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Reputation Matters: Spillover Effects for Developing Countries in the Enforcement of US Food Safety Measures

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***Abstract**:*

We use data on US food import refusals to show for the first time that reputational spillovers are important factors in the enforcement of food safety measures. The odds of a country experiencing at least one import refusal increase by over 100% if there was a refusal of the same product from a neighboring country in the preceding year. Similarly, the odds of a refusal increase by 62% if there was a refusal of a related product from the same country in the preceding year. These findings have important policy implications for exporters of agricultural products, particularly in middle-income developing countries.

Keywords: Product standards – SPS measures – Import refusals – Developing countries.

JEL Codes: F13; F15; O24.

1. Introduction

Non-tariff measures have become progressively more important trade policy instruments as applied tariff rates have fallen across the world in recent years. From a development perspective, technical regulations and product standards are a particularly important type of non-tariff measure because they highlight the fact that the favorable market access accorded under duty and quota-free preferential schemes remains conditional on compliance with regulations in areas such as consumer safety. Previous research shows that product standards and technical regulations in the large, developed markets can have two contradictory sets of effects for developing country exporters. On the one hand, the costs of compliance—retooling, product re-design, testing, and certification—can be substantial enough to keep many small and medium enterprises out of international markets, thereby affecting the pattern of international specialization (e.g., Essaji, 2008). But at the same time, foreign standards can also provide the impetus for firms and sectors to upgrade production technologies and realize beneficial productivity gains (e.g., Maertens and Swinnen, 2009). The question of which types of standards tend to promote which set of effects is clearly of vital policy importance to developing country exporters. The issue of how best to direct technical assistance resources so as to support the upgrading of standards systems and development of compliance mechanisms in developing countries is also an important part of broader Aid for Trade discussions.

Most previous work on standards and technical regulations has focused on the rules themselves, rather than their design and application or enforcement through specific at-the-border mechanisms. One reason is the lack of accessible and comprehensive data. Assessing the existence and the level of stringency of standards is, of course, an important matter when analyzing constraints faced by developing country exporters. However, the challenge is also to appraise and analyze exporting countries' compliance capacity. As highlighted by Henson and Olale (2011), there are in principle numerous compliance indicators available, but they are often incomplete and/or not publicly available. Therefore, there has been very little systematic analysis across countries and time based on such indicators.

The recent literature discloses a number of contributions that seek to deepen understanding in this area by using new data and approaches. Karov et al. (2009) focus on identifying the trade impacts of US phytosanitary regulations at the product-country level by analyzing the effects of treatment requirements and grants of new market access. Similarly, Alberini et al. (2005) examine implementation of the FDA's seafood HACCP program using a dataset of plant inspections. Another set of papers uses import rejection data, in general from the European Union or the United States, in order to study food safety compliance in international trade. Examples include: Ababouch et al. (2005); Allshouse et al. (2008); Buzby and Regmi (2009); and Buzby et al. (2008).

In this paper, we use a database on US refusals of imported consignments of food on safety grounds to focus on one important example of the de facto implementation of product standards. The advantage of looking at measures such as import refusals is that they are implemented on a country- and product-specific basis, rather than being the same de jure for all exporters. We can therefore see in the data whether or not developing countries are more strongly affected by particular measures, and which categories of developing countries are the hardest hit. Most standards and regulations are effectively most-favored nation (MFN) measures, which makes it difficult to identify their effects by exploiting cross-country variation in outcome measures, such as trade flows. Focusing on a country- and product-specific measure, such as import refusals, provides a potentially much richer source of data in which identification can be based on cross-country as well as cross-product and through-time variation.

Rather than focusing on the trade impacts of product standards and their application—as much past work has—we look instead at the determinants of import refusals by the US authorities. Import refusals—and the inspections on which they are based—are not random. A range of factors influence the authorities' decision to inspect, and potentially to reject, particular goods. Product-specific factors such as risk to human life and health, or quarantine risk, are important, and we control for them in our analysis. Similarly, country specific factors, such as the development of standards and quarantine systems, are also important, and we again control for them.

In the interests of exploring the determinants of import refusals from a point of view that is of particular interest to developing country exporters, we focus on two novel effects. First, we find that the probability that a given country's exports of a particular product are subject to refusal by US authorities depends on past refusals affecting the same product from *neighboring countries*, after controlling for other factors. We call this the “neighbor reputation effect”. Specifically, the odds of a country experiencing at least one import refusal increase by over 100% if there was a refusal of the same product from a neighboring country in the preceding year. Our second finding is that the probability that a given country’s exports of a particular product are subject to refusal by US authorities depends on past refusals affecting *related products* from the same country. We call this the “sector reputation effect”. Again, this effect is quantitatively important: the odds of a refusal increase by 62% if there was a refusal of a related product from the same country in the preceding year. Neither the neighbor reputation effect nor the sector reputation effect has previously been documented in the literature. Defining and documenting these effects builds on and extends the existing literature.

The approach to reputation used in this paper draws on Tirole (1996), who defines collective reputation as an aggregate of individual reputations: past behavior of a group’s members is used to predict individual future behavior. This paper suggests testing the assumption of a collective reputation effect at the region, and sector levels. Therefore, even though compliance is defined at the firm level, it is potentially the collective reputation of a set of neighboring countries, or a group of producers of related products, that matters. In this paper, we thus extend the definition of collective reputation to include the possibility of reputational spillovers from related sectors and neighboring countries.

In analyzing the determinants of import refusals, we are building on and extending two recent contributions to the literature. Baylis et al. (2010) use information on EU notifications, and find that increased use of notifications is linked to a decreased level of protection through tariffs. They also see that European countries that would intuitively be demanders of protection tend to be at the origin of more notifications than their EU partners, which suggests that political economy motives may be at work in the notification system. Baylis et al. (2009) provide one of the first empirical investigations of the determinants of US import refusals. Their analysis highlights a set of factors that can potentially trigger refusals. Their findings suggest that refusals are influenced by political pressure (the “standards for sale” effect; cf. Grossman and Helpman, 1984 for the case of tariffs). But more intriguing, they also find that contrary to prior expectations (the "learning curve" effect), countries with experience in exporting products to the US are actually subject to relatively more refusals—or more recent exporters face fewer refusals than established ones, even after controlling for export volumes—thereby suggesting some degree of "stickiness" in the refusal determination process.

In assessing the determinants of import refusals, it is important to keep in mind that the refusals themselves can have significant economic impacts, although estimates vary according to the methodology adopted. Based on expert opinions of the proportion of a range of agri-food exports subject to import refusals, Jaffee and Henson (2004) put the order of magnitude of the value of losses in the billions of dollars for 2000-2001. However, deriving losses using reported volumes of refused consignments multiplied by the average unit cost inferred from trade data, results in a value of rejections that appears relatively small (Ababouch et al., 2005; Diaz, Jaffee and Rioz, 2008; and UNIDO, 2011). Even if, as suggested by the second set of analyses, the value of losses is small relative to trade flows, there is emerging evidence that import refusals have significant impacts on trade, perhaps through indirect channels. Baylis et al. (2010) use data on EU import alerts—closely related to refusals[1]—in a gravity model to show that they tend to decrease trade.[2] The first stage of the empirical approach taken by Jaud et al. (2009) tests whether EU import alerts contribute to increase trade costs and thus supplier concentration. Jouanjean (2012) shows that, after controlling for other factors, the occurrence of import refusals has a downgrading impact on countries' average export price.

