The Quality Response to Real Exchange Rate Shocks:

A Panel SVAR Analysis on China's Agricultural Exports

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Abstract This paper applies a panel structural VAR model to uncover both the dynamics and inter-product/market differences in responses of product quality to real exchange rate (RER) shocks with complete data of China's monthly agricultural exports. It finds that RER appreciations promote the quality of China's agricultural exports on average in contrast to discouraging exports, but the effect is mostly short-run—the average response peaks in the immediate month after the shock and phases out in three months. Following domestic price and quality itself, RER shocks account for 3% on average in quality variations as the third contributor. The quality response to RER shocks, however, substantially differs across both products and markets.

1 INTRODUCTION

The exchange rate plays an important role in international trade. The rate of Chinese yuan is of particular interest to researchers. With a series of exchange rate reforms, yuan's misalignment issue has diminished in recent years, which is expected to have far-reaching implications on exports. On the one hand, many studies have noted the negative export impact resulting from real exchange rate appreciations (Cushman, 1983; Forbes, 2002; Marquez & Schindler, 2007; Berman et al., 2012; Li et al., 2015). On the other hand, however, aggravated market competition, restructured product mix, and ameliorated vertical integration might lead to quality improvements to enhance firms' capability to cope with the challenge of losing price competitiveness, which would increase exports in the long run.

Empirical evidence on this latter view that currency appreciation facilitates quality upgrading, however, has been focused on manufactured products, and findings are mixed at best. To be specific, some supported the view by highlighting following channels. First, the intensified competition could provide stronger incentives to upgrade export quality (Flach, 2016; Dai et al., 2018). Second, seeing the elasticity of demand and quality-adjusted price, the structure of export basket might improve as low-quality products exit the market and the share of high-quality goods increases (Auer & Chaney, 2009; Chen & Juvenal, 2016; Fauceglia, 2019). Third, firms would use higher-quality intermediate inputs as import costs decrease (Feng et al., 2016; Hu et al., 2019). In contrast, other studies argued that exchange rate appreciations may result in consumption shifts to low-quality products (Hummels & Skiba, 2004; Xing & Zhao, 2008).

Though China is the fourth largest exporter and the third largest importer of agricultural products in the world (European Commission, 2019), the impact of exchange rates on traded agricultural goods has not been well examined in the literature (Tian & Yu, 2017). This study will fill in the gap by investigating the impact of real exchange rate on the quality of exported agricultural goods in China. The quality response of agricultural products could differ from that of manufactured goods for a number of reasons. First, since agricultural products are perishable, the quality tends to vary during the export process including packaging, shipping and storage. Both the market distance and product attributes related with perishability will thus influence the incentive to upgrade product quality after exchange rate appreciations. Second, some quality attributes of agricultural products (e.g. color and size) are relatively easy to observe as those of manufactured goods, but others (e.g. taste, safety and nutrition) tend to be intrinsic. While the intrinsic quality of processed agricultural products could be signaled using tools such as advertising and branding, producers of primary goods often have greater difficulties to do so. Third, the quality response of agricultural products might be particularly strong in the short run, because seasonality in production and difficulty in preservation indicate that supply can hardly be postponed or reduced during appreciations. Thus, to consider quality responses to real exchange rate shocks of agricultural products, it is necessary to distinguish different time horizons and emphasize heterogeneities on both market and product dimensions.

Panel data models often utilized in current studies are difficult to accommodate quality changes of agricultural products, which might feature noticeable dynamic patterns and inter-sectoral/market heterogeneities as we discussed above, for two limitations. First, such models are designed for "large N and small T" data. The reliance on disaggregated annual data in these works, therefore, indicates that they only measure the average influence of exchange rate movements on product quality within a year. Second, panel data models account for time-invariant heterogeneities with fixed effects and limited channels of heterogeneous responses with specified interaction terms. Inter-sectoral/market differences throughout the complete dynamics of quality responses to exchange rate shocks are not fully reflected.

In this paper, we first extend the Melitz (2003) model to theorize the relationship between real exchange rate (RER) and product quality. Resting on this framework, we derive a panel structural VAR (PSVAR) empirical setup with five endogenous variables, i.e. RER, quality, unit price in yuan, quantity, and the destination's real income, which enables us to estimate the complete dynamic path of quality responses after RER shocks in each product-market duplet. The use of monthly data of China's agricultural exports, coupled with the PSVAR model, allows us to disentangle the short-run effects from those in the long run. This distinction is important not only because the ability to inter-temporally smooth the competition pressure can be limited for agricultural exporters, which is mentioned above, but also because it helps to unveil possible driving forces behind quality changes. For example, an immediate quality response can be evidence to improvement of quality structure in the export basket. In contrast, if an RER shock leads to increased innovations or better intermediate inputs, quality responses in the long run will be expected. According to Pedroni (2013), each shock in the PSVAR model can be divided into a common and an idiosyncratic component, with the former indicating systematic disturbances received by all panel units and the latter representing the impact only on a particular individual. Comparing the quality response to each RER shock component, we would infer whether the quality of agricultural products is more sensitive to an overall appreciation or a market-specific appreciation of the same scale. Finally, taking estimated quality responses from RER shocks to empirical models, we explore product and destination characteristics that determine quality responses.

Compared with estimating the data of each panel unit separately, the PSVAR model utilizes the information of both inter-temporal and cross-sectional variations when teasing out the heterogenous response dynamics. Due to the length of our monthly data, individual time series might not be long enough either to reflect the true underlying data-generating process. Meanwhile, the PSVAR model retains the advantage of VAR models by allowing all variables to be endogenous, which avoids the challenge to find valid IVs for the potential issue of endogeneity in RER changes. As a typical VAR system, the PSVAR model only considers a few factors. However, the monthly data frequency helps to alleviate the concern of confounding factors as long as they move at the year level.

As demonstrated by Feenstra and Romalis (2014), product quality is determined by technology and demand. Among empirical investigations into the quality of agricultural products, nevertheless, most of them took a supply-side perspective. By highlighting the role of climate and environmental conditions, institution of cooperatives, food quality and safety regulations, and inspection measures, they revealed how the technology choice and constraints influence the quality of agricultural outputs (Jaffee & Masakure, 2005; Jones et al., 2005; Pennerstorfer & Weiss, 2013; Khan et al., 2017). The influence of exchange rate, however, works primarily through the demand channel seeing that RER appreciations are fundamentally equivalent to "tariffication" (Thorstensen et al., 2012). Though the role of consumer demand in the growth of high-quality agricultural products has been noticed in the literature (Pingali, 2007), it remains unclear how exactly demand shocks lead to quality adjustments. The monthly data allows us investigate demand-side impacts without controlling supply-side factors, in particular technology, which are moving at a relatively lower frequency.[1]

[1] In addition, since our PSVAR model is estimated at the product-market level, technology will be absorbed by fixed effects, unless it varies across exports of the same product to different destinations, which is not a likely case in reality.

The rest of this paper is organized as follows. In Sector 2, a theoretical model is set up to figure out the vector of endogenous variables to be considered. Section 3 specifies the PSVAR model and introduces estimation strategies. Data and variable definitions are discussed in Section 4. The results are presented in Sector 5. Section 6 concludes the paper.

2 THEORETICAL FRAMEWORK

Consider products at various quality levels as different varieties of agricultural outputs. Quality could then be modelled as a multiplier of quantity in consumer's utility *a la* Khandelwal, Shcott, and Wei (2013). Let ω indicate product varieties. The utility function of a representative consumer in the CES form, with σ as the elasticity of substitution, thus becomes:

$$U_{ct} = \left(\int_{\omega\in\Omega}\big(\lambda_{ct}(\omega)q_{ct}(\omega)\big)^{\frac{\sigma-1}{\sigma}}d\omega\right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

The subscript c is an index for country and t is that for time. λ and q respectively represent quality and quantity consumed out of variety ω, which nests in the set of all varieties Ω. Apparently, utility grows when either quality or quantity increases. According to Equation (1), demand for variety ω is determined as

$$q_{ct}(\omega) = Q_{ct}\lambda_{ct}(\omega)^{\sigma-1}\left(\frac{P_{ct}}{p_{ct}(\omega)}\right)^{\sigma}, \tag{2}$$

with Q and P respectively denoting the aggregate consumption quantity and the average price.

The Law of One Price implies that for an imported variety, its price will be determined by both the nominal exchange rate e (indirect quote) and the price in the exporting country π according to $p_{ct}(\omega) = e_{ct}\pi_{ct}(\omega)$. Since $RER_{ct} = e_{ct}\Pi_t/P_{ct}$ by definition, where Π is the average price in the exporting country, we can rewrite Equation (2) as follows:

$$\lambda_{ct}(\omega) = \left(\frac{q_{ct}(\omega)}{Q_{ct}}\right)^{\frac{1}{\sigma-1}} \left(\frac{\Pi_t}{RER_{ct}\pi_{ct}(\omega)}\right)^{-\frac{\sigma}{\sigma-1}}. \tag{3}$$

Equation (3) suggests that the quality of China's exports of variety ω to country c is related to five factors: (1) the aggregate consumption of country c, Q; (2) the quantity of this variety that China exports to country c, q; (3) the bilateral RER between yuan and country c's currency, RER (indirect quote); (4) the price of this variety in yuan, π; and (5) China's aggregate price index, Π. However, since China's price index is invariant across either importing countries or product varieties, it would be automatically excluded from the PSVAR model according to estimation strategies as we describe below. We are thus eventually concerned with the remaining four factors together with quality itself as the vector of endogenous variables in the VAR system. Due to the difficulty to measure aggregate quantity Q, the real GDP per capita of each importing country is utilized as the proxy of Q according to Hallak (2006).

3 EMPIRICAL SPECIFICATION AND ESTIMATION STRATEGY

Consistent with Equation (3), we specify a PSVAR model, which is proposed by Pedroni (2013) and recently applied for instance by Gamtessa & Olani (2018), Hao, Pedroni, Colson, and Wetzstein (2017), and Mishra, Montiel, Pedroni, and Spilimbergo (2014), with the log value of five endogenous variables. The log transformation allows us to interpret estimated response without the concern over the measurement units. Let $y_{cht} = (\ln \lambda_{cht}, \ln q_{cht}, \ln \pi_{cht}, \ln RER_{ct}, \ln RGDPPC_{ct})'$ be a vector of these variables, with subscript h replacing ω in the theoretical model to denote product variety. In line with Pedroni (2013), we then consider a PSVAR model as follows:

$$y_{cht} = \sum_{s=0}^{\tau_{ch}} A_{ch,s} L^s \epsilon_{cht}, \;\; \epsilon_{cht} = \Lambda_{ch} \bar{\epsilon}_t + \tilde{\epsilon}_{cht}. \tag{4}$$

In Equation (4), ϵ_{cht} is the vector of exogenous structural shocks which satisfy $E(\epsilon_{cht}) = 0$ and $E(\epsilon_{cht}\epsilon'_{cht}) = I$.

Equation (4) illustrates that the PSVAR model extends the VAR framework by assuming both cross-sectional and inter-temporal dependence of data. In particular, the cross-sectional dependence is modelled in the error term specification by decomposing each shock ϵ_{cht} into a common and an idiosyncratic component that are orthogonal to each other by construction. The common component $\bar{\epsilon}_t$ is received systematically by all product-market duplets, although in each duplet its contribution relies on the diagonal loading matrix Λ_{ch}. The idiosyncratic component $\tilde{\epsilon}_{cht}$ instead reflects cross-sectionally independent disturbances. Inter-temporal dependence is modelled in the auto-regressive specification of Equation (4), as in conventional VAR models. The lag operator L allows the current endogenous variables to depend on shocks in the past. The coefficient matrix $A_{ch,s}$ delineates the impact of shocks which took place *s* periods ago.

It must be noted that the PSVAR model in Equation (4) considers heterogeneities in the impulse response rates across product-market duplets throughout the entire dynamics, which is a remarkable improvement over conventional panel data models. In particular, cross-sectional heterogeneities are incorporated into both cross-sectional and inter-temporal dependence relationships. On the one hand, regarding auto-regressive relationships, all coefficient matrices $A_{ch,s}$ are allowed to differ across panel units. On the other hand, for contemporaneous relationships, cross-sectional heterogeneities are considered in both the loading matrix Λ_{ch} for the common component in exogenous shocks and the idiosyncratic component which is specific to each panel unit.

The PSVAR model can be estimated through five steps following Pedroni (2013). First, all the variables are demeaned within each product-market duplet to eliminate time-invariant fixed effects and then first-differenced to guarantee stationarity[2]. We remove possible seasonality in monthly data by incorporating monthly fixed effects into the demeaning process. Second, the reduced-form VAR model for each product-market duplet associated with the structural specification in Equation (4) is estimated, with the maximal lag order being selected by the information criteria[3] and allowed to differ across panel units. We can then back out structural shocks from the reduced-form estimations with the help of identification assumptions as we describe below. Third, estimation in the previous step is repeated for the "average" series[4] across all product-market duplets with a number of N_t, which is defined as $\bar{y}_t = \sum_{ch} y_{cht}/N_t$. We can thus back out common components in structural shocks $\bar{\epsilon}_t$. Fourth, taking correlation coefficients between ϵ_{cht} and $\bar{\epsilon}_t$ as diagonal elements, the loading matrix Λ_{ch} in each product-market duplet could then be calculated. We thus derive impulse response functions (IRFs) to common shock components using coefficient matrices defined as $\bar{A}_{ch,s} = A_{ch,s}\Lambda_{ch}$. Finally, according to orthogonality conditions, we can derive coefficient matrices for IRFs to idiosyncratic shock components as $\tilde{A}_{ch,s} = A_{ch,s} - \bar{A}_{ch,s}$. We also follow Pedroni (2013) to normalize $\tilde{A}_{ch,s}$.

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2 Test results for panel unit roots are available in Appendix Table A1.

3 According to Lütkepohl (2005) and Pedroni (2013), the maximal lag order is selected according to the overall performance of five criteria which include the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), the Hannan and Quinn information criterion (HQIC), and Likelihood ratio (LR).

4 These series are also stationary. Test results for unit roots are available in Appendix Table A2.

Typically, though the composite shock and its common component are specified as having a size of unit, the idiosyncratic component is not. Our normalization rescales IRFs as if they follow a unit-sized idiosyncratic shock component. Therefore, estimated IRFs to different shock components can be directly compared.

To orthogonalize reduced-form residuals and back out the structural form of our panel VAR model in the second step above, we have to impose identifying restrictions on the model dynamics. Restrictions are specified on the matrix of contemporaneous coefficients $A_{ch,0}$, since we are more interested in the short-run relationships among variables than those on the steady state, and long-run identifying restrictions might yield inaccurate IRF estimates (Christiano et al., 2006; Erceg et al., 2005; Faust & Leeper, 1997). Specifically, we assume that $A(0)_{5,i} = 0$ for any $i \neq 5$, i.e. the real GDP per capita of each destination is not contemporaneously affected by shocks to other variables. The reason is that the macro economy is usually taken as given to individual markets of each product at least in the short run (Lastrapes, 2006) and the instantaneous exchange rate pass-through is limited (Gopinath & Rigobon, 2008). We also assume that $A(0)_{4,j} = 0$ for $j = 1, 2, 3$, i.e. RER is not contemporaneously influenced by China's export quality, quantity, and domestic price, for a similar reason. Finally, restrictions $A(0)_{1,2} = 0$ (i.e. quality is not contemporaneously affected by quantity) and $A(0)_{3,2} = A(0)_{3,4} = 0$ (i.e. the price measured in yuan is not contemporaneously affected by either export quantity or RER) are imposed, since quality and quantity are independent choices by exporters according to Feenstra and Romalis (2014) and in models of monopolistic competition the price of a given product variety in China depends only on the unit cost and demand elasticity. With a vector of five variables, the above restrictions would guarantee an exact identification.

4 DATA AND VARIABLES

4.1 Measurement of Quality

In reality, quality is reflected by a wide range of intrinsic characteristics of agricultural products such as color, flavor, freshness, texture, and nutrition contents. Although some traits are explicit to consumers (e.g. color) whereas others tend to be hidden (e.g. nutrition contents), they can eventually be reflected in consumption behaviors with the help of signaling (Yu and Abler, 2009; Auriol & Schilizzi, 2015). It has been found that conditional on price, quality determines the purchasing decision of consumers (Barrett et al., 2010; Tian & Yu, 2017; Kyriacou & Rouphael, 2018). Consider two baskets of apples for example, it can be inferred that the one with greater sales to have higher quality (e.g. fresher or sweeter) if price is the same. Following Khandelwal, Schott, and Wei (2013), we thus define quality as product attributes making consumers willing to purchase more, conditional on product price. Accordingly, quality is estimated using the demand-side approach as follows:

$$\ln q_{cht} = -\sigma \ln p^*_{cht} + \phi_h + \phi_{ct} + \eta_{cht}. \tag{5}$$

In Equation (5), q_{cht} and p^*_{cht} are respectively the export quantity and price (in foreign currencies) of China's agricultural product *h* in market *c* and period *t*. The market-time fixed effect ϕ_{ct} reflects both the income level and aggregative price of the market, which may influence the export quantity respectively through income and substitution effect channels. The product fixed effect ϕ_h, instead, is introduced since prices and quantities may not be comparable across products.

According to Khandelwal, Schott, and Wei (2013), quality is measured by an OLS estimation of Equation (6) in log value as follows:

$$\ln \hat{\lambda}_{cht} = \hat{\eta}_{cht}/(\sigma - 1). \tag{6}$$

In order to avoid the concern of endogeneity, we choose the elasticity of substitution σ according to estimates of Broda and Weinstein (2006), which vary across products (σ_h). We normalize the estimated quality as an index between 0 and 1, so it can be compared across periods and markets. That is,

$$norm(\ln \hat{\lambda}_{cht}) = \frac{\ln \hat{\lambda}_{cht} - \min \ln \hat{\lambda}_h}{\max \ln \hat{\lambda}_h - \min \ln \hat{\lambda}_h}, \tag{7}$$

where $\min \ln \hat{\lambda}_h$ and $\max \ln \hat{\lambda}_h$ are respectively the minimum and maximum quality estimates of product h in the entire sample period.

4.2 Data

Our analysis relies on monthly data between 2002 and 2015 complied from three sources. The first is trade statistics of the Development Research Center of the State Council of China (DRCnet), which include all Chinese product-destination level export value and quantity. The second source is International Financial Statistics (IFS), which offers both bilateral nominal exchange rates and each country's CPI such that the bilateral RER could be computed. The third is country data of Economist Intelligence Unit (EIU), which provides real GDP and population data to calculate the real GDP per capita. Since real GDP and population data are respectively reported on a quarterly and yearly basis we convert them to a monthly frequency using the Chow-Lin method with Eviews before calculating the monthly real GDP per capita.

For the purpose of this paper, we consider agricultural exports of China defined as products in the first 24 chapters under the HS coding system according to Beestermöller, Disdier, and Fontagné (2018). Products with different and unconvertible quantity units (e.g. from kg to box) over the sample period are excluded, so we can measure product price as the ratio between the total value and volume of export. Although the export value is measured in US dollars in DRCnet, the product price in yuan or each destination's currency can be calculated using nominal exchange rates. However, agricultural exports reported at the HS 8-digit level are aggregated up to the 6-digit level to match with the elasticity of substitution estimated by Broda and Weistein (2006). Those with missing estimates of the elasticity, less than 7% in China's agricultural exports by value, are excluded. For each product-market duplet, there might be gaps in China's export data. We fill sporadic gaps, which account for 2.2% of all gaps in our data, by linear interpolation using adjacent values. Product-market duplets still with gaps after this filling would be excluded, in order to avoid failures in estimating the PSVAR model.

We eventually come up with 165,163 observations for 989 product-market duplets through 168 months. To alleviate the influence of extreme values, data is winsorized at the 1% level at both ends. Table 1 provides descriptive statistics of our sample.

[Table 1 about here]

5 ESTIMATION RESULTS

5.1 Impulse Responses of Export Quality

Figure 1 demonstrates IRFs of product quality in China's agricultural exports to an exogenous unit-sized shock on RER, real GDP per capita, product price in yuan, export quantity, and the quality itself (driven for example by the discovery of disease-resistant species) respectively. Since IRFs differ across product-market duplets, we present the median IRF with IRFs at the 25% and 75% quantiles in each panel of Figure 1 to show dynamic distributions. Besides, we are concerned with composite shocks at the moment, without dividing them into common and idiosyncratic components.

[Figure 1 about here]

Panel (a) indicates that on average, an RER appreciation shock of yuan would lead to an overall quality upgrading of China's agricultural exports. According to the median IRF, the instantaneous quality response in the period when the shock takes place is close to zero. However, in the following month, a noticeably positive quality response is observed, which could result from the fact that low-quality products exit the market and the share of high-quality goods increases. The response turns negative, albeit tiny, in the second month after the shock, which is likely due to the *Alchian-Allen effect* as the relative price advantage of low-quality goods might become more pronounced when local distribution costs account for a smaller share in the final price to consumers after the appreciation. The average quality response converges to zero since the third months, implying that in most cases the influence of RER shocks is concentrated in the short run. It implies that quality changes are more likely driven by an ameliorated quality structure of export basket, rather than alternative forces pointed out in the literature such as sustained innovations or better intermediate inputs. Summing up estimated median quality response during the first three months, we find that a 1% RER appreciation of yuan produces on average a 0.001% increase of export quality. Such relatively instantaneous quality responses are in line with high risks of fulfilling agricultural trade contracts[5], although contracts are typically signed a considerable time ahead of exports. It implies that in reality, agricultural exporters could still enjoy the room to adjust their export baskets even in the short term.

There are, nevertheless, substantial heterogeneities across product-market duplets in the quality response as indicated by IRFs at the 25% and 75% quantiles. IRF at the 25% quantile illustrates that for some products or markets, the quality response might remain negative following an appreciation shock. Persistent quality downgrading could be cost-related, since to offset cost increments resulting from appreciations, some exporters may use less-costly inputs (Álvarez & López, 2009). By contrast, IRF at the 75% quantile suggests persistent quality upgrading for some other products and markets. That is, the RER appreciation might result in sustained innovations and improved inputs. In Section 5.3, we will explore product and market characteristics giving rise to these heterogeneities in quality responses. The substantial heterogeneities along the dynamic path of IRFs lend support to the choice of the PSVAR model over conventional panel data models.

In the rest panels of Figure 1, we respectively demonstrate the quality response to other shocks,

[5] Both exporters and importers have incentives to terminate or change contracts before shipment to avoid potential losses during exchange rate appreciations. For instance, orders may be canceled if importers expect to pay more than the market price, or when exporters find that the increase of production and trade costs makes the order unprofitable (for such cases in practice, see reports at http://www.mofcom.gov.cn/aarticle/resume/dybg/201204/20120408084531.html). Due to the long agricultural production cycle, exporters and importers may also allow for the possibility to cancel orders once the price increases beyond a prespecified level when contracts are signed (see https://hzdaily.hangzhou.com.cn/dskb/html/2010-11/14/content_968123.htm for the case).

including those on the real GDP per capita, product price in yuan, export quantity, and quality itself. Despite of notable heterogeneities as indicated by IRFs at the 25% and 75% quantiles again, we find a negative instantaneous response of export quality to the shock on real GDP per capita on average. A possible reason is that though income increases would in general induce more imports, higher quality products usually require a longer production time (Deloof & Jegers, 1996) and thus should respond more slowly. A positive response follows in the next month, which could result from the ameliorated export basket of China as the demand in the destination market improved. The median quality response to a shock on the price in yuan is largely positive and instantaneous, which imply that firms tend to sell higher-quality products that typically feature larger profit margins when their domestic prices are boosted, for example, by cost increases. In contrast, the quality response to quantity shocks is small and fluctuates around zero. Finally, the quality response to a shock on itself (driven for example by a productivity shock) is largely negative and instantaneous on average. The negative response may arise from the *Chamberlin effect*. That is, when high-quality products become available to consumers with relatively low preferences for quality, the average valuation of quality in the entire market decreases.

Summing up IRFs of quality to each shock within the first three months, we find that on average, quality responses to price and quality shocks are the largest, which are followed by responses to RER shocks. In contrast, quality responses to shocks on the real GDP per capita and quantity are the smallest. This is supported by the results of variance decompositions presented in Figure 2 as well. At the median level, the shock on quality itself and price in yuan are the largest contributors to quality variations in the short run, with an account of more than 95% of the total variations. In the long run, their combined contribution decreases to 80%. RER is the third largest contributor to quality variations, with the median contribution increasing from 0.5% in the short run to 3% in the long run. The contribution of RER exceeds 5% in some product-market duplets, according to estimates at the 75% quantile.

[Figure 2 about here]

Aside from quality impacts, RER appreciations would also influence both the export quantity and the domestic price of Chinese agricultural products. Consistent with Li, Ma, and Xu (2015), we find that on average, appreciations result in a reduced export quantity. Quantity contractions are the largest in the first month after the RER shock, and converge to zero afterwards. RER appreciations would also reduce product price measured in yuan. The median response also reaches the maximum in the first month after the shock, and then converges to zero. Nevertheless, the magnitude of price responses tends to be small, which is in line with Li, Ma, and Xu (2015) and implies that the exchange rate pass-through is high for Chinese exports. Specific estimated IRFs of quantity and price can be found in Appendix Figure A1.

5.2 Comparison of Quality Responses to Different Components of RER Shocks

In order to assess whether the product quality in China's agricultural exports is more sensitive to a common shock across all products and markets or a product-market specific idiosyncratic shock, we distinctively derive quality responses to common and idiosyncratic components in a

RER shock, and compare cumulated responses at the median level in three windows in Figure 3. These three windows are (1) 0-1 month, (2) 0-3 months, and (3) 0-12 months after the shock, corresponding respectively to the short, medium and long run.

In all these windows, we find that the scale of quality responses to the idiosyncratic RER shock component dominates that of responses to the common shock component. As the solid line in Figure 3 illustrates, the ratio of the scale of quality responses to the idiosyncratic component over that to the common component is around 2 and slightly decreases when a longer window is concerned. It implies that when an idiosyncratic shock hits a specific product-market duplet, the influence tends to be relatively transitory as the quality structure of export basket may be adjusted in a relatively prompt manner. In contrast, the influence of a systematic RER shock is more lasting, since it can be difficult to adjust the export basket immediately if yuan appreciates in all markets. Despite this difference, nonetheless, Figure 3 shows that overall speaking, the quality impact of either component is concentrated in the first three months following the shock, since response to both shock components only grow slightly as the window extends.

[Figure 3 about here]

5.3 Determinants of Quality Responses to the RER shock

Figure 1 demonstrates that IRFs of product quality among Chinese agricultural exports to the RER shock are substantially different across product-market duplets. To reveal how such differences depend on product and market characteristics, we consider the following empirical specification on determinants of cumulated quality response in each product-market duplet over a particular window:

$$\delta_{ch} = \beta_0 + \beta_1 RCA_{ch} + \boldsymbol{\beta}_2 \cdot \mathbf{x}_c + \phi_h + \varepsilon_{ch} \tag{8}$$

In Equation (8), subscripts *c* and *h* respectively represent the destination market and product variety. For each product-market duplet ch, δ_{ch} is cumulated quality responses to the RER shock in a specific window which is estimated from the PSVAR model above, and RCA_{ch} is the revealed comparative advantage of China in product h—defined as the ratio of the proportion of product h in China's total export value over the ratio for the world—relative to the revealed comparative advantage of market *c*. It can be derived from the BACI database. Meanwhile, we control a vector of market-specific characteristics denoted by $\mathbf{x}_c$, which includes two variables: (1) the real GDP per capita of the destination market, and (2) its distance from China which is reported in the CEPII database. Seeing difficulties to measure many product characteristics such as the easiness to demonstrate intrinsic product quality and preservation conditions, we introduce product-specific fixed effects in Equation (8) which is denoted by ϕ_h. β_0 and ε_{ch} are the constant and error terms as usual. Since the dependent variable δ_{ch} represents the average estimated response during the entire sample period, we use predetermined values in 2001 to measure all independent variables including product and market characteristics to avoid the concern of endogeneity. Estimation results would remain similar, however, if independent variables are instead measured by average values through the sample period as Hao, Pedroni, Colson and Wetzstein (2017).[6] Finally, RCA_{ch},

[6] Results are reported in Appendix Table A3.

which is a ratio between two export shares and such that the scale lacks a clear meaning, is rescaled on the support of [0, 1] to make it an effective index for the ranking of China's relative competitiveness in each product-market duplet during estimation.

In line with Figure 3, we again alternatively consider three particular windows for cumulated quality responses when estimating Equation (8), i.e. 0-1 month (the short run), 0-3 months (the medium run) and 0-12 months (the long run). Table 2 reports estimation results. It demonstrates that for all three windows of examination, the cumulated quality response is always negatively correlated with the destination market's real GDP per capita and its geographic distance from China. The price elasticity of demand in richer markets is usually smaller. Therefore, exporters to destinations with higher levels of real GDP per capita would have a weaker motivation to improve product quality when the RER shock reduces the price competitiveness of their products. Due to the perishability of agricultural products, quality improvements of agricultural exports might be more costly in relatively distant markets. Therefore, cumulated quality responses also tend to be smaller. Comparing across columns, it can be noted that the effect of distance is relatively important compared with that of real GDP per capita in the short run, whereas the two effects become more similar in the medium and long run. It implies that when an exporter considers improving the average product quality in the short run, typically by ameliorating the combination of products of various qualities, market proximity is the dominant concern. In contrast, when it considers enhancing quality in the medium and long run, e.g. through a sustained devotion to quality improvements, it would weigh the tradeoff between the distance and real GDP per capita of the market with a similar stress on each factor. Table 2 also points out that the cumulated quality responses are negatively correlated with China's revealed comparative advantage over that of the import market for the same product, though the effect is insignificant in the short run. This indicates that RER appreciations would be more detrimental for products and markets where China lacks a strong comparative advantage, and thus will induce greater quality-improving incentives.

[Table 2 about here]

Product fixed effects in Equation (8) capture all product-specific characteristics that are difficult to measure. To reveal possible characteristics embedded in these fixed effects, we compare estimates of fixed effects across products along two dimensions. The first is the processing degree of products that indicates whether products are relatively primary or processed. And the second is the share of processing trade in total exports from China, which reflects the importance of imported intermediate inputs. To facilitate the comparison, we normalize estimated fixed effects as follows to rescale them on the support of [0, 1]:

$$R_h = (fe_h - \min fe_h)/(\max fe_h - \min fe_h) \tag{9}$$

In Equation (9), fe_h denotes the estimated fixed effect of an HS six-digit product h, and $\max fe_h$ and $\min fe_h$ respectively indicate the maximal and minimal values across all products in the sample. Therefore, R_h, to which we will refer as the "rescaled product fixed effects", is effectively an index for the ranking of estimated fixed effects for product h.

We categorize HS six-digit products into two groups, which will be denoted as the group of less processed goods and that of more processed goods, according to Chen and Duan (2001).[7] In Figure 4, we compare the distribution of rescaled product fixed effects, R_h, between the two groups, where the solid line through the box indicates the median value of the distribution, the upper and lower edges specify the interquartile range, and the whiskers represent upper and lower adjacent values. The result demonstrates that regardless of which window is under examination, the majority of less processed products always have larger fixed effects, i.e. greater quality responses, relative to more processed goods, as indicated by the median value and both the upper and lower hinges (i.e. the 75th and 25th percentiles respectively). The finding of greater quality responses for less processed products upon an RER appreciation shock is in line with the fact that these products usually feature lower profit margins or more difficulties in preservation. Thus, the motivation of quality improvements tends to be stronger. RER appreciations may also induce exporters of less processed products to transform their relatively low-quality commodities to more processed alternatives, instead of being exported as raw products. In addition, the greater quality responses for less-processed products are also compatible with our finding in Table 2 that responses decrease with China's comparative advantage, since these products are typically land or resource intensive such that China does not enjoy strong competitiveness.

[Figure 4 about here]

[7] Specifically, less processed goods include bulk commodities including grain, oilseed, and plant-based fibers such as cotton, raw rubber and non-manufactured tobacco, as well as processed intermediates that require further processing for human consumption including flour, feed, live animals, animal fats or oil, and animal-based fibers. In contrast, more processed goods include consumer-ready commodities that are either with special handling such as containerization, e.g. preserved vegetables and fruits, or highly transformed, e.g. processed meat, manufactured tobacco, and beverages.

In Figure 5, we compare the estimated fixed effects according to the share of processing trade of each product in China's exports. Seeing that this share remains zero for many HS six-digit products during the sample period, we aggregate up products to the 24 HS chapters. That is, we first calculate the average fixed effects among products in each chapter and rescale it on the support of [0, 1], which is denoted as R_j, and then compute the share of processing trade in all exports under that chapter. We find that in general, the rescaled product fixed effects are smaller in chapters that include products relying more heavily on processing trade. The less sensitive quality responses in chapters with more processing trade is in line with similar findings documented in the literature (Dai et al., 2018) and have two possible explanations. First, a considerable amount of inputs is imported in processing trade. Therefore, RER appreciations result in both revenue and cost reductions, leaving profits hardly affected. Second, the room for quality improvements tends to be limited in processing trade, since critical technologies are controlled by foreign suppliers.

[Figure 5 about here]

6 CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, a PSVAR model is utilized to unveil both the dynamics and inter-product/market heterogeneities in quality responses of Chinese agricultural exports to the shock on yuan's RER. We find that on average, RER appreciations lead to quality improvements in the short run—the average response peaks in the month following the shock and phases out in three months. Quality responses substantially differ across product-market duplets and are more sensitive to the duplet-specific RER shock. Response heterogeneities rely on both market (e.g. geographic distance and income) and product (e.g. revealed comparative advantage) features. Besides, more sensitive quality responses are found among products that are relatively primary and exported less through processing trade.

The relatively instantaneous impact of RER appreciations on the product quality of agricultural exports highlights the importance for policy makers to closely track RER movements and efficiently share the information and predictions with agricultural exporters. The notably heterogeneous quality responses across product-market duplets suggest that the information would be particularly valuable for exports that are less competitive, relatively primary and exported through ordinary trade, as well as with nearby and less developed partners.

Our results have important policy implications both for the governments and exporting companies. The concentration of quality responses in the short run implies that quality improvements in China's agricultural exports after RER appreciations could primarily be a result of product amelioration in export baskets, i.e. reducing the composition of relatively low-quality products and increasing that of high-quality goods. Sustainably enhancing product quality, for example, with supports on R&D activities and the implementation of advanced technologies, thus remains a critical challenge to both the government and agricultural exporters to cope with RER appreciations. Seeing their less responsive quality improvements, such supports would be particularly important in exports to developed and distant markets.

Finally, improvements of product quality are associated with decreases in both export quantity and price. It thus implies that export profits are reduced with the appreciation shock. To alleviate these negative impacts, exporters might diversify RER uncertainties by both expanding export partners and relying on the domestic market. In the meantime, increasing and improving foreign exchange rate protection tools in a developing country like China where the financial sector is less mature would also provide exporters with stronger capabilities to withstand external shocks.

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Tables and Figures

Table 1. Descriptive Statistics of Variables in the PSVAR System

Variables	Obs.	Mean	Std. dev.	P10	P90
ln(quality)	165,163	0.528	0.181	0.294	0.770
ln(quantity)	165,163	12.41	1.940	10.03	14.85
ln(price in yuan)	165,163	2.525	1.113	1.318	3.979
ln(RER)	165,163	0.295	2.554	-2.283	4.809
ln(real GDP per capita)	165,163	8.828	0.821	7.613	9.428

Source. Development Research Center of the State Council of China (DRCnet), International Financial Statistics (IFS), Economist Intelligence Unit (EIU) and authors' calculations.

Table 2. Determinants of Cumulated Quality Responses to RER Shocks

Cumulated quality responses to the RER shock	(1) 0-1 month	(2) 0-3 months	(3) 0-12 months
ln(real GDP per capita)	-0.0004*	-0.0006**	-0.0008***
	(0.0002)	(0.0002)	(0.0002)
ln(distance)	-0.0012***	-0.0005*	-0.0009***
	(0.0003)	(0.0003)	(0.0003)
RCA	-0.0225	-0.0396***	-0.0421***
	(0.0144)	(0.0144)	(0.0144)
Product fixed effects	Yes	Yes	Yes
Observations	863	863	862
Adjusted R^2	0.1620	0.1067	0.1187

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Independent variables are measured by predetermined values in 2001 with definitions in text. Belgium and five other product-market duplets are excluded due to the lack of data to compute revealed comparative advantage. Variables are winsorized for extreme values.

Source. Authors' calculations using PSVAR model and OLS regression.

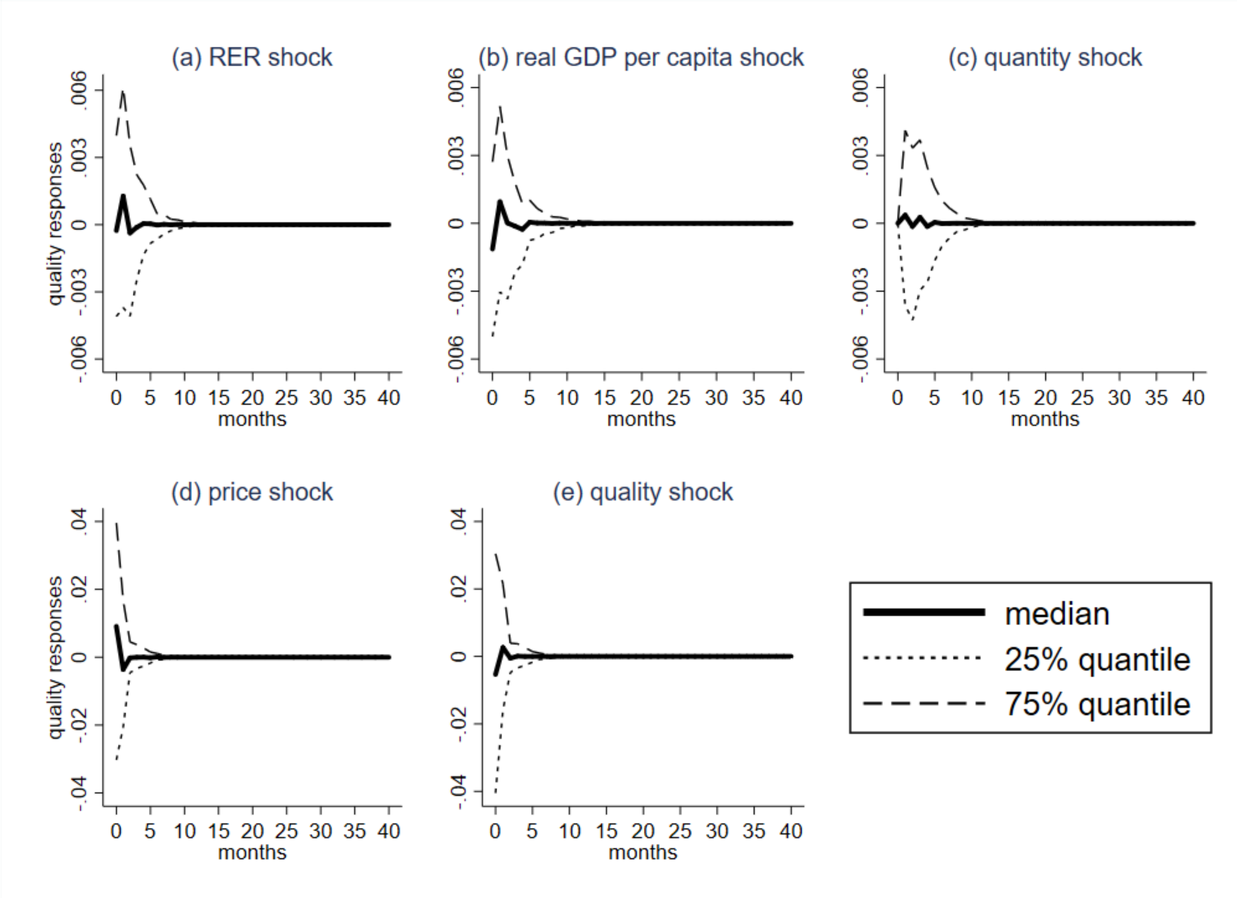

Figure 1. IRFs of Quality to Various Composite Shocks

Source. Authors' calculations using PSVAR model.

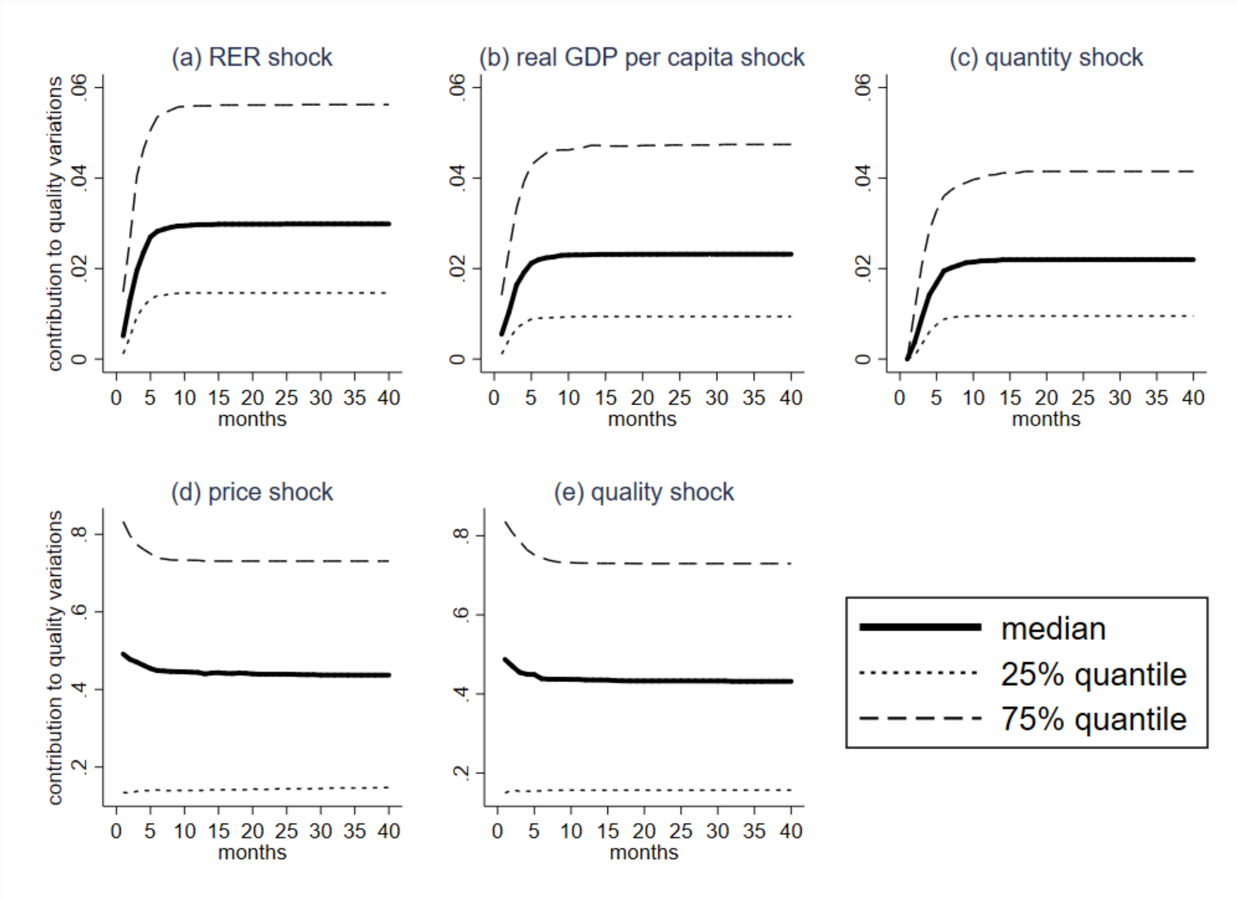

Figure 2. Variance Decompositions of Quality Variations

Source. Authors' calculations using PSVAR model.

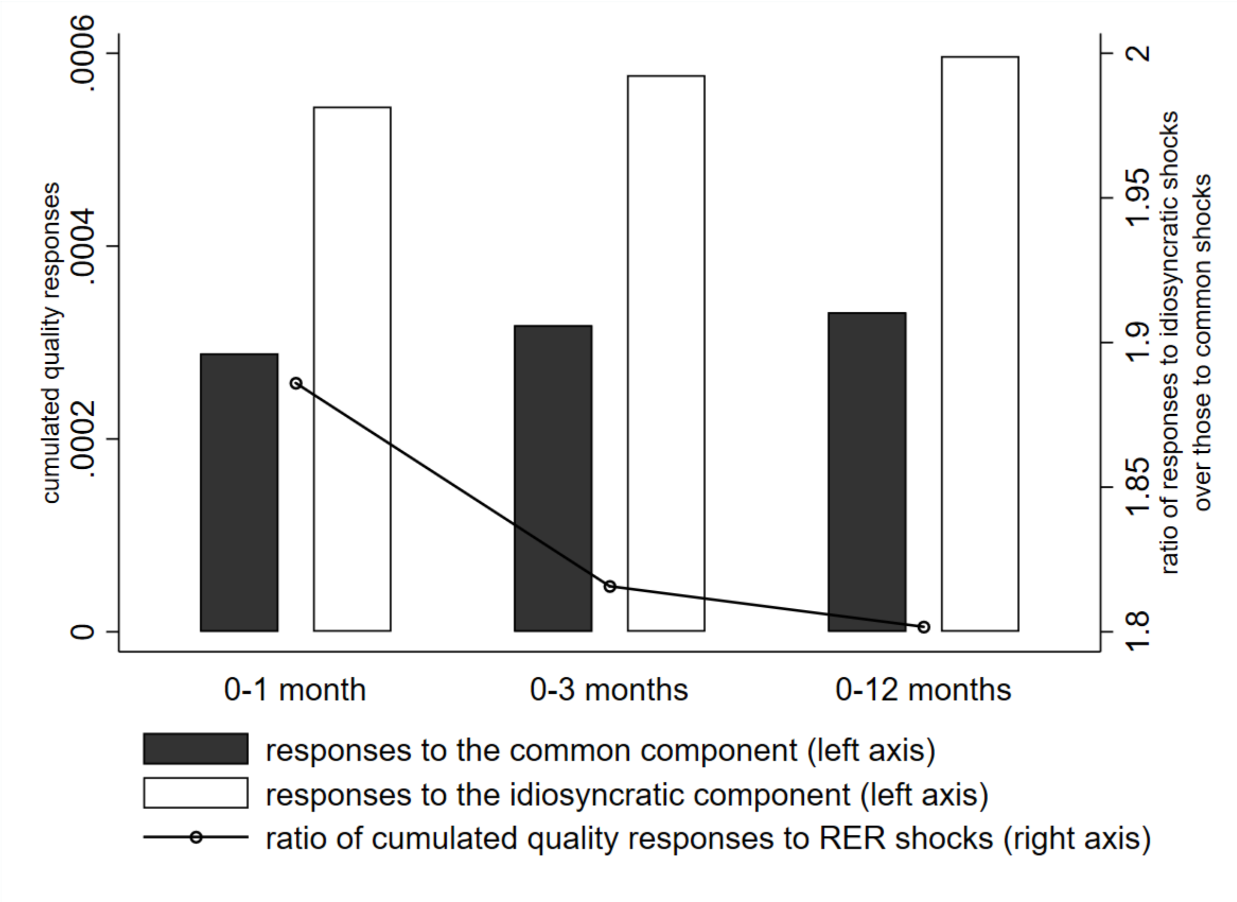

Figure 3. Comparison of Cumulated Quality Responses to Different RER Shock Components

Notes. The reported cumulated responses are medians in all product-market duplets.

Source. Authors' calculations using PSVAR model.

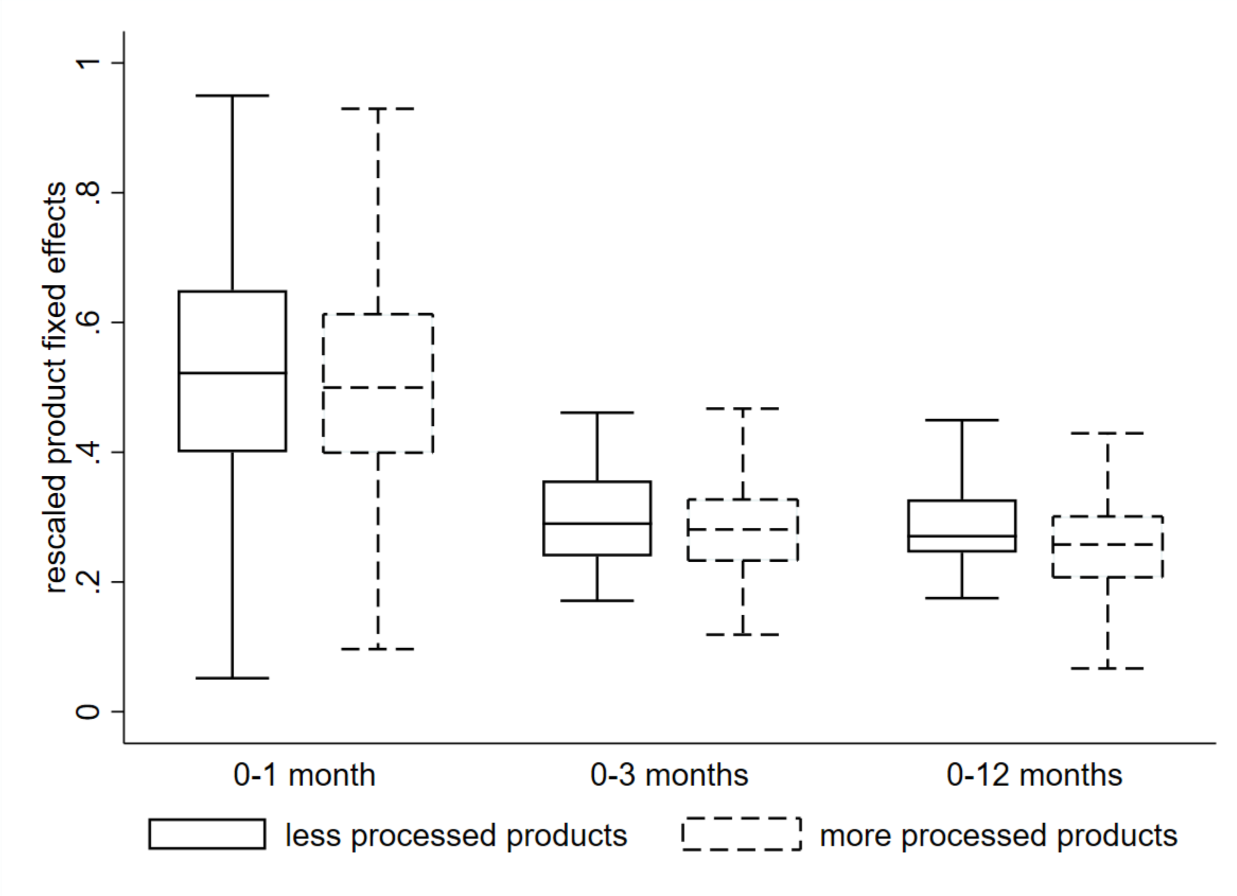

Figure 4. Rescaled Product Fixed Effects (R_h) and the Processing Degree of Products

Note: Product fixed effects are estimated from Equation (8) and rescaled to the range of [0, 1] according to Equation (9). The solid line through the box indicates the median value of the distribution of R_h, the upper and lower edges specify the interquartile range, and the whiskers represent upper and lower adjacent values. Outside values are excluded.

Source. Authors' calculations using PSVAR model and OLS regression.

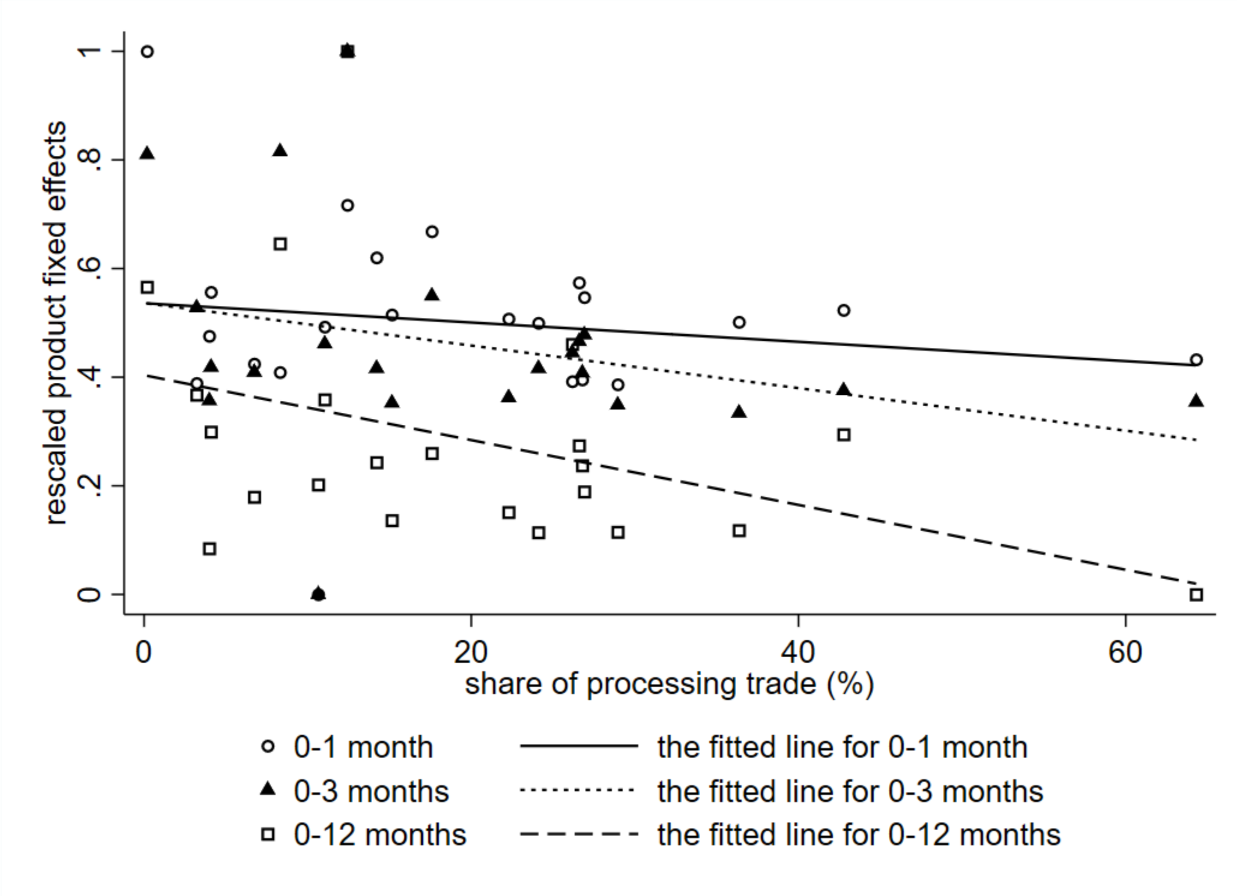

Figure 5. Rescaled Product Fixed Effects (R_j) and the Share of Processing Trade

Note: Product fixed effects are estimated from Equation (8) and averaged by chapters before rescaling on the support of [0, 1] according to Equation (9).

Source. Authors' calculations using PSVAR model and OLS regression.

APPENDIX

Table A1. Test Results for Panel Unit Roots

Variable	IPS			ADF-	PP-
	AIC	BIC	HQIC	Fisher	Fisher
quality	-310	-430	-360	64100	71300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
quantity	-300	-410	-330	58000	71300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
price in yuan	-320	-430	-370	67800	71200
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RER	-280	-310	-300	69300	69300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
real GDP per	-140	-140	-130	49600	39100
capita	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note. (1) probabilities for IPS tests are computed using W-t-bar statistics. (2) probabilities for Fisher tests are computed using a modifies inverse chi-square distribution. (3) The values in parentheses present p-value.

Source. Authors' calculations.

Table A2. Unit Root Test results for "Average" Series

Test	quality	quantity	price in yuan	RER	real GDP per capita
ADF	-22.325	-24.084	-15.999	-9.054	-4.045
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0012)
PP	-25.066	-34.988	-15.984	-8.970	-4.234
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)

Note. (1) Probabilities for Augmented Dickey-Fuller (ADF) tests are computed using Dickey-Fuller test statistic. (2) Probabilities for Phillips-Perron (PP) tests are computed using Phillips-Perron tau test statistic. (3) The values in parentheses present p-value.

Source. Authors' calculations.

Table A3. Robustness Check on Determinants of Cumulated Quality Responses to RER Shocks

Cumulated quality responses to the RER shock	(1) 0-1 month	(2) 0-3 months	(3) 0-12 months
ln(real GDP per capita)	-0.0006**	-0.0007***	-0.0009***
	(0.0003)	(0.0003)	(0.0002)
ln(distance)	-0.0012***	-0.0007**	-0.0010***
	(0.0003)	(0.0003)	(0.0003)
RCA	-0.0213	-0.0720***	-0.0595**
	(0.0268)	(0.0263)	(0.0246)
Product fixed effects	Yes	Yes	Yes
Observations	865	866	865
Adjusted R^2	0.1384	0.0899	0.1090

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Independent variables are measured by average values between 2002 and 2015 with definitions in text. Belgium and five other product-market duplets are excluded due to the lack of data to compute revealed comparative advantage. Variables are winsorized for extreme values.

Source. Authors' calculations using PSVAR model and OLS regression.

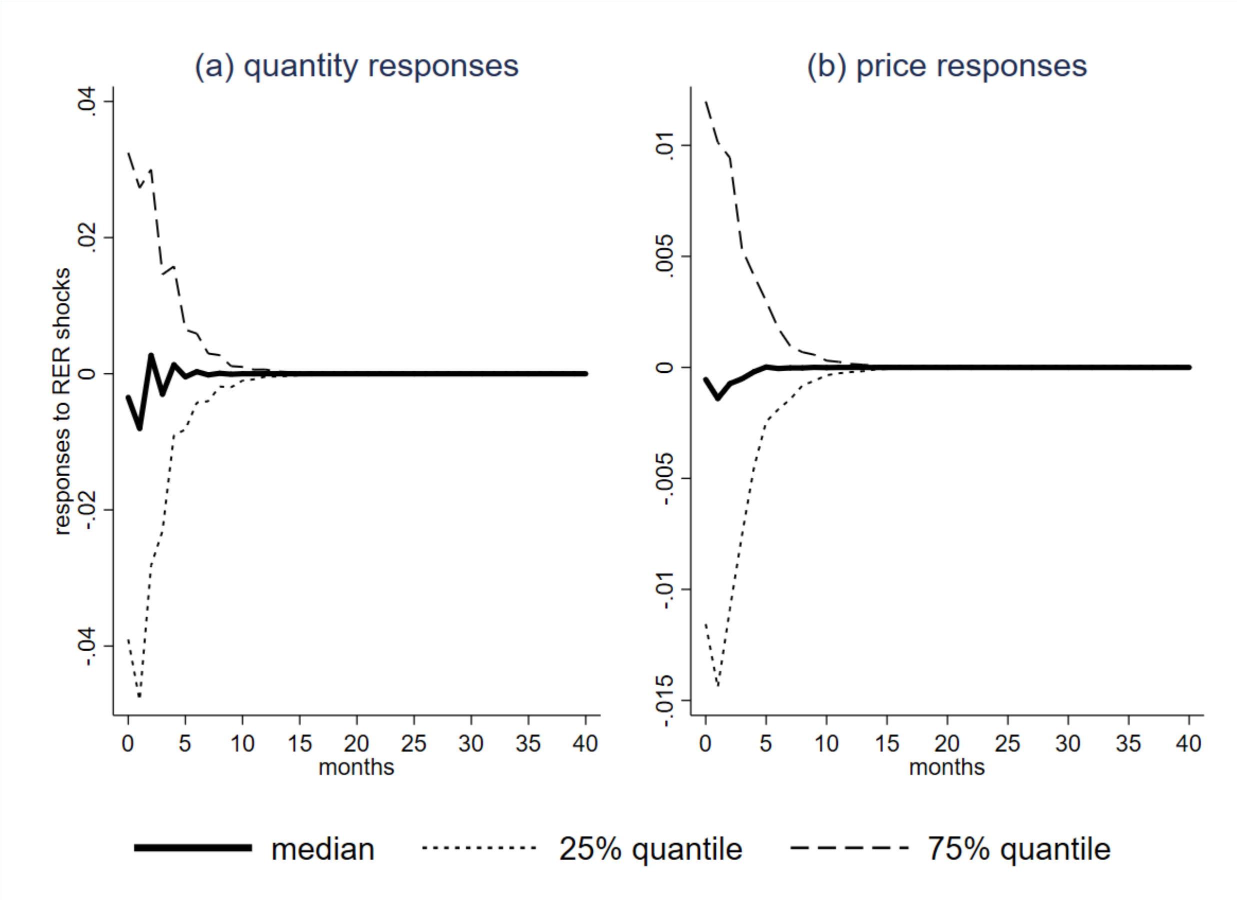

Figure A1. Quantity and Price Responses to RER shocks

Source. Authors' calculations using PSVAR model.