PRONTO

FP7-SSH-2013-2
GA: 613504
Start date of the project: 01/02/2014 - Project duration: 48 months

Deliverable N°	2.2
Deliverable name	Working paper addressing the impact of uncertainty on exporters
Work Package	WP2 Improving Comparative Quality of Data
Status-Version	Working paper
Lead Participant	Ecole d'Economie de Paris
Date (this version):	02/09/2015 (subject to revision)
Date of paper:	July 2015
EC Distribution	Public

Abstract
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Uncertainty and Exports: Firm Level Evidence on The Impact of EU Border Inspections on Chinese Agri-food Exports

Matthias Beestermöller,
Anne-Celia Disdier
and Lionel Fontagné*†

August 2015

Abstract: We address the microeconomic impact of the risk of rejection at the EU border for Chinese exporters of food products. We combine information from the Rapid Alert System for Food and Feed (RASFF) with firm level export data from China by product-destination over the period 2000-2011. We show that border rejections reduce the number of competitors, the number of varieties available to consumer and unevenly affect different-sized exporters.

JEL classification: *F12, F14, F15, O24, Q17, Q18*
Keywords: *Rapid Alert System for Food and Feed (RASFF), non tariff measures, uncertainty, China, firm heterogeneity, food safety*

*This paper has received funding from the FP7 of the European Commission (EC), under the PRONTO Project (Productivity, Non-Tariff Measures and Openness), grant agreement 613504. Views expressed here do not engage the EC. We acknowledge useful comments and suggestions by Carsten Eckel, Peter Egger, Lisandra Flach as well as conference participants from Munich for helpful comments. Matthias Beestermöller gratefully acknowledges financial support from the GRK 1928.

†Affiliations: Beestermöller: University of Munich, matthias.beestermoeller@econ.lmu.de; Disdier (*corresponding author*): PSE & INRA, anne-celia.disdier@ens.fr; Fontagné: PSE – Université Paris 1 & CEPII, lionel.fontagne@univ-paris1.fr.

1. Introduction

Trade liberalization has driven the average applied tariff for Chinese agri-food exports to the EU down to as low as 13 per cent in 2007.[1] However, access to the market remains difficult as individual exporters must meet regulatory standards, face procedural obstacles and enforcement. Non-tariff measures (NTMs) act as substantial barriers in the exporting decision because they increase the cost of exporting (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), but also introduce an element of uncertainty. This problem is magnified for food products due to stringent Sanitary and phytosanitary (SPS) regulations[2] in most developed markets. If exporting firms are unable to meet the required restrictions with a high enough probability, strict regulation and controls act as a deterrent to trade. Exporters from developing countries are most likely to struggle in meeting stringent sanitary standards due to insufficient traceability, deficient storage, limited access to certification bodies etc. (Essaji, 2008). While EU standards are not meant to discriminate against imported goods, exporters in poor countries may thus be priced out of exporting all together. Furthermore, exporters from developing economies may hold their comparative advantage in sectors heavily affected by sanitary concerns. For example, global seafood trade has increased manifold over the past two decades (Baylis et al., 2010).

Uncertainty is related to possible border rejection of shipments not complying with sanitary regulations. The cost of matching a standard is certain, while being rejected at the border is a risk faced by the exporter. The risk is shaped by variance in the quality of exported products (which can be reduced by investments in quality or controls prior to shipment) and intensity of controls at the EU border. The latter intensity is observable by the exporter, but likely endogenous to past rejections signalling a high variance in the quality of exported products.

[1] Source: MacMap-HS6 (Guimbard et al., 2012)

[2] Sanitary risk refers to food-borne human illness and animal diseases, and phyto-sanitary to the risks of plant pests and disease transmissions. Standards are a legitimate instrument for health, safety and environmental policy. They however may act as a deterrent to trade if exporting firms are unable to meet the required restrictions.

This is where externalities among exporters of the same country/region may appear for a given category of product, as part of the cost of being rejected is beared by competitors of the same exporting country. All in all, border rejection is providing incomparable information on NTMs: while information on the occurrence of regulations provides evidence on *de jure* NTMs, rejection is shedding light on an impact *de facto*. The uncertainty component of NTM-related barriers has surprisingly been mostly overlooked in the literature on NTMs. Two exceptions are Jaud et al. (2013) and Grundke and Moser (2014). Grundke and Moser (2014) adopt the exporter perspective and consider to what extent refusals embed entry in the US market. Estimating a gravity equation for 93 imported product-categories to the U.S. for the period 2002-2012, they show that the cost of these refusals (the cost of not complying with US standards) falls on developing countries. EU refusals are used as an instrument because they are expected to be exogenous to U.S. demand. Although they do not explicitly mention uncertainty as a trade barrier, the reasoning of Grundke and Moser (2014) is in terms of demand for protection in the U.S. and stricter enforcement of NTMs. Jaud et al. (2013) adopt the importer perspective and consider aggregate flows, with no firm dimension. Starting from the evidence of an increasing diversification of EU import sources in agri-products, combined with a concentration on a limited number of exporting countries, they conclude that entrants start small, while incumbent exporters, who proved safe, grab most of the EU market shares. Although Jaud et al. (2013) do neither mention uncertainty in the import market, the mechanism they refer to is clearly linked to this (i.e. sanitary risk in the importing country).

We adopt a different perspective here: we consider the exporter side of the (EU) market and address the microeconomic impact of the risk of rejection at the border. Food sanitary standards have become an important policy concern in the EU[3] making this market particularly sensitive to the issue at stake. While access to the EU market has become easier, exporters actually face strict food safety requirements that are often more restrictive than multilateral codex ones. These requirements are often suspected to go well beyond the requirements due to sanitary

[3]For example, the 2013 meat adulteration scandal, where food advertised as containing beef was found to contain undeclared horse meat, has highlighted the importance of regulation.

concerns. Enforcing SPS measures is difficult. Most imports of foodstuffs have passed through multiple middlemen before they reach manufacturers. This makes it extremely difficult to trace their origins. While, regulatory agencies only conduct spot checks, inspections are not random. Certain producers, destinations or products may be under special focus. Exporters thus face considerable uncertainty about the likelihood and costs involved in exporting. The exporting country we choose is China, a large and diversified developing economy having repeatedly faced problems in rich import markets for food stuff exports. In a nutshell, Chinese exporters might well be spotted by controls. Interestingly we have information on individual exports of the universe of Chinese exporters to the EU, at the product level. Although we cannot identify which individual exporter has been rejected, we have information on the concerned product and the origin (China) of the product. Accordingly, studying the effect of standards that Chinese agri-food exporters must satisfy on the European market is an original approach.

Against this background our contribution is threefold: Firstly, we add to a growing empirical literature examining the impact of restrictive NTMs' at the firm-level and using information on *de facto* NTMs (see for example Fontagné et al. (2015) for a combination of these two dimensions). Micro-data at the firm-level allows studying the effect of SPS regulations on firm-level participation (extensive margin) as well as adjustments (intensive margin). Further, this paper pays explicit attention to the role of firm heterogeneity. Theory suggests that large and more productive firms are likely to react differently to SPS measures than small ones. While not all NTMs are barriers, border rejections are cases where regulations are actually enforced, raising an obstacle to trade.