Against this background, the paper proceeds as follows. In the next section, we provide an outline of the US import refusals regime. Based on that description, Section 3 presents our dataset, focusing on the import refusals data. We present some preliminary analysis that supports our hypotheses using descriptive statistical techniques, then proceed to develop a fully-specified econometric model of import refusals.

[1] The terminology for the European and US systems differs. US alerts designate particularly sensitive categories of products for which pre-determined automatic refusal will apply (we discuss this further below). Under the EU system, alerts encompass both market notifications for products that are already circulating in the European market (alert and information notifications) and border rejections.
[2] It is unclear whether Baylis et al. (2010) use only border rejections in their work or the total number of rejections and notifications. Presumably we believe this is the latter as in Jaud, Cadot and Suwa-Eisenmann et al. (2009).

Section 4 presents and discusses the results from our model, and conducts robustness checks. Section 5 concludes with a discussion of policy implications, and avenues for further research.

2. The US Import Refusals Regime

To gain admission to the US market, imported foods must meet food safety requirements applying to the product and country of origin. Broadly speaking, food safety measures are aimed at safeguarding the US market from sanitary risks. At the federal level, there are three agencies involved in the oversight of food and food ingredients safety: the US Department of Agriculture's Food Safety and Inspection Service (FSIS), the Food and Drug Administration (FDA), and the Environmental Protection Agency (EPA). FSIS ensures the safety of imported meats, poultry, and processed egg products. FDA covers all other products. EPA licenses pesticide products and monitors pesticide residues in products.

The FDA enforces the Federal Food, Drug and Cosmetics Act (FD&C) as well as other laws designed to protect consumer health, welfare, and safety. Under Sec. 801 of FD&C, products are subject to inspection when imported. Imported food products are expected to meet the same standards as domestic products, i.e. they must be pure, wholesome, safe to eat, and produced under sanitary conditions. Food imports must also contain informative and truthful labeling in English.[3] Another important requirement is that since 1997, producers must follow FDA's good agricultural practices (GAP) for the control and management of microbial food safety. Likewise, since 1995 fish products imports must meet hazard analysis and critical control point (HACCP) standards, as must domestic producers. Other measures applying to seafood include traceability requirements such as the identity preservation system for molluscans, and labeling of origin and method of production (wild harvest or farm raised). Other programs concerning food products in general are also in place such as the acidified and low acid canned foods regulations. Acidified and Low Acid Canned Foods must be manufactured in accordance with FDA regulations. Food canning establishments must also register with the FDA.

[3] http://www.fda.gov/ForIndustry/ImportProgram/ImportProgramOverview/default.htm.

All the measures described above are defined on the principle of national treatment: importers and domestic producers are subject to exactly the same requirements. There is, however, a significant difference in de facto treatment between domestic goods and imported products with respect to food safety: the Act allows for refusal of imported FDA-regulated products for “appearing” to be adulterated or misbranded. The law is interpreted in a broad sense as allowing the FDA to make admissibility decisions based not only on physical evidence such as examination, facility inspection, or laboratory results, but also based on historical data, information from other sources (e.g. about a disease outbreak), labeling, and any other evidence.[4] Factors such as reputation can clearly come into play in this decision. In other words, if there is a suspicion that a product from a given origin will not meet FDA standards, it can be detained. Therefore the standard of proof for determination of refusal for food import products is much less strict than for domestic products, which must be based on an actual violation. This supports the hypothesis that refusals may be partly path-dependent (as noted by Baylis et al., 2009) since past histories of violation from similar products and origins are criteria that may be used to decide whether there is a suspicion of adulteration or misbranding, which can in turn justify a refusal.

Under the Public Health Security and Bioterrorism Preparedness and Response Act of 2002, the FDA issued regulations in December 2003 requiring two things: 1) that food facilities (including foreign) be registered with the FDA; and 2) FDA be given advanced notice of shipments of imported food. The information required for prior notice varies, based on the type of entry, mode of transportation for entry, and whether the food is in its natural state. Upon reviewing the notice, the FDA can decide to release the product, request additional information or documents, request physical examination of the product, or recommend detention of the product. Detention means that in the absence of petition or reconditioning of the goods from the exporter, the product will not be released into US territory and will either be re-exported or destroyed within approximately 90 days. Physical examination entails verification of labeling, of the

[4] Presentation by Domenic Veneziano, Director, FDA Division of Import Operations at the Food & Agriculture Border Gateway Summit January 16, 2008.
http://www.michigan.gov/documents/mda/FDA_importproc_224440_7.pdf accessed 22 November 2011.

container integrity, sampling, and verification, and leads to either a recommendation of release or detention. According to the literature, about 1-2% of all food shipments are subject to physical examination by the FDA, and a fraction of these are subject to sampling (Buzby et al., 2009; Baylis et al., 2009).

The FDA relies on a system of alerts for particularly sensitive categories of products in order to help it save and allocate inspection resources. Alerts are issued when the FDA determines that there is a particular risk associated with a product, producer/exporter, country or region of origin. In most circumstances, alerts determine that firms and products identified are subject to detention without physical examination (DWPE). In this case, the FDA automatically detains the concerned products until it is demonstrated that the violation has been remedied. As noted by Baylis *et al.* (2009) alerts are strikingly rarely changed: three quarters of alerts in place in 2009 had been in place for more than 10 years, and a significant portion of them (one quarter of all alerts) for more than 20 years. Alerts appear to be decided on similar legal basis to refusals, e.g. the standard of "appearance". According to the FDA, alerts are triggered by historical violations at the following levels: commodities; manufacturers/shippers; growers; importers; geographic area; and countries of origin.[5] Sources of information come from FDA's own field offices, but also foreign inspections and evidence from other countries.

3. Methodology and Data

As the above discussion demonstrates, US border authorities exercise broad discretions when implementing the import refusals regime. As previously noted and as suggested by the FDA itself, there is a strong possibility of path dependence: the authorities might look at historical patterns of compliance in allocating scarce enforcement resources, leading to a correlation between past and present import refusals, even after controlling for other factors. We refer to this as the "compliance history" effect at the country-product level, and it reflects the stickiness found in import refusals in previous empirical work, such as

[5] Presentation by Domenic Veneziano, Director, FDA Division of Import Operations at the Food & Agriculture Border Gateway Summit January 16, 2008. http://www.michigan.gov/documents/mda/FDA_importproc_224440_7.pdf accessed 22 November 2011.

