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Trade impact of maximum residue limits in fresh fruits and vegetables

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ABSTRACT

Interfering maximum residue limits (MRLs) for pesticides with agricultural trade is becoming important for food and trade policies in the early 21st century. Differing levels for pesticide residues among countries have the potential to disrupt trade significantly. We employ a non-linear and disaggregated stringency index to quantify the degree of regulatory heterogeneity levels for pesticides between trading nations for fruits and vegetables in 2013 and 2014 and investigate the trade-restricting nature of this measure using the structural gravity framework. Our findings indicate that stricter importer MRLs reduce bilateral trade to the tune of 8.8%. Looking closer at MRLs with US partners, the effect of stricter MRLs is quite elastic concerning its impact on the US - EU trade. In particular, the estimates imply that a more stringent MRL's policy decreases the US export of fruits and vegetables to the EU members by a striking 13.8%. At the disaggregated level of MRL indices over different classes of chemicals, the results indicate that there is a significant gap in regulations regarding MRLs among several major US foreign markets for fruits and vegetables, particularly in the EU and the Trans-Pacific trading partners.

1. Introduction

Most agricultural economists and policy-makers agree that new twenty-first century obstacles to trade, such as Sanitary and Phytosanitary (SPS) measures—which is an important feature of Non-Tariff Measures (NTMs)—are more obscure in nature, yet they have the potential to be more trade distorting in comparison to traditional instruments of import protection, such as tariffs (Josling et al., 2004; Organization for Economic Co-operation and Development, 2005; World Trade Organization, 2012; Beghin et al., 2015; Yeung et al., 2017). SPS measures are playing a more influential role in shaping agricultural and food product trade, both positively and negatively, and the ability of the US and other countries to secure meaningful agricultural market access depends increasingly on more strict regulatory standards maintained by importing countries (Disdier and van, 2010; Disdier and Marette, 2010; Grant et al., 2015). In 2019, a record 2361 SPS notifications were received by the World Trade Organization (WTO) concerning food safety and animal or plant health regulations, more than fivefold growth since 2000 (World Trade Organization WTO, 2021). In principle, SPS regulations are aimed to facilitate production and trade by helping to maintain plant, animal and human health and through quality signaling (Beghin et al., 2015). However, these measures can deliberately or unintentionally impede trade (Center for International Development, 2004). The *2016 National Trade Estimate on Foreign Trade Barriers Report* (United States Trade, 2016) highlighted SPS measures not only as serving an important function in facilitating international trade but also emphasized the lack of transparency and discriminatory measures that can act as significant barriers to US trade.

Under WTO's Agreement on SPS measures, countries are allowed to set their own standards; however, their regulations should be science based, not discriminatory between countries with similar conditions and not used as instruments for protectionism (Grant and Arita, 2016; Peterson et al., 2013). While there is evidence that countries may use SPS measures as instruments to protect domestic producers (Crivelli and Groeschl, 2016), the current literature has not led to a consensus about the impact of SPS measures on trade nor has it led to a unified framework from which to address SPS policy reforms in multilateral and bilateral trade negotiations. Our research addresses this gap in the literature. In particular, some regulations facilitate trade while representing important quality and/or safety enhancements of the product (Xiong and Beghin, 2014; Ishaq et al., 2016). Thus, evidence on the trade impacts of SPS measures to date has been mixed (Swann et al., 1996; Disdier et al., 2008; World Trade Organization, 2012; Xiong and Beghin, 2012; Beghin, Maertens and Swinnen, 2015; Crivelli and Groeschl,

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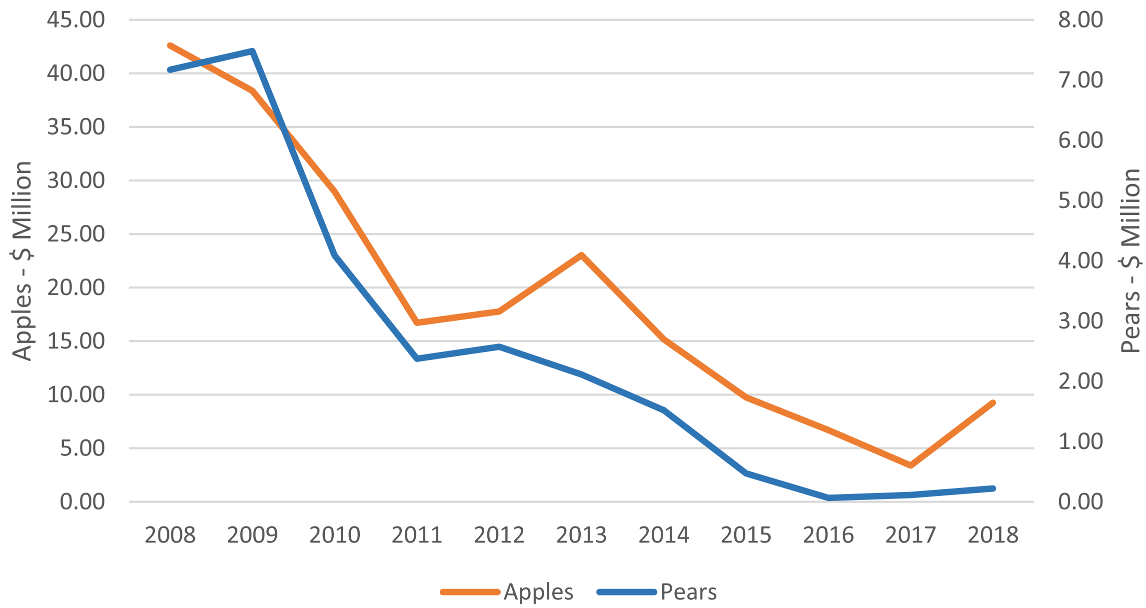

Fig. 1. US Apple and Pear Exports to the EU ($ Mill). Source: UNCOMTRADE, https://comtrade.un.org/.

2016).

Among the many SPS regulations in place to protect animal and plant health from imported pests and diseases, a particular type of SPS regulations known as Maximum Residue Limits (MRLs) or tolerances are designed to safeguard human health and have become a focal point of a growing body of empirical literature and SPS-specific trade concerns raised in the WTO's SPS committee (Otsuki et al., 2001; Wilson and Otsuki, 2004; Wilson et al., 2003; Disdier and Marette, 2010; Winchester, 2012; Xiong and Beghin, 2013; Xiong and Beghin, 2014; Ferro et al., 2015; Ishaq et al., 2016; Shingal et al., 2017; Grant and Arita, 2016). MRLs are the maximum legal level of concentration of pesticides or feed additives that a country will accept on the surfaces of food products (Environmental Protection Agency [EPA], accessed 2014). Based on the WTO's data, more than 60% of non-tariff barriers to trade (NTBs) notifications to the WTO are related to SPS; and among those notifications, 36% belongs to MRLs Kurbis (2019). Three decades ago, the concept of Maximum Residue Limits (MRLs) was unheard of; but in recent years, MRLs for pesticides arguably have become the first action growers should consider in their pest management decisions (Cline, 2011).[1] For example, from the standpoint of US exporters, agricultural products can be exported to roughly 200 countries; but it also seems like there are 200 sets of regulations regarding these countries' MRL policies (Cline, 2011). The lack of globally harmonized standards on pesticide residues are a growing concern for the US growers and exporters who export one out of every three planted acres (Bopp, 2019). This is true for all countries around the world, and MRLs' significance in the agri-food trade is growing at a rapid pace.

The problem of differing levels for pesticide residues among countries is growing and interfering with agricultural trade, and it has the potential to disrupt trade significantly given the widespread use of pesticides in agricultural production globally (Yeung et al., 2017). A growing body of empirical research explores the relationship between more stringent tolerance limits and trade flows (Otsuki et al., 2001; Wilson and Otsuki, 2004; Wilson et al., 2003; Disdier and Marette, 2010; Winchester et al., 2012; Xiong and Beghin, 2013, 2014; Ferro et al., 2015; and Shingal et al., 2017). The main objective of our research examines this relationship while employing a non-linear and disaggregated stringency index. While SPS and MRL regulations aim to facilitate trade, these measures can deliberately, or unintentionally, impede trade. Even if unintentional, differing MRLs can have significant trade implications. MRLs have become a critical regulatory measure to limit human exposure to chemicals and veterinary drug residue. Overly restrictive tolerances set by importing countries may provide incremental reductions to human and environmental chemical exposure but will almost certainly increase compliance costs for foreign and domestic producers, consumer prices of food products in importing countries and, in some cases, may shut off trade as products get rejected at a port of entry (Xiong and Beghin, 2012). Thus, it reduces the quantities of food exported and profitable trade opportunities. Most developed countries established their own MRL systems, given growing consumer concerns for the natural environment and for human health as well as the recognition that MRLs represent food safety standards (Yeung et al., 2017). Others are in the process of establishing nationally based MRLs. Establishing nationally based MRLs by countries create more heterogeneous regulations, and it may act as trade barriers.

