China Economic Review 48 (2018) 66–82

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Impact of European food safety border inspections on agri-food exports: Evidence from Chinese firms☆

Matthias Beestermöller[a], Anne-Célia Disdier[b,*], Lionel Fontagné[c]

[a] University of Munich, Germany
[b] PSE-INRA, France
[c] PSE-Université Paris 1, CEPII, France

ARTICLE INFO

JEL classification:
F14
L25
Q17
Q18

Keywords:
Food safety
Border inspections
Import refusals
Uncertainty
Firm heterogeneity

ABSTRACT

The cost of complying with a sanitary standard is certain. However, such measure introduces uncertainty for exporters in relation to border rejections. Shipments may fail to pass inspections and may be refused entry into the importing country. This risk is shaped by variance in the quality of the exported product, and the stringency of the border controls. We examine how the risk of rejection at European borders on safety grounds is affecting Chinese agri-food exporters. We combine information from the European Rapid Alert System for Food and Feed with Chinese firm-level export data by product, destination and year for the period 2000–2011. Information externalities and reputation effects are important. Border rejections amplify the turnover among firms at the extensive margin of trade. This risk is curbing small exporters and resulting in a concentration of Chinese exports among big exporters.

1. Introduction

Trade liberalization drove the average tariff applied to Chinese agri-food exports to the European Union (EU) to a low of 14.6% in 2011.[1] However, access to the European market remains difficult since individual exporters are required to meet regulatory standards, and face procedural obstacles and enforcement. Non-tariff measures (NTMs) may act as substantial barriers in the decision to export because they potentially increase the cost of exporting.[2] This problem is magnified for agri-food products due to stringent sanitary and phytosanitary (SPS) regulations[3] in most developed markets. Exporting countries holding a comparative advantage in these products are often struggling to meet stringent sanitary standards due to inadequate traceability, poor storage, limited access to certification bodies, etc. (Essaji, 2008). While European standards – which often are more restrictive than international ones – are not

☆ This paper benefited from funding from the European Commission (EC)'s Seventh Framework Programme under grant agreement no. 613504 (PRONTO). Views expressed here do not engage the EC. We thank Matthieu Crozet, Carsten Eckel, Peter Egger, Lisandra Flach, Sébastien Jean, Sandra Poncet, Ferdinand Rauch, Georg Schaur, and the participants at ETSG 2015, WIIW 2015, the University of Munich seminar, the CEPII seminar, the PSE-Paris 1 Workshop on "Chinese firms in a globalized world", and the CEPR workshop "Quantifying Non-Tariff Barriers to Trade and Investment" for their helpful suggestions. This version also benefited from insightful comments and suggestions by two anonymous referees. Matthias Beestermöller gratefully acknowledges support from the DFG Research Training Group 1928 and Egon-Sohmen-Foundation.

* Corresponding author.
E-mail addresses: matthias.beestermoeller@econ.lmu.de (M. Beestermöller), anne-celia.disdier@ens.fr (A.-C. Disdier), lionel.fontagne@univ-paris1.fr (L. Fontagné).

[1] Source: TRAINS (Trade Analysis Information System) database.

[2] E.g., fixed costs such as implementing standards and building up compliance capacities, and recurring costs of documentation for traceability and certification of quality inspections.

[3] Sanitary risk refers to food-borne human illness and animal diseases, and phyto-sanitary risk refers to risks from plant pests and transmission of diseases.

https://doi.org/10.1016/j.chieco.2017.11.004
Received 7 April 2017; Received in revised form 25 August 2017; Accepted 13 November 2017
Available online 21 November 2017
1043-951X/

designed to discriminate against imported goods, certain countries can be priced out of exporting completely.

Interestingly, NTMs also introduce an element of uncertainty related to possible border rejections if shipments do not comply with regulations. The majority of rejections are related to adulteration or misbranding. If exporting firms are unable to meet the required restrictions with a high enough probability, strict regulation and control act as deterrents to trade, especially in sectors heavily affected by sanitary concerns and import refusals, such as seafood (Baylis, Nogueira, & Pace, 2011). While the cost of matching a standard is usually certain, being rejected at the importer's border is a risk faced by the exporter.[4] The risk is shaped by the variance in the quality of the exported products (which can be reduced by investment in quality or controls prior to shipment) and the stringency of the controls at the border. This latter is observable by the exporter but likely endogenous to past rejections, signaling a high level of variance in the quality of the exported products. This is where externalities among exporters from the same country and/or region can emerge for a given product category since part of the cost of being rejected is borne by competitors from the same exporting country. A spell of rejections ultimately can lead to an outright ban on a product from a particular origin;[5] rejections are due to production methods and/or climatic conditions affecting a given country. Taken together, border rejections provide valuable information on NTMs: while details on the occurrence of regulations give evidence on *de jure* NTMs, knowledge about rejections sheds light on their *de facto* trade impact.[6]

NTMs have attracted a lot of attention in the recent trade literature (for a detailed review, see Ederington & Ruta, 2016). The two main issues highlighted are information sources and trade restrictiveness. All these studies face a dilemma: either using indirect evidence on border protection within a gravity perspective which risks capturing much more than NTMs, or using direct – *de jure* – evidence on the presence of NTMs but based on outdated and incomplete data (such as notifications to the WTO).[7] Somewhat surprisingly, the uncertainty component of NTM-related barriers has been mostly overlooked in the literature on NTMs and border inspections. To the best of our knowledge, there are four main papers that provide econometric investigations of the impact of import refusals on agri-food trade but none uses firm-level export data. Three papers deal with inspections conducted by the United States (US), while the fourth examines European refusals. Baylis, Martens, and Nogueira (2009) investigate whether exporters learn from import refusals and whether these refusals are driven by political economy concerns. The analysis is conducted at the macro-level and studies the number of refusals by country of origin, product, and month over the period 1998–2004. The results show that new exporters are less affected than experienced ones by refusals, suggesting that inspections are not random but are targeted at exporters identified previously as unsafe. Furthermore, refusals are not driven only by safety concerns but also by domestic political concerns (such as decreased employment in some sectors). Jouanjean, Maur, and Shepherd (2015) focus more on reputation. Their sample includes US refusals aggregated by country of origin, 4-digit sectors, and year for the period 1998–2008. The authors highlight a neighbor and a sector reputation effect. If the same product from a neighboring country was refused in the previous year, then the odds of a country experiencing at least one import refusal increase by over 100%. At the sector level, the odds of a refusal increase by 62% if a related product from the same country was refused in the preceding year. Grundke and Moser (2014) also adopt an exporter perspective and consider to what extent refusals deter entry in the US. Estimating a gravity equation for 93 product-categories imported to the US in the period 2002–2012, they show that the cost of not complying with US standards is borne by developing countries. EU refusals are used as an instrument because they are expected to be exogenous to US demand. The reasoning made by Grundke and Moser (2014) refers to demand for protection in the US and stricter enforcement of NTMs but like the two previous papers, does not explicitly include uncertainty as a trade barrier. Using data on EU refusals, Jaud, Cadot, and Suwa-Eisenmann (2013) adopt an importer perspective and consider aggregate flows at the product level with no firm dimension. Building on evidence of increasing diversification of EU import sources in agri-food products combined with concentration on a small number of exporting countries, they conclude that entrants start small, while incumbent exporters, which have proved safe, grab most of the EU market share. Although Jaud et al. (2013) also do not mention uncertainty in the import market, the mechanism they refer to is clearly linked to this factor (i.e. sanitary risk in the importing country).

In the present paper we adopt a different perspective: we assess the microeconomic impact of the risk of rejection at the European border on export flows to that market. Food sanitary standards have become an important policy concern in the EU[8] making this market particularly sensitive to the issue at stake. While access to the European market has become easier following tariff reductions, exporters in fact face restrictive food safety requirements and possible rejection. Importantly, we do not investigate the potential effects of European rejections on exports to non-European markets. An interesting falsification test would be to see whether the European rejections have any effect on the exports to non-European countries.[9] However, the latter countries also implement inspection policies and reject unsafe products at their borders. In the absence of information of these rejections, any falsification test is likely to be biased and we only consider the trade effects of European rejections on exports to European countries.

We explicitly investigate the effects of rejections on the export decisions of Chinese firms serving the European market. Overall, China – a large and diversified economy which has encountered repeated problems in rich import markets for foodstuff exports – is an

[4] The cost of matching a standard is certain for the exporter producing a good with its own inputs. If the exporter sources his inputs from many different suppliers, then the cost of achieving a standard may be less certain and would depend on how well the suppliers can reach a given level of product quality.

[5] E.g., in April 2014 the EU banned imports of mangoes from India following the discovery of fruit flies in multiple consignments.

[6] For additional evidence on the importance of distinguishing between *de jure* and *de facto* institutions see e.g. Acemoglu and Robinson (2006).

[7] See Chen and Novy (2012) on the distinction between direct and indirect approaches.

[8] E.g., the 2013 meat adulteration scandal, where food advertised as containing beef was found to contain undeclared horse meat, highlighted the importance of regulations to address market failures.

[9] Trade diversion and deflection effects have been studied for seafood products by Baylis et al. (2011), who highlight some diversion effects, mostly for products facing relatively non-threatening sanitary alerts. In that case, export flows are directed mainly to other high-income countries.

interesting case study. Combining information on rejections with firm level exports allows us to explore the impact of NTMs on individual exports in terms of uncertainty introduced. We apply our data to the issues of reputation and uncertainty raised in the literature.

According to different papers, uncertainty is an impediment to trade on the *importing* country side of the transaction. The starting point is the quality (or safety) of the product, which is not observable. For repeated sales, reputation is based on repeated imports of safe goods from a given origin. What is important is whether the consumer/importer can identify precisely the identity of the exporter. The classical case in the Industrial Organization literature is when the consumer knows the identity of the producer (Shapiro, 1983). The case where the exporter's identity is unknown is more challenging, and applies particularly to commercial relationships with remote countries. In such cases, an expectation of the quality of a product sold by a given firm is formed based on the exporting country's total record of quality problems (in our case, border rejections). Then, individual exporters suffer from the problems encountered by other exporters of the same good from the same country. In an international context, these information externalities can be accommodated – or magnified – by minimum quality standards or origin labeling (Falvey, 1989). Since information externalities are not internalized by the individual exporter, the quality provided by a large country with many firms tends to be low, leading to a collective reputation problem. McQuade, Salant, and Winfree (2012) propose a theory related to these effects.

