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Key words: Quality, Productivity, Pro-competitive Effect, Gains from Trade

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1 Introduction

How competition from the international market affects the behavior of domestic firms and varieties is an important research theme in the trade and development literature. For example, Amiti and Konings (2007), Topalova and Khandelwal (2011), Amiti and Khandelwal (2013), and Yu (2015) document findings that import competition leads to increases in domestic firms' productivity, or quality upgrading of varieties close to the technology frontier. Although this strand of literature has provided ample evidence, the effects of different margins of competition from the international market have not yet been well explored. An important margin of international trade patterns is the product quality of trade. Previous literature on quality in international trade is devoted to accurately inferring and measuring quality (Khandelwal, 2010; Hallak and Schott, 2011; Feenstra and Romalis, 2014), or uses quality as a key mechanism to rationalize micro-level behavior (Verhoogen, 2008; Kugler and Verhoogen, 2012) Because better quality is generally valued by consumers, the higher quality of goods produced by foreign competitors is likely to generate a pro-competitive effect on domestic firms. In this paper, we study whether increases in the product quality of foreign competitors can lead to increases in domestic firms' productivity.

China's export boom has yielded tremendous influence on the world economy and provides an environment to perform our analysis. Most studies related to China's exports focus on the effects of China's exports on the labor market and consumers, paying relatively less attention to how China's exports shape the behavior of local firms.[1] Furthermore, existing studies primarily focus on the effects on developed economies, in particular the United States. This paper takes advantage of access to micro-level data from Indonesia and China. It develops a new procedure to measure the firm-product-destination-year-level export quality of Chinese exporters, and empirically studies how variations in China's export quality affect the productivity of Indonesian firms that compete in the same market. The paper focuses on a particular pro-competitive effect, namely, quality competition induced by foreign competitors, to generate new implications related to productivity gains from trade. The paper also provides a new perspective in understanding the effect of the "China shock" on firms in a developing economy. By documenting the effect of increases in quality competition from China on Indonesian firm productivity, we seek to characterize the impact of China's exports on individual firms, which generally has not been thoroughly explored in past studies.

As the largest member country of the Association of Southeast Asian Nations,

[1] For example, Autor, Dorn, and Hanson (2013); Pierce and Schott (2016); and Caliendo, Dvorkin, and Parro (2017) focus on Chinese exports' effects on the U.S. labor market; Amiti, Dai, Feenstra and Romalis (2017) and Redding and Weinstein (2017) study how China's export boom affects consumers' welfare in the United States and Chile.

Indonesia's interaction and integration in international trade with China makes it extremely suitable for our research purpose. China's exports account for a substantial market share in Indonesia. Of around 3,800 HS 6-digit products that Indonesia imports, 61.9% of them had non-zero imports from China in 2008, and 71.3% in 2012. Among the HS 6-digit products with positive imports from China, the average share of China in the total imports grew from 29.8% in 2008 to 33.5% in 2012. Meanwhile, around 95% of Indonesian firms did not use imported inputs from China during the sample period. China's considerable penetration in the Indonesian market ensures the economic significance and sensibility of our results, and the scarce usage of imported inputs from China among Indonesian firms suggests that our focus on the output market rather than the input market captures the first-order impact of China's export quality variations on Indonesian firms.

Inspired by Feenstra and Romalis (2014), we develop a procedure to measure micro-level export quality by exploiting a firm's trade-off between production cost and per-unit trade cost in a theoretical framework of optimal quality determination. Following Feenstra and Romalis (2014), we rely on the endogenous choice of quality for individual firms, and admit the impact of production efficiency, consumers' taste for quality, input cost, and per-unit shipping cost on quality choice. A cost minimization motive stemming from the trade-off between production cost and per-unit shipping cost interacted with consumers' taste for quality pins down optimal quality choice. A firm combines production inputs and shipping inputs to serve each market, and the relative amount of production inputs with respect to shipping inputs (quantity used to ship goods) suggests the relative cost of shipping adjusted by taste for quality.

We use these relationships to construct firm-product (up to Harmonized System 6-digit level) -destination-year-level export quality from China that is comparable across markets and over time. Moreover, our data resource allows us to summarize the quality competition from China faced by an Indonesian firm in the output market (including the domestic market and various export markets) in a novel firm-level global quality competition measure. We then study how an increase in the firm-specific global quality competition measure for a firm over time affects its total factor productivity (TFP). Our results suggest that higher global quality competition from China induces an Indonesian firm to improve its TFP. The results are robust when we control for the potential effects of output tariff, input tariff, and quality competition from other countries. We further confirm the pro-competitive effect by showing that such an effect is more likely to emerge for less concentrated industries, and that multi-product firms react to increased global quality competition from China by dropping products. We also find that such an effect mainly exists in continuing firms.

Our paper joins the small but growing strand of literature studying the productivity gains from trade. Recent micro-level evidence suggests that substantial gains from trade originate from firm-level responses to trade policy transitions. One of the most prevalent and robust findings across countries is that tariff reductions improve firm productivity in the home country. Two mechanisms are well discussed. The first mechanism is the pro-competitive effect induced by output tariff reductions. When output tariffs decrease, domestic firms are faced with tougher competition in the domestic market and are forced to reduce inefficiency, generating productivity gains. The second mechanism is the input-facilitation effect induced by input tariff reductions. When input tariffs decrease, domestic firms can gain access to intermediate inputs with lower prices and higher qualities, especially for developing countries. Better access to imported inputs increases firm productivity as well.

Amiti and Konings (2007) and Brandt, Van Biesebroeck, Wang and Zhang (2017) find that industry-level output and input tariff reductions both increase firm productivity for Indonesian and Chinese firms respectively. Topalova and Khandelwal (2011) construct firm-specific tariff measures and confirm these findings using Indian data. Using Chinese data, Yu (2015) finds that the effect of input tariff reductions on productivity is decreasing in firms' share of processing trade.[2] Amiti and Khandelwal (2013) also find that import competition helps to facilitate quality upgrading for products close to the quality frontier but depresses quality upgrading for products far from the quality frontier. Goldberg, Khandelwal, Pavcnik and Topalova (2009) find that input tariff reductions cause importation of more input varieties and therefore facilitate the productivity growth of the importing firms. In this paper, we specify a channel that has not been well-discussed in the existing literature. Import competition may result from the quantity margin or the quality margin. Although in the previous literature the effects of both margins are mixed, by directly measuring the quality competition from China faced by an Indonesian firm in the global market, we are able to quantify the effect of the quality margin on firm productivity.

Our paper is also closely related to studies aiming at inferring and measuring product quality. Unit value has been used to measure product quality in many studies (Hallak, 2006; Schott, 2004; Manova and Zhang, 2012; Alessandria and Kaboski, 2011; and others). Khandelwal (2010) incorporates quality as a demand shifter in a discrete choice preference framework and generates an empirical specification to estimate import product quality using U.S. import trade data on quantity and price. The intuition is that, conditional on price, variety with higher market share should be assigned higher quality. Hallak and Schott (2011) generate a similar intuition that exports from a country with trade surpluses should be assigned higher quality. Khandelwal, Schott, and Wei (2013) incorporate quality as a demand shifter in a constant elasticity of substitution utility function and estimate export product quality conditional on destination, year, and product.[3] Feenstra and Romalis (2014)

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[2] Processing trade refers to the production activity that the firm imports intermediate inputs, processes these inputs to produce outputs, and exports these outputs to other countries. Therefore, imported inputs (exported outputs) related to processing trade are defined as processing imports (exports). In contrast, inputs used for the production of ordinary exports are mainly from domestic market.

[3] Khandelwal, Schott, and Wei's (2013) approach can identify variations in qualities of different varieties for a given destination, year, and product. However, because the comparison is conditional on

jointly consider supply and demand and generate an aggregate quality index for each country in each product, which is comparable across countries.

Similar to Feenstra and Romalis (2014), our approach is based on the trade-off between production cost and per-unit trade cost. The main difference between our approach and that of Feenstra and Romalis (2014) is that they rely on UN Comtrade data to estimate a country's import/export quality-adjusted price index and quality index in each product. Instead, we use micro-level production and trade data to develop a procedure to measure firm-product-destination-year-level product quality. Therefore, we are interested in estimating product quality at the micro level; Feenstra and Romalis (2014) focus on differences in quality at the macro level. More importantly, our approach can be readily applied to a standardized micro-level production and trade data set.

Broadly, our paper contributes to the study of how China's surging exports impact other countries and extends the study of the "China shock" to firm-level reactions and behaviors. Autor, Dorn, and Hanson (2013) provide evidence suggesting that local labor markets in the United States that experience larger import penetration from China are associated with higher unemployment, lower labor force participation, and declining wages. Pierce and Schott (2016) highlight that China's permanent most favored nation status granted by the United States after 2001 and the consequent surge of China's exports to the United States caused higher employment loss in the United States. Caliendo, Dvorkin, and Parro (2017) use a quantitative general equilibrium framework featuring labor market dynamics and input-output linkages to examine the impact of China's increasing exports to the U.S. market. They find that most manufacturing labor markets lose jobs, but welfare in general increases, because the United States has greater access to cheaper intermediate inputs from China. Amiti, Dai, Feenstra and Romalis (2017) find that the China trade shock reduced the U.S. price index and hence led to U.S. consumer welfare gain. The gain was driven by China's permanent most favored nation status granted by the United States, and China's decreased input tariffs.

Studies related to firm behavior mainly focus on developed countries. Bloom, Draca, and Van Reenen (2016) find that China's increasing exports to European countries induced more innovation activities by European firms. However, Autor, Dorn, Hanson, Pisano and Shu (2016) examine a similar issue for the United States and find the opposite results. Martin and Mejean (2014) find that competition from lower-wage countries tended to push French exporters to upgrade product quality. The literature on the impacts of China's exports on other countries does not emphasize the reaction of firms and tends to focus on cases in developed countries.

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destination, year, and product, it is unable to generate estimated qualities that are comparable across destinations or years.

Our paper offers an alternative mechanism to understand the impact of China's export growth. We pay attention to how increased product quality from China faced by Indonesian firms in the global market intensifies competition and triggers productivity improvement. We therefore contribute to the research agenda by characterizing the China shock from the quality perspective. Moreover, while existing studies are more concerned with North-South trade (Xu, 2003; Ing, 2009), our study is closely related to the economic outcomes of South-South trade, in particular its implications for productivity growth.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework and measurement of China's micro-level export quality. Section 3 describes our data and the construction of our key variables, including firm TFP and a firm-specific indicator that measures quality competition in the global output market from China faced by an Indonesian firm. Section 4 discusses our specification and identification, presents our baseline results, explores several potential mechanisms, and performs robustness checks. Section 5 concludes.

2 Measuring China's Export Quality

In this section, we develop a new method for measuring export quality at the micro level. In our theoretical model, quality is the attributes of a product that increase consumer satisfaction, but is costly to produce, as in Hallak (2006); Verhoogen (2008); Khandelwal (2010); Hallak and Schott (2011); Johnson (2012); Khandelwal, Schott, and Wei (2013); Feenstra and Romalis (2014); and others. We first lay out the theoretical framework under which a firm's optimal quality choice is determined in a cost minimization problem. The firm incurs two types of cost in serving customers: production cost and per-unit shipping cost. The cost of shipping relative to production determines the optimal quality level that minimizes the total cost. If the shipping cost is relatively high, then the firm tends to produce better-quality goods to avoid incurring too much shipping cost. Furthermore, because rich consumers value quality differently than poor consumers do, a firm also sets different qualities according to the income levels of the destinations.

We show that the total quality units being served to customers require production inputs and shipping inputs, and the total physical units reveal information on the shipping inputs being used. Therefore, the ratio between total physical units and production inputs implies the cost of shipping relative to production. We exploit these relationships to estimate export quality.

Our method differs from most of the existing literature, which mainly relies on the demand-side relationship between market share and price to identify quality. In particular, existing methods usually infer product quality as the residual of market share conditional on price and destination-year fixed effects. This implementation makes the estimated qualities not comparable across destinations and years. Our method can identify quality variations across firms, destinations, and years, in that we avoid using any destination-year fixed effects in the estimation procedure. Such a property is important for us to study how the variation in the quality of Chinese exports over time affects the productivity of Indonesian firms.

2.1 Optimal Quality Choice in Cost Minimization

We assume that the output of a firm is in terms of quality units. To be specific, total quality unit Q is determined by the total physical unit q and quality level per physical unit z, namely

$$Q = q \cdot z \quad \text{……(1)}$$

Quality z determines the satisfaction level a consumer obtains when consuming one unit of a particular variety and is related to the attractiveness of that variety. We assume that Q enters consumers' utility U and U is increasing in Q. Therefore, quality increases consumers' valuation of a particular variety and increases consumers' utility.