Secondly, we are to the best of our knowledge, the first paper to look at the effect of SPS measures on firm-level exports from a large and significant developing economy. Our data covers the universe of Chinese agri-food exports over more than a decade (2000-2011) and includes HS6 product and destination information. Using this detailed data permits us to further test for evidence of trade redirection to other destinations. Since its accession to the WTO in 2001, China's impressive trade growth has further accelerated. China is arguably the

most dynamic and important economy and exporter. At the same time anecdotes suggest that Chinese agri-food exporters are struggling to meet sanitary standards.[4]

Thirdly, we focus on a specific trade-impeding indicator of SPS regulations using a dataset of border rejections at the EU border rarely mobilised.[5] The Rapid Alert System for Food and Feed (RASFF) database records all rejections[6] of shipments due to sanitary concerns at the EU border. Among other information it includes information on the origin of the shipment and a verbal product description. We manually match the verbal product descriptions in RASFF with HS codes at the HS4 level of disaggregation. What we do is combining the Chinese firm-level data with the RASFF. Our combined dataset thus permits us to analyze the trade impact of regulatory measures that threaten to result in outright border rejections. Our *de facto* NTM measure can be considered a substantial barrier for exporters.

We find that border rejections reduce the number of competitors, the number of varieties available to consumer and unevenly affect different-sized exporters. Our results indicate a positive relationship between the extensive margin (probability to exit) and EU rejections, as well as some weak evidence on the intensive margin and trade readjustments. Market shares across Chinese firms within the EU market seem therefore to be redistributed between small and more productive firms. Finally, we find evidence in support of trade reorientation towards less developed markets.

This paper proceeds as follows. Section 2 reviews the related literature and motivates our research question. Data is presented in Section 3. The next section provides descriptive statistics about rejections at the EU border. Econometric evidence on the impact of border rejections at the firm level is detailed in Section 5. Section 6 addresses endogeneity issues. The last section concludes.

[4]For example, the 2008 food scandal involving Chinese milk adulateration with melamine received much publicity.

[5]The exception is again Jaud et al. (2013), although the treatment of the data is totally different.

[6]Throughout this paper we use the terms import refusal, notification, alert and border rejection interchangeably. As described in the Data Appendix, we focus on the subset notifications where a product fails to enter the EU market.

2. Related Literature

NTMs have attracted a lot of attention in the trade literature. The two main issues are sources of information and computation of tariff equivalents. Because they raise problems of safety and traceability in an international context, food products and the related SPS measures have been largely studied. Milestones in this strand of literature are the computation of tariff equivalents by Kee et al. (2009) and the light shed on the stringency of the related measures and their magnified impact on developing countries by Disdier et al. (2008). All this literature is indeed confronted to a dilemma: either using indirect evidence on border protection in a gravity perspective with the risk of capturing much more than NTMs, or using direct – *de jure* – evidence on the presence of NTMs (notifications at the WTO) with the risk of outdated and incomplete data.[7] But more importantly, two issues must be taken seriously. First, not all NTMs are barriers which casts doubt on the validity of systematic assessment of their trade reducing impact; second not all exporters are evenly affected which suggests to look at the micro impact of these measures. Hence the need to rely on individual firm response to measures identified as obstacles stressed by Fontagné et al. (2015). We embrace the latter approach in the following, combining information on rejections with Chinese export data at the firm level. Such combination authorizes exploring the impact of NTMs in terms of uncertainty on individual exports.

Most of the large (and old) literature addressing the impact of uncertainty on exports is about exchange rate uncertainty (see e.g. (Hooper and Kohlhagen, 1978)) and initially concluded to a limited impact on aggregate trade volumes. Focusing on developing economies exports, the conclusion is more nuanced (Caballero and Corbo, 1989; Grobar, 1993). But this broad picture may hinder an uneven impact among firms. An application to China using micro data is Héricourt and Poncet (2013). The negative impact of Real Exchange Rate volatility on firm-level export performance is magnified when exporters are located in provinces with low financial development.

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

Uncertainty on trade costs has been however addressed from two point of views. From the point of view of the *exporting* country, deficiency of infrastructures (Nordås and Piermartini, 2004), or simply red tape, generate uncertainty on the delivery date and possibly quality of the delivered batch, which is indeed an obstacle to trade. Using information on internal transport costs for a sub-sample of 24 Sub-Saharan countries Freund and Rocha (2010) show that inland transit time uncertainty reduces export values. An extra-day of time uncertainty – defined as the maximum and the average number of days it takes for an exporter to complete exporting procedures – induces a 13 % reduction in export values. Building on an argument about uncertainty related to water in the tariffs raised by Francois and Martin (2004), Handley (2014) shows in an heterogeneous firms model, that trade policy uncertainty is delaying entry of exporters into new markets. The argument is that in presence of sunk entry costs in export markets, uncertainty about future tariffs is creating a real option value of waiting. Binding tariffs is reducing such uncertainty. Osnago et al. (2015) illustrate these effects of trade policy uncertainty at a more aggregated level, considering the margins of exports of 149 countries, at the product level. A one percent reduction in the difference between bound and applied tariffs is shown to increase exports by one percent, controlling for the level of tariffs. This is why commitments at the WTO, beyond reduction in the tariff level, are important. Groppo and Piermartini (2014) show that WTO tariff commitments reduce the probability of a tariff increase for all WTO Members from 1996 to 2011, at the product level, in a range of -10% to -16% depending of the specifications. Feng et al. (2014) focus on China and measure the uneven impact of uncertainty on heterogenous exporters. Using firm-product data and considering the U.S. market in the years surrounding China's WTO accession, they show reduction in tariff uncertainty induced reallocation of export across Chinese firms. Entries and exits were boosted, to the very benefit of exporters providing higher quality products at lower prices.

Uncertainty is also a trade impediment on the *importing* country side of the transactions. The starting point here is the quality (or safety) of the product, which is not observable. For experience goods, reputation is coming form repeated imports of safe goods from a given

origin. The important issue here 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 exporter's identity is unknown is more challenging, and particularly adapted to commercial relationships with developing countries. In such case, quality expectations on a product sold by a given firm will be possibly by the record of quality problems (here: border rejections) of the exporting country as a whole. In such case, individual exporters will suffer from 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). As information externalities are not internalized by the individual exporters, the quality provided by a large country with many firms will tend to be low, leading to a collective reputation problem. McQuade et al. (2012) provide a theory pointing to such effects and argue that it fits well the Chinese case.

3. Data

We combine firm level export data from China with rejection data of Chinese products at the EU border. Here we summarize the most relevant features of our data. For a much more detailed description of the data sources and cleaning, as well as very basic descriptive statistics please refer to Appendix A.

The Chinese dataset contains information on firm exports by product and destination on an annual basis from 2000-2011. We use administrative (customs) data which contains the universe of Chinese exports over the sample period. This data is preferable to surveys used elsewhere in the literature as it avoids issues of stratification or sampling issues such as selection effects.

We combine these exports with a unique database of agri-food shipments that have suffered rejection at the EU border due to food safety reasons: The Rapid Alert System for Food and Feed (RASFF).

