% ($e^{0.25} - 1 \approx 0.284$) higher than that is faced by the 25th percentile firm. However, since firms with different productivity (among other characteristics) select different input quality, the distribution of unit input prices, $P_{Mjt} = p_{jt}\nu_{jt}^{\phi}$, is affected by firms' endogenous quality choice. This distribution (also plotted in Figure 4) is much more dispersed , with an interquartile range of 4.65. The comparison shows that purging the quality out of the unit input prices reduces the dispersion significantly. This further highlights the importance of modelling the endogenous quality choice when investigating the impact from trade participation and policies. While trade raises productivity and lowers the input price menu, it may raise the unit price of material inputs because firms may endogenously choose high-quality inputs after participating in import or export.

We also calculate the correlation among our recovered key variables and firm size. We find a very weak correlation between productivity and (quality-adjusted) input prices, both of which are net of input quality. The correlation is 0.043. This contrasts to the literature which usually find a strong positive correlation between productivity and unit input price. The reason is that in the literature the unit input price, and probably productivity measure as well, contain input quality. If more productive firms tend to choose high-quality inputs, then the quality-inclusive input price will be positively correlated with productivity. This conjecture is supported by the strong positive correlation between productivity and input quality, $\text{corr}(\omega, \log(\nu)) = 0.745$. We also checked how these variables are correlated with firm size, as measured by employment size. We find a positive correlation between productivity and firm size, with a correlation of 0.206. Larger firms also use material inputs of higher quality, with a correlation of 0.264. This is reasonable, because larger firms in general have higher productivity as reported above, which leads them to endogenously choose higher quality inputs. However, the quality-adjusted input price of large firms is lower, as captured by the negative correlation between firm size and (quality-adjusted) input prices (-0.535). This may be due to that larger firms are more likely to engage in import or they have stronger bargaining power to secure a better quality-adjusted input prices.

5.4 Dynamic Estimation Results

As the first step of the CCP approach, we estimate the offline conditional choice probability of import and export as a function of observed state variables: trade status, productivity, input price, wage rate, and capital stock. The estimation results are reported in Table 4.[15] First, past export and import experience has a substantial impact on current trade participation. An importer (exporter) in the last period is more likely to continue importing (exporting), which is consistent with the well-documented fact that trade participation is persistent. This suggests a significant sunk costs involved in importing and exporting that we have taken into account in our dynamic modelling. Interestingly, we also find that an previous exporter (importer) is more likely to import (export) in the following period. Specifically, Table 5 presents the average marginal effects of state variables on firm's trade participation. In the first row, we report the average marginal effects of export experience last year on the probabilities of import and export this year respectively. The previous export experience increase the probability of next-year import by 8.0% and that of next-year export by 59.4% on average. Similarly, in the second row, we find that the import experience last year increases the probability of import this year substantially by 45.0%, and it also increases the probability of export this year by 16.0% on average. Moreover, as shown in the last row of Table 4, the correlation between the unobservable factors that affect importing and exporting is 0.204. This suggests the presence of complementarity between importing and exporting in terms of trade costs that will be taken into account in our flexible trade cost specification (10).

Table 4 also shows firms' endogenous selection on import and export based on productivity and input prices. The estimate $\psi^e_\omega = 0.088$ suggests that more productive firms are more likely to export, reprising a well-known result in the literature. Accordingly, as calculated in Table 5, a 10% increase of productivity increases export probability by 0.42%. Similarly, lower input prices also increases the export probability. As calculated in Table 5, lowering input prices by 10% can increase export probability by 1.58%. In contrast, the selection of import based on productivity

[15] In the empirical estimation, we categorize the firms into three categories 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 remain as middle wage firms.

and input prices are much weaker. The direct impact of productivity on import probability is, although positive, much smaller and insignificant. The coefficient $\psi^i_\omega = 0.017$, translating to a 0.07% increase of the import probability on average when productivity increases by 10%. The impact of input prices on the import probability is negative but insignificant. $\psi^i_m = -0.298$ implies that a 10% reduction of input prices increases the import probability by 0.38%, although statistically insignificantly.

We use the offline CCP results to match with the dynamic model predicted probabilities from the forward-simulated simulation, as illustrated by (45), in order to estimate the trade cost parameters. For the dynamic estimation, we assume the annual discount factor is $\delta = .95$, but our results are qualitatively robust to other choices of the discount factor. The estimates are reported in Table 6. We find that the trade cost parameters are much larger when a firm starts up exporting (or importing) than the case when the firm has engaged in exporting (or importing) in the last period. This is reasonable because typically new importers and exporters need to pay additional costs to learn about the foreign market regulations, to search for foreign business partners, and to establish partnership or distribution networks. This is consistent with the findings in the literature that, with other things being equal, sunk cost is much larger than fixed cost for both importing and exporting. In particular, the estimates suggest a total fixed cost of 1.4 million US dollars for a firm continuing exporting and importing, which takes 8.1% out from the gross profit for these firms on average; while the parameters for sunk costs implies that the firms have to pay 16.7% and 28.6% of their profit on average to start up exporting and importing respectively. Finally, there is substantial heterogeneity in fixed and sunk costs of trade across firms, as captured by the parameter $\hat{\lambda}_\xi = 4.587$, which is a measure of the dispersion of trade cost shocks.

Interestingly, the estimate of our flexible trade cost exhibits evidence of a strong two-fold trade cost complementarity, which echoes the finding from the offline CCP estimate in Table 4. First, the firm can save on import costs if it had export exposure last period; similarly, importing experience in the past also helps the firm to reduce export costs. This is captured by $\hat{\lambda}_{00;01} > \hat{\lambda}_{10;01}$ and $\hat{\lambda}_{00;10} > \hat{\lambda}_{01;10}$. This is logical because importing from foreign markets in the past period helps the firm to get familiar with the regulations and market conditions in the foreign markets, makes it easier to search for a business partner, or establishes distribution networks in the coming year, all of which reduces the cost of exporting, and vice versa. This suggests another dimension of gain from trade through strategic timing of trade decisions: engaging in importing (exporting) reduces the trade cost of exporting (importing) in the future. Second, if the firm chooses to export and import at the same time, then the total cost paid is lower than the sum of the costs when the firm engages in exporting and importing separately. 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 from both activities can be shared which reduces the total trade cost.