Non-harmonized MRLs are a global issue. For developing countries, meeting the MRL requirements of developed countries can be especially challenging (Wilson and Otsuki, 2004; Handford et al., 2015). In particular, regulating pesticides and setting standards for minimum residue levels are very important for many developing countries because their economies depend on agri-food exports, and agriculture continues to represent the most significant exports and foreign exchange earnings (McCalla and Nash, 2007). Thus, with tighter food safety standards set by importing countries, the cost of compliance can escalate (Wilson and Otsuki, 2004). However, these obstacles are not limited to developing countries. Statistics show that US exports of apples and pears to the European Union (EU) have declined by 80% and 97%, respectively, between 2008 and 2018 (see Fig. 1) partially due to stringent residue limits revised by the EU in 2008 (United Nation Comtrade Database UN Comtrade, 2019). The EU set a lower MRL of diphenylamine (DPA), a plant regulator applied to apples and pears, to the extent that all imports and even domestically produced apples and pears were affected by this new EU MRL for DPA. Consequently, the US changed its destinations of apple and pear exports to less MRL stringent Asian markets. In the *2014 SPS Measures Report* (United States Trade Representative USTR, 2014), the Office of the US Trade Representative specifically highlighted MRLs as a discriminatory SPS measure affecting the US fruit and vegetable trade, particularly with Europe—one continent that is part of the US's

[1] Jehle, the director of technical services for Sunview Vineyards in California, stated it.

largest free trade negotiation (EU-US) since the North American Free Trade Agreement (NAFTA). Arita et al. (2017) also emphasize the US fruit and vegetable producers concerns over the EU's MRL stringency policies.

While several studies are focusing on the relationship between MRLs and trade (Otsuki et al., 2001; Wilson and Otsuki, 2004; Wilson et al., 2003; Disdier and Marette, 2010; Winchester, 2012; Xiong and Beghin, 2013; Xiong and Beghin, 2014; Ferro et al., 2015; Shingal et al., 2017), current empirical work has not coincided with the impact of MRLs on trade. There are often numerous residue limits that apply to any given product; therefore, comparing the stringency of MRLs between trade partners across countries is very complicated. Otsuki et al. (2001), Wilson and Otsuki (2004), Wilson et al. (2003), and Disdier and Marette (2010) only look at a single residue limit standard and corroborate the significant adverse effects of more stringent maximum residue limits.[2] A drawback with these case study approaches that focus on one chemical is that if other MRLs are operating, the empirical analysis may overstate the impacts of the specific chemical maximum residue limit.

In addition to one-case studies, other empirical research built an MRL index. This empirical research developed a bilateral dis(similarity) index between trading partners (Achterbosch, 2009; Drogue and DeMaria, 2012; Winchester et al., 2012; Ferro et al., 2015; Shingal et al., 2017) and except for Shingal et al. (2017), they all conclude that MRL stringency hinders trade. However, their index has some limiting assumptions that may overstate or underestimate the impact of MRLs stringency on trade.[3] Xiong and Beghin (2014) overturned the estimated effect in previous studies by considering both trade costs and possible demand, thereby enhancing effects of MRLs applying a targeted stringency index.[4] However, their index is relative to MRLs registered by Codex [5]but does not consider the regulatory differences between origin and destination countries. Furthermore, Codex only established a limited number of MRLs for pesticides.

This article is part of the growing literature that attempts to understand the trade impacts of maximum residue limits. More specifically, we overcome many of the limitations in previous studies (refer to footnote 3) by incorporating a non-linear and disaggregated bilateral stringency index to quantify the degree of regulatory heterogeneity levels for pesticides between trading nations for fruits and vegetables trade.

The first specific objective of our empirical approaches provides new evidence on key regulatory differences, not only globally but in the large mega-regional trade agreements. The Trans-Atlantic Trade and Investment Partnership (T-TIP) and the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP)[6] are two examples of these trade agreements that explicitly address the SPS issues in their negations. While the US is not a member of CPTPP, the results of this research are useful for any bilateral trade agreement between the US and any CPTPP nations individually, e.g., Japan (*Inside US* Trade, April 2019). In particular, MRL stands out as one of the significant barriers for the US fresh fruit and vegetable exports (*USTR,* 2014). In the second specific objective, we incorporate the disaggregated bilateral stringency indices over different classes of chemicals, fungicides, herbicides, and insecticides to investigate which measures are responsible for trade disruptions. To the best of our knowledge, this is the first study to disaggregate the stringency index by chemical class to investigate their potential trade-distorting nature. This objective is one of the main contributions of this research. One of the limitations of previous studies in this line of work is that they often employ an aggregate measure of stringency or dissimilarity over all chemicals. However, this index makes it difficult to determine which measures are responsible for trade disruptions. To address this concern, we disaggregate the bilateral stringency index (BSI) of MRL stringency into separate indices for different chemicals. Thus, we consider three broad classes of pesticides—herbicides, insecticides, and fungicides—to identify whether MRL policy dissimilarities between the destination and origin regions vary systematically across different classes of chemicals (c).

The third specific objective explores whether MRL policies constitute a market entry barrier to all exporters. Our findings provide new evidence on the effect of MRLs on the US fruit and vegetable exports to the EU and CPTPP trading nations. The results confirm that MRL policy impedes US exports to the EU while it enhances trade with respect to the US exports to the CPTPP markets. At the disaggregated level of MRL indices over different classes of chemicals, the results reveal specific chemical classes on which trade negotiators can focus attention. For example, herbicide indices of MRL stringency appear to enhance US exports to CPTPP markets. Lastly, our results suggest that MRL policies likely impart significantly fixed and variable export trade costs, judging by the negative and significant extensive and intensive margin results.

This paper has four further sections. The data and the empirical methodology are explained in Section 2; Section 3 details the regression analyses and discusses the economic interpretations. Conclusions and policy implications are discussed in Section 4.

2. Data and methodology

2.1. Data

To explore the impacts of bilateral MRL stringency on trade flow, we utilize the global MRL database maintained by the Foreign Agricultural Service (Global MRL database, 2013, https://www.bryantchristie.com/ or https://www.globalmrl.com/home) and obtained the information on MRLs during 2013 and 2014. Because the global MRL database is frequently updated and without archives, we extracted the MRL data first in December 2013 and then again in December 2014. The established MRL data for each fruit and vegetable by each individual country including CODEX standards were retrieved. The total number of pesticides with established MRLs reported in the global MRL database is 256 chemicals. However, not all pesticides with established MRLs are approved for use. Therefore, we have retrieved data from the National Agricultural Statistics Service (NASS) producer surveys that report 162 chemicals used in fruit and vegetable production. NASS develops surveys to determine on-farm chemical use and pest management

[2] Otsuki et al. (2001) on the EU's aflatoxin standard on African groundnut exports, Wilson and Otsuki (2004) for MRLs on chlorpyrifos in banana exports, Wilson et al. (2003) on the effect of residue limit standards on tetracyclinein beef exports, Chen et al. (2008) on food safety standards impacting China's exports of vegetables, fish and aquatic products, and Disdier and Marette (2010) on antibiotics impacting crustaceans exports.

[3] While these measures of heterogeneity attempt to capture the (dis)similarity between trading partners, they have three common shortcomings in the case of MRLs for pesticides. First, their index ignores heterogeneity when the exporter has more stringent regulations, assuming these more stringent MRLs do not impact trade. The second drawback is that these indices assign equal weights to all chemicals in computing the index because they are linear in MRLs (linear in terms of the functional form of the index). The latter can be misleading because it is tough for an exporter to achieve an importing country's stricter MRLs; and from the mathematical perspective, the impact of MRLs is increasing in stringency. A more stringent importer's MRL is harder to achieve for exporters. Therefore, using a liner index in MRLs would underestimate the impact of more stringent MRLs established by destination countries. Third, their index is aggregated over all chemicals with established MRLs, making it difficult to determine which measures are responsible for trade disruptions.

[4] Xiong and Beghin (2014) used stringency index developed by Li and Beghin's (2014).

[5] Codex standards established by the Food and Agricultural Organization (FAO) and the World Health Organization (WHO).

