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Trade Elasticities and Trade Disputes: New Evidence from Tariffs and Relative Preference Margins

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I. Background

Since 1995 and the creation of the World Trade Organization (WTO), world agricultural and food trade has increased over three-fold from $575 billion in 1995 to nearly $1.6 trillion in 2016. Total world trade has grown more than twenty-seven fold in volume terms since 1950 - more than three times the growth in world output – and tariffs on manufactured (agricultural) goods average less than 5 (15) percent in most industrialized nations. Twenty new members have joined the WTO since 2001 bringing total membership to 164. These accomplishments are often attributed to both multilateral trade liberalization vis á vis the WTO in reducing barriers to trade and successfully resolving trade disputes and the proliferation of free trade agreements (FTAs) offering preferential tariffs and market access to member countries.

However the ongoing tit-for-tat trade dispute between the U.S. and some of its significant trading partners, including North American Free Trade Agreement (NAFTA) members Canada and Mexico, China and the European Union (EU) has escalated into what some are calling an outright "trade war".[1] To recap, in January 2018, President Trump imposed tariffs on washing machines and solar panels. Shortly after, China launched a dumping investigation on US Sorghum exports valued at $1 billion in 2016 and $836 million in 2017 - a retaliatory policy that was later withdrawn on May 18, 2018. Washing machine and solar panel tariffs were followed by the March 1, 2018 announcement by the U.S. that it will levy 25% tariffs on steel and 10% tariffs on aluminum products for national security reasons under Section 232 of the Trade Expansion Act of 1962. On Friday March 23 the steel and aluminum tariffs become effective, and at that time, Canada, Mexico, the European Union, Australia, Argentina, South Korea, and Brazil were offered exemptions until May 1, 2018, representing 63 percent of steel and aluminum trade with the U.S.[2]

A day earlier, on March 22, 2018, the Trump administration announced new tariffs on up to $60 billion dollars of imports over China's intellectual property (IPR) practices and forced technology transfers. This was immediately followed, and somewhat confusingly so, on March 23, 2018 by China's announced retaliatory tariffs on $3 billion worth of Chinese imports from the US in response to US Steel and aluminum tariffs (i.e., not the intellectual property announcement from the Trump administration that coincided a day earlier). China's tariff response to US steel and aluminum tariffs went into effect April 2, 2018 and are structured as follows: (i) 25 percent tariffs on $2 billion of imports on products such as pork and recycled aluminum, and (ii) 15 percent tariffs on $1 billion of imports of products such as fresh fruit, dried fruit and nuts, wine, ethanol, ginseng, and seamless steel pipes.[3]

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[1] https://www.washingtonpost.com/graphics/2018/business/trump-tariff-trade-war/?noredirect=on&utm_term=.5840432c1ade

[2] https://piie.com/blogs/trade-investment-policy-watch/trumps-long-awaited-steel-and-aluminum-tariffs-are-just

[3] The State Council Information Office of the People's Republic of China, April 2018,

On April 3, 2018, the Trump administration released its list of 1,333 Chinese products under consideration for 25 percent tariffs under Section 301 Trade Act of 1974, covering $46.2 billion of U.S. imports to address China's IPR practices and forced technology transfers in business relationships. A day later on April 4, 2018, China immediately announced its retaliatory list covering 106 products worth $49.8 billion that could be subject to 25% import tariffs on products originating from the U.S. in response to the Trump administration's IPR tariffs. Importantly for U.S. agriculture, this list includes soybeans (HS chapter 12), the U.S.'s largest agricultural export to China valued at $14.2 billion in 2016 and $13.9 billion in 2017. The U.S. is second only to Brazil in soybean exports to China valued at nearly $21 billion in 2017. Together, Brazil and the U.S. exported 88 percent of China's global soybean imports and provide 61 percent of total world soybean imports. Corn, wheat, cotton, beef, wine, and a number of other U.S. agricultural product exports were also included on China's product retaliation list.[4]

On May 21, 2018, China and the U.S. temporarily agreed to place the trade dispute "on-hold" after a tentative agreement following meetings in Washington that would see China increase its purchases of U.S. products and reduce the bilateral trade deficit. This followed China's May 18th, 2018 decision to end tariffs on U.S. sorghum imports in response to U.S. duties on washing machines and solar panels. Shortly thereafter, however, the White House released its revised list of Chinese products subject to 25 percent tariffs, in two phases starting July 6, 2018. China Immediately followed by issuing an updated retaliation list of 25 percent tariffs on U.S. products, 38% of which are agricultural and food products, starting July 6, 2018 (Bown and Kolb, 2018).

