

Mao, Rui; Xing, Mengying; Yu, Xiaohua

Article — Published Version

Quality response to real exchange rate shocks: A panel SVAR analysis on China's agricultural exports

Agricultural Economics

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Mao, Rui; Xing, Mengying; Yu, Xiaohua (2021) : Quality response to real exchange rate shocks: A panel SVAR analysis on China's agricultural exports, *Agricultural Economics*, ISSN 1574-0862, Wiley, Hoboken, NJ, Vol. 52, Iss. 5, pp. 719-731, <https://doi.org/10.1111/agec.12650>

This Version is available at:

<https://hdl.handle.net/10419/284777>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc/4.0/>

ORIGINAL ARTICLE

Quality response to real exchange rate shocks: A panel SVAR analysis on China's agricultural exports

Rui Mao¹ | Mengying Xing¹ | Xiaohua Yu²

¹ China Academy for Rural Development & School of Public Affairs, Zhejiang University, Hangzhou, China

² Agricultural Economics in Developing and Transition Countries, Department of Agricultural Economics and Rural Development, University of Göttingen, Göttingen, Germany

Correspondence

Xiaohua Yu, Agricultural Economics in Developing and Transition Countries, Department of Agricultural Economics and Rural Development, University of Göttingen, Göttingen, Germany.
Email: xyu@gwdg.de

Abstract

This article applies a panel structural VAR model using complete data of China's monthly agricultural exports to uncover both the dynamics and interproduct and intermarket differences in the responses of product quality to real exchange rate (RER) shocks. It finds that RER appreciation promotes the quality of China's agricultural exports on average compared to discouraging exports, but the effect is fully shown in the short run. The average response peaks in the month immediately after the shock and the average cumulative response converges to a constant level in three months. The quality response to RER shocks substantially differs across both products and markets. More sensitive responses of quality upgrading are found among exports that are less competitive, relatively primary, more reliant on ordinary trade, and exported with nearby and less developed partners. Therefore, greater supports on R&D activities and the adoption of advanced technologies might be needed among other exports.

KEYWORDS

agricultural export quality, panel SVAR, real exchange rate

JEL CLASSIFICATION

F10, F41

1 | INTRODUCTION

Exchange rates play an important role in international trade. The exchange rates of the Chinese yuan are of particular interest to researchers. With a series of exchange rate reforms, the 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 appreciation (Baek & Koo, 2011; Berman et al., 2012; Cushman, 1983; Lamb, 2000; Li et al., 2015; Yanikkaya et al., 2013). On the other hand, however, aggravated market competition, restructured product mixes,

and ameliorated vertical integration might lead to quality improvements that 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 the findings are mixed at best. To be specific, some have supported the view by highlighting the following channels. First, the intensified competition could provide stronger incentives to upgrade export quality (Dai et al., 2018; Flach, 2016). Second, due to the elasticity of demand and quality-adjusted price, the structure of the export basket might

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial](https://creativecommons.org/licenses/by-nc/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

© 2021 The Authors. *Agricultural Economics* published by Wiley Periodicals LLC on behalf of International Association of Agricultural Economists

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 have argued that exchange rate appreciation 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 (Devadoss et al., 2015). This study will fill in the gap by investigating the impact of the 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 appreciation. Second, some quality attributes of agricultural products (e.g., color and size) are relatively easy to observe, similar to 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, the producers of primary goods often have greater difficulties doing so. Third, the quality response of agricultural products might be particularly strong in the short run because the seasonality of production and difficulty of preservation indicate that the supply can hardly be postponed or reduced during exchange rate appreciation. Thus, to consider the quality responses to the real exchange rate shocks of agricultural products, it is necessary to distinguish different time horizons and emphasize heterogeneities in both market and product dimensions. The main benefit of revealing interproduct and intermarket heterogeneities is that such distinctions could address the aggregation bias and thus decipher competing findings in the literature about the impact of exchange rate appreciations on quality (Hummels & Skiba, 2004; Xing & Zhao, 2008). The value of characterizing inter-temporal dynamics of the quality responses is that they may inform possible channels through which quality changes take place. Particularly, the literature has pointed out three channels including the export basket reshuffling, innovations and changed inputs (Auer & Chaney, 2009; Feng et al., 2016; Flach, 2016). While long-term quality changes could arise from the latter two channels, a finding of quality changes primarily restricted in the short run tends to suggest that exporters have

responded to appreciations merely by reshuffling products in their export baskets. Therefore, different dynamic patterns could deliver distinct policy implications to support quality upgrading during exchange rate appreciations.

Panel data models often utilized in current studies have difficulties accommodating the quality changes of agricultural products, which might feature noticeable dynamic patterns and intersectoral and intermarket heterogeneities, as we discussed above, for two limitations. First, these 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 for heterogeneous responses with specified interaction terms. Intersectoral and intermarket differences throughout the complete dynamics of quality responses to exchange rate shocks are not fully reflected.