The RASFF is a cross-border information exchange about emergency sanitary measures taken related to food and feed risks between the food safety authorities from the European Economic Area[8]. It is not a voluntary exchange but members must immediately notify the European Commission about any serious health risk deriving from food or feed using RASFF. Data on RASFF is publicly available starting from 1995. We record all notifications by EU member states regarding non-EU members over the period 1995-2012. Throughout, we treat the EU border as the relevant location of observing notifications. Finally, we identify our crucial alert of interest - whether a product successfully entered the common market or not. Since we are concerned about rejections due to SPS concerns, we restrict our analysis to agricultural exports (HS chapters 1-24). The database contains information on products in verbal form. We painstakingly assign product codes at the HS4 level to the verbal product descriptions (for a detailed description of this novel method see Appendix B).

In summary, we have information on individual exports of the universe of Chinese exporters to the EU at the product level matched with EU border rejections. This allows us to measure the impact of uncertainty from sanitary riskiness and regulations on trade. We take the view point of the exporter. Although we cannot identify which individual exporter has been rejected, we have annual information on the concerned product and the origin (China) of the product. Our combined dataset allows us to analyze the impact on Chinese exporters of regulatory measures that threaten to result in outright border rejections.

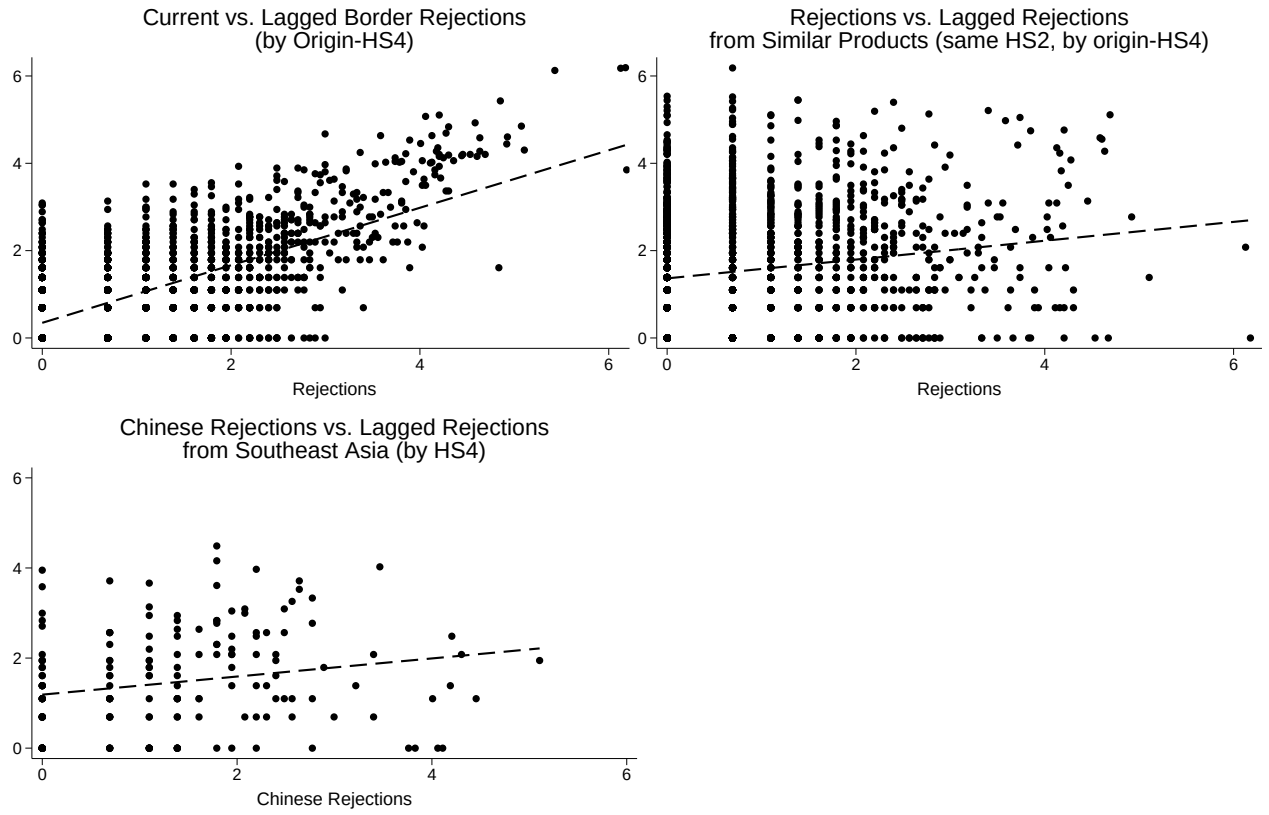
4. Descriptive Statistics

We consider two basic descriptive statistics. First, in Figure 1 we consider some simple correlations of the data. We compare rejections with a country-product lagged rejections, lagged rejections in similar products and lag rejections from neighboring countries in the same product. They provide descriptive evidence of some reputation and spillovers. In all three plots,

[8]EEA: EU-28, Norway, Liechtenstein, Iceland and Switzerland. Throughout this paper we refer to the EEA as EU.

there is a positive association, and as expected it is strongest in the case of own reputation. Of course, this analysis is based on simple correlations. It does not take account of intervening influences.

Figure 1
Descriptive statistics: RASFF reputation



5. Estimation

We run estimations at the extensive and intensive margins of trade. We follow the strategy used by Fontagné et al. (2015). In particular, we estimate different forms of equation

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

where i refers to firm, s to HS4-product, j to destination, and t to year.

We aggregate all observations at the HS4 level (which is the level used for rejections' coding). One issue could be that some firms may export different HS6 products within one HS4 sector (but not really the case: see the table in the Appendix). Since RASFF countries exchange information on rejections, one product rejected to one RASFF border will not be able to enter the RASFF market at another border. Therefore, we do not consider flows to each RASFF countries separately, but aggregated all flows to RASFF area.

Definition of our variables

- Dependent variables, $y_{i,s,j,t}$:
  - exit = 1 if firm exports the HS4 product to the market in $t-1$ but not in t (counterfactual: firms that export a given HS4 in $t-1$ and also in t.
  - entry = = 1 if firm exports the HS4 product to the market in t but not in $t-1$ (counterfactual: firms that do not enter the market, i.e.e do not export a given HS4 in $t-1$ and in t.
  - For the intensive margin, we consider the value of the export flows by the firm for a given HS4 in year t. We focus on surviving firms (i.e. firms that were already present in $t-1$ and continue to export in year t. In other words, we do not consider firms that start to export in year t.)
- Explanatory variables, rejection$_{s,j,t-1}$:
  - Dummy for past rejection = 1 if at least one shipment of that HS4 was rejected at the RASFF border in $t-1$ (0 otherwise). To avoid endogeneity, we consider past rejections (before year t and actual exports (in t))
  - Cumulated number of past rejections: Simply the sum of shipments of that HS4 that were rejected in the past until year $t-1$
  - Firm size: Same definition for firm size (i.e. based on past exports & also centered around the median, since we do not have characteristics on firms).

