Quality, Input Choices and Learning by Exporting: Evidence from Chinese Exporters*

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Abstract

Using the detailed Chinese firm level exports information between 2000 and 2006, this paper estimates market- and product-specific demand functions for China's Electrical Machineries exports and recover the latent quality as the demand residual. I apply an instrument based on the idea of Hausman-Nevo instrument to our multi-market and multi-origin data for identification. I then combine our quality measure with other firm level observations to identify factors that are behind the cross firm and over time variation in the measured quality. I find importing activities to be significantly associated with quality differentiation, especially among Chinese non-state owned firms in their shipments to high income destinations. Studying the within firm over time evolution of quality, I find evidence for quality learning from experience of exporting to high income markets.

JEL Classifications: F12, F14, O12, O14.
Keywords: Trade; Quality; Imported Inputs; Learning by Exporting; Firm Heterogeneity.

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1. Introduction

Quality and cost advantages can both contribute to a firm's profitability. Improving quality enables a firm to charge a higher price without losing market share, while cost advantage allows a firm to profit from selling more at lower prices. In the early stage of their participation in international trade, less-developed economies export mainly products with low quality content that utilize their comparative advantage of cheap labour. One concern about this development strategy is that when product quality and quantity are imperfect substitutes, the markets for low quality products are limited; as a result, it is not guaranteed that the less-developed economies can benefit from trade and the economic growth supported by this specialization in low-end manufacturing products may not be tenable.[1] Studies on the industrial policies of the newly industrialized economies suggest that the transition toward more sophisticated products and the cultivation of dynamic comparative advantage are crucial.[2]

Despite the important role of quality, there are not many empirical studies explicitly focusing on the quality differentiation by exporters from developing countries. This is possibly due to the lack of directly observable information on quality.[3] In this study, I estimate the firm-, product- and market-specific quality of China's exports using rich export information from China's customs. I then combine the quality estimates with other firm level information to identify channels through which quality is differentiated across firms and improved over time. I find the quality of shipment to high income countries is positively associated with the usage of imported inputs and wage per employee among Chinese non-state owned firms. I also find the current quality of Chinese non-state owned firms is positively correlated with the past exporting exposure to high income countries after controlling for quality in the past year. We take this as evidence of learning by exporting in the quality aspect.

I focus on one specific category of products, those classified HS code 85 which includes *"electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles"*. There are two reasons why I choose to focus on these products. First, it accounts for a large proportion of China's total ordinary trade. Among the 97 2-digit HS chapters, it has been the top one in China's exports through ordinary trade since 2001. Its share in 2006 is 12%. Second,

[1]The discussion on the demand-side determinants of the pattern of trade can be traced back to Linder (1961). Summaries of early literature can be found in Deardorff (1984) and Leamer and Levinsohn (1995). Later related developments include the theoretical models developed in Copeland and Kotwal (1996), Murphy and Shleifer (1997) and empirical test by Hallak (2006, 2010). Sutton (2007) provides a mechanism that can generate a quality threshold. Hallak and Sivadasan (2009) introduces quality minimum requirement into the seminal heterogeneous firm trade model of Melitz (2003) and analyses the consequence.

[2]For summaries on related studies, see Balassa (1988), Rodrik (1995), Harrison and Rodriguez-Clare (2010).

[3]Brooks (2006) argues that low quality contributes to the low export intensity observed among Colombian plants. But the quality measure is based on unit value and constructed at industry level. Hallak and Sivadasan (2009) investigates firm level data and finds conditional exporter premium in output unit value and/or factor use in India, the United States, Chile, and Colombia. The conditional premium in unit value is interpreted as reflecting selection on quality.

these products are highly differentiated[4], intensive in R&D and thus have a potential for quality differentiation and upgrading.

Direct measures of quality are rare. One common practice is to use unit value as a proxy for quality.[5] However, this is problematic because high price can indicate both high quality and low cost efficiency. A better alternative, when information on both price and quantity is available, is to use the quantity sold conditional on price, i.e, the demand residual. Quality is any attribute of a product that can increase consumers' willingness to pay[6] and thus a demand shifter. A quality improvement shifts a demand curve upward and outward, accordingly, holding price constant, larger market share is a reflection of higher quality.[7] I estimate market- and product group-specific demand functions to measure price elasticities as precisely as possible.[8] I then define the residual of such a demand system estimation as "quality" with the goal of examining its properties.

Because the unobserved quality affects both quantities demanded and prices, I require exogenous cost shifters for price to consistently estimate it s coefficient using the instrumental variables estimation. The rich information I have on the origins and destinations of firms' exports provides such an instrument, following Hausman (1996) and Nevo (2001). For each destination market m, I carefully select markets subject to demand shifters independent of those on market m. I then use the average price that firms in the same production location charge on these other markets as an instrument for the prices they charge on market m. As expected, our instrumental variable strategy increases the magnitude of the OLS estimates by 100% on average. The estimates are robust to small changes in the criteria in selecting the set of markets for instruments. These allow me to recover latent quality as measured by the residual of this demand equation.

I then investigate the channels through which quality varies across firms and how it evolves over time. I focus on firms' input choices in the cross section and export experience to assess factors that correlate with firms' quality. First, I find that importing activity matters as importing positively correlates with export quality. Furthermore, the association between importing and quality varies across export destinations, firm ownership types and sources of imports. The positive relationship holds only for exports to high income destinations, and is strongest for non-state owned Chinese firms; for capital goods only imports from high income countries matters. I also find a positive association between firms' wage expenditure per employee and the esti-

[4] According to the index developed in Rauch (1999).

[5] Hallak and Schott (2011) provides a list of research based on this measure.

[6] The attribute can be related to either objective characteristics of a product or subjective evaluation by consumers.

[7] This idea of relating unobserved quality to conditional market share originated from the IO literature. Examples of recent studies on trade based on this idea are Hummels and Klenow (2005), Hallak and Schott (2011), Gervais (2010), and Khandelwal (2010). This method does not distinguish between objective aspects of quality such as technology and the subjective evaluation by consumers.

[8] Throughout the paper, product group is defined as one 4-digit HS line; product is defined as one 8-digit HS line. I refer to one 8-digit product produced by a firm as a variety.

mated quality of their shipment to high and medium income destinations with the quality-wage relationship highest for non-state owned Chinese firms. It is significant for foreign invested firms and state-owned Chinese firms but of smaller magnitude. I do not find a significant relationship between firms' capital-labour ratio and estimated quality. Focusing on the evolution of quality over time, I find that conditional on the quality of the previous year, firms with more past experience exporting to rich consumers have higher current quality. I take this as evidence of quality upgrading by exporting.

I make several contributions to the existing literature. First, the unit value and quantity information in my data allows me to use demand residual as a measure of quality. This is an improvement over unit value as a proxy for quality as it is not confounded by difference in cost efficiency. Even though this method is not new, this paper is the first to my knowledge to explore the multi-origin and multi-market structure of the transaction-level trade data to recover the latent quality of exports at the firm-product-market-time level. The multi-market and multi-origin structure of the micro trade data also provides room for constructing instruments that better satisfy the identifying assumptions in the demand estimation.[9]

Second, given that quality is one specific aspect of productivity, our investigation of the association between quality and other firm activities is related to a more general literature on importing and productivity. Some studies have found positive impacts of imported inputs on productivity, for example, Amiti and Konings (2007) for Indonesia, Kasahara and Rodrigue (2008) for Chile and Halpern et al. (2005) for Hungary.[10] With a richer set of measures on firm performance and importing activities, Kugler and Verhoogen (2009) and Manova and Zhang (2011) also find positive association for Colombian firms and Chinese firms[11] respectively. Regarding the specific channels through which imported inputs affect productivity, Goldberg et al. (2010) identify expanded product scope to be an important one in India. My study is among the first to investigate the contribution of importing activity to productivity through quality upgrading without relying on unit value as a proxy.

My finding of a positive impact of past exporting experience on the quality evolution process also contributes to the large literature on learning by exporting. This paper differs from the

[9] Firm level input prices have often been used as price instruments in estimating the output demand function. However, my investigation of the relationship between the estimated quality and firms' input choices suggests input prices are endogenous because firms use different input to produce output of different quality. This calls into question the validity of input prices as instruments for output price in demand estimation. My instrument is less susceptible to this concern because it is origin-destination specific instead of firm specific.

[10] Muendler (2004) finds no such evidence for Brazil.

[11] For the importing related analysis, I have the same data source as Manova and Zhang (2011) but I focus on a different set of firms. Manova and Zhang (2011) study firms involved in processing trade while I focus on firms that export through ordinary trade. The advantage of focusing on processing and assembly exporters is that one knows for sure the related imports will be used in producing for foreign markets. This does not apply to firms exporting through ordinary trade as these firms sell a substantial portion of their output to China's domestic market. However, on the other hand, one may be concerned to what extent firms involved in processing and assembly trade are behaving like profit maximizing agents in making decisions on input, output and price. Many of the processing firms operate only as a producing unit of a much longer value-generating chain with important decisions made elsewhere. Firms that export through ordinary trade are less of concern in this aspect.

existing studies in that I focus specifically on the role of learning in quality upgrading.[12] Quality upgrading is especially important for firms in developing countries like China for two reasons. First, given the size of and the intense price competition in China's domestic market, potential improvement in cost efficiency might be limited for an exporter. Second, China is still a poor developing country where consumers' willingness to pay for quality is low such that in a closed economy, a firm's incentive for quality upgrading is unclear. The exposure to international markets, and especially to consumers in high income countries who demand more quality, makes investment in quality upgrading more rewarding and thus stimulates firms to learn. The evidence of learning in quality also provides one possible explanation for the specific pattern in the cause of exceptional exporter performance found in the empirical literature on learning by exporting: as reviewed in Wagner (2007) and Harrison and Rodriguez-Clare (2010), the exporter premium is found to be due to the self-selection of more productive firms into export markets in the cases of many countries; while the evidence of learning, a causal relationship from past exporting experience to current productivity, is more often than not found in development countries.[13]

The remainder of the paper is organized as follows. In Section 2, I develop a simple model to motivate the empirical work and highlight my identification strategy. In Section 3, I give a brief overview of the data explored in this study. In Section 4, I present the demand estimation. In Section 5, I present the empirical analysis on the association between quality and input choices. In Section 6, I present the evidence on quality learning by exporting. Section 7 concludes.

2. Model

This section presents a model of a firm's endogenous quality choice. The model is in the same spirit as existing work in that it delivers the same result of heterogeneous firms choosing different technology or inputs to differentiate quality.[14] But it has a few distinct features. First, the model shows that a firm's decision on input and output quality is independent of quality adjusted input factor price; as a result, the difference in quality adjusted factor prices across production locations generates variation in output price that is independent of quality variation and can be used to identify parameters in the output demand function. This provides a foundation for the exclusion restrictions in the demand estimation in Section 5. Second, the model shows that

[12] The existing studies have been focusing on the impact of past experience on performance measures such as average variable cost, labour productivity, or total factor productivity (TFP). These measures are usually revenue or value-added based. Foster et al. (2008) show that the recovered TFP from a production function contains information on both cost efficiency and demand shocks. As a result, any identified learning effect based on these measures would contain both improvement in cost efficiency and quality upgrading.

[13] For example, Van Biesebroeck (2005) for African countries, De Loecker (2007) for Slovenia, Blalock and Gertler (2004) for Indonesia and Park et al. (2010) for China. De Loecker (2007) also finds firms learn more from exporting to higher income destinations. There is also evidence on learning by exporting from developed countries, for example Lileeva and Trefler (2010), where it is the change in market size that provides the incentive to learn.