Finally, to check the fit of our model we compare transition probabilities from the raw data, our CCP estimation, and the policy function of the dynamic model after all the parameters are estimated. The results reported in Table 7 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: $\hat{\lambda}_{10,11} < \hat{\lambda}_{01,11}$. 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 6.

6 Counterfactual Analysis

The model illustrates how dynamic gains from international trade arise from trade participation's effect on firm productivity and input prices, themselves influence incentives for trade participation as well as overall profitability in the future. Understanding and measuring the mechanisms through which trade participation influences firm performance is of particular interest to policy makers in order 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: (1) How important are the productivity and input price channels in terms of overall gains from trade? and more specifically, (2) How did the cut in import tariffs associated with WTO accession affect Chinese paint manufacturers propensity to import and export? Moreover, what effects did it have on productivity, input prices, and as a result, firm value?

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

Our first counterfactual quantifies the importance of the productivity channel: we remove the effect of trade on productivity, (by setting $f_e = f_i = 0$) and resolve the model to determine how the connection between trade and productivity affects firms performance. To evaluate how the change affects the industry, we compare simulation of all firms in the data starting from 2006 and going forward 15 years under the estimated parameterization and that removing the productivity channel. The simulation is conducted for 30 times each firm under both the restricted model and the full model and then averaged. The differences in firm value between the baseline and this counterfactual represent the effect on firms due to removal of the gains to trade through increased productivity. The first panel of Table 8 tracks how removing the productivity channel impacts productivity, input prices, and trade participation. The bottom line reports the overall effect on firm valuations: if the productivity effects of trade are removed, average firm value will drop by 0.9%, equivalent to 5 million USD (present discounted value, using our discount factor of .95). Table 8 shows the this loss of firm value is due to a large drop of productivity after removing the productivity channel, which leads to a decrease of productivity by about 29% in the restricted model relative to the full model. Trade participation is substantially reduced: export probability is reduced by 3.5 percentage and import by 5.4 percentage. Meanwhile, the decline in importing means more firms face a higher input price. After 15 years, the quality-adjusted input price is about 2.8% higher after shutting down the productivity channel compared with that predicted in the full model, which augments the loss of firm value (as an indirectly effect from removal of the productivity channel).

In the second counterfactual, we evaluate the impact of the input price channel on firm value by quantifying the loss of firm value when shutting down the impact of trade participation on input prices. Similar to above, we shut down the input price channel by setting $g_{i0} = g_{i1} = 0$, solve both static production decisions and dynamic decisions of international trade in the restricted model, and compare the firm values in this restricted model with these predicted in the full model. The mean loss of firm value in this industry is reported at the bottom of the second panel of Table 8: shutting down the input price channel, the lowers average firm value in the industry by 1.2%, equivalent to about 6.7 million USD. So the importance of input price channel is of similar order of magnitude compared with that of the productivity channel, with the impact of the input price channel being about one third larger. This implies that ignoring input prices in the literature may exaggerate the gains from trade by contributing the gains through input prices to the gains through productivity; while the two channels may have very different mechanisms.

The bottom panel of Table 8 shows that the indirect effects of removing the input price gap plays a large role in the overall impact on firm values. We find that, after 15 years the average quality-adjusted input price is 9.2% higher than that predicted in the full model. This difference is substantially larger than that in the case when productivity channel is removed, which is intuitive since this counterfactual directly adjusts input prices. Moreover, removing gains in input prices has a strong impact on trade participation, the proportion of importing firms falls by 8.4 percent, and the proportion of exporting firms falls by 4 percent. These are extremely strong effects given that in the data 12.4 percent of firms import and 12.9 percent export. This stronger reaction of firms to a change in the input price process with regard to trade (and particularly importing) is in part driven by the fact that we find input prices to be highly persistent over time relative to productivity. This reduction in trade participation reduces firm productivity by a substantial amount, 14.9%. This large indirect effect of the input price channel through trade participation and productivity explains why we find a stronger impact of shutting down the input price channel even though it appears to have a smaller direct effect relative to productivity.

In addition to the comparison of the channels of gains from trade, we also evaluate the magnitudes of gains from exporting and importing as two sources of the gains. We conduct two counterfactuals to quantify this difference. In particular, in one counterfactual, we remove import gains completely by setting $f_i = g_{i0} = g_{i1} = 0$. Similar to the previous experiment, we simulate the restricted model for all firms in 2006 for 15 years and 30 times, with profit and trade participation re-optimized in each year. We then calculate the mean of key variables of cover the 30 replications, and compare them with that predicted in the full model. The results are reported in the first panel of Table 9. Shutting down the import gains via both the productivity channel and the input price channel has substantial impacts. After 15 years, productivity is 25.2% lower, the quality-adjusted input price is 9.2% higher, and the percentages of exporting and importing firms drops by 4.6 percent and 9.9 percent respectively, compared with that predicted in the full model.[16] They together amount to a loss of average firm value by 1.4% (equivalent to 8 million USD) after removing the import gains.