[6] CPTPP is the Trans-Pacific Partnerships agreement (TPP) excluding the US; the US formally withdrew from the TPP in January 2017. The remaining eleven countries moved forward and the CPTPP entered into force on December 30, 2018 (*Inside US* Trade April 2019).

Table 1
Summary Statistics.

Variable	Mean	Std. Dev.	Min	Max
Trade flow	$796,281	$11.6 mil.	$0.000	$1660.0 mil.
Log Distance	8.587	1.000	4.394	9.894
RTA	0.372	0.483	0.000	1.000
BSI	1.039	0.317	0.000	2.715
BSI-Fungicides	1.040	0.340	0.000	2.717
BSI-Herbicides	1.051	0.402	0.000	2.711
BSI-Insecticides	1.045	0.367	0.000	2.715
$BSI_{\text{US-EU}}$	1.596	0.214	1.054	2.200
$BSI_{\text{US-CPTPP}}$	1.123	0.239	0.000	2.225

Note: Number of observation equal to 257,647.

information for agricultural commodities. Each chemical's biological name is then matched with the chemical identifier reported in the global MRL database. Once the list of active chemicals is created, it is then merged with the global MRL data, leaving us with a three-dimensional database of MRLs that varies by country, commodity, and the pesticide chemical name. Our product sample includes 51 fruit (26) and vegetable (25) products at the 6-digit level of harmonized system for 85 countries (expanded to 95 countries—exporters and importers[7]) with reported MRL tolerances for 162 pesticides used in production over the sample period 2013 and 2014 (Appendix, Tables 7, 8 and 9). The raw unbalanced dataset after dropping all missing observations is 393,386 observations[8] and consist of a year, country, commodity and pesticide dimension. 42% of observations are missing because either an MRL is not registered for use or an established MRL has not been registered in a given country. While some countries maintain default values (e.g., the EU introduces a default value of 0.01 ppm) if no MRL is reported, replacing these missing values with default values does not add much information to our sample (35% of the observations are still missing; a list of fruit and vegetable crops, countries, and pesticides are provided in the appendix, Tables 6, 7 and 8, respectively).

In order to provide more accurate stringency measures and to determine which measures are responsible for trade disruptions, we disaggregate the stringency index into separate indices over the class of commonly used pesticides in agriculture. Pesticides applicable for fruits and vegetables can be divided into several classes of chemicals—herbicide, insecticide and fungicide. Each of them has different characteristics in type and different amounts of resistance in fruits and vegetables. Therefore, we add another dimension to our dataset, which is the type of chemical. Each chemical is mapped to each class of chemical. The dataset consists of 63 insecticides, 45 herbicides, 42 fungicides, and 12 "other." If a type of chemical does not belong to one of the three classes of chemicals, we call it "other." However, the "other" category is ignored because the number of active chemicals in this category are negligible. A quick look at the correlation coefficient between any two classes of chemicals can confirm whether there is a relationship between these classes. The correlation coefficient between BSI-herbicides and BSI-fungicides is 0.2 and is similar for other pairs, 0.5 for BSI-insecticides and BSI-fungicides, and 0.3 for BSI-herbicides and BSI-insecticides. These correlation coefficients show that the relationship between any two pair is not significant. Thus, disaggregating the BSI into these classes of chemical provides more information and results in a better understanding of MRL impacts on trade.

The bilateral annual export flows of fresh fruits and vegetables between trading partners are obtained from the United Nations Commodity Trade Statistics Database at the 6-digit level of the harmonized system. Geographical distance is taken from the *Center d'Etudes Prospectives et d'Informations Internationales* (CEPII) geo-distance dataset (Mayer and Zignago 2006).[9] Information on Regional Trade Agreements (RTAs) data is obtained from Grant (2013) and De Sousa (2012). Table 1 presents the summary statistics for the variables in the empirical model. The sample contains 95 exporters and importers, 51 fruit and vegetable products over a two-year sample period, 2013 and 2014[10]; the final sample includes 257,647 observations, of which 65% observations are zero trade flows.[11]

2.2. *Empirical* approach

To address our three specific objectives, we quantify the extent to which MRL policy dissimilarities reduce fruit and vegetable trade between trading partners. The theoretical model is based on the theoretical structural gravity equation presented in Anderson and van Wincoop (2003), Baldwin and Taglioni (2006) and Anderson and Yotov (2016). Furthermore, the product-level model of bilateral trade built upon the assumption of all varieties of commodity are differentiated by their source and consumer preferences in the destination region presented in Peterson et al. (2013) and Grant et al. (2015). The model is based on a representative consumer in region d and maximizes its CES utility function conditional on her budget. The model assumes all varieties of commodity k are differentiated by origin region o, and the consumer preferences in destination region d for commodity k are weakly separable (see Peterson et al., 2013 for more details). The empirical model is built upon this well-known theoretical model (see Peterson et al., 2013 for more details).

We employ a multiplicative trade costs function of transportation margins (Anderson and van Wincoop, 2003; Grant et al., 2015). This function (equation (1)) consists of three factors, including bilateral MRL stringency, geographical distance, and free trade agreements to transport commodity k from producers in origin region o to consumers in destination region d. To capture the extent to which bilateral stringency of MRL impacts trade costs, we employ the bilateral stringency index explained later in this section as a proxy for trade costs, along with geographical distance and an indicator of free trade agreements.

In equation (1), we initially assume trade costs are variable; however, later in this section, we examine the extent to which BSI impacts the probability of exporting. Thus, we will consider bilateral MRL stringency, not only as a variable cost of trade but also as a fixed cost of trade, when firms are required to cover the fixed costs to start a new relationship.

$$t_{odk}^{1-\sigma_k} = dist_{od}^{\delta_1}(RTA_{od}^{\delta_2})\exp\left(\prod_c BSI_{codk}^{\delta_c}\right)Z_{odk}^{\delta_0} \quad (1)$$

[7] The number of countries is extended to 95 from the original numbers, which were 85. In particular, we kept those EU members who have fruits and vegetables trade flow but did not report MRLs in the global MRL database. The missing MRL values are replaced with the MRLs reported by EU. EU has harmonized its MRL system since 2008.

[8] It should be noted and as discussed later in this section, the final sample includes 257,647 observations after merging the MRL dataset with the trade dataset.

[9] CEPII is an independent European research institute on the international economy stationed in Paris, France. CEPII's research program and datasets can be accessed at www.cepii.com. CEPII uses the great circle formula to calculate the geographic distance between countries, referenced by latitudes and longitudes of the largest urban agglomerations in terms of population (CEPII, 2005).

[10] Information on MRLs during 2013 and 2014 are obtained from the global MRL database maintained by the Foreign Agricultural Service (FAS) (see mrldatabase.com). Since the global MRL database is frequently updated and without archives, we extracted the MRL data first in December 2013 and then again in December 2014.

[11] In order to explore if a country has the potential to export a given commodity, we assume if an exporter did not export a given commodity at least 3 times over a period of 10 years (2004–2014), we consider that the exporter does not have the potential to export a given commodity. We make this assumption because retrieving data at 6-digit level of fresh fruits and vegetables from FAO is not feasible.

where σ_k is the elasticity of substitution between all varieties of commodity k. $dist_{od}$ is the geographical distance between origin regions o and destination d, RTA_{od} is an indicator of free trade agreements between o and d. $BSI_{odk;}$ (equation (2)) is the bilateral stringency index for commodity k from origin regions o to destination d and c is the classes of pesticides (three classes of herbicides, insecticides, and fungicides; see detail explanations later in this section). Z_{odk} are other potentially unobserved determinants of trade costs.

The bilateral stringency index (BSI- equation (2)) is constructed based on Li and Beghin's (2013) non-linear exponential index between origin region o and destination region d for the c classes of chemicals used in the production of product k as follows:

$$BSI_{codk} = \left(\frac{1}{N_{ck}}\right)\sum_{p\in N_{ck}} exp\left(\frac{MRL_{opk} - MRL_{dpk}}{MRL_{opk}}\right) \quad (2)$$

N_{ck} denotes the number of chemicals in chemical class c used in the production of commodity k. MRL_{opk} describes the maximum residue limit for the p^{th} chemical in class c for commodity k in region o, and MRL_{dpk} is the maximum residue limit for the p^{th} chemical in class c for commodity k in region d. Thus, our indices vary not only by product and/or country but potentially by type of chemical.