[14] For example, models in Verhoogen (2008), Johnson (2011), Kugler and Verhoogen (2011), Baldwin and Harrigan (2011) and Hallak and Sivadasan (2009).

when the demand elasticities of quality vary across markets, firms will differentiate quality across markets. On one hand, firms ship higher quality goods to high income markets where demand is more responsive to quality upgrading. On the other hand, in markets where consumers' willingness to pay for quality is very low, no firm has the incentive to offer a higher quality version of its variety. As a result, the price variation in these markets across firms from different production locations will just reflect the variation in the quality adjusted factor price across production locations and can be used to construct instruments to identify the demand curves in markets where quality is differentiated. This provides a foundation for the construction of the instrumental variables I employ in the demand estimation in Section 4. Third, if there exists stronger complementarity between imported inputs and firms' efficiency in producing quality, it is cheaper to use imported inputs to produce high quality products. Combining the last two points, the model predicts a positive correlation between the use of imported inputs and the quality in high income markets. I am going to confront this prediction with data in Section 5.

2.1. Demand

Assume a Dixit-Stiglitz CES utility function for a representative consumer in country m

$$U_m = \left(\int_{i \in V_m} \xi_i^{\gamma_m} q_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where i denotes varieties, V_m is the set of varieties available to consumers in market m, q_i is consumption of variety i and ξ_i is quality of variety i. As in Hallak (2006), γ_m captures the intensity of consumers' preference for quality in market m. σ is the elasticity of substitution among varieties of the same quality.

Given a budget E_m, each variety's price p_i, and quality ξ_i, utility maximization leads to the following demand function

$$q_i = A_m \xi_i^{\gamma_m(\sigma-1)} p_i^{-\sigma} \tag{2}$$

where $A_m = \frac{E_m}{\int_{i \in V_m} p_i^{1-\sigma} \xi_i^{\gamma_m(\sigma-1)} di}$ is an aggregate demand shifter on market m that is common across varieties. ξ_i enters the demand equation for variety i as a demand shifter.[15] Conditional on the same price, quantity demanded is increasing in ξ. Moreover, given a same improvement in ξ_{fm}, the intensity of consumers' preference for quality γ_m determines the magnitude of the shift.[16]

[15] $\xi_i^{\gamma_m(\sigma-1)}$ will also be my measure of quality.
[16] This is true for any $\xi_{fm} > 1$ which is the only interesting case for us.

2.2. *Supply*

2.2.1. *Production Technology, Factor Markets and Unit Cost Function*

The production involves two types of activities: quality-independent activity and quality-differentiating activity. These activities are not necessarily undertaken within a firm. They can be embedded in the intermediate input or capital service that a firm purchases from its suppliers, in other words, employing x hours of either type of activity is equivalent to employing inputs with x hours of labour embedded. To allow firms to differentiate quality across markets, I denote the variety of firm f in market m by fm. Using L_{fm} and S_{fm} for the hours of quality-independent and quality-differentiating activities respectively, I assume the following production function for variety fm with quality ξ_{fm}

$$Q(L_{fm}, S_{fm}; \xi_{fm}) = min \left\{ \phi_f L_{fm} \ , \ \frac{S_{fm}^{\frac{1}{\eta}}}{\left(\frac{\xi_{fm}^{\lambda}}{1-\rho} - \frac{\rho \mu_f^{\lambda}}{1-\rho} \right)^{\frac{1}{\lambda}}} \right\} \tag{3}$$

where (1) ϕ_f represents firm f's efficiency in conducting quality-independent activity or using quality-independent input; (2) μ_f represents its efficiency in conducting quality-differentiating activity or using quality-differentiating input; (3) $\eta > 1$ captures the degree of diminishing return of labour in producing quality; (4) $\lambda < 0$ captures the degree of complementarity between quality efficiency μ and input quality in producing output quality; and (5) ρ captures the relative importance of quality efficiency versus input quality in producing quality. The production process can be explained in the following way. To produce one unit of variety fm with quality ξ_{fm}, firm f needs to employ $l_{fm} = l_f = \frac{1}{\phi_f}$ hours of quality-independent activity and one unit of quality-differentiating input of quality $\widetilde{s}_{fm}$, where $\widetilde{s}_{fm} = s_{fm}^{\frac{1}{\eta}}$ and s is the amount of quality-differentiating activity embedded in one unit of the quality-differentiating input. The relationship between output quality ξ_{fm} and input quality $\widetilde{s}_{fm}$ is represented by the following quality production function[17]

$$\xi_{fm} = \left(\rho \mu_f^{\lambda} + (1-\rho) \widetilde{s}_{fm}^{\lambda} \right)^{\frac{1}{\lambda}} \tag{4}$$

Suppose that input factor markets are local. Specifically, for firms in region j, the cost per labour hour is w_j. As a result, the unit cost function conditional on input quality $\widetilde{s}_{fm}$ for firm

[17] This production function is based on the one in Kugler and Verhoogen (2011).

f at location j is[18]

$$c_j(\phi_f, \widetilde{s}_{fm}) = w_j \left(\frac{1}{\phi_f} + \widetilde{s}_{fm}^{\eta} \right) \tag{5}$$

2.2.2. Firm Optimization

Given the demand equation specified in (2), the optimal price conditional on input quality $\widetilde{s}_{fm}$ is a constant mark-up over unit cost:

$$p(\widetilde{s}_{fm}; \phi_f) = \frac{\sigma}{\sigma - 1} w_j(f) \left(\frac{1}{\phi_f} + \widetilde{s}_{fm}^{\eta} \right) \tag{6}$$

Define $\overline{A}_m = \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} A_m$. The associated operating profits from market m are

$$\pi(\widetilde{s}_{fm}; \phi_f, \mu_f) = \overline{A}_m w_{j(f)}^{1-\sigma} \left(\rho \mu_f^{\lambda} + (1-\rho) \widetilde{s}_{fm}^{\lambda} \right)^{\frac{\gamma_m(\sigma-1)}{\lambda}} \left(\frac{1}{\phi_f} + \widetilde{s}_{fm}^{\eta} \right)^{1-\sigma} \tag{7}$$

Firm f chooses input quality $\widetilde{s}_{fm}$ to maximize the profits in (7). The first order condition gives

$$\frac{\gamma_m}{\phi_f} = \frac{\rho \eta}{1-\rho} \mu_f^{\lambda} {\widetilde{s}_{fm}^{*}}^{\eta-\lambda} + (\eta - \gamma_m) {\widetilde{s}_{fm}^{*}}^{\eta} \tag{8}$$

It can be proved that the solution to (8) exists and is unique. A sufficient condition for the second order condition to hold is $\gamma_m < \eta$, i.e, the cost function is sufficiently convex in quality relative to the demand function. Equation (8) suggests the optimal input quality by firm f for its shipment to market m, $\widetilde{s}_{fm}^{*}$, is a function of consumers' preference for quality γ_m and the two efficiencies ϕ_f and μ_f, i.e, $\widetilde{s}_{fm}^{*} = \widetilde{s}(\mu_f, \phi_f, \gamma_m)$. Given the quality production function in (4), the optimal output quality depends on the same factors, thus

$$\xi_{fm}^{*} = \xi(\mu_f, \phi_f, \gamma_m) \tag{9}$$

[18] Notice from (4) that for a given firm, there is a one-to-one relationship between input quality $\widetilde{s}$ and ξ. The corresponding unit cost function conditional on output quality ξ_{fm} is $c_j(\phi_f, \mu_f, \xi_{fm}) = w_j \left(\frac{1}{\phi_f} + \left(\frac{\xi_{fm}^{\lambda}}{1-\rho} - \frac{\rho \mu_f^{\lambda}}{1-\rho} \right)^{\frac{\eta}{\lambda}} \right)$.

With $\widetilde{s}_{fm} = \widetilde{s}^*_{fm}$, the conditional optimal price in (6) becomes

$$p^*_{fm} = \frac{\sigma}{\sigma - 1} w_j \left(\frac{1}{\phi_f} + \widetilde{s}^{*\,\eta}_{fm} \right) = p(\mu_f, \phi_f, \gamma_m, w_{j(f)}) \tag{10}$$

Comparing function $\xi(\mu, \phi, \gamma)$ in (9) and function $p(\xi, \mu, \gamma, w)$ in (10), I find local factor price level w affects only the price but not the quality. For a demand estimation with quality sold on the left hand side, price on the right hand side and ξ being part of the error term, it is exactly the variation in w that can be used to identify the price coefficient.

2.2.3. Quality Determinants

Comparative static analysis of ξ^*_{fm} reveals that

$$(A) \qquad \frac{d\xi^*_{fm}}{d\mu_f} > 0$$

This means the optimal quality ξ^* is increasing in a firm's efficiency in using quality-differentiating input. This is the direct result of the complementarity between firms' quality efficiency μ and input quality $\widetilde{s}$.

$$(B) \qquad \frac{d\xi^*_{fm}}{d\phi_f} < 0$$

This means the optimal quality ξ^* is decreasing in a firm's quality-independent efficiency ϕ. This is because firms with disadvantage in ϕ have the incentive to compensate for this with choosing higher quality.

$$(C) \qquad \frac{d\xi^*_{fm}}{d\gamma_m} > 0$$

This means the optimal quality increases in the intensity of consumers' preference for quality γ. This is because larger γ implies a larger shift in demand for a given improvement in ξ. For the extreme case of $\gamma_{m'} = 0$, the profit maximization condition in (8) suggests all firms will choose $\widetilde{s}^*_{fm'} = 0$. The optimal pricing in (10) becomes

$$p^*_{fm'} = \frac{\sigma}{\sigma - 1} w_j \frac{1}{\phi_f} \tag{11}$$

The average over all firms from the same production location j is then

$$\overline{p}^*_{jm'} = \frac{\sigma}{\sigma - 1} w_j \int \frac{g_{jm'}(\phi)}{\phi} d\phi \tag{12}$$

where $g_{jm'}(\phi)$ is the marginal distribution of ϕ conditional on producing in location j and selling to market m'. Assuming the same distribution of ϕ conditional on selling to m' across production locations, i.e, $g_{jm'}(\phi) = g_{m'}(\phi)\ for\ \forall j$, the variation in $\overline{p}^*_{jm'}$ across j would reflect only variation in w_j.

2.2.4. Introducing Imported Inputs

We introduce imported inputs as quality-differentiating inputs with stronger complementarity with firms' quality-differentiating efficiency μ. The quality production function associated with imported input is then

$$\xi_{fm} = \left(\rho \mu_f^{\lambda'} + (1-\rho)\widetilde{s}_{fm}^{\lambda'}\right)^{\frac{1}{\lambda'}} \tag{13}$$

where $\lambda' < \lambda < 0$, implies a higher degree of complementarity between $\widetilde{s}$ and μ. It can be proved that firm f with $\phi_f \mu_f^{\eta} = \frac{(1-\rho)\gamma_m}{\eta-(1-\rho)\gamma_m}$ is indifferent between domestic and imported quality-differentiating input. Firms with either higher μ or lower ϕ will find it more profitable to import input with higher quality content $\widetilde{s}$ and produce higher ξ; on the opposite, it is more profitable for firms with either lower μ or higher ϕ to use domestic quality-differentiating input with lower quality content $\widetilde{s}$ and produce lower quality ξ.

2.2.5. Summary

Summarizing the model delivers three important results. First, firms' underlying attributes and consumers' quality preference are the common factors that determine firms' choices on input quality, output quality and price. The optimal price also depends on local quality adjusted factor price. As a result, the variation in the quality adjusted factor price across production locations provides variation that is orthogonal to the variation in quality. This provides micro-foundations for my instrumental variables strategy in the demand estimation in Section 4. Second, firms have a stronger incentive to upgrade quality when and where demand is more responsive to quality change. Third, if imported quality-differentiating inputs are more complementary to firms' quality efficiency, firms that want to produce high quality products will find it cheaper to use imported inputs. Combining the last two points, we expect to see imported inputs to allow quality upgrading for sales to quality sensitive markets.