After the initial exemptions from U.S. steel and aluminum duties expired on May 1, 2018, President Trump offered Canada and Mexico a "final" somewhat conditional one month extension to June 1st, 2018 citing the renegotiation of NAFTA and Mexico and Canada voluntarily limiting steel and aluminum exports to the U.S. The EU was also granted a one month extension and South Korea was granted a permanent exemption after it agreed to limit steel and aluminum exports to the U.S.[5] However, negotiations between NAFTA partners to date have not succeed and on June 1, 2018, U.S. Commerce Secretary, Wilbur Ross, announced that the U.S. will apply 25% steel and 10% aluminum tariffs on Canada and Mexico. Mexico immediately imposed new duties on U.S. steel, pork, cheese, whiskey, potatoes, and apples, among other goods, estimated at $3 billion[6]. On June 22, 2018, the EU activated its previous tariff retaliation threat against the U.S., covering $3.2 billion of U.S. products, 30% of which are agricultural and food products in 2017[7]. On July 1, 2018, Canada countered the U.S. steel and aluminum tariffs with its own tariff retaliation list covering $16.6 billion worth of imports from the U.S.

Finally, on July 10, 2018, the Trump administration effectively doubled-down on its trade dispute with China saying it will impose tariffs on approximately $200 billion worth of imports from China and is prepared to levy tariffs on up to $450 billion worth of Chinese products

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http://www.scio.gov.cn/xwfbh/xwbfbh/wqfbh/37601/38181/xgzc38187/Document/1626839/1626839.htm

[4] http://www.scio.gov.cn/xwfbh/xwbfbh/wqfbh/37601/38181/xgzc38187/Document/1626839/1626839.htm

[5] Brazil, Argentina, and Australia were granted indefinite exemptions, pending negotiations with the U.S.

[6] The Ministry of Economy in the Official Gazette of the Federation, Mexico, June 2018, http://www.dof.gob.mx/nota_detalle.php?codigo=5525036&fecha=05/06/2018

[7] The European Union, June 2018, http://trade.ec.europa.eu/doclib/docs/2018/march/tradoc_156648.pdf

covering nearly all U.S. imports from China. On July 11, 2018, China pledged retaliation against the latest tariff threat by the U.S. However, it is unclear whether China will include non-tariff measures as a policy tool because its imports from the U.S. at $130 billion are one-quarter of the $505 billion the U.S. imported from China in 2017.

Agricultural products are often caught in the cross-fire of trade disputes rooted in manufacturing or non-tariff related measures such as threats to national security for steel, aluminum and auto imports, or IPR and technology transfer concerns in business relationships. For example, China's updated list subject to 25 percent tariffs includes grains, oilseeds, cotton, pork and beef valued at well over $16 billion and Mexico's retaliatory list includes pork valued at over $1.0 billion in trade between the two NAFTA partners. It remains uncertain whether these tariff threats will continue to escalate, or whether the U.S. and partner countries will find common ground and de-escalate the trade dispute. Tariffs implemented by a large country reduce the price competiveness of agricultural producers in exporting countries, raise prices for consumers in the importing country and can lead to domestic industry contraction and losses as declines in export market shares can have persistent economic effects lasting beyond the initial trade dispute. This is because firms delay shipments and investments when trade policy uncertainty rises (Freund et al. 2018). However, the extent to which retaliatory tariffs lead to significant trade disruptions and domestic producer losses depends critically on the elasticity of import demand or how easily importing countries can substitute toward alternative sources of supply. In the language of computable general equilibrium modeling, this parameter is often referred to as "micro" level elasticity.