Similarly, in the other counterfactual, we remove the export gain by setting $f_e = 0$ (note that exporting has no significant effect on quality-adjusted input prices) and evaluate its impact on firms using the same way as above for the same group of firms. The results are reported in the

[16]The reason importing is not completely eliminated under this scenario is due only to our assumption that fixed and sunk costs are distributed according to an extreme value distribution.

second panel of Table 9. Under this scenario, firms may still wish to export in order to sell to the foreign market, but doing so will not result in any productivity gains. Compared with the full model, the average productivity is 9.8% lower, the average quality-adjusted input price is 0.5% higher, and export and import probabilities are also lower by 1.5 percentage and 1.0 percentage respectively after 15 years in the restricted model. These differences, together, map to a reduction of average firm value by 0.3% (equivalently 1.6 million US dollars), which is significantly smaller than that when the importing gains are removed (8.0 million US dollars). The are also much smaller than simply removing the effect of importing on input prices alone (Table 8). This is due to the fact that import, compared with export, has an larger direct impact on both productivity and input prices, as documented in Table 3, which is further magnified by firm dynamic import and export decisions, translating to a much higher impact on firm value. Of course, an important caveat is that above we removed essentially all incentives to import, while this counterfactual maintains the traditional market access incentive to export.

6.2 Gains from WTO Tariff Reduction

So far, we have found that import price incentives can play a large role in trade participation and firm performance. Our model predicts that policy shocks that affect input prices, such as an import tariff cut, not only have a direct impact on quality-adjusted input prices, but also indirectly affect productivity through trade participation. Both the direct and indirect channel may contribute to the overall gains from the policy liberalization. China's accession to the WTO in 2001 provided a natural experiment in which the import tariff rate was reduced quickly in a short period, namely from 15% in 2000 to 7% in 2006 on average for the paint industry inputs.[17] As estimated in our model, this directly reduces the quality-adjusted input prices of importers relative to exporters, thus enlarging the benefits of importing and leading to more importing firms. The increased importing increases future productivity, lowers aggregate input prices further, and encourages more trade participation in the future. This dynamic mechanism serves as an indirect impact of the tariff cut.

We now use our model illustrate the impact of tariff reductions on the Chinese paint industry. Specifically, note that the difference between g_{i0} and g_{i1} reflects the increased effect of importing on quality-adjusted input prices because of the WTO accession. By setting $g_{i1} = g_{i0}$, i.e., fixing

[17] Notice that this section studies the direct WTO effect on quality-adjusted prices due to tariff cut. We acknowledge that the accession may have effects in other aspects as well. As a robustness check, we tested if accessing WTO reduced the unobserved fixed and sunk costs of trade participation, by estimating the full model with year-varying trade costs. We found no difference of the trade costs across years.

input price gains from import after the accession at the pre-WTO level, we remove the WTO effect on the input price gains from importing. We calculate the firm value for each firm in this counterfactual in the same way as the previous experiments, and compare it with that computed from the full model. We find that removing WTO effect on input price reduces average firm value by 0.4% (equivalently 2.1 million US dollars). This loss of firm value first of all is due to the impact on input prices, but operates through multiple channels. After 15 years, the input price is about 2.6% higher after removing the WTO effect. This reduces the probability of trade participation, which further augments the loss of firm value by changing the future productivity path. After 15 years, the import probability is lower by 2.7 percentage points and export by 1.3 percentage points, and the productivity is also reduced by 3.7%, compared with the full model. This suggests that tariff cut after the accession had significant impact on input prices, trade participation as well as productivity.[18] These results suggest that focusing exclusively on the impact of price reductions due to import tariff liberalization may substantially underestimate liberalization's benefits with respect to intermediate materials.

7 Conclusion

This paper directly models firms' import decision as providing two potential gains: improved access to intermediate materials (either through lower prices or higher quality) and future productivity improvements ("learning by importing"). We combine these effects with the benefits of exporting (market access and productivity gains) to construct a dynamic structural model of trade participation and input choice. Our model establishes separate channels though which policies can endogenously impact trade participation and firm outcomes.

One reason that input prices have received less attention in the literature as an incentive to import is that the are rarely directly measured in the data. We surmount this obstacle by proposing an approach to recover the firm-level productivity and input prices, by extending the methodology developed in Grieco et al. (2015) 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 of firms. In order to evaluate the long-term gains trade participation, we then estimate a model of firm 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

[18]Our results compliments the finding in Yu (2014). Yu (2014) has documented that tariff reductions after China's accession to WTO have positive impacts on firm productivity. The difference is that our paper explores and quantifies the direct and indirect mechanisms through the input price channel, the productivity channel, and firms' dynamic endogenous choices of import and export; all of which contribute to the overall impact.

increased productivity and reduced input prices. The gains from both channels are of similar order of magnitude, with stronger effect from the input price channel.

Finally, we show how a policy that reduces import tariffs can affect both firms incentive to import and export, resulting in substantial changes in firm productivity and firm value. We specifically examine the role of reduced import tariffs as part of China's accession to the WTO, and find that this policy increased firm value in the industry by an average of 0.4 percent (2.1 million US dollars) due to a direct effect on reducing input prices and an induced boost of productivity and trade participation.

References

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

Amiti, M. and J. Konings (2007): "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review*, 97, 1611–1638.

Atalay, E. (2014): "Materials Prices and Productivity," *Journal of the European Economic Association*, 12, 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.

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 *Producer Dynamics: New Evidence from Micro Data*, ed. by T. Dunne, J. B. Jensen, and M. J. Roberts, Chicago: University of Chicago Press, 513 – 552.

Blalock, G. and F. Veloso (2007): "Imports, Productivity Growth, and Supply Chain Learning," *World Development*, Volume 35, Issue 7, pp. 1134–1151.

Clerides, S. K., S. Lach, and J. R. Tybout (1998): "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco," *The Quarterly Journal of Economics*, 113, 903–947.

Das, S., M. J. Roberts, and J. R. Tybout (2007): "Market Entry Costs, Producer Heterogeneity and Export Dynamics," *Econometrica*, 75, 837–873.

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, 445–510.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98, 394–425.