We assume that in each destination market k there are multiple firms under monopolistic competition. Firms j differ in exogenous production efficiency φ_j. Similar to Feenstra and Romalis (2014), the technology that is used to produce quality z_{jk} is assumed as the following:

$$z_{jk} = (\varphi_j l_{jk} + a_k)^{\theta} \quad \text{……(2)}$$

l_{jk} is the quantity of effective composite inputs that the firm needs to produce quality z_{jk} for each unit of physical output.[4] As suggested by Hallak (2006) and Fajgelbaum, Grossman and Helpman (2011), consumer's valuation of quality also affects firms' quality choice. We recognize this effect and explicitly build in this mechanism by introducing a_k. $a_k > 0$ is consumers' baseline valuation when $l_{jk} = 0$ and varies by k. This parameter characterizes how consumers in different markets evaluate the firm's efforts in producing quality. To illustrate, suppose $a_k > a_l$ for two markets served by firm j. To ensure that consumers in the two markets obtain the same satisfaction level, $z_{jk} = z_{jl}$, firm j should invest more in market l so that $l_{jl} > l_{jk}$. The inverse of a_k can therefore be interpreted as the taste for quality, and higher effort in l_{jk} is required to attract

[4] We assume that l_{jk} is a combination of various inputs, for example, capital, labor, and intermediate inputs. w is then defined as the composite input price associated with the combination of these inputs. In a later section, we describe how to construct the empirical counterpart of l_{jk} and the associated w. Here we simply regard l_{jk} as a composite input.

consumers with a higher taste for quality.[5] We therefore assume that a_k is decreasing in per capita income in market k, to capture the association between per capita income and taste for quality.

θ measures the diminishing returns to production inputs in producing quality z_{jk}, and is assumed to be between 0 and 1. Equation (2) implies the following unit cost function to produce one unit of physical output associated with quality level z_{jk} :

$$c(w, z_{jk}, \varphi_j) = w \cdot l_{jk} = \frac{w}{\varphi_j}(z_{jk}^{\frac{1}{\theta}} - a_k) \quad \ldots\ldots(3)$$

Equation (3) states that, given the firm's quality choice z_{jk}, the unit cost to produce one unit of physical output is increasing in input price w, increasing in product quality z_{jk}, and decreasing in production efficiency φ_j. $0 < \theta < 1$ implies that quality upgrading is subject to diminishing marginal returns. As θ increases, the marginal cost of upgrading quality decreases. Higher a_k suggests consumers' higher valuation when $l_{jk} = 0$, lower taste for quality given the same level of production inputs used, and therefore lower unit cost of production to be incurred given z_{jk}.

When selling goods to a particular destination k, firms are also subject to trade cost. There are two types of trade cost: per-unit shipping cost T_{jk} (capturing additive trade costs such as shipping, transportation, and distribution costs), and iceberg trade cost τ_{jk} (capturing multiplicative trade costs, such as tariffs). T_{jk} reflects the transportation and distribution costs associated with destination k, and we allow it to vary across firms. As a result, the total cost of producing and shipping one unit of physical output, TC, becomes

$$TC(w, z_{jk}, \varphi_j, T_{jk}, \tau_{jk}) = \tau_{jk}[c(w, z_{jk}, \varphi_j) + T_{jk}] = \tau_{jk}[\frac{w}{\varphi_j}(z_{jk}^{\frac{1}{\theta}} - a_k) + T_{jk}] \quad \ldots\ldots(4)$$

Given the total quality unit Q_{jk} that firm j wants to produce to serve market k, the optimal quality z_{jk} minimizes the total cost of production and shipping, namely

[5] Lower a_k suggests that consumers in market k are more sensitive to variations in the firm's quality effort l_{jk}, and forces the firm to put more effort into producing quality. For example, compared with a poor country, a rich country has a stronger preference for apparel made of delicate materials with fashionable styles over basic-style apparel made of cotton.

$$\min_{z_{jk};q_{jk}} TC(w, z_{jk}, \varphi_j, T_{jk}, \tau_{jk})q_{jk} \text{ s.t. } Q_{jk} = q_{jk} \cdot z_{jk}$$

$$\Rightarrow \min_{z_{jk}} TC(w, z_{jk}, \varphi_j, T_{jk}, \tau_{jk}) \frac{Q_{jk}}{z_{jk}}$$

……(5)

This motivation can be justified in a world where the consumer relies on the total quality units she consumes to derive utility. The optimal quality z_{jk} therefore minimizes the cost to produce and ship one quality unit:

$$\min_{z_{jk}} \frac{TC(w, z_{jk}, \varphi_j, T_{jk}, \tau_{jk})}{z_{jk}} = \tau_{jk} \frac{\frac{w}{\varphi_j}(z_{jk}^{\frac{1}{\theta}} - a_k) + T_{jk}}{z_{jk}}$$

The optimal quality is thus:

$$z_{jk} = [\frac{\theta}{1-\theta}(\frac{T_{jk}\varphi_j}{w} - a_k)]^{\theta}$$

……(6)

Equation (6) suggests that quality is increasing in the term $\frac{T_{jk}\varphi_j}{w} - a_k$. We define this term as firm-specific "cost of shipping relative to production." This is intuitive because this term increases when per-unit shipping cost T_{jk} increases or when firm-specific production cost $\frac{w}{\varphi_j}$ decreases. When such a relative cost is high, the firm tends to embed more quality units into a single physical unit and avoid incurring too much shipping cost. A decrease in production input cost w or increase in firm production efficiency φ_j causes a similar effect, because the effective production cost decreases. Furthermore, when consumers have higher taste for quality (lower a_k), the firm also endogenously supplies higher quality. Higher taste for quality offers lower baseline per-unit valuation on a particular product, equivalent to higher per-unit cost for a firm to maintain its consumers at a given level of satisfaction. Therefore, higher taste for quality acts as a per-unit cost wedge and introduces economies of scale in quality upgrading.

The trade-off between average production cost and average shipping cost (and the wedge due to taste for quality) therefore determines the optimal quality. Higher shipping cost associated with a destination induces the firm to ship better-quality goods to that destination. This is the within-firm "Washington apple effect." Lower input cost induces firms to upgrade quality, and more productive firms tend to produce higher-quality goods. Moreover, the firm tends to serve high-income markets with higher-quality products. This property captures the idea that high-income countries demand high-quality goods.

The optimal quality in log is therefore:

$$\ln z_{jk} = \theta \ln(\frac{T_{jk}}{w} - \frac{a_k}{\varphi_j}) + \theta \ln \varphi_j + \theta \ln \frac{\theta}{1-\theta} \qquad \ldots\ldots(7)$$

With the optimal quality solved, the production inputs used for each physical unit l_{jk} are

$$l_{jk} = \frac{(z_{jk})^{\frac{1}{\theta}}}{\varphi_j} = \frac{\theta}{1-\theta}(\frac{T_{jk}}{w} - \frac{a_k}{\varphi_j})$$

Therefore, we can define the total amount of production inputs used to produce q_{jk} units of physical output with quality level z_{jk} as X_{jk}, taking into account the iceberg trade cost. Namely,

$$X_{jk} = \tau_{jk} q_{jk} l_{jk} = \frac{\theta}{1-\theta}(\frac{T_{jk}}{w} - \frac{a_k}{\varphi_j})\tau_{jk} q_{jk}$$

Defining free-on-board (FOB) physical units as $q^*_{jk} = \tau_{jk} q_{jk}$ and rearranging, we get

$$\frac{X_{jk}}{q^*_{jk}} = \frac{\theta}{1-\theta}(\frac{T_{jk}}{w} - \frac{a_k}{\varphi_j}) \qquad \ldots\ldots(8)$$

This expression suggests that the ratio between the firm's spending on production inputs, wX_{jk}, and spending on shipping inputs, $(T_{jk} - \frac{wa_k}{\varphi_j})q^*_{jk}$, is constant. The per-unit shipping cost is adjusted by the taste for quality in market k, as we highlight that higher taste for quality (lower a_k) acts as a per-unit cost wedge that increases the firm's actual per-unit cost in serving consumers. Such a relationship stems from the firm's cost minimization behavior.

The total FOB quality unit, $Q^*_{jk} \equiv q^*_{jk} z_{jk}$, is

$$Q^*_{jk} = q^*_{jk}(\frac{\theta}{1-\theta}\frac{T_{jk}\varphi_j}{w} - a_k)^{\theta} = (\varphi_j X_{jk})^{\theta} q^{*(1-\theta)}_{jk} \qquad \ldots\ldots(9)$$

Therefore, total quality units produced and shipped, Q^*_{jk}, are obtained by combining production inputs X_{jk} and shipping inputs q^*_{jk}. Productivity φ_j acts as a production input-augmented technology advancement. Using the ratio between production inputs and shipping inputs and the total FOB quality units, we rearrange and arrive at the following equations:

$$\ln q^*_{jk} = \ln X_{jk} - \ln\left(\frac{T_{jk}}{w} - \frac{a_k}{\varphi_j}\right) - \ln\frac{\theta}{1-\theta}$$
$$\ln Q^*_{jk} = (1-\theta)\ln q^*_{jk} + \theta \ln X_{jk} + \theta \ln \varphi_j$$
……(10)

……(11)

2.2 Estimating Quality

With the subscripts indicating different products g (defined as HS 6-digit products) and year t, the expressions for physical units q^*_{jkgt} and quality units Q^*_{jkgt} become:

$$\ln q^*_{jkgt} = \ln X_{jkgt} - \ln\left(\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}\right) - \ln\frac{\theta_g}{1-\theta_g}$$
$$\ln Q^*_{jkgt} = (1-\theta_g)\ln q^*_{jkgt} + \theta_g \ln X_{jkgt} + \theta_g \ln \varphi_{jgt} + \varepsilon_{jkgt}$$
……(12)

……(13)

where ε_{jkgt} is a mean-zero error term due to measurement error in the dependent variable or the idiosyncratic random output shocks that are realized after all the input decisions are made.

We now turn to additional parametric assumptions on the structure of composite input X_{jkgt}. Following Ackerberg, Caves, and Frazer (2015), we assume X_{jkgt} to be Leontief in materials, as in Equation (14):

$$X_{jkgt} = \min\{K^{\alpha_g}_{jkgt} \cdot L^{1-\alpha_g}_{jkgt}, \beta_g \cdot M_{jkgt}\}$$
……(14)

K_{jkgt}, L_{jkgt}, and M_{jkgt} are capital, labor, and materials, respectively, used by firm j to produce product g, which is shipped to k in year t. Capital and labor are assumed to be substitutable for each other with constant returns to scale, while materials are not substitutable for capital or labor. This production specification is defined as structural value-added and is motivated by Ackerberg, Caves, and Frazer (2015) and Gandhi, Navarro, and Rivers (2016).[6]

[6] The reason for specifying a structural value-added specification rather than a gross output specification (where the materials enter a Cobb-Douglas production function together with capital and labor) is that under the scalar unobservable assumptions, without further restrictions, the gross production function cannot be identified. This argument is shown by Bond and Soderbom (2005) for the case of a Cobb-Douglas production function, and Gandhi, Navarro, and Rivers (2016) for more general cases.

The implied cost for a unit of composite input, w_{gt}, is therefore:

$$w_{gt} = \frac{r_{gt}^{M}}{\beta_g} + \left(\frac{r_{gt}^{K}}{\alpha_g}\right)^{\alpha_g}\left(\frac{r_{gt}^{L}}{1-\alpha_g}\right)^{1-\alpha_g} \quad \text{……(15)}$$

r_{gt}^{M}, r_{gt}^{K} and r_{gt}^{L} are the prices of one unit of effective material, capital, and labor, respectively. Equation (14) simply states that

$$\ln X_{jkgt} = \alpha_g \ln K_{jkgt} + (1-\alpha_g)\ln L_{jkgt} \quad \text{……(16)}$$

The cost share of capital α_g is assumed to be dependent on g to reflect different production technologies across different products. Each α_g lies between 0 and 1. We combine Equations (16), (12), and (13) to generate

$$\ln q_{jkgt}^{*} = \alpha_g \ln K_{jkgt} + (1-\alpha_g)\ln L_{jkgt} - \ln\left(\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}\right) - \ln\frac{\theta_g}{1-\theta_g}$$

$$\ln Q_{jkgt}^{*} - (1-\theta_g)\ln q_{jkgt}^{*} = \theta_g\alpha_g \ln K_{jkgt} + \theta_g(1-\alpha_g)\ln L_{jkgt} + \theta_g \ln\varphi_{jgt} + \varepsilon_{jkgt}$$

……(17)

……(18)

We use an iteration procedure to estimate $\ln z_{jkgt}$. The iteration procedure consists of three equations, namely Equations (7), (17), and (18). With K_{jkgt}, L_{jkgt} and q_{jkgt}^{*} available, given θ_g, α_g and $\ln\varphi_{jgt}$, we can estimate $\ln\left(\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}\right)$ according to Equation (17). The estimated $\ln\left(\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}\right)$, together with $\ln\varphi_{jgt}$ and θ_g, forms an estimate for $\ln z_{jkgt}$ according to Equation (7). Combining $\ln z_{jkgt}$ and $\ln q_{jkgt}^{*}$ we again can estimate Equation (18) to update estimates of θ_g, α_g and $\ln\varphi_{jgt}$.