We applied an exponential form because it maps heterogeneous *BSI* differences onto the range zero (exp(-∞)) and 2.72 (exp(1)) and penalizes larger MRL differences between o and d relatively more. For example, if the destination region has a much stricter MRL for chemical p in class c (i.e., 0.1 ppm) compared with the origin region (i.e., 5 ppm), reflecting a heterogeneous regulatory situation, then the ratio of MRLs will approach a value of unity and the BSI function will approach its upper limit of $\exp(1) = 2.72$. Conversely, if the origin region has a much stricter MRL for chemical p in class c compared to the destination region, then the ratio of MRLs will be negative and in the limit the exponential function will approach zero, reflecting the fact that the destination region MRL is not likely to represent a "barrier" to trade because exporting firms are already required to meet a more stringent domestic tolerance. Finally, if the origin and destination regions have the same MRL for chemical p in class c, then the ratio equals zero and the BSI is $\exp(0) = 1$, reflecting an equivalent or harmonized SPS situation.

The product line gravity model in Peterson et al. (2013) and Grant et al. (2015) uses time-varying country-specific fixed effects for unobservable price indices, as suggested by Anderson and Yotov (2016), Baldwin and Taglioni (2006), Feenstra (2004), Anderson and van Wincoop (2003), and many others. To capture expenditure, production value, and price indices, we use time-invariant country and commodity-specific fixed effects (o, d, and k) as consistent alternatives. The reason for using time-invariant country and commodity-specific fixed effect is the MRL data availability limits our analysis to two years of data; therefore, we adopt the above alternative approach. These dummy variables control for production levels in the exporting country, expenditures in importing countries, and the unobserved price indices.

The final alteration is the issue of zero trade flows. Omitting zero trade flows leads to biased estimates due to sampling selection issues (Jayasinghe et al., 2009; Martin and Pham, 2008; Helpman et al., 2008), notably if the reason for the existence of zero trade is correlated with right-hand side variables, such as MRL policies. We first apply the Poisson pseudo-maximum likelihood (PPML) estimation framework to avoid omitting zero trade flows as suggested in the trade literature. PPML is a better approach to incorporate zero trade flows compared to an Ordinary Least Squares (OLS) (Santos Silva and Tenreyro, 2011). Further, we encounter an excessive number of zeros in the observation because of the nature of our data, fruit, and vegetable trade flows (for more detail, see Peterson et al., 2013). Therefore, the PPML model may not address this latter issue because of its restricting assumption of equal dispersion between the conditional mean and variance (Cameron and Trivedi, 2005). Thus, the Negative Binomial specification is developed to accommodate problems of over- or under-dispersion. The baseline model of product line trade flows is:

$$X_{odk} = exp\left(\pi_o + \pi_d + \pi_k + \sum_c \delta_c BSI_{codk} + \delta_1 lnDist_{od} + \delta_2 RTA_{od} + \sum_c \delta_{c_{(US-EU)}} BSI_{codk} I_{US-EU} + \sum_c \delta_{c_{(US-CPTPP)}} BSI_{codk} I_{US-CPTPP}\right)\varepsilon_{odk} \quad (3)$$

where X_{odk} is the export value of bilateral fresh fruit and vegetable trade between o and d, and $I_{US\text{-}EU}$ and $I_{US\text{-}CPTPP}$ are indicator variables equal to one if o is the US and d belongs to the EU or CPTPP countries, respectively. By including these terms, we allow the EU and CPTPP MRL policies with respect to US exports to have potentially different trade impacts. π_o, π_d and π_k are exporter, importer, and commodity fixed effects, and ε_{odkt} is the multiplicative error term. While the PPML model controls for zero trade flows and sample selection bias, based on the nature of our data, a zero-trade observation may indicate a more restrictive MRL policy imposed by a destination country. In particular, an important consideration of MRL policies is whether exporting nations facing stringent MRL policies in destination markets actually export at all. Estimating the PPML model on two sets of data, first on positive export data and then on positive and zero export data, provides some information on whether omitting zeros lead to significantly different BSI results. Helpman et al. (2008) offer an intuitive approach[12] through development of a model of selection into exporting. This approach considers the fixed costs firms need to cover in order to export commodity k from region o to region d. Based on Melitz's (2003) firm heterogeneity framework, only the most productive firms are able to enter export markets.

Furthermore, Crivelli and Groeschl (2016) explain how different SPS measures can have heterogeneous effects on trade, particularly the costs of trade, including fixed and variable costs. The Helpman et al. (2008) model developed from Heckman (1979) enables us to first deal effectively with the zero trade observations and further allows us to distinguish the effect of MRL policy on the extensive (i.e., probability of exporting) and intensive (intensity of exports) margins of trade (Cipollina et al., 2010). Other studies in this line, Crivelli and Groeschl (2016), Disdier and Marette (2010), Jayasinghe, Beghin, and Moschini (2010), and Xiong and Beghin (2012) examine the impact of different SPS measures on the extensive and intensive margins of trade.[13]

Thus, the third objective of our empirical modeling is whether exporting nations facing stringent MRL policies in destination markets actually export at all. To do so, we investigate the impact of regulatory stringency of MRL standards on both the probability and level of trade, while controlling for sample selection issues. A two-stage Heckman model is employed to distinguish the impact of MRL policy on the probability of exporting and the intensity of exports. Heckman's (1979) model retains the log-linear transformation of the model and treats zero trade flows as censored observations. The model includes both a selection and outcome equation as follows:

$$Y^*_{odk} = \pi_o + \pi_d + \pi_k + \sum_c \delta_c BSI_{codk} + \delta_1 lnDist_{od} + \delta_2 RTA_{od} + \delta_3 Lang_{od} + \mu_{odk} \quad (4)$$

[12] We also use this approach as a robustness check with our previous findings in the PPML and Negative Binomial Models. Our results, as shown in the result section, are consistent across these models.

[13] While Crivelli and Groeschl (2016) in their study use a broader measure (concern over SPS measures reported to the WTO by exporter at HS4 product line), the three other studies focus on a specific measure. Disdier and Marette (2010) use country specific MRLs; Jayasinghe, Beghin and Moschini (2010) apply SPS regulations using export certification; and Xiong and Beghin (2012) use aflatoxin contaminants.

Table 2
Bilateral Stringency Indices Impacts on Exports of Fruits and Vegetables.

Estimation Method Fixed Effects Included	(1) PPML	(2) Negative Binomial	(3) PPML	(4) Negative Binomial
BSI	−0.88***	−0.44***	−0.86***	−0.41***
	(0.15)	(0.08)	(0.15)	(0.08)
BSI $_{US\text{-}EU}$			−1.38***	−1.58***
			(0.14)	(0.09)
BSI $_{US\text{-}CPTPP}$			−0.15	0.39***
			(0.2)	(0.11)
Log Distance	−0.99***	−1.34***	−1.00***	−1.36***
	(0.03)	(0.02)	(0.03)	(0.02)
RTA	1.07***	0.80***	0.98***	0.73***
	(0.1)	(0.05)	(0.1)	(0.05)
Observations	257,647	257,647	257,647	257,647
(pseudo) R^2	0.572	0.308	0.598	0.309

Note: The dependent variable is the level of exports in column (1) and (3). The dependent variable in column (2) and (4) are scaled by million. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10%, 5% and 1% levels, respectively. Fixed effects included importer, exporter & commodity.

Table 3
Bilateral Stringency Indices Impacts on Exports of Fruits and Vegetables.

Estimation Method Fixed Effects Included	(2) PPML	(3) Negative Binomial	(5) PPML	(6) Negative Binomial
BSI-Fungicides	0.002	−0.34***	−0.04	−0.32***
	(0.14)	(0.08)	(0.14)	(0.08)
BSI-Herbicides	−0.47***	−0.34***	−0.51***	−0.31***
	(0.09)	(0.06)	(0.1)	(0.06)
BSI-Insecticides	−1.05***	−0.68***	−0.95***	−0.65***
	(0.18)	(0.08)	(0.18)	(0.08)
BSI-Fungicides $_{US\text{-}EU}$			−0.33	−0.87**
			(0.91)	(0.38)
BSI-Herbicides $_{US\text{-}EU}$			0.55	0.84*
			(0.73)	(0.5)
BSI-Insecticides $_{US\text{-}EU}$			−1.51	−1.46***
			(0.93)	(0.53)
BSI-Fungicides $_{US\text{-}CPTPP}$			0.54	0.5
			(0.33)	(0.33)
BSI-Herbicides $_{US\text{-}CPTPP}$			1.14***	−0.32
			(0.3)	(0.26)
BSI-Insecticides $_{US\text{-}CPTPP}$			−1.61***	0.29
			(0.38)	(0.4)
Log Distance	−1.00***	−1.37***	−1.02***	−1.39***
	(0.04)	(0.02)	(0.04)	(0.03)
RTA	1.08***	0.84***	0.97***	0.75***
	(0.1)	(0.05)	(0.11)	(0.05)
Observations	207,258	207,258	207,258	207,258
(pseudo) R^2	0.614	0.312	0.592	0.313

Note: The dependent variable is the level of exports in column (1) and (3). The dependent variable in column (2) and (4) are scaled by million. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10%, 5% and 1% levels, respectively. Fixed effects included importer, exporter & commodity.

$$lnX^*_{odk} = \pi_o + \pi_d + \pi_k + \sum_c \delta_c BSI_{codk} + \delta_1 lnDist_{od} + \delta_2 RTA_{od} + \mu_{odk} \quad (5)$$

where Y^*_{odk} is a latent variable predicting whether or not bilateral trade between o and d is observed, and ln (X^*_{odk}) is the natural logarithm of the intensity of bilateral trade. Y^*_{odk} and lnX^*_{odk} are not observable in the selection and outcome equations, respectively, but we do observe $Y_{odk} = 1$ if $Y^*_{odk} > 0$ and $Y_{odk} = 0$ if $Y^*_{odk} \leq 0$ and $lnX_{odk} = lnX^*_{odk}$ if $Y^*_{odk} > 0$ and lnX_{odk} is not observed if $Y^*_{odk} \leq 0$. The model can be estimated by a two-step procedure suggested by Heckman (1979) or the one-step maximum likelihood estimation where the selection and outcome equation are estimated simultaneously. The two-step procedure first estimates the bivariate selection equation using a Probit model, and it generates the standard inverse of the Mills ratio[14], which is subsequently included as an additional regressor in the outcome equation.

The advantage of the Heckman model is that it can effectively estimate both the extensive and intensive margins of trade by explicitly modeling zero trade flows. That is, it allows us to determine if stringent MRL policies impact the probability of exporting, the intensity of exports, or both. In this model, an appropriate exclusion restriction is often required[15], Helpman et al. (2008) use common religion as an exclusion restriction variable. Crivelli and Groeschl (2016) also include common religion as an excluded variable.

One of the main questions in considering exclusion restriction variables is whether we have data on truly independent variables that could belong in the selection equation but not in the outcome equation (Martin and Pham, 2008). In the Heckman model developed by Helpman et al. (2008) or Badwin and Harrigan (2011), variables associated with the fixed costs of establishing trade flows would appear to qualify as the derivation of this model. Therefore, “variables such as the common-religion dummy used by Helpman et al (2008); common-language dummies” used by Martin and Pham (2008) and Disdier and Marette (2010); “or the ‘Doing Business’ indicators on the costs of starting business (exports to a new destination) seem plausible as indicators of fixed cost of exporting rather than variable cost of exporting.” (Martin and Pham, 2008, p. 26) Thus, we include common language, $Lang_{od}$, as an exclusion restriction because common language may help to facilitate understanding of destination market information on rules and regulations of MRL standards and may help expedite product compliance issues. This variable is assumed to satisfy an exclusion restriction in the sense that it directly affects the probability of exporting to a new market.

3. Results

The empirical results are presented in this section to test and quantify the extent to which regulatory heterogeneity in MRL policies disrupt bilateral trade in fresh fruits and vegetables. Furthermore, the empirical results also establish a more casual link between MRL policy dissimilarities and trade using a Heckman selection model that controls for the potential endogeneity of bilateral stringency index (Martin and Pham, 2008). The results shed light on the degree to which differences in MRL regulatory stringencies affect bilateral exports of fruits and vegetables between trading partners. We first discuss the aggregated BSI impacts on trade flows (Table 2). Second, the results of augmenting the model with indicators for US exports to the CPTPP and the EU markets and the interaction of these with the BSI are explained (Table 2). In the third section, we distinguish between the different classes of chemicals to determine if the negative and significant trade flow effects of the aggregate BSI results are systematically driven by a particular class of chemicals (Table 3). Then, we estimate the model with three sub-samples to examine which CPTPP countries are driving the fact that the CPTPP BSI coefficient is much less strict than EU BSI for US exports

[14] The inverse Mills ratio is the ratio of the probability density function (PDF) over the cumulative distribution function (CDF) (Cameron and Trivedi, 2005).
[15] While Cameron and Trivedi (2010) note that the system is theoretically just identified through the non-linearity of the inverse mills ratio; for practical purposes, they suggest the model requires an exclusion restriction in the selection equation.

Table 4
Bilateral Stringency Indices—Sub-Group CPTPP markets.

Estimation Method	Negative Binomial			
	Original Model	Sub-Group		
Fixed Effects Included	(1)	(2)	(3)	(4)
BSI	−0.41***	−0.41***	−0.41***	−0.41***
	(0.08)	(0.07)	(0.07)	(0.07)
BSI $_{US-EU}$	−1.58***	−1.60***	−1.53***	−1.63***
	(0.09)	(0.09)	(0.09)	(0.09)
BSI $_{US-CPTPP}$	0.39***			
	(0.11)			
BSI $_{US-CPTPP\ (excluding\ Canada\ and\ Mexico)}$		0.37***		
		(0.11)		
BSI $_{US-CPTPP\ (excluding\ Canada)}$			0.59***	
			(0.10)	
BSI $_{US-CPTPP\ (excluding\ Mexico)}$				0.18***
				(0.11)
Observations	257,647	257,647	257,647	257,647
(pseudo) R^2	0.309	0.309	0.309	0.309

Note: The dependent variable in all columns are scaled by a million. Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10%, 5% and 1% levels, respectively. Fixed effects included importer, exporter & commodity.

(Table 4). Finally, we examine the impact of MRL policy dissimilarities on the probability of exporting and the intensity of exports using a Heckman model (Table 5) and the marginal effects of the parameter estimated in the selection equation in the Heckman model (Table 6). In all regressions, importer, exporter, and commodity fixed effects are included, and standard errors are clustered by country-pairs.

3.1. *Poisson pseudo **maximum** likelihood (PPML) model and negative Binomial model*

Table 2 considers the aggregate BSI effects across all countries and between the US-EU and US-CPTPP. The results for geographical distance and belonging to a mutual regional trade agreement are of the correct sign and statistically significant across all specifications. In terms of MRL policy, the BSI showcases a negative and statistically significant sign across all model specifications, including PPML and negative binomial models, in columns (1)-(4) suggesting that higher BSIs—indicative of a more stringent tolerance in the destination compared to the origin market—significantly reduce bilateral fresh fruit and vegetable exports. The economic interpretation is similar to a semi-elasticity since the dependent variable is in logs, while the BSI is a levels index. A stricter BSI equivalent to an increase in the BSI by 0.1 at the mean (the mean BSI equals 1.039, which is about a 10.39% increase) reduces fruit and vegetable exports by 8.8% in the PPML model (column 1) and 4.4% in the Negative Binomial Model (column 2).

These results are across all countries and products in the database. When we introduce individual controls for US exports to the EU and CPTPP markets (Table 2, columns 3 and 4), the results paint an asymmetric picture of MRL trade impacts. The BSI coefficient across two models is more negative and statistically significant for US exports to the EU but has a positive and statistically significant interaction coefficient for US trade with CPTPP partners (in the Negative Binomial Model, columns 4).[16] The result of the F-test for the difference between the estimated coefficients also confirms that the US-EU and US-CPTPP coefficients are statistically different (p-value = 0.00). Quantitatively, the estimates imply that stricter bilateral stringencies of MRLs (by 0.1 at mean) declines the US export of fruits and vegetables to the EU members by a striking 13.8% in the PPML model (Table 2, column 3) and 15.8% in the Negative Binomial Model (Table 2, column 4). Thus, the effect of stricter MRLs is quite elastic with respect to its effect on US-EU trade in both PPML and Negative Binomial Model.

In addition to the baseline estimations, we also allow the BSI effect to vary over fungicides, herbicides, and insecticides (Table 3).[17] In a format similar to Table 2, columns (1) and (2) report the results of chemical class-specific BSIs across all trading partners, while columns (3) and (4) distinguish between US-EU and US-CPTPP markets. The results are robust. With the exception of fungicides in the PPML model (not significant), more restrictive MRL policies tend to impose negative and statistically significant trade distortions (columns 1 and 2). In columns (3) and (4), the impact of BSIs for different classes of chemicals on the US-EU and the US-CPTPP markets are more sensitive and fragile, given the lower number of observations in these categories, making identification more challenging. However, some interesting findings emerge. First, the mostly negative BSI effects reported in columns (3) and (4) turn out to be driven almost entirely by fungicides and insecticides for the US-EU and insecticides, in particular, for the US-CPTPP markets.

Furthermore, to examine which of the CPTTP countries are driving the fact that the CPTPP BSI coefficient is much less strict than EU BSI for US exports, we estimate the model with three sub-groups for the $I_{US\text{-}CPTPP}$ variable (Table 4).[18] In particular, among CPTPP members, Canada (64.5%) and Mexico (15.8%) have the highest share of US export of fruits and vegetables, which is 80.3% on average over the study period (United Nation Comtrade Database UN Comtrade, 2019). Thus, we first exclude Canada and Mexico from the list of CPTPP members (column 2), the CPTPP BSI for US export coefficient (0.37) magnitude decreases slightly (nothing else changes) and indicates negligible changes of BSI coefficient (from 0.39 to 0.37), excluding Canada and Mexico, compared to the original model. However, if we only exclude Canada from the list of CPTPP market data (column 3), the parameter estimated became even more positive compared to the original model (from 0.39 to 0.59). In the third model, when we exclude Mexico from the list of CPTPP market data, the CPTPP BSI coefficient drops from 0.39 (full sample column 1) to 0.18 (column 4). Thus, the less positive BSI reported in column 4 turns out to be driven partially by Mexico.

3.2. *Intensive and extensive margins of trade*

In this section for the Heckman model, we first discuss the aggregated BSI impact on the probability of exporting and the intensity of exports. Second, we discuss the results of aggregate BSI impact on the US exports to EU and CPTPP markets based on the augmented model. Third, the results of chemical class-specific BSIs across all trading partners are presented. Finally, we report and discuss the results of the disaggregate BSIs based on the different classes of chemicals for US exports to EU and CPTPP markets. In all regressions, importer, exporter, and commodity fixed effects are included, and standard errors are clustered by country-pairs. Furthermore, through all specifications, we include common language as the exclusion restriction in the selection model. We also use

[16] The mean BSI index for EU and CPTPP markets are 1.59 and 1.12, respectively. We further conducted a non-parametric two-sample Wilcoxon rank-sum test to test whether differences between the indices across the EU and CPTPP markets are significantly different. The equality of the BSI indices was easily rejected.

[17] The last category of chemical class “Other” are dropped from regression estimations because a small number of observations belonging to this category.

[18] Because of the excessive amount of zero trade values in our data, we only report the results of Negative Binomial for these model specifications, as suggested by trade literature. It should also be noted that, for these model specifications, we did not estimate the BSI effect over difference class of chemicals due to the limited number of observations in these categories.

Table 5
Bilateral Stringency Indices Impacts on Exports of Fruits and Vegetables.

Estimation Method	Heckman Selection Model							
	(1) *Selection Pr(exp_{odk} > 0)*	(2) *Outcome Equation*	(3) *Selection Equation*	(4) *Outcome Equation*	(5) *Selection Equation*	(6) *Outcome Equation*	(7) *Selection Equation*	(8) *Outcome Equation*
BSI	−0.17***	−0.51***	−0.17***	−0.49***				
	(0.02)	(0.05)	(0.02)	(0.05)				
BSI $_{US-EU}$			−0.78***	−1.15***				
			(0.04)	(0.07)				
BSI $_{US-CPTPP}$			−0.02	1.06***				
			(0.06)	(0.11)				
BSI-Fungicides					−0.09***	−0.32***	−0.09***	−0.28***
					(0.02)	(0.06)	(0.02)	(0.06)
BSI-Herbicides					−0.11***	−0.23***	−0.11***	−0.21***
					(0.01)	(0.04)	(0.01)	(0.04)
BSI-Insecticides					−0.09***	−0.50***	−0.09***	−0.46***
					(0.02)	(0.07)	(0.02)	(0.07)
BSI-Fungicides $_{US-EU}$							−0.26	−0.05
							(0.23)	(0.37)
BSI-Herbicides $_{US-EU}$							−0.03	0.16
							(0.19)	(0.39)
BSI-Insecticides $_{US-EU}$							−0.46**	−1.30***
							(0.22)	(0.5)
BSI-Fungicides $_{US-CPTPP}$							−0.34***	−0.21
							(0.09)	(0.34)
BSI-Herbicides $_{US-CPTPP}$							0.21**	0.58**
							(0.07)	(0.25)
BSI-Insecticides $_{US-CPTPP}$							0.08	0.68*
							(0.11)	(0.37)
Log Distance	−0.71***	−1.23***	−0.71***	−1.26***	−0.73***	−1.26***	−0.73***	−1.30***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
RTA	0.29***	0.62***	0.29***	0.52***	0.25***	0.69***	0.25***	0.57***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Common Language	0.31***		0.31***		0.29***		0.29***	
	(0.01)		(0.01)		(0.02)		(0.02)	
Observations	257,647		257,647		207,258		207,258	
Estimated rho	0.093***		0.109***		0.096***		0.129***	
	(0.009)		(0.009)		(0.010)		(0.009)	
Estimated lambda	0.275***		0.325***		0.284***		0.383***	
	(0.028)		(0.027)		(0.030)		(0.028)	

Note: Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10%, 5% and 1% levels, respectively. Fixed effects included importer, exporter & commodity. Common language is the exclusion restriction variable in the model.

common religion as an exclusion restriction[19], and the results are robust (Results available upon request).

In the Heckman model, the aggregated BSI impact on the probability of exporting and the intensity of exports are presented in Table 5. The results in columns (1) and (2) suggest that MRL stringency reduces the probability of market entry by −0.03 (selection equation, where the marginal effect [20]of MRL stringency is −0.03) as well as decreases the intensity of exports by −0.51. Columns (3) and (5) distinguish the impact of MRL stringency on the probability of exporting and the intensity of export between US-EU and US-CPTPP markets. MRL policy indicates a negative impact on the decision to export between US-EU and US-CPTPP (the marginal effect for the estimated parameter of MRL policy for US export to EU is negative and statistically significant (-0.12), but not statistically significant for US export to CPTPP markets); however, the impact of MRL tolerances between US-EU and US-CPTPP markets on the volume of trade is opposite. MRL policy plays an impeding role on the intensity of US exports to EU (−1.15), while this impact is trade enhancing with respect to the US exports to CPTPP markets (1.06 and statistically significant). Previous studies in this line also find consistent results. Similar to the former result for US-EU, Jayasinghe, Beghin, and Moschini (2010) also find a negative and statistically significant impact of MRLs on the probability and volume of US export demand for corn seeds. However, similar to the latter result for US-CPTPP markets, Disdier and Marette (2010) find that even though the impact of MRLs on extensive margin is negative but insignificant, it negatively and significantly affects the intensive margin of imported crustaceans.

Furthermore, Crivelli and Groeschl's (2016) find similar results for their study of the impact of SPS measures on the extensive and intensive margin of trade. Their results (similar to us with respect to the US export to CPTPP markets) show SPS measures have a negative and significant impact on the market entry, which increases fixed costs of trade. Additionally, columns (5) and (6) report the results of chemical class-specific BSIs across all trading partners. The results show MRL policy has a negative impact across all chemical classifications at both margins of trade. Lastly, columns (7) and (8) report the results of chemical class-specific BSIs while distinguishing MRL policy effects between US-EU and US-CPTPP markets. Overall, our findings are mostly consistent

[19] Common religion may also strongly affect the export decision; however, once the new trade relation has been created, it may not impact the amount of trade. Data on common religion across country pairs are collected from Elhanan Helpman's homepage. In their study, Helpman et al. (2008) calculate the index of common religion between trading partners as (% Protestants in region o × % Protestants in region d) + (% Catholics in region o × % Catholics in region d) + (% Muslims in region o × % Muslims in region d).

[20] Since the selection equation is a probit model, we also estimate the marginal effects of the parameter estimated in the selection equation.

Table 6
Marginal Effects of Bilateral Stringency Indices Impacts on Exports of Fruits and Vegetables.

Estimation Method	Heckman Selection Model – Marginal Effects			
	(1) *Selection Equation*	(3) *Selection Equation*	(5) *Selection Equation*	(7) *Selection Equation*
BSI	−0.035***	−0.035***		
	(0.002)	(0.002)		
BSI US-EU		−0.117***		
		(0.005)		
BSI US-CPTPP		−0.003		
		(0.010)		
BSI-Fungicides			−0.014***	−0.014***
			(0.003)	(0.003)
BSI-Herbicides			−0.017***	−0.017***
			(0.002)	(0.002)
BSI-Insecticides			−0.014***	−0.014***
			(0.002)	(0.002)
BSI-Fungicides US-EU				−0.043
				(0.033)
BSI-Herbicides US-EU				−0.003
				(0.029)
BSI-Insecticides US-EU				−0.069**
				(0.033)
BSI-Fungicides US-CPTPP				−0.051***
				(0.014)
BSI-Herbicides US-CPTPP				0.033**
				(0.011)
BSI-Insecticides US-CPTPP				0.015
				(0.015)
Log Distance	−0.113***	−0.113***	−0.113***	−0.113***
	(0.001)	(0.001)	(0.001)	(0.001)
RTA	0.046***	0.046***	0.046***	0.046***
	(0.002)	(0.002)	(0.002)	(0.002)
Common Language	0.049***	0.049***	0.049***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	257,647	257,647	207,258	207,258

Note: Robust standard errors are in parentheses. One, two and three asterisks denote significance at the 10%, 5% and 1% levels, respectively. Fixed effects included importer, exporter & commodity. Common language is the exclusion restriction variable in the model.

with our previous specifications. For those parameters estimated that are statistically significant, MRL policy has a negative effect on the extensive and intensive margins of trade for US-EU, while the negative effect on the extensive margin of trade but positive effect on the intensive margin of trade for US-CPTPP markets. The coefficients on the gravity control variables are consistent with existing gravity estimation literature on trade and through all specifications. The geographical distance between two trade partners has a negative impact on bilateral trades on both the probability of exporting and the volume of trade, while having RTAs fosters exports of fruits and vegetables between trade partners at both margins of trade. Common language reduces the fixed costs of trade and positively affects the probability of exporting.[21]

4. Conclusions

Using a bilateral stringency index, we developed an econometric model to understand the trade restricting nature of divergent maximum residue limits for US trade of fruits and vegetables in 2013 and 2014. Importantly, our augmented trade model distinguishes the impact of MRL policies on exports across all potential destination markets, and between the US as an exporter and its main trading partners in the CPTPP and EU nations.[22] We contribute to the analysis of SPS measures by estimating the impact of bilateral MRL stringency using various

Table 7
List of Commodities.

Fruits	6-digit Code	Vegetable	6-digit Code
APPLES	80,810	ASPARAGUS	70,920
APRICOTS	80,910	BROCCOLI	70,490
AVOCADOS	80,440	BRUSSELS SPROUTS	70,420
BANANAS	80,300	CARROTS	70,610
CHERRIES	80,920	CAULIFLOWER	70,410
CITRUS NES	80,590	CELERY	70,940
CRANBERRIES & BLUEBERRIES	81,040	CUCUMBERS	70,700
CURRANTS	81,030	EGGPLANTS	70,930
DATES	80,410	FRESH BEANS	70,820
FIGS	80,420	GARLIC	70,320
GRAPEFRUIT	80,540	GLOBE ARTICHOKES	70,910
GRAPES	80,610	HEAD LETTUCE	70,511
KIWIFRUIT	81,050	LEAF LETTUCE	70,519
LEMONS & LIMES	80,550	LEEKS	70,390
MANDARINS & CLEMENTINES	80,520	LEGUMES EXC PEAS BEANS	70,890
MANGOES	80,450	MUSHROOMS & TRUFFLES	70,951
MELON	80,719	ONIONS	70,310
ORANGES	80,510	PEAS	70,810
PAPAYAS	80,720	PEPPERS	70,960
PEACHES & NECTARINES	80,930	POTATOES	70,190
PEARS & QUINCES	80,820	RADISHES ETC	70,690
PINEAPPLES	80,430	SPINACH	70,970
PLUMS & SLOES	80,940	SQUASH, PUMPKINS, ARTICHOKE, OKRA	70,990
RASPBERRIES & BLACKBERRIES	81,020	TOMATOES	70,200
STRAWBERRIES	81,010	WITLOOF CHICORY	70,521
WATERMELONS	80,711		

[21] The results are consistent when we include common religion as the exclusion restriction in the model.

[22] Despite the US's removal from this agreement, the results of this research are useful for any bilateral trade agreement between the US and CPTPP countries individually (i.e., Japan). The US trade negotiators seek to consider including some provisions in the CPTPP agreement in the future bilateral and regional trade agreements. The US has existing free trade agreements with six members of the CPTPP, with many provisions similar to those in the new CPTPP agreement. Thus, it has significant policy implications for the US and trade negotiators. Significant provisions in the CPTPP agreement impact agricultural and food trade, which made this agreement different from previous regional and multilateral agreements. The CPTPP agreement considers the establishment of committees on agricultural trade and SPS measures to lower non-tariff barriers, harmonize regulations, and decrease the associated compliance costs. The general SPS provisions of CPTPP go beyond the WTO SPS Agreement— namely the rapid response mechanism, which helps resolve SPS problems that lead to shipments being detained at the port of entry (Gonzalez 2016; Inside US Trade 2016). This mechanism would require the importing party that stopped a shipment based on an adverse SPS result to provide notification within seven days. The latter is a crucial provision in CPTPP's SPS chapter that tightens the WTO standards to make it harder for countries to restrict imports on food safety grounds (Inside US Trade 2016 and 2018). The 2016 National Grain and Feed Association report (NGFA) highlights "this rapid response to SPS measures and other technical barriers would reduce delays, disputes, rejections and risk" (Gonzalez 2016). In regards to T-TIP, negotiations between the US and the EU are still ongoing, and the US had withdrawn from the Trans-Pacific Partnership (TPP) on January 23, 2017. MRLs are critical as in the last round of negotiation, negotiators from both sides (EU and US) have spent much time discussing the regulatory area, including regulatory coherence, technical barriers to trade, plant, and animal health including SPS measures.

Table 8
List of Countries.

List of Countries	ISO Code	List of Countries	ISO Code
Angola	AGO	Pakistan	PAK
Albania	ALB	Panama	PAN
United Arab Emirates	ARE	Philippines	PHL
Argentina	ARG	Qatar	QAT
Antigua and Barbuda	ATG	Russia	RUS
Bangladesh	BGD	Saudi Arabia	SAU
Bahrain	BHR	El Salvador	SLV
Bahamas	BHS	Thailand	THA
Bermuda	BMU	Trinidad and Tobago	TTO
Brazil	BRA	Tunisia	TUN
Barbados	BRB	Turkey	TUR
Switzerland	CHE	Taiwan	TWN
China	CHN	United States	USA
Codex	COD	Venezuela	VEN
Colombia	COL	South Africa	ZAF
Costa Rica	CRI	Belgium	BLX
Cuba	CUB	Germany	DEU
Cayman Islands	CYM	Denmark	DNK
Dominican Republic	DOM	Spain	ESP
Algeria	DZA	Finland	FIN
Ecuador	ECU	France	FRA
Egypt	EGY	United Kingdom	GBR
Guatemala	GTM	Greece	GRC
Hong Kong	HKG	Ireland	IRL
Honduras	HND	Italy	ITA
Haiti	HTI	Netherlands	NLD
Indonesia	IDN	Poland	POL
India	IND	Portugal	PRT
Iceland	ISL	French Polynesia	PYF
Israel	ISR	Sweden	SWE
Jamaica	JAM	Australia	AUS
Jordan	JOR	Brunei	BRN
Kenya	KEN	Canada	CAN
Cambodia	KHM	Chile	CHL
Nevis	KNA	Japan	JPN
Kuwait	KWT	Korea	KOR
Lebanon	LBN	Mexico	MEX
St. Lucia	LCA	Malaysia	MYS
Sri Lanka	LKA	New Zealand	NZL
Morocco	MAR	Peru	PER
Nicaragua	NIC	Singapore	SGP
Norway	NOR	Vietnam	VNM
Oman	OMN		

econometric specifications (PPML, Negative Binomial model and Heckman models) and employing a non-linear, stringency index disaggregated by chemical class. Our main findings shed light on the trade impeding impact of MRL stringency on exports for fruits and vegetables across all trading partners. More stringent MRL policies requires more careful production, testing, and compliance costs to serve international markets with stricter food safety guidelines.

Next, we introduce individual controls for US exports to the EU and CPTPP markets. Here, the results paint a contrasting picture of MRL effects on US exports. The results suggest that EU MRLs impede US exports to the EU, while these policies enhance trade with respect to US exports to CPTPP markets. The former results might be because the EU and US regulatory approaches are very different. The EU regulates based on hazard identification without taking into account exposure or risk. This method is not consistent with the science-based risk assessment procedures for regulating the crop protection products approach delineated in both the US Environmental Protection Agency's (EPA) regulations and the WTO SPS agreement (Crop Life, 2013). This regulatory heterogeneity also presents more significant economic and trade impacts, and trade negotiators should emphasize the dissimilarity of MRL tolerances in the T-TIP negotiations. The latter result between the US and CPTPP countries is suggestive of the potentially demand-enhancing effects of MRL policies. Therefore, it is crucial to take into account the preference of consumers in the destination country concerning food safety.

Additionally, we also allow the BSI effect to vary over different classes of chemicals, including fungicides, herbicides, and insecticides. The results have important policy implications because they suggest specific chemical classes on which trade negotiators can focus attention. We find that divergent MRLs on insecticides are the most trade restrictive chemical class considered. Insecticides are followed by herbicide indices of MRL stringency, where differing MRL stringencies also impeded US exports. On the other hand, the trade effect of more stringent fungicide MRLs was generally not statistically or economically harmful to trade. In terms of EU and CPTPP markets, the results indicate that more stringent herbicide MRL policies among the CPTPP countries serve as a potential demand-enhancing impact. Thus, the results reveal consumers' food safety concerns and preferences are significant to consider in production of fruits and vegetables.

We furthermore examine exactly which CPTPP members are driving the fact that the CPTPP BSI coefficient is less strict than EU BSI for US exports. The results indicate that the BSI coefficient became even more positive when excluding Canada with the highest share of US imports of fruits and vegetables among the CPTPP markets. Thus, the latter suggests that Canada has a more stringent MRL policy among CPTPP countries. More importantly, when we exclude Mexico from the CPTPP market data, the estimated parameter for BSI becomes less positive. While the positive sign of BSI coefficient for the CPTPP market indicates the importance of considering consumers' food safety concerns, harmonized MRL policies between the US and Mexico facilitate trade because Mexico displays a similar pesticide regime to the United States over the study period.

Lastly, an important question concerning MRL policies is whether exporting nations facing stringent MRL policies in destination markets actually export at all? Here, we estimate the impact of MRL policies as a market entry barrier to all potential exporters by decomposing exports into an extensive and intensive margin of trade. Our results suggest that MRL stringency decreases both the probability of exports as well as the intensity of exports across all trading partners. Thus, MRL policies likely impart significant fixed and variable trade costs of exporting, judging by the negative and significant extensive and intensive margin results. Hence, a more stringent MRL policy appears to constitute a market entry barrier to all exporters.

Furthermore, the results of introducing individual controls for US exports to the EU and CPTPP markets indicate MRL policy has a negative impact on the decision to export between US-EU and US-CPTPP and an impeding role on the intensity of US exports to EU. One possibility that the EU standards rise in cost with volume might be because in Northern European four firms cover grocery retail (40%). These retailers may choose to respond to consumer preferences for goods produced with particular technologies. The concentration of retail in the EU can result in large negative effects on demand for imported goods affected by Non-Tariff Measures (Arita et al., 2017). Because consumers' preferences lead to a change in purchasing. This could be one possibility and explanation for these findings. We hope future research investigates this suggestion. On the other hand, with respect to the US exports to CPTPP markets, MRL policy has a positive impact on the intensity of trade. The results suggest that those exporters who overcome the fixed costs of trade indicate the safety of their products to consumers, and consequently, boost trade.

Quantifying the impact of SPS and MRL measures are crucial to trade and consumer welfare. The main limitation of this body of research is collecting comprehensive maximum residue limit data. These results have important implications for producers and exporters. Policy makers who are involved in agricultural trade negotiations also benefit from an understanding of the, particularly the ones who are interested and vested in measures that make trade less complex for both trading partners as well as the ones who are engaged in trade agreements, in addition to those who are negotiating in harmonizing more stringent maximum residue limits or tackling equivalency or reciprocity in the context of trade benefits. Future research may be considered not only

Table 9
List of Chemicals that are used in Production of Fruit or Vegetable Crop based on Data provided by the USDA/NASS Surveys of Pesticide.

Chemicals	Cat	Chemicals	Cat	Chemicals	Cat	Chemicals	Cat	Chemicals	Cat
1,3-Dichloropropene	O	Cypermethrin	I	Fenhexamid	F	Metalaxyl	F	Pyraflufen-ethyl	H
1-Naphthaleneacetic acid	O	Cyprodinil	F	Fenpropathrin	I	Metalaxyl-M (Mefenoxam)	F	Pyrethrins	I
2,4-D	H	Cyromazine	I	Fenpyroximate	I	Metaldehyde	O	Pyridaben	I
Abamectin	I	DCPA	H	Ferbam	F	Metconazole	F	Pyrimethanil	F
Acephate	I	Deltamethrin	I	Flonicamid	I	Methidathion	I	Pyriproxyfen	I
Acequinocyl	I	Diazinon	I	Fluazifop-P-butyl	H	Methomyl	I	Rimsulfuron	H
Acetamiprid	I	Dicamba	H	Fluazinam	F	Methoxyfenozide	I	Saflufenacil	H
Acibenzolar-S-methyl	O	Dichlobenil	H	Flubendiamide	I	Metiram	F	Sethoxydim	H
Aldicarb	I	Dicloran	F	Fludioxonil	F	Metrafenone	O	Simazine	H
Azoxystrobin	F	Dicofol	I	Flumioxazin	H	Metribuzin	H	S-metolachlor	H
Bensulide	H	Difenoconazole	F	Fluopicolide	F	Myclobutanil	F	Spinetoram	I
Bentazon	H	Diflubenzuron	I	Fluroxypyr	H	Naled	I	Spinosad	I
Beta-cyfluthrin	I	Dimethenamid	H	Flutriafol	O	Napropamide	H	Spirodiclofen	O
Bifenazate	I	Dimethenamid-P	H	Fomesafen	H	Naptalam	H	Spiromesifen	I
Bifenthrin	I	Dimethoate	I	Forchlorfenuron	O	Norflurazon	H	Spirotetramat	I
Boscalid	F	Dimethomorph	F	Formetanate hydrochloride	I	Novaluron	I	Streptomycin	F
Bromacil	O	Dinotefuran	I	Fosetyl-Al	F	Oryzalin	H	Sulfentrazone	H
Buprofezin	I	Diquat dibromide	H	Gamma Cyhalothrin	I	Oxamyl	I	Tebuconazole	F
Captan	F	Disulfoton	I	Glufosinate-ammonium	H	Oxydemeton-methyl	I	Tebufenozide	I
Carbaryl	I	Diuron	H	Glyphosate	H	Oxyfluorfen	H	Terbacil	H
Carfentrazone-ethyl	H	Dodine	F	Halosulfuron-methyl	H	Oxytetracycline	F	Thiacloprid	I
Chlorantraniliprole	I	Emamectin	I	Hexazinone	H	Paraquat dichloride	H	Thiamethoxam	I
Chlorothalonil	F	Endosulfan	I	Hexythiazox	I	Pendimethalin	H	Thiazopyr	H
Chlorpyrifos	I	EPTC	H	Imidacloprid	I	Permethrin	I	Thiophanate-methyl	F
Clethodim	H	Esfenvalerate	I	Indaziflam	O	Phosmet	I	Thiram	F
Clofentezine	I	Ethalfluralin	H	Indoxacarb	I	Piperonyl Butoxide	I	Trifloxystrobin	F
Clomazone	H	Ethephon	O	Iprodione	F	Prohexadione calcium	O	Triflumizole	F
Clopyralid	H	Etoxazole	I	Kresoxim-methyl	F	Prometryn	H	Trifluralin	H
Clothianidin	I	Famoxadone	F	Lambda Cyhalothrin	I	Propamocarb hydrochloride	F	Zeta-Cypermethrin	I
Cryolite	I	Fenamidone	F	Linuron	H	Propargite	I	Ziram	F
Cyazofamid	F	Fenarimol	F	Malathion	I	Propiconazole	F	Zoxamide	F
Cyfluthrin	I	Fenbuconazole	F	Mancozeb	F	Pymetrozine	I		
Cymoxanil	F	Fenbutatin-oxide	I	Mesotrione	H	Pyraclostrobin	F		

Source: MRLglobal database and NASS survey USDA. F stands for Fungicides, I stands for Insecticides, H stands for herbicides and O stands for Other category of pesticides.

looking at the EU and CPTPP but at all US bilateral trade relationships explicitly to paint a picture of MRL effects on US exports and across main fruit and vegetable producers and exporters. Future studies may expand this analysis to other products (e.g., the meat sector). Further, interdisciplinary research with plant, soil and food scientists is needed to investigate the reasoning for the varied trade flow results across chemical types.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

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