Fox, J. and V. Smeets (2011): "Does Input QUality Drive Measured Productivity Differences in Firm Productivity," *International Economic Review*, 52, 961–989.

Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova (2009): "Trade Liberalization and New Imported Inputs," *American Economic Review*, 99, 494–500.

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): "Firm Heterogeneity, Exporting and Foreign Direct Investment," *Economic Journal*, 117, F134–F161.

Grieco, P., S. Li, and H. Zhang (2015): "Production Function Estimation with Unobserved Input Price Dispersion," *International Economic Review, forthcoming.*

Halpern, L., M. Koren, and A. Szeidl (2011): "Imported Inputs and Productivity," *Center for Firms in the Global Economy (CeFiG) Working Papers.*

Hotz, V. J. and R. A. Miller (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, 60, 497–529.

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994): "A Simulation Estimator for Dynamic Models of Discrete Choice," *The Review of Economic Studies*, 61, 265–289.

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

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, 106 – 118.

Khandelwal, A. and P. Topalova (2011): "Trade Liberalization and Firm Productivity: The Case of India," *The Review of Economics and Statistics*, 93 (3), 995–1009.

Kugler, M. and E. Verhoogen (2009): "Plants and Imported Inputs: New Facts and an Interpretation," *American Economic Review*, 99, 501–07.

——— (2012): "Prices, Plant Size, and Product Quality," *Review of Economic Studies*, 79, 307–339.

Levinsohn, J. and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 70, 317–341.

Ornaghi, C. (2006): "Assessing the Effects of Measurement Errors on the Estimation of Production Functions," *Journal of Applied Econometrics*, 21, 879–891.

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

Van Biesebroeck, J. (2005): "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms," *Journal of International Economics*, 67, 373–391.

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): "Processing trade, tariff reductions and firm productivity: Evidence from Chinese firms," *The Economic Journal*, 125, 943–988.

Zhang, H. (2014): "Static and Dynamic Gains from Costly Importing of Intermediate Inputs: Evidence from Colombia," *working paper, University of Hong Kong.*

Appendices

A Definitions of Key Variables and Notations

For clarification purpose, this appendix summarizes the definitions and relations of key variables and notations used in this paper.

M_{jt}: the quantity of material inputs in its purchase unit. The associated price is P_{Mjt}. It is plausible that high quality of input has two effects: it increases the quality of output (Hicks-neutral) and it is more efficient (non-Hicks-neutral) in production. The former is captured in the firm capability $h(\omega_{jt}, \nu_{jt})$, while the latter, its own efficiency, is adjusted in its unit price which is left to be estimated. Thus, in this paper M_{jt} is also in the efficient unit of production, and as a result, any heterogeneity in its (non-Hicks-neutral) efficiency is contained in P_{Mjt}. Nonetheless, this does not affect what we measure in p_{jt} because it is quality-exclusive.

P_{Mjt}: the unit input price. As the material inputs are differentiated by quality, high quality material has a higher unit price. In this paper, we use the specification: $P_{Mjt} = P_M(p_{jt}, \nu_{jt}) = p_{jt}\nu_{jt}^{\phi}$. Thus, $P_M(p_{jt}, \nu_{jt})$ can be considered as a price menu (about quality) for a firm. ϕ is assumed to be positive to make sure the cost of quality is increasing. p_{jt} has subscript jt to capture the *heterogeneity of the menu* faced by different firms in different periods, due to geographic difference or international trade engagement (e.g., importing). For this reason, p_{jt} is called the quality-adjusted input price or materials access index. We use quality-adjusted input price and input price interchangeably.

p_{jt}: the quality-adjusted input price or materials access index, as explained above.

ν_{jt}: the quality (level) of the material input. High quality of input increases the quality of output, as in Kugler and Verhoogen (2009) and Kugler and Verhoogen (2012). For example, the paint with high quality additives, as alternative of heavy metal in the paint, can make the paint more environmental friendly and is viewed as high quality products. Therefore, ν_{jt} appears in firm capability $h(\omega_{jt}, \nu_{jt})$. Note that this does not mean ν_{jt} affect production decisions in a Hicks-neutral way: ν_{jt} also influences the unit input price which changes the optimal mixture of labor, material, and capital in the production.

$h(\omega_{jt}, \nu_{jt})$: the firm capability. Note that, in this paper, as we do not have output price data at the firm level, h is actually revenue-based and it is the counterpart of total factor productivity in the literature. Thus it contains the firm-level demand heterogeneity introduced by output quality resulted from different input quality choice. For this reason, we allow h to depends on ν_{jt}. Thus, the other component, ω_{jt}, contains the part of total factor productivity that is not directly related to input quality ν_{jt}, and we call it productivity measure through the paper.

ω_{jt}: productivity, as described above.

B Trade Types in Chinese Paint Industry

This appendix summarizes the definition and shares of different trade types in 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. The only difference from ordinary trade is that part or all of the inputs are purchased from abroad.

Processing trade with assembly
In the processing trade with assembly, the firm receives inputs from foreign supplier(s) and produce the output as written in the contract. 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.

C 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.

C.1 CCP Estimation of Import and Export Decisions

The observed state space includes four continuous variables and one discrete choice variables of four choices. 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. The identification of these parameters is clear.

We summarize the estimation procedure briefly as follows:

1. Inputs to the dynamic model estimated off line:

   (a) Estimate the conditional probability (CCP) (40) and (41) 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 to link the strategy $\sigma(s_{jt}, \xi_{jt})$ to 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. Instead of recovering the strategy, we "draw" the endogenous choice action from the choice probability and then compute the conditional cost shock to simulate a path of optimal choice for each firm.