We develop a five-step iteration procedure to implement the estimation as follows:

Step 1. Given the values of $\widehat{\theta}_g^{\,n}$ and $\widehat{\alpha}_g^{\,n}$ (superscript denotes the nth iteration), compute the estimated value of $\widehat{\ln\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}}^{\,n}$ according to Equation (17):

$$\ln \widehat{\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}}^{n} = \widehat{\alpha}_g^n \ln K_{jkgt} + (1 - \widehat{\alpha}_g^n) \ln L_{jkgt} - \ln \frac{\widehat{\theta}_g^n}{1 - \widehat{\theta}_g^n} - \ln q_{jkgt}^*$$

Step 2. Construct the estimate of product quality $\ln \widehat{z}_{jkgt}^n$ according to Equation (7), given the values of $\ln \widehat{\varphi}_{jgt}^n$ and $\ln \widehat{\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}}^{n}$:

$$\ln \widehat{z}_{jkgt}^n = \widehat{\theta}_g^n \ln \frac{\widehat{\theta}_g^n}{1 - \widehat{\theta}_g^n} + \widehat{\theta}_g^n \ln \widehat{\frac{T_{jkgt}}{w_{gt}} - \frac{a_{kgt}}{\varphi_{jgt}}}^{n} + \widehat{\theta}_g^n \ln \widehat{\varphi}_{jgt}^n$$

Step 3. Generate the estimate of $\ln \widehat{Q_{jkgt}^*}^n$, namely,

$$\ln \widehat{Q_{jkgt}^*}^n = \ln \widehat{z}_{jkgt}^n + \ln q_{jkgt}^*$$

Step 4. Estimate Equation (18) to generate updated estimates of $\ln \widehat{\varphi}_{jgt}^{n+1}$, $\widehat{\theta}_g^{n+1}$ and $\widehat{\alpha}_g^{n+1}$:

$$\ln \widehat{Q_{jkgt}^*}^n - (1 - \widehat{\theta}_g^n) \ln q_{jkgt}^* = \widehat{\theta}_g^{n+1} \ln \widehat{\varphi}_{jgt}^{n+1} + \widehat{\theta}_g^{n+1} \widehat{\alpha}_g^{n+1} \ln K_{jkgt} + \widehat{\theta}_g^{n+1} (1 - \widehat{\alpha}_g^{n+1}) \ln L_{jkgt}$$

Using ordinary least squares (OLS) to estimate Equation (18) may incur potential simultaneity bias, since inputs $\ln K_{jkgt}$ and $\ln L_{jkgt}$ might be correlated with production efficiency $\ln \varphi_{jgt}$. To mitigate the potential simultaneity bias, we use the control function approach proposed by Ackerberg, Caves, and Frazer (2015) (ACF henceforth). We use intermediate inputs as the proxy variable.[7] In Appendix A, we describe in detail the algorithm used to implement the control function approach with intermediate inputs (or materials) as the proxy variable. The estimation delivers updated estimates of $\ln \widehat{\varphi}_{jgt}^{n+1}$, $\widehat{\theta}_g^{n+1}$ and $\widehat{\alpha}_g^{n+1}$.

Step 5. If the following convergence condition is not met, repeat Steps 1 to 4.

[7] We use intermediate inputs rather than investment as the proxy variable in the control function because depreciation for Chinese manufacturing firms is missing during 2008 to 2010. We have to assume that firm-level depreciation rates are the same for an industry in a year and rely on the industry-level depreciation rate to calculate real capital stock at the firm level. Consequently, the constructed investment variable reflects our assumption on the depreciation rate and might be less precise.

$$\max\left\{\left|\hat{\theta}_g^{n+1}\hat{\alpha}_g^{n+1} - \hat{\theta}_g^{n}\hat{\alpha}_g^{n}\right|, \left|\hat{\theta}_g^{n+1}(1 - \hat{\alpha}_g^{n+1}) - \hat{\theta}_g^{n}(1 - \hat{\alpha}_g^{n})\right|\right\} < tolerance$$

$tolerance$ is set to be 0.0001. Once convergence is achieved, repeat Steps 1 and 2 to generate the final estimate of product quality $\ln z_{jkgt}$.

We implement the iteration procedure for each HS 4-digit product and obtain estimates of $\ln z_{jkgt}$ for each Chinese exporter j selling product g in each destination k in year t.[8] Different from quality estimated using a demand-side approach, $\ln z_{jkgt}$ is comparable across destinations and years. This property allows us to construct a quality competition index that captures quality shocks over time.

To ensure that the measures of quality across different products g are comparable, we normalize the estimated quality by subtracting $\ln z_{jkgt}$ from the "reference quality level" in its own product category, which we define as the 5% quantile of the quality distribution of product g in the year when product g first appears in the sample:[9]

$$qual_{jkgt} = \ln z_{jkgt} - \ln z_{g0}^{5\%} \qquad \text{……(19)}$$

The normalization makes $qual_{jkgt}$ comparable across products g in the sense that it is the deviation with respect to a common benchmark in each product g. We proceed to aggregate micro-level quality $qual_{jkgt}$ to the destination-product-year level by calculating the value-weighted average:

$$qual_{kgt} = \frac{\sum_j R_{jkgt}^{*} \times qual_{jkgt}}{\sum_j R_{jkgt}^{*}} \qquad \text{……(20)}$$

where R_{jkgt}^{*} is firm j's sales of product g to destination k in year t. Therefore,

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[8] In principle, we can perform the estimation for each HS 6-digit product. However, since the average sample size for each product gets smaller, moving from aggregate classification to disaggregate classification, we fail to generate sensible estimates for some HS 6-digit products due to insufficient observations. We therefore perform the estimation at the HS 4-digit level to incorporate as much trade volume as possible, while at the same time preserving substantial variations in production technologies across products.

[9] For example, before normalization, we cannot compare a pencil's quality with a car's quality. After such a normalization, we can at least say that a pencil's quality ranking in its own category is higher than a car's quality ranking in its own category.

$qual_{kgt}$ captures the quality impact from China in product g to a particular destination k in year t.

3 Data and Variable Construction

Our empirical analysis employs several disaggregated data sets to calculate our key variables. In this section, we first describe the sources of our data sets. We then present how we construct the two key variables: Indonesian firm TFP and a firm-level indicator to measure global quality competition from China.

3.1 Data Sources

3.1.1 Chinese Data

We rely on the Chinese product-level trade data set and Chinese firm-level production data to construct micro-level estimated export quality $qual_{jkgt}$ and $qual_{kgt}$. The Chinese product-level trade data set comes from the General Administration of Customs of China (Chinese Customs data set, CC). The CC data set records information on export dollar value, export quantity, destination, product category up to the HS 8-digit level, and export mode for each exporter. The time span we have access to is from 2000 to 2013. As noted by Yu (2015) and Dai, Maitra, and Yu (2016), in China, processing exporting possesses entirely different production features from ordinary exporting. Ordinary exporters are in charge of the whole production procedure and typically rely on local inputs. Processing exporters sign contracts with foreign counterparties; carry out the tasks of manufacturing, processing, and assembly; and are heavily dependent on imported intermediate inputs that are usually provided by their foreign counterparties. Therefore, the quality and technology embedded in processing exports may largely reflect those of the foreign counterparties. To avoid unnecessary complication induced by the mixture of export mode, we focus on the impact of ordinary exporting. We combine each firm's export value and volume to the HS 2007 6-digit level to each destination in each year before constructing China's firm-product-year-level export quality.

Chinese firm-level production data are collected and maintained by China's National Bureau of Statistics. We call this the ASM data set, for the Annual Survey of Manufacturers. The data set covers all state-owned industrial firms and all non-state-owned industrial firms with annual sales exceeding a certain threshold (RMB 5 million from 1998 to 2010, and RMB 20 million from 2011 to 2013). Therefore, the ASM data set consists of large and medium-size enterprises.[10] The data set records comprehensive production information

[10] We admit the limitation that some small manufacturers also export, which may not be included in the ASM sample. However, since most of the trade volumes come from large manufacturers, we assume that neglecting those small exporters does not give rise to systematic measurement errors on aggregate export quality.

(gross output, material inputs, employment, export sales, and other firm characteristics) and financial information (assets, fixed assets, and other variables). The data set spans from 1998 to 2013. All firms are classified according to the China Industrial Classification (CIC henceforth) at the 4-digit level, which is comparable to the International Standard Industry Classification (ISIC henceforth) 4-digit industries.

We acknowledge the shortcomings of the ASM data set, according to Brandt, Van Biesebroeck, and Zhang (2012) and Feenstra, Li, and Yu (2014). A part of the sample in ASM suffers from missing or misleading information. Hence, we conduct a data-filtering procedure before using the data. Following Yu (2015), we delete observations that have missing values in assets, net value of fixed assets, sales, gross output, or firm identity number; greater value in current assets than total assets; greater value in fixed assets than total assets; greater value in net value of fixed assets than total assets; or establishment month less than 1 or greater than 12.

A point worth noting is that the CC data set has a different coding system for firm identity number from that in the ASM data set. We therefore follow Yu (2015) to match the two data sets using firms' Chinese name, as well as firms' zip code and last seven digits of the phone number.

The matched data set contains all the variables needed for the calculation of export quality. Firm-level number of employees L_{jt} and materials inputs M_{jt} are available. Firm-level real capital stock K_{jt} is constructed via the perpetual inventory method proposed by Brandt, Van Biesebroeck, and Zhang (2012).[11] Firm j 's FOB sales and quantity of product g in destination k in year t, R^*_{jkgt} and q^*_{jkgt}, are also available. We proxy K_{jkgt} and L_{jkgt} using the following formula:[12]

[11] This is done for the sample period when firm-level depreciation is available. We use the actual reported depreciation in the perpetual inventory method. For the sample period when firm-level depreciation is missing (2008–10), we calculate the depreciation rate at the CIC 2-digit industry level (increase in accumulated depreciation of the whole industry in that year divided by fixed assets at original price of the whole industry in that year), and use this depreciation rate to calculate firm-level depreciation and conduct the perpetual inventory method.

[12] We admit that such an approximation can be subject to measurement error because the input share of a product (to a market) is not necessarily proportional to the revenue share of that product (to that market). Therefore, when estimating the production function of quality units, we exploit the variations in input uses across firms to identify the parameters.

$$K_{jkgt} = \frac{R^*_{jkgt}}{R^*_{jt}} \cdot K_{jt}$$

$$L_{jkgt} = \frac{R^*_{jkgt}}{R^*_{jt}} \cdot L_{jt}$$

……(21)

……(22)

where $R^*_{jt} = \sum_{k,g} R^*_{jkgt}$.

We need an initial guess for the values of $\ln\widehat{\varphi}^0_{jgt}$, $\widehat{\theta}^0_g$, and $\widehat{\alpha}^0_g$ to initialize the estimation. The initial guess for production efficiency $\ln\widehat{\varphi}^0_{jgt}$ is obtained by estimating Equation (23) for each CIC 2-digit industry separately, using the ACF algorithm

$$\ln R^*_{jt} = \ln\varphi^{Initial}_{jt} + \rho_K \ln K_{jt} + \rho_L \ln L_{jt} \qquad ……(23)$$

where we take $\ln\widehat{\varphi}^0_{jgt} = \ln\varphi^{Initial}_{jt}$. We then obtain the estimated $\ln\widehat{\varphi}^0_{jgt}$, $\widehat{\rho}_K$, and $\widehat{\rho}_L$. The initial estimated $\widehat{\alpha}^0_g$ is computed as in Equation (24):

$$\widehat{\alpha}^0_g = \frac{\widehat{\rho}_K}{\widehat{\rho}_K + \widehat{\rho}_L} \qquad ……(24)$$

For $\widehat{\theta}^0_g$, Feenstra and Romalis (2014) provide estimates for each SITC 4-digit level product. We map their estimated values onto the HS 6-digit level to generate $\widehat{\theta}^{FR}_g$ as the initial value for θ_g. Among the 750 HS 4-digit products that we estimate, the mean and median values of θ_g are 0.553 and 0.542, and the standard deviation is 0.104.

As unit value has been used to measure quality by many previous studies, we first investigate how our measure of quality varies with unit value. Specifically, we estimate the following specification:

$$\ln uv_{jkgt} = \beta_1 \ln z_{jkgt} + \beta_2 \ln z_{jkgt} \times Diff_g + \mu_{kgt} + \varepsilon_{jkgt} \qquad ……(25)$$

We introduce an interaction term of our measured quality and a dummy indicating whether product g is differentiated. μ_{kgt} are the destination-product-year fixed effects.

The definition of $Diff_g$ follows Rauch (1999).[13] β_1 is expected to be positive, because for most products, price should be increasing in quality. β_2 is also expected to be positive. The intuition is that among differentiated products, the variations in prices should be more informative in signaling the variations in qualities.

[Table 1 here]

Table 1 reports the estimation results. Both β_1 and β_2 are estimated to be positive at the 1% significance level. This suggests that our measured quality is positively associated with unit value, and such a positive correlation is stronger for differentiated goods than for homogeneous goods.

We provide a simple description of the median $qual_{jkgt}$ evolution for each CIC 2-digit industry in Table A1 from 2008 to 2012, the period for which we carry out the analysis with Indonesian firm-level data. Most of the industries increase export quality during the sample period. However, there are substantial variations in the evolution of China's export qualities across industries, with leather and communication & computers experiencing the largest increases in export quality, and petroleum and ferrous metals experiencing the largest declines.

3.1.2 Indonesian Data

We use the Indonesian firm-level production data to construct firm-level TFP. The Indonesian firm-level production data are from the Manufacturing Survey of Large and Medium-sized Firms (Survey Industry, or SI). We call this data set the Indonesian firm data set, IFD, which is issued by Statistics Indonesia (Badan Pusat Statistik). The survey is conducted every year, covering all manufacturers in Indonesia with more than 20 employees. The data period that we have access to is from 2008 to 2012. The IFD data set contains firm-level information on output, expenditure on domestic and imported materials, capital, employment, domestic sales, export and import status, shares of exports and imports, and other firm characteristics, which are essential for us to construct Indonesian firm TFP.