In our approach, the source of uncertainty is the inspection. The exporter may be rejected at the importer's border, and this risk is shaped by the quality of exported product and the inspection policy set by the importing country. Firms cannot necessarily eliminate the uncertainty by respecting the standard. Indeed, the cost of compliance may be too high for some firms and even if firms are able to comply with it, deficient infrastructures, insufficient storage capacities, or inadequate traceability in the exporting country may alter the quality of the product before its shipping. Furthermore, if the importer cannot distinguish between 'safe' and 'unsafe' trading partners or if determining this is too costly, we expect negative spillovers among other exporters of the same good and/or nationality following a spell of border rejections.

Most foodstuffs imports have passed through multiple middlemen before reaching supermarket shelves which makes it extremely difficult to trace their origins. While regulatory agencies conduct only spot checks, inspections are not random. Certain countries, firms or products may be subject to special focus. Similarly, repeated controls are not random if the custom officer expects large variance in quality from one shipment to the next. Even under the assumption of an equal distribution of quality failures across countries and random inspections, large countries will be targeted more frequently by rejections in the case of controls which disregard the origin of the products. This question relates to the broader literature on profiling controlled individuals and the associated discrimination bias. The terminology *statistical discrimination* used in the literature on optimal auditing characterizes a situation where officers target a specific group in order to maximize successful searches – not based on their own (e.g. racial) preferences. Knowles, Persico, and Todd (2001) use information on outcomes (the success rate of controls) to disentangle racial prejudice from such statistical discrimination – a line of reasoning introduced by Becker (1957). While related to our question about spotting shipments failing to comply with regulations, statistical discrimination goes beyond this paper. We do not have information on the number of shipments nor the spell of controls, but solely on the spell of rejections. Hence, we can neither assess whether Chinese firms are over-represented or not in controls, nor whether the rate of rejection of shipments is equal across groups. Nevertheless, Chinese exporters face considerable uncertainty concerning the likelihood and costs involved in exporting since they could well be targeted by control officers maximizing the chance of identifying a fraudulent shipment. We have product level information on individual exports from the universe of Chinese firms exporting to the European market. Although we cannot identify individual exporters that have been rejected, we have information on the product concerned, the product origin (China), and the year of rejection.

From this perspective our contribution is threefold. Firstly, we add to the growing empirical literature examining the impact of restrictive NTMs at the firm-level using information on *de facto* NTMs (see for example Fontagné, Orefice, Piermartini, & Rocha, 2015, for a combination of these two dimensions). While not all NTMs are barriers, border rejections represent cases where regulations are enforced, inducing potential trade frictions. Firm level micro-data allow us to study the effect of these rejections on firms' participation in the export market (extensive margin) and adjustments in the exported value (intensive margin). Also, we pay explicit attention to the role of firm heterogeneity. The theory suggests that large and more productive firms are likely to react differently to NTMs than small firms.

Secondly, to the best of our knowledge, this is the first paper to look at the effect of SPS measures on firm-level exports from a large emerging economy. Our data cover the universe of Chinese agri-food exports over a period of more than a decade (2000–2011), and include HS6 product and destination information. Since its accession to the WTO in 2001, China's impressive trade growth has accelerated further. Arguably, China is the world's most dynamic and important economy and exporter. At the same time, anecdotal evidence suggests that Chinese agri-food exporters are struggling to meet sanitary standards.[10]

Thirdly, we focus on a specific trade-impeding indicator of SPS regulations using a rarely exploited dataset of rejections at the European border.[11] Our *de facto* NTM measure can be considered as a substantial barrier for exporters. The Rapid Alert System for Food and Feed (RASFF) database records all European border rejections[12] of shipments due to sanitary concerns. Among other

[10] Frequent scandals and anecdote have documented the problems among Chinese exporters to meet sanitary standards. They can indeed be over-reported in the Press. E.g., on Oct. 17, 2012, the German newspaper *Der Spiegel* pointed to recurring health issues: "In recent years, China has become a major food supplier to Europe. But the low-cost goods are grown in an environment rife with pesticides and antibiotics, disproportionately cited for contamination and subject to an inspection regime full of holes."

[11] The exception again is Jaud et al. (2013), although the data are treated in a totally different way.

[12] Throughout this paper we use the terms import refusal and border rejection interchangeably. As described in Section 2 on the data, we focus on the subset of

information, it includes the origin of the rejected shipment and a verbal product description. We manually matched the verbal product descriptions in RASFF with HS codes at the 4-digit level of disaggregation. We merged Chinese firm-level data with the RASFF data. The resulting dataset permits us to analyze the impact of border rejections on firms' export decisions.

Our results suggest that border rejections increase firm turnover at the extensive margin of trade. Some Chinese exporters stop exporting to the European market while at the same time, new Chinese firms enter this market. Small firms are affected more strongly than big exporters by this turnover. These results are in line with the recent trade literature showing that in a heterogenous firm setting, firms that are small and not productive enough are more likely to exit the export market. In addition, we show some concentration of Chinese exports among big exporters at the intensive margin of trade.

The paper is organized as follows. Data on border rejections and Chinese firms' exports are presented in Section 2. The empirical strategy is described in Section 3. Section 4 reports the estimation results and robustness checks. Section 5 concludes.

2. Data and descriptive statistics

This section first describes our two main data sources and then provides some descriptive statistics.

2.1. Data

Although products subject to sanitary requirements experience systematic pre-shipment controls in the exporting country, random controls at the border of the importing country ensure fairness of the process and retain the possibility of recognizing problems related to transportation. If a problem is identified, the shipment is likely to be rejected. We combine information on rejections of agri-food shipments at the European border with Chinese firm level export data. This allows us to measure the impact of uncertainty (from sanitary riskiness) and regulations on firms' export decisions. Although we cannot identify individual exporters that have been rejected, we have annual information on the product concerned and the origin (China) of the flow.

2.1.1. Food alerts and border rejections

The RASFF,[13] created in 1979, consists of a cross-border information exchange system on emergency sanitary measures in the European Economic Area (EEA).[14] RASFF members must notify the European Commission (EC) about any serious health risk deriving from food or feed. Starting from 1979, all notifications are publicly available via the RASFF portal.

To construct our dataset, we record all notifications by RASFF member states over the period 1979–2011, and make several assumptions:

- First, we keep notifications over the whole period 1979–2011 even if our firm data cover a shorter period (see below) in order to exploit the variation in notifications over time and their cumulated effect on trade flows.
- Over our sample period, two rounds of RASFF membership enlargements occurred, both of which we account for. The list of RASFF members is reported in Table 1.[15] We treat the RASFF border as the relevant location for observing notifications and consider all notifications by RASFF members regarding non-RASFF countries. We ignore notifications concerning products originating from other RASFF countries. Controls may be more stringent at some borders compared to others (e.g. if the staff is better trained or more conscientious in some locations). However in the absence of information on the rate of inspections for each RASFF entry point, we do not control for the issue.
- Since we are concerned about rejections due to SPS concerns, we restrict our analysis to agri-food products, i.e. products belonging to chapters 01-24 of the HS classification.
- Some shipments may be rejected but after some improvements – e.g. in the product labeling – allowed entry into the RASFF market. However, the majority of inspected shipments declared 'unsafe' are refused entry into RASFF market permanently. Since we are interested in *de facto* restrictive rejections, we limit our analysis to this second group of shipments. Using information available on the RASFF portal, we can identify whether or not future entry was allowed. We retain only observations related to permanent import refusals.[16]
- If a rejection specifies two origin countries (only 4% of the rejections in our sample), we split the observation into two: one for each origin.

After these cleaning procedures, we have a total of 14,860 rejections during the period 1979–2011, 1690 of which are related to

(*footnote continued*)
notifications where a product fails to enter the European market. According to the statistics provided in RASFF annual reports, border rejections represent the biggest fraction of total notifications.

[13] http://ec.europa.eu/food/safety/rasff/index_en.htm.

[14] EEA includes the EU27 countries plus Iceland, Liechtenstein, and Norway.

[15] We exclude Switzerland which from 2009 is included in RASFF border controls of products of animal origin but not in other types of controls.

[16] More precisely for the period 2008–2011, we use information on border rejections, which is reported on the RASFF portal and refers to consignments that have failed entry to the RASFF market and which are not allowed to enter through another border post. Before 2008, this precise information on border rejections was not available. We exploit information on notifications and on the action taken by RASFF authorities (e.g. import not authorized; product destruction; product placed under customs seals; destruction or return after official permission; re-export to a third market; containers detained) to identify border rejections. This change in rejections' identification before and after 2008 does not affect our estimation results.

Table 1
RASFF members.

Since 1995		From 2004		From 2007
Austria	Italy	Cyprus	Lithuania	Bulgaria
Belgium	Liechtenstein*	Czech Rep.	Malta	Romania
Denmark	Luxembourg	Estonia	Poland	
Finland	Netherlands	Hungary	Slovenia	
France	Norway*	Latvia	Slovakia	
Germany	Portugal			
Greece	Spain			
Iceland*	Sweden			
Ireland	United Kingdom			

* Not EU, but EEA members

Chinese shipments.

The RASFF portal contains information on products only in verbal form. We coded the rejection data at the HS 4-digit level – the most disaggregated level at which we can identify rejections. A detailed description of the applied methodology is provided in Appendix A.1. Using this approach, we are able to match 89% of all rejections with an HS4 code (13,241 out of 14,860), and 91% of Chinese rejections (1537 out of 1690).

Unfortunately, the RASFF portal does not provide the quantity or value of rejected products, nor the name of the exporting firms. Therefore, in our empirical analysis, we will use the incidence of rejections as the unit of measurement of the rejection variable.