3. Estimate the net choice-specific value $\widetilde{V}^{\xi}(s_{jt}|ie_{jt+1})$ for any choice ie_{jt+1} (optimal or not), which is defined in (42) as $\widetilde{V}^{\xi}(s_{jt}|ie_{jt+1}) \equiv V^{\xi}(s_{jt}, \xi_{jt}|ie_{jt+1}) - \lambda_{\xi}\xi_{jt}$. 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

$$\begin{aligned}
&\widetilde{V}^{\xi}(s_{jt}|ie_{jt+1}) = \pi(s_{jt}) - C(ie_{jt+1}; ie_{jt}) \\
&+\delta E_{s_{jt+1}|s_{jt},ie_{jt+1}} E_{ie_{jt+2}|s_{jt+1}} E_{\xi_{jt+1}|s_{jt+1},ie_{jt+2}} \Bigg[\pi(s_{jt+1}) - C(ie_{jt+2}; ie_{jt+1}) + \lambda_{\xi}\xi_{jt+1} \\
&+\delta E_{s_{jt+2}|s_{jt+1},ie_{jt+2}} E_{ie_{jt+3}|s_{jt+1}} E_{\xi_{jt+2}|s_{jt+2},ie_{jt+3}} \Bigg[\pi(s_{jt+2}) - C(ie_{jt+3}; ie_{jt+2}) + \lambda_{\xi}\xi_{jt+2} + ... \Bigg]\Bigg]
\end{aligned} \tag{46}$$

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 with iid Logit assumption of the cost shocks ξ_{ie}, with

$$E(\xi_{jt}|s_{jt}, ie_{jt+1}) = \gamma - ln(\Pr(ie_{jt+1}|s_{jt})). \tag{47}$$

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 iid errors 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 iid 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) $\pi(s_{jt}, ie_{jt+1}) - C(ie_{jt+1}; ie_{jt})$.

- 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

$$\begin{aligned}
&\widetilde{V}_n^{\xi}(s_{jt}|ie_{jt+1}) = \pi(s_{jt}) - C(ie_{jt+1}; ie_{jt}) \qquad (48)\\
&+\delta\Bigg[\pi(s_{jt+1}) - C(ie_{jt+2}; ie_{jt+1}) + \lambda_{\xi}(\gamma - ln(\Pr(ie_{jt+2}|s_{jt+1}))) + ...\\
&+\delta\Bigg[\pi(s_{jt+2}) - C(ie_{jt+3}; ie_{jt+2}) + \lambda_{\xi}(\gamma - ln(\Pr(ie_{jt+3}|s_{jt+2}))) + ...\\
&+\delta\Bigg[\pi(s_{jt+T}) - C(ie_{jt+T+1}; ie_{jt+T}) + \lambda_{\xi}(\gamma - ln(\Pr(ie_{jt+T+1}|s_{jt+T})))\Bigg]\Bigg]\Bigg]\\
=\ & \sum_{\tau=0}^{T}\delta^{\tau}\pi(s_{jt+\tau}) - \sum_{\tau=0}^{T}\delta^{\tau}\left[C(ie_{jt+\tau+1}; ie_{jt+\tau})\right] + \lambda_{\xi}\sum_{\tau=1}^{T}\delta^{\tau}\left[\gamma - ln(\Pr(ie_{jt+\tau}|s_{jt+\tau}))\right]
\end{aligned}$$

The first term summarizes the component of firm value from profit; the second term refers to the deterministic part of the trade cost; the last term is due to the trade cost shocks conditional on the path of trade status. The parameters of interest in the dynamic estimation include λ, which are buried in the cost function $C(ie_{jt+\tau+1}; ie_{jt+\tau})$ 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. (10) we can rearrange the above net choice-specific value, by separating parameters and simulated data, as follows

$$\widetilde{V}_n^{\xi}(s_{jt}|ie_{jt+1}) = \sum_{\tau=0}^{T}\delta^{\tau}\pi(s_{jt+\tau}) + \Pi'\lambda, \qquad (49)$$

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

$$\Pi = \left(\sum_{\tau=0}^{T}\delta^{\tau}CIE_{jt+\tau}, -\sum_{\tau=1}^{T}\delta^{\tau}\left[\gamma - ln(\Pr(ie_{jt+\tau}|s_{jt+\tau}))\right]\right)'. \qquad (50)$$

Where the collection of trade status

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

which determines what trade costs the firm should pay.

We simulate model for N paths for each firm following the above procedure. The generated approximated net-choice-specific value function can be formed as follows

$$\begin{aligned}\overline{V}^{\xi}(s_{jt}|ie_{jt+1}) &= \frac{1}{N}\sum_{n=1}^{N}\hat{V}^{n}(s_{jt}, ie_{jt+1}) \\ &= \frac{1}{N}\sum_{n=1}^{N}\left(\sum_{\tau=0}^{T}\delta^{\tau}\pi(s_{jt+\tau}) + \Pi'\lambda\right) \\ &= \frac{1}{N}\sum_{n=1}^{N}\left(\sum_{\tau=0}^{T}\delta^{\tau}\pi(s_{jt+\tau})\right) + \left(\frac{1}{N}\sum_{n=1}^{N}\Pi\right)'\lambda\lambda \end{aligned} \tag{51}$$

4. Construct the likelihood function. Given $\overline{V}^{\xi}(s_{jt}|ie_{jt+1})$, and the assumption that the cost shocks are iid drawn from type I extreme distribution, we can construct the model-predicted choice probability as shown in Equation (43). The latter equation leads to Equation (44). The model parameters, λ can then be estimated by matching (44).