3. Data

3.1. Customs Data

My primary data set is China's Customs records for 2000-2006. This dataset provides information on the 8-digit HS product code, quantity, total value, exporter and importer identity, ownership type, origin, destination, form of trade, and transportation method associated with every export and import transaction by Chinese firms. The original data is at the monthly level. To estimate the demand functions, I aggregate observations by year in cells defined by exporter identity, destination market, 8-digit HS code and 4-digit zip code origin, the county level, in China. According to customs documents, origin is the location of production in most of the cases. I use origin as one dimension of the cell that defines an observation out of the concern that products produced by the same firm at different locations may not be the same.

There are two aspects of China's exports that require special attention. First, a lot of Chinese exporters are involved in processing trade,[19] which can be identified from the "form of trade" variable in the customs data. Due to possible transfer pricing, the prices may very well reflect only part of the production costs. As a result, these transactions may not be informative about demand conditions on the destination markets. For the purpose of estimating price elasticities, I use only export transactions labelled as ordinary trade. Second, a substantial amount of export transactions are conducted by trading agencies instead of manufacturing firms. Trading agencies can be identified by names in the Customs data.[20] Since I can not identify the original producers, I exclude these indirect exports in our analysis.

The composition of China's total exports of HS85 products in the year 2000, 2003 and 2006 are shown in Panel A of Table 1[21]. Direct export in the form of ordinary trade is the focus of this study. Since many of the exports to Hong Kong will be re-exported to other markets that are not recorded in China's customs, they are also excluded.[22] I also drop transactions where the unit value falls below the 1st and above the 99th percentile within each 8-digit HS product-destination market-year panel. I summarize the exporting and importing activities of firms in our Customs working sample in Panel B of Table 1.

[19] About half of China's exports are through ordinary trade and the other half are through processing and assembly trade. In processing trade, Chinese firms import parts duty-free from abroad, process and assemble them, and export the final products.

[20] I use Chinese characters with the meaning of "trading" or "importing and exporting" as identifiers. The same practice is also adopted in Khandelwal et al. (2011a), Manova and Zhang (2011) and Khandelwal et al. (2011b).

[21] Processing and assembly exports account for the majority of the "Other" category

[22] For discussions on China's export through Hong Kong, see Fung and Lau (2003) and Ferrantino and Wang (2008).

Table 1: Data Summary

	2000		2003		2006	
Panel A: Exports decomposition (Billion USD)						
	Other	**Ordinary**	Other	**Ordinary**	Other	**Ordinary**
Indirect	4.68	3.23	7.04	4.67	9.72	9.17
Direct	34.42	**3.45**	66.94	**9.45**	176.80	**31.88**
Panel B: Customs working sample						
# of exporter	3,465		9,366		18,105	
median exp. value (USD)	38,305		59,176		67,253	
median # of HS8 product exp.	4		6		5	
median # of destination	6		11		12	
% imp. IMT[(1)]	56%		53%		41%	
% imp. CAP[(2)]	38%		39%		29%	
median value of imp. IMT (USD)	163,976		123,843		127,544	
median value of imp. CAP (USD)	68,655		56,496		59,709	
median # of HS8 imp. IMT	9		8		7	
median # of HS8 imp. CAP	4		4		4	
Panel C: Matched working sample						
# of exporter	1,332		3,377		7,484	
median exp. value (USD)	44,846		100,069		159,560	
median # of HS8 product exp.	3		4		5	
median # of destination	7		13		16	
median size by employment	262		244		220	
median wage (CHN Yuan)	11,920		10,381		14,789	
% imp. IMT	59%		60%		55%	
% imp. CAP	39%		45%		40%	
median value of imp. IMT (USD)	124,574		154,527		177,175	
median value of imp. CAP (USD)	49,198		53,265		60,613	
median # of HS8 imp. IMT	9		10		9	
median # of HS8 imp. CAP	4		4		4	
% imp. IMT from RICH	48%		50%		45%	
% imp. CAP from RICH	31%		36%		32%	
median value of imp. IMT from RICH (USD)	108,389		115,161		114,360	
median value of imp. CAP from RICH (USD)	59,548		51,076		54,400	
median # of HS8 imp. IMT from RICH	8		7		7	
median # of HS8 imp. CAP from RICH	4		4		3	

[(1)] *IMT refers to intermediate input;* [(2)] *CAP refers to capital goods;*

3.2. China's Annual Manufacturing Survey Data

Our second source of data is China's Annual Manufacturing Survey (AMS) 2000-2006 data. ASM covers all State Owned Enterprises (SOE) and firms of other types of ownership with annual sales above 5 million RMB. The survey collects information on firms' industry classification (CIC), capital stock, wage cost, total employment, total exports, total output value, etc. I match the Customs data and the ASM data by firms' names. I summarize the exporting and importing activities of the matched sample in Panel C of Table 1. Given that ASM selects firms on size, firms in the matched sample are unsurprisingly larger on average in terms of export scale. But there is no substantial and systematic difference in other measures of trading activities between the two samples.

3.3. Other Data

Information on destination markets' per capita GDP is from the Penn World Tables. Pair-wise distances between countries are from CEPII.

4. Demand Estimation

4.1. Specification

The unit of observation is exporting firm f, destination market m, 8-digit HS product h and year t. My estimation equation is

$$ln\left(Q_{fmht}\right) = \alpha^{g_{(m)}j_{(h)}} \times ln\left(P_{fmht}\right) + A_{mht} + \xi_{fmht} + \epsilon_{fmht} \tag{14}$$

where $ln\left(Q_{fmht}\right)$ is the log of physical quantity sold of product h by firm f to country m in year t; $ln\left(P_{fmht}\right)$ is log of the associated unit value; A_{mht} are market-product-time fixed effects that absorb factors that are common to all exporters of product h to market m in year t; ξ_{fmht} denotes product quality, which is unobservable but very likely to affect price and quantity simultaneously; ϵ_{fmht} absorbs all exporter idiosyncratic demand shocks that are independent of price.$g_{(.)}$ and $j_{(.)}$, to be explained in more details below, refer to the market group to which country m belongs and the product group to which product h belongs.

The purpose of estimating the demand function is to recover quality as demand residuals, literally the quantity sold purged of the influence of price and aggregate demand factors. Thus it is essential to estimate the price coefficient properly. There are two issues that need to be addressed. First, unobserved quality is very likely to simultaneously determine price on the right hand side and quantity on the left hand side, for the obvious reason that varieties of better quality are usually more costly to produce and demanded in larger quantities conditional on price. This leads to an upward bias of the OLS estimation. We are going to construct and use a Hausman-Nevo instrument that captures cost shocks that are specific to different production locations in China to identify the price coefficient. I discuss this further in the next subsection. Second, price sensitivity is not necessarily the same across markets and products. Given my goal of recovering quality, it is not enough just to be able to consistently estimate an average price coefficient for the reason that a constant demand elasticity imposed when heterogeneity exists will contaminate our quality measure. Consequently, I allow the price coefficient α to vary across market group g and product group j. We divide the global markets into seven groups according to geographic location and level of development.[23] The seven groups are: the United States and Canada (NA); Latin American countries (LA); European Union member countries(EU); Singapore, Japan and Korea (SJK); other countries in Asia (RAS); Australia and New Zealand (AZ); African countries (AF). Product group g is defined along the 4-digit HS lines.[24] Once I get consistent estimates of the elasticities, I can purge the influence of price by subtracting $\widehat{\alpha}^{g(m)j(h)} \times ln\left(P_{fmht}\right)$ from $ln\left(Q_{fmht}\right)$ and the influence of aggregate demand factors A_{mht} by demeaning within each mht cell. In the end, our quality measure would be an estimate of the residual $\xi_{fmht} + \epsilon_{fmht}$, denoted by $r\widehat{\xi}_{fmht}$.

4.2. Identification Strategy

Given the rich information we have on the origins and destinations of firms' exports, we can construct a Hausman-Nevo instrument to identify price coefficients. With multi-market observations on prices, such an instrument uses price on other markets as instruments. This type of instrument has been used in studies on ready-to-eat cereal markets by Hausman (1997) and Nevo (2001). In general, there are two sources of variation in observed prices: one is variation in production, transportation or distribution cost and the other is variation in product quality.[25] The first type of variation is useful in identifying price sensitivity of demand, while the second gives rise to endogeneity problems and can lead to inconsistent estimates. A useful instrument must pick up variation of the first type to be relevant, and be free of the second type to be valid. In a multi-market context, the two-source variation argument takes a more specific form: prices charged by firms on two different markets can be correlated either because of common cost shocks or common demand shocks. To capture common cost shocks, I construct the instrument using prices charged by firms producing at the same 4-digit zip code location in China; to avoid common demand shocks, I use prices from carefully selected markets that are enough far away both geographically and in levels of development.

[23] We drop the observations associated with exports to the non-EU member European countries. The estimates for this group is very imprecise because of small number of observations relative to the number of countries and products.

[24] Thus the specification in (14) is equivalent to regressing lnQ on lnP, controlling for market by product and by year fixed effects for each market group and 4-digit HS4 sector separately.

[25] Here we are abstracting from the potential heterogeneity in firms' market power and markup adjustment, which might be another source of price variation.

For an illustrative example, think about firms in Dongguan, a manufacturing cluster in China's Pearl River Delta area, that export to both Japan and Kenya. Because the two markets are quite far away both on a geographic map and in levels of economic development, one can reasonably believe they have very different demand structures and are subject to independent demand shocks. On the other hand, these firms may share common cost shocks due to the localization of input markets. This allows me to use the prices that exporters from Dongguan charge in Kenya to construct instruments for the prices they charge in Japan, and vice versa.

I use the 4-digit zip code[26] as production origin identifier and apply two criteria in selecting the set of markets in constructing instruments. For an observation subscripted with $fmht$, the prices charged by any exporter f' shipping goods from location $o_{(f)}$, the 4-digit zip code area where firm f is located, to any market m' in year t will be used to construct instrument for $ln\left(P_{fmht}\right)$ if

1. The geographical distance between country m and m' is above the 30th percentile in the distribution of geographical distance among all country pairs.

2. The per capita GDP of country m' is at least 1.5 times the standard deviation of the world distribution away from that of country m.

The instrument for $ln\left(P_{fmht}\right)$ is then the average of prices within $f'm'h't$

$$IV_{fmht} = \overline{lnP}_{f'm'h't} \tag{15}$$

Notice the average is taken across all f', m' and h'. The f's and m's are chosen as aforementioned; the h's cover all the 8-digit HS lines under chapter HS85. It is the destination market and year specific, across 4-digit zip code region variation that is kept in our instrument for identification. The exclusion restriction, which in this context requires that the demand shocks from markets where the average price is used as an instrument to be independent of the demand shocks on the market where the prices are instrumented for, are embedded in our market selection criteria. The first one rules out markets that may share geographically local demand shocks; the second addresses the possibility that exporting firms may ship products of the same quality to markets with similar degree of development and thus similar preference for quality.[27]

[26] This is at the prefecture level. NUMBER NEEDED HERE unique locations can be identified

[27] There are cases where no observation $f'm'h't$ exists, i.e, there is no firm f' in the same 4-digit zip code region $o_{(f)}$ as firm f shipping to any market m' that satisfies the two selection criteria in year t. As a result, the instrument constructed as above would be missing valued. It turns out we have this problem for about 11% of our sample. In order not to lose observations, we construct proxy values for these cases. The details are in Appendix A.

4.3. Results and Discussion

The OLS estimates of the price coefficients are reported in Table 2. Panel A shows the results from regressions where all 8-digit product lines are pooled together. The row labelled "World" shows the result pooling all market groups together. The panel labelled "Whole sample" reports estimation results using all observations with missing values in instrumental variables being proxied. The "No Proxy Sample" panel reports the results using only observations with non-missing values for the instrumental variable. The magnitude of the estimates is around 0.8 or 0.9. The "No Proxy" subsample results are quite similar to the whole sample results. Panel B reports the estimates for one example 4-digit HS category 8538.[28] Panel C presents summaries of estimates from regressions for each product group separately. The first column reports the number of 4-digit HS lines with negative estimates at 10% significance level. The second column reports the number of observations associated with these estimates. The last four columns report the mean and median of the estimates for the whole sample and the no proxy subsample respectively. The magnitude here is also around 0.8 or 0.9.

The IV estimates of the price coefficients are reported in Table 3. The layout of this table is the same as Table 2, except that we include in the middle panel two columns of summaries of the OLS estimates for the set of product groups with significant IV estimates.

The magnitude of the IV estimates is generally larger than the OLS estimates, suggesting that higher prices partially reflect high quality. I obtain significant estimates for 38 out of 48 product categories for market group NA and only 19 out of 48 for group AF; the proportions of observations associated with significant estimates are much more substantial. For NA and EU, it is above 80%; for SJK, AZ, RAS, LA and AF it is around 60%s. Overall, about 78% of observations are associated with significant estimates. Since we proxy the value of instrument for observations where it is missing, it is important to check whether the estimation results using the no proxy subsample are significantly different from those using the whole sample. [29] It turns out the subsample results are in general very close to the whole sample results.

We use unit values from markets with per capita GDP 1.5 times standard deviation away, either richer or poorer, to construct instruments. One might be concerned that the co-variation

[28]This is the category whose OLS estimate is about the median among the 48 in the "World" regression. The HS description is as following: Parts suitable for use solely or principally with the apparatus of heading 8535, 8536 or 8537; HS8535: Electrical apparatus for switching or protecting electrical circuits, or for making connections to or in electrical circuits; HS8536: Electrical apparatus for switching or protecting electrical circuits, or for making connections to or in electrical circuits; HS8537: Boards, panels, consoles, desks, cabinets and other bases, equipped with two or more apparatus of heading 8535 or 8536, for electric control or the distribution of electricity.

[29]There are two potential reasons why they can be different. First, if the firms, or markets or products of observations for which the instrument value is missing are systematically different from those with non-missing values, given that our proxy strategy is to fill in the missing values with local averages of available values at the same product location, the systematic difference would show up as differences in the whole sample and subsample estimates. Second, since we utilize all the available values of instrument at the production location level to construct proxy for one third of the missing values, the market selection rules are bypassed, thus any difference found may also reflect inconsistency from invalid instrument.

Table 2: Demand Estimation, by OLS

Panel A: All products pooled

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	683700	-0.850	0.004	607030	-0.843	0.004
NA[(1)]	65885	-0.801	0.010	64051	-0.798	0.010
EU[(2)]	173826	-0.830	0.007	160422	-0.825	0.008
SJK[(3)]	76759	-0.822	0.011	67925	-0.810	0.012
AZ[(4)]	21522	-0.795	0.015	20773	-0.796	0.016
RAS[(5)]	213921	-0.882	0.006	187109	-0.879	0.006
LA[(6)]	61766	-0.885	0.012	49973	-0.887	0.013
AF[(7)]	51346	-0.902	0.013	42754	-0.898	0.014

Panel B: Example product group HS4=8538

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	17688	-0.859	0.018	16156	-0.875	0.019
NA	1655	-0.934	0.038	1618	-0.928	0.042
EU	4109	-0.766	0.041	3825	-0.754	0.041
SJK	2459	-0.963	0.034	2258	-0.989	0.036
AZ	526	-0.662	0.065	513	-0.672	0.070
RAS	5748	-0.844	0.026	5203	-0.874	0.025
LA	1437	-0.942	0.061	1257	-1.025	0.075
AF	1314	-0.861	0.072	1148	-0.890	0.091

Panel C: Summaries of regressions by 4-digit HS product group (48 groups in total)

	# HS4	# of obs.	Whole Sample		No Proxy Sample	
	neg. & sig.[(8)]	neg.& sig.	mean	median	mean	median
World	48	683700	-0.832	-0.873	-0.825	-0.875
NA	47	65817	-0.827	-0.832	-0.813	-0.827
EU	46	173466	-0.811	-0.840	-0.811	-0.832
SJK	48	76759	-0.835	-0.884	-0.821	-0.846
AZ	41	20740	-0.865	-0.816	-0.857	-0.812
RAS	47	213671	-0.874	-0.906	-0.866	-0.874
LA	41	60611	-0.920	-0.889	-0.921	-0.882
AF	42	50688	-0.919	-0.894	-0.900	-0.902

All regressions cluster standard errors by 8-digit HS product, market and year.

(1) *Refers to US and Canada;*

(2) *Refers to EU member countries;*

(3) *Refers to Japan, South Korea and Singapore;*

(4) *Refers to Australia and New Zealand;*

(5) *Refers to the rest of Asia except Hong Kong;*

(6) *Refers to Latin American countries;*

(7) *Refers to African countries.*

(8) *Significant at %10 level.*

Table 3: Demand Estimation, by 2SLS[1]

Panel A: All products pooled

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	683700	-1.434	0.025	607030	-1.408	0.027
NA	65885	-1.490	0.062	64051	-1.477	0.065
EU	173826	-1.389	0.035	160422	-1.354	0.036
SJK	76759	-1.454	0.099	67925	-1.465	0.106
AZ	21522	-1.144	0.084	20773	-1.214	0.083
RAS	213921	-1.510	0.059	187109	-1.443	0.060
LA	61766	-1.494	0.104	49973	-1.520	0.120
AF	51346	-1.203	0.082	42754	-1.213	0.095

Panel B: Example product group HS4=8538

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	17688	-1.371	0.101	16156	-1.430	0.104
NA	1655	-1.362	0.318	1618	-1.424	0.319
EU	4109	-1.336	0.204	3825	-1.271	0.215
SJK	2459	-1.427	0.254	2258	-1.462	0.188
AZ	526	-0.415	0.267	513	-0.469	0.281
RAS	5748	-1.507	0.191	5203	-1.477	0.200
LA	1437	-1.272	0.365	1257	-1.624	0.488
AF	1314	-1.671	0.680	1148	-2.115	0.866

Panel C: Summaries of regressions by 4-digit HS product group (48 groups in total)

	# HS4	# of obs.	Whole Sample		OLS Comparison		No Proxy Sample	
	neg. & sig.	neg.& sig.	mean	median	mean	median	mean	median
World	34	530653	-1.700	-1.555	-0.845	-0.906	-1.636	-1.421
NA	38	56268	-1.795	-1.449	-0.833	-0.844	-1.730	-1.432
EU	31	150502	-1.687	-1.336	-0.810	-0.843	-1.713	-1.296
SJK	24	47015	-1.757	-1.423	-0.845	-0.915	-1.816	-1.445
AZ	21	13347	-1.818	-1.485	-0.760	-0.772	-1.729	-1.337
RAS	26	145269	-2.139	-1.781	-0.926	-0.945	-2.079	-1.713
LA	20	36934	-1.771	-1.684	-0.956	-0.932	-1.857	-1.788
AF	19	30246	-1.764	-1.406	-0.924	-0.925	-1.640	-1.259

All regressions cluster standard errors by 8-digit HS product, market and year.

[1] *The market selection criteria for constructing instruments in these regressions are:*

(a) geographical distance being above the 30th percentile;

(b) per capita GDP disparity being larger than 1.5 times the standard deviation.

Other notes as Table 2.

with unit values on richer markets are more susceptible of being due to quality differentiation, and only the co-variation with those on poorer markets should be used to pick up cost covariation for identification. We try an alternative instrument constructed with only unit values on markets that are 1.5 times standard deviation poorer and get similar results as Table 3. The exact results in the same format as Table 3 can be found in Table H.1 in the appendix.

The large number of destinations provides me flexibility in constructing instruments and in turn makes over-identification tests possible. We supplement our main instruments with another two stricter alternative instruments to do the specification tests. One of the alternative instruments is constructed by adopting a per capita GDP disparity criterion of 1.75 times the standard deviation away while holding the geographical distance criterion at 30th percentile; for the second alternative, we hold the per capita GDP criterion at 1.5 times the standard deviation and increase the geographical criterion to be above the 40th percentile. The specification tests results for our median product HS8538 are presented in Table 4. As suggested by the *p-value*s in columns (5) and (6), regressions for all market groups pass the over-identifying restriction tests and the orthogonal tests on our main instrument. Column (7) reports the *p-value*s testing the redundancy of the two additional instruments constructed with stricter rules in selecting markets, and they are shown to be redundant in all market groups except RAS. But the inclusion of additional instruments does not change the estimate of price coefficient; it is -1.507 with both specifications. Market group NA and AF have *p-value*s greater than 10% in the weak identification tests, but it is mainly driven by the inclusion of redundant instruments. As shown in column (9), both *p-value*s drop below 10% when we exclude the two additional instruments.

Table 4: Specification Tests in Demand Estimation for HS8538

	(1) # of obs.	(2) coef. est.	(3) std. error	(4) 1st Stage F-stat p-value	(5) OVID. Test Hansen-J p-value	(6) Othog. Test Main IV[1] C-stat, p-value	(7) Redundancy Test Alt. IVs[2] p-value	(8) 1st Stage Main IV only F-stat, p-value
World	17258	-1.368	0.099	0.000	0.278	0.221	0.044	
NA	1652	-1.370	0.334	0.123	0.987	0.931	0.861	0.018
EU	4023	-1.378	0.199	0.000	0.397	0.240	0.189	
SJK	2454	-1.453	0.241	0.002	0.660	0.687	0.720	
AZ	520	-0.428	0.265	0.050	0.421	0.222	0.876	
RAS	5632	-1.507	0.166	0.000	0.254	0.434	0.009	
LA	1363	-1.155	0.287	0.017	0.321	0.144	0.140	
AF	1197	-1.474	0.558	0.192	0.541	0.979	0.819	0.067

All regressions cluster standard errors by 8-digit HS product, market and year.

(1) *The market selection criteria for constructing our main instrument are:*

(a) geographical distance being above the 30th percentile;

(b) per capita GDP disparity being larger than 1.5 times the standard deviation.

(2) *The alternative instruments are constructed by changing the two selection criteria for our main IV one at a time. The alternative criteria are:*

(a) geographical distance being above the 40th percentile;

(b) per capita GDP disparity being larger than 1.75 times the standard deviation.

Other notes as Table 2.

I face a trade-off between instrument validity and instrument strength in selecting the geographical distance and per capita GDP disparity cut-offs: the further away the two markets, the more likely they have independent demand shocks and the more confident we are in the validity of our instrument; on the other hand, the stricter we are in selecting markets, the more observations would need proxy values for instruments and the less variation can be utilized, and in turn, the less efficient our estimates would be. Thus it is desirable to find a balance point where the estimation results are robust to small changes in cut-offs. Consistent with the results of our specification tests, the two alternative instruments give similar estimation results as our main instrument. The exact results using the two alternative instruments are in Table H.2 and H.3 in the appendix.

With price coefficients in hand, I calculate the following firm, product, market and year specific residuals as our quality measure.

$$r\widehat{\xi}_{fhmt} = ln\left(Q_{fmht}\right) - \widehat{\alpha}^{g_{(m)}j_{(h)}} \times ln\left(P_{fmht}\right) - \widehat{A}_{mht} \tag{16}$$

This measure contains the last two terms $\xi_{fmht} + \epsilon_{fmht}$ in (14). The quality estimates need to be normalized to be comparable across products in the following analysis. We normalize $r\widehat{\xi}_{fhmt}$ by their product-year specific standard deviations.[30] As a result, the differences in the standardized variables are in units of year and product specific standard deviation. We denote the normalized quality estimates by $\widehat{\xi}_{fhmt}$.

5. Quality and Input Choices

I now investigate the correlation between exporters' output quality and input choices and the heterogeneity of this association across destination markets and firms of different ownership type. This will find correlated factor that are important in firms' quality production function. I first look at firms' import decisions and then decisions on domestically employed labour and the related capital labour ratio. Our regression specification is

$$\widehat{\xi}_{fhmt} = \delta^{GO} \times ACTIVITY_{ft} + CONTROLS_{ft}\Delta^{G} + \nu_{fhmt} \tag{17}$$

where $ACTIVITY_{ft}$ is firm and time specific measures of input choices, including various import measures, average wage payment per employee and capital-labour ratio, and δ is market group G and ownership type O specific. To ease presentation, I combine destination markets in larger groups. Since our quality measure is by construction the deviation from market specific mean, I need to be make sure the deviation is comparable across markets in the same group; in other

[30] Product specific normalization allows for different quality ranges across product; year and product specific normalization further allows the range for any specific product to change over time.

words, the mean quality of markets in the same group should be about the same. I group high income countries Canada, the United States, European member countries, Singapore, Korea, Japan, Australia and New Zealand into $G1$. I group other Asian countries and Latin American countries into $G2$. These are mostly medium income countries. The remaining African countries are labelled as $G3$. These are mostly poor countries. I run regression (17) for each of the three G groups separately. Considering firms of different ownership type may not have the same access to or need to incur different costs to reach some factor markets, I further allow the coefficients of our variables of interests, δ, to vary across four different ownership types: non-state owned Chinese firms (CHN), foreign invested firms (FGN), Hong Kong, Macao or Taiwan invested firms (HMT) and stata-owned Chinese firms (SOE). I include as control variables polynomials of firm size, firms' ownership type, CIC industry fixed effects and experience interacted with year effects.[31]

5.1. Imported Inputs

China's customs records provide information on firms' imports in as much detail as firms' exports. This allows me to construct not only extensive measures as import status dummies but also intensive measures such as the total or unit value of imports, and the number of imported varieties. I include only firms' ordinary imports as those for processing and assembly are under strict regulation and can not be used to produce for ordinary exports. I further differentiate the origins of imports according to whether the imports are from one of the 20 most advanced countries. These 20 countries are: Luxembourg, Norway, the United States, Singapore, Switzerland, Netherlands, Austria, Canada, Iceland, Denmark, Australia, Belgium, Germany, Japan, France, Sweden, Italy, Britain, Finland and Spain. I am especially interested in the imports of intermediate inputs and capital goods. I use the UN's BEC (Classification by Broad Economic Categories) classification to identify intermediate inputs and capital goods such that I can assess potentially different roles of these two types of inputs.

Results related to import status dummies are reported in Table 5. The activity measure in column (1) is a dummy indicating whether a firm imports any intermediate inputs or capital goods; in column (2) it is an indicator of importing intermediate inputs; in column (3) it is an indicator of importing intermediate inputs from any of the 20 most developed countries; in column (4) it is an indicator of importing intermediate inputs from other countries; columns (5) - (7) are defined in the same way but for capital goods. Panel A reports the results for high income destination markets; Panel B is for the medium income group and Panel C is for the low income group.

There are two important findings. First, the importing status dummy is positively and significantly associated with product quality for high income destination countries in Panel A.

[31] Year and experience interactive effects are controlled with current and the first observed year pair-wise dummies.

Second, the positive association is significant only for the non-state owned Chinese firms. For the sample of Chinese non-state owned firms in Panel A, I rerun the regressions including firm by market fixed effects and find that the association becomes insignificant. With the same set of observations, I run the regressions year by year and find results similar to those reported in Table 5.[32] Consequently, it is mainly the cross-sectional variation in quality and importing status that drives the empirical results in 5.

I then investigate the intensive margins of imports. The results related to imported intermediate inputs are shown in Table 6. From column (1) to (7), the variables of interest are total value of imported intermediate inputs, total value from the 20 top countries, total value from other countries, total number of varieties,[33] total number from the 20 top countries, total number from other countries and average unit value. I have shown in Table 1 that a median importing firm may purchase 6 lines of 8-digit HS product from rich countries alone. To make measures of unit value comparable across different produce lines, I first take the residuals after removing the 8-digit HS product by year specific means from the log of unit values and then take the weighted average across products within a firm. Again, a positive and significant association between import measures and product quality exists only in exports to the rich countries and the association is strongest for the non-state owned Chinese firms. All three measures, the value, the number of varieties and the unit value, are related to quality. I also conduct joint test of the overall significance of import measures for foreign invested firms and it turns out only the total value of imports from the top 20 countries and the unit value of imports matter for foreign invested firms.

Table 7 is in the same format as Table 6 but for imports of capital goods. As in the previous two tables, importing behaviour is only related to quality differentiation in exports to rich markets. Regarding the source of imports, it is only the imports from the top 20 developed markets that matter, both in terms of the value of imports and the number of imported varieties. The coefficient for the unit value of imports is marginally significant for both the non-state owned Chinese firms and foreign invested firms.

My empirical findings echo previous studies by Amiti and Konings (2007), Kasahara and Rodrigue (2008), Halpern et al. (2005), Kugler and Verhoogen (2011), Goldberg et al. (2010) and Manova and Zhang (2011) in several aspects. First, active importing participation is associated with better performance. Second, the number of varieties matter. Third, the unit value of imports matter. Our distinct contribution is threefold. First, I find direct evidence of different behaviour in quality differentiation across markets[34] and illustrate the economic force behind it in our simple model in Section 2. Second, my empirical results suggest imports play different roles for firms of different ownership type in China: the importer premium is most significant

[32]Results from these regressions are available upon requests

[33]Varieties are defined along the 8-digit HS product lines. I try alternative definition of HS product line by origin country and the empirical results are basically the same

[34]Manova and Zhang (2011) report indirect evidence of quality differentiation across markets.

Table 5: Quality and Import Status

Dependent Variable: $\widehat{\xi}_{fhmt}$

ACTIVITY DUMMIES	(1) ALL IMPORTS	(2) ITM.[1] ANY SOURCE	(3) ITM. from RICH[3]	(4) ITM. from OTH.[4]	(5) CAP.[2] ANY SOURCE	(6) CAP. from RICH	(7) CAP. from OTH.
Panel A: Destinations being US, Canada, EU Members, Japan, South Korea, Singapore, Australia or New Zealand							
ACTIVITY[5]	0.087***	0.099***	0.092***	0.100***	0.067**	0.074**	0.036
	(0.021)	(0.022)	(0.024)	(0.025)	(0.024)	(0.027)	(0.028)
ACT.×FGN[6]	-0.096**	-0.103**	-0.054	-0.140***	-0.093**	-0.054	-0.094*
	(0.033)	(0.034)	(0.034)	(0.035)	(0.033)	(0.035)	(0.038)
ACT.×HMT[7]	-0.088*	-0.125**	-0.107*	-0.164***	-0.119*	-0.102	-0.165**
	(0.038)	(0.040)	(0.043)	(0.046)	(0.046)	(0.058)	(0.054)
ACT.×SOE[8]	-0.013	-0.057	-0.043	-0.124**	-0.021	-0.064	-0.051
	(0.054)	(0.051)	(0.052)	(0.047)	(0.047)	(0.048)	(0.050)
Observations	140236	140236	140236	140236	140236	140236	140236
Panel B: Destinations being the rest of Asia or Latin American countries							
ACTIVITY	-0.000	0.005	0.002	0.036	-0.031	-0.035	-0.028
	(0.023)	(0.026)	(0.028)	(0.029)	(0.028)	(0.031)	(0.031)
ACT.×FGN	0.017	0.013	0.043	-0.035	0.018	0.059	-0.022
	(0.036)	(0.038)	(0.039)	(0.040)	(0.040)	(0.043)	(0.044)
ACT.×HMT	-0.062	-0.075	-0.080	-0.114**	-0.077	-0.081	-0.093*
	(0.037)	(0.039)	(0.043)	(0.043)	(0.043)	(0.051)	(0.047)
ACT.×SOE	0.076	0.080	-0.017	0.052	0.022	-0.007	-0.002
	(0.056)	(0.054)	(0.053)	(0.052)	(0.050)	(0.048)	(0.054)
Observations	103179	103179	103179	103179	103179	103179	103179
Panel C: Destinations being African countries							
ACTIVITY	0.037	0.027	0.023	0.003	-0.010	0.023	-0.077
	(0.036)	(0.042)	(0.050)	(0.045)	(0.040)	(0.038)	(0.040)
ACT.×FGN	-0.065	-0.064	-0.057	-0.053	-0.045	-0.048	-0.006
	(0.056)	(0.060)	(0.067)	(0.065)	(0.064)	(0.066)	(0.072)
ACT.×HMT	-0.106	-0.115	-0.067	-0.127	-0.079	-0.071	-0.067
	(0.054)	(0.060)	(0.070)	(0.068)	(0.062)	(0.068)	(0.072)
ACT.×SOE	0.062	0.062	-0.160	0.053	-0.146	-0.202**	-0.102
	(0.109)	(0.107)	(0.108)	(0.107)	(0.098)	(0.078)	(0.098)
Observations	17831	17831	17831	17831	17831	17831	17831
Controls							
SIZE[9]	Y	Y	Y	Y	Y	Y	Y
OWNERSHIP	Y	Y	Y	Y	Y	Y	Y
CIC FEs	Y	Y	Y	Y	Y	Y	Y
YEAR AND EX. EXP.[10]	Y	Y	Y	Y	Y	Y	Y
MKT GROUP[11]	Y	Y	Y	Y	Y	Y	Y

Robust standard errors, clustered at firm level, in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(1) *Refers to intermediate input;* (2) *Refers to capital goods;*

(3) *Refers to 20 richest countries;* (4) *Refers to countries other than the 20 richest ones;*

(5) *The reference group of ownership type is non-state owned Chinese firms;*

(6) *Refers to foreign invested firms;* (7) *Refers to Hong Kong, Macao or Taiwan invested firms;* (8) *Refers to state owned firms;*

(9) *Controlled with a third order polynomial of the log of employment;*

(10) *Controlled with first year by current year dummies; first year refers to the year when a firm is first observed in our sample;*

(11) *Refers to the market grouping in demand estimation.*

Table 6: Quality and Imported Intermediate Inputs

Dependent Variable: $\widehat{\xi}_{fhmt}$

ACTIVITY MEASURES	(1) TOTAL VALUE	(2) VALUE from RICH	(3) VALUE from OTH.	(4) # of HS LINES	(5) HS LINES from RICH	(6) HS LINES from OTH.	(7) UNIT VALUE
Panel A: Destinations being US, Canada, EU Members, Japan, South Korea, Singapore, Australia or New Zealand							
ACTIVITY	0.011***	0.010***	0.011***	0.052***	0.058***	0.050**	0.032**
	(0.002)	(0.002)	(0.003)	(0.013)	(0.015)	(0.019)	(0.012)
ACT.×FGN	-0.007*	-0.003	-0.010**	-0.054***	-0.046**	-0.069***	0.003
	(0.003)	(0.003)	(0.003)	(0.015)	(0.017)	(0.020)	(0.015)
ACT.×HMT	-0.013**	-0.011*	-0.016**	-0.092***	-0.095**	-0.114***	-0.015
	(0.004)	(0.005)	(0.005)	(0.025)	(0.035)	(0.029)	(0.018)
ACT.×SOE	-0.009*	-0.006	-0.012**	-0.048*	-0.056*	-0.050	-0.052
	(0.004)	(0.004)	(0.004)	(0.021)	(0.024)	(0.026)	(0.029)
Observations	140236	140236	140236	140236	140236	140236	86520
Panel B: Destinations being the rest of Asia or Latin American countries							
ACTIVITY	0.003	0.002	0.006*	0.012	0.016	0.014	-0.009
	(0.003)	(0.003)	(0.003)	(0.015)	(0.018)	(0.019)	(0.015)
ACT.×FGN	0.004	0.007*	-0.003	0.002	0.013	-0.023	0.035
	(0.003)	(0.003)	(0.003)	(0.017)	(0.019)	(0.021)	(0.020)
ACT.×HMT	-0.007*	-0.007	-0.012**	-0.043*	-0.047*	-0.055*	0.003
	(0.004)	(0.004)	(0.004)	(0.018)	(0.023)	(0.022)	(0.019)
ACT.×SOE	0.006	0.001	0.003	0.004	-0.012	0.010	0.006
	(0.004)	(0.004)	(0.004)	(0.020)	(0.025)	(0.024)	(0.030)
Observations	103179	103179	103179	103179	103179	103179	54076
Panel C: Destinations being African countries							
ACTIVITY	0.003	0.003	0.001	0.010	0.018	-0.015	0.015
	(0.004)	(0.005)	(0.004)	(0.024)	(0.027)	(0.029)	(0.018)
ACT.×FGN	-0.005	-0.004	-0.005	-0.018	-0.016	-0.019	0.048
	(0.005)	(0.006)	(0.005)	(0.027)	(0.031)	(0.032)	(0.034)
ACT.×HMT	-0.009	-0.005	-0.011	-0.050	-0.036	-0.059	0.029
	(0.006)	(0.007)	(0.006)	(0.031)	(0.042)	(0.035)	(0.041)
ACT.×SOE	0.003	-0.010	0.003	-0.022	-0.067	-0.003	-0.007
	(0.007)	(0.008)	(0.007)	(0.029)	(0.045)	(0.033)	(0.039)
Observations	17831	17831	17831	17831	17831	17831	7257
Controls							
SIZE	Y	Y	Y	Y	Y	Y	Y
OWNERSHIP	Y	Y	Y	Y	Y	Y	Y
CIC FEs	Y	Y	Y	Y	Y	Y	Y
YEAR AND EX. EXP.	Y	Y	Y	Y	Y	Y	Y
MARKET GROUP	Y	Y	Y	Y	Y	Y	Y

Robust standard errors, clustered at firm level, in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes as Table 5.

Table 7: Quality and Imported Capital Goods

Dependent Variable: $\widehat{\xi}_{fhmt}$

ACTIVITY MEASURES	(1) TOTAL VALUE	(2) VALUE from RICH	(3) VALUE from OTH.	(4) # of HS LINES	(5) HS LINES from RICH	(6) HS LINES from OTH.	(7) UNIT VALUE
Panel A: Destinations being US, Canada, EU Members, Japan, South Korea, Singapore, Australia or New Zealand							
ACTIVITY	0.008***	0.009***	0.005	0.038*	0.053**	0.029	0.020*
	(0.002)	(0.003)	(0.003)	(0.016)	(0.020)	(0.021)	(0.009)
ACT.×FGN	-0.007*	-0.005	-0.008*	-0.053**	-0.052*	-0.067**	-0.002
	(0.003)	(0.003)	(0.003)	(0.018)	(0.021)	(0.023)	(0.011)
ACT.×HMT	-0.016**	-0.013	-0.020**	-0.112***	-0.127*	-0.138***	-0.003
	(0.006)	(0.007)	(0.006)	(0.034)	(0.050)	(0.039)	(0.014)
ACT.×SOE	-0.008	-0.010*	-0.007	-0.050*	-0.070**	-0.037	-0.059**
	(0.004)	(0.004)	(0.004)	(0.022)	(0.026)	(0.025)	(0.021)
Observations	140236	140236	140236	140236	140236	140236	68250
Panel B: Destinations being the rest of Asia or Latin American countries							
ACTIVITY	-0.002	-0.002	-0.002	-0.032	-0.026	-0.042	0.004
	(0.003)	(0.003)	(0.003)	(0.019)	(0.025)	(0.023)	(0.012)
ACT.×FGN	0.003	0.007	-0.001	0.026	0.038	-0.000	0.022
	(0.004)	(0.004)	(0.004)	(0.021)	(0.026)	(0.026)	(0.017)
ACT.×HMT	-0.010*	-0.007	-0.012*	-0.033	-0.035	-0.042	-0.024
	(0.004)	(0.005)	(0.005)	(0.025)	(0.032)	(0.029)	(0.017)
ACT.×SOE	-0.001	-0.001	-0.002	0.010	0.008	0.012	-0.024
	(0.004)	(0.004)	(0.004)	(0.023)	(0.028)	(0.026)	(0.026)
Observations	103179	103179	103179	103179	103179	103179	42925
Panel C: Destinations being African countries							
ACTIVITY	-0.002	0.001	-0.009**	-0.034	-0.008	-0.082**	0.024*
	(0.003)	(0.003)	(0.003)	(0.022)	(0.026)	(0.027)	(0.011)
ACT.×FGN	-0.004	-0.003	-0.003	0.006	-0.003	0.010	0.008
	(0.005)	(0.005)	(0.006)	(0.027)	(0.030)	(0.034)	(0.023)
ACT.×HMT	-0.007	-0.004	-0.009	-0.035	-0.023	-0.039	-0.037
	(0.006)	(0.007)	(0.007)	(0.037)	(0.051)	(0.040)	(0.025)
ACT.×SOE	-0.014	-0.017*	-0.008	-0.051	-0.068	-0.028	-0.069*
	(0.007)	(0.007)	(0.007)	(0.030)	(0.037)	(0.031)	(0.027)
Observations	17831	17831	17831	17831	17831	17831	6019
Controls							
SIZE	Y	Y	Y	Y	Y	Y	Y
OWNERSHIP	Y	Y	Y	Y	Y	Y	Y
CIC FEs	Y	Y	Y	Y	Y	Y	Y
YEAR AND EX. EXP.	Y	Y	Y	Y	Y	Y	Y
MKT. GROUP	Y	Y	Y	Y	Y	Y	Y

Robust standard errors, clustered at firm level, in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes as Table 5.

Coefficients in grey boxes are jointly significant and positive.

for the non-state owned Chinese firms; it is roughly zero for state-owned firms and Hong Kong, Macao or Taiwan invested firms. For foreign invested firms, only imports from the top 20 advanced countries or imports of high unit value matter. Third, the source of imports matter, especially for capital goods. This suggests focusing on an overall import status dummy or even overall share of imported inputs alone may miss some important dimensions of firms' choices of input and output quality.[35]

5.2. Quality, Wage and Capital Labour Ratio

In this subsection, I investigate the relationship between our quality measure and firms' domestic inputs. Even though I do not have as detailed information on firms' domestically sourced inputs as imported inputs, ASM does have information on firms' total wage payments and capital stock, which allows me to investigate how quality is related to wage per employee and capital intensity. ASM has only book value of firms' capital stock; I use the real capital stock calculated in Brandt et al. (2011) to construct capital labour ratio as our measure of capital intensity. My investigation of firms' import choices suggests that firms use more expensive imports to produce higher quality, especially on the quality sensitive markets. I expect the same pattern to hold for firms' domestically sourced input, more specifically, I expect firms that pay higher wages produce higher quality.[36] The regression results are presented in Table 8. I find quality to be significantly and positively correlated with wage for exports to both the high and medium income destinations with the former stronger. Regarding the heterogeneity across ownership types, the association is again the strongest for the non-state owned Chinese firms and the second strongest for foreign invested firms. Unlike import activities, it is also significant for state-owned firms and Hong Kong, Macao and Taiwan invested firms, for the latter only in their exports to the rich destinations. I do not find any pattern in the relationship between quality and capital labour ratio.[37]

6. Quality Dynamics

In this section, I study how quality offered by a firm evolves overtime, more specifically, whether past experience of selling to high income markets helps to improve quality. There is a large

[35] One caveat of our analysis is that I do not have information on domestically sourced intermediate inputs and capital goods. Also, some firms may purchase foreign inputs from specialized importing firms and I do not observe transactions between manufacturing firms and trading firms either.

[36] This is related to the large literature on the relationship between wage and export performance. Quality upgrading has been documented as one of the channels through which trade openness and the associated skilled biased technology change lead to higher skill premium and income inequality. Goldberg and Pavcnik (2007) provide a nice review of the studies on globalization and income distribution. Verhoogen (2008) particularly shows how the late-1994 peso crisis leads to the differential quality upgrading of Mexican exporters and larger within-industry wage inequality.

[37] Quality is suggested to be correlated with capital intensity in Verhoogen (2008) and Hallak and Sivadasan (2009)

Table 8: Quality and Domestic Input

Dependent Variable: $\widehat{\xi}_{fhmt}$

ACTIVITY MEASURE	(1)	(2) WAGE	(3)	(4)	(5) K/L RATIO	(6)
	High Inc. Markets	Medium Inc.[2] Markets	Low Inc.[3] Markets	High Inc. Markets	Medium Inc. Markets	Low Inc. Markets
ACTIVITY	0.074***	0.051***	0.044	0.017	0.010	-0.033
	(0.015)	(0.015)	(0.023)	(0.011)	(0.011)	(0.017)
ACT.×FGN	-0.033**	-0.014	-0.043	-0.017	0.021	0.021
	(0.012)	(0.013)	(0.024)	(0.014)	(0.017)	(0.031)
ACT.×HMT	-0.038*	-0.030*	-0.021	-0.059**	-0.021	0.003
	(0.017)	(0.015)	(0.024)	(0.018)	(0.018)	(0.025)
ACT.×SOE	-0.023	-0.011	-0.004	-0.052	-0.003	-0.033
	(0.020)	(0.014)	(0.018)	(0.030)	(0.036)	(0.058)
Observations	140096	103087	17828	139921	102950	17806
p-values from Joint Significance Tests						
ACTIVITY + ACT.×FGN	0.004	0.020				
ACTIVITY + ACT.×HMT	0.052	0.222				
ACTIVITY + ACT.×SOE	0.028	0.051				
Controls						
SIZE	Y	Y	Y	Y	Y	Y
OWNERSHIP	Y	Y	Y	Y	Y	Y
CIC by ZIP4 REGION FEs[4]	Y	Y	Y	Y	Y	Y
YEAR AND EX. EXP.	Y	Y	Y	Y	Y	Y
MKT. GROUP	Y	Y	Y	Y	Y	Y

Robust standard errors, clustered at firm level, in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[1] *Refers to the rich markets grouped in Panel A in Table 5;*

[2] *Refers to the median income markets grouped in Panel B in Table 5;*

[3] *Refers to the poor markets grouped in Panel C in Table 5;*

[4] *Industry fixed effects are interacted with regional fixed effects to purge the regional difference in factor prices;*

Other notes as Table 5.

literature on learning by exporting, but quality upgrading, one specific aspect of learning, has not yet received much attention. The majority of these studies look for evidence of learning by investigating the impact of past exporting experience on performance measures such as average variable cost, labour productivity, or total factor productivity measured as the estimation residual from a production function. Since all these measures are either revenue or value-added based, any identified learning effect would confound improvements in cost effectiveness and quality upgrading. But learning in quality might be especially important for a developing country like China. China has a large domestic market and the competition along the cost dimension is intense on the domestic market, thus the room for improvement through international experience is limited; on the other hand, China is still a developing country where consumers are less demanding in quality than those in developed countries. When Chinese firms begin to serve richer consumers, it is especially on the quality aspect that firms need to and have the opportunity to learn and improve. Our quality estimates make it possible to investigate this specific channel channel of learning.

Table 9 provides an overview of market participation in our sample. For each ownership type, I report the number of firms and the number of observations associated with these firms in three years. [38] I also report the shares associated with three categories of experience: active on the top 20 high income markets in the previous year, active only on other markets in the previous year and new exporters. Except for non-state owned Chinese firms, more than half of them have been selling to the top 20 rich markets. The difference in the share of observations and share of number of firms suggests that these firms are selling more products to more destinations.

Table 9: Summaries on Market Participation

		2001		2003		2005	
		obs.	firm	obs.	firm	obs.	firm
Non SOE	total #	10397	944	28809	3182	71843	8077
	% with experience[(1)]	55%	24%	64%	30%	58%	28%
	% w/o experience	9%	13%	10%	12%	9%	13%
	% first time exporter	35%	63%	26%	58%	33%	59%
SOE	total #	17839	1384	21197	1497	23012	1406
	% with experience	69%	34%	85%	49%	80%	53%
	% w/o experience	11%	19%	8%	21%	7%	20%
	% first time exporter	20%	47%	7%	30%	13%	27%
Foreign	total #	6693	1428	15269	2664	30084	4287
	% with experience	61%	35%	75%	44%	80%	48%
	% w/o experience	10%	10%	7%	14%	6%	14%
	% first time exporter	29%	55%	18%	42%	14%	38%
Joint	total #	11174	1682	17643	2186	25088	2655
	% with experience	73%	42%	83%	57%	85%	58%
	% w/o experience	9%	12%	7%	13%	6%	14%
	% first time exporter	18%	46%	10%	30%	9%	28%

(1) *Experience refers to being active on the top 20 high income countries in the previous year.*

I calculate the weighted average of the per capita GDP of a firm's destination markets using

[38] Remember our unit of observation is firm by product by market by year.

export value as the weight. I use this as a measure of firms' exporting experience. I adopt the following empirical specification from the learning studies on productivity evolution.[39]

$$\widehat{\xi}_{fhmt} = \theta \times EXPOSURE_{ft-1} + f(\overline{\widehat{\xi}}_{fmt-1}) + CONTROLS_{ft}\Phi + \nu_{fhmt} \tag{18}$$

where $EXPOSURE_{ft-1}$ is the weighted per capita GDP of the markets firm f ships to in the previous year. $\widehat{\xi}_{fhmt-1}$ is firm f's quality measure of the same product h on the same market m in the previous year $t-1$. ν_{fhmt} is the innovative part of evolution or random demand shocks. I also include year by experience fixed effects as control variables. Without adding more controls, the coefficient of the experience variable can not be interpreted as learning effect, as any correlation between the experience measure and current quality can also be due to selection if firms' idiosyncratic attributes determine both past experience and current quality. Without being controlled for, these attributes will be part of the error term that might be correlated with both current quality on the left hand side and our variable of interest, $EXPOSURE$ on the right hand side. I introduce a third order polynomial of the average quality of the shipments by firm f to market m in year $t-1$ ($\overline{\widehat{\xi}}_{fmt-1}$) to control for selection. This restricts my sample to observations by exporters that have been active for at least two consecutive years on market m. These observations account for about one third of our original sample. To assess the robustness of the results, I try three alternative specifications of the f function. In the first alternative, I introduce firm size in the previous year. In the second alternative, instead of conditional on the market specific quality in the previous year, I conditional on the market group average where market group is defined in the same way as in Section 5.[40] In the third alternative, I add lagged size controls to the second alternative. I run the regression in (18) for each type of ownership separately. The results are presented in Table 10.

The first column reports the results pooling all types of ownership together. Column (2) to (5) are for non-state owned Chinese firms, state-owned Chinese firms, foreign invested firms and joint venture with foreign investment in order. Selection is controlled by conditioning on market specific quality in the previous year in Panel A. The coefficient for $EXPOSURE$ is positive and significant in the regression pooling all ownership types. A 10% change in the average per capita GDP of a firm's previous markets helps to improve the firm's current quality by 0.16% standard deviations. Running regressions for each ownership type separately, the pattern still holds for non-state owned Chinese firms. The estimates are insignificant for state-owned Chinese firms and foreign invested firms. It is about the same magnitude for joint ventures but only marginally significant. Regression results from the three alternative specifications are reported in Panel B-D. In Panel B I introduce lagged size as additional controls. The size measure comes

[39] For one recent example of studies using this specification, see Aw et al. (2011).

[40] Canada, the United States, European member countries, Singapore, Korea, Japan, Australia and New Zealand are in one group $G1$. Other Asian countries and Latin American countries are in $G2$. African countries are in $G3$.

Table 10: Learning by Exporting in Quality

	(1) All	(2) Non SOE	(3) SOE	(4) Foreign	(5) Joint
Panel A: Conditional on market specific quality in the previous year[(1)]					
$\widehat{\theta}$	0.016***	0.020***	0.002	-0.011	0.015*
	(0.004)	(0.007)	(0.010)	(0.014)	(0.009)
Observations	214766	72470	43733	47778	50265
Adjusted R^2	0.370	0.335	0.304	0.444	0.383
Panel B: Add size measures in the previous year as control variables[(2)]					
$\widehat{\theta}$	0.001	0.017**	-0.023	-0.029**	0.018
	(0.006)	(0.009)	(0.022)	(0.014)	(0.012)
Observations	109486	34779	8714	30453	35321
Adjusted R^2	0.384	0.330	0.360	0.439	0.381
Panel C: Conditional on market group specific quality in the previous year[(3)]					
$\widehat{\theta}$	-0.003	0.016***	-0.016*	-0.016	-0.014
	(0.004)	(0.006)	(0.009)	(0.014)	(0.010)
Observations	500017	179711	109906	103300	105769
Adjusted R^2	0.062	0.052	0.027	0.101	0.070
Panel D: Add size measures in the previous year as control variables[(4)]					
$\widehat{\theta}$	-0.011	0.016*	-0.041**	-0.018	-0.006
	(0.007)	(0.009)	(0.020)	(0.018)	(0.013)
Observations	227900	74391	18178	63705	71167
Adjusted R^2	0.070	0.051	0.050	0.097	0.069
Controls					
QUALITY EST.IN YEAR $t-1$	Y	Y	Y	Y	Y
YEAR AND EX. EXP.	Y	Y	Y	Y	Y

Robust standard errors, clustered at firm level, in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(1) We use $f(\bar{\bar{\xi}}_{fmt-1})$ to control for selection.

(2) We use $f(\bar{\bar{\xi}}_{fmt-1}, lnL_{ft-1})$ to control for selection.

(3) We use $f(\bar{\bar{\xi}}_{f1t-1}, \bar{\bar{\xi}}_{f2t-1}, \bar{\bar{\xi}}_{f3t-1})$ to control for selection.

(1) We use $f(\bar{\bar{\xi}}_{f1t-1}, \bar{\bar{\xi}}_{f2t-1}, \bar{\bar{\xi}}_{f3t-1}, lnL_{ft-1})$ to control for selection.

from ASM and thus these regressions use only the matched sample. In Panel C, I condition on the market group specific average quality in the previous year. This allows me to include more observations.[41] In Panel D, I add lagged size measure as in Panel B. The estimates for non-state owned Chinese firms are positive and significant in all specifications and are about the same magnitude.

7. Conclusion

Using the detailed price and quantity information on firms' exports between 2000 and 2006 from China's customs data, I estimate market-product specific demand functions for China's exports and recover the latent quality as the demand residual. I then proceed to investigate the channel through which quality varies across firms and over time. Combining my quality measure with the customs imports data and China's Annual Manufacturing Survey data, I investigate the association between quality and firms' input choices. I find importing activities, primarily by non-state owned Chinese firms and in some cases foreign invested firms, are positively and significantly associated with higher quality in exports to quality sensitive destinations. The association between quality and wage per employee has similar pattern and exists more generally. I also find evidence of quality upgrading through exporting to rich countries.

There are several directions for future work. First, I establish association between input choice and quality differentiation; a more interesting question is how changes in factor markets might affect firms' quality choice. This can be explored with China's tariff reduction in accordance with WTO commitments. Second, I find impact of past exporting experience on quality. A related question is how potential learning would affect firms' market participation decision. Third,I can apply the same analysis to more product categories to assess if the results found in this paper vary across industries in a meaningful way.

References

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

Aw, Bee Yan, Mark J. Roberts, and Daniel Yi Xu (2011), "R & D investment, exporting, and productivity dynamics." *The American Economic Review*, 101, 1312–1344.

Balassa, Bela (1988), "The lessons of east asian development: An overview." *Economic Development and Cultural Change*, 36, S273–S290.

[41] To illustrate why, imagine a firm that sells to the US in 2000 and begins to sell to Canada in 2001. In the specifications in Panel A, the observations associated with this firm's shipment to Canada in 2001 will be dropped because there is no quality measure on Canadian market for this firm in 2000. In Panel B, these observations can be included as I can condition on its 2000 quality measure from the US market.

Baldwin, Richard and James Harrigan (2011), “Zeros, quality, and space: Trade theory and trade evidence.” *American Economic Journal: Microeconomics*, 3, 60–88.

Blalock, Garrick and Paul J. Gertler (2004), “Learning from exporting revisited in a less developed setting.” *Journal of Development Economics*, 75, 397 – 416.

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang (2011), “Creative accounting or creative destruction? firm-level productivity growth in chinese manufacturing.” *Journal of Development Economics*. Forthcoming.

Brooks, Eileen L. (2006), “Why don’t firms export more? product quality and colombian plants.” *Journal of Development Economics*, 80, 160 – 178.

Copeland, Brian R. and Ashok Kotwal (1996), “Product quality and the theory of comparative advantage.” *European Economic Review*, 40, 1745 – 1760.

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

Deardorff, Alan V. (1984), “Testing trade theories and predicting trade flows.” In *Handbook of International Economics* (Ronald W. Jones and Peter B. Kenen, eds.), volume 1, Elsevier Science B.V.

Ferrantino, Michael J. and Zhi Wang (2008), “Accounting for discrepancies in bilateral trade: The case of china, hong kong, and the united states.” *China Economic Review*, 19, 502 – 520.

Foster, Lucia, John Haltiwanger, and Chad Syverson (2008), “Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?” *The American Economic Review*, 98, 394–425.

Fung, K.C. and Lawrence J. Lau (2003), “Adjusted estimates of united statescchina bilateral trade balances: 1995 c 2002.” *Journal of Asian Economics*, 14, 489 – 496.

Gervais, Antoine (2010), “Product quality, firm heterogeneity and international trade.” Working Paper, University of Notre Dame.

Goldberg, Pinelopi K., Amit K. Khandelwal, Nina Pavcnik, and Petia Topalova (2010), “Imported intermediate inputs and domestic product growth: Evidence from india.” *The Quarterly Journal of Economics*, 125, 1727–1767.

Goldberg, Pinelopi Koujianou and Nina Pavcnik (2007), “Distributional effects of globalization in developing countries.” *Journal of Economic Literature*, 45, 39–82.

Hallak, Juan C. (2006), “Product quality and the direction of trade.” *Journal of International Economics*, 68, 238 – 265.

Hallak, Juan C. and Peter K. Schott (2011), “Estimating cross-country differences in product quality.” *The Quarterly Journal of Economics*, 126, 417–474.

Hallak, Juan C. and Jagadeesh Sivadasan (2009), “Firms’ exporting behavior under quality constraints.”

Halpern, Laszlo, Mikls Koren, and Adam Szeidl (2005), "Imports and productivity." CEPR Discussion Paper.

Harrison, Ann and Andrs Rodriguez-Clare (2010), "Trade, foreign investment, and industrial policy for developing countries." In *Handbook of Development Economics* (Dani Rodrik and Mark R. Rosenzweig, eds.), volume 5, Elsevier Science B.V.

Hausman, Jerry A. (1996), "Valuation of new goods under perfect and imperfect competition." In *The Economics of New Goods* (Timothy F. Bresnahan and Robert J. Gordon, eds.), University of Chicago Press.

Hummels, David and Peter J. Klenow (2005), "The variety and quality of a nation's exports." *The American Economic Review*, 95, 704–723.

Johnson, Robert C. (2011), "Trade and prices with heterogeneous firms." *Journal of International Economics*. Forthcoming.

Kasahara, Hiroyuki and Joel Rodrigue (2008), "Does the use of imported intermediates increase productivity? plant-level evidence." *Journal of Development Economics*, 87, 106 – 118.

Khandelwal, Amit (2010), "The long and short (of) quality ladders." *Review of Economic Studies*, 77, 1450 C 1476.

Khandelwal, Amit K., Peter K. Schott, and Shang-Jin Wei (2011a), "Trade liberalization and embedded institutional reform: Evidence from chinese exporters."

Khandelwal, Amit K., Shang-Jin Wei, and JaeBin Ahn (2011b), "The role of intermediaries in facilitating trade." *Journal of International Economics*, 84.

Kugler, Maurice and Eric Verhoogen (2009), "Plants and imported inputs: New facts and an interpretation." *American Economic Review Papers and Proceedings*, 99, 501–07.

Kugler, Maurice and Eric Verhoogen (2011), "Prices, plant size, and product quality." *Review of Economic Studies*. Forthcoming.

Leamer, Edward E. and James Levinsohn (1995), "International trade theory: The evidence." In *Handbook of International Economics* (Gene M. Grossman and Kenneth Rogoff, eds.), volume 3, Elsevier Science B.V.

Lileeva, Alla and Daniel Trefler (2010), "Improved access to foreign markets raises plant-level productivity for some plants." *The Quarterly Journal of Economics*, 125, 1051–1099.

Linder, Staffan B. (1961), *An Essay on Trade and Transformation*. Almqvist & Wiksell, Stockholm.

Manova, Kalina B. and Zhiwei Zhang (2011), "Export prices across firms and destinations." *Quarterly Journal of Economics*. Forthcoming.

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

Muendler, Marc-Andreas (2004), "Trade, technology and productivity: A study of brazilian manufacturers 1986-1998." *SSRN eLibrary*.

Murphy, Kevin M. and Andrei Shleifer (1997), "Quality and trade." *Journal of Development Economics*, 53, 1 – 15.

Nevo, Aviv (2001), "Measuring market power in the ready-to-eat cereal industry." *Econometrica*, 69, 307–342.

Park, Albert, Dean Yang, Xinzheng Shi, and Yuan Jiang (2010), "Exporting and firm performance: Chinese exporters and the asian financial crisis." *The Review of Economics and Statistics*, 92, 822–842.

Rauch, James E. (1999), "Networks versus markets in international trade." *Journal of International Economics*, 48, 7 – 35.

Rodrik, Dani (1995), "Trade and industrial policy reform." In *Handbook of Development Economics* (Jere Behrman and T.N. Srinivasan, eds.), volume 3B, Elsevier Science B.V.

Sutton, John (2007), "Quality, trade and the moving window: The globalisation process." *The Economic Journal*, 117, F469–F498.

Van Biesebroeck, Johannes (2005), "Exporting raises productivity in sub-saharan african manufacturing firms." *Journal of International Economics*, 67, 373–391.

Verhoogen, Eric A. (2008), "Trade, quality upgrading, and wage inequality in the mexican manufacturing sector." *The Quarterly Journal of Economics*, 123, 489–530.

Wagner, Joachim (2007), "Exports and productivity: A survey of the evidence from firm-level data." *World Economy*, 30, 60–82.

8. Appendix

8.1. Appendix A: Proxy for Instrumental Variable with Missing Values

When no observation $f'm'h't$ exists, i.e, there is no firm f' in the same 4-digit zip code region $o_{(f)}$ as firm f shipping to any market m' that satisfies the two selection criteria in year t, I construct a proxy value for the instrumental variable of observation $fmht$ along the following two steps:

1. First, I use the average value of the instrument in years when it is not missing as a proxy, that is, I have

$$IV_{fmht} = \overline{IV}_{o_{(f)}mt'} \tag{19}$$

   where the average is taken across t'. This helps to fill about 2/3 of the missing values.

2. If an instrument still takes missing value, I relax the restriction on m' and use the average of the value of the instrument by firms in region $o_{(f)}$ on any market as a proxy, that is, I have

$$IV_{fmht} = \overline{IV}_{o_{(f)}m"t'} \tag{20}$$

   where the average is taken across $m"$ and t'; and $m"$ can be any market. This helps to fill almost all the remaining 1/3 the missing values.

These two steps helps to reduce the incidence of missing values in instrument to 0.26%. To evaluate the impact of using proxy values I am going to compare the estimation results from both the whole sample and the sample dropping observations with proxy values. If they differ a lot, it raises concern about either the representativeness of the sample that do not need proxy or the quality of the instrument with proxy values. It turns out with our preferred instruments, the results from the two samples are in general similar. instruments.

8.2. Appendix B: Demand Estimation with Alternative Instruments

Table H.1: Demand Estimation, Alternative Instrument 1[(1)]

Panel A: All products pooled

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	683700	-1.483	0.034	518748	-1.431	0.037
NA	65885	-1.495	0.063	64051	-1.478	0.065
EU	173826	-1.388	0.035	160384	-1.353	0.036
SJK	76759	-1.433	0.095	67799	-1.460	0.104
AZ	21522	-1.142	0.084	20773	-1.214	0.083
RAS	213921	-1.753	0.128	140186	-1.587	0.177
LA	61766	-1.549	0.135	43807	-1.528	0.164
AF	51346	-1.190	0.177	8721	-0.642	1.359

Panel B: Example product group HS4=8538

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	17688	-1.453	0.105	14062	-1.527	0.127
NA	1655	-1.352	0.339	1618	-1.432	0.318
EU	4109	-1.323	0.204	3825	-1.264	0.215
SJK	2459	-1.408	0.258	2255	-1.462	0.190
AZ	526	-0.419	0.265	513	-0.469	0.281
RAS	5748	-1.701	0.200	4158	-1.879	0.331
LA	1437	-0.970	0.380	1146	-1.159	0.452
AF	1314	-2.061	0.827	250	3.031	8.808

Panel C: Summaries of regressions by 4-digit HS product group (48 groups in total)

	# HS4	# of obs.	Whole Sample		OLS Comparison		No Proxy Sample	
	neg. & sig.	neg.& sig.	mean	median	mean	median	mean	median
World	33	523228	-1.750	-1.511	-0.850	-0.902	-1.796	-1.460
NA	37	56208	-1.817	-1.441	-0.837	-0.848	-1.753	-1.436
EU	31	150502	-1.686	-1.323	-0.810	-0.843	-1.711	-1.295
SJK	23	46167	-1.792	-1.408	-0.853	-0.919	-1.860	-1.462
AZ	21	13347	-1.819	-1.483	-0.760	-0.772	-1.728	-1.337
RAS	23	151017	-2.002	-1.701	-0.947	-0.974	-1.354	-1.742
LA	21	37913	-1.974	-1.992	-0.961	-0.922	-1.739	-1.905
AF	21	25599	-2.266	-1.992	-0.937	-0.918	-1.222	-1.242

All regressions cluster standard errors by 8-digit HS product, market and year.

[(1)] *The market selection criteria for constructing instruments in these regressions are:*

(a) geographical distance being above the 30th percentile;

(b) per capita GDP disparity being larger than 1.5 times the standard deviation below.

Other notes as Table 2.

Table H.2: Demand Estimation, Alternative Instrument 2[1]

Panel A: All products pooled

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	683700	-1.456	0.027	583269	-1.427	0.029
NA	65885	-1.508	0.064	64045	-1.498	0.067
EU	173826	-1.447	0.041	153241	-1.415	0.043
SJK	76759	-1.424	0.108	65140	-1.416	0.119
AZ	21522	-1.099	0.086	20615	-1.154	0.087
RAS	213921	-1.527	0.061	178437	-1.470	0.065
LA	61766	-1.525	0.107	49590	-1.554	0.123
AF	51346	-1.338	0.084	41407	-1.228	0.092

Panel B: Example product group HS4=8538

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	17688	-1.358	0.106	15509	-1.398	0.105
NA	1655	-1.365	0.327	1618	-1.429	0.323
EU	4109	-1.326	0.212	3656	-1.292	0.222
SJK	2459	-1.279	0.374	2133	-1.412	0.316
AZ	526	-0.408	0.260	513	-0.458	0.269
RAS	5748	-1.529	0.166	4985	-1.517	0.181
LA	1437	-1.188	0.338	1251	-1.457	0.421
AF	1314	-2.025	1.192	1109	-1.601	0.480

Panel C: Summaries of regressions by 4-digit HS product group (48 groups in total)

	# HS4 neg. & sig.	# of obs. neg.& sig.	Whole Sample		OLS Comparison		No Proxy Sample	
			mean	median	mean	median	mean	median
World	33	526113	-1.794	-1.509	-0.854	-0.910	-1.676	-1.425
NA	38	56268	-1.798	-1.449	-0.833	-0.844	-1.755	-1.479
EU	28	131888	-1.643	-1.311	-0.803	-0.845	-1.635	-1.349
SJK	20	43574	-1.853	-1.636	-0.837	-0.915	-1.979	-1.591
AZ	20	11034	-1.681	-1.350	-0.756	-0.756	-1.574	-1.288
RAS	25	143892	-2.052	-1.809	-0.933	-0.946	-1.994	-1.729
LA	21	37070	-1.806	-1.740	-0.949	-0.922	-1.886	-1.573
AF	25	34396	-1.769	-1.459	-0.842	-0.876	-1.585	-1.298

All regressions cluster standard errors by 8-digit HS product, market and year.

[1] *The market selection criteria for constructing instruments in these regressions are:*

(a) geographical distance being above the 40th percentile;

(b) per capita GDP disparity being larger than 1.5 times the standard deviation away.

Other notes as Table 2.

Table H.3: Demand Estimation, Alternative Instrument 3[1]

Panel A: All products pooled

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	683700	-1.437	0.030	568399	-1.413	0.033
NA	65885	-1.511	0.064	63959	-1.503	0.067
EU	173826	-1.378	0.037	155945	-1.342	0.039
SJK	76759	-1.379	0.103	65720	-1.401	0.118
AZ	21522	-1.141	0.087	20615	-1.243	0.089
RAS	213921	-1.548	0.073	176634	-1.527	0.079
LA	61766	-1.651	0.215	40831	-1.589	0.333
AF	51346	-1.258	0.100	34032	-1.161	0.136

Panel B: Example product group HS4=8538

	Whole Sample			No Proxy Sample		
	# of obs.	ceoff. est.	std. err.	# of obs.	ceoff. est.	std. err.
World	17688	-1.283	0.115	15274	-1.374	0.124
NA	1655	-1.359	0.320	1617	-1.452	0.318
EU	4109	-1.215	0.235	3742	-1.142	0.223
SJK	2459	-1.477	0.237	2199	-1.381	0.164
AZ	526	-0.380	0.270	512	-0.426	0.288
RAS	5748	-1.357	0.201	4961	-1.497	0.255
LA	1437	-0.860	1.054	1096	-2.300	6.542
AF	1314	-1.444	0.718	861	-2.688	3.046

Panel C: Summaries of regressions by 4-digit HS product group (48 groups in total)

	# HS4	# of obs.	Whole Sample		OLS Comparison		No Proxy Sample	
	neg. & sig.	neg.& sig.	mean	median	mean	median	mean	median
World	33	526113	-1.730	-1.535	-0.854	-0.910	-1.664	-1.461
NA	36	55097	-1.831	-1.415	-0.837	-0.849	-1.765	-1.444
EU	29	127102	-1.621	-1.321	-0.818	-0.843	-1.597	-1.280
SJK	20	36629	-2.117	-1.643	-0.871	-0.920	-2.322	-1.582
AZ	21	11454	-1.663	-1.343	-0.766	-0.772	-1.514	-1.363
RAS	27	161769	-2.084	-1.883	-0.927	-0.946	-1.922	-1.753
LA	16	34259	-1.761	-1.448	-0.970	-0.916	-1.682	-1.454
AF	19	31441	-1.649	-1.444	-0.887	-0.908	-2.840	-1.367

All regressions cluster standard errors by 8-digit HS product, market and year.

[1] *The market selection criteria for constructing instruments in these regressions are:*

(a) geographical distance being above the 30th percentile;

(b) per capita GDP disparity being larger than 1.75 times the standard deviation away.

Other notes as Table 2.