The purpose of this report is to develop an estimation framework that uses cross-sectional variation in tariffs and relative preferential tariff margins for a given country-year-product to identify the responsiveness of agricultural imports to changes in relative prices as they relate to bilateral applied tariffs inclusive of preferential margins. Because of the explosion of free trade agreements in world trade since 1995, many of the most significant agricultural export suppliers enjoy some sort of preferential tariff treatment in a common import market (Sharma, Boys and Grant 2018). Empirical research on international trade flows and import demand elasticities has generally not considered how relative preferential margins influences bilateral trade particularly when competing exporters are receiving preferential benefits of their own with a common trade partner (see for e.g., Hertel et al. 2007; Chaney 2008; Kee et al. 2008; Hillberry and Hummels 2013; Feenstra et al. 2014). Thus, trade depends not only on the direct bilateral applied tariff the U.S. faces in a given import market but also on the relative tariff preference competing exporters enjoy in the same market (Fugazza and Nicita 2013). In this report, we focus on many, although not all, of the agricultural products raised in the list of China and Mexico's retaliatory tariffs against the U.S. to estimate the potential impact of escalating tariffs on China and Mexico imports from the U.S. and competing suppliers, and to provide instructive policy implications for the U.S. farmers, industries, and policymakers. Our product list includes (Harmonized System (HS) product codes in parentheses): soybeans (1201), corn (1005), wheat (1001), rice (1006), sorghum (1007), cotton (5201), cheese (0406), apples (080810), pork (0203 and specific swine products in 0206) and beef (0201, 0202 and bovine products in 0206).

Global computable general equilibrium models are undoubtedly one of the most valuable methods to uncover the potential gains and losses of trade policy shocks because they are able to represent the world economy in a multi-country, multi-commodity setting to show how production, consumption, factor employment, prices and trade flows, calibrated to match baseline data adjust to policy shocks such as changes in tariff rates. However as with any simulation model, CGE models are built on a number of assumptions to maintain internal consistency and are particularly sensitive to the “micro” elasticity of substitution measuring how easily goods from one country can be substituted for goods from another – a parameter that’s been difficult to estimate. Moreover, recent evidence on the micro elasticity has been scant to date, especially for agricultural products. This report aims to fill this void for select agricultural products. Key policy questions include:

1) How sensitive are global agricultural exports to changes in tariffs and relative preferential tariff margins?
2) Are some products more vulnerable than others to tariff threats?
3) What are the potential trade implications of tariff retaliation against U.S. and global farm products?

II. Commodity Trade Statistics

The U.S. continues to be the top global exporter of wheat, corn, and sorghum, and ranks second in exports of soybeans and pork products since 2013. For example in 2017, the U.S. exported 55.32 million metric tons (MMT) of soybean ($21.52 billion), 27.24 MMT of wheat ($6.08 billion), 53.04 MMT of corn ($9.56 billion), 1.12 MMT of rice ($0.62 billion), 5.73 MMT of sorghum ($1.08 billion), 3.25 MMT of cotton ($5.83 billion), 0.91 MMT of beef ($6.17 billion) and 1.72 MMT of pork products ($4.56 billion). Mexico and Japan are the top two importers of U.S. exports of wheat, corn and pork, collectively accounting for 25%, 51%, and 49% of U.S. exports on a volume basis, respectively. South Korea and Japan are the top two importers of U.S. beef products, collectively accounting for 47% on a volume basis. China is the top importer of U.S. sorghum and soybean exports accounting for 57% and 80% of U.S. exports on a volume basis.[8] Mexico, Canada and India are the largest destinations for U.S. fresh apples with exports valued at $275, $167 and $97 million, respectively, in 2017, and represent 55% of U.S. fresh apple exports globally. U.S. variety cheese exports are concentrated in Mexico South Korea, Japan and Australia who collectively absorb 60 percent, or $863 million in 2017, of total U.S. cheese exports.

China’s soybean imports totaled 95.54 MMT worth nearly $40 billion, or roughly 60 percent of world soybean imports in 2017. Both the U.S. and Brazil have been important suppliers of Chinese soybeans, collectively accounting for 87% of its soybean imports on a volume basis (Brazil 53%, U.S. 34%). However, with China’s July 6, 2018 announcement that it will apply retaliatory tariffs of 25% on its soybean imports from the U.S., early evidence appears to suggest Chinese firms are purchasing more aggressively from the South American countries. In addition, China plans to remove import tariffs on animal feed ingredients including soybeans from five neighboring Asian countries to promote substitutes away for U.S. supplies. Prices of benchmark Chicago soybean futures have slumped about 6 percent since news of the latest round of trade tensions broke[9], and Brazil soybean cash premiums

[8] Figures are based on United Nations Comtrade Data, accessed May and June, 2018.
[9] https://www.cnbc.com/2018/07/05/reuters-america-grains-soybeans-close-at-2-12-year-low-as-china-tariffs-loom.html

over futures prices have hit a 14-year high (AgriCensus Daily Report, July 2018).