In this article, we first extend the Melitz (2003) model to theorize the relationship between the real exchange rate (RER) and product quality. Based on this framework, we derive a panel structural VAR (PSVAR) empirical setup with five endogenous variables, that is, the RER, quality, the unit price in yuan, quantity, and the destination's real income, which enables us to estimate the complete dynamic path of the 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 intertemporally smooth the competitive pressure can be limited for agricultural exporters, which is mentioned above but also because it helps to unveil the possible driving forces behind quality changes. For example, an immediate quality response can be evidence of an improvement of the 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, using the estimated quality responses from RER shocks to empirical models, we explore the 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 intertemporal and cross-sectional variations when assessing the heterogeneous response dynamics. Due to the length of our monthly data, individual time series might not be long enough 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 of finding 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.

Most of the current literature on the relationship between exchange rate and agricultural trade has been concerned with the trade volume. They consistently concluded that both currency appreciations and an increased exchange rate volatility could result in reduced agricultural exports (Baek & Koo, 2011; Lamb, 2000; Yanikkaya et al., 2013). Specifically, they found the agricultural export volume to decline by 0.05–1.98% on average with a 1% appreciation of the exporter currency. According to Baek and Koo (2011), export reductions are heterogeneous both across products and over time. Responses of products that are consumer-oriented and those in the long run are found to be the greatest. This article contributes to these studies by revealing the response of product quality following exchange rate shocks, aside from changes in the trade volume. As demonstrated by Feenstra and Romalis (2014), product quality is determined by technology and demand. Nevertheless, among the empirical investigations into the quality of agricultural products, most of them took a supply-side perspective. By highlighting the role of climate and environmental conditions, cooperative institutions, 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; Khan et al., 2017; Pennerstorfer & Weiss, 2013). The influence of the exchange rate, however, works primarily through the demand channel since RER appreciation is fundamentally equivalent to “tariffication” (Thorstensen et al., 2012). Though the role of consumer demand in the growth of high-quality agricultural products has been noted in the literature (Pingali, 2007), it remains unclear how exactly demand shocks lead to quality adjustments. The monthly data allow us to investigate demand-side impacts without controlling supply-side factors such as technology.¹

The rest of this article is organized as follows. In Section 2, a theoretical model is established to determine 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 Section 5. Section 6 concludes the article.

2 | THEORETICAL FRAMEWORK

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

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

The subscript c indexes the country and t indexes time. λ and q , respectively, represent the 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, the demand for variety ω is determined as follows:

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

where Q and P , respectively, denote the aggregate quantity consumed 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:

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

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

¹ According to Gong (2018), the total factor productivity of China’s agricultural sector has been growing slowly and smoothly since 1978. In particular, from 2002–2015, technological volatility remained rather small.

Therefore, supply side factors will be reasonably picked up by panel-specific linear trends as we introduce in the data processing described in Section 3.

variety that China exports to country c , q ; (3) the bilateral RER between the 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 the estimation strategies that we describe in the following. 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 of measuring 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 was proposed by Pedroni (2013) and recently applied, for instance, by Gamtessa and Olani (2018), Hao et al. (2017), and Mishra et al. (2014), with the log values of five endogenous variables. The log transformation allows us to interpret the estimated response without any concern regarding the measurement units. Let $y_{cht} = (\ln \lambda_{cht}, \ln q_{cht}, \ln \pi_{cht}, \ln RER_{ct}, \ln RGDP_{ct})'$ be a vector of these variables. The subscripts c , h , and t denote the country, product and time period, respectively. λ , q , and π , respectively, represent the export quality, quantity and price in yuan. RER is the bilateral real exchange rate between the yuan and each importing country's currency in indirect quotes and $RGDP_{ct}$ is the real GDP per capita of each importing country. In line with Pedroni (2013), we then consider a PSVAR model as follows:

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

In Equation 4, ϵ_{cht} is the vector of exogenous structural shocks that are assumed to be white noise processes that satisfy *i.i.d.* $N(0, I)$.

Equation 4 illustrates that the PSVAR model extends the VAR framework by assuming both cross-sectional and intertemporal dependence of data. In particular, the cross-sectional dependence is modeled 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 duplex, its contribution relies on the diagonal loading matrix Λ_{ch} . The idiosyncratic component $\tilde{\epsilon}_{cht}$ instead reflects cross-sectionally independent dis-

turbances. Intertemporal dependence is modeled in the autoregressive specification of Equation 4, as in conventional VAR models. The lag operator L allows the current endogenous variables to depend on past shocks. The coefficient matrix $A_{ch,s}$ delineates the impact of the shocks that took place s periods ago.

It must be noted that the PSVAR model in Equation 4 considers the 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 intertemporal dependent relationships. On the one hand, regarding autoregressive 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 duplex to eliminate time-invariant fixed effects and then first-differenced to guarantee stationarity². We remove the possible seasonality and annual trend in monthly data by incorporating monthly fixed effects and a linear trend term into the demeaning process. Second, the reduced-form VAR model for each product-market duplex associated with the structural specification in Equation 4 is estimated, with the maximal lag order being selected by the information criteria³ and allowed to differ across panel units. We can then separate the structural shocks from the reduced-form estimations using identification assumptions, as we describe below. Third, the estimation in the previous step is repeated for the "average" series⁴ 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 separate the common components in structural shocks $\bar{\epsilon}_t$. Fourth, taking the correlation coefficients between ϵ_{cht} and $\bar{\epsilon}_t$ as the diagonal elements, the loading matrix Λ_{ch} in each product-market duplex could then be calculated. Typically, the composite shock and its common component are specified as

² The stationarity of these variables are examined by Im-Pesaran-Shin and Fisher-type tests. Results are available from the authors upon request.