Table 1: Summary statistics of paint industry

Statistics	Value
Median Total Sales	2.018
Median Wage Expenditure	0.098
Median Material Expenditure	1.573
Median Capital Stock	0.329
Median Number of Workers	58
Median Material share over Total Variable Cost	0.943
Median Export Revenue (conditional on exporting)	0.996
Median Import Value (conditional on importing)	0.719
Exporting observation (%)	12.9
Importing observation (%)	12.4
Industrial-level Export-Revenue Share (%, all firms)	11.2
Industrial-level Export-Revenue Share (%, exporting firms)	34.8
Industrial-level Import-material Expenditure Share (%, all firms)	8.9
Industrial-level Import-material Expenditure Share (%, importing firms)	42.2
Number of observations	7781

[1] All monetary value in this table is in million USD of 2000.

Table 2: Production and demand function parameter estimates

parameter	estimate	parameter	estimate
η^D	-7.106	α_M	0.883
	(0.208)		(0.000)
η^X	-6.405	α_L	0.054
	(0.000)		(0.003)
σ	1.251	α_K	0.063
	(0.043)		(0.003)

Table 3: Estimates of quality parameters and evolution for ω and $\log(p)$

Parameter	I	II	III	IV	V
$\frac{1}{1-\theta}$	0.804	0.800	0.800	0.802	0.801
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
ϕ	0.983	0.986	0.986	0.985	0.985
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
f_0	2.505	2.341	2.340	2.653	2.653
	(0.111)	(0.115)	(0.115)	(0.112)	(0.112)
f_e	0.077	0.087	0.087	0.102	0.102
	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)
f_i	0.267	0.262	0.261	0.264	0.264
	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)
f_{wto}		0.185	0.185		
		(0.038)	(0.038)		
f_ω	0.642	0.640	0.640	0.638	0.638
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
g_0	0.641	0.623	0.633	0.555	0.563
	(0.076)	(0.072)	(0.075)	(0.071)	(0.074)
g_e	-0.003		-0.003		-0.003
	(0.004)		(0.004)		(0.004)
g_i	-0.023				
	(0.004)				
g_{i0}		-0.019	-0.019	-0.016	-0.016
		(0.008)	(0.004)	(0.008)	(0.008)
g_{i1}		-0.025	-0.023	-0.026	-0.025
		(0.004)	(0.005)	(0.004)	(0.004)
g_{wto}		-0.020	-0.020		
		(0.005)	(0.005)		
f_p	0.935	0.939	0.938	0.943	0.943
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Year dummies	No	No	No	Yes	Yes

Table 4: Conditional choice of export and import probability estimates

	Import		Export
ψ_0^i	0.451	ψ_0^e	4.180
	(2.833)		(2.046)
ψ_e^i	0.607	ψ_e^e	2.405
	(0.098)		(0.071)
ψ_i^i	3.299	ψ_i^e	0.590
	(0.090)		(0.078)
ψ_ω^i	0.017	ψ_ω^e	0.088
	(0.057)		(0.042)
ψ_m^i	-0.298	ψ_m^e	-0.664
	(0.277)		(0.202)
ψ_k^i	0.091	ψ_k^e	0.083
	(0.037)		(0.027)
ψ_{low}^i	-0.019	ψ_{low}^e	-0.010
	(0.125)		(0.085)
ψ_{high}^i	0.231	ψ_{high}^e	-0.077
	(0.117)		(0.088)
Correlation:	0.204		
	(0.066)		

Table 5: Mean marginal effects on future trade probability

Next period:	Import	Export
Export	0.080	0.594
Import	0.450	0.160
ω	0.007	0.042
$\ln p$	-0.038	-0.158

[1] The marginal effects of productivity and input prices are averaged over firms actually participating in trade.

Table 6: Estimate of trade cost distribution parameters

Parameter	Estimate	Parameter	Estimate
$\lambda_{00,01}$	5.345	$\lambda_{01,01}$	0.087
	(0.107)		(0.028)
$\lambda_{00,10}$	7.071	$\lambda_{01,10}$	5.722
	(0.152)		(0.460)
$\lambda_{00,11}$	11.626	$\lambda_{01,11}$	6.135
	(0.163)		(0.293)
$\lambda_{10,01}$	4.279	$\lambda_{11,01}$	0.689
	(0.448)		(0.449)
$\lambda_{10,10}$	0.148	$\lambda_{11,10}$	0.264
	(0.018)		(0.473)
$\lambda_{10,11}$	4.643	$\lambda_{11,11}$	0.040
	(0.299)		(0.005)
λ_{ξ}	4.587		
	(0.041)		

Table 7: 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	0.059	0.057	0.063
Offline CCP Predicted	**Neither**	**Export Only**	**Import Only**	**Both**
Neither	0.967	0.024	0.008	0.001
Export Only	0.277	0.667	0.008	0.048
Import Only	0.126	0.008	0.749	0.118
Both	0.010	0.032	0.101	0.857
Overall	0.818	0.062	0.056	0.064
Model Predicted	**Neither**	**Export Only**	**Import Only**	**Both**
Neither	0.970	0.022	0.007	0.001
Export Only	0.162	0.788	0.007	0.044
Import Only	0.080	0.006	0.828	0.086
Both	0.009	0.023	0.078	0.889
Overall	0.811	0.066	0.059	0.064

Table 8: Removal of gain channels: industrial aggregate values differing from the baseline

Year	2	5	10	15
No Gain on Prod.				
Percentage change in aggregated productivity	-19.0	-27.0	-29.0	-29.1
Percentage change in aggregated input price	0.1	0.5	1.6	2.8
Change in proportion of exporters	-0.6	-1.5	-2.6	-3.5
Change in proportion of importers	-1.0	-2.2	-4.0	-5.4
Percentage change in firm value	-0.9 (-5.0 million USD)			
No Gain on Price				
Percentage change in aggregated productivity	-0.8	-4.8	-11.1	-14.9
Percentage change in aggregated input price	1.7	4.0	7.0	9.2
Change in proportion of exporters	-0.6	-1.7	-3.1	-4.0
Change in proportion of importers	-1.7	-3.7	-6.4	-8.4
Percentage change in firm value	-1.2 (-6.7 million USD)			