Taheripour and Tyner (2018) used the Global Trade Analysis Project-Biofuels (GTAP-BIO) CGE simulation model to examine increased soybean tariffs by China on U.S. imports. They found that Chinese soybean imports from the U.S. could drop by as much 71 percent if China were to impose trade restrictions ranging from 10-30 percent additional tariffs. Total U.S. soybean exports could fall by 40 percent; total U.S. soybean production could decrease by 17 percent; and U.S. soybean producer prices could drop by a more modest 4 to 5 percent after the tariffs take effect. Note that the 4-5 percent producer price decline is much less than the 30 percent policy shock to tariffs. This is because, Chinese buyers will seek other more reliable suppliers as relative prices for U.S. soybeans increase due to the tariffs. However, greater (lesser) demand for soybeans from competing non-U.S. (U.S.) exporters will raise (lower) their soybean export price. Moreover, as competing soybean export suppliers (i.e., Brazil and Argentina) reorient soybean trade toward China and away from other important markets such as Thailand, Japan, Taiwan and Korea, their demand for U.S. soybeans will increase not only because the U.S. relative price of soybeans is more attractive but also to backfill soybean imports that were previously supplied by non-U.S. competing suppliers. In addition, other macroeconomic factors are at play that are not always represented in CGE models such as the ability of bilateral exchange rates to absorb part of the retaliatory tariff shocks. In the end, after the initial tariff shock works its way through global commodity markets, the price change will depend on both import demand elasticities of Chinese and other important soybean importing countries, and the export supply elasticities capturing the ability of U.S. and competing suppliers to reorient soybean exports to other markets.

China's imports of wheat, corn, sorghum, cheese and apples totaled 4.3 MMT (valued at $1.1 billion), 2.8 MMT ($602 million), 5.1 MMT ($1 billion), 0.11 MMT ($498 million) and 0.08 MMT ($127 million) in the global marketplace in 2017, respectively. The U.S. share of China's imports of these five commodities by volume was 36%, 27%, 94%, 12% and 40%, respectively. China's imports of beef products (fresh, chilled, and frozen) totaled 0.695 MMT valued at $3.07 billion. Starting June 2017, U.S. beef exports returned to China after a 13-year ban over mad cow disease (Bovine Spongiform Encephalopathy) that began in December 2003. Total beef imports from the U.S. amounted to 2,205 tons valued at $25 million after the market reopened in the second half of 2017. Mexico imported 0.137 MMT of beef products worth of $789 million in the world market in 2017, of which 80.4% was supplied by the U.S.

In 2017, China and Mexico imported 2.6 MMT (valued at $4.69 billion) and 1.1 MMT ($1.98 billion) of pork products, including all fresh, chilled, frozen, and prepared pork meats. Mexico is the largest volume market for U.S. pork accounting for one third of total U.S. pork and variety meat exports by volume and 24% by value in 2017 (US Meat Export Federation, 2018). The U.S. is the dominant supplier of pork and variety meats to Mexico representing nearly 89% by volume of Mexico's total pork imports. Unlike Mexico, the share of U.S. pork exports in the Chinese market stands at 13%. According to USMEF, Mexican and Chinese markets are important to U.S. pork producers as both countries purchase traditional meat cuts as well as pork cuts that are of lesser value to domestic consumers such as raw hams and "variety meats" like tongues, ears, snouts, livers and hearts.