Baylis et al. (2009). In addition, the structure of the US import refusal system is suggestive of two other effects that might be in operation. One is a "sector reputation" effect, by which we mean the possibility that import refusals for a particular product are associated with past import refusals affecting closely related products. The second is a "neighbor reputation" effect, namely the possibility that import refusals affecting a given product from one country might be more likely if neighboring exporters of the same product have a history of non-compliance. In the remainder of this section, we outline the data and model we will use to test for the existence of these two effects.

3.1 US Import Refusals Data

This paper uses a dataset of US import refusals for the period 1998-2008. It extends the data used in Jouanjean (2011), and covers FDA Industry Codes 16 (fishery and seafood products), 20-22 (fruit and fruit products), and 24-25 (vegetables and vegetable products). Those codes were matched to HS codes and fully cover HS chapters 3 (fish and crustaceans) and 7 (vegetables). The data also cover all of chapter 8 (fruits) except nuts, and partially cover chapter 9 (coffee, tea, mate, and spices) for some spices. Finally, they cover the preparation of fish and crustaceans products in chapters 16 (preparations of meat, fish, and crustaceans), as well as in chapter 20 (preparations of vegetables, fruits, and nuts), except for preparations of nuts. The reason for focusing on these sectors is that they are products of particular export interest to many developing countries. Refusals in these sectors accounted for over 27% of all FDA import refusals[6] and 49% of the Food and Food-Related Products import refusals over the 1998-2008 period . We are therefore confident that by focusing on these three sectors, we are capturing an important part of overall import refusal activity in the US. Within the chosen sectors, the list of refusals in our dataset is exhaustive.

[6] Including Food and Food-Related Products; Miscellaneous Food-related items; Cosmetics; Vitamins, Minerals, Proteins, and Unconventional Dietary Specialties (Human and Animal Use); Pharmaceutical Necessities and Containers; Antibiotics (Human and Animal Use); Biologics, Human Drugs, Animal Use Products, Medical Device and In-Vitro Diagnostic Products, Non-Medical Radiation Emitting Products.

This subsection describes the US import refusals regime in more detail, focusing on the way in which the data used here were collected.

The FDA makes refusals information public in their Import Refusal Report (IRR). Reports provide information on the manufacturer's name and country of origin, as well as the dates and motives for the consignment refusal. To gain access to historical refusals data, we submitted a Freedom of Information Act request in September 2009, which the FDA satisfied by supplying data in May 2010.

Product codes supplied by the exporter allow for a very specific definition of the transformation process the imported product has undergone (raw, dried, and pasteurized etc.) and it is usually precise enough to define a straightforward correspondence with the HS 4-digit classification. The only part of the correspondence in which additional issues arise involves the FDA process code relating to "packaged food" under which exporters/importers tend to regroup various types of products that sometimes should have been coded otherwise. Thus, more careful handling was necessary. First, according to product subclasses providing information on containers, we make the straightforward assumption that products in metal and glass containers are transformed, and thus fall into HS Chapter 16 for "fish and fishery products", and HS Chapter 20 for "fruit and fruit products", and "vegetables and vegetable products". Second, for containers of different materials, we analyzed product description data in which the FDA agent filled in a precise definition of the product. We also verified the information about refused products on companies' websites. We have therefore been able to recode FDA import refusals for 46 HS 4-digit products from 225 exporting countries to the US between 1998 and 2008.

Since refusals affect individual firms, not countries as such, an important issue of aggregation arises. If we could match the FDA firm-level refusal data with appropriate firm-level control variables, it would clearly be preferable to undertake our analysis at the firm-level. However, doing so would require matching the FDA data to datasets of firms in a large number of countries. That exercise would be extremely difficult, even in developed countries, but is practically impossible in the developing countries that are the primary focus of this paper. We have therefore aggregated the refusals data to the country-sector-year level.

Obtaining control variables at that level of aggregation is much more straightforward, as we discuss in the next section.

3.2 Other Data

In addition to the dataset on FDA import refusals discussed in the previous subsection, we use standard data sources for the remaining variables used in our analysis (Table 1; see Table 2 for descriptive statistics). We source trade data from UN-Comtrade, accessed via the World Bank's WITS platform. We use US import data to control for the fact that larger countries have a correspondingly greater number of shipments than smaller ones, and so are likely to see a higher number of refusals. The import data are for 1998-2008 at the HS four-digit level, including all exporting countries. In light of the high quality of US import data, we replace all missing values with zero to indicate that no trade took place for the given exporter-product-year combination. We only include trade data for which we have corresponding refusals data, namely HS chapters 3, 7, 8, 9, 16, and 20 from which we exclude nuts and meat preparations since those products belong to other FDA industry codes not analyzed in this paper. As an additional control variable, we source per capita GDP data in PPP terms from the World Development Indicators, as a proxy for the exporting country's development level. Finally, we include US effectively applied import tariffs as an additional explanatory variable. Effectively applied import tariffs take account of preferences accorded under regional trade agreements, as well as unilateral preference schemes in favor of certain developing countries. These data are sourced from UNCTAD's TRAINS database via the World Bank's WITS platform. Since many missing values are returned, we use the world average by product-year combination when data on effectively applied import tariffs are unavailable on a bilateral basis.

3.3 Preliminary Analysis

Before moving to a fully-specified econometric model, it is useful to examine some simple correlations in the data to see whether they support our hypotheses, namely the sector reputation effect, and the neighbor reputation effect. As outlined above, we expect to see positive associations between, on the one hand, the number of refusals for a given country-product-year combination, and, on the other, the number of refusals affecting related products—those in the same HS 2-digit chapter—from the same country in the previous year (sector reputation), and the number of refusals affecting the same product from related countries—the five geographically closest to the exporter—in the previous year (neighbor reputation).

In both cases (Figures 1-2), the data provide support for our propositions. The positive correlations in both figures are 1% statistically significant. In terms of slope coefficients, the stronger gradient of the line of best fit in Figure 2 compared with Figure 1 provides some preliminary evidence that neighbor reputation may be quantitatively more important than sector reputation.

We can also use the data to obtain a preliminary idea of the relative importance of the reputation mechanisms for developing as opposed to developed countries. For high income countries (developed), the correlation between refusals affecting one country and those affecting its five closest neighbors is 0.23, and the correlation between refusals for one product and refusals for related products is 0.22. For countries in the low and middle income groups (developing), however, the first correlation is stronger, at 0.49, although the second correlation is weaker, at 0.15. Our preliminary analysis therefore suggests that at least some kinds of reputational spillovers might matter more for developing countries than for developed ones.

Of course, the descriptive analysis we have presented is based on simple correlations only. It does not take account of intervening influences. To address this issue more fully, the next subsection develops an econometric model, for which we report estimation results in the next section.

3.4 Empirical Model

As discussed above, we are primarily interested in assessing the impact of reputational spillover effects in the enforcement of US food safety regulations through import refusals. We define two dependent variables that will enable us to use similar sets of independent variables to estimate on the one hand a model using a fixed effects logit estimator, and, on the other, a model using a fixed effects negative binomial estimator. The first, $RefusalsDum_{ikt}$, is a dummy variable equal to unity if a country-HS four-digit product-year combination has at least one import refusal. The second, $Refusals_{ikt}$, is a count of the number of import refusals affecting a particular country-product-year combination.

As independent variables, we include two measures of reputational spillovers. The first, "sector reputation", is a lagged dummy equal to unity if there was at least one refusal affecting products in the same HS two-digit chapter from a given exporter, but excluding the number of refusals affecting the HS four-digit product in question; for the count data model, we use a similarly defined count variable. Sector reputation is therefore a measure of the extent to which related products are subject to import refusals. The second variable, "neighbor reputation", is a lagged dummy equal to unity if there is at least one refusal affecting the same product exported from geographically close countries; again, the count data model includes a similarly defined count variable. We define "closeness" using geodesic distance as the benchmark, i.e. the five closest countries to the exporter. If reputational spillover effects are present in the data, we expect both of these variables to have positive and statistically significant coefficients.

To take account of other influences, we specify full sets of fixed effects by exporter, product (HS 4-digit), and year.[7] The exporter fixed effects account for factors that are country-specific, such as distance from the US market, common language (which affects labelling requirements), and, to a large extent, membership of the same regional trade agreement, as well as each country's level of development in respect of its standards, quality, and quarantine systems. The year fixed effects control for events that affect all countries and industries in the same way, such as changes in macroeconomic conditions or budget allocations to border inspection. The product fixed effects are particularly important, because they allow us to control for the inherent riskiness of particular products. Certain products are surely subject to a higher number of refusals because they are, for example, highly perishable or easily adulterated. Fixed effects are an efficient way of accounting for such possibilities.

[7] We have also attempted to estimate models with fixed effects by country-industry and by year. However, they generally fail to converge due to the large number of fixed effects involved, and the fact that identification is then purely limited to variation at the country-industry-year level. Alternative estimators that would be computationally feasible, such as OLS, are well known to have undesirable properties with both limited dependent variables and count data. In the former case, OLS can produce estimated probabilities that do not fall within the zero to one bound. In the latter case, OLS can produce estimated counts that are not integers.

In addition to fixed effects, we also include a number of variables as controls. First, the persistence or "stickiness" in US import alerts and refusals that has been referred to in the previous literature (e.g., Baylis et al., 2009) suggests that it is important to include a lagged dependent variable to take account of that possibility. Persistence could be due to a number of causes, including a higher probability of inspections, or a failure by producers to upgrade quality in the face of past refusals. If there is indeed persistence in the refusals data, we would expect a positive and statistically significant coefficient on this variable.

The previous literature also suggests that countries that are established exporters tend, perhaps surprisingly, to experience a greater number of import refusals (Baylis et al., 2009). In addition, it seems likely that countries that export more tend to experience a greater number of refusals simply because there is a correspondingly higher number of shipments. We therefore use the lagged value of imports into the US as an independent variable for these two reasons. We use imports in levels, rather than taking logarithms, to ensure that observations with zero trade are retained in the estimation sample.

Because of the potential for political economy mechanisms to be in operation—as suggested in the previous literature (e.g., Baylis et al., 2010)—we also include effectively applied tariffs as a control variable, with missing values interpolated as discussed above. Although the import refusals regime is designed to safeguard consumer safety, it is plausible that the influence of industry lobbies might result in more refusals than simple safety concerns might dictate. If such political economy forces are at work, we would expect to see a positive correlation between tariffs and import refusals, i.e. more refusals in more heavily protected sectors. Due to the inclusion of tariffs in our dataset as a measure of political economy activity, it is unnecessary to include additional variables that capture the same activity, such as industry-level lobby contributions.

The logarithm of the exporting country's per capita GDP is used as a proxy for the exporter's compliance capacity and level of development.[8] In subsequent regressions, we estimate using separate sub-samples for different World Bank income groups to allow for more complex income and development effects in the determination of import refusals.

Bringing these points together allows us to specify our baseline models, using the two dependent variables (dummy and count):

$$(1)\ Pr(RefusalsDum_{ikt}=1)$$

$$= b_0 + \underbrace{b_1 RefusalsDum_{ikt-1}}_{Compliance\ History} + \underbrace{b_2 RefusalsDum_{ikt-1}^{HS2}}_{Sector\ Reputation} + \underbrace{b_3 RefusalsDum_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$$

$$+ b_4 Imports_{ikt-1} + b_5 \log(1+Tariff_{ikt}) + b_6 \log(GDPPC_{it}) + \sum_i f_i + \sum_k f_k$$

$$+ \sum_t f_t$$

$$(2)\ Refusals_{ikt}$$

$$= b_0 + \underbrace{b_1 Refusals_{ikt-1}}_{Compliance\ History} + \underbrace{b_2 Refusals_{ikt-1}^{HS2}}_{Sector\ Reputation} + \underbrace{b_3 Refusals_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$$

$$+ b_4 Imports_{ikt-1} + b_5 \log(1+Tariff_{ikt}) + b_6 \log(GDPPC_{it}) + \sum_i f_i + \sum_k f_k$$

$$+ \sum_t f_t$$

where f indicates fixed effects in the exporter (i), product (k), and time (t) dimensions. As noted above, equation (1) is estimated as a fixed effects logit model, and equation (2) is estimated as a fixed effects negative binomial model.

[8] An alternative, or complementary, proxy might be refusals data from other developed countries. However, this paper's focus is on the refusals regime in the US, and the substantial amount of additional data collection involved is outside its scope.

4. Estimation Results and Discussion

4.1 Fixed Effects Logit Results

Table 2 presents results using the dummy variable $RefusalsDum_{ikt}$ as the dependent variable. The baseline model is in column 1. Our main variables of interest, the two reputational spillover dummies, are both positively signed and one percent statistically significant. Converting the estimated parameters to odds ratios by exponentiation suggests that the effects are also highly economically significant. For example, an import refusal affecting other products in the same HS two-digit chapter increases the odds of a refusal by 62%, and an import refusal affecting the same product exported by neighboring countries increases the odds of a refusal by 110%. These results clearly suggest that reputation matters in the enforcement of US SPS regulations through the import refusals system, and that it is not just persistence in the refusals data that drive the results, because we control for that effect separately via a lagged dependent variable: a country's track record with similar products, and even the track record of neighboring countries, also have a significant impact on import refusal behavior by the US authorities.

Turning to the control variables, we also find signs and magnitudes that accord with intuition, and parameters that are one percent statistically significant in all but one case. As expected, a higher level of imports is associated with a greater probability of suffering at least one refusal. Interestingly, the tariff rate is also positively associated with the probability of refusal: US authorities are more likely to issue refusals affecting products that are relatively strongly protected as opposed to those with lower tariff rates. This finding could be consistent with the influence of political economy forces in the implementation of US SPS measures through the refusals system. Although further work would be necessary to confirm that this is the case, the association we have found here is nonetheless striking, and reflects a dynamic that has been mentioned previously in the literature (e.g., Baylis et al., 2010). Finally, the coefficient on per capita income is negative, which is in line with expectations: poorer countries with presumably less developed SPS infrastructure are more likely to suffer import refusals. However, the effect is not statistically significant. The influence of country income on refusal behavior is something we discuss in more detail below.

The remaining columns of Table 2 use alternative specifications to ensure that our initial results are robust. In columns 2 and 3, we change the definition of "neighboring" countries to be respectively the three closest countries and the single closest country. As can be seen from the table, our finding on the importance of neighborhood reputation is robust to the first change, but the neighborhood reputation variable becomes statistically insignificant in the final case. What matters from a reputational point of view is therefore a country's geographical region in broad terms, not just the behavior of its closest neighbor.

As an additional check, column 4 of Table 2 limits the sample to those partner country-product combinations for which at least some trade is observed during the sample period. The rationale behind this limitation is that the refusals regime only affects actual or potential exporters,[9] but the sample used for the baseline model includes a large number of data points where no trade is taking place. In any case, little turns on this sampling issue in practice. Column 4 shows that even though the sample size is reduced by about 45% due to this restriction, the estimated coefficients remain very close to the baseline in sign, significance, and magnitude.

Finally, column 5 extends the baseline specification by using a distributed lag model to examine the possibility that reputational spillover effects are more persistent over time than the baseline model allows for by only using one lag. We consider three lags of the dependent variable to capture long-term persistence, as well as three lags of each of the reputation variables. We indeed find that the variables of interest are positively signed and one percent statistically significant in all but two cases (the second and third lags of the sector reputation dummy). As might be expected, these results suggest that reputation is sticky, in the sense that it changes only slowly over time.

To provide some further detail on the baseline results, Table 3 presents regression results for sub-samples limited by World Bank geographical region. Moving across the table, it is clear that for all regions except Sub-Saharan Africa, there is strong persistence in the import refusals data: the compliance history coefficient is positively signed and at least 5% statistically significant. Comparing the magnitude of the

[9] For some sectors in our sample, this number is also a good proxy for the set of countries allowed access to the US market under the SPS regime.

coefficient across specifications suggests that import refusals are particularly sticky for Latin America and the Caribbean, which is an important exporter of agricultural products to the USA.

Similarly, the sector reputation effect also has a positive and statistically significant coefficient in all regions except Sub-Saharan Africa. In this case, however, the effect is strongest in the South Asia region. By contrast, results for the neighbor reputation variable are more mixed. The coefficient is only positive and statistically significant for four of the six regions: Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, and Sub-Saharan Africa.

Table 4 expands on these results by considering samples limited to individual World Bank income groups. The lagged dependent variable has a positive and statistically significant coefficient in all three regressions, but its magnitude is much larger in the case of high- and middle-income countries (columns 1-2) than in that of low-income countries (column 3). By contrast, the sector reputation variable only has a statistically significant coefficient for high- and middle-income countries, and the effect is noticeably stronger in the latter case. In line with this result, neighborhood reputation has a statistically significant coefficient in all three regressions, but its magnitude is much stronger for low- and particularly middle-income countries than for high-income countries.

Together, these results tend to suggest that the reputation effects we have identified may act as a particularly significant barrier to market access for middle-income countries—exactly the group that contains a number of important agricultural exporters, such as Brazil and South Africa. One possibility is that trade flows from low income countries are too small to attract the attention of the refusals system, and it is only once some threshold is passed that reputation begins to play a significant role in the issuance of refusals. The data show that average US imports from middle income countries by product are over 12 times higher than those from low income countries. Vietnam, the largest low income exporter in the product categories under consideration, exported $825m to the US in 2008. By comparison, Mexico, the largest middle income exporter, exported $6.7bn. Given the need to ration enforcement resources, it is plausible that larger exporters—such as middle income countries—attract more attention from US SPS authorities than small ones. Such a dynamic would explain the observed pattern of results here.

Overall, the lack of significance of the reputation variables for low income countries and Sub-Saharan Africa does not come as too much of a surprise. Exports to the US from countries belonging to those groups are highly irregular, which affects the neighbor reputation variable, and are concentrated on a small subset of food products, which affects the sector reputation variable. In any case, our results clearly demonstrate that enforcement of the US SPS regime through import refusals can have important development policy implications, a point that has previously been noted in the literature on standards and trade, where differential impacts by country income group have also been identified (e.g., Disdier et al., 2008).

To provide further detail on our results, Table 5 provides separate estimations for each HS 2-digit sector, excluding sector 9 (coffee, tea, mate, and spices) due to too few observations. The lagged dependent variable has a positive and statistically significant coefficient in all but one regression (preparations of meat, fish, and crustaceans). The neighborhood reputation coefficient is positive and 1% statistically significant in all regressions. The neighborhood reputation effect is particularly strong in fruits, preparations of meat, fish, and crustaceans, and preparations of vegetables and fruits. In terms of the control variables, the value of imports has a positive coefficient in all regressions, and it is statistically significant in three cases. The relationship between tariffs and refusals is similarly positive and statistically significant in two cases. There is only one case in which per capita income has a statistically significant coefficient, and it is negative, as expected.

The only result that needs significant explanation in Table 5 relates to the sector reputation variables. Contrary to expectations, they have coefficients that are negative and statistically significant. The reason for this undoubtedly lies in the structure of the regressions. By limiting each one to a single two digit sector, the sector reputation variable becomes very closely correlated with the country fixed effects: it is only to the extent that the sector reputation dummy varies over time that its coefficient can be separately identified. Since, as we have noted above, there is considerable persistence in the refusals data, it is likely that this correlation drives the unexpected results we observe on this variable.

4.2 Fixed Effects Negative Binomial Results

The regression results discussed in the previous section were all based on a fixed effects logit model in which the dependent variable is a dummy equal to unity in the case of at least one import refusal for a given exporter-product-year combination. In this section, we use a different dependent variable, namely a count of the number of import refusals per exporter-product-year combination. This approach allows us to introduce more nuance into the dependent and independent variables, and ensure that our results are robust to these alternative measures.

Table 6 presents results using equation (2) estimated as a fixed effects negative binomial regression, which we prefer to the Poisson estimator due to likely over-dispersion in the data.[10] Each column corresponds to a similar logit model in Table 2. Results between the two sets of specifications are very similar in qualitative terms. In all five models in Table 5, the coefficient on the lagged dependent variable is positive and statistically significant at the one percent level, which indicates that the refusals data tend to be highly persistent through time. The same is true of the sector reputation and neighborhood reputation coefficients, including in the last case all the five and three country definitions of neighborhood, but not the nearest neighbor definition. It makes very little difference whether all trade relationships are included in the sample (column 1), or only those with some positive trade during the sample period (column 4). When a distributed lag specification is used (column 5), we again find substantial evidence that reputation is sticky: the coefficients on all variables except the second and third lags of sector reputation and the third lag of neighborhood reputation are positive and at least five percent statistically significant.

Among the control variables, results are in line with those from the logit models. Import value has the expected positive and statistically significant coefficient in all cases. The same is true of tariffs, which supports the potential political economy dynamic referred to above. Per capita income again has the expected negative coefficient, but it is not statistically significant.

[10] To assess whether the negative binomial model is indeed a better fit for the data than Poisson, we compare the Bayesian Information Criteria (BICs) associated with both models. We find that the BIC for the negative binomial is substantially smaller than that for Poisson, which indicates superior model fit.

We can use the estimated coefficients from the negative binomial model to give a more detailed quantitative interpretation to our results. The coefficients for sector reputation and neighbor reputation indicate that one additional import refusal for related products or neighboring countries is associated with, respectively, increases of 0.4% and 1.2% in the number of refusals for a given product in the current year. These findings reinforce the conclusions of the logit model, in which we also found that neighbor reputation and, to a lesser extent, sector reputation both matter for import refusals.

5. Conclusion

This paper has produced some of the first direct evidence and quantification that reputational spillover effects matter in the enforcement of US SPS measures through the import refusals system. Specifically, countries tend to experience fewer import refusals if they have fewer import refusals affecting related products in the past. There is also a neighborhood dynamic at work: countries are less likely to experience import refusals if neighboring countries have experienced fewer import refusals in the past. The effects are particularly important for middle income developing countries, which is exactly the group for which agricultural exports to the US are the most important.

As modern border controls, including SPS ones, increasingly rely on risk-based approaches (Widdowson and Holloway, 2011), we should expect certain categories of exports to build a higher risk profile than others, which means that they will be subject to higher levels of controls and thus detection of non-compliance. Risk-based methods are, however, not very transparent in the methodology they use—presumably to avoid circumventing tactics—and may create unnecessary uncertainty for traders. A natural candidate determinant for shipments presenting a higher risk of non-compliance is reputation, which our research shows applies not only in a direct sense, but also in a spillover sense from related products and countries.

Although more research is clearly needed in a number of areas—more on this below—some important policy implications would seem to follow from our findings. First, developing country exporters of agricultural products seeking to break into the US market need to focus on building SPS capacity so as to become reliable sources. It is not sufficient to export a mix of compliant and non-compliant goods: reputation matters, and the presence of the latter will make it harder to get the former into the market as well. Consistency and reliability of production are therefore key issues in the development of SPS capacity in agricultural exporters, and particularly in middle-income countries that have the potential to be significant competitors for US production.

Since we capture our effects at the product and country level, our findings also have implications for the need for developing country producers and exporters wishing to sell in the US market to organize themselves in order to enforce sanitary compliance: persistence in the refusals data suggests that if one rogue exporter triggers a refusal, the risks of subsequent future refusals on others may increase. More generally, this finding is in line with the observation that SPS measures tend to require strong sectoral organization on the part of the exporters (see also Jouanjean et al., 2011).

Second, our results strongly suggest that a comprehensive approach to SPS compliance in developing countries is likely to be more effective than a piecemeal one. Although it might seem sensible to concentrate limited SPS capacity building resources on a small number of products that are individually important, such an approach neglects the importance of the sectoral spillover effects evident in our data. Building capacity across the sector as a whole can have important benefits for individual products.

Similarly, the likelihood that regional reputation matters for SPS enforcement also has important policy implications. Regional approaches to the development of standards systems are becoming more common in developing countries for many reasons, such as the ability for small, poor countries to pool technical and financial resources (Maur and Shepherd, 2011). Our findings suggest an additional reason for encouraging regional standards cooperation: geographical spillovers mean that compliance by a country's neighbors can help it achieve more effective market access.

Our results are also suggestive that care should be taken when using import refusals as a tool for appraising developing countries' trade compliance capacities in order to direct capacity building spending. One reason is that non-compliant exporters are sometimes not able to export and therefore no refusals can be observed. Second, the analysis presents counter-intuitive results with low income countries facing a lower probability of having refusals. This observation points out interesting results in terms of the efficiency of FDA risk management strategy: low profile countries, exporting low amounts and/or not regularly have lower probabilities of being refused entry. In the case of low-income countries, there may be a higher probability that exported products are less compliant, yet they are less likely to be refused entry. The FDA is currently implementing a reform to handle such issues. Therefore, even though the results of the analysis highlight that middle income countries are more likely to be targeted by import refusals, this does not mean that low income countries are more complaint and not in need of Aid for Trade initiatives in building compliance capacities.

Currently, there is only a very small literature examining SPS measures at the level of enforcement mechanisms, such as alerts or import refusals. Further work in this area has the potential to bring significant insights into the workings of product standards more generally, and in particular their effects on developing country exporters. Baylis et al. (2009) make a first attempt to assess the trade impacts of import refusals. Extending their work to take account of the types of reputation spillover effects we have identified here could be a fruitful avenue for future research. Our own work highlights the need to treat import refusals as endogenous in gravity model settings, which is an important dimension in which the robustness of previous assessments needs to be established. Similarly, Baylis et al. (2010) provide some initial evidence suggesting that political economy forces may be relevant in determining the application of SPS measures. Our own findings reinforce that impression. Since very little is known about the political economy determinants of product standards (c.f. Kono, 2006), this too would be an interesting research question to pursue using data similar to those we have used here.

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Tables

Table 1: Data and sources.

Variable	Description	Year	Source
$GDPPC_{it}$	Per capita GDP of country i in year t (in PPP terms).	1998-2008.	World Development Indicators.
$Imports_{ikt}$	Imports of product k from country i in year t, in thousand USD.	1998-2008.	UN-Comtrade via WITS.
$Refusals_{ikt}$	Number of import refusals affecting product k exported from country i in year t.	1998-2008.	Authors.
$RefusalsDum_{ikt}$	Dummy variable equal to unity if $Refusals_{ikt} \geq 1$.	1998-2008.	Authors.
$Refusals_{ikt}^{HS2}$	Number of import refusals affecting products other than product k in the same HS two-digit sector, from country i in year t.	1998-2008.	Authors.
$RefusalsDum_{ikt}^{HS2}$	Dummy variable equal to unity if $Refusals_{ikt}^{HS2} \geq 1$.	1998-2008.	Authors.
$Refusals_{ikt}^{Neighbors}$	Number of import refusals affecting product k exported by country i's neighboring countries in year t. Neighboring countries are defined alternately as the five closest neighbors, the three closest neighbors, and the closest neighbor.	1998-2008.	Authors.
$RefusalsDum_{ikt}^{Neighbors}$	Dummy variable equal to unity if $Refusals_{ikt}^{Neighbors} \geq 1$.	1998-2008.	Authors.
$Tariff_{ikt}$	Effectively applied US tariff on product k from country i in year t.	1998-2008.	UNCTAD Trains via WITS.

Table 2: Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
$GDPPC_{it}$	88458.000	10812.360	12791.730	241.806	84043.170
$Imports_{ikt}$	165600.000	2096.452	24022.750	0.000	1280785.000
$Refusals_{ikt}$	165600.000	0.297	4.394	0.000	469.000
$RefusalsDum_{ikt}$	165600.000	0.032	0.176	0.000	1.000
$Refusals_{ikt}^{HS2}$	165600.000	2.212	15.994	0.000	641.000
$RefusalsDum_{ikt}^{HS2}$	165600.000	0.121	0.326	0.000	1.000
$Refusals_{ikt}^{Neighbors}$	165600.000	1.382	9.630	0.000	469.000
$RefusalsDum_{ikt}^{Neighbors}$	165600.000	0.109	0.312	0.000	1.000
$Tariff_{ikt}$	113850.000	2.338	3.359	0.000	98.850

Table 3: Logit regression results.

	(1) Baseline	(2) Neighborhood 3	(3) Neighborhood 1	(4) Imports > 0	(5) Lags
$\underbrace{RefusalsDum_{ikt-1}}_{Compliance\ History}$	4.384***	3.873***	5.635***	4.283***	3.142***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\underbrace{RefusalsDum_{ikt-2}}_{Compliance\ History}$					2.064***
					(0.000)
$\underbrace{RefusalsDum_{ikt-3}}_{Compliance\ History}$					2.066***
					(0.000)
$\underbrace{RefusalsDum_{ikt-1}^{HS2}}_{Sector\ Reputation}$	1.623***	1.643***	1.667***	1.521***	1.429***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\underbrace{RefusalsDum_{ikt-2}^{HS2}}_{Sector\ Reputation}$					1.087
					(0.250)
$\underbrace{RefusalsDum_{ikt-3}^{HS2}}_{Sector\ Reputation}$					0.957
					(0.542)
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$	2.104***			1.916***	1.661***
	(0.000)			(0.000)	(0.000)
$\underbrace{RefusalsDum_{ikt-2}^{Neighbors}}_{5\ Neighbor\ Reputation}$					1.359***
					(0.000)
$\underbrace{RefusalsDum_{ikt-3}^{Neighbors}}_{5\ Neighbor\ Reputation}$					1.220***
					(0.009)
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{3\ Neighbor\ Reputation}$		2.074***			
		(0.000)			
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{1\ Neighbor\ Reputation}$			1.260		
			(0.232)		
$Imports_{ikt-1}$	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(1 + Tariff_{ikt})$	55.501***	66.002***	74.938***	46.206***	29.188***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.004)
$\log(GDPPC_{it})$	0.940	0.908	0.912	0.985	0.889
	(0.822)	(0.723)	(0.727)	(0.956)	(0.720)
Pseudo-R2	0.476	0.474	0.472	0.387	0.496
Observations	54760	54760	54760	29839	54760

*The dependent variable is $RefusalsDum_{ikt}$ and estimation is by conditional fixed effects logit in all cases. All models include fixed effects by partner country, HS four-digit product, and year. Prob. values based on robust standard errors corrected for clustering by partner country are in parentheses. Statistical significance is indicated by * (10%), ** (5%), and *** (1%). Coefficients are reported as odds ratios.*

Table 4: Logit regression results by World Bank region.

	(1) East Asia & Pacific	(2) Europe & Central Asia	(3) Latin America & Caribbean	(4) Middle East & North Africa	(5) South Asia	(6) Sub-Saharan Africa
$\underbrace{RefusalsDum_{ikt-1}}_{Compliance\ History}$	2.687***	1.982***	4.545***	3.548***	2.470***	1.426
	(0.000)	(0.019)	(0.000)	(0.000)	(0.009)	(0.268)
$\underbrace{RefusalsDum_{ikt-1}^{HS2}}_{Sector\ Reputation}$	1.970***	1.989***	1.384**	1.691**	2.621***	1.404
	(0.006)	(0.002)	(0.041)	(0.033)	(0.000)	(0.370)
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$	1.171***	2.335***	1.622***	1.741**	0.692	1.934*
	(0.539)	(0.001)	(0.001)	(0.017)	(0.588)	(0.056)
$Imports_{ikt-1}$	1.000***	1.000	1.000***	1.000	1.000***	1.000***
	(0.000)	(0.449)	(0.001)	(0.161)	(0.000)	(0.008)
$\log(1 + Tariff_{ikt})$	518.532***	0.397	0.001*	545405.8***	98.629	0.001
	(0.000)	(0.767)	(0.054)	(0.000)	(0.170)	(0.362)
$\log(GDPPC_{it})$	0.643	4.032	1.398	6.336	0.033*	0.048*
	(0.470)	(0.205)	(0.627)	(0.349)	(0.060)	(0.093)
Pseudo-R2	0.659	0.443	0.428	0.404	0.498	0.332
Observations	4092	3564	10725	2310	1612	6534

*The dependent variable is $RefusalsDum_{ikt}$ and estimation is by fixed effects logit in all cases. All models include fixed effects by partner country, HS four-digit product, and year. Prob. values based on robust standard errors corrected for clustering by partner country are in parentheses. Statistical significance is indicated by * (10%), ** (5%), and *** (1%). Coefficients are reported as odds ratios.*

Table 5: Logit regression results by World Bank income group.

	(1) High Income	(2) Middle Income	(3) Low Income
$\underbrace{RefusalsDum_{ikt-1}}_{Compliance\ History}$	4.366***	4.183***	2.579***
	(0.000)	(0.000)	(0.000)
$\underbrace{RefusalsDum_{ikt-1}^{HS2}}_{Sector\ Reputation}$	1.481***	1.695***	0.935
	(0.004)	(0.000)	(0.807)
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$	1.516***	2.374***	2.158***
	(0.000)	(0.000)	(0.007)
$Imports_{ikt-1}$	1.000	1.000***	1.000***
	(0.284)	(0.000)	(0.001)
$\log(1 + Tariff_{ikt})$	12.434	132.859**	77.303***
	(0.254)	(0.022)	(0.004)
$\log(GDPPC_{it})$	0.737	1.363	0.037***
	(0.607)	(0.446)	(0.002)
Pseudo-R2	0.447	0.478	0.514
Observations	16224	28600	6664

*The dependent variable is $RefusalsDum_{ikt}$ and estimation is by fixed effects logit in all cases. All models include fixed effects by partner country, HS four-digit product, and year. Prob. values based on robust standard errors corrected for clustering by partner country are in parentheses. Statistical significance is indicated by * (10%), ** (5%), and *** (1%). Coefficients are reported as odds ratios.*

Table 6: Logit regression results by HS 2-digit sector.

	(1) Fish & Crustaceans	(2) Vegetables	(3) Fruits	(4) Preparations of Fish & Crustaceans	(5) Preparations of Vegetables & Fruits
$\underbrace{RefusalsDum_{ikt-1}}_{Compliance\ History}$	3.671***	4.884***	4.052***	1.221	2.140***
	(0.000)	(0.000)	(0.000)	(0.304)	(0.000)
$\underbrace{RefusalsDum_{ikt-1}^{HS2}}_{Sector\ Reputation}$	0.653***	0.564***	0.571***	0.529***	0.765**
	(0.002)	(0.001)	(0.000)	(0.005)	(0.033)
$\underbrace{RefusalsDum_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$	1.599***	1.717***	1.887***	1.934***	1.841***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.000)
$Imports_{ikt-1}$	1.000	1.000*	1.000***	1.000	1.000**
	(0.175)	(0.091)	(0.002)	(0.340)	(0.024)
$\log(1 + Tariff_{ikt})$	0.525	216.039**	1876.118***	0.014	0.954
	(0.943)	(0.031)	(0.000)	(0.492)	(0.977)
$\log(GDPPC_{it})$	0.591	0.350*	2.204	0.783	1.523
	(0.409)	(0.071)	(0.243)	(0.853)	(0.510)
Pseudo-R2	0.423	0.402	0.400	0.395	0.422
Observations	5055	9659	8420	1826	9009

*The dependent variable is $RefusalsDum_{ikt}$ and estimation is by fixed effects logit in all cases. All models include fixed effects by partner country, HS four-digit product, and year. Prob. values based on robust standard errors corrected for clustering by partner country are in parentheses. Statistical significance is indicated by * (10%), ** (5%), and *** (1%). Coefficients are reported as odds ratios.*

Table 7: Negative binomial regression results.

	(1)	(2)	(3)	(4)	(5)
	Baseline	Neighborhood 3	Neighborhood 1	Imports > 0	Lags
$\underbrace{Refusals_{ikt-1}}_{Compliance\ History}$	0.048***	0.048***	0.058***	0.047***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\underbrace{Refusals_{ikt-2}}_{Compliance\ History}$					0.012***
					(0.000)
$\underbrace{Refusals_{ikt-3}}_{Compliance\ History}$					0.012***
					(0.000)
$\underbrace{Refusals_{ikt-1}^{HS2}}_{Sector\ Reputation}$	0.004***	0.004***	0.004***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\underbrace{Refusals_{ikt-2}^{HS2}}_{Sector\ Reputation}$					-0.001
					(0.567)
$\underbrace{Refusals_{ikt-3}^{HS2}}_{Sector\ Reputation}$					0.001
					(0.135)
$\underbrace{Refusals_{ikt-1}^{Neighbors}}_{5\ Neighbor\ Reputation}$	0.012***			0.011***	0.009***
	(0.000)			(0.000)	(0.000)
$\underbrace{Refusals_{ikt-2}^{Neighbors}}_{5\ Neighbor\ Reputation}$					0.006**
					(0.032)
$\underbrace{Refusals_{ikt-3}^{Neighbors}}_{5\ Neighbor\ Reputation}$					-0.002
					(0.410)
$\underbrace{Refusals_{ikt-1}^{Neighbors}}_{3\ Neighbor\ Reputation}$		0.014***			
		(0.000)			
$\underbrace{Refusals_{ikt-1}^{Neighbors}}_{1\ Neighbor\ Reputation}$			0.006		
			(0.268)		
$Imports_{ikt-1}$	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(1 + Tariff_{ikt})$	4.792***	4.904***	4.867***	4.296***	4.633***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
$\log(GDPPC_{it})$	-0.159	-0.171	-0.145	-0.139	-0.221
	(0.695)	(0.679)	(0.720)	(0.740)	(0.604)
R2	0.042	0.040	0.038	0.043	0.016
Observations	88458	88458	88458	38131	88458

The dependent variable is $\text{Refusals}_{\text{ikt}}$ and estimation is by fixed effects negative binomial in all cases. All models include fixed effects by partner country, HS four-digit product, and year. Prob. values based on robust standard errors corrected for clustering by partner country are in parentheses. Statistical significance is indicated by * (10%), ** (5%), and *** (1%). R2 is calculated as the square of the correlation coefficient between actual and fitted values.

Figures

Figure 1: Refusals versus lagged refusals affecting similar products (same HS2 group).

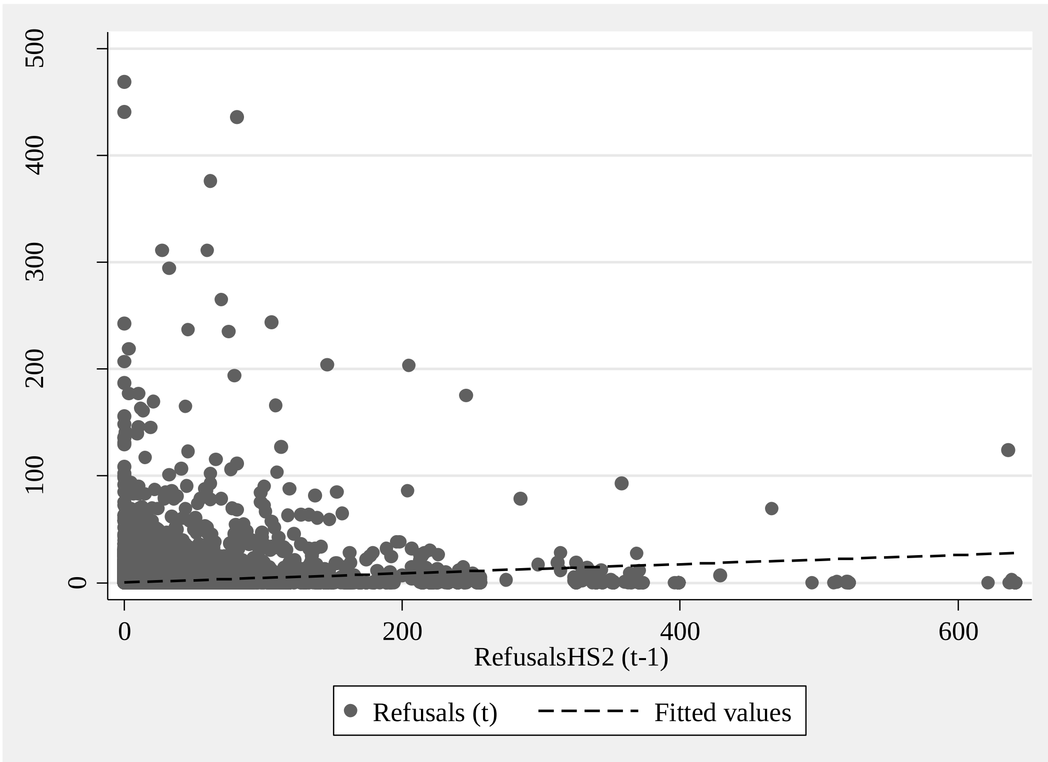

Figure 2: Refusals vs. lagged refusals affecting the five closest countries.