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Dynamic and spillover effects of USA import refusals on China's agricultural trade: Evidence from monthly data

*Jiehong Zhou, Yu Wang, Rui Mao**

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

**Corresponding author:* rmao@zju.edu.cn

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Abstract: Border inspections by developed nations are an essential export barrier to developing countries. Import refusals, in particular, not only exhibit dynamic impacts on exporters' performance in the refused destination but may also spill over into exports toward third markets. Using a panel structural vector autoregression model, the complete dynamics of China's agricultural export in response to United States Food and Drug Administration (FDA) import refusals is estimated at the monthly level. Despite notable heterogeneities across sectors, negative and positive reactions that last mostly less than a year are revealed respectively for the quantity and price of China's exports to USA on average. The impact of idiosyncratic component dominates that of common component in the refusal shock, highlighting the sensitivity of exports to sector-specific border inspections. Relative to other refusal charges, larger export contractions tend to follow adulteration charges. The trade effect of FDA refusals spills over into other main export destinations of China. While non-adulteration charges result in trade deflections on average, a contagious export reduction is observed in most non-US markets. These results provide insights for exporters to make strategies with a focus on specific sectors, charges, third markets and especially on the short run to cope with import refusals.

Keywords: agricultural exports; import refusals; panel structural vector autoregression; spillover effects

Agricultural trade is vital to developing nations. These countries, however, face escalated export barriers of food safety regulations by their technologically advanced partners. The literature has documented mixed evidence on the trade effect of food safety regulations. While such regulations might impede exports, pro-export effects can occur if higher standards and stricter inspections reduce the information asymmetry between consumers and foreign producers (Leland 1979).

Recently, distinctions between trade effects of *de jure* safety standards and those of *de facto* regulations have been acknowledged. It has been pointed out that using *de jure* standards might result in twofold problems. On the one hand, the same standard can be differently enforced across countries (Baylis et al. 2010; Tran et al. 2012), and even in the same country, the enforcement is likely to differ with the product's country of origin (Anders and Caswell 2009). On the other hand, even for a given pair of trade partners, the enforcement of the same standard might change over time (Grant and Anders 2011). Grundke and Moser (2019), for example, showed that product standards of the USA have been increasingly enforced since the subprime crisis. With the focus shifted to *de facto* regulations, several

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recent studies revealed trade reductions upon the EU and United States Food and Drug Administration (FDA) import refusals (Baylis et al. 2010; Grant and Anders 2011). Merging EU rejections with firm-level data of China, Beestermöller et al. (2018) highlighted the uncertainty effect that could trigger negative spillovers on exports across firms in the same region or industry. From the perspective of importers, Jaud et al. (2013) found that border inspections gave rise to diversified product sources to cope with risks. However, both the dynamics and heterogeneities in the trade effects of *de facto* regulations remain largely unknown.

In this paper, we intend to investigate these questions using monthly data of China and the USA. Since the accession to the World Trade Organization, China has witnessed one of the most rapid growth in agricultural exports among developing nations even compared with the rest of the fast-growing BRIC countries, i.e. Brazil, Russia, India (Bojnec et al. 2014). China's agricultural exports used to serve mainly neighbouring markets. In recent years, nevertheless, the importance of developed countries, or the USA in particular, has notably increased. In 2016, China was the fourth largest agricultural exporter to the USA with a share of 3.8% in terms of value. As a result, the USA trade restrictions on China's agricultural goods heightened. Among import refusals of the FDA in 2016 for example, 9.8% targeted Chinese exporters.

To quantify the influence of FDA import refusals on China's agricultural exports, we give a specific focus in this paper to reveal how the impact evolved over time, differed across products and types of refusal charges, as well as spill over into China's export performance in non-US markets. Previous studies mostly dealt with annual data using cross-sectional or panel models. They typically face the challenge of inverse causality between import refusals and export performance. Thanks to the monthly nature of our data, the panel structural vector autoregression (SVAR) model is adopted in this paper, which allows all variables to be endogenous. Besides, since the monthly distribution of import refusals is not constant [Figure S1 in eletronic supplementary material (ESM), for the supplementary material see the electronic version], if the impact of refusals is short-lived, then the estimated trade effect for a year with refusals concentrated in its beginning would be different from that for a year with refusals concentrated at the end. Based on monthly estimates, we will be able to characterise the complete dynamics of export responses in both the short and long run. Finally, monthly estimates are also less likely to suffer from the threat of confounding factors such as changes in macro policies and consumer tastes, which are difficult to be completely controlled at the year level.