We also interact our variables on rejections (dummy and cumulated number) with the size of the firm. These interaction terms allow us to examine whether small are more affected by rejections than big firms.

Same set of fixed effects as in Fontagne et al. (i.e. firm and HS2-year fixed effects)

5.1. What happen to Chinese firms on RASFF markets?

Table 1 presents the impact of Chinese rejections (without re-entry) on the exit of Chinese firms from RASFF markets. Wholesalers are excluded from the estimations (same for all tables). In columns (1) and (2), we simply include a dummy for past rejections of Chinese shipment for that HS4 in $t-1$ (and we investigate exit in year t). In columns (3) and (4), we include the cumulated of past rejections (of Chinese shipments for that HS4) over time until $t-1$. In both cases, past rejections increase the probability of exit of Chinese firms, once we control for firm size. The exit affects more small firms than big firms (negative and significant estimated coefficient on the interaction term between past rejection and firm size). We also see that - everything else equal, i.e. independently of past rejections - small firms tend to exit more (negative and significant coefficient on the firm size variable).

Table 2 reports the impact of Chinese rejections (without re-entry) on the entry of Chinese firms from RASFF markets. Same types of regressions than in Table 1, except that we now focus on entry of new Chinese firms on RASFF markets. We observe that rejections tend to favor the exit of new firms. Big firms tend to enter (positive and significant coefficient on the firm size variable) but this result is not related to rejections. In fact, we tend to observe the opposite. The estimated coefficient on the interaction term is not significant in column (2), and it is even negative and significant in column (4). Interestingly the comparison of the magnitude of estimated coefficients in Table 1 and 2 show that the impact of past rejections is much stronger on firm exit than on firm entry. Adjusted R^2 are also much lower in Table 2.

Table 1
Exit from RASFF markets and Chinese Rejections

	Exit from RASFF markets i year t			
	(1)	(2)	(3)	(4)
Dummy = 1 if at least one rejection in $t-1$	-0.024^a	0.184^a		
	(0.006)	(0.040)		
Dummy for rejection$_{t-1}$ X Firm size		-0.015^a		
		(0.003)		
Cumulated nb. of past rejections until $t-1$			-0.019^a	0.086^a
			(0.003)	(0.016)
Cum. nb. past rejections X Firm size				-0.007^a
				(0.001)
Firm size		-0.056^a		-0.054^a
		(0.003)		(0.003)
Observations	49,277	49,277	49,277	49,277
Adjusted R^2	0.219	0.230	0.220	0.231

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. ^{a}: p<0.01.

Our results at the extensive margin of trade suggest that border rejections induce some turnover among firms exporting to the RASFF markets, with exit of some firms and entry of new firms.

We now focus on the intensive margin of trade. Table 3 describes the results. We consider only surviving firms, i.e. firms that are present in years $t-1$ and t and look at their export values to RASFF markets. Our results highlight three main facts. First, bigger firms tend to survive and increase their exports to RASFF markets (estimated coefficient on size variable is positive and significant). Second, Firms that survive to shipments' rejections tend to increase their exports to RASFF markets (estimated coefficients on rejections variables are positive and significant). Third, this increase in exports is stronger for bigger firms (esitmated coefficients on the interaction terms are positive and significant). Therefore, our results suggest that border rejections increase the concentration at the intensive margin of trade.

To conclude on the global impact of rejections on exports of Chinese firms to RASFF markets, we observe a double-movement: some diversification at the extensive margin of trade and some concentration at the intensive one. This conclusion is in line with Jaud et al. (2013).

Table 2

Entry in RASFF markets and Chinese rejections

	Entry on RASFF markets in t			
	(1)	(2)	(3)	(4)
Dummy = 1 if at least one rejection in $t-1$	0.002[a]	0.003[a]		
	(0.0004)	(0.0004)		
Dummy for rejection$_{t-1}$ X Firm size		0.0001		
		(0.0001)		
Cumulated nb. of past rejections until $t-1$			0.002[a]	0.002[a]
			(0.0001)	(0.0002)
Cum. nb. past rejections X Firm size				-0.0001[b]
				(0.0001)
Firm size		0.002[a]		0.002[a]
		(0.0001)		(0.0001)
Observations	1,234,322	1,234,322	1,234,322	1,234,322
Adjusted R^2	0.056	0.061	0.056	0.061

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. [a]: p<0.01; [b]: p<0.05.

Table 3

Intensive margin on RASFF markets and Chinese rejections

	Ln exports to RASFF markets in t			
	(1)	(2)	(3)	(4)
Dummy = 1 if at least one rejection in $t-1$	0.270[a]	0.153[a]		
	(0.031)	(0.047)		
Dummy for rejection$_{t-1}$ X Firm size		0.044[a]		
		(0.013)		
Cumulated nb. of past rejections until $t-1$			0.162[a]	0.101[a]
			(0.013)	(0.021)
Cum. nb. past rejections X Firm size				0.021[a]
				(0.005)
Firm size		0.154[a]		0.147[a]
		(0.013)		(0.014)
Observations	38,841	38,841	38,841	38,841
Adjusted R^2	0.488	0.491	0.489	0.492

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. [a]: p<0.01.

5.2. What happen to Chinese firms on non-RASFF markets?

We now investigate whether the rejections at the RASFF borders have an impact on Chinese firms' exports to other markets. We distinguish between exports to OECD (Australia, Canada, Japan, New Zealand, South Korea, Switzerland, and the US) and to developing markets. The main justification for that distinction is that standards and inspections may be more stringent on OECD markets (i.e. relatively similar to the ones observed on the RASFF market) and less stringent in developing countries.

As previously done for RASFF countries, we aggregate all flows exported by one firm in one HS4 and one year to all individual countries within the OECD vs. developing area and work with the aggregate flow at the firm-year-HS4-region level. Table 4 reports the Chinese flows to OECD countries, while Table 5 describes the exports to the developing markets. Furthermore, we run the estimations for all the Chinese firms, as well as for the sub-sample of firms that were present and exited the RASFF market. The aim of this last set of regressions is to investigate whether we observe some re-orientation of export flows from RASFF to non-RASFF markets following the rejections. The first four columns of Tables 4 and 5 deal with the extensive margin of trade (exit and entry), while the two last columns report the results for the intensive margin of trade. Due to space constraints, we use only the cumulated number of past rejections as an explanatory variable (with is also our preferred measure). However, we obtain similar results if we run the estimations with the simple dummy of $t-1$ rejections.

Two main conclusions could be derived from our results. First, the results are relatively similar for both Chinese exports to the OECD market and to the developing market. This result is quite unexpected given the income differences between the two groups of regions. Second, results are similar to what we previously obtained for exports to the RASFF market, but only when we consider the whole sample of Chinese exporters. However, if we restrict our estimations to the firms that exit in year t the RASFF market, we observed that their exports to other OECD and developing countries in the same year t has not (positively or negatively) affected by the

rejections on the RASFF market. Almost all estimated coefficients on the cumulated number of past rejections and on the interaction term between this number and the firm size are not significant for RASFF exiters (only the firm size seems to drive the probability of exit and the value of exports for these firms on non-RASFF markets).