2.1.2. Chinese exports at the firm-level

Chinese customs data[17] provide information on exports by firm, product (6-digit of the HS classification), destination and year. Customs data, which include the universe of Chinese exports, are preferable to surveys often used in the literature since customs data avoid stratification or sampling issues such as selection effects. Our dataset covers the period 2000–2011 and identifies whether the firm is a wholesaler or not.

In our empirical analysis, we restrict our attention to non-wholesalers. While intermediaries play an important role in trade, we want to focus on the direct decisions of firms. Intermediaries might display different export behavior and might react less strongly to border rejections.

We aggregate all exports by firm-destination-year at the HS4 level (the level at which we code border rejections). It is possible that some firms might export different HS6 products within one HS4 sector. To address this concern, we verify that the large majority of HS4-firm observations also uniquely identify an HS6 shipment (see Table A.2 in Appendix A.2). Even among multi-HS4 product firms, around 70% of HS4 sectors include only a single HS6 product.[18]

2.2. Descriptive statistics

Table 2 reports the number of Chinese exporters (excluding wholesalers) present in all world markets, and in the RASFF market. For clarity, the statistics are reported every two years. On average, between 24% and 32% of Chinese exporters are present in the RASFF market. The number of active exporters rose between 2001 and 2007 and after 2009, with a small drop in export activity during the 2008–2009 crisis. The sample of products exported over time is relatively stable, with a decrease after 2007. Contrary to the number of exporters, no further increase is observed at the end of the crisis. Many exporters to the RASFF market are single-product firms. On average, firms export 1.6 products to the RASFF market (the median is equal to 1). Fig. 1 plots Chinese agri-food exports (in logs) over the sample period. World exports and flows to the RASFF market are represented. In line with the growth in the number of exporting firms, exports tend also to increase over the period (except in 2009).

Fig. 2 provides statistics related to RASFF rejections for all shipments regardless of origin.[19] We consider the number of rejections over time and the main origins of rejected shipments. A significant rise in the number of RASFF rejections between 2000 and 2003 is depicted in panel (1). This increase primarily reflects growing attention to sanitary risks (e.g. bovine spongiform encephalopathy, dioxins, and mycotoxins) and increased application of the system by RASFF members. The increase in rejections in 2003 is also likely due to Central and Eastern European Countries harmonizing their regulations before their accession to the EU in 2004. Since 2003, the number of rejections is between 1000 and 1500 annually, with significant decreases in 2006 and 2007 not driven either by the change in RASFF members or the moving EU border. China, is one of the countries most affected by RASFF rejections, contributing for 11.6% of all rejections (panel (2)).[20]

[17] We thank Sandra Poncet for providing the data.

[18] Econometric estimations conducted only on firms exporting a single HS6 product within an HS4 sector do not provide results significantly different from the ones obtained with the whole sample of firms. Table A.2 shows also that the majority of firms are present in only one HS4 sector. Therefore, in our sample spillovers within firms and across HS4 sectors are likely to be small.

[19] We focus on the period 2000–2011, which is the one covered by Chinese customs data. Few rejections (less than 5%) occurred between 1979 and 1999.

[20] Turkey and Iran are ranked among the top rejected origin countries. Mycotoxins are a well known issue of Turkish exports of pistachios and dried figs, and Iranian pistachios. All Iranian exports of pistachios are double checked for freedom from mycotoxins.

Table 2
Chinese firms: descriptive statistics.

		2001	2003	2005	2007	2009	2011
World agri-food exports							
Nb. of firms		7340	8834	12,321	12,259	11,314	11,604
Nb. of HS4 products		192	195	196	192	185	185
Agri-food exports to RASFF market							
Nb. of firms		1800	2083	3176	3604	3548	3730
Nb. of HS4 products		137	135	150	151	140	136
Nb. of HS4 products per firm	Mean	1.68	1.57	1.64	1.68	1.61	1.59
	Median	1	1	1	1	1	1

Note: Authors' computation. These statistics exclude wholesalers.

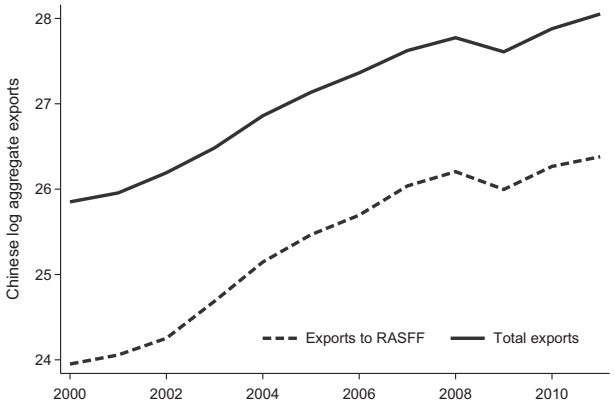

Fig. 1. Chinese agri-food exports between 2000–2011. Note: Authors' computation (excluding wholesalers).

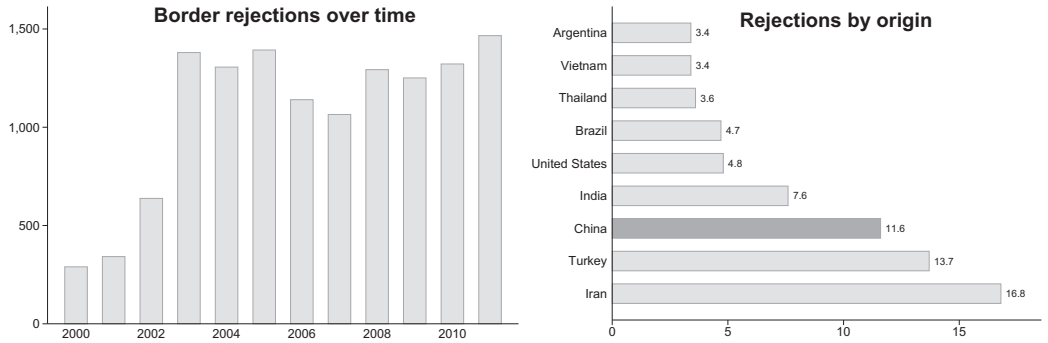

Fig. 2. RASFF rejections on all shipments. Note: Authors' computation. Panel (1) provides the number of rejections over time; Panel (2) reports the main origins of rejected shipments and depicts the share of each origin in total rejections.

Fig. 3 reports the number of RASFF rejections affecting Chinese shipments (panel (1)) and the main HS2 industries affected by rejections (panel (2), share in total rejections in %). There is an increasing trend in rejections of Chinese shipments over time (with a dip in 2009 related to the crisis) suggesting a positive correlation between Chinese exports (see Fig. 1) and Chinese rejections at the RASFF border. Also, we observe a strong increase in the number of rejections in 2008. This increase could indicate China diverting exports from countries strongly hit by the economic crisis to the EU. Firms exporting to countries with lower standards might try to export to the EU if the demand in lower standard countries decreases. If their products do not satisfy EU requirements, this could result in an increase in rejections. An alternative explanation is related to protectionism. At the beginning of the 2008–2009 crisis, inspections and rejections were used potentially in a protectionist way, i.e. to protect European producers from Chinese competition. In our empirical analysis, we include industry-time fixed effects to control for this increasing trend. Panel (2) shows that oil seeds (HS12) and fish and fishery products (HS03) are the Chinese industries most affected by rejections, accounting for more than 60% of all rejections. The very high share of industry HS12 in Chinese rejections relates to mycotoxin problems in peanuts (HS1202). All in all, our sample shows a positive (around 0.15, $p < 0.05$) and significant correlation between RASFF rejections of Chinese shipments at the HS4 level and changes in Chinese aggregate exports in the affected HS4 categories. This suggests that rejections in a particular HS4 product category have the effect of depressing overall European imports from China in that HS4. Similarly, our sample shows a

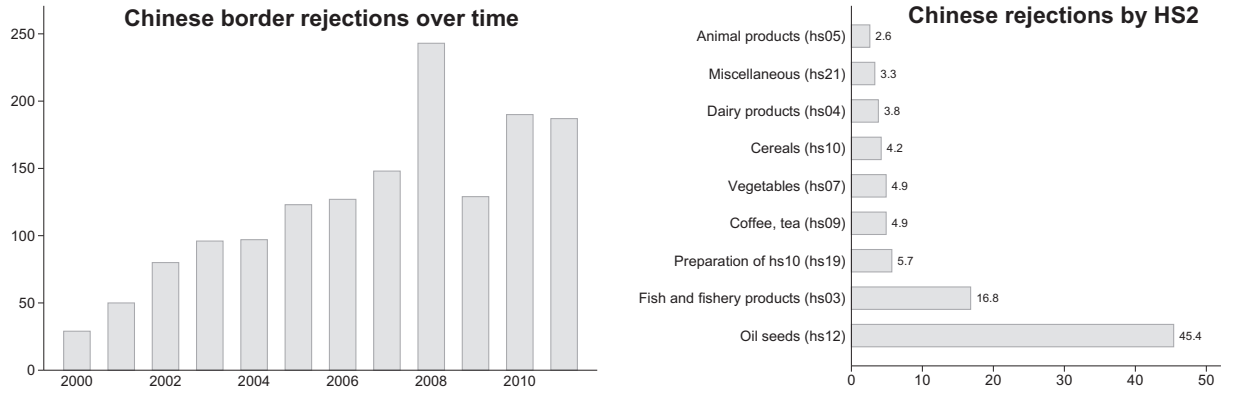

Fig. 3. RASFF rejections on Chinese shipments. Note: Authors' computation. Panel (1) provides the number of Chinese rejections over time; Panel (2) reports the main HS2 industries affected by rejections and depicts the share of each industry in total rejections.

positive and significant (around 0.12, $p < 0.05$) correlation between the price dispersion across Chinese exporters for a given HS4-year and the occurrence of rejections, suggesting that the probability of rejection relates to heterogeneity in export quality (proxied here by price).