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 the likelihood ratio (LR).

⁴ The stationarity of these variables are examined by Im-Pesaran-Shin and Fisher-type tests. Results are available from the authors upon request.

having a size of a unit. We thus derive the impulse response functions (IRFs) to a unit-sized common shock component using coefficient matrices defined as $\bar{A}_{ch,s} = A_{ch,s} \Lambda_{ch}$, where $A_{ch,s}$ is the coefficient matrix estimated from the reduced-form VAR model for each product-market duplet in the second step. Finally, according to orthogonality conditions and the normalization method proposed in Pedroni (2013), we derive the normalized coefficient matrices for the IRFs to idiosyncratic shock components as $\bar{A}_{ch,s} = A_{ch,s} (I - \Lambda_{ch} \Lambda'_{ch})^{1/2}$. Our normalization rescales the IRFs as if they follow a unit-sized idiosyncratic shock component. Therefore, the estimated IRFs to different shock components can be directly compared and the total responses to the composite shocks are the sum of $\bar{A}_{ch,s}$ and $\bar{A}_{ch,s}$.

To orthogonalize the reduced-form residuals and separate the structural form of our panel VAR model in the second step above, we have to impose identifying restrictions on the model dynamics. The 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 in 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 $i \neq 5$, that is, the real GDP per capita of each destination is not contemporaneously affected by the shocks to other variables. The reason is that the macro economy is usually taken as given for the 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 $j = 1, 2$, and 3 , that is, the 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 the export quantity or RER) are imposed since quality and quantity are independent choices by exporters according to Feenstra and Romalis (2014), and the nominal price tends to be sticky in the short run (Anderson & Simester, 2010). 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 affected by a wide range of intrinsic characteristics of agricultural products such as color, flavor, freshness, texture, and nutritional content. 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 by signaling (Auriol & Schilizzi, 2015; Yu & Abler, 2009). It has been found that conditional on price, quality determines the purchasing decisions of consumers (Barrett et al., 2010; Kyriacou & Roupheal, 2018; Tian & Yu, 2017). For example, consider two baskets of apples. It can be inferred that the one with greater sales is higher quality (e.g., fresher or sweeter) if price is the same. Following Khandelwal et al. (2013), we thus define quality as the product attributes making consumers willing to purchase more, conditional on the product price. Accordingly, quality is estimated using the demand-side approach as follows:

$$\ln q_{cht} = -\sigma_h \ln p_{cht}^* + \phi_h + \phi_{ct} + \eta_{cht}. \quad (5)$$

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 through income and substitution effect channels, respectively. The product fixed effect ϕ_h , instead, is introduced since prices and quantities may not be comparable across products.

According to Khandelwal et al. (2013), quality is measured by an OLS estimation of Equation 6 in log value as follows:

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

To avoid the endogeneity concern, we choose the elasticity of substitution σ_h according to estimates of Broda and Weinstein (2006). We normalize the estimated quality as an index from 0 to 1 so it can be compared across periods and markets; that is:

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

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 from 2002 to 2015 compiled from three sources. The first is the trade statistics from the Development Research Center of the State Council of China (DRCnet), which include all Chinese product-destination level export values and quantities. The second source is the International Financial Statistics (IFS),

TABLE 1 Descriptive statistics of variables in the PSVAR system

Variables	Obs.	Mean	Std. dev.	P10	P90
ln(quality)	166,152	0.528	0.181	0.294	0.771
ln(quantity)	166,152	12.41	1.941	10.03	14.85
ln(price in yuan)	166,152	2.523	1.113	1.316	3.976
ln(RER)	5,040	0.563	2.706	-2.307	4.712
ln(real GDP per capita)	5,040	8.504	1.092	6.858	9.471

which offers both bilateral nominal exchange rates and each country's CPI, which allow the bilateral RER to be computed. The third is the country data of the 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 article, we define the agricultural exports of China as the products in the first 24 chapters under the HS coding system according to Beestermöller et al. (2018). Products with different and unconvertible quantity units (e.g., from kg to boxes) over the sample period are excluded so we can measure product price as the ratio between the total value and the export volume. 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 the elasticity of substitution estimated by Broda and Weinstein (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 the sporadic gaps, which account for 2.2% of all gaps in our data, via linear interpolation using adjacent values. The product-market duplets that still have gaps after this filling would be excluded in order to avoid failures in estimating the PSVAR model.

We eventually come up with 166,152 observations for 989 product-market duplets through 168 months. To alleviate the influence of extreme values, the data are winsorized at the 1% level at both ends. Table 1 provides the descriptive statistics of our sample.