China's wheat, rice, and corn imports are subject to an average applied in-quota tariff of 1% (65% out-of-quota), a 2% applied tariff on sorghum imports, and a 3% tariff on soybean imports. China's MFN tariffs on cheese, apples, beef and pork imports are 12%, 10%, 12% and 20%, respectively. With China's retaliatory tariffs, U.S. exports of these products will encounter an additional 25 percentage points above the normally applied MFN tariff, potentially forcing U.S. products to become the least price competitive compared to competing suppliers. Similarly, Mexico's retaliatory duties on pork would erase the important duty-free preferential tariff treatment the U.S. enjoys under NAFTA. Mexico's retaliatory duties on U.S. pork exports increased in two phases - to 10% until July 5, 2018, rising to 20% thereafter.[10]

III. Empirical Methods

The trade elasticity, or elasticity of substitution across sources of supply (i.e., the Armington Elasticity) has been frequently investigated despite difficulty in identification of this parameter (see for example, Feenstra 1994; Hummels 2001; Melitz 2003; Hertel et al. 2007; Romalis 2007; Chaney 2008; Kee et al. 2008; Hillberry and Hummels 2013; Feenstra et al. 2014; among others). Trade elasticities are often categorized into two groups based on a nested Constant Elasticity of Substitution (CES) preference structure. First, "macro" elasticities identify the ease of substitution between domestic and a composite import good. That is, how easily can the representative consumer in the importing country shift consumption between domestic and imported goods as relative prices change? The second, and perhaps more important elasticity parameter for policy scenarios, is often called the "micro" elasticity capturing the degree to which importing countries can substitute between different export supply sources. Empirical findings from these studies have shown that the macro elasticity is significantly lower, typically close to unity, than the micro elasticity which is often estimated to be around 3 or 4. However, these estimates are sensitive to the estimation and identification method, the level of product aggregation/disaggregation, the countries included in the sample, and the sample period. As we demonstrate in some but not all estimations, the micro elasticity is also sensitive to relative preference margins vis á vis competing suppliers, the market concentration of imports, and whether importing countries belong to a common free trade agreement with export partner countries (i.e., U.S.-Mexico).

In this report, we focus on the micro elasticity - the import demand elasticity between different sources of supply. We assume relative price variation is driven by shocks to tariffs and relative preferential tariff margins whereby increasing applied tariffs or a less favorable relative preference margin leads to (export) supply changes along the demand curve (i.e. holding constant the level of demand in a given year) for a given importer-year-product market. In other words, we examine how the volume of import demand for agricultural products from different export sources changes in response to relative price changes as measured by applied tariffs directly and relative applied tariffs vis á vis competing suppliers. As explained

[10] It is also worth noting that Mexico's Ministry of Economy announced the opening of a 350,000 metric ton duty-free quota on imported pork leg and shoulder cuts (bone-in and boneless) that will be in effect through the end of 2018. The quota is open to Mexican pork processors and imports can be sourced from any country eligible to export pork to Mexico. It remains to be seen whether this strategy is an effort to diversify export suppliers away from the U.S. or whether the U.S. will be able to continue accessing the Mexican import market for pork at the favorable in-quota tariff rate.

in the next section, we use applied tariffs matched to trade data to provide updated micro import demand elasticities of grains, oilseeds, cotton, cheese, apples, beef and pork products for the most recent seven years from 2010-2016.

Our theoretical model is based on a two-level nested CES preference in Armington structure. The aggregate demand for commodity k in importing country j, Q_k, is modeled as being a CES function of domestic (Q_{kH}) and imported (Q_{kF}) goods in the first level, while imports from different countries (q_{kc}) are combined in a CES function in the second level:

$$Q_k = \left(b_{kH} Q_{kH}^{\theta_k^D} + b_{kF} Q_{kF}^{\theta_k^D}\right)^{\frac{1}{\theta_k^D}}, \quad \theta_k^D = \frac{\sigma_k^D - 1}{\sigma_k^D}$$
$$Q_{kF} = \left(\sum_c b_{kc} q_{kc}^{\theta_k}\right)^{\frac{1}{\theta_k}}, \quad \theta_k = \frac{\sigma_k - 1}{\sigma_k} \qquad (1)$$

The parameters b_{kH} and b_{kF} represent commodity-specific preference weights on domestic versus imported goods, and σ_k^D is the macro elasticity of substitution between domestic and imported sources of good k in country j. b_{kc} represents the technology and other taste-specific characteristics for commodity k imported from exporting country c, and σ_k is the micro elasticity of substitution among imports from different exporters.