While the literature has investigated the influence of refusal shocks on export value, different responses in export quantity and unit price are considered in this study. On the one hand, cheaper products may be more likely to suffer from foodborne diseases if the low price reflects poor processing and packaging conditions, such that refusals tend to reduce the portion of these products. On the other hand, import refusals may encourage exporters to supply products with better quality, which can result in higher prices as well. Previous studies revealed that the quality of agricultural products depends on the development stage, market size, comparative advantage, trade costs, and inequality of the exporting economy (Bojnec and Ferto 2017). However, import refusals could also encourage quality upgrading when exporters take such a strategy to enhance product competitiveness (Jaffee and Henson 2005). According to Hong (2015), quality accounts for 80% of the unit price. Hence, we take unit price as a proxy of product quality and expect a positive impact of import refusals on it.

In addition, we also explore a full array of heterogeneities in export responses across sectors and types of refusal charges. Due to product characteristics such as perishability, the impact of refusals typically differs across sectors. The panel SVAR model that we use specifies such heterogeneities in both contemporaneous and lagged coefficients of correlation, such that the dynamic export response to import refusals is entirely sector-specific. Inter-sectoral heterogeneities are also reflected in refusal shocks. In particular, our model decomposes the shock terms into common and sector-specific idiosyncratic components. While the common component represents systematic changes in the level of border inspections, e.g. resulting from amendments to the Federal Food, Drug, and Cosmetic (FD&C) Act, the idiosyncratic component reflects sector-specific changes in the decision-making of import refusals, e.g. in response to greater safety concerns about fishery products. To account for heterogeneous effects across refusal charge types, we categorise charges based on their indication of potential risks. Export responses to each type of refusal charges are then estimated and compared.

Finally, we examine whether and how FDA refusal charges influence the agricultural export performance

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of China in non-US markets, which is known as the spillover effect. Instead of taking all non-US markets as a whole like previous studies, country-specific investigations are performed in this paper. Hence, we can distinguish deflective effects, i.e. increased Chinese exports to a third market following FDA charges, and contagious effects i.e. decreased exports to a third market. In each country-specific estimation, we also take heterogeneities across sectors and charge types into account.

DATA

Our data of FDA import refusals ranges from 2002 to 2016, and are collected from Import Refusal Reports (IRR) published by the FDA (IRR 2019). IRR records each refusal entry at the firm-product-date level. It does not include information about the quantity, value or weight of the refused shipment, unfortunately. Our export data of China are released by the Development Research Centre of the State Council (DRC) (China's International Trade Data 2019). Since exports are monthly, we aggregate the number of refusal charges on each product by month to match the two datasets.

The challenge in this process of merging is that the two datasets adopt different systems of product classification. Specifically, the FDA product codes are used in IRR, while the harmonization system (HS) is adopted by the DRC. Fortunately, each product under the FDA system is described in details by the container and status of processing, storage or dosage. Therefore, we can manually make a correspondence between the two coding systems. The FDA product codes are found to be matched most accurately with HS codes at the 4-digit level. To avoid ambiguity, we are only concerned with products for which a one-to-one matching is established. These include 87 goods, which account for 47.3% of 184 agricultural products under the HS code. Refusals on these goods can cover 90.7% of all refusals listed in IRR on agricultural products.

While estimating export responses to refusal shocks at the HS 4-digit level is possible based on product data, this might conceal the facts that refusal charges across products within the same sector tend to be correlated and that increased refusal risks in a product might spill over into related products (Jouanjean et al. 2015). The United State Department of Agricultural provides a system to categorise related HS 4-digit products into 12 sectors. Table S1 [electronic supplementary material (ESM); for the supplementary material see the electronic version] confirms that the number of refusal charges on an HS 4-digit product increases with that for other products in the same sector, but has no statistically significant relations with refusal charges on products in different sectors.[1] To proceed with the analysis, we thus aggregate monthly refusal charges up to these sectors and consider their impacts on China's sector-level exports. The evolutionary pattern and sectoral distribution of refusals and exports, as well as preliminary evidence on the trade impact of refusal charges, can be found in Supplementary material S1 [electronic supplementary material (ESM); for the supplementary material see the electronic version].