5 | ESTIMATION RESULTS

5.1 | Impulse responses of export quality

Figure 1 demonstrates the cumulative IRFs (CIRFs) of product quality in China's agricultural exports to an exoge-

nous 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), respectively⁵. Since the CIRFs differ across product-market duplets, we present the median CIRF with the CIRFs at the 25% and 75% quantiles in each panel of Figure 1 to show the dynamic distributions. In addition, we are concerned with the composite shocks at the moment without dividing them into common and idiosyncratic components.

Panel (a) indicates that on average, an RER appreciation shock to the yuan would lead to an overall quality upgrade of China's agricultural exports. According to the median CIRF, the instantaneous quality response in the period when the shock takes place is close to zero. However, in the following month, a noticeably positive cumulative 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 cumulative response decreases, albeit by a tiny amount, 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 cumulative quality response converges to a constant level since the third month, implying that in most cases the complete impact of RER shocks is fully revealed in the short run. This implies that quality changes are more likely driven by an ameliorated quality structure of the export basket rather than alternative forces, such as sustained innovations or better intermediate inputs, highlighted in the literature. We find that a 1% RER appreciation of the yuan produces on average a 0.001% increase of export quality during the first three months. Such relatively instantaneous quality responses are in line with the high risks of fulfilling agricultural trade contracts⁶, although contracts are typically signed a considerable time ahead of exports. This implies that in reality, agricultural exporters could still enjoy room to adjust their export baskets, even in the short term.

⁵ IRFs are the responses of the change of product quality in the period of interest. To reveal the responses of the quality level, we calculate the cumulative IRFs (CIRFs) by summing up the IRFs from the period when shocks take place to the period of interest.

⁶ Both exporters and importers have incentives to terminate or change contracts before shipment to avoid potential losses during exchange rate appreciation. For instance, orders may be canceled if importers expect to pay more than the market price or when exporters find that the increased 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 orders to be canceled 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).

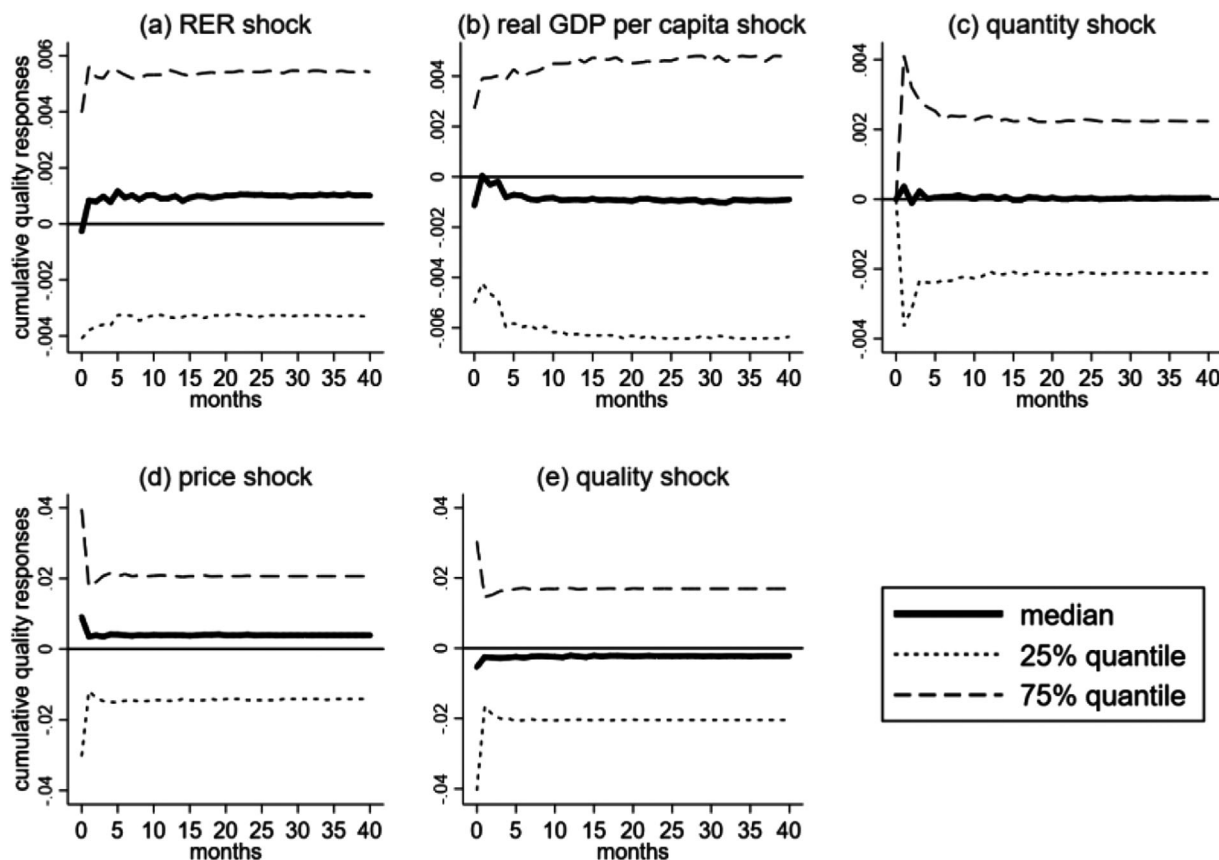


FIGURE 1 Cumulative IRFs of quality to various composite shocks

There are, nevertheless, substantial heterogeneities across product-market duplets in the cumulative quality response, as indicated by the CIRFs at the 25% and 75% quantiles. CIRF at the 25% quantile illustrates that for some products or markets, the cumulative quality response might remain negative following an appreciation shock. Persistent quality downgrading could be cost-related since to offset the cost increments resulting from appreciation, some exporters may use cheaper inputs (Álvarez & López, 2009). By contrast, the CIRF 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 the product and market characteristics giving rise to these heterogeneities in quality responses. The substantial heterogeneities along the dynamic path of CIRFs lend support to the choice of the PSVAR model over conventional panel data models.