Our results tend to suggest that RASFF rejections also affect - in a similar way - exports of Chinese firms to other markets (with the same trends: a turnover at the extensive margin and some concentration of the intensive one). One potential explanation is that RASFF rejections provide information on the quality of Chinese products to non-RASFF importers, who may react by looking for new suppliers and/or by importing more from the suppliers they already know and trust.

Table 4
Chinese exports to OECD (non-RASFF) markets.

	Exit		Entry		Ln exports	
	All firms	RASFF exiters	All firms	RASFF exiters	All firms	RASFF exiters
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulated nb. of past rejections until $t-1$	0.068^a	-0.044	0.004^a	0.017	0.022^c	0.148
	(0.008)	(0.069)	(0.0003)	(0.018)	(0.012)	(0.125)
Cum. nb. past rejections X Firm size	-0.006^a	0.002	-0.0005^a	-0.001	0.001	-0.022
	(0.001)	(0.005)	(0.0001)	(0.001)	(0.003)	(0.030)
Firm size	-0.042^a	-0.068^a	0.006^a	-0.001	0.139^a	0.247^a
	(0.001)	(0.013)	(0.0001)	(0.008)	(0.0001)	(0.085)
Observations	163,147	7,383	1,120,452	10,895	111,556	4,774
Adjusted R^2	0.180	0.285	0.066	0.130	0.376	0.364

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. ^{a}: p<0.01.

5.3. Robustness checks

The main issue affecting our previous results is the endogeneity. To control for it, we replicate our main estimations using rejections on RASFF borders for other countries than China. We consider two alternative sets of countries: i) all countries – except China – affected by at least one rejection for a given HS4 in a given year. However, this sample mix very different countries

Table 5
Chinese exports to developing markets.

	Exit		Entry		Ln exports	
	All firms	RASFF exiters	All firms	RASFF exiters	All firms	RASFF exiters
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulated nb. of past rejections until $t-1$	0.034^a	-0.037	0.004^a	-0.001	0.066^a	0.177^c
	(0.007)	(0.061)	(0.0003)	(0.018)	(0.012)	(0.095)
Cum. nb. past rejections X Firm size	-0.004^a	0.002	-0.0003^a	0.001	0.020^a	-0.004
	(0.001)	(0.004)	(0.0001)	(0.001)	(0.003)	(0.024)
Firm size	-0.037^a	-0.067^a	0.007^a	-0.001	0.124^a	0.417^a
	(0.001)	(0.013)	(0.0001)	(0.004)	(0.008)	(0.080)
Observations	137,790	6,619	1,145,809	11,659	87,647	4,385
Adjusted R^2	0.287	0.311	0.068	0.133	0.479	0.446

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. ^{a}: p<0.01; ^{c}: p<0.1.

located on different continents and subject to various sanitary issues. We therefore select a second set of countries, more closely related to China (and which are therefore more likely to face similar sanitary rejections than Chinese products on RASFF markets). This second set includes the following South-East Asian countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

Table 6 replicates our main estimations on the impact of rejections on Chinese exports to RASFF markets, while Tables 7 and 8 do the same but for Chinese exports to non-RASFF markets. Since, previous results in Tables 4 and 5 were rather similar, we do not distinguish between OECD and developing exports and aggregate all together Chinese exports to non-RASFF markets at the firm-HS4-year level. Table 7 includes all Chinese exporters, while the sample is restricted to RASFF exiters in Table 8.

Our previous conclusions remain unchanged. The magnitude of some estimated coefficients - especially for the exit and for the intensive margin of trade - are slightly smaller, but the sign and significance are still present. Therefore, our previous conclusions were not driven by some endogeneity bias occurring between Chinese exports and Chinese rejections, and we still observe

this double-effect: diversification at the extensive margin and concentration at the intensive one both on RASFF and non-RASFF markets.

Table 6

Chinese exports to RASFF markets. Robustness checks

	Past rejections from All countries (except China)			Past rejections from South-East Asian countries		
	Exit	Entry	Ln exports	Exit	Entry	Ln exports
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulated nb. of past rejections until $t-1$	0.046^a	0.001^a	0.040^a	0.054^a	0.001^a	0.084^a
	(0.011)	(0.0001)	(0.015)	(0.017)	(0.0001)	(0.023)
Cum. nb. past rejections X Firm size	-0.004^a	-0.0001^a	0.005	-0.005^a	-0.0001	0.001
	(0.001)	(0.0001)	(0.004)	(0.001)	(0.0001)	(0.006)
Firm size	-0.054^a	0.002^a	0.159^a	-0.057^a	0.002^a	0.167^a
	(0.003)	(0.0001)	(0.015)	(0.003)	(0.0001)	(0.013)
Observations	49,277	1,234,322	38,841	49,277	1,234,322	38,841
Adjusted R^2	0.230	0.061	0.490	0.230	0.061	0.490

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. ^{a}: p<0.01.

Table 7

Chinese exports to non-RASFF (OECD and developing) markets. Robustness checks (all firms)

	Past rejections from All countries (except China)			Past rejections from South-East Asian countries		
	Exit	Entry	Ln exports	Exit	Entry	Ln exports
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulated nb. of past rejections until $t-1$	0.036^a	0.004^a	0.008	0.033^a	0.006^a	0.025^a
	(0.004)	(0.0003)	(0.006)	(0.005)	(0.0005)	(0.009)
Cum. nb. past rejections X Firm size	-0.003^a	-0.001^a	0.003^c	-0.003^a	-0.001^a	0.001
	(0.0003)	(0.0001)	(0.002)	(0.0004)	(0.0001)	(0.002)
Firm size	-0.035^a	0.014^a	0.152^a	-0.037^a	0.013^a	0.157^a
	(0.001)	(0.0001)	(0.007)	(0.001)	(0.0001)	(0.006)
Observations	258,984	1,024,615	160,977	258,984	1,024,615	160,977
Adjusted R^2	0.234	0.056	0.406	0.234	0.056	0.406

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. ^{a}: p<0.01; ^{c}: p<0.1.

Table 8
Chinese exports to non-RASFF (OECD and developing) markets. Robustness checks (RASFF exiters)

	Past rejections from All countries (except China)			Past rejections from South-East Asian countries		
	Exit	Entry	Ln exports	Exit	Entry	Ln exports
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulated nb. of past rejections until $t-1$	-0.011	-0.018	-0.001	0.024	-0.006	0.110
	(0.033)	(0.017)	(0.057)	(0.051)	(0.027)	(0.088)
Cum. nb. past rejections X Firm size	0.001	0.001	-0.001	-0.001	0.001	-0.033
	(0.002)	(0.001)	(0.014)	(0.003)	(0.002)	(0.021)
Firm size	-0.068[a]	-0.006	0.320[a]	-0.065[a]	-0.004	0.342[a]
	(0.010)	(0.005)	(0.061)	(0.0009)	(0.005)	(0.058)
Observations	10,158	8,120	6,886	10,158	8,120	6,886
Adjusted R^2	0.282	0.171	0.398	0.282	0.171	0.399

Note: Fixed effects for firms and HS2-year is all estimations (not reported).
Standard errors in parentheses. [a]: p<0.01.