Table 9: Removal of gain sources: industrial aggregate values differing from the baseline

Year	2	5	10	15
No Import Gain				
Percentage change in aggregated productivity	-14.6	-21.7	-24.5	-25.2
Percentage change in aggregated input price	1.7	4.0	7.0	9.2
Change in proportion of exporters	-0.9	-2.2	-3.6	-4.6
Change in proportion of importers	-2.3	-4.7	-7.8	-9.9
Percentage change in firm value	-1.4 (-8.0 million USD)			
No Export Gain				
Percentage change in aggregated productivity	-5.3	-8.1	-9.3	-9.8
Percentage change in aggregated input price	0.0	0.1	0.3	0.5
Change in proportion of exporters	-0.3	-0.7	-1.1	-1.5
Change in proportion of importers	-0.2	-0.4	-0.7	-1.0
Percentage change in firm value	-0.3 (-1.6 million USD)			

Table 10: No WTO price effect: industrial aggregate values differing from the baseline

Year	2	5	10	15
Percentage change in aggregated productivity	-0.1	-1.0	-2.7	-3.7
Percentage change in aggregated input price	0.4	1.0	1.8	2.6
Change in proportion of exporters	-0.1	-0.4	-0.9	-1.3
Change in proportion of importers	-0.5	-1.0	-2.0	-2.7
Percentage change in firm value	-0.4 (-2.1 million USD)			