In the remaining panels of Figure 1, we respectively demonstrate the cumulative quality response to other shocks, including those to the real GDP per capita, product price in yuan, export quantity, and quality itself. Despite the notable heterogeneities as indicated by the CIRFs 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. In the next month, the cumulative response turns positive, albeit by a tiny amount, which could result from the ameliorated export basket of China as the demand in the destination market improved. The median cumulative quality response to a shock on the price in yuan is largely positive and instantaneous, which implies 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 cumulative quality response to quantity shocks is always small and fluctuates around zero. Finally, the instantaneous quality response to a shock on itself (driven, for example, by a productivity shock) is largely negative and the cumulative quality response remains negative in the long run 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.

Comparing the CIRFs 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, the quality responses to shocks to the real GDP per capita and quantity are the smallest. This is supported by the results of the variance decompositions as well.⁷ At the median level, the shocks to quality itself and price in yuan are the largest contributors to quality variations in the short run, accounting for more than 95% of the total variations. In the long run, their combined contribution decreases to 80%. The 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 the RER exceeds 5% in some product-market duplets, according to estimates at the 75% quantile.

Aside from quality impacts, RER appreciation would also influence both the export quantity and the domestic price of Chinese agricultural products. Consistent with the existing studies (Baek & Koo, 2011; Lamb, 2000; Yanikkaya et al., 2013), we find that on average, appreciation results in a reduced export quantity. Cumulative quantity contractions peak in the first month after an RER shock and then keep the status afterwards. RER appreciation would also reduce the product price measured in yuan. The median cumulative response reaches the maximum in the third month after the shock, and then it remains unchanged. Nevertheless, the magnitude of the price responses tends to be small, which is in line with Li et al. (2015) and implies that the exchange rate pass-through is high for Chinese exports.⁸

5.2 | Comparison of the quality responses to different components of RER shocks

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 the quality responses to the common and idiosyncratic components in an RER shock and compare the cumulative responses at the median level in three windows in Figure 2. 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 runs.

In all these windows, we find that the scale of the quality responses to the idiosyncratic RER shock component dominates that of the responses to the common shock component. As the solid line in Figure 2 illustrates, the ratio of the scale of quality responses to the idiosyncratic component

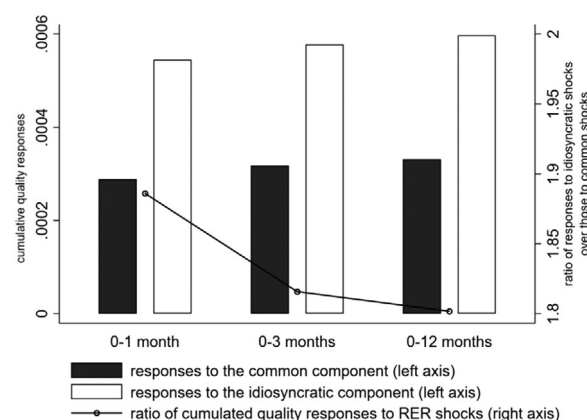


FIGURE 2 Comparison of cumulative quality responses to different RER shock components

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

over that to the common component is approximately 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 converges to a constant level in a shorter time as the quality structure of the export basket may be adjusted in a relatively prompt manner. In contrast, the influence of a systematic RER shock grows relatively slowly while being more lasting since it can be difficult to adjust the export basket immediately if the yuan appreciates in all markets. Despite this difference, nonetheless, Figure 2 shows that overall, the quality adjustment induced by either component is mostly accomplished in the first three months following the shock since the response to both shock components only slightly increases as the window is extended.

5.3 | Determinants of the quality responses to an RER shock

Figure 1 demonstrates that the CIRFs of product quality among Chinese agricultural exports to an 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 of the determinants of the cumulative quality response in each product-market duplet over a particular window:

$$\delta_{ch} = \beta_0 + \beta_1 RCA_{ch} + \beta_2 \cdot \mathbf{x}_c + \phi_h + \varepsilon_{ch} \quad (8)$$

In Equation 8, subscripts c and h , respectively represent the destination market and product variety. For each product-market duplet ch , δ_{ch} is the cumulative quality responses to the RER shock in a specific window,

⁷ Results are available from the authors upon request.

⁸ The specific estimated CIRFs of quantity and price are available from the authors upon request.

TABLE 2 Determinants of cumulative quality responses to RER shocks

Cumulative 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* (0.0002)	−0.0006** (0.0002)	−0.0008*** (0.0002)
ln(distance)	−0.0012*** (0.0003)	−0.0005* (0.0003)	−0.0009*** (0.0003)
RCA	−0.0225 (0.0144)	−0.0396*** (0.0144)	−0.0421*** (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.

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.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

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 , where the revealed comparative advantage is computed using 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. Since there are many difficulties measuring many product characteristics such as the intrinsic product quality and preservation conditions, we introduce product-specific fixed effects in Equation 8, which are denoted by ϕ_h . β_0 , and ε_{ch} are, respectively, 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 endogeneity concern. The estimation results would remain similar, however, if independent variables are instead measured by the average values through the sample period as Hao et al. (2017).⁹ Finally, RCA_{ch} , which is the ratio between two export shares and could cause the scale to lack a clear meaning, is rescaled to the range 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 2, we again alternatively consider three particular windows for the cumulative quality

responses when estimating Equation 8, that is, 0–1 month (the short run), 0–3 months (the medium run) and 0–12 months (the long run). Table 2 reports the estimation results. The table demonstrates that for all three windows of examination, the cumulative 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, cumulative quality responses also tend to be smaller. Comparing 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 runs. This 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 runs, for example, 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 emphasis given to each factor. Table 2 also shows that the cumulative 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 appreciation would be more detrimental for products and markets

⁹ The results are available from the authors upon request.

where China lacks a strong comparative advantage, and thus it will induce greater quality-improving incentives.

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

$$R_h = (fe_h - \min fe_h) / (\max fe_h - \min fe_h) \quad (9)$$

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 the estimated fixed effects for product h .

We categorize the 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).¹⁰ In Figure 3, we compare the distribution of the 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 the upper and lower adjacent values. The result demonstrates that regardless of which window is under examination, the majority of the less processed products always have larger fixed effects, that is, 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 are more difficult to preserve. Thus, the motivation of quality improvements tends to be stronger. RER appre-

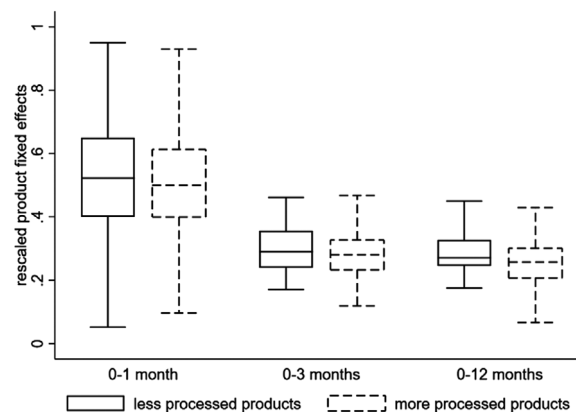


FIGURE 3 Rescaled product fixed effects (R_h) and the processing degree of products

Notes. 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.

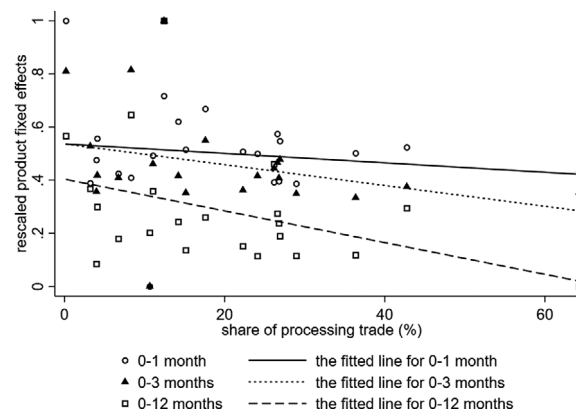


FIGURE 4 Rescaled product fixed effects (R_j) and the share of processing trade

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

ciation 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.

In Figure 4, we compare the estimated fixed effects according to the share of the processing trade of each product in China's exports. Seeing that this share remains zero

¹⁰ Specifically, less processed goods include bulk commodities including grain, oilseed, and plant-based fibers such as cotton, raw rubber and non-manufactured tobacco; 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 either require special handling such as containerization, for example, preserved vegetables and fruits, or are highly transformed, for example, processed meat, manufactured tobacco, and beverages.

for many HS six-digit products during the sample period, we aggregate the products to the 24 HS chapters. That is, we first calculate the average fixed effects among products in each chapter and rescale it to the range of [0, 1], which is denoted as R_j ; and then we compute the share of the 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 responses of quality upgrading 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 are imported in the processing trade. Therefore, RER appreciation results in both revenue and cost reductions, leaving profits hardly affected. Second, the room for quality improvement tends to be limited in the processing trade since critical technologies are controlled by foreign suppliers.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

In this article, a PSVAR model is utilized to unveil both the dynamics and interproduct and intermarket heterogeneities in the quality responses of Chinese agricultural exports to a shock to yuan's RER. We find that on average, RER appreciation leads to quality improvements, but the effect is fully shown in the short run—the average response peaks in the month following the shock and the average cumulative response converge to a constant level in three months. The quality responses substantially differ across product-market duplets and are more sensitive to a duplet-specific RER shock. Response heterogeneities rely on both market (e.g., geographic distance and income) and product (e.g., revealed comparative advantage) features. In addition, more sensitive responses of quality upgrading are found among products that are relatively primary and exported less through the processing trade.

The relatively instantaneous impact of RER appreciation 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, more reliant on ordinary trade, and exported with nearby and less developed partners.

Our results have important policy implications for both governments and exporting companies. The concentration of quality responses in the short run implies that quality

improvements in China's agricultural exports after RER appreciation could primarily be a result of product amelioration in export baskets, that is, reducing the composition of relatively low-quality products and increasing that of high-quality goods. Sustainably enhancing product quality, for example, with support for R&D activities and the implementation of advanced technologies to cope with RER appreciation thus remain a critical challenge for both the government and agricultural exporters. Seeing their less responsive quality improvements, such support would be particularly important in exports to developed and distant markets.

Finally, product quality improvements are associated with decreases in both export quantity and price. This thus implies that export profits are reduced with the appreciation shock. To alleviate these negative impacts, exporters might diversify their 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 such as China where the financial sector is less mature would also provide exporters with stronger capabilities to withstand external shocks.

ACKNOWLEDGMENTS

The authors thank the editor, Awudu Abdulai and the anonymous reviewers. This research was supported by the National Natural Science Fund of China (No. 71873119), the MOE Social Science Fund (No. 19JHQ060), and Zhejiang University-IFPRI Center for International Development Studies. Rui Mao is the CTF Young Scholar.

Open access funding enabled and organized by Projekt DEAL.

REFERENCES

- Álvarez, R., & López, R. A. (2009). Skill upgrading and the real exchange rate. *World Economy*, 32(8), 1165–1179.
- Anderson, E. T., & Simester, D. I. (2010). Price stickiness and customer antagonism. *Quarterly Journal of Economics*, 125(2), 729–765.
- Auer, R., & Chaney, T. (2009). Exchange rate pass-through in a competitive model of pricing-to-market. *Journal of Money, Credit and Banking*, 41, 151–175.
- Auriol, E., & Schilizzi, S. G. (2015). Quality signaling through certification in developing countries. *Journal of Development Economics*, 116, 105–121.
- Baek, J. & Koo, W. W. (2011). How sensitive is U.S. agricultural trade to the bilateral exchange rate? Evidence from bulk and consumer-oriented products. *Agricultural Economics*, 42(3), 387–403.
- Barrett, D. M., Beaulieu, J. C., & Shewfelt, R. (2010). Color, flavor, texture, and nutritional quality of fresh-cut fruits and vegetables: Desirable levels, instrumental and sensory measurement, and the effects of processing. *Critical Reviews in Food Science and Nutrition*, 50(5), 369–389.

- Beestermöller, M., Disdier, A. C., & Fontagné, L. (2018). Impact of European food safety border inspections on agri-food exports: Evidence from Chinese firms. *China Economic Review*, 48, 66–82.
- Berman, N., Martin, P., & Mayer, T. (2012). How do different exporters react to exchange rate changes? *Quarterly Journal of Economics*, 127(1), 437–492.
- Broda, C., & Weinstein, D. E. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics*, 121(2), 541–585.
- Chen, K. Z., & Duan, Y. (2001). Competitiveness of Canadian agri-food exports against competitors in Asia: 1980–97. *Journal of International Food & Agribusiness Marketing*, 11(4), 1–19.
- Chen, N., & Juvenal, L. (2016). Quality, trade, and exchange rate pass-through. *Journal of International Economics*, 100, 61–80.
- Christiano, L. J., Eichenbaum, M. S., & Vigfusson, R. J. (2006). Alternative procedures for estimating vector autoregressions identified with long-run restrictions. *Journal of the European Economic Association*, 4, 475–483.
- Cushman, D. O. (1983). The effects of real exchange rate risk on international trade. *Journal of International Economics*, 15(1–2), 45–63.
- Dai, M., Yu, M., & Zhao, C. (2018). Export tightening, competition, and firm innovation: Evidence from the Renminbi appreciation. *Review of Development Economics*, 22(1), 263–286.
- Deloof, M., & Jegers, M. (1996). Trade credit, product quality, and intragroup trade: Some European evidence. *Financial Management*, 25(3), 33.
- Devadoss, S., Hilland, A., Mittelhammer, R., & Foltz, J. (2015). The effects of the Yuan-dollar exchange rate on agricultural commodity trade between the United States, China, and their competitors. *Agricultural Economics*, 45(S1), 23–37.
- Erceg, C. J., Guerrieri, L., & Gust, C. J. (2005). Can long-run restrictions identify technology shocks? *Journal of the European Economic Association*, 3(6), 1237–1278.
- European Commission. (2019). Agri-food Trade in 2018, *Monitoring Agricultural Policy*, MAP2019-1. https://ec.europa.eu/info/sites/default/files/food-farming-fisheries/trade/documents/agri-food-trade-2018_en.pdf
- Fauceglia, D. (2020). Exchange rate fluctuations and quality composition of exports: Evidence from Swiss product-level data. *World Economy*, 6, 1592–1618.
- Faust, J., & Leeper, E. M. (1997). When do long-run identifying restrictions give reliable results? *Journal of Business & Economic Statistics*, 15(3), 345–353.
- Feenstra, R. C., & Romalis, J. (2014). International prices and endogenous quality. *Quarterly Journal of Economics*, 129(2), 477–527.
- Feng, L., Li, Z., & Swenson, D. L. (2016). The connection between imported intermediate inputs and exports: Evidence from Chinese firms. *Journal of International Economics*, 101, 86–101.
- Flach, L. (2016). Quality upgrading and price heterogeneity: Evidence from Brazilian exporters. *Journal of International Economics*, 102, 282–290.
- Gamtessa, S., & Olani, A. B. (2018). Energy price, energy efficiency, and capital productivity: Empirical investigations and policy implications. *Energy Economics*, 72, 650–666.
- Gong, B. (2018). Agricultural reforms and production in China: Changes in provincial production function and productivity in 1978–2015. *Journal of Development Economics*, 132, 18–31.
- Gopinath, G., & Rigobon, R. (2008). Sticky borders. *Quarterly Journal of Economics*, 123(2), 531–575.
- Hallak, J. C. (2006). Product quality and the direction of trade. *Journal of International Economics*, 68(1), 238–265.
- Hao, N., Pedroni, P., Colson, G., & Wetzstein, M. (2017). The linkage between the US ethanol market and developing countries' maize prices: A panel SVAR analysis. *Agricultural Economics*, 48(5), 629–638.
- Hu, C., Parsley, D. C., & Tan, Y. (2019). *Exchange Rate Induced Export Quality Upgrading: A Firm-Level Perspective*. Vanderbilt Owen Graduate School of Management Research Paper, (3011013).
- Hummels, D., & Skiba, A. (2004). Shipping the good apples out? An empirical confirmation of the Alchian-Allen conjecture. *Journal of Political Economy*, 112(6), 1384–1402.
- Jaffee, S., & Masakure, O. (2005). Strategic use of private standards to enhance international competitiveness: Vegetable exports from Kenya and elsewhere. *Food Policy*, 30(3), 316–333.
- Jones, G. V., White, M. A., Cooper, O. R., & Storchmann, K. (2005). Climate change and global wine quality. *Climatic Change*, 73(3), 319–343.
- Khan, I., Tango, C. N., Miskeen, S., Lee, B. H., & Oh, D. H. (2017). Hurdle technology: A novel approach for enhanced food quality and safety—A review. *Food Control*, 73, 1426–1444.
- Khandelwal, A. K., Schott, P. K., & Wei, S. J. (2013). Trade liberalization and embedded institutional reform: Evidence from Chinese exporters. *American Economic Review*, 103(6), 2169–2195.
- Kyriacou, M. C., & Rouphael, Y. (2018). Towards a new definition of quality for fresh fruits and vegetables. *Scientia Horticulturae*, 234, 463–469.
- Lamb, R. L. (2000). Food crops, exports, and the short-run policy response of agriculture in Africa. *Agricultural Economics*, 22(3), 271–298.
- Lastrapes, W. D. (2006). Inflation and the distribution of relative prices: The role of productivity and money supply shocks. *Journal of Money, Credit and Banking*, 38(8), 2159–2198.
- Li, H., Ma, H., & Xu, Y. (2015). How do exchange rate movements affect Chinese exports—A firm-level investigation. *Journal of International Economics*, 97(1), 148–161.
- Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer Science & Business Media.
- Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6), 1695–1725.
- Mishra, P., Montiel, P. J., Pedroni, P. L., & Spilimbergo, A. (2014). Monetary policy and bank lending rates in low-income countries: Heterogeneous panel estimates. *Journal of Development Economics*, 111, 117–131.
- Pedroni, P. (2013). Structural panel VARs. *Econometrics*, 1(2), 180–206.
- Pennerstorfer, D., & Weiss, C. R. (2013). Product quality in the agri-food chain: Do cooperatives offer high-quality wine? *European Review of Agricultural Economics*, 40(1), 143–162.
- Pingali, P. (2007). Westernization of Asian diets and the transformation of food systems: Implications for research and policy. *Food Policy*, 32(3), 281–298.
- Thorstensen, V., Marçal, E., & Ferraz, L. (2012). Impacts of exchange rates on international trade policy instruments: The case of tariffs. *Journal of World Trade*, 46(3), 597–634.
- Tian, X., & Yu, X. (2017). The quality of imported fruits in China. *Emerging Markets Finance and Trade*, 53(7), 1603–1618.

- Xing, Y., & Zhao, L. (2008). Reverse imports, foreign direct investment and exchange rates. *Japan and the World Economy*, 20(2), 275–289.
- Yanikkaya, H., Kaya, H. , & Kocturk, O. M. (2013). The effect of real exchange rates and their volatilities on the selected agricultural commodity exports: A case study on Turkey, 1971–2010. *Agricultural Economics*, 59(5), 235–245.
- Yu, X., & Abler, D. G. (2009). The demand for food quality in rural China. *American Journal of Agricultural Economics*, 91(1), 57–69.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Mao, R., Xing, M., & Yu, X. Quality response to real exchange rate shocks: A panel SVAR analysis on China's agricultural exports. *Agricultural Economics*. 202152;;719–731. <https://doi.org/10.1111/agec.12650>