6. Concluding Remarks

We address the microeconomic impact of the risk of rejection at the EU border for Chinese exporters of food products. We combine information from the Rapid Alert System for Food and Feed (RASFF) with firm level export data from China by product-destination over the period 2000-2011. We show that border rejections reduce the number of competitors, the number of varieties available to consumer and unevenly affect different-sized exporters.

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A. Appendix A: Data

A.1. Food alert and border rejection data

We use EUROSTAT's Rapid Alert System for Food and Feed (RASFF) database[9]. For our research purposes it provides an indicator for a goods' sanitary riskyness - the difficulty of producers to comply with SPS requirements. Our database records all notifications by EU member states over the period 1995-2012 (33,842 observations).

If an alert specified two origin countries we split the observation into two: one for each origin. We ignore notifications concerning products from within the EU as we care about notifications which affect the EU border. Over our sample period there are two rounds of RASFF membership enlargements[10]. Throughout the sample-period we treat the EU border as the relevant location of observing notifications as depicted in table A.1. 25,247 alerts regarding non-EU member states remain.

The database contains information on products in verbal form. We painstakenly match the individual product data manually. We code the notification data to the HS 4-digit level - the most disaggregated level at which we can identify notifications. We are able match 86% of all alerts with an HS4 code (20,208 out of 23,552), and 89% of Chinese alerts (2,453 out of 2743). We provide a detailed description of the applied methodology in Appendix B. The full Stata do files with the matching correspondence and code mapping RASFF notifications and HS codes are available on request from the authors.

We now turn to the types of alerts. Our crucial indicator of interest concerns whether a product successfully entered the European market or not - this binary variable we call "enter". Using

[9] Available at http://ec.europa.eu/food/food/rapidalert (accessed 12/03/2014).

[10] We use the RASFF website http://ec.europa.eu/food/food/rapidalert/ and the 30-year RASFF anniversary report to identify membership. Iceland, Liechtenstein and Norway are part of RASFF as part of their EEA membership. We exclude Swizerland which from 2009 is included in RASFF border controls of prodcuts of animal origin. We refer to RASFF and EU membership interchangeably throughout this paper.

Table A.1
RASFF members

pre 2000		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

the information of three variables - notifcation_basis, action_taken and distribution_status [11] - we identify entry as outlined in Figure A.2.

Figure A.1 plots basic RASFF descriptive statistics. Panel (1) documents that the number of notifications in the RASFF database has risen significantly over time. This rise primarily reflects the growing awareness for sanitary standards, such as BSE and dioxins, and use of the system by the RASFF members. It is not driven by the changing inclusion of RASFF members and the moving EU border. Our country of interest, China, is among the most affected by EU notifications (panel (4))[12], and fruits and nuts make up for almost half of all notifications. Figure

[11] There are three types of RASFF notifications: informations, alerts and border rejections. An alert requires rapid action such as removal of a product from the market or supermarket shelves. It thus represents cases of discoveries after a good has entered EU. Information notifications, on the other hand, do not require rapid action as a good has not entered the market (was rejected at the border) or is no longer present on the market. Border rejections concern food and feed consignments that have failed to enter the EU and ensure that a rejected product does not re-enter the EU through another border post. Border rejections are explicitly reported in RASFF starting in 2008, and are previously included in information notifications. However, using the variables distribution_status, which is available from 2004, and action_taken. Using the information of these three variables - notifcation_basis, action_taken and distribution_status - we code the variable entry as outlined in Figure A.2. By this method we code 18,456 notifications of which of which 13,436 we identify as no entry.

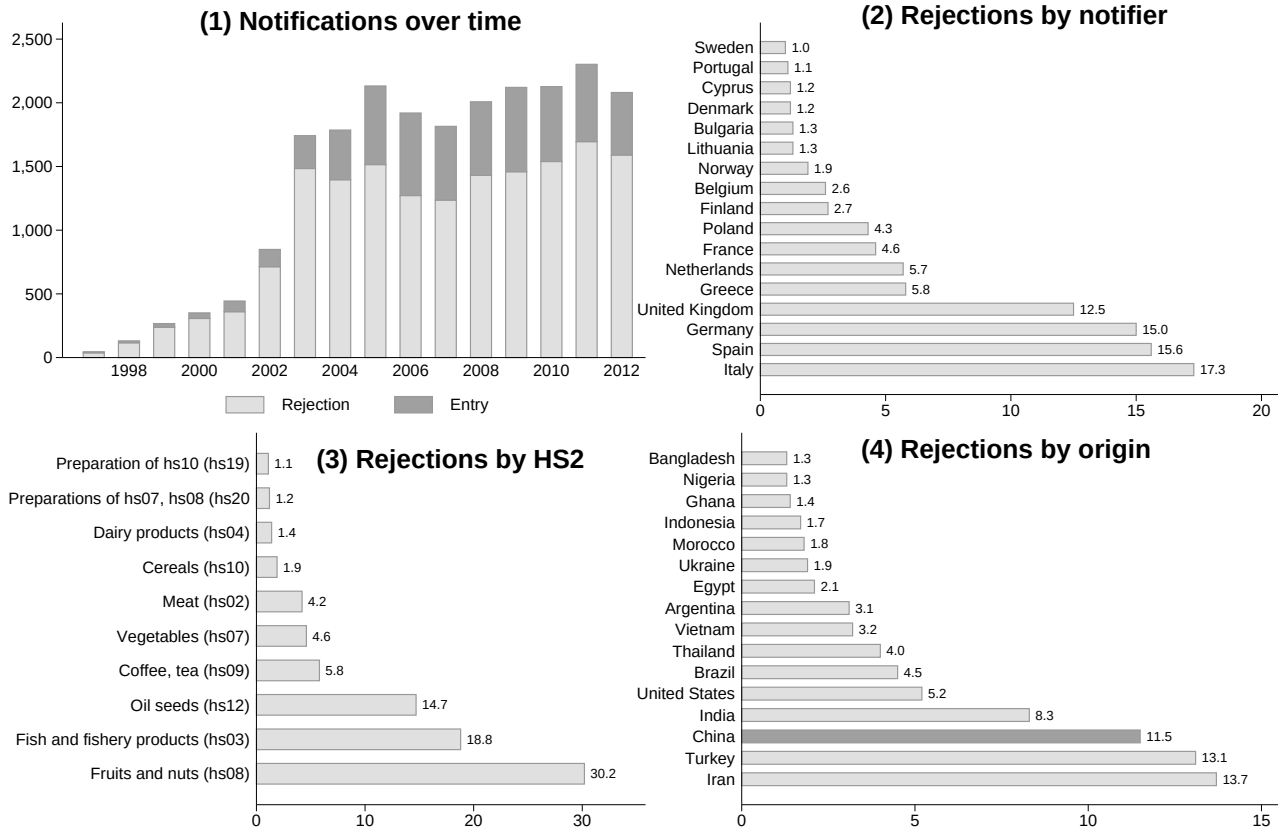
[12] Turkey and Iran are also among the top notified origin countries. Aflatoxin's are a well known issue of Iranian pistachio exports. All Iranian pistacho exports are double checked to be Aflatoxin free.