Fig. 4 shows whether there is some hysteresis driving RASFF rejections. It plots simple correlations of the data, comparing current and lagged rejections (in logs) at the same country-HS4 product dimension, for all countries (panel (1)), and for China (panel (2)). Lagged rejections (in $t-1$) are represented on the y-axis, and current ones on the x-axis. Fig. 4 provides descriptive evidence of positive correlations. It also highlights that inspections (and therefore rejections) clearly are not random but are driven largely by past rejections. Of course, this analysis is based on simple correlations and does not control for HS4 product and exporter characteristics.

3. Empirical strategy

We investigate the trade impact of RASFF border rejections on Chinese firms. As discussed above, border inspections and possible rejections create some uncertainty and have an impact on exports. Furthermore, this impact is likely to be heterogeneous across exporters. First, not all shipments are inspected and inspections are not random. Certain firms or products, presenting higher safety risks, tend to attract particular scrutiny. Second, some exporters, especially the biggest ones, are more able to invest in maintaining the quality of their products or in controls prior to shipment, thus reducing their risk of rejections.

An apparent limitation of our data set is that the RASFF data do not allow direct identification of the shipments and exporting firms hit by a rejection. Hence we can only estimate the effect of a rejection of a particular product on all exporters of that product. Thus, our estimated effect combines the direct effect of rejections on hit firms, as well as the indirect one on other Chinese competitors exporting the same product. What are the implications of such data restriction for our estimation strategy?

Beyond the negative impact on the affected exporter, there are spillover effects of a refused shipment of a given HS4 product from one Chinese firm to other Chinese firms exporting in the same HS4 category. One would expect that the impact on trade would be greater for firms that had a shipment rejected than for firms that did not have rejected shipments. One reason for this would be that inspectors in the RASFF member countries would likely target their enforcement activities towards firms that had previous shipments rejected (statistical discrimination as discussed above), given that export firm identity is likely known to inspectors for a variety of reason, including traceability requirements.

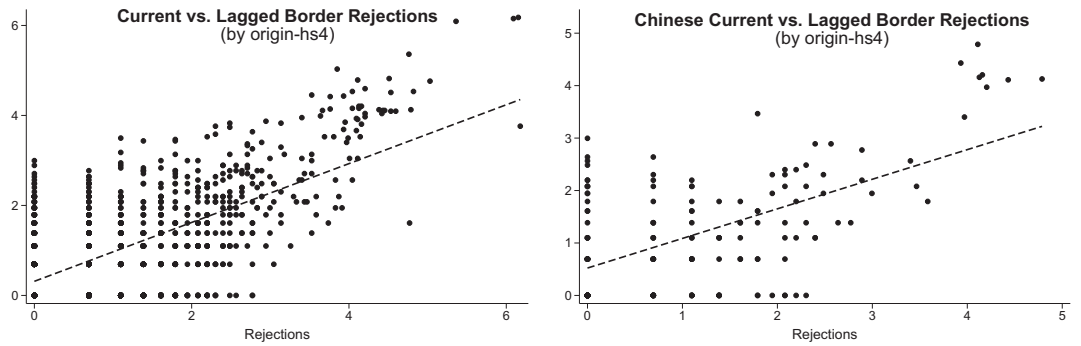

Fig. 4. Correlation between current and lagged RASFF rejections (in logs). Note: Authors' computation (y-axis: lagged rejections in logs (in $t-1$); x-axis: current rejections in logs (in t)).

Identifying both the direct and spillover effects of border refusals would require dummy variables for whether a firm had a shipment refused and if another firm exporting in the same HS4 category s had a shipment refused. We would have $reject_1 = 1$ if firm i had a border refusal in period $t-1$ and 0 otherwise; and $reject_2 = 1$ if another firm in category s had a border refusal in period $t-1$ and 0 otherwise. This would lead to three different outcomes: firm i had the only border refusal in period $t-1$ in category s ($reject_1 = 1$ and $reject_2 = 0$); another firm exporting in category s had a border refusal ($reject_1 = 0$ and $reject_2 = 1$); and both firm i and another firm in category s had a border refusal ($reject_1 = 1$ and $reject_2 = 1$). The base case would be when no border refusals occur. So $\beta_{d,1}$, the parameter estimate associated with $reject_1$, would measure the direct effect of having a border refusal. $\beta_{s,1}$, the parameter estimate associated with $reject_2$, would measure any spillovers to other firms. Finally, $(\beta_{d,1} + \beta_{s,1})$ would measure the direct and spillover effects for a firm that had a border refusal and other refusals in the same HS4 category also occurred.

This would be the "true" model to be estimated. However, two issues raise obstacles on that natural route. Firstly, although a rejected shipment is not present in EU import statistics it has passed through the Chinese customs and might well be present in Chinese transaction level custom data. Thus the impact on a Chinese exporter of having a shipment rejected might well not be observed in the current period – hence our choice of considering the spell of rejections in $t-1$. Secondly, in the absence of information on the affected Chinese exporter, we can only observe the overall effect of the rejection on the Chinese exports of a given category of product. Our rejection variable thus appears to be a combination of $reject_1$ and $reject_2$ as defined above.

Against this background we estimate exporter behaviors at the extensive and intensive margins of trade as a function of rejection measures and their effect jointly with firm characteristics. We follow the empirical strategy suggested by Fontagné et al. (2015) and estimate the following equation:

$$y_{i,s,t} = \alpha + \beta_1 \quad \text{rejection}_{s,t-1} + \beta_2 \quad ln(\text{size})_{i,t-1} + \beta_3 \quad [\text{rejection}_{s,t-1} \times ln(\text{size})_{i,t-1}] + \mu_i + \psi_s + \phi_{HS2,t} + \epsilon_{i,s,t},$$

where i refers to the firm, s to the HS4-digit product category, and t to the year.

As already mentioned, the RASFF border is the relevant location for our study. Since RASFF countries exchange information on rejections, one product rejected at one RASFF border will not be able to enter the RASFF market via another border. Therefore, we do not consider export flows to each RASFF country separately, but aggregate exports to all RASFF countries. Thus, the RASFF market as a whole is the only destination in our analysis. The aggregation of all RASFF countries into a single destination presents another advantage. A product could be rejected by a country which is not its final destination. However, Chinese customs data report only final destinations. This divergence between the final destination and the country of rejection could bias the results of an analysis conducted at the country-level. Aggregation at the RASFF market level addresses this issue.

Considering the RASFF market as a whole does not allow us to properly control for tariff protection. However, in our analysis, this is not a major issue. All importing countries (except Iceland, Liechtenstein, and Norway) are part of the EU and apply the same common external tariffs. Therefore, tariffs are almost invariant across RASFF countries. Also, the tariffs imposed by RASFF countries on Chinese products did not vary significantly between 2000 and 2011, and a large part of any variation is captured by the set of industry-year fixed effects included in our estimations (cf. infra).[21] Therefore, the absence of a control for tariffs does not bias our results.

We define different dependent variables, $y_{i,s,t}$:

- A dummy for exit that equals 1 if the firm exports the HS4 product to the RASFF market in $t-1$ but not in t (0 otherwise). The counterfactual is firms that export a given HS4 to RASFF countries in $t-1$ and also in t. We disregard re-entry in later periods;[22]
- A dummy for entry that equals 1 if the firm exports the HS4 product to the RASFF market in t but not in $t-1$ (0 otherwise). Here, the counterfactual is firms that do not enter the market, i.e. do not export a given HS4 to RASFF countries in $t-1$ or in t.

The entry and exit variables capture the (firm-HS4) extensive margin of trade. They are not analogous. As highlighted by the counterfactual, exit is conditional on the firm being active in $t-1$, while entry is conditional on not exporting in $t-1$.

- In addition to the exit and entry dummies, we also define the number (in logs) of Chinese firms exporting to the RASFF market for each HS4 category and year t.
- At the intensive margin of trade, we consider the value of the export flows – specifically, the value exported by the firm to the RASFF market for a given HS4 product in year t. We focus on incumbents (surviving firms, i.e. firms that are already present in $t-1$ and continue to export in year t. In other words, we do not consider firms that start or cease to export in year t. Thus, we retain only strictly positive flows. Besides, the value of the export flows, we also look at the export quantities and the export prices (measured using the unit values).

Our set of explanatory variables includes border rejections and firm characteristics. We consider two different measures for border rejections. As suggested by Essaji (2008), we use lagged rejections as internal instruments (i.e. before actual exports in t). Our rejection measures ($\text{rejection}_{s,t-1}$) are:

[21] Typically, the EU simple average tariff on Chinese agri-food imports equals 16.9% in 2000 and 14.6% in 2011 (source: TRAINS database). Furthermore, trade remedies such as antidumping or countervailing duties are not an issue in our sample. Indeed, almost all measures adopted by RASFF countries against China deal with manufacturing products and not agri-food ones.

[22] Recall that we focus on the RASFF market only and do not consider exports to non-RASFF countries. Therefore, a firm may exit the European market but may continue to export to non-RASFF countries.

- A dummy for past rejections that equals 1 if at least one shipment from China of that particular HS4 product was rejected at the RASFF border in $t-1$ (0 otherwise);
- The cumulated number (in logs) of past rejections from China for that HS4 product. It is computed simply as the sum of Chinese shipments of that particular HS4 product which were rejected in the past (i.e. from 1979 until year $t-1$). We then take ln(1 + cumulated number of past rejections).

The trade literature (Melitz, 2003) highlights that firms' export performance is heterogeneous and driven largely by their productivity. Unfortunately, Chinese customs data do not provide details on firms' characteristics (e.g. productivity, employment, total sales). Thus, to control for firm heterogeneity and its impact on export performance, we refer to firm size, defined as the log of their total agri-food exports in $t-1$ ($\ln(\text{size})_{i,t-1}$).[23] As shown in the literature (Mayer & Ottaviano, 2008), export values are a good proxy for firm size. For ease of interpretation, we center firm size around the median size of all firms in that year.

To capture some heterogeneous effects on the impact of rejections across firms, we interact our rejection variables (dummy and cumulated number in logs) with firm size. A precise account of these heterogeneous effects is crucial for the interpretation of the empirical results, and therefore the interaction term between rejections and firm size is our main variable of interest.