METHODS

We estimate export responses to refusal charges using the panel SVAR model (Pedroni 2013; Hao et al. 2017). While most previous studies rely on cross-sectional or panel specifications like the gravity model, such strategies could result in biased estimates with monthly data for violating the assumption of a finite time dimension. Applying time-series models to data of each sector will also be problematic since it assumes away the inter-sectoral correlation in refusal charges due to changes in the overall enforcement of inspections. As a combination of these strategies, the panel SVAR model allows both inter-temporal and cross-sectional dependence in data series. Moreover, it improves panel estimations by specifying inter-sectoral heterogeneities through the entire dynamics of responses. It also improves inter-temporal estimations by compensating the limited length of individual time series with cross-sectional data variations.

In particular, our model considers a vector y_{it} of three endogenous variables, i.e. the number of refusal charges $charge_{it}$, the log of China's agricultural export quantities to the USA $\ln q_{it}$, and the log of unit price $\ln uv_{it}$, with subscripts i denoting sectors and t denoting periods. The model takes the following form:

$$y_{it} = \sum_{s=0}^{p_i} A_{i,s} L^s \varepsilon_{it} \tag{1}$$

[1]During the estimation, we control the historical numbers of refusal charges on this product to reflect the path dependency. China's export value of this product to the USA is also controlled seeing that the decision of refusals may result from export growth, which is in line with Jouanjean et al. (2015).

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where p_i is the length of lag effects. Inter-sectoral heterogeneities are fully reflected in Equation (1) in that it allows contemporaneous and lagged coefficient matrices $A_{i,s}$ to be sector-dependent. L^S is the lag operator at period s; heterogeneities are also considered in the nature of shocks. More specifically, the error term ε_{it} is modelled as a vector of composite shocks that include common and idiosyncratic components. In particular, $\varepsilon_{it} = \Lambda_i \bar{\varepsilon}_t + \varepsilon_{it}$, where $\bar{\varepsilon}_t$ is a vector of common shocks that reflects changes in the overall enforcement of inspections or in the export performance, while $\tilde{\varepsilon}_{it}$ is a vector of idiosyncratic shocks that reflect sectoral-specific shocks such as increased inspections on fruit products or export surges of fishery goods. In other words, common shocks are systematic disturbances across all sectors, and idiosyncratic shocks are sector-specific disturbances that are orthogonal to common shocks. Λ_i is the loading matrix of common shocks in sector i.

To estimate Equation (1) and derive impulse response functions (IRFs) of this vector autoregression (VAR) system, the algorithm of Pedroni (2013) is adopted. The specific procedure can be found in Supplementary material S2 [electronic supplementary material (ESM); for the supplementary material see the electronic version]. To back out structural shocks from the reduced-form model, we assume that refusal charges had an instantaneous impact on export quantities, but its impact on unit prices would take place with a lag since prices usually are determined in contracts beforehand. In addition, both export quantities and unit prices could affect FDA inspections, either because refusal charges might be used as a hidden tool of trade protectionism or when the value affected the FDA's perception about the quality and safety of imported goods (Schott 2008; Grundke and Moser 2019). But both effects should happen with a lag since it is reasonable to assume that the FDA could not immediately respond to changes in import flows. Finally, seeing that quantity and price are interdependent in the supply function, export quantities and unit prices could exhibit instantaneous effects on each other.

During empirical analysis, we adjust the date of refusal charges in IRR forward by 20 days since FDA usually issues a Notice of Detention roughly 20 days before making the refusal decision.[2] Such a gap in time between the Notice of Detention and the decision of refusal charges also explains why in Figure S4 [electronic supplementary material (ESM); for the supplementary material see the electronic version], a stop of export surges could be observed one month ahead of normalised date 0 when the first import refusal took place.