Table A.2
Coding variable enter/border rejection

No Entry into RASFF – *entry = 0*	
Action taken:	
Import not authorised	Re-dispatch
Destruction, Seizure	Official detention
Placed under customs seals	Re-dispatch or destruction
Product recalled or destroyed	Prohibition of use
Product seized and will be destroyed	
Destruction or return after official permission	
Destination of the product changed	
Notification basis and action taken:	
Border control - con. Detained	Return to consignor
Entry into RASFF – *entry = 1*	
Action taken:	
No action taken	Relabelling
Product past use-by-date	No stock left
Screening sample	Official report
Reinforced checking	Withdrawal from recipient
Withdrawal from market	Recall from consumers
Physical chemical treatment	Physical treatment - sorting
Product recall or withdrawal	Product already consumed
Physical treatment - heat or acid	
Physical treatment - blanching	
Prohibition to trade - sales ban	
Product removed from market	
Notification basis:	
Consumer complaint	Control on the market
Food poisoning	Companys own check

A.2 uncovers a clearly positive relationship between Chinese exports and Chinese notifications at the EU border.

Figure A.1
Descriptive statistics: RASFF notifications



A.2. Chinese firm-level exports

We combine the RASFF notifications data with annual firm-level export data from China. The data cover the universe of exports and contain information on firm exports by product and destination on an annual basis. The sample period is 2000-2011[13]. The trade data is reported at the HS 6-digit product level. Since we code the RASFF alerts are at the HS4 level we aggregate our data to this level. At the HS4 level we need not worry about revisions to the HS commodity codes: the product data is time-consistent.

[13]See PONCET PAPER for further studies using this data

Table A.3

Chinese Descriptive Statistics

		2001	2003	2005	2007	2009	2011
Aggregate Exports							
Firms		10976	12926	17151	20501	17703	18419
Products		196	198	199	192	189	187
Fraction wholesaler		.55	.44	.44	.55	.44	.44
Products per firm	mean	3.82	3.25	3.07	2.82	2.42	2.38
	median	2	2	2	2	1	1
Europe							
Firms		3068	3257	4631	5575	5344	5544
Products		157	148	156	156	144	139
Fraction wholesaler		.54	.49	.45	.44	.4	.39
Products per firm	mean	2.14	1.91	1.88	1.82	1.74	1.71
	median	1	1	1	1	1	1
Products per firm	mean	1.68	1.56	1.63	1.65	1.6	1.59
(excl. wholesaler)	median	1	1	1	1	1	1

Figure A.2
Descriptive statistics: RASFF notifications

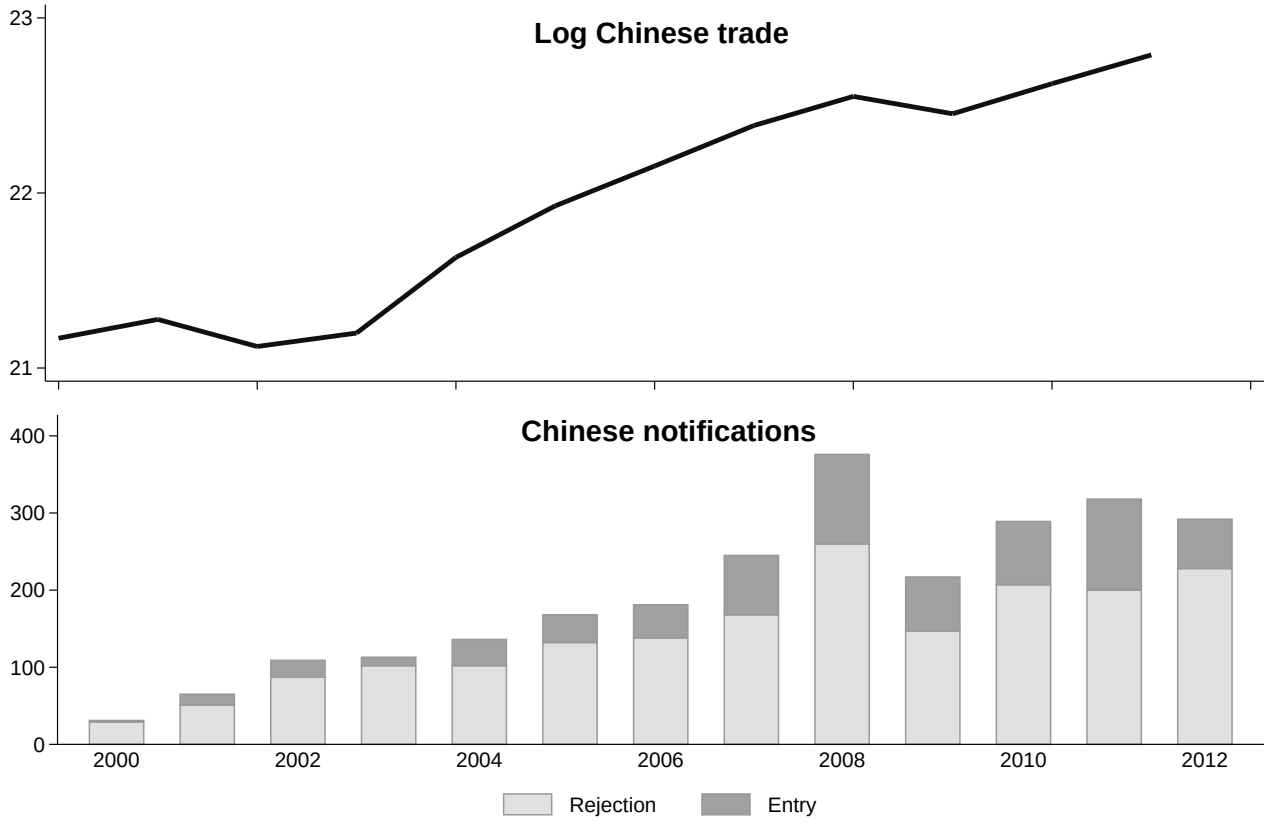


Table A.3 plots basic descriptive statistics. In line with China's growth in exports the number of active exports is rising. A clear drop in activity following the 2007 financial crisis is visible. The fraction of Chinese firms that are wholesalers is gradually declining over time, which explains why Chinese exporters appear to become less diversified over time. Table A.4 plots survival rates of Chinese firm cohorts over time. In line with a large empirical literature on exporting firms, we find that initial survival rates are low, but improve in subsequent years conditional on survival. Survival rates in Europe are slightly lower than for the whole sample possibly in part due to the greater difficulty of meeting SPS regulations.

PONCET discusses the importance and role of wholesalers...