Finally, we include fixed effects to control for unobserved heterogeneity. We introduce HS2 industry-year ($\phi_{HS2,t}$), HS4 product category (ψ_s), and firm (μ_i) fixed effects. HS2 industry-year fixed effects control for business cycles and import-demand shocks at the industry level. HS4 fixed effects capture the fact that rejections may be more frequent in product categories where EU food safety standards are particularly stringent and/or in categories where shipments occur many times over the course of a year (e.g. for perishable products). Firm fixed effects control for time-invariant characteristics specific to a firm such as average size.

We estimate all equations by ordinary least squares (OLS). The extensive margin dependent variables are dichotomous in nature. However, we prefer the linear probability model (LPM) to non-linear models such as logit or probit since LPM avoids the incidental parameter problem in the presence of the large number of fixed effects we employ. Besides, the LPM model provides good estimates of the partial effects on the response probability near the center of the distribution of the explanatory variables' vector (Wooldridge, 2010).[24] The estimations use the Stata Package REGHDFE developed by Correia (2014). Because maintaining singleton groups in linear regressions where fixed effects are nested might lead to incorrect inferences, we exclude groups containing only one observation (Correia, 2015). Therefore, the number of observations differs across estimations. The results are similar when retaining singleton groups and are available upon request.

Throughout, we exclude wholesalers from our estimations; as already mentioned, we want to focus on the firm's decisions. However, we conduct a series of robustness checks with wholesalers; our main conclusions remain unchanged (cf. infra).

4. Results

First, we study whether rejections of Chinese shipments affect Chinese exports to the RASFF market. The analysis is performed at both the extensive and intensive margins of trade. We then test the robustness of our results. Since our estimations rely on border rejections and not on regulations per se, our results should be seen as a lower bound estimate of the total effect of regulations on trade patterns. Indeed, regulatory costs faced by firms that succeeded to enter the RASFF market are not captured by the border rejections. Similarly, border rejections do not capture the costs incurred by firms that are rejected at the border.

4.1. Extensive margin of trade

The first three columns in Table 3 present the impact of Chinese rejections on the exit of Chinese firms from the RASFF market. In columns (1) and (2), rejections are measured using a dummy that is set to 1 if at least one shipment of the same HS4 was rejected in $t-1$. We investigate exit in year t. Column (3) reports the cumulated number (in logs) of past rejections of Chinese shipments for that HS4 over time until $t-1$. In all columns we control for firm size. Columns (2) and (3) also include an interaction term between firm size and past rejections. As firm size has been centered (measured as the deviation from the median), we can decompose the effect of past rejections on small firms (firms below median size) versus on big firms (firms above median size).

In column(1), past rejections increase the probability of exit of Chinese firms from the RASFF market. The effect remains and becomes more significant when we control for heterogeneity in the impact of rejections across firms (columns (2) and (3)). According to column (3), adding one more past rejection raises the probability of exit for the median firm by 7.8%. In addition, exit affects small firms more than big firms; the estimated coefficient of the interaction term between firm size and rejections is negative. In line with the large literature on firm-level exports, we find also that – everything else being equal, i.e. regardless of past border rejections – small firms tend to exit more.

Columns (4) –(6) in Table 3 report the impact of Chinese rejections on the entry of Chinese firms into the RASFF market. The estimations include the same explanatory variables as in columns (1) –(3). We find that rejections tend to favor the entry of new

[23] More precisely, firm size is computed as ln(1 + total agri-food exports in $t-1$). This approach allows us to keep brand new firms for which lagged size is equal to zero in our entry estimations. Note that in our sample, firms' size and productivity are not necessarily correlated. Many large Chinese firms are indeed state owned enterprises that are shielded from market competition.

[24] The LPM model is often used in the trade literature (see for example Chen & Mattoo, 2008). An alternative approach consists in using a random effects probit model. However in this model, the unobservable random variable should have a normal distribution and be independent from the observable variables, which is a strong assumption (Wooldridge, 2010).

Table 3
Extensive-margin estimations.

	Exit from the RASFF market in year t			Entry in the RASFF market in year t			Ln number of firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy = 1 if at least one rejection in $t-1$	0.016[b]	0.141[a]		0.0001	0.005		
	(0.008)	(0.031)		(0.003)	(0.003)		
Dummy for rejection in $t-1$ X Ln firm size		−0.010[a]			−0.002[a]		
		(0.002)			(0.0004)		
Ln cumulated nb. of past rejections until $t-1$			0.078[a]			0.004[b]	−0.253[a]
			(0.013)			(0.002)	(0.069)
Ln cum. nb. past rejections X Ln firm size			−0.005[a]			−0.001[a]	0.050[a]
			(0.001)			(0.0001)	(0.011)
Ln firm size	−0.048[a]	−0.044[a]	−0.042[a]	0.013[a]	0.014[a]	0.014[a]	−0.123[a]
	(0.002)	(0.002)	(0.002)	(0.0003)	(0.0002)	(0.0003)	(0.010)
Observations	45919	45919	45919	178817	178817	178817	1517
R^2	0.335	0.335	0.336	0.078	0.078	0.079	0.957

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in columns (1)–(6) and for HS4 product category and HS2 industry-year in column (7) (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$ in columns (1)–(6). In column (7), firm size is measured as the mean size of firms within an HS4 product category in $t-1$. Columns (1)–(3): Exit-probabilities. Columns (4)–(6): Entry-probabilities. Column (7): Number of firms. [a]: $p<0.01$, [b]: $p<0.05$.

firms. The estimated coefficient on the cumulated number of past rejections is positive and significant ($p < 0.05$) (column (6)). The magnitude of the effect is equal to 0.4%. Also, it seems that rejections promote the entry of small firms more than big firms; the estimated coefficient of the interaction term between firm size and rejections is negative and significant ($p < 0.01$). Finally, regardless of past rejections, big firms enter the RASFF market more easily than small ones. Comparison of estimated coefficients of the exit and entry probability reveals that past rejections have a much stronger impact on firm exit than on firm entry. The R^2 are also significantly lower in columns (4) –(6).

Overall, our results are in line with Jaud et al. (2013), who find that sanitary risk increases the diversification of European imports at the extensive margin. Here, we observe turnover among Chinese firms exporting to the RASFF market. Past rejections increase both the exit of Chinese exporters and the entry of new ones, and the effect on both exit and entry is stronger for small firms.

The last column in Table 3, rather than examining exit and entry probabilities, aggregates the observations at the HS4 product category-year level and considers the number (in logs) of Chinese firms exporting to the RASFF market for each HS4 product category-year combination. Firm size is measured as the mean size of firms within an HS4 product category and for year $t-1$. This variable thus provides information on the heterogeneity in the mean size of firms across HS4 categories and years. Interestingly, the estimated coefficient of the cumulated number of past rejections is negative and significant ($p < 0.01$), suggesting that exit tends to dominate entry. Border rejections reduce the total number of Chinese firms exporting to the RASFF market. Also, the number of small firms shows a bigger decrease compared to big firms, and the estimated coefficient of the interaction with firm size is positive and strongly significant. Finally, as expected, the presence in the market of big firms in the past has a negative effect on the number of firms currently in the market.

4.2. Intensive margin of trade

Next, we focus on the intensive margin of trade (Table 4). Columns (1) –(3) look at the value exported by incumbent firms (i.e. firms present in years $t-1$ and t) to the RASFF market. Our results highlight three main facts. First and independent of border rejections, bigger firms tend to survive and increase their exports to the RASFF market (the variable for firm size is significant, with $p < 0.01$). Second and everything else equals, firms that continue exporting products hit by rejections slightly decrease their exports to the RASFF market. While the dummy for past rejections has a negative but not significant impact on the export values (column (2)), the estimated coefficient on the cumulated number of past rejections (in logs) is negative and significant (column (3)). Third, some heterogeneity is observable across firms. The interaction term between the cumulated number of past rejections and firm size suggests that big incumbent firms (above median size) increase their exports to the RASFF market in the year(s) following a rejection (column (3)). Therefore, large firms do benefit from the exit of small exporters consecutive with a rejection.

Column (4) investigates the impact of border rejections on the quantity exported by incumbents, while column (5) examines the price – measured as the unit value – of the products exported by these firms.[25] The heterogeneous effect of past rejections across firms remains significant for quantity (column (4)) and is similar in magnitude with the one highlighted for value (column (3)). Finally, cumulated past rejections slightly increase the price of products, suggesting that firms facing higher costs due to the standard requirements, pass-through at least part of this cost increase into their export prices. The estimated coefficient on the interaction term between rejections and firm size is however not significant, suggesting the absence of differentiated price impact for small and big incumbents.

[25] Some prices exhibit extreme values. We exclude these outliers by deleting the top and bottom 1% of the price observations.

Table 4
Intensive-margin estimations.

	Ln exports to the RASFF market in t (Incumbent firms)				
	Value			Quantity	Unit value
	(1)	(2)	(3)	(4)	(5)
Dummy = 1 if at least one rejection in $t-1$	0.026	−0.183			
	(0.035)	(0.161)			
Dummy for rejection in $t-1$ X Ln firm size		0.016			
		(0.012)			
Ln cumulated nb. of past rejections until $t-1$			−0.159[b]	−0.202[a]	0.046[c]
			(0.070)	(0.072)	(0.025)
Ln cum. nb. past rejections X Ln firm size			0.013[b]	0.015[a]	−0.002
			(0.005)	(0.005)	(0.002)
Ln firm size	0.166[a]	0.161[a]	0.152[a]	0.136[a]	0.016[a]
	(0.010)	(0.011)	(0.011)	(0.012)	(0.004)
Observations	29165	29165	29165	29155	28691
R^2	0.630	0.630	0.630	0.666	0.829

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. [a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.1$.