Focusing on the micro elasticity in the second level and suppressing the agricultural commodity *k* subscripts to ease of notation, the import demand equation for importer j from a particular exporter i can be derived and written as follows:

$$q_{ij} = (b_i)^{\sigma} \left(\frac{p_{ij}}{P_j}\right)^{-\sigma} E_j \qquad (2)$$

where q_{ij} is the bilateral trade volume between exporting country i and importing country j for commodity k; p_{ij} is the landed destination price of the exporter's commodity k sold in importing market j, it can be rewritten via the price linkage equation as $p_{ij} = p_i(1 + \tau_{ij})$ where p_i is the factory gate prices charged by exporter country i that are invariant with respect to destination markets; τ_{ij} includes tariff and trade costs that are specific to commodity *k* and vary bilaterally; $P_j = \left(\sum_i b_i^{\sigma}(p_{ij})^{1-\sigma}\right)^{1/(1-\sigma)}$ is the CES price index over multiple sources for the importing country j; and E_j denotes total import expenditure for the importing country j on commodity k.

Multiplying by landed destination prices $p_{ij} = p_i(1 + \tau_{ij})$ and taking the logarithm of equation (2) with the addition of time period subscripts to denote the panel nature of the data yields our baseline empirical model:

$$\ln V_{ijt} = \ln pq_{ijt} = \alpha_{it} + \alpha_{jt} + (1 - \sigma)\ln(1 + \tau_{ijt}) + \varepsilon_{ijt} \qquad (3)$$

$$\alpha_{jt} = \sigma \ln P_{jt} + E_{jt}$$

where V_{ijt} is the bilateral import of country j from exporter i, α_{it} and α_{jt} are exporter-specific and importer-specific time-varying fixed effects to control for all potential time-varying country-specific unobserved effects including exporter production capability (b_{it}), import expenditure (E_{jt}), multilateral prices and trade costs specific to each importing and exporting country such as non-tariff regulations that importing countries notify to the WTO and export taxes or subsidies that are independent of origin or destination market, respectively.

Note that in equation (2) the trade between exporter i and importer j depends on not only the bilateral trade cost p_{ij} but also on relative trade costs $\left(p_{ij}/P_j\right) = (p_i(1-\tau_{ij})/P_j)$, relative to multilateral prices with all partners in the rest of world in a given importing country j. Hence, to control for the tariff component of the relative trade costs, we incorporate an index of bilateral relative preferential margin (RPM) in the model measuring the advantage that an exporting country i has in exporting its commodity k to a destination country j compared to competing exporters (not including i) in that market (Hoekman and Nicita 2008; UNTCAD 2011).

Specifically, the formula for calculating RPM is written as:

$$RPM_{ij} = \left(1 - \frac{(1+\tau_{ij})}{\frac{1}{N-1}\sum_{r,r\neq i}(1+\tau_{rj})}\right), \quad i = 1, \dots, N \tag{4}$$

There are two ways to calculate the RPM. One is to use a trade share weighted average of the denominator in equation (4) to compute the average tariff faced by competing suppliers in j's import market, and the other method is to use simple averages of bilateral tariffs faced by competing suppliers. In this study, we use the simple-average RPM to avoid the endogeneity issues of zero trade flows associated with prohibitive tariffs. However, it is noted that the simple-averaged RPM should be viewed as the upper bound threshold of RPM values compared to an RPM based on trade weights.

The interpretation of equation (4) is straightforward. A positive valued (negative) RPM index implies that exporter i enjoys a relative tariff advantage (disadvantage) in its exports of commodity k to destination country j compared to its competing exporters ($r \neq i$) in a given import market. For example, the numerator in equation (4) is China's Most Favored Nation (MFN) tariff of 3% faced by U.S. soybean exports. The denominator is the counterfactual tariff if soybean exports were to originate from other competing suppliers, some of which enjoy duty free preferential tariff in China such as free trade agreement partners in the Association of Southeast Asian Nations (ASEAN), Chile, New Zealand, and more recently, Australia. The counterfactual average tariff on competing suppliers exclusive of the U.S. is 2.3% in 2017. The relative preferential margin is the difference between the simple-averaged preferential tariff imposed by China on U.S. soybeans and the counterfactual tariff, which is calculated as $1 - \frac{1+3\%}{1+2.3\%} = -0.68\%$. Thus, U.S. soybean exports to China exclusive of any retaliatory tariffs are disadvantaged, on average, as the RMP index is less than zero. If the tariff goes up from 3% to 28% because of China's retaliatory tariff of 25%, the corresponding RPM for U.S.

soybean exports to China is -25.12%, which implies a significant disadvantage for U.S. soybean suppliers when compared to competing suppliers.