Indonesian product-level data are also available from 2008 to 2012. This data set is also provided by Statistics Indonesia. The product-level data record information on domestic sales, export (import) dollar value, export (import) volume, destination (source), and product category up to the HS 10-digit level for each firm in each year. We aggregate each firm's domestic sales and export value (converted to Indonesian rupiahs) to each

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[13] If a product is defined as differentiated by Rauch (1999), we let $Diff_g = 1$. If a product is defined as reference-priced or open exchange, we let $Diff_g = 0$. We use the "conservative" classification by Rauch (1999).

destination (including the domestic market) in each year to the HS 2007 6-digit level before constructing the firm-specific indicator that measures global quality competition from China (elaborated in section 3.3), since the HS 6-digit level is the most disaggregated product level compatible across countries.

An important note is that the firm identity numbers in the Indonesian product-level trade data use the same coding system as those in the IFD data set. Therefore, we can easily match the product-level information with the SI data set using firm identity numbers (Kode Identitas Pendirian Usaha).

3.2 Measures of TFP

We use the IFD data to construct firm-level TFP by estimating a Cobb-Douglas production function for each ISIC rev.4 2-digit industry:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \qquad \text{……(26)}$$

where y_{it}, k_{it}, l_{it}, and m_{it} are firm i 's deflated output value, real capital, number of production workers, and deflated materials in year t in log, respectively. ω_{it} is the log TFP we aim to estimate.

To construct industry-level output deflators, we first manually concord the Wholesale Price Index (WPI) with the ISIC rev.4 2-digit industry level. We then average the WPI within each ISIC rev.4 2-digit industry to generate industry-specific output deflators following Amiti and Konings (2007), where the WPI price indices are obtained from the CEIC database. We then use the output deflators to deflate the nominal output of the firm and take log to obtain y_{it}.

We use the industry-specific output deflators to construct industry-specific input deflators. We obtain each industry’s domestic input shares, from itself and other industries, using the Indonesian input-output table. We then construct domestic input deflators for each industry by weighting all industries’ output deflators with their cost shares as intermediate inputs in the particular industry. The weighted deflators are therefore industry-level domestic input deflators. We generate imported input deflators through a similar procedure, assuming the input-output structure is identical for domestic and imported inputs, since the information on input-output linkage is not available for imported goods. Industry-level imported price indices are obtained from the CEIC Premium database. m_{it} is obtained by summing firm i 's expenses on domestic materials deflated by domestic input deflators and firm i 's expenses on imported materials deflated by imported input deflators in year t and taking log.

While a firm reports its capital stock in nominal value, we need to construct capital deflators to calculate the real value. We first deflate firm i ’s different types of capital in year t (including land, buildings, vehicles, machinery, and other capital) using the corresponding WPI.[14] Summing the different types of deflated capital and taking log, we obtain k_{it}. The labor input, l_{it}, is simply firm i 's number of production workers in year t in log.

We follow the algorithm of Amiti and Konings (2007) and adopt Olley and Pakes' algorithm (1996) to estimate the production function and calculate TFP. Using OLS to estimate the production function suffers from endogeneity, because a production input decision, such as the amount of labor, is likely to be affected by firm productivity. Thus, in an OLS estimation, the right-hand-side variables are correlated with the residuals. Using investment as a proxy variable to construct a control function, Olley and Pakes' (1996) algorithm can tackle this simultaneity problem. Moreover, Olley and Pakes (1996) also deal with selection bias resulting from firms' exit decision.

As in Amiti and Konings (2007), we allow the firm's export and import decisions to affect the firm's investment decision, and therefore incorporate them into the Olley-Pakes algorithm. Specifically, exporting and importing may involve fixed costs related to searching for suitable customers and suppliers, therefore affecting the firm's investment decision. We also allow the control function to be year-specific; therefore, our estimation reflects potential effects of aggregate shocks during the sample period, for example, the financial crisis.[15]

We describe our augmented algorithm in detail in Appendix B. We conduct the augmented Olley-Pakes algorithm for each ISIC rev.4 2-digit industry. We then construct firm i 's TFP in log in year t as follow:

$$\ln TFP_{it} = y_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_m m_{it}$$

3.3 Global Quality Competition Indicator

We construct a firm-specific index to measure the effect of global quality competition from China on Indonesian firms. The index, GQC_{it}, is as follow:

[14] The WPI is not available for land and other capital, so we replace it with the Indonesian Consumer Price Index.

[15] To ensure robustness, we also use labor productivity, TFP calculated using the Levinsohn-Petrin algorithm, and TFP calculated using the Ackerberg-Caves-Frazer algorithm in our analysis.

$$GQC_{it} = \frac{\sum_{k,g} v_{ikg0} \cdot qual_{kgt}}{\sum_{k,g} v_{ikg0}} \qquad \text{……(27)}$$

where v_{ikg0} is firm i 's sales of product g in destination market k (including the domestic market) in the initial year when firm i first appears in the data set. Therefore, GQC_{it} is the Bartik-type (1991) weighted average quality of China's exports, with the weight being the share of each product-destination combination in firm i 's total sales in the initial year.

GQC_{it} summarizes the quality competition from China faced by a particular Indonesian firm across all markets (defined by product-destination combination kg). There are two sources of variation in GQC_{it}. First, in each product-destination pair, quality competition from China is tough when $qual_{kgt}$, the weighted average export quality of China in market kg, is high. $qual_{kgt}$ reflects the intensity of quality competition from China in market kg faced by an Indonesian firm. Second, the firm's sales composition (in the initial year) also induces variations in GQC_{it}. If the firm sells a large fraction of its products in a particular market kg where China's export quality is high, the firm is faced with tougher quality competition from China compared with another firm selling only a tiny fraction of its products in market kg. The use of the initial weight eliminates the potential endogeneity problem that the firm might adjust its sales composition across markets in response to quality competition from China $qual_{kgt}$. GQC_{it} therefore captures the quality competition effects in different markets (for example, China's export quality to the U.S. market could be higher than that to the Indonesian market, so the quality competition is tougher in the United States for an Indonesian firm), and the quality competition effects due to different sales compositions (for example, a firm that initially sells 80% of its products in the United States and 20% in Indonesia could experience larger impact than a firm that initially sells 80% of its products in Indonesia and 20% in the United States).

Table 2 reports the evolution of firm-level TFP and firm-specific GQC_{it} over the whole sample period. Both variables increase from 2008 to 2012. The mean and median TFPs grow by 30% and 21%, respectively. The mean and median values of GQC_{it} grow by 14% and 20%, respectively. We also report the evolution of firm-level normalized TFP over the sample period. The mean and median normalized TFP grow by 16% and 14%, respectively.[16] Figure 1 plots the evolution of median GQC_{it} and median normalized log

[16] As suggested by Arkolakis (2010), TFPs in levels might not be comparable across industries. We compute the average log TFP for each ISIC 2-digit industry. We then subtract the industry-specific

TFP across years.

[Table 2 here]

4 Empirical Analysis

In this section, we first lay out the empirical specification to study how the quality competition shock from China affects Indonesian manufacturers' TFP and highlight our identification strategy. We then present our empirical results for the baseline specification. We include potential confronting factors, such as the output tariff, input tariff, and quality competition from other countries. We then explore several mechanisms through which the quality competition shock may impact productivity, including trade status, industrial concentration, product turnover, and extensive margin. We conclude by offering several robustness checks of our main results, including alternative measures and alternative specifications.

4.1 Specification and Identification

Our main specification of interest is the following:

$$\ln TFP_{it} = \beta \times GQC_{it-1} + \mu_i + \mu_{rt} + \varepsilon_{it} \quad \text{……(28)}$$

Equation (28) adopts the two-step approach used by Pavcnik (2002), Amiti and Konings (2007), Brandt, Van Biesebroeck, Wang and Zhang (2017), and others. We estimate $\ln TFP_{it}$ in the first step and Equation (28) in the second step. Since an industry's rapid TFP growth might intensify the competition in that industry and thus raise the threshold for entering that market, there might be a potential reverse causality problem between $\ln TFP_{it}$ and GQC_{it}. For instance, if Indonesia experiences rapid TFP growth in the textile industry, then it is relatively more difficult for Chinese firms to break into Indonesia's domestic textile market, or any markets to which Indonesian textile firms are selling. As a result, only those Chinese firms producing high-quality goods can compete in these markets, raising China's export quality to these markets via a selection mechanism, and thus contaminating our identification by introducing a causal relationship running from $\ln TFP_{it}$ to GQC_{it}. We alleviate the potential endogeneity problem by lagging GQC for one period, since the future value of $\ln TFP_{it}$ is unlikely to affect the past value of GQC_{it-1}. Firm fixed effects μ_i and island-year fixed effects μ_{rt} are also included. The residual ε_{it} is assumed to be uncorrelated to all the explanatory variables. Taking differences yields:

average log TFP from firm-level log TFP to obtain normalized TFP $\ln TFP_{it}^{Normalized}$.

$$\Delta \ln TFP_{it} = \beta \times \Delta GQC_{it-1} + \theta X_{it} + \mu_{rt} + \Delta\varepsilon_{it} \quad \ldots\ldots(29)$$

Our first-difference strategy removes the firm-specific fixed effects μ_i. We pay particular attention to the estimate of β, the coefficient of the change in the firm-level global quality competition index from China ΔGQC_{it-1}, on the change in firm-level log TFP. We also include firm-level control variables X_{it} in the specification, including dummies indicating whether the firm is foreign-owned (FIE_{it}), an exporter (FX_{it}), and an importer (FM_{it}). The inclusion of μ_{rt} suggests that we are exploiting the variation in trends across firms, taking out the island-year-specific trends (and firm-specific intercepts). A positive β thus implies that a firm experiencing rapid growth of GQC relative to the island-year mean growth is more likely to have higher TFP growth than a firm experiencing mild growth of GQC relative to the island-year mean growth. Standard errors are clustered at the firm level.

4.2 Baseline Results

We estimate Equation (29) under various specifications and report the results in Table 3. In column 1, we find that an increase in GQC_{it-1} is associated with significant TFP growth at the 1% significance level. In columns 2 and 3, we include FIE_{it}, and FX_{it} and FM_{it}, respectively, and the effect of GQC_{it-1} persists. In column 4, we include FIE_{it}, FX_{it}, and FM_{it} in the specification and the point estimate of ΔGQC_{it-1} remains positive and significant at the 1% level. In columns 5 and 6, we include year fixed effects and island-year fixed effects, and the economic and statistical significance of GQC_{it-1} barely changes.

Our baseline results suggest that intense quality competition from China raises Indonesian firms' TFP in a nontrivial manner. The main message remains when controlling for ownership, trade status, firm fixed effects, and island-year fixed effects. In later sections, we argue that this effect operates through a pro-competitive mechanism to improve firm TFP.

[Table 3 here]

We continue to incorporate additional variables into our baseline specification. Amiti and Konings (2007) document that output and input tariffs are important determinants of firm TFP. We therefore construct firm-level measures of output and input tariffs and control for them in our regression.

Specifically, the firm-level output tariff τ_{it}^{O} and input tariff τ_{it}^{I} are constructed as follows:

$$\tau_{it}^{O} = (1 + \frac{\sum_g v_{ig0}^{O} \cdot tariff_{gt}}{\sum_s v_{is0}^{O}})$$

$$\tau_{it}^{I} = (1 + \frac{\sum_g v_{ig0}^{I} \cdot tariff_{gt}}{\sum_s v_{is0}^{I}})$$

……(30)

……(31)

where $tariff_{gt}$ is the simple average tariff of HS 6-digit product g in year t. v_{ig0}^{O} and v_{ig0}^{I} are firm i 's value of output and value of materials purchased in product g in the initial year when firm i first appears in the data. v_{igt}^{O} and v_{igt}^{I} are available in the Indonesian Manufacturing Survey data. Using the initial weight therefore alleviates the potential endogeneity problem if firms adjust these weights in response to changes in tariffs.

Table 4 reports the results including $\Delta \ln \tau_{it-1}^{O}$ and $\Delta \ln \tau_{it-1}^{I}$. Column 1 includes only $\Delta \ln \tau_{it-1}^{O}$ and column 2 includes only $\Delta \ln \tau_{it-1}^{I}$. The effect of ΔGQC_{it-1} on $\Delta \ln TFP_{it}$ is almost invariant. In column 3, we include output and input tariffs, and the estimates of β remain consistent and robust. That including output and input tariffs seldom changes the magnitude of the estimated β suggests that the impact of tariffs is likely to be orthogonal to the quality competition shock from China in which we are interested. Moreover, the insignificant effects of output and input tariffs on firm-level TFP might be because tariffs over the sample period remain quite stable. The average firm-level output tariff decreases by only 1.5%, and the average firm-level input tariff decreases by only 0.3%. The lack of variations in output and input tariffs give rise to the imprecise and insignificant effects of $\Delta \ln \tau_{it-1}^{O}$ and $\Delta \ln \tau_{it-1}^{I}$ on firm-level TFP growth.

Columns 4 to 6 provide robustness checks by using alternative tariff measures. Namely, we replace $tariff_{gt}$, the simple-average tariff of HS 6-digit product g in year t, by $tariff_{gt}^{W}$, the weighted average tariff of HS 6-digit product g in year t, and generate $\ln \tau_{it-1}^{O,W}$ and $\ln \tau_{it-1}^{I,W}$. The results remain almost identical to those in columns 1 to 3.

[Table 4 here]

Since we are interested in quality competition from China, nothing prevents the possibility that other countries are also generating quality competition effects that also improve firm TFP. Moreover if, for some industries, Indonesian consumers' preference for quality increases, then consequently, on the one hand, import quality in these industries may increase as a result of the increase in preference for quality, while on the other hand, firm TFP in these industries can also increase due to the higher quality standard desired by consumers. Such a demand-driven connection between $\Delta \ln TFP_{it}$ and ΔGQC_{it-1} is theoretically plausible, but is in contrast to our hypothesis, where we argue that quality competition from China is the cause rather than a co-varying variable of $\Delta \ln TFP_{it}$.

Because of the concerns above, it is crucial for us to control for the quality of imports from other countries. On the one hand, this will ensure that our measure ΔGQC indeed captures the quality competition shock from China, rather than a universal increase in import quality from around the world. On the other hand, an indicator of the quality of imports is useful in controlling (if any) the demand-driven components that affect import quality and local firm TFP simultaneously, leaving the variations that we exploit in the estimation purely supply-driven by China.

We construct two indicators to capture the overall quality of imports. Specifically,

$$OQC_{it-1}^{FR} = \frac{\sum_g v_{ig0}^{O} \cdot qual_{gt}^{FR}}{\sum_s v_{is0}^{O}} \quad \text{……(32)}$$

$$OQC_{it-1}^{UV} = \frac{\sum_g v_{ig0}^{O} \cdot qual_{gt}^{UV}}{\sum_s v_{is0}^{O}} \quad \text{……(33)}$$

OQC_{it-1}^{FR} is the firm-level weighted average quality of imports, where initial weights are used. $qual_{gt}^{FR}$ is the quality of Indonesia's imports of HS 6-digit product g in year t, as measured by Feenstra and Romalis (2014).[17] An alternative measure, OQC_{it-1}^{UV}, replaces $qual_{gt}^{FR}$ with $qual_{gt}^{UV}$, the unit value of Indonesia's imports of HS 6-digit product g in year t. We include these quality measures in our baseline specification.[18]

In Table 5, we report the results when ΔOQC_{it-1}^{FR} and ΔOQC_{it-1}^{UV} are used. Columns 1 and 2 show that the point estimate of β does not deviate from the previous results, while OQC_{it-1}^{FR} and OQC_{it-1}^{UV} do not yield any significant impact on $\ln TFP_{it}$. One implication

[17] As the quality of imports measured by Feenstra and Romalis (2014) is at the SITC rev.2 4-digit level, we use the concordance between SITC 4-digit and HS 6-digit to construct the quality of Indonesia's imports at the HS 6-digit level.

[18] We do not use the quality estimates as in Khandelwal, Schott, and Wei (2013) and Fan, Li, and Yeaple (2015, 2018), because their approaches are suitable to identify the quality of an individual variety up to some normalization within a destination-year combination. As a result, the average quality of all varieties selling in a destination cannot be identified.

is that the impact of ΔGQC_{it-1} on $\Delta \ln TFP_{it}$ is mainly driven by a supply-side China shock rather than a supply-side global shock in quality, or any Indonesian demand shocks.

Columns 3 and 4 perform another set of robustness checks by replacing FIE_{it}, FX_{it}, and FM_{it} by the corresponding continuous share measures between 0 and 1. The estimated β remains similar in significance and magnitude to those in the other specifications. We define the specification in column 4 in Table 5 as our main specification and adopt such a specification in the following analysis.

[Table 5 here]

4.3 Channels and Mechanisms

Our baseline results deliver robust and consistent impact of quality competition from China on Indonesian firm TFP. In this subsection, we explore various channels and mechanisms through which this impact could be rationalized. We first investigate whether the trade status of a firm would affect the impact of quality competition. We then examine the competition and product turnover channels. We finally consider whether the effect primarily stems from the intensive margin or the extensive margin.

4.3.1 Trade Status and TFP

A firm can be an exporter or importer, and its trade status may affect how the quality competition shock from China transmits to the firm level. An exporter might feature geographic diversification and therefore be able to skew its sales toward other markets when quality competition from China is particularly tough in some market. Thus, the impact of ΔGQC on $\Delta \ln TFP_{it}$ might be smaller for exporters compared with non-exporters. An importer can get access to imported inputs more easily and thus could leverage this advantage to improve its TFP. Therefore, the impact of ΔGQC on $\Delta \ln TFP_{it}$ might be larger for importers compared with non-importers. We therefore estimate the following specification:

$$\begin{aligned}\Delta \ln TFP_{it} = {} & \beta \times \Delta GQC_{it-1} + \alpha_E \times \Delta GQC_{it-1} \cdot FX_{it} + \alpha_I \times \Delta GQC_{it-1} \cdot FM_{it} \\ & + \theta X_{it} + \mu_{rt} + \varepsilon_{it}\end{aligned}$$

……(34)

Specifically, we interact ΔGQC_{it-1} with export status and import status, respectively, to allow for heterogeneous effects of ΔGQC_{it-1} on different groups of firms. The estimation results are reported in Table 6. Columns 1 to 3 include $\Delta GQC_{it-1} \cdot FX_{it}$, $\Delta GQC_{it-1} \cdot FM_{it}$, and both, respectively. It is worth noting that the estimated β remains positive and significant. α_E is negative, while α_I is positive, but both coefficients are not significant across all specifications. Therefore, the trade status of a firm is not a key mechanism through which firm TFP is affected by quality competition from China. In columns 4 to 6, we adopt foreign-owned share, export share, and import share to replace FIE_{it}, FX_{it}, and FM_{it}, and the main results remain invariant.

[Table 6 here]

4.3.2 Competition

We next examine whether the competition channel is in force. For each ISIC 2-digit industry, we calculate the Herfindahl-Hirschman Index (HHI henceforth) based on gross output. We then divide all industries into "low HHI" and "high HHI" categories, based on whether the value of the HHI exceeds 0.1 (the 75% quantile) or not. Intuitively, a less concentrated industry is more likely to foster the pro-competitive channel when faced with intense quality competition from China. To examine this hypothesis, we estimate our main specification for the low HHI and high HHI subsamples separately.

Columns 1 to 3 in Table 7 report the results. In column 1, where the low HHI sample is used, ΔGQC_{it-1} yields a significantly positive effect on $\ln TFP_{it}$. In contrast, in column 2, where the high HHI sample is used, the coefficient of ΔGQC_{it-1} is negative and not significant. In column 3, where we interact ΔGQC_{it-1} with a high HHI dummy, we find that the coefficient of ΔGQC_{it-1} is positive and significant at the 1% level, whereas the coefficient of the interaction term is negative and significant at the 5% level. This set of subsample analysis results supports the hypothesis that GQC_{it-1} affects TFP via a pro-competitive channel, and less concentrated industries are more likely to benefit from such pro-competitive effect.

4.3.3 Product Turnover

We examine another important mechanism of productivity improvement that has been advocated in the literature on international trade: product turnover. Bernard, Redding, and Schott (2010) and Mayer, Melitz, and Ottaviano (2014) highlight the product adding, dropping, and switching behaviors of multi-product firms and the implications on firm productivity of such within-firm reactions across products. In our context, when quality competition from China intensifies, multi-product firms may drop their marginal products that are far from the firms' core competence and skew sales to their best products. Such product-level entry and exit could be an important source of productivity improvement at the firm level. We therefore divide the sample into multi-product firms and single-product firms based on the number of HS 6-digit products the firm is selling across all destinations. We then estimate our main specification for the two subsamples separately.

Column 4 in Table 7 reports the results for multi-product firms. An increase in ΔGQC_{it-1} is associated with a significant increase in firm TFP at the 1% level. Column 5 shows that this effect in the sample of single-product firms is also positive and significant at the 5% level. In column 6, we interact ΔGQC_{it-1} with a "multi-product" dummy. The coefficient of ΔGQC_{it-1} is positive and significant, and the coefficient of the interaction term is positive although not significant. Therefore, there is suggestive evidence that multi-product firms have a larger margin of adjustment than single-product firms.

[Table 7 here]

We further directly examine whether an increase in ΔGQC_{it-1} induces firms to drop products. We estimate the following specification:

$$Num\_pro_{it} = \beta \times \Delta GQC_{it-1} + \theta X_{it} + \mu_l + \mu_{rt} + \varepsilon_{it} \quad \ldots\ldots(35)$$

where we now include 2-digit industry fixed effects, μ_l. In columns 1 and 3 in Table 8, we use Poisson regression to estimate Equation (35), while in columns 2 and 4, we use negative binomial regression. In the first two columns, we include industry-specific fixed effects, and in the last two columns, we include industry-specific fixed effects and island-year-specific fixed effects. The results show that an increase in ΔGQC_{it-1} is associated with a significant decrease in the number of products a firm produces. The evidence for product turnover implies that under a quality competition shock from China, Indonesian firms react by adjusting their product scopes, dropping marginal products and retaining their most competitive products. Through these product turnovers, firm TFPs increase, and this effect is mainly present in multi-product firms.

[Table 8 here]

4.3.4 Intensive Margin vs Extensive Margin

We next discuss whether the firm TFP growth induced by quality competition from China happens on the intensive margin or the extensive margin. On the one hand, intensified competition forces firms to improve their productivity. On the other hand, tougher competition can also wipe out inefficient firms via the selection mechanism.

We divide the sample into non-exit and exit subsamples according to whether the firm exits the market in the next period. We then estimate our main specification for the two subsamples. Columns 1 to 3 in Table 9 report the results. Such an analysis reveals that the intensive margin plays a major role in productivity growth in the face of quality competition from China. For the non-exit sample, an increase in ΔGQC_{it-1} is associated with a significant increase in firm TFP at the 1% level. In contrast, in the exit sample, the coefficient of ΔGQC_{it-1} is negative and insignificant. In column 3, we interact ΔGQC_{it-1} with the exit dummy. While the coefficient of ΔGQC_{it-1} is positive and remains significant at the 1% level, the coefficient of the interaction term is negative although insignificant. Our evidence shows that exiting firms fail to improve TFP when quality competition from China becomes tougher.

To ensure the robustness of this result, we alternatively divide the sample into a "balanced" sample of firms that are active in all five years during 2008–12, and an "unbalanced sample" of the rest of the firms. The estimation results are very similar to those in columns 1 to 3 in Table 9. The analysis in this subsection implies that the improvement in TFP induced by quality competition from China can be primarily attributed to the contribution at the intensive margin.

[Table 9 here]

4.4 Robustness

In this subsection, we present several robustness checks to ensure that our results are not driven by the particular choice of variables or specifications.

Our key dependent variable of interest is firm TFP, which is calculated via the Olley and Pakes (1996) algorithm. In Table 10, we adopt three alternative measures of firm TFP: labor productivity, TFP calculated via Levinsohn and Petrin's (2003) algorithm (LP henceforth), and TFP calculated via Ackerberg, Caves, and Frazer's (2015) algorithm (ACF henceforth). Specifically, labor productivity is calculated as value added per worker, while LP TFP and ACF TFP are calculated by running the LP and ACF algorithms for each ISIC 2-digit industry, respectively.

Table 10 reports the results using alternative measures of TFP. We also include each firm's capital-labor ratio as a control variable. In all columns, the effect of ΔGQC_{it-1} on TFP remains positive and significant at least at the 10% level. Therefore, our main results are robust to the choice of dependent variable.

[Table 10 here]

One might worry that some industry-specific intercepts or trends that are correlated with our key independent variable, ΔGQC_{it-1}, are driving our results. In particular, if some industries experience faster technology advancement globally, we may observe both faster TFP growth of Indonesian firms and faster export quality growth of Chinese firms for that industry. Furthermore, it may also be argued that inclusion of industry-specific intercepts is necessary to make firm-level TFP across different industries comparable. To address these concerns, we include industry-specific fixed effects and industry-year-specific fixed effects in our regressions. Table 11 reports the results. In columns 1 and 2, we include industry-specific fixed effects. An increase in ΔGQC_{it-1} is associated with a significant increase in $\Delta \ln TFP_{it}$ at the 1% level. In columns 3 and 4, we switch to industry-year-specific fixed effects and find that the effect of ΔGQC_{it-1} on $\Delta \ln TFP_{it}$ remains positive and significant at the 1% level. Therefore, our results are not driven by any industry-specific common trends.

[Table 11 here]

We finally experiment with alternative specifications in Table 12. In columns 1 and 2, we report the results of adding firm-specific fixed effects. The effect of ΔGQC_{it-1} on

$\Delta \ln TFP_{it}$ is still positive and significant at the 1% level, and the magnitude of the estimated coefficient increases. In columns 3 and 4, we replicate our baseline specification based on two-period difference. The effect remains positive and significant at the 1% level. In columns 5 and 6, we add firm-specific fixed effects in the two-period difference specification. The same message is preserved. Our main results are thus robust to alternative specifications.

[Table 12 here]

5 Concluding Remarks

China's rapid export growth generates various economic outcomes and policy concerns for countries around the world. In this paper, we pay particular attention to variation in China's export quality, and study how quality competition from China affects Indonesian firm productivity. We construct a firm-specific indicator that measures the quality competition from China faced by an Indonesian firm in the global market (the domestic and export markets), based on the theoretical framework that stresses firms' optimal quality choice as the outcome of the trade-off between production cost and per-unit trade cost. We take advantage of the variation over time in the firm-specific quality competition measure and estimate its impact on individual firm TFP for Indonesia.

Our results suggest that higher global quality competition from China induces an Indonesian firm to improve its TFP, a pro-competitive effect stemming from variation in the quality of competitors. The results are robust when we control for the potential effects of the output tariff, input tariff, and quality competition from other countries. We further confirm the pro-competitive effect by showing that such an effect is more likely to emerge for less concentrated industries, and multi-product firms react to increased global quality competition from China by dropping products. We also find that such an effect mainly exists in continuing firms. Our study suggests a new dimension in understanding the impact of China's export growth, and a source of productivity gains from trade related to the quality margin.

References

[1]. Ackerberg, D. A., K. Caves, and G. Frazer. 2015. Identification Properties of Recent Production Function Estimators. *Econometrica* 83 (6): 2411–51.

[2]. Alessandria, G., and J. P. Kaboski. 2011. Pricing-to-Market and the Failure of Absolute PPP. *American Economic Journal: Macroeconomics* 3 (1): 91–127.

[3]. Amiti, M., M. Dai, R. C. Feenstra, and J. Romalis. 2017. How Did China's WTO Entry Benefit US Consumers? *NBER Working Paper* No. w23487. National Bureau of Economic Research, Cambridge, MA.

[4]. Amiti, M., and A. K. Khandelwal. 2013. Import Competition and Quality Upgrading. *Review of Economics and Statistics* 95 (2): 476–90.

[5]. Amiti, M., and J. Konings. 2007. Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review* 97 (5): 1611–38.

[6]. Arkolakis, C. 2010. Market Penetration Costs and the New Consumers Margin in International Trade. *Journal of Political Economy* 118(6): 1151–99.

[7]. Autor, D. H., D. Dorn, and G. H. Hanson. 2013. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review* 103 (6): 2121–68.

[8]. Autor, D. H., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu. 2016. Foreign Competition and Domestic Innovation: Evidence from US Patents. *NBER Working Paper* 22879. National Bureau of Economic Research, Cambridge, MA.

[9]. Bartik, T. J. 1991. Boon or Boondoggle? The Debate over State and Local Economic Development Policies. In *Who Benefits from State and Local Economic Development Policies*, edited by Timothy J. Bartik, 1–16. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

[10]. Bernard, A. B., S. J. Redding, and P. K. Schott. 2010. Multiple-Product Firms and Product Switching. *American Economic Review* 100 (1): 70–97.

[11]. Bloom, N., M. Draca, and J. Van Reenen. 2016. Trade-Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies* 83 (1): 87–117.

[12]. Bond, S., and M. Soderbom. 2005. Adjustment Costs and the Identification of Cobb-Douglas Production Functions. *IFS Working Papers*, No. 05/04. Institute for Fiscal Studies, London.

[13]. Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang. 2017. WTO Accession and Performance of Chinese Manufacturing Firms. *American Economic Review* 107 (9): 2784–2820.

[14]. Brandt, L., J. Van Biesebroeck, and Y. Zhang. 2012. Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics* 97 (2): 339–51.

[15]. Caliendo, L., M. Dvorkin, and F. Parro. 2017. Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *NBER Working Paper* 77999. National Bureau of Economic Research, MA.

[16]. Dai, M., M. Maitra, and M. Yu. 2016. Unexceptional Exporter Performance in China? The Role of Processing Trade. *Journal of Development Economics* 121 (7): 177–89.

[17]. Fajgelbaum, P. D., G. M. Grossman and E. Helpman. 2011. Income Distribution, Product Quality, and International Trade. *Journal of Political Economy* 119(4): 721–65.

[18]. Fan, H., Y. A. Li, and S. R. Yeaple. 2015. Trade Liberalization, Quality, and Export Prices. *Review of Economics and Statistics* 97 (5): 1033–51.

[19]. Fan, H., Y. A. Li, and S. R. Yeaple. 2018. On the Relationship between Quality and Productivity: Evidence from China's Accession to the WTO. *Journal of International Economics* 110: 28–49.

[20]. Feenstra, R. C., Z. Li, and M. Yu. 2014. Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China. *Review of Economics and Statistics* 96 (4): 729–44.

[21]. Feenstra, R. C., and J. Romalis. 2014. International Prices and Endogenous Quality. *Quarterly Journal of Economics* 129 (2): 477–527.

[22]. Gandhi, A., S. Navarro, and D. Rivers. 2016. On the Identification of Production Functions: How Heterogeneous is Productivity? Center for Human Capital and Productivity, Western University, Ontario, Canada.

[23]. Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova. 2009. Trade Liberalization and New Imported Inputs. *American Economic Review* 99 (2): 494–500.

[24]. Hallak, J. C. 2006. Product Quality and the Direction of Trade. *Journal of International Economics* 68 (1): 238–65.

[25]. Hallak, J. C., and P. K. Schott. 2011. Estimating Cross-Country Differences in Product Quality. *Quarterly Journal of Economics* 126 (1): 417–74.

[26]. Ing, L. Y. 2009. Lower Tariff, Rising Skill Premium in Developing Countries: Is It a Coincidence? *World Economy* 32 (7): 1115–33.

[27]. Johnson, R. C. 2012. Trade and Prices with Heterogeneous Firms. *Journal of International Economics* 86 (1): 43–56.

[28]. Khandelwal, A. 2010. The Long and Short (of) Quality Ladders. *Review of Economic Studies* 77 (4): 1450–76.

[29]. Khandelwal, A. K., P. K. Schott, and S. J. Wei. 2013. Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters. *American Economic Review* 103 (6): 2169–95.

[30]. Kugler, M., and E. A. Verhoogen. 2012. Prices, Plant Size, and Product Quality. *Review of Economic Studies* 79(1): 307–39.

[31]. Levinsohn, J., and A. Petrin. 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies* 70 (2): 317–41.

[32]. Manova, K., and Z. Zhang. 2012. Export Prices across Firms and Destinations. *Quarterly Journal of Economics* 127 (1): 379–436.

[33]. Martin, J., and I. Mejean. 2014. Low-wage Country Competition and the Quality Content of High-wage Country Exports. *Journal of International Economics* 93 (1): 140–52.

[34]. Mayer, T., M. J. Melitz, and G. I. Ottaviano. 2014. Market Size, Competition, and the Product Mix of Exporters. *American Economic Review* 104 (2): 495–536.

[35]. Olley, G. S., and A. Pakes. 1996. The Dynamics of Productivity in the Telecommunications Equipment. *Econometrica* 64 (6): 1263–97.

[36]. Pavcnik, N. 2002. Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants. *Review of Economic Studies* 69 (1): 245–76.

[37]. Pierce, J. R., and P. K. Schott. 2016. The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review* 106 (7): 1632–62.

[38]. Rauch, J. E. 1999. Networks Versus Markets in International Trade. *Journal of International Economics* 48(1): 7–35.

[39]. Redding, S. J., and D. E. Weinstein. 2017. Aggregating from Micro to Macro Patterns of Trade. *NBER Working Paper* No. w24051. National Bureau of Economic Research, Cambridge, MA.

[40]. Schott, P. K. 2004. Across-Product Versus Within-Product Specialization in International Trade. *Quarterly Journal of Economics* 119 (2): 647–78.

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

[42]. Verhoogen, E. A. 2008. Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector. *Quarterly Journal of Economics* 123 (2): 489–530.

[43]. Xu, B. 2003. Trade Liberalization, Wage Inequality, and Endogenously Determined Nontraded Goods. *Journal of International Economics* 60 (2): 417–31.

[44]. Yu, M. 2015. Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms. *Economic Journal* 125 (585): 943–88.

6 Appendix A: Step 4 in Estimating Export Quality

We propose a five-step iteration procedure to estimate quality. Among the five steps, Step 4 includes estimation of Equation (18) using a two-stage control function approach proposed by ACF (2015) to mitigate the simultaneity problem.

$$\ln Q^{*}_{jkgt} - (1 - \theta_g) \ln q^{*}_{jkgt} = \theta_g \ln \varphi_{jgt} + \theta_g \alpha_g \ln K_{jkgt} + \theta_g (1 - \alpha_g) \ln L_{jkgt}$$

We describe this approach in detail in this appendix. Throughout this appendix, the two-stage estimation is done for each HS 4-digit product separately, so we abstract the subscript g for conciseness.

We first rewrite the equation (log quality unit g) as Equation (A1):

$$y_{jkt} = \beta_k \cdot k_{jkt} + \beta_l \cdot l_{jkt} + \omega_{jt} + \varepsilon_{jkt} \quad \text{……(A1)}$$

y_{jkt} is $\ln Q^{*}_{jkt} - (1 - \theta_g) \ln q^{*}_{jkgt}$. k_{jkt}, and l_{jkt} are simply the log form of K_{jkt} and L_{jkt}. ω_{jt} is $(\beta_k + \beta_l) \ln \varphi_{jt}$ and ε_{jkt} is the idiosyncratic random shocks due to measurement errors. Both ω_{jt} and ε_{jkt} are unobserved.

ω_{jt} is likely to be correlated with k_{jkt} and l_{jkt} and therefore induces endogeneity. We follow ACF (2015) to introduce an observable input demand proxy variable m_{jkt} which satisfies Equation (A2):

$$m_{jkt} = g(\omega_{jt}, k_{jkt}, l_{jkt}) \quad \text{……(A2)}$$

Equation (A2) states that conditional on k_{jkt} and l_{jkt}, intermediate input m_{jkt} is the function of ω_{jt}. We impose the following assumption.

Assumption A1. *Conditional on* k_{jkt} and l_{jkt}, $m_{jkt} = g(\omega_{jt}, k_{jkt}, l_{jkt})$ *is invertible in* ω_{jt}.

Under the assumption that $g(\omega_{jt}, k_{jkt}, l_{jkt})$ is conditionally invertible, we can transform ω_{jt} into Equation (A3):

$$\omega_{jt} = g^{-1}_{\omega}(m_{jkt}, k_{jkt}, l_{jkt}) \quad \text{……(A3)}$$

And we proxy m_{jkgt} by:

$$m_{jkgt} = \ln\left(\frac{R^*_{jkgt}}{R^*_{jt}} \cdot M_{jt}\right)$$

M_{jt} is the absolute value of real intermediate inputs, which is obtained from the ASM data set. R^*_{jkgt} is the total value of sales of firm j in product g to destination k in year t, while $R^*_{jt} = \sum_{k,g} R^*_{jkgt}$.

Plugging Equation (A2) into Equation (A1), we obtain:

$$y_{jkt} = \beta_k k_{jkt} + \beta_l l_{jkt} + g^{-1}_{\omega}(m_{jkt}, k_{jkt}, l_{jkt}) + \varepsilon_{jkt} = \Phi(m_{jkt}, k_{jkt}, l_{jkt}) + \varepsilon_{jkt} \quad \text{……(A4)}$$

We use third-order polynomials of $(m_{jkt}, k_{jkt}, l_{jkt})$ to non-parametrically approximate $\Phi(m_{jkt}, k_{jkt}, l_{jkt})$. Therefore, estimating Equation (A4) generates an estimated $\widehat{\Phi}_{jkt} \equiv \widehat{\Phi}(m_{jkt}, k_{jkt}, l_{jkt})$ of Φ_{jkt}. This completes the first-stage estimation.

Before we proceed to the second-stage estimation, we specify that the production efficiency $\ln \varphi_{jt}$ follows an AR(1) process, which is equivalent to the claim that ω_{jt} follows an AR(1) process:

$$\omega_{jt} = \rho\omega_{jt-1} + \delta_{jt}$$

δ_{jt} is the innovation in production efficiency orthogonal to ω_{jt-1}. Therefore, the following moment condition holds:

$$E[\delta_{jt} + \varepsilon_{jkt} | I_{jkt-1}] = 0 \Rightarrow$$

$$E[y_{jkt} - \beta_k k_{jkt} - \beta_l l_{jkt} - \rho(\Phi_{jkt-1} - \beta_k k_{jkt-1} - \beta_l l_{jkt-1}) | I_{jkt-1}] = 0 \quad \text{……(A5)}$$

We define y_{jt}, Φ_{jt-1}, $k_{jt(t-1)}$ and $l_{jt(t-1)}$:

$$y_{jt} = \sum_{k \in \Omega_{jt}} y_{jkt}; \; \Phi_{jt-1} = \sum_{k \in \Omega_{jt}} \Phi_{jkt-1}$$
$$k_{jt(t-1)} = \sum_{k \in \Omega_{jt}} k_{jkt(t-1)}; \; l_{jt(t-1)} = \sum_{k \in \Omega_{jt}} l_{jkt(t-1)};$$

Ω_{jt} is the set of destinations where firm j sells (product g) in year t. Summing Equation (A5) within each firm-year combination across destination k generates the following moment condition, Equation (A6):

$$E[y_{jt} - \beta_k k_{jt} - \beta_l l_{jt} - \rho(\Phi_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1})|I_{jt-1}] = 0 \quad \text{......(A6)}$$

Following ACF (2015), we specify $I_{jt-1} = \{1, k_{jt}, l_{jt}, \Phi_{jt-1}, k_{jt-1}, l_{jt-1}\}$. Therefore, we use nonlinear least squares to estimate Equation (A7) to complete the second-stage estimation.

$$y_{jt} = \beta_k k_{jt} + \beta_l l_{jt} + \rho(\Phi_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}) + \xi_{jt} \quad \text{......(A7)}$$

$\xi_{jt} = \delta_{jt} + \sum_{k\in\Omega_{jt}} \varepsilon_{jkt}$. This procedure jointly estimates β_k and β_l. So $\hat{\theta} = \hat{\beta}_k + \hat{\beta}_l$ and $\hat{\alpha} = \frac{\hat{\beta}_k}{\hat{\theta}}$. We can proceed to calculate the estimated value for $\ln\varphi_{jt}$, as in Equation (A8):

$$\ln\varphi_{jt} = \frac{y_{jt} - \hat{\beta}_k \cdot k_{jt} - \hat{\beta}_l \cdot l_{jt}}{\hat{\theta} \cdot \sum_k 1(k \in \Omega_{jt})} \quad \text{......(A8)}$$

$1(k \in \Omega_{jt})$ is a dummy variable indicating whether destination k is among one of the destinations where firm j sells (product g) in year t. We implement this control function approach for each HS 4-digit product to get $\hat{\theta}_g$, $\hat{\alpha}_g$, and $\ln\hat{\varphi}_{jgt}$.

7 Appendix B: Production Function Estimation

We augment the Olley-Pakes algorithm with export/import status and year-specific effects to estimate the following production function for Indonesian firms:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \quad \ldots\ldots\text{(B1)}$$

where the productivity ω_{it} follows a first-order Markov process:

$$\omega_{it} = h(\omega_{it-1}) + \zeta_{it}$$

with ζ_{it} being a mean-zero shock conditional on ω_{it-1}.

The augmented procedure consists of three stages. In the first stage, we specify the control function using firm investment as a proxy variable and use a nonparametric function to control for simultaneity bias when estimating β_l and β_m. In the second stage, we estimate the survival probability of a firm. In the third stage, we incorporate the survival probability and the control function to estimate β_k consistently.

Stage 1. According to Olley and Pakes (1996), a firm's investment I_{it} is an increasing function of productivity ω_{it} and capital stock k_{it}. Meanwhile, the firm's investment can also be affected by its export/import decision and aggregate shocks, as suggested by Amiti and Konings (2007). We therefore specify the following investment function:

$$I_{it} = I(\omega_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t) \quad \ldots\ldots\text{(B2)}$$

FX_{it} and FM_{it} are dummies equal to one when i is an exporter and importer, respectively, in year t. δ_t are year dummies. We implicitly assume that export/import status is predetermined, as in Amiti and Konings (2007). If $I(\bullet)$ is invertible in ω_{it}, then we have

$$\omega_{it} = I^{-1}(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t) \quad \ldots\ldots\text{(B3)}$$

Inserting Equation (B3) into Equation (B1), we have

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + g(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t) + \varepsilon_{it} \quad \ldots\ldots\text{(B4)}$$

with $g(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t) = \beta_k k_{it} + I^{-1}(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t)$.

Following Olley and Pakes (1996) and Amiti and Konings (2007), we use higher polynomials of $(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t)$ to non-parametrically approximate

$g(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t)$. We can therefore consistently estimate β_l and β_m in Equation (B4). We also obtain consistent estimates of $g(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t)$, $\hat{g}_{it}$.

Stage 2. Before we can consistently estimate β_k, we need to take care of the potential selection bias stemming from the firm's exit decision. We first estimate a probit model as follow:

$$Survival_{it} = f(k_{it-1}, I_{it-1}) \qquad \text{……(B5)}$$

$Survival_{it}$ is a dummy equal to one if i is still active in t and equal to zero if i is not active in t. $f(k_{it-1}, I_{it-1})$ is again nonparametrically approximated by higher polynomials of (k_{it-1}, I_{it-1}). We can therefore obtain an estimate of firm i 's survival probability in year t, $\hat{p}_{it}$.

Stage 3. We define $r_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}$. Since the firm's investment decision is also affected by future survival probability $\hat{p}_{it}$, we have

$$\begin{aligned} r_{it} &= \beta_k k_{it} + I^{-1}(I_{it}, k_{it}, FX_{it}, FM_{it}, \delta_t) \\ &= \beta_k k_{it} + h(\omega_{it-1}) + \zeta_{it} + \varepsilon_{it} \\ &= \beta_k k_{it} + F(\hat{g}_{it-1} - \beta_k k_{it-1}, \hat{p}_{it}) + \zeta_{it} + \varepsilon_{it} \end{aligned} \qquad \text{……(B6)}$$

Again, we use higher polynomials of $(\hat{g}_{it-1} - \beta_k k_{it-1}, \hat{p}_{it})$ to approximate $F(\hat{g}_{it-1} - \beta_k k_{it-1}, \hat{p}_{it})$, and nonlinear least squares to estimate Equation (B6). This generates a consistent estimate of β_k.

We perform the procedures above for each ISIC rev.4 2-digit industry.

8 Tables

Table 1. Price and Measured Quality of Chinese Products

	Dependent variable: $\ln uv_{jkgt}$			
Explanatory variable	(1)	(2)	(3)	(4)
$\ln z_{jkgt}$	1.066***	1.068***	1.203***	1.200***
	(0.001)	(0.001)	(0.001)	(0.001)
$Diff_g$	0.946***	0.921***		
	(0.004)	(0.004)		
$\ln z_{jkgt} \times Diff_g$	0.199***	0.192***	0.030***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
Year fixed effects	No	Yes	Yes	No
Product fixed effects	No	No	Yes	No
Product-destination-year fixed effects	No	No	No	Yes
Observations	7,639,763	7,639,763	7,639,763	7,639,763
R-squared	0.880	0.882	0.965	0.972

Note: Robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 2. Evolution of Indonesian TFP and Quality Competition: 2008–12

		$\ln TFP_{it}$		$\ln TFP_{it}^{Normalized}$		GQC_{it}	
Year	Obs.	Mean	Median	Mean	Median	Mean	Median
2008	6,133	3.220	3.120	-0.085	-0.114	0.957	0.777
2009	6,580	3.324	3.190	-0.070	-0.071	0.984	0.779
2010	6,485	3.299	3.165	0.018	-0.034	0.959	0.789
2011	7,094	3.423	3.207	0.033	-0.012	0.954	0.843
2012	7,163	3.526	3.335	0.087	0.032	1.096	0.974

Table 3. Baseline Results

	Dependent variable: $\Delta \ln TFP_{it}$					
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.047***	0.047***	0.047***	0.046***	0.045***	0.046***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
$FIE_{it} = 1$		-0.017		-0.004	-0.004	-0.004
if foreign share > 10%		(0.016)		(0.018)	(0.018)	(0.018)
$FX_{it} = 1$			-0.010	-0.010	-0.011	-0.011
if export share > 0%			(0.011)	(0.011)	(0.011)	(0.011)
$FM_{it} = 1$			-0.019	-0.018	-0.017	-0.016
if import share > 0%			(0.012)	(0.014)	(0.014)	(0.014)
Year fixed effects	No	No	No	No	Yes	No
Island-year fixed effects	No	No	No	No	No	Yes
Observations	13,444	13,444	13,444	13,444	13,444	13,444
R-squared	0.002	0.002	0.002	0.002	0.003	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4. Controlling for Output and Input Tariffs

	Dependent variable: $\Delta \ln TFP_{it}$					
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.046***	0.046***	0.046***	0.046***	0.046***	0.046***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)
$\Delta \ln \tau^{O}_{it-1}$	0.555		0.545			
	(0.416)		(0.415)			
$\Delta \ln \tau^{I}_{it-1}$		0.528	0.541			
		(0.766)	(0.777)			
$\Delta \ln \tau^{O,W}_{it-1}$				0.540		0.532
				(0.413)		(0.413)
$\Delta \ln \tau^{I,W}_{it-1}$					0.313	0.311
					(0.795)	(0.811)
$FIE_{it} = 1$	-0.007	-0.003	-0.006	-0.007	-0.004	-0.007
if foreign share > 10%	(0.020)	(0.018)	(0.020)	(0.020)	(0.018)	(0.020)
$FX_{it} = 1$	-0.010	-0.010	-0.009	-0.010	-0.011	-0.009
if export share > 0%	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$FM_{it} = 1$	-0.016	-0.016	-0.016	-0.016	-0.016	-0.016
if import share > 0%	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,708	13,444	12,708	12,708	13,444	12,708
R-squared	0.005	0.005	0.005	0.005	0.005	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5. Control for Quality Competition from Other Countries

	Dependent variable: $\Delta \ln TFP_{it}$			
Explanatory variable	(1)	(2)	(3)	(4)
ΔGQC_{it-1}	0.046***	0.046***	0.046***	0.046***
	(0.013)	(0.013)	(0.013)	(0.013)
$\Delta \ln \tau_{it-1}^{O}$	0.518	0.543	0.516	0.542
	(0.416)	(0.415)	(0.416)	(0.416)
$\Delta \ln \tau_{it-1}^{I}$	0.583	0.543	0.578	0.538
	(0.780)	(0.777)	(0.781)	(0.778)
ΔOQC_{it-1}^{FR}	-0.033		-0.033	
	(0.033)		(0.033)	
ΔOQC_{it-1}^{UV}		0.002		0.002
		(0.008)		(0.008)
$FIE_{it} = 1$	-0.007	-0.006		
if foreign share > 10%	(0.020)	(0.020)		
$FX_{it} = 1$	-0.009	-0.009		
if export share > 0%	(0.012)	(0.012)		
$FM_{it} = 1$	-0.017	-0.016		
if import share > 0%	(0.014)	(0.014)		
Foreign share			-0.011	-0.010
			(0.022)	(0.022)
Export share			-0.019	-0.018
			(0.019)	(0.019)
Import share			-0.021	-0.021
			(0.024)	(0.024)
Island-year fixed effects	Yes	Yes	Yes	Yes
Observations	12,708	12,708	12,708	12,708
R-squared	0.005	0.005	0.005	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6. Interaction with Export and Import Status

	Dependent variable: $\Delta \ln TFP_{it}$					
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.057***	0.042***	0.053***	0.049***	0.042***	0.044***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$FX_{it} = 1$	-0.011		-0.009			
if export share > 0%	(0.012)		(0.012)			
$\Delta GQC_{it-1} \times FX_{it}$	-0.041		-0.044			
	(0.028)		(0.031)			
Export share				-0.019		-0.018
				(0.019)		(0.019)
$\Delta GQC_{it-1} \times$ export share				-0.060		-0.074
				(0.052)		(0.055)
$FM_{it} = 1$		-0.018	-0.016			
if import share > 0%		(0.014)	(0.014)			
$\Delta GQC_{it-1} \times FM_{it}$		0.020	0.027			
		(0.038)	(0.039)			
Import share					-0.023	-0.021
					(0.024)	(0.024)
$\Delta GQC_{it-1} \times$ import share					0.038	0.051
					(0.050)	(0.052)
$FIE_{it} = 1$	-0.014	-0.009	-0.006			
if foreign share > 10%	(0.018)	(0.019)	(0.020)			
Foreign share				-0.017	-0.016	-0.010
				(0.020)	(0.021)	(0.022)
Tariff and quality controls	Yes	Yes	Yes	Yes	Yes	Yes
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,708	12,708	12,708	12,708	12,708	12,708
R-squared	0.005	0.005	0.005	0.005	0.005	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7. Channels and Mechanisms: Competition and Product Turnover

	Dependent variable: $\Delta \ln TFP_{it}$					
	Low HHI	High HHI	Full sample	Multi-prod	Sing. prod	Full sample
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.052***	-0.037	0.052***	0.068***	0.039**	0.039**
	(0.013)	(0.035)	(0.013)	(0.020)	(0.015)	(0.015)
HHI_high			-0.007			
			(0.026)			
$\Delta GQC_{it-1} \times HHI\_high$			-0.089**			
			(0.035)			
Multi_product						0.006
						(0.011)
$\Delta GQC_{it-1} \times Multi\_product$						0.029
						(0.025)
$\Delta \ln \tau^{O}_{it-1}$	0.743*	-2.856	0.582	0.777	0.402	0.537
	(0.413)	(2.531)	(0.415)	(0.635)	(0.536)	(0.416)
$\Delta \ln \tau^{I}_{it-1}$	0.316	2.377	0.502	-0.699	0.918	0.558
	(0.804)	(3.078)	(0.778)	(1.576)	(0.888)	(0.779)
ΔOQC_UV_{it-1}	0.002	-0.001	0.002	-0.009	0.010	0.003
	(0.008)	(0.026)	(0.008)	(0.012)	(0.009)	(0.008)
Foreign share	0.013	-0.149**	-0.008	0.001	-0.030	-0.008
	(0.021)	(0.065)	(0.020)	(0.027)	(0.029)	(0.019)
Export share	-0.015	0.054	-0.009	-0.001	-0.018	-0.010
	(0.013)	(0.047)	(0.012)	(0.016)	(0.017)	(0.012)
Import share	-0.021	0.013	-0.016	-0.008	-0.026	-0.017
	(0.015)	(0.056)	(0.014)	(0.021)	(0.021)	(0.014)
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,801	907	12,708	4,891	7,817	12,708
R-squared	0.006	0.039	0.005	0.007	0.005	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8. Adjustment of Product Scope

	Dependent variable: Number of products			
	(1)	(2)	(3)	(4)
Explanatory variable	Poisson	Neg. binomial	Poisson	Neg. binomial
ΔGQC_{it-1}	-0.023*	-0.017*	-0.026*	-0.016*
	(0.013)	(0.009)	(0.014)	(0.009)
$\Delta \ln \tau^{O}_{it-1}$	1.378	0.780	1.282	0.846
	(0.874)	(0.667)	(0.944)	(0.704)
$\Delta \ln \tau^{I}_{it-1}$	1.590	0.982	1.412	0.929
	(1.652)	(0.899)	(1.651)	(0.918)
ΔOQC^{UV}_{it-1}	0.001	0.001	0.002	0.001
	(0.021)	(0.011)	(0.021)	(0.011)
Foreign share	0.256***	0.269***	0.249***	0.260***
	(0.083)	(0.069)	(0.082)	(0.066)
Export share	1.595***	1.668***	1.580***	1.648***
	(0.066)	(0.064)	(0.063)	(0.061)
Import share	0.310***	0.246***	0.343***	0.282***
	(0.093)	(0.068)	(0.091)	(0.066)
ISIC 2-digit fixed effects	Yes	Yes	Yes	Yes
Island-year fixed effects	No	No	Yes	Yes
Observations	12,708	12,708	12,708	12,708

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9. Channels and Mechanisms: Intensive or Extensive Margin

	Dependent variable: $\Delta \ln TFP_{it}$					
	Non-exit	Exit	Full sample	Unbalance	Balance	Full sample
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.050***	-0.019	0.050***	0.031	0.053***	0.052***
	(0.014)	(0.049)	(0.014)	(0.029)	(0.014)	(0.014)
$Exit_{it}$			0.027			
			(0.032)			
$\Delta GQC_{it-1} \times Exit_{it}$			-0.064			
			(0.047)			
$Unbalanced_i$						-0.011
						(0.013)
$\Delta GQC_{it-1} \times Unbalanced_i$						-0.021
						(0.032)
$\Delta \ln \tau^{O}_{it-1}$	0.465	-0.512	0.416	-0.374	0.734*	0.536
	(0.416)	(1.837)	(0.412)	(1.077)	(0.434)	(0.416)
$\Delta \ln \tau^{I}_{it-1}$	0.822	-3.835*	0.540	-2.950**	1.081	0.516
	(0.820)	(2.024)	(0.782)	(1.390)	(0.852)	(0.775)
ΔOQC_UV_{it-1}	-0.005	0.020	-0.001	0.006	-0.000	0.002
	(0.009)	(0.027)	(0.009)	(0.014)	(0.009)	(0.008)
$FIE_{it} = 1$	-0.007	0.123	0.003	-0.026	-0.000	-0.007
if foreign share > 10%	(0.026)	(0.163)	(0.027)	(0.055)	(0.020)	(0.020)
$FX_{it} = 1$	0.007	-0.110*	-0.007	-0.002	-0.011	-0.010
if export share > 0%	(0.016)	(0.065)	(0.016)	(0.026)	(0.014)	(0.012)
$FM_{it} = 1$	-0.044**	0.098	-0.031	-0.028	-0.011	-0.016
if import share > 0%	(0.019)	(0.093)	(0.019)	(0.038)	(0.014)	(0.014)
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,288	1,052	8,340	3,507	9,201	12,708
R-squared	0.007	0.011	0.006	0.006	0.007	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 10. Alternative Measures and Controls

Dependent variable:	Δ Labor productivity		$\Delta \ln TFP_{it}$ by LP		$\Delta \ln TFP_{it}$ by ACF	
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.053***	0.053***	0.042***	0.042***	0.039*	0.039*
	(0.020)	(0.020)	(0.014)	(0.014)	(0.021)	(0.021)
$\Delta \ln \tau^{O}_{it-1}$	0.626	0.639	0.710*	0.698	0.844	0.823
	(0.600)	(0.600)	(0.429)	(0.428)	(0.580)	(0.578)
$\Delta \ln \tau^{I}_{it-1}$	1.321	1.336	1.033	1.019	1.125	1.101
	(0.915)	(0.915)	(1.289)	(1.291)	(0.953)	(0.954)
ΔOQC_UV_{it-1}	0.002	0.002	0.009	0.009	-0.008	-0.008
	(0.012)	(0.012)	(0.007)	(0.007)	(0.013)	(0.013)
$\Delta K_{it-1}/L_{it-1}$		-0.011		0.012		0.022*
		(0.011)		(0.008)		(0.012)
$FIE_{it} = 1$	-0.026	-0.027	-0.023	-0.022	-0.007	-0.006
if foreign share > 10%	(0.025)	(0.025)	(0.020)	(0.021)	(0.026)	(0.026)
$FX_{it} = 1$	-0.027*	-0.026*	-0.006	-0.006	-0.021	-0.021
if export share > 0%	(0.016)	(0.016)	(0.012)	(0.012)	(0.017)	(0.017)
$FM_{it} = 1$	-0.001	-0.001	-0.019	-0.019	0.011	0.011
if import share > 0%	(0.019)	(0.019)	(0.015)	(0.015)	(0.020)	(0.020)
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,319	12,319	12,696	12,696	12,696	12,696
R-squared	0.006	0.006	0.007	0.007	0.004	0.005

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 11. Industry-Specific Fixed Effects

	Dependent variable: $\Delta \ln TFP_{it}$			
Explanatory variable	(1)	(2)	(3)	(4)
ΔGQC_{it-1}	0.045***	0.045***	0.042***	0.042***
	(0.012)	(0.012)	(0.013)	(0.013)
$\Delta \ln \tau^{O}_{it-1}$	-0.113	-0.133	-0.224	-0.239
	(0.468)	(0.467)	(0.506)	(0.505)
$\Delta \ln \tau^{I}_{it-1}$	0.870	0.849	0.489	0.460
	(0.742)	(0.744)	(0.742)	(0.744)
ΔOQC_UV_{it-1}	-0.005	-0.005	-0.008	-0.008
	(0.008)	(0.008)	(0.008)	(0.008)
$\Delta K_{it-1}/L_{it-1}$		0.019**		0.017**
		(0.008)		(0.008)
$FIE_{it} = 1$	-0.040*	-0.039*	-0.039*	-0.038*
if foreign share > 10%	(0.021)	(0.021)	(0.021)	(0.021)
$FX_{it} = 1$	-0.009	-0.009	-0.013	-0.013
if export share > 0%	(0.012)	(0.012)	(0.012)	(0.012)
$FM_{it} = 1$	-0.043***	-0.043***	-0.041***	-0.041***
if import share > 0%	(0.015)	(0.015)	(0.015)	(0.015)
ISIC 2-digit fixed effects	Yes	Yes	No	No
ISIC 2-digit-year fixed effects	No	No	Yes	Yes
Island-year fixed effects	Yes	Yes	Yes	Yes
Observations	12,708	12,708	12,708	12,708
R-squared	0.040	0.041	0.054	0.055

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 12. Alternative Specifications

	Dependent variable: $\Delta \ln TFP_{it}$					
	1-period difference		2-period difference			
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)
ΔGQC_{it-1}	0.052***	0.052***	0.057***	0.056***	0.066***	0.064***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.016)	(0.017)
$\Delta \ln \tau^{O}_{it-1}$		0.301		0.108		-0.316
		(0.634)		(0.642)		(0.711)
$\Delta \ln \tau^{I}_{it-1}$		0.295		-0.306		0.168
		(1.108)		(1.332)		(1.762)
ΔOQC_UV_{it-1}		-0.005		-0.001		0.001
		(0.009)		(0.010)		(0.014)
$FIE_{it} = 1$	-0.259*	-0.294*	-0.048	-0.048	-1.435**	-1.546**
if foreign share > 10%	(0.142)	(0.157)	(0.039)	(0.044)	(0.703)	(0.772)
$FX_{it} = 1$	-0.021	-0.021	0.014	0.019	0.000	-0.000
if export share > 0%	(0.029)	(0.029)	(0.023)	(0.025)	(0.092)	(0.092)
$FM_{it} = 1$	-0.107*	-0.127*	0.055**	0.060**	0.025	0.000
if import share > 0%	(0.065)	(0.069)	(0.026)	(0.027)	(0.230)	(0.244)
Island-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	No	Yes	Yes
Observations	13,444	12,708	7,722	7,288	7,722	7,288
R-squared	0.008	0.008	0.008	0.008	0.016	0.017

Note: The first-difference removes firm-specific fixed effects in Equation (28). Robust standard errors corrected for clustering at the firm level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A1. Evolution of Median Export Quality from China, 2008–12, by CIC 2-Digit

CIC 2-digit	2008	2009	2010	2011	2012	2012-2007
Processing of food 13	0.544	0.573	0.673	0.719	0.637	0.093
Manufacturing of food 14	0.600	0.515	0.550	0.568	0.572	-0.028
Beverage 15	0.681	0.603	0.628	0.629	0.729	0.048
Textile 17	0.904	0.877	0.894	0.905	0.929	0.025
Apparel 18	1.289	1.278	1.312	1.369	1.368	0.079
Leather 19	1.426	1.663	1.601	1.703	1.732	0.306
Wood 20	0.935	0.957	1.009	0.990	1.084	0.149
Furniture 21	1.970	2.012	1.980	1.993	2.020	0.050
Paper 22	1.224	1.308	1.220	1.288	1.359	0.135
Printing 23	1.900	1.971	1.892	1.890	1.980	0.080
Cultural & sports 24	1.313	1.329	1.276	1.389	1.400	0.087
Petroleum 25	0.182	0.131	0.231	0.076	-0.138	-0.320
Chemical 26	0.840	0.835	0.867	0.829	0.810	-0.030
Medicine 27	1.439	1.541	1.540	1.233	1.339	-0.100
Chemical fiber 28	0.675	0.650	0.646	0.757	0.833	0.158
Rubber 29	1.191	1.102	1.183	1.098	1.119	-0.072
Plastic 30	1.271	1.313	1.341	1.346	1.373	0.102
Non-metallic 31	0.971	0.931	1.026	0.891	0.933	-0.038
Ferrous metals 32	0.504	0.405	0.365	0.371	0.384	-0.120
Non-ferrous metals 33	.	1.873	0.956	0.867	0.907	.
Metal products 34	1.213	1.213	1.210	1.239	1.273	0.060
General machinery 35	1.574	1.575	1.619	1.610	1.706	0.132
Special machinery 36	2.008	2.017	2.005	1.995	2.129	0.121
Transportation vehicle 37	1.466	1.472	1.478	1.457	1.521	0.055
Electrical 40	1.255	1.279	1.236	1.264	1.305	0.050
Communication & computers 41	2.008	2.053	2.068	2.118	2.231	0.223
Measuring & office 42	1.707	1.841	1.734	2.005	2.108	0.401
Artwork & other 43	1.324	1.280	1.313	1.334	1.318	-0.006

Note: "." indicates missing value.

9 Figure

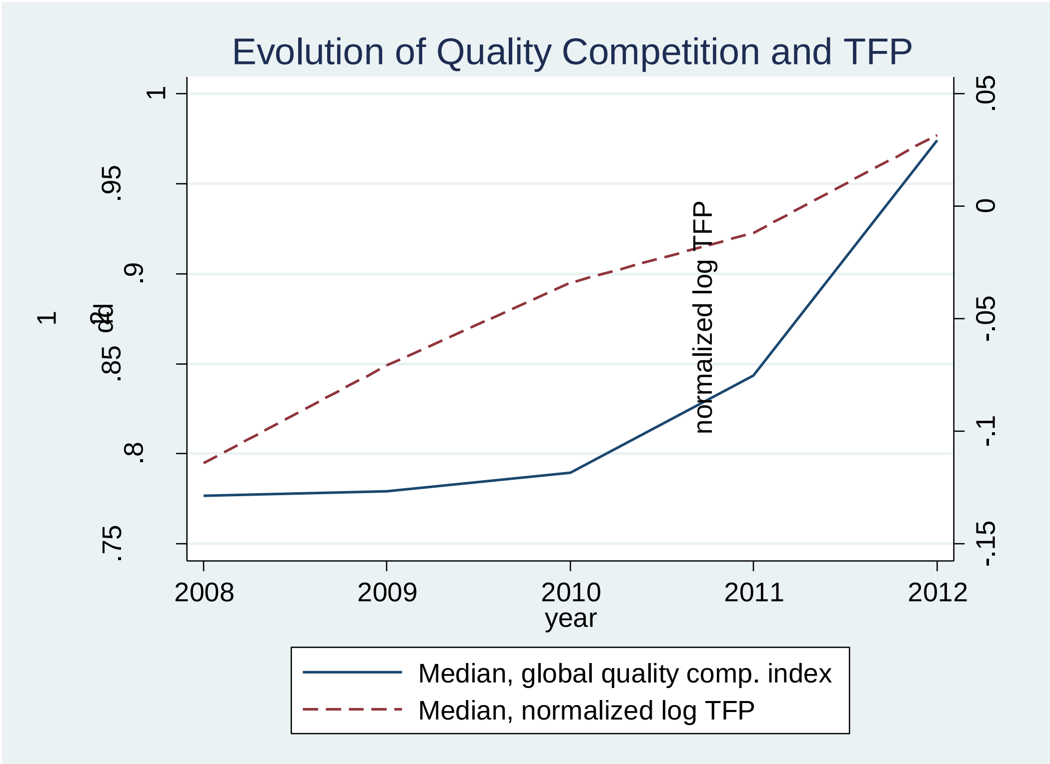

Figure 1. Global Quality Competition Index and Normalized Log TFP