RESULTS

Benchmark results

According to the estimation algorithm for the panel SVAR model above, we could obtain IRFs for the number of refusal charges, export quantities and unit prices to composite shocks in each variable, as well as responses to common and idiosyncratic components in these composite shocks. For each group of IRFs, we present the median response across sectors with responses at 25 and 75% quantiles to reflect inter-sectoral heterogeneities. Figure 1 presents IRFs of export quantities and unit prices to refusal charge shocks.[3]

Following a unity sized composite shock in refusal charges, we find on average negative responses in export quantities but positive responses in unit prices. To be specific, the median IRF indicates a 0.8% decline of China's export quantities to the USA in the first month following refusal charges. The drop deepens in the second month to 2.1%. It then gradually converges to zero in 11 months. In contrast, the median IRF of unit prices implies a 0.2% growth after the refusal shock. It increases in the second month and then fluctuates around zero after seven months. Taking the two median IRFs together, we can infer that the price response is relatively small in scale and short in duration than the quantity response, so refusal charges result in a reduction of the overall export value. Such a reduction is driven by quantity contractions. Because refusal charges might induce exporters of low-price products to avoid the USA market or upgrade the product quality, the average price of products actually increases. Both responses in quantities and prices, however, are short-lived.

Substantial gaps between IRFs at 25 and 75% quantiles imply notable inter-sectoral heterogeneities in quantity

[2]FDA's Regulatory Procedures Manual (FDA 2017) allows ten business days from the date of detention. To allow for weekends, holidays, and mailing time the Notice of FDA Action generally specifies a timeframe of 20 calendar days following the date of detention shown on the notice.

[3]Other IRFs of the panel SVAR system can be found in Figure S5 (electronic supplementary material (ESM); for the supplementary material see the electronic version).

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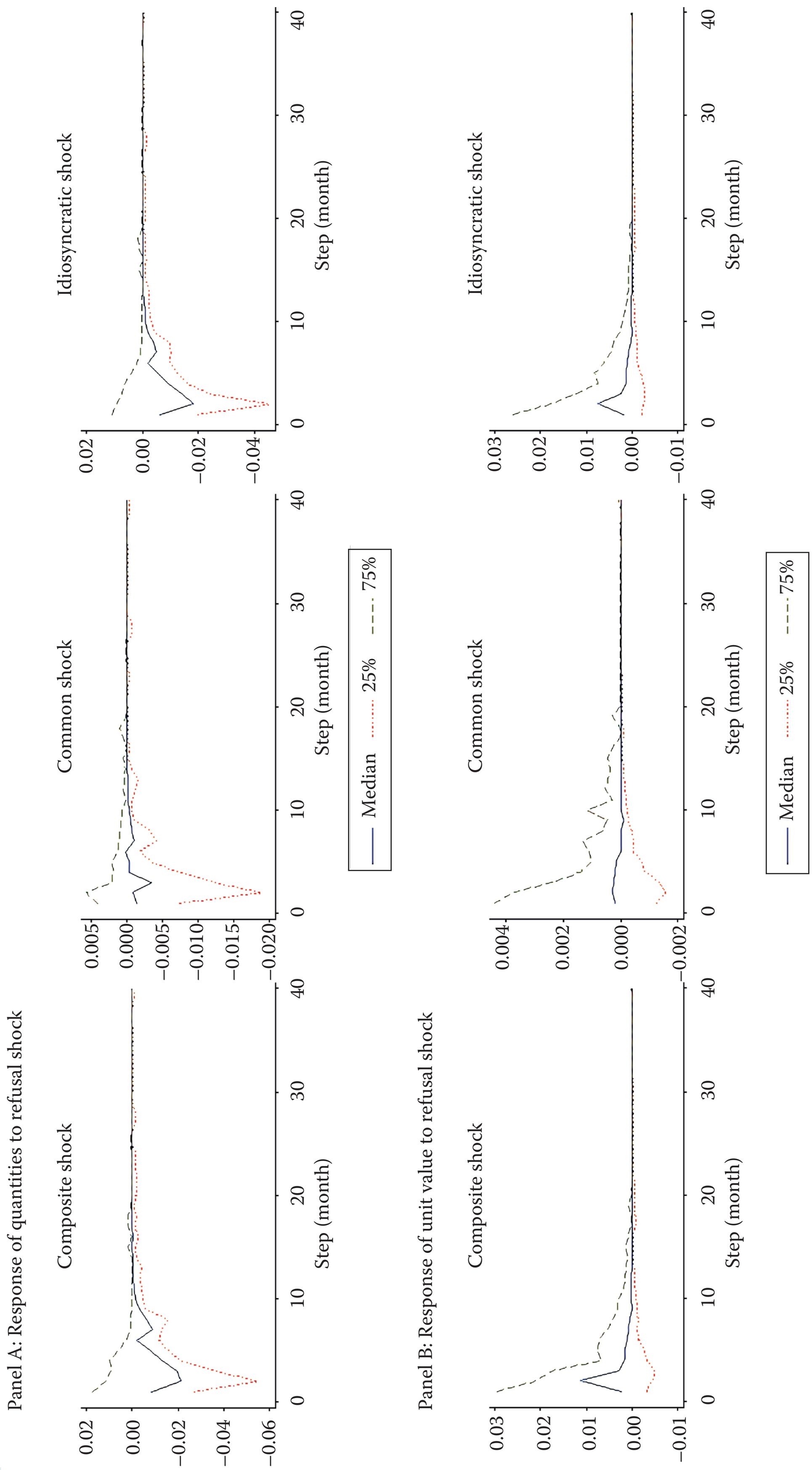

Figure 1. Impulse response functions (IRFs) of China's agricultural export quantities and unit prices to United States Food and Drug Administration (FDA) refusal charge shocks

Source: authors' elaboration

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and price reactions. In particular, while 5.5% of export quantities decline and 2.9% of price increase following the refusal shock in 25% of these sectors, in several other sectors 1.7% of quantities increase, and 0.3% of price decline can be observed. The quantity growth in these sectors, however, would only last for six months, which is shorter than the negative responses found in other quantiles. Such a temporary quantity expansion might stem from the reduced information asymmetry that USA consumers face. But its short duration suggests that pro-export effects would be short-living for a one-time intensification of inspections. As for price, it might reduce after the refusal shock if exporters cut the price to cope with contracted demand. It is interesting to note that while the median IRF of export prices converges to zero in roughly seven months, both responses at the 25 and 75% quantiles extended for more than a year. Hence, while in the short term most sectors experience price increases, responses in the median term are featured with inter-sectoral variations which may suggest differential quality choice and pricing strategies after the shock.

Decomposing composite shocks into common and idiosyncratic components, Figure 1 reveals that IRFs of export quantities and prices to both components share a similar pattern in general. However, fourfold differences can still be observed. On the one hand, responses to common shocks are much smaller than those to idiosyncratic shocks. The median IRFs imply that during the first 11 months following the refusal shock, total negative reactions to the idiosyncratic component in export quantities are 8.1 times of those to the common component. Similarly, as shown by the median IRFs, total price reactions to the idiosyncratic component during the first seven months are 15.2 times of that to the common component. In addition, seeing the IRFs of each sector, there are more sectors that would experience quantity contractions and price increases relative to the case of the common shock.

On the other hand, as indicated by IRFs at the median and 25% quantile, negative responses of export quantities to the idiosyncratic component in the refusal shock start converging toward zero slightly earlier than those to the common component. Hence, common refusal shocks would result in more stable, though smaller, quantity impacts in the short term. As to price responses, IRFs at the 75% quantile demonstrate that in the most responsive sectors, the initial speed of convergence toward zero is also faster for responses to the idiosyncratic component than those to the common component. However, differences in the speed of convergence are less notable in IRFs at the median and 25% quantile.

Differential export impacts between adulteration and non-adulteration charges

The benchmark results, however, cannot reveal potentially distinct export impacts of various types of refusal charges. The two main charges that the FDA imposed on agricultural products are adulteration and misbranding, which respectively accounted for 74.5 and 24.3% of all charges in 2016. Charges of adulteration are usually indicative of higher health risks than other violations. According to the FD&C Act, an adulteration charge is released if a product is found to be prepared, packed or held under insanitary conditions, and may thus be contaminated with filth or rendered injurious to health. These charges thus might trigger consumer concerns on food safety in other Chinese products of the same sector. Charges of misbranding, in contrast, are mostly imposed on products that either involve untruthful or misleading statements on labels, or with a lack of appropriate labelling or packaging. Such issues could be promptly addressed, and are less likely to impair the consumer confidence in related products. In fact, addressing misbranding issues can reduce the information asymmetry that USA consumers face and promote trade (Leland 1979). We thus consider two broad groups of refusal charges, adulteration charges and non-adulteration charges, with the latter dominated by misbranding issues. To compare the impact on exports between these groups of charges, we take the number of charges in each group to the panel SVAR system to derive IRFs of the export performance. For a clearer comparison, we present reactions of sectoral export values without distinguishing quantity and price. In fact, the different impact between charge groups arises mainly from quantity responses. Also, we only demonstrate median export reactions to the composite refusal charge shock so that the comparative results can be better observed.

According to Figure 2, export reductions are revealed in general from a unity sized adulteration charge shock. The median IRF indicates a 0.7% immediate export decline upon the shock and an export contraction of more than 1.1% in the following period on average. On the contrary, the median IRF to a unity sized non-adulteration charge shock implies a 0.7% immediate export growth. However, these pro-export effects appear to be short-living. The reason is that the effect

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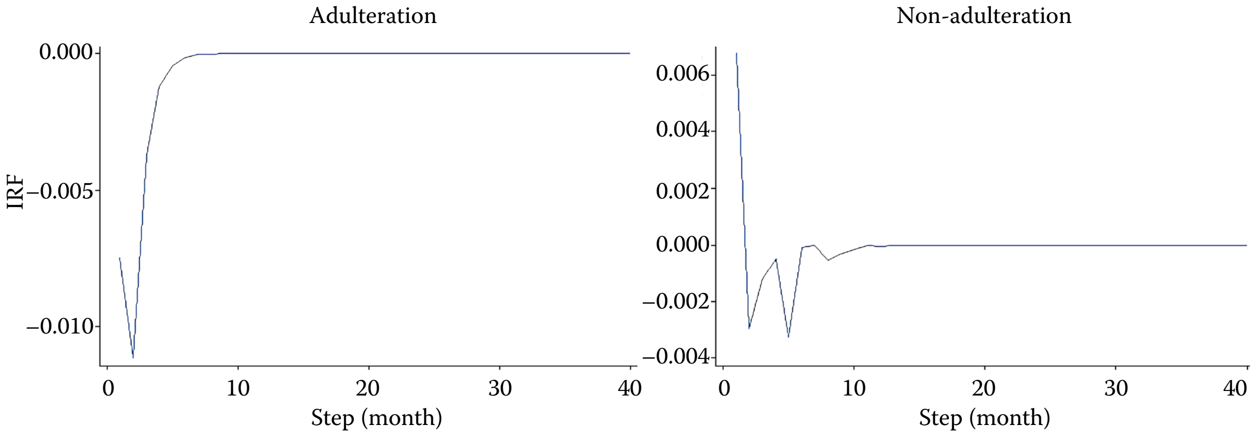

Figure 2. Impulse response functions (IRFs) of China's agricultural exports to United States Food and Drug Administration (FDA) adulteration and non-adulteration charge shocks

Source: authors' elaboration

of addressing issues such as misbranding resembles comparative statics between situations with different levels of information asymmetry. It thus may only result in a one-time shift in the consumer preference for Chinese products.

Spillover effects of FDA refusals on China's exports to non-US markets

FDA import refusal charges on Chinese products may influence China's agricultural export performance in non-US markets. Such spillovers include both deflective and contagious consequences. On the one hand, when Chinese agricultural products are refused to enter the USA market, they may find alternative buyers in other countries (Bown and Crowley 2007). Such re-exports to a non-US market is defined as trade deflection, which can be identified by increased Chinese exports to that market following FDA refusal charges. On the other hand, refusals by the USA may deter purchases of Chinese products in other countries, either because the charged problems are not limited to exports toward the USA or due to reputation deteriorations (Grant and Potoski 2015). Such contracted Chinese exports to a non-US market following FDA refusal charges are called trade contagion.

In this section, country-specific spillover effects are investigated for the top five non-US destinations of Chinese agricultural exports, including Japan (30.7%), Hong Kong (12.7%), ASEAN (11.0%), the EU (9.1%) and Korea (8.7%).[4] Spillover effects can be estimated by respectively replacing China's exports to the USA in the SVAR system by China's exports to each of the non-US markets. This approach resembles that of Baylis et al. (2010) and Grant and Anders (2011) except that they took the rest of the world as one group. Of course, exports to non-US destinations are affected by border inspections in these markets as well. Unfortunately, their refusal data are not all publicly available. Furthermore, there is no evidence either that their refusals are systematically correlated with those of the FDA. Specifically, the correlation coefficient between United States refusal charges and those of EU that we are able to collect is only 0.03. If border inspections in these markets are statistically orthogonal to those in the USA, excluding refusal charges in non-US markets from the VAR system would not bias estimated IRFs.