Finally, we consider a potential issues due to our level of aggregation (HS4). If rejections occur at an HS6 level, but our level of analysis ist at an HS4 level of aggregation, we may observe

Table A.4

Number of active firms and percent of those firms that are still active in subsequent years

	2001	2003	2005	2007	2009	2011
Firms	10976	12926	17151	20501	17703	18419
survival 2001	1	.6	.43	.31	.23	.19
survival 2003		1	.64	.46	.35	.28
survival 2005			1	.61	.44	.36
survival 2007				1	.55	.44
survival 2009					1	.68
Europe						
Firms	3068	3257	4631	5575	5344	5544
survival 2001	1	.49	.35	.26	.2	.15
survival 2003		1	.56	.41	.31	.25
survival 2005			1	.58	.42	.34
survival 2007				1	.55	.43
survival 2009					1	.63

mechanically higher survival rates of larger firms: Large firms are more likely to export multiple HS6 within an HS4. If a firm's product line is hit by rejection, there is a higher likelihood of related HS6 that are unaffected. These flows are more likely to be continued. Thus, at an HS4 level, we observe large firms to be less likely to exit, even though the specific HS6 affected is affected equally badly.

We investigate how often firms have multiple HS6 within an HS4. At the firm-HS4 level we record the number of HS6 within each HS4. In Table 1, we summarize for different multiproduct firms (i.e. how many different HS4 this firm exports), how many HS6 are in each HS4. We find that even for large firms with multiple HS4 production lines, the large majority (three quarters) of HS4 only contain a single HS6-export line.

Table A.5

Percentage of HS6 within HS4 by Multiproduct Firm

	1	2	3	4	5	% firms	% exports
1	88.64	8.92	1.54	0.64	0.26	44.35	15.57
2	84.56	11.69	2.31	0.95	0.49	17.75	11.02
3	82.06	13.13	2.86	1.10	0.85	9.74	8.96
4	80.24	14.03	3.33	1.31	1.09	6.46	8.65
5	77.40	16.40	3.87	1.26	1.07	4.75	8.00
6	75.14	16.89	4.84	1.90	1.23	3.43	6.64
7	74.03	17.26	5.12	2.11	1.49	2.67	6.34
8	73.34	16.35	5.81	2.45	2.05	2.16	5.39
9	73.72	17.02	5.52	1.83	1.92	1.51	4.47
10+	72.46	17.76	5.62	2.17	1.99	7.18	24.95

Note: Columns 1-5: By row, fractions of firm-hs4 exports that have underlying number of HS6 products.

B. Appendix B: Matching RASFF alerts with HS4 commodity codes

A novel contribution of this paper is that we assign product codes to the verbal product descriptions of the Rapid Alert System for Food and Feed (RASFF) notifications. This allows us to match the notifications with trade data and measure the impact of sanitary riskiness and regulation on trade.

The RASFF database contains information on products in verbal form. We use two variables: *product*, a sector variable (e.g. alcoholic beverage, cereals and bakery products); and *subject*. *Subject* describes the reason for rejection, the product and origin of the shipment in verbal form (e.g. "undeclared sulphite in wine from Chile"). We split *subject* such that it only contains the relevant information on the product (i.e. "wine"). Next, we rearrange some *product* classifications such that its observations are more directly aligned with HS2 sectors (e.g. "fish and fish products" and "farmed fish and products thereof (other than crustaceans

and molluscs) - (obsolete)" are combined). We also undertake some manual 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 agricultural exports (HS chapters 01-24).

Using *subject* and *product* we assign observations to the harmonized coding system from the World Customs Organization in which our Chinese firm-level data is coded. We code the notification data 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. Jaud et al. (2013) also use the RASFF database and manually code the data to CN8. However, we require the standard HS codes for our analysis.

Our baseline database contains 33,842 observations and is thus too numerous to assign HS codes on an individual basis. Instead we identify the sector (HS2) level using the *product* variable wherever possible, and assign the more disaggregated individual product code using Stata's *regexm* code. *Regexm* searches the variable *subject* for keywords associated with a specific HS4 code. For example, within *product* "fish" we can "frozen hake fillets" can be assigned HS4 code 0304 using keywords "hake" and "frozen". By the same method "chilled hake" is assigned HS4 code 0302, and "austral hake" cannot be assigned an HS4 code. The full Stata do files with the matching correspondence and code mapping RASFF notifications and HS codes are available on request from the authors.

Using this methodology, we successfully match 86% of alerts with an HS4 code (20,208 out of 23,552). Among border rejections of China we match 89% (2,453 out of 2743). The incidence of rejection is fairly heterogenous across products, but cluster in some sectors. Our notifications are split over 123 different HS4 codes out of potentially 201 in the 24 chapters of agricultural products (for China we identify 78 different products). The majority of notifications concerns nuts and fish products as depicted in figure A.1. We conduct an additional eye-ball check of the mapping in table B.6. We compare the percentage of Chinese exports and rejections by HS2 product category and over time. While we do not expect a strong correlation (small

export sectors may quite plausibly be affected by disproportional number of rejections), we confirm that there are no large sectors without alerts and no tiny agricultural sectors with many alerts.

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

Table B.6

Chinese border rejections and percent of agricultural export by HS2 and year

		2001		2003		2005		2007		2009		2011	
	HS Code	**% trade**	**rej.**	**% trade**	**rej.**	**% trade**	**rej.**	**% trade**	**rej.**	**% trade**	**rej.**	**% trade**	**rej.**
1	Animals	0.1		0.1				0.1		0.1			
2	Meat	3.9	3	0.1	2	0.4	14	0.4	3	0.4	2	0.4	4
3	Fish	21	23	20.1	22	23.3	16	22.8	42	27.7	19	26.8	25
4	Dairy	2.3			1	0.3	4	0.3	11	1.10	4	1.4	6
5	Animal origin	12.1		6.6	21	11.3	1	8.5	6	9.7	1	9.7	3
6	Plants	0.5		0.9		0.6		0.6	1	0.7		0.6	
7	Vegetables	12.2	3	12.3	10	10.8	8	11.1	4	10.1	10	11.1	21
8	Fruits, Nuts	2.3	1	6.1	1	4.1		5.3	6	5.3	6	4.40	43
9	Coffee, Spices	2.7	8	2.5	1	2.3	4	2	7	3	12	3.5	21
10	Cereals	0.3	1	0.5	2	0.2	2	0.3	11	0.2	14	0.2	31
11	Milling	0.1		0.1				0.2		0.2		0.4	
12	Grains	10.3	22	10.3	36	9	88	6.6	90	6.5	78	5.9	59
13	Lac	0.7		0.7		0.7		0.9	3	1.9		3	
14	Veg. plaiting	0.5		0.5		0.3		0.3		0.3		0.4	
15	Fats, oils	0.9		1.6		1.6		0.9	1	0.8		1.10	2
16	Meat prep.	4.40		4.3		8.30		6.6		4.40		5.3	
17	Confectionery	0.6		1.10		1.2	4	1.10	7	1.10	4	1	7
18	Cocoa	0.2		0.2		0.5		0.8		0.5		0.8	
19	Cereals	2.3		2.3	3	2.1	3	1.7	2	2.1	15	2	43
20	Veg. prep.	18.1		23.9	1	18.3	3	23.8	3	15.7	3	14	8
21	Misc. prep	1.10	3	1.4	4	1.2	4	1.4	14	1.4	13	1.5	3
22	Beverages	1.10		1		0.9	1	0.6		0.6		0.5	
23	Residues	0.6		0.4		0.3		1.5	4	2.8	3	3.2	4
24	Tobacco	1.9		3		2.3		2.1		3.4		2.4	