Our results at the intensive margin show some concentration of Chinese exports among big exporters. The effect is stronger for products hit by past rejections. These results confirm Jaud et al. (2013), who also highlight concentration at the intensive margin, especially for risky products. When rejections are more frequent and cumulate, European importers concentrate their orders on large, and plausibly more reliable Chinese exporters, who increase their exports to the RASFF market.

Thus, on the global impact of rejections on the exports of Chinese firms to the RASFF market, we observe two effects: some turnover of firms at the extensive margin of trade, accompanied by some level of concentration at the intensive margin.

4.3. Robustness checks

In this section, we investigate the robustness of our results to alternative specifications and samples. All the tests are performed using our preferred estimations, i.e. those including the cumulated number of past rejections (in logs) as a measure of border rejections, and the interaction term between this rejection measure and firm size (in logs). Three estimations are run in each case: one for the probability that the Chinese firms will exit the RASFF market, one for the probability of entry into that market, and one for the intensive margin of trade.

First, the number of rejections for a given product may be correlated with the number of firms exporting that product. Typically, one HS4 product could be associated with many rejections simply because many firms export that product, while another product could be associated with few rejections because few firms export it. Note that in both cases, the number of rejections per firm would be similar. To address this issue, the first three columns of Table 5 replicate our main estimations controlling for the number of firms per HS4-year. Our main results are unchanged. At the intensive trade margin, the number of firms is positively correlated with firms' export flows to the RASFF market.

In the last three columns of Table 5, the standard errors are clustered at the HS4 product-year level. Given that both the dependent variable and our main variable of interest (e.g. the interaction term between rejections and firm size) vary at the firm-HS4-year level,

Table 5
Robustness: Number of exporting firms and cluster.

	Number of exporting firms in HS4-year			Clustered std. errors		
	Exit	Entry	IM	Exit	Entry	IM
	(1)	(2)	(3)	(4)	(5)	(6)
Ln cumulated nb. of past rejections until $t-1$	0.071[a]	0.007[a]	−0.147[b]	0.078[a]	0.004	−0.159
	(0.013)	(0.002)	(0.070)	(0.018)	(0.003)	(0.106)
Ln cum. nb. past rejections X Ln firm size	−0.005[a]	−0.001[a]	0.014[a]	−0.005[a]	−0.001[a]	0.013[c]
	(0.001)	(0.0001)	(0.005)	(0.001)	(0.0002)	(0.007)
Ln firm size	−0.041[a]	0.015[a]	0.147[a]	−0.042[a]	0.014[a]	0.152[a]
	(0.002)	(0.0003)	(0.011)	(0.003)	(0.0005)	(0.014)
Ln nb. of exporting firms in HS4-year	−0.132[a]	0.088[a]	0.629[a]			
	(0.011)	(0.003)	(0.055)			
Observations	45753	176246	29165	45919	178817	29165
R^2	0.337	0.086	0.632	0.336	0.079	0.630

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. Columns (1)–(3): Controlling for the number of exporting firms per HS4-year. Columns (4)–(6): With standard errors clustered at the HS4 product-year level. [a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.10$.

Table 6
Robustness: Number of destinations served by firms.

	Number of destinations per firm within an HS4		
	Exit	Entry	IM
	(1)	(2)	(3)
Ln cumulated nb. of past rejections until $t-1$	0.019[a]	0.011[a]	−0.129[a]
	(0.007)	(0.002)	(0.033)
Ln cum. nb. past rejections X Ln nb. dest. per firm-HS4	−0.004[b]	−0.008[a]	0.055[a]
	(0.002)	(0.001)	(0.009)
Ln nb. of destinations per firm within an HS4	−0.213[a]	0.032[a]	1.098[a]
	(0.004)	(0.002)	(0.020)
Observations	45815	178817	29165
R^2	0.326	0.059	0.626

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Instead of firm size, we consider the number (in logs) of destinations served by each firm within an HS4 over the period. [a]: $p<0.01$, [b]: $p<0.05$.

we do not need to cluster our standard errors. However, we test the robustness of our results by introducing clusters. For the exit, our previous results are unchanged. For the entry and the intensive margin, the estimates on the cumulated number of past rejections become insignificant. However, the interaction term between rejections and firm size remains significant in all regressions.

Instead of using firm size (proxied by firm exports), Table 6 includes the number of destination countries served by each firm within an HS4 product over the period. This alternative measure presents two advantages. First, it is computed over the whole period and is therefore time-invariant, which reduces the endogeneity issue. Second, it better proxies firm efficiency. We also interact this number of served destinations with the cumulated number of past rejections. Results validate previous conclusions highlighted with firm size. All estimates are significant at least at the 5% level.

Another potential bias relates to endogeneity, which may stem from our focus on Chinese rejections and Chinese firms' exports. Potential bias is reduced by the use of lagged rejections. In addition, below, we replicate our main estimations adding also the rejections affecting non-Chinese shipments, as well as an interaction term between these non-Chinese rejections and firm size. Table 7 reports the results. Regarding Chinese rejections, we still observe that they increase Chinese firms' exit from the RASFF market. Small firms are more impacted. At the entry, the estimated coefficient is still positive but becomes insignificant, while the interaction term with firm size remains negative and significant. Finally at the intensive margin, Chinese rejections decrease the value exported by Chinese firms but less so for big firms. More interestingly, our results show that non-Chinese rejections do not affect the export probabilities and have almost no impact on the value of exports of Chinese firms. The absence of effect is observed for all Chinese firms whatever their size, the interaction terms between non-Chinese rejections and Chinese firm size being not significant. All in all, the strong effect of Chinese rejections and the absence of impact of non-Chinese rejections on Chinese exports confirms that the mechanism at play in our analysis is likely to be a reputation effect. Chinese exports of a specific HS4 product category are diminished when a RASFF rejection hits Chinese-origin products but the reputation of Chinese suppliers is not damaged by RASFF rejections of similar products originating from other countries. Furthermore, rejections related to Chinese products imported into Europe shape the participation of Chinese firms. The occurrence of rejections for a given product category increases the probability of additional controls on similar products from Chinese origin, which curbs Chinese export participation. Chinese exporters fear tighter controls on the type of products they export, even if these controls do not necessarily target their own flows. Results at the intensive margin of trade first confirm the expected market shares redistribution. Chinese firms substitute at least partially for competitors following

Table 7
Robustness: Chinese versus non-Chinese rejections.

	Exit	Entry	IM
	(1)	(2)	(3)
Ln cum. nb. of past Chinese rejections until $t-1$	0.077[a]	0.003	−0.282[a]
	(0.018)	(0.002)	(0.097)
Ln cum. nb. of past non-Chinese rejections until $t-1$	−0.003	0.003	0.143[c]
	(0.014)	(0.002)	(0.076)
Ln cum. nb. past Chinese rejections X Ln firm size	−0.005[a]	−0.001[a]	0.021[a]
	(0.001)	(0.0002)	(0.007)
Ln cum. nb. past non-Chinese rejections X Ln firm size	−0.0003	−0.0002	−0.008
	(0.001)	(0.0002)	(0.005)
Ln firm size	−0.042[a]	0.015[a]	0.160[a]
	(0.002)	(0.0003)	(0.012)
Observations	45919	178817	29165
R^2	0.336	0.079	0.630

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. [a]: $p<0.01$, [c]: $p<0.10$.

Table 8
Robustness: Rejections over the last two years and trade flows intensity.

	Rejections over the last 2 years			Trade flows intensity		
	Exit	Entry	IM	Exit	Entry	IM
	(1)	(2)	(3)	(4)	(5)	(6)
Ln cum. nb. of past rej. in $t-1$ and $t-2$	0.066[a]	0.004[c]	−0.191[c]	0.406[a]	0.044[a]	−0.663
	(0.016)	(0.002)	(0.103)	(0.088)	(0.014)	(0.476)
Ln cum. nb. past rej. X Ln firm size	−0.004[a]	−0.001[a]	0.015[b]	−0.028[a]	−0.008[a]	0.064[c]
	(0.001)	(0.0002)	(0.008)	(0.006)	(0.001)	(0.033)
Ln firm size	−0.045[a]	0.014[a]	0.155[a]	−0.043[a]	0.014[a]	0.156[a]
	(0.002)	(0.0002)	(0.013)	(0.002)	(0.0003)	(0.014)
Observations	45919	178817	30999	45877	177116	29152
R^2	0.335	0.078	0.655	0.335	0.079	0.629

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. Columns (1)–(3): Cumulated number of past rejections over $t-1$ and $t-2$ only. Columns (4)–(6): Cumulated number of past rejections weighted by the cumulated number of past export flows. [a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.10$.

rejection of Chinese products. Second, Chinese firms do not benefit equally from this redistribution of market shares: the heterogeneous effect of past rejections on small vs. big firms is still observed.

A potential issue raised by the previous estimations is the "sensitivity" of exported products to past controls. Previous regressions consider the cumulated number of past rejections between 1979 and year $t-1$. However, rejections from the 1980s do not necessarily affect Chinese exports in the 2000s. To address this issue, the first three columns in Table 8 focus on the cumulated number of past rejections over the last two years only, i.e. in $t-1$ and $t-2$. Our previous results both at the extensive and intensive margins of trade remain unchanged.

Another source of potential bias relates to the concentration of Chinese exports in some specific HS4 product categories. The last three columns in Table 8 account for the intensity of Chinese export flows to the RASFF market for each HS4 product category. The number of rejections affecting Chinese shipments varies across product categories (see panel (2) of Fig. 3). Part of this variation is due to the sanitary risk which of course might differ across products, but part comes from the intensity of trade between China and RASFF countries. A HS4 product category characterized by many flows is likely – all else being equal – to encounter a higher number of rejections. To control for the intensity of trade, different weighting schemes can be used (e.g. trade volume, number of export flows). Here, we weight the cumulated number of past rejections by the cumulated number of past export flows, computed as the cumulated number of export flows by Chinese firms to RASFF countries within one HS4 category over time. At the extensive margin of trade (both on exit and entry), the results confirm, and even strengthen our previous findings. The magnitude of estimated coefficients is indeed stronger than the one reported in Table 3. By contrast at the intensive margin of trade, previous results disappear and the effects become not significant at the 5% level.