Figure 3 demonstrates the median IRFs of China's agricultural exports to these non-US markets following a unity sized composite shock of FDA refusal charges. Differential spillover effects stemming from various types of FDA charges are considered as well. In all these non-US markets, median IRFs of China's exports to a non-adulteration FDA charge shock are mostly positive. The largest instantaneous export growth is observed in Korea with a rate of 2.9%. Although featuring more fluctuations, spillovers to Hong Kong and ASEAN countries remain largely positive. These findings suggest that export deflections toward

[4]The number in parentheses indicates the value share of the market destination in the total agricultural exports of China during the sample period.

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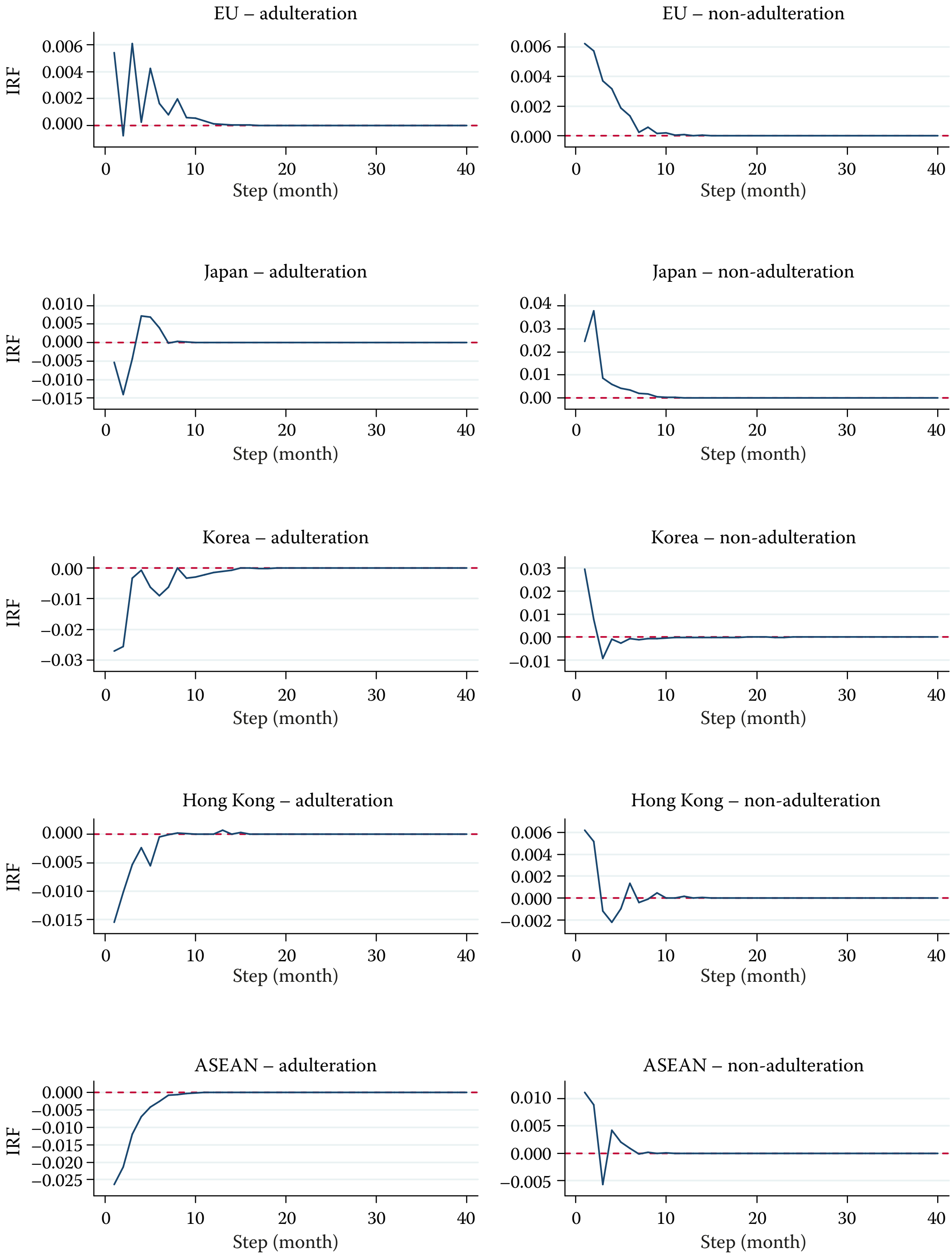

Figure 3. Impulse response functions (IRFs) of China's agricultural exports in main non-US markets to United States Food and Drug Administration (FDA) refusal charge shocks

red stripped line is the 0-reference line for identification of the response and the blue line is the response line

Source: authors' elaboration

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non-US markets tend to follow non-adulteration FDA charges. Since the majority of non-adulteration charges are related to misbranding issues and countries could have different requirements about product labelling, it might not be difficult for the refused Chinese products by the USA to be re-exported to other markets. In addition, non-adulteration charges are less likely to impair the consumer preference for Chinese products in non-US markets so that exporters might increase exports to these destinations.

By contrast, spillover effects following a shock of adulteration charges by FDA are more diverse across non-US markets. On the one hand, export deflections to the EU are observed on average for 13 months after the shock. These export expansions are of a similar scale to those caused by a non-adulteration FDA charge shock but feature more fluctuations. Deflections to the EU suggest that their consumers are not easily affected by FDA refusal decisions. It also implies that the consumer preference in the EU might be relatively close to that in the USA, so Chinese exports to the USA might be re-exported to the EU relatively easily. On the other hand, contagious contractions of exports from China to Korea, ASEAN, Hong Kong and Japan are revealed after the adulteration FDA charge shock. In Korea, ASEAN and Hong Kong, China's exports are found to decrease immediately by 2.7, 2.6 and 1.5% respectively. Trade contractions remain for more than eight months after the shock. In Japan, contagious declines in China's exports are observed in the first three months, which are then followed by export rebound for three months. The net change in China's exports to Japan is however negative at –0.6% during the six months after the shock. To sum up, FDA's adulteration charges would typically render contagious reductions of China's exports in its major non-US markets except the EU.

CONCLUSION

In this paper, we investigated the influence of FDA import refusal charges on China's agricultural exports to the United States on a monthly basis. Using a panel SVAR model, we were able to account for intersectoral heterogeneities in the complete dynamics of responses as well as in the nature of shocks generating these responses. Estimated results confirm the importance of characterising such dynamics and heterogeneities which have mostly been concealed in previous studies. We also gave first-hand evidence on the distinction between quantity responses and those of price, with the latter implying a potential effect of refusals on quality improvement. Finally, we estimated the spillover effects of FDA refusals on Chinese products for China's exports to non-US markets. In contrast to the literature, country-wise estimates are obtained in this paper. Two patterns of spillovers, i.e. trade deflection and contagion, are thus revealed depending on both the destination and type of FDA charges.

Our study underscores the necessity for both Chinese firms and governments to track changes in sector-specific border inspections, in particular for critical products such as fish and shellfish that are not only the most in China's agricultural export basket to the USA but also especially vulnerable to FDA shocks.[5] Differentiated strategies shall also be formulated in line with sector-specific response patterns. For example, FDA charges can substantially deter China's cocoa and chocolate exports to the USA in a year, whereas such negative impacts would almost disappear afterwards. In contrast, for cereal goods, China's export responses to FDA charges will strengthen over time and can be notably prolonged beyond a year. Therefore, though effectively controlling the spread of refusal risks among China's cocoa and chocolate makers is essential in the short run, long-term efforts are required for cereal producers. Finally, our results highlight the role of non-US markets in coping with FDA charge shocks by Chinese exporters. On the one hand, deepening the EU market will be beneficial since it is the main destination of deflection for Chinese products refused by FDA. On the other hand, seeing contagious contraction of China's exports to other countries that typically have a strong trade cooperation with the United States, e.g. Korea through the United States-Korea Free Trade Agreement, it is also urgent for China to prevent such contagions by enhancing consumer confidence, customer relationship, and information symmetry in these destinations.

While this paper focuses on the impact of border inspections on exports, it is equally important to investigate how the trade performance influences import refusal decisions. The possibility of using import refusals as a hidden tool of trade protectionism

[5]The sector of fish and shellfish exhibits the third largest negative responses to FDA charge shocks in the short (no more than three months), median (between three and 12 months), and long run (more than 12 months) across all sectors.

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has been suggested in several recent studies. With monthly data and estimation techniques of our paper, the complete dynamics and inter-sectoral heterogeneities of such protectionism can be uncovered. Future studies on these issues would provide exporters with precise information to predict and prepare for unfavourable border responses by their importing partners.

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