Figure 1: Import tariff change and firm-level growth of trade

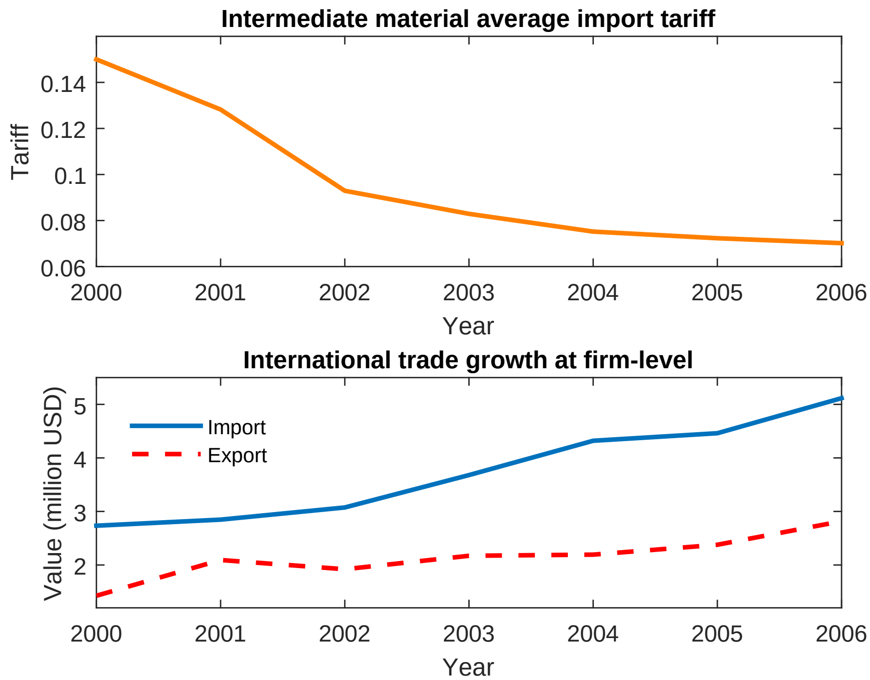

Figure 2: productivity and input prices: ω and $\ln p$

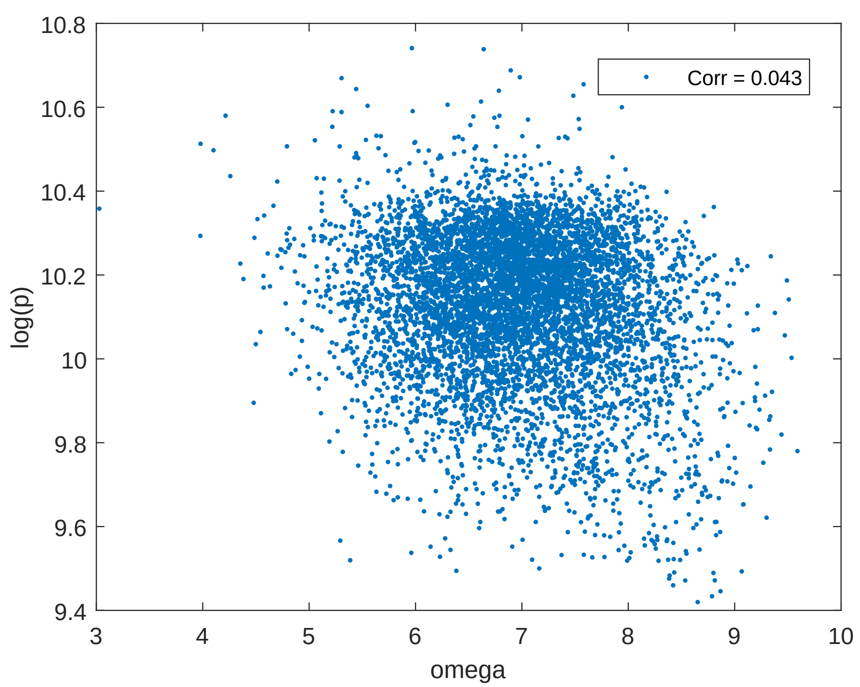

Figure 3: Densities of $\log(h)$ and ω

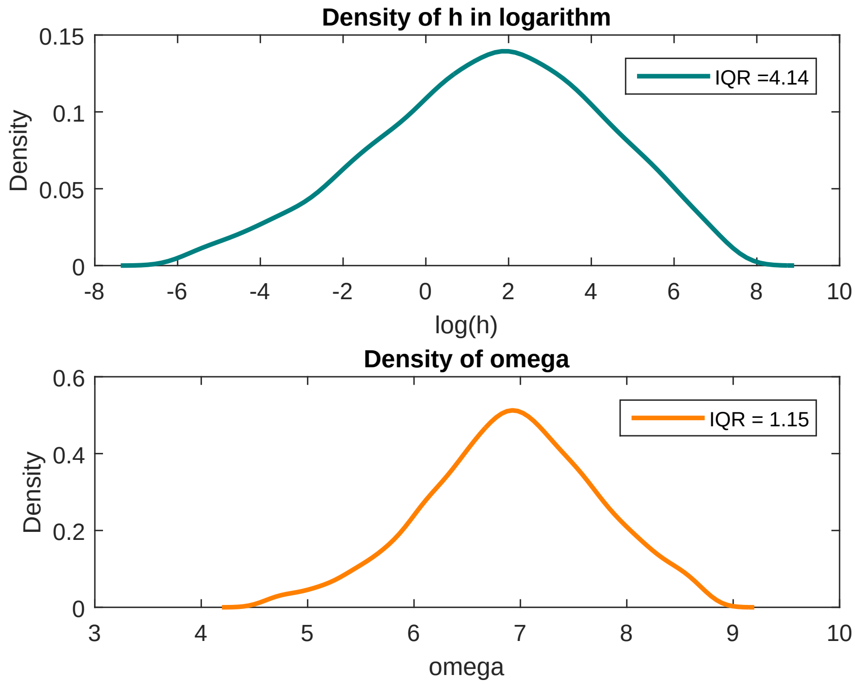

Figure 4: Densities of $\log(P_M)$ and $\log(p)$

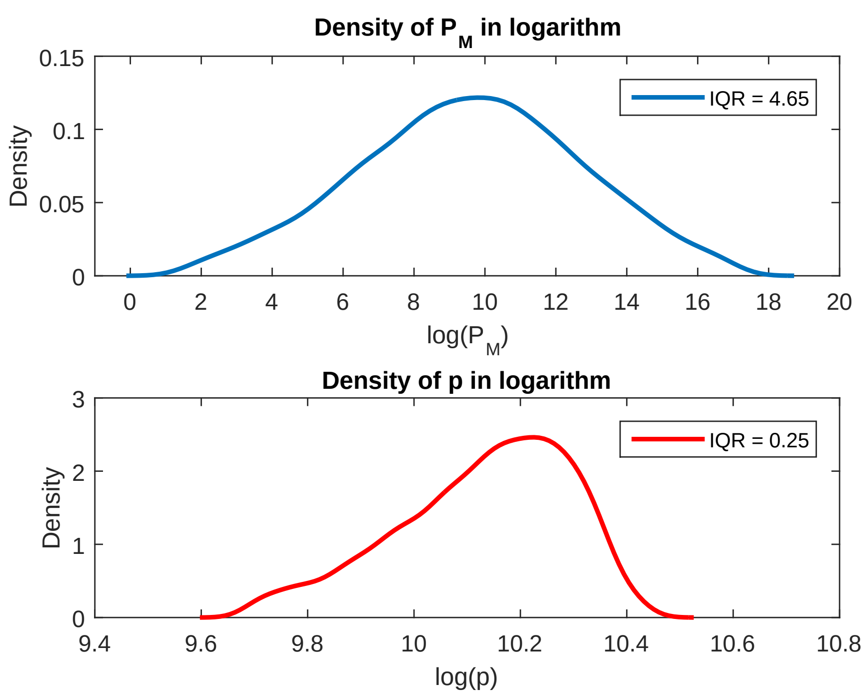

Figure 5: Density of ω by four types of firms

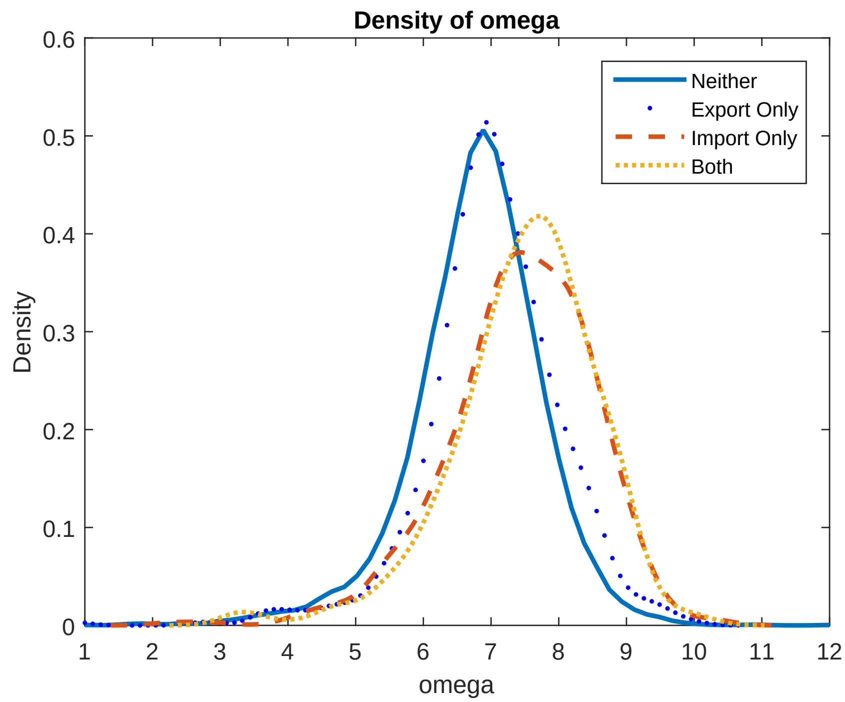

Figure 6: Density of $\log(p)$ by four types of firms