Next, we test whether our results are sensitive to the sample of firms considered in the estimations. First, we exclude firms exporting to the RASFF market only over a short period. To do so, we compute the number of years of presence of each Chinese firm exporting to the RASFF market. We then restrict our sample to firms where the number of years of presence is above the median. The first three columns in Table 9 present the results of these estimations. The sample restriction has no impact on our previous conclusions.

We then control for the Chinese firms' experience as exporters, by computing their number of years of presence in the RASFF market. Since firm experience and firm size are strongly correlated, we replace firm size by firm experience in our estimations in the

Table 9
Robustness: firms' presence and experience in the export market.

	Above median nb. year of presence			Firm experience In export market		
	Exit	Entry	IM	Exit	Entry	IM
	(1)	(2)	(3)	(4)	(5)	(6)
Ln cum. nb. of past rej. until $t-1$	0.079[a]	0.005[b]	−0.159[b]	0.036[b]	0.028[a]	−0.121[a]
	(0.014)	(0.002)	(0.070)	(0.015)	(0.005)	(0.037)
Ln cum. nb. past rej. X Ln firm size/experience	−0.005[a]	−0.001[a]	0.013[a]	−0.012[c]	−0.013[a]	0.067[a]
	(0.001)	(0.0001)	(0.005)	(0.006)	(0.002)	(0.016)
Ln firm size/experience	−0.042[a]	0.014[a]	0.152[a]	−0.354[a]	0.038[a]	1.217[a]
	(0.002)	(0.0003)	(0.011)	(0.031)	(0.010)	(0.041)
Observations	44976	133843	29165	45919	178817	29165
R^2	0.307	0.090	0.630	0.328	0.059	0.644

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. Firm experience is defined as the firm's number of years of exports in t for the considered HS4 product (in logs). Columns (1)–(3): Firms with a number of years of presence above the median. Columns (4)–(6): Controlling for firm experience in the export market. [a]: $p<0.01$, [b]: $p<0.05$, [c]: $p<0.10$.

Table 10
Robustness: Alternative sets of fixed effects and wholesalers.

	Alternative sets of fixed effects			Wholesalers		
	Exit	Entry	IM	Exit	Entry	IM
	(1)	(2)	(3)	(4)	(5)	(6)
Ln cumulated nb. of past rejections until $t-1$	0.132[a]	0.007[a]	0.021	0.064[a]	0.004[a]	−0.181[a]
	(0.017)	(0.002)	(0.064)	(0.010)	(0.001)	(0.055)
Ln cum. nb. past rejections X Ln firm size	−0.009[a]	−0.002[a]	0.003	−0.005[a]	−0.002[a]	0.014[a]
	(0.001)	(0.0002)	(0.004)	(0.001)	(0.0001)	(0.004)
Ln firm size	−0.058[a]	0.019[a]	0.183[a]	−0.038[a]	0.015[a]	0.135[a]
	(0.003)	(0.0003)	(0.009)	(0.002)	(0.0002)	(0.009)
Observations	39847	177655	26910	83150	352144	49108
R^2	0.394	0.105	0.805	0.318	0.067	0.535

Note: Fixed effects for firm-HS4 product and year in the first three columns and for firm, HS4 product category, and HS2 industry-year in the last three columns (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. Columns (1)–(3): With alternative fixed effects. Columns (4)–(6): With wholesalers. [a]: $p<0.01$.

last three columns of Table 9. Results are robust to this change. Note that the magnitude of the estimates on the firm experience and on the interaction term between experience and the cumulated number of past rejections is stronger than the one obtained with firm size (proxied by the value of firm exports).

The next robustness check controls for the ability of each firm in producing a good, by considering alternative sets of fixed effects (i.e. firm-HS4 product and year fixed effects). Results presented in the first three columns of Table 10 are robust concerning the extensive margin of trade, but become non-significant at the intensive one.

The three last columns in Table 10 add wholesalers to the sample of firms. So far, our analysis has been restricted to non-wholesalers in order to examine active firm export decisions. However, wholesalers represent a non-negligible number of Chinese exporters. In fact, their inclusion in the sample has almost no impact on the estimated coefficients at the extensive margin of trade (exit and entry). At the intensive margin of trade, the presence of wholesalers reinforces our previous findings, the estimated coefficients on the cumulated number of past rejections and on the interaction term with firm size being now significant at the 1% level.

Table 11 tests whether rejections have a differentiated impact on foreign, private, and state-owned firms. Ownership information is missing in our database for some firms and results should therefore be interpreted with caution. To perform the test, we first defined three dummies related to ownership: (i) foreign or Sino-foreign joint-ventures; (ii) private firms; (iii) state-owned and collective firms. We then interact these dummies with the cumulated number of past rejections. Our results suggest that rejections have no differentiated impact on the exit of foreign, private and state-owned firms from the RASFF market. The three estimates on the interaction terms between past rejections and ownership in column (1) of Table 11 are not significant. At the entry margin (column (2)), all firms are negatively impacted by rejections, but the negative effect is stronger for state-owned and collective firms and lower for private firms. The effect for foreign and Sino-foreign firms lies in-between. Finally at the intensive margin of trade (column (3)), a rather big increase in trade flows is observed for foreign and Sino-foreign incumbents, and to a lesser extent for state-owned and collective ones. The impact on private incumbents is not significant.

Firms exporting to other OECD markets (i.e. Australia, Canada, Japan, New Zealand, Switzerland, South Korea, and the US) may

Table 11
Robustness: Controlling for firm ownership.

	Exit	Entry	IM
	(1)	(2)	(3)
Ln cumulated nb. of past rejections until $t-1$	0.085[a]	0.048[a]	−0.214[a]
	(0.014)	(0.002)	(0.076)
Ln cum. nb. past rejections X Ln firm size	−0.005[a]	−0.001[a]	0.012[a]
	(0.001)	(0.0001)	(0.005)
Ln cum. nb. past rejections X Dummy "Foreign and Sino-foreign firms"	−0.005	−0.064[a]	0.155[a]
	(0.007)	(0.002)	(0.033)
Ln cum. nb. past rejections X Dummy "Private firms"	−0.011	−0.048[a]	0.054
	(0.007)	(0.002)	(0.034)
Ln cum. nb. past rejections X Dummy "State-owned and collective firms"	−0.002	−0.076[a]	0.100[a]
	(0.008)	(0.002)	(0.037)
Ln firm size	−0.042[a]	0.014[a]	0.152[a]
	(0.002)	(0.0003)	(0.011)
Observations	45919	178817	29165
R^2	0.336	0.085	0.630

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. [a]: $p<0.01$, [c]: $p<0.10$.

Table 12
Robustness: OECD presence in $t-1$.

	Exit		Entry		IM	
	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Ln cum. nb. of past rej. until $t-1$	0.111[a]	0.061[a]	0.001	−0.006	−0.185	−0.160[b]
	(0.033)	(0.015)	(0.002)	(0.005)	(0.158)	(0.081)
Ln cum. nb. past rej. X Ln firm size	−0.008[a]	−0.004[a]	−0.001[a]	−0.001[b]	0.020[b]	0.011[b]
	(0.002)	(0.001)	(0.0003)	(0.0002)	(0.011)	(0.006)
Ln firm size	−0.055[a]	−0.037[a]	0.014[a]	0.006[a]	0.086[a]	0.157[a]
	(0.006)	(0.003)	(0.0005)	(0.001)	(0.028)	(0.013)
Observations	8966	35603	125980	51458	4980	23331
R^2	0.476	0.326	0.109	0.146	0.767	0.615

Note: Fixed effects for firm, HS4 product category, and HS2 industry-year in all estimations (not reported). Robust standard errors in parentheses. Firm size is defined as the firm's total agri-food exports (in logs) in $t-1$. Columns (1), (3), and (5): Firms not exporting to at least one OECD market (other than the RASFF market) in $t-1$. Columns (2), (4), and (6): Firms exporting to at least one OECD market (other than the RASFF market) in $t-1$. [a]: $p<0.01$, [b]: $p<0.05$.

be more successful in passing RASFF inspections. Other OECD markets also impose stringent safety regulations, and conduct inspections. Therefore, firms exporting to these markets are more likely to sell safe products and to be bigger which may help them to deal with inspections and their related costs and uncertainty. Table 12 distinguishes between firms exporting to at least one OECD market (other than the RASFF market) in $t-1$ vs. other firms, and investigates whether rejections have different trade effects on these two groups of firms. We first observe that our previous conclusions – diversification at the extensive margin and concentration at the intensive one – are accurate for both groups of firms. However, there are some differences in the magnitude of the estimated coefficients. Exit from the RASFF market due to border rejections is less likely for firms already exporting to another OECD market in $t-1$. In addition, this effect is magnified for big firms (columns (1) and (2)). Also, entry to the RASFF market induced by rejections is weaker for big firms (columns (3) and (4)). At the intensive trade margin, big incumbent firms exporting to OECD markets in $t-1$ are also more likely to increase their exports to the RASFF market in t compared to other firms (columns (5) and (6)).

5. Concluding remarks

In this paper, we were interested in whether a rise in uncertainty related to the risk of border rejections affects imports from China. If border rejections result in an increased focus and increased likelihood of inspection, a series of import refusals could induce negative spillovers for competitors from the same origin and/or exporting the same product.

Our results show that Chinese exporters of agri-food products are more likely to exit the European market if the product they export has been rejected in previous years. At the same time, rejections favor the entry of new firms. This highlights some diversification effect at the extensive margin of trade. At the intensive margin, border rejections boost the exports of incumbent firms, suggesting some concentration effect. Furthermore, the microeconomic impact of the risk of rejection is heterogeneous across firms. Turnover at the extensive margin mainly concerns small firms, while concentration at the intensive margin benefits big firms more. Overall, the number of firms tends to decrease but the size of the surviving firms increases. Our results confirm the key role played by uncertainty, and that big firms are more resilient than small ones to the risk of border rejections.

Our results contribute to the large literature on firm heterogeneity and trade. We provide a more nuanced understanding of the impact of *de facto* restrictive regulations on exporting firms. Furthermore given the importance of food safety and importers' emphasis on sourcing from reliable producers, our results suggest that policy makers and law enforcers should adopt a comprehensive approach and pay attention to individual firms while focusing on whole sectors.

Appendix A. Appendix

A.1. Matching RASFF rejections with HS4 product codes

One of the contributions made by this paper is the method developed to assign product codes to the verbal descriptions provided for notifications on the RASFF portal. Attributing product codes is a prerequisite for matching sanitary rejections with Chinese export data.

To assign a product code to each notification, we exploit information on variables *product category* (e.g. "alcoholic beverages") and *subject* (e.g. "undeclared sulphite in Wine from Chile") reported by the RASFF authorities. We assign observations to the HS classification in which our Chinese firm-level data are coded. We code to the HS 4-digit level - the most disaggregated level at which we can identify notifications. We use the 2002 revision of the HS classification.

A manual assignment of HS4 codes on an individual basis is not possible given the number of notifications in our database (14,860 observations for the period 2000–2011 after the cleaning procedure described in Section 2). Therefore, to assign product codes we implement the following approach. We first split *subject* in order to extract the relevant information on the product (e.g. "wine"). Next, we rearrange some *product* categories and align them more directly with HS2 industries (e.g. "fish and fish products" and

"farmed fish and products thereof - other than crustaceans and molluscs" are combined). We also conduct some re-assignments of observations across *product* categories to ensure consistency. Finally, we disregard observations from *product* category "food contact materials" as we are only interested in agri-food products (HS chapters 01-24).

We identify the industry (HS2) wherever possible, and assign the HS4 product code using Stata's *regexm* function. *Regexm* searches for keywords associated with a specific HS4 code. For example, within *product* "fish", "frozen hake fillets" can be assigned HS4 code 0304 ("Fish fillets and other fish meat - whether or not minced, fresh, chilled or frozen") using keywords "fillets" and "frozen". Using the same method "chilled hake" is assigned HS4 code 0302 ("Fish, fresh or chilled, excluding fish fillets and other fish meat of heading No 0304"). The full Stata do-files with the matching correspondence and code mapping RASFF notifications and HS codes are available on request from the authors.

This methodology has several advantages. Firstly, it is easily checked, verified, and replicated, and ensures consistent treatment of RASFF observations. Secondly, it can be extended to more data at very low cost. For example, it can be applied to additional observations as more RASFF notifications become available over time.

Using this strategy, we successfully match 89% of rejections with an HS4 code (13,241 out of 14,860). Among border rejections applied to China we match 91% (1537 out of 1690). The incidence of rejections is fairly heterogeneous across products but is clustered in some industries. Our rejections are split over 115 different HS4 codes out of potentially 201 in the 24 chapters of agri-food products (for China we identify 67 different HS4 products). If we look at all the rejections, the majority of notifications concern HS08 "Edible fruits and nuts", HS03 "Fish and Crustaceans, Molluscs", and HS12 "oil seeds and oleaginous fruits". For China, HS12 and HS03 are the two main chapters affected by border rejections. We conduct an additional visual check of the mapping in Table A.1. We compare the percentage of Chinese exports and rejections by HS2 industries. While we do not expect a strong correlation (small export industries could plausibly be affected by a disproportionate number of rejections), we are able to confirm that there are no large industries without rejections and no tiny agri-food industries with many rejections.

Table A.1
Chinese border rejections and percent of agri-food exports by HS2 (2000–2011).

HS chapter		% Chinese agri-food exports	Nb. of rejections
01	Live animals	0.1	0
02	Meat and edible meat offal	0.6	32
03	Fish and crustaceans, molluscs	24.5	258
04	Dairy produce	0.9	59
05	Products of animal origin	9.9	40
06	Live trees and other plants	0.6	0
07	Edible vegetables	11.2	75
08	Edible fruits and nuts	4.6	24
09	Coffee, tea, maté and spices	2.9	76
10	Cereals	0.2	65
11	Products of the milling industry	0.2	0
12	Oil seeds and oleaginous fruits	7.4	698
13	Lac; gums, resins	1.6	2
14	Vegetable plaiting materials	0.4	0
15	Animal or vegetable fats and oils;	1.2	1
16	Preparations of meat, of fish or of crustaceans, molluscs	5.5	1
17	Sugar and sugar confectionery	1.0	26
18	Cocoa and cocoa preparations	0.6	1
19	Preparations of cereals, flour, starch or milk	2.0	87
20	Preparations of vegetables, fruit, nuts	17.7	29
21	Miscellaneous edible preparations	1.4	51
22	Beverages, spirits and vinegar	0.7	4
23	Residues and waste from the food industries	2.2	8
24	Tobacco	2.7	0

Note: Authors' computation.

A.2. Chinese firm-level exports

Table A.2 investigates whether aggregation of the observations at the 4-digit level is a potential source of bias. If rejections occur at the HS6 product level but our analysis is performed at the HS4 product category level, we could observe automatic higher survival rates (and lower levels of exit) for larger firms. Large firms might export multiple HS6 products within an HS4 category. Even if one firm's HS6 product is affected by rejections, other HS6 products may remain unaffected. Thus, at the HS4 level, we may observe large firms as less likely to exit the RASFF market.

Table A.2
Percentage of HS6 products within HS4 categories for Chinese firms (2000–2011).

Nb. of HS4	Nb. of HS6 within HS4					% Firms	% Exports
	1	2	3	4	5+		
1	89.66	8.52	1.19	.43	.19	12.69	15.48
2	86.52	10.71	1.71	.73	.33	10.2	10.96
3	84.12	12.16	2.27	.83	.62	8.42	8.85
4	82.38	13.41	2.39	1.01	.81	7.4	8.64
5	79.83	15.3	3.08	.91	.87	6.75	7.91
6	77.56	16.05	3.9	1.45	1.03	5.88	6.61
7	76.29	16.4	4.36	1.69	1.26	5.34	6.26
8	75.15	16.43	4.7	2	1.71	4.88	5.46
9	75.68	16.56	4.74	1.44	1.59	3.82	4.39
10+	73.84	18.11	4.86	1.58	1.61	34.62	25.43

Note: Authors' computation. Excluding wholesalers.

To address this issue, we record the number of HS6 products exported by a firm within each HS4 product category. Table A.2 summarizes the results. Columns (1) to (5) report the fractions of firm-HS4 exports that have the underlying number of HS6 products. We observe that firms – even multi-HS4 firms – usually export only one HS6 product within each HS4 category. 89.66% of firms present in only one HS4 category export just one HS6 product within that HS4 category (and 8.52% of these firms export two HS6 products within that HS4 category). At the other end of the spectrum, for firms present in 10 or more HS4 product categories, only one HS6 product per HS4 category is exported in 73.84% of the cases (and two products in 18.11% of the cases).

References

Acemoglu, D., & Robinson, J. A. (2006). De facto political power and institutional persistence. *American Economic Association Papers and Proceedings, 96*(2), 325–330.
Baylis, K., Martens, A., & Nogueira, L. (2009). What drives import refusals. *American Journal of Agricultural Economics, 91*(5), 1477–1483.
Baylis, K., Nogueira, L., & Pace, K. (2011). Food import refusals: Evidence from the European Union. *American Journal of Agricultural Economics, 93*(2), 566–572.
Becker, G. S. (1957). *The economics of discrimination*. University Chicago Press.
Chen, M., & Mattoo, A. (2008). Regionalism in standards: Good or bad for trade? *Canadian Journal of Economics, 41*(3), 838–863.
Chen, N., & Novy, D. (2012). On the measurement of trade costs: Direct vs. indirect approaches to quantifying standards and technical regulations. *World Trade Review, 11*(3), 401–414.
Correia, S. (2014, July). REGHDFE: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects. *Statistical software components*. Boston College Department of Economics.
Correia, S. (2015). Singletons, cluster-robust standard errors and fixed effects: A bad mix. *Technical note*. Duke University.
Ederington, J., & Ruta, M. (2016). Nontariff measures and the world trading system. In K. Bagwell, & R. Staiger (Eds.). *Handbook of commercial policy* (pp. 211–277). North-Holland.
Essaji, A. (2008). Technical regulations and specialization in international trade. *Journal of International Economics, 76*(2), 166–176.
Falvey, R. E. (1989). Trade, quality reputations and commercial policy. *International Economic Review,* (3), 607–622.
Fontagné, L., Orefice, G., Piermartini, R., & Rocha, N. (2015). Product standards and margins of trade: Firm level evidence. *Journal of international economics, 97*(1), 29–44.
Grundke, R., & Moser, C. (2014). Hidden protectionism? Evidence from non-tariff barriers to trade in the united states. *Eth zurich kof working papers 369*.
Jaud, M., Cadot, O., & Suwa-Eisenmann, A. (2013). Do food scares explain supplier concentration? An analysis of EU agri-food imports. *European Review of Agricultural Economics, 40*(5), 873–890.
Jouanjean, M.-A., Maur, J.-C., & Shepherd, B. (2015). Reputation matters: Spillover effects for developing countries in the enforcement of US food safety measures. *Food Policy, 55*, 81–91.
Knowles, J., Persico, N., & Todd, P. (2001). Racial bias in motor vehicle searches: Theory and evidence. *Journal of Political Economy, 109*(1), 203–229.
Mayer, T., & Ottaviano, G. (2008). The happy few: The internationalisation of European firms. *Intereconomics: Review of European Economic Policy, 43*(3), 135–148.
McQuade, T. J., Salant, S. W., & Winfree, J. A. (2012). Markets with untraceable goods of unknown quality: Beyond the small-country case. *Resources for the future discussion paper 09-31-rev*.
Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica, 71*(6), 1695–1725.
Shapiro, C. (1983). Premiums for high quality products as returns to reputations. *The Quarterly Journal of Economics, 98*(4), 659–680.
Wooldridge, J. (2010). *Econometric analysis of cross section and panel data*. MIT Press, Cambridge MA.