In addition to relative tariff margins, we also control for market structure as some destination markets such as China's soybean imports are dominated by just a few exporters (the U.S. and Brazil) while other markets are comprised of many exporters. The market concentration index or Herfindahl-Hirschman index (HHI) is incorporated into the model estimation. For the importer j of commodity k, the index is calculated as $HHI_{jk} = \sum_i (s_{1jk}^2 + s_{2jk}^2 + \cdots + s_{ijk}^2 + \cdots)$, where s_{ijk}^2 is the square of importer j's share of commodity k imports from exporter i, $i = 1, \ldots, N$. The HHI increases as the number of competing suppliers in the destination market decreases and as the disparity in size between those suppliers increases. In other words, the HHI index is increasing in the market concentration of destination market j's imports of commodity k.

Econometric estimation of the commodity-specific micro trade elasticities follows the empirical implementation of gravity models in Hertel et al. (2007). Different from Hertel et al. (2007) which used trade and tariff/freight data from 1994 and 1990, respectively, (see Hummels 1999) and an identification strategy of within-sector variation in these trade costs, we collect more recent trade and tariff data to reflect current patterns in international agricultural trade. We use an identification strategy that exploits cross sectional variation in tariffs and relative preferential tariffs conditional on time-varying importer- and exporter-specific intercept shifters. With the proliferation of free trade agreements offering preferential tariffs and market access to member countries (Grant 2013; Grant et al. 2017), it is likely that a significant portion of agricultural trade can be explained by examining relative preference margins. Moreover, Hertel et al. (2007) aggregated import demand for all commodities in a GTAP sector, which include multiple HS 4- and 6-digit codes and used importer-by-commodity and exporter-by-commodity intercepts by stacking commodity imports for a given year. Instead, we estimate commodity-by-commodity equations in HS 4-digit (and some HS6-digit) codes to provide more specific micro elasticity estimates.

Finally, we improve on previous elasticity studies in the estimation strategy. Because the log of zero is undefined in equation (3), the dependent variable is limited to country-pairs where trade is strictly positive (Santos-Silva and Tenreyro (SST) 2006; Helpman, Melitz and Rubinstein 2008; Peterson et al. 2013; Grant 2015). However, if prohibitive tariffs or other unobservable non-tariff trade barriers exist, countries may not export to a given trade partner. This explains why zeros may exist in the trade data, but not for random reasons. The Poisson Pseudo-Maximum Likelihood (PPML) model is an appealing alternative that is robust to different patterns of heteroscedasticity and provides a natural way to address sample selection issues arising from the omission of zero trade flows (SST 2006, 2011; Yotov et al. 2016). Moreover, the PPML model is the preferred specification for structural gravity estimation in both partial (as in this study) and general equilibrium (Yotov et al. 2016). The PPML method estimates the gravity equation multiplicatively without taking the logarithm of V_{ijt} provided the conditional mean and variance are proportional.

IV. Data

Import value and quantity data for soybeans, corn, wheat, rice, sorghum, cotton, cheese, apples, pork and beef for the top 75 agricultural trading countries from 2010 to 2016 are collected from the UN Comtrade Database[11]. The bilateral Most-Favored Nation (MFN) tariff and average applied tariffs inclusive of numerous preferential rates operating within free trade agreements are collected from International Trade Centre – Market Access Map (ITC-MacMap) Database[12]. Other trade related variables (such as the bilateral distance, common border, common language, common regional trade agreement (RTA), etc.) are retrieved from Centre d'Etudes Prospectives et d'Informations Internationales (CEPII)[13].

Table 1 above presents descriptive summary trade and tariff statistics relating to China and Mexico's imports of the 10 products of interest in this study. As is shown in Table 1, the U.S. has been a significant export supplier of soybeans, wheat, corn and sorghum and to a lesser extent rice, cotton, cheese and beef to China, and almost all selected products in Mexico in the past five years. For example, shares of imports from the U.S. are generally higher than one-third in the Chinese market and over two-thirds in the Mexican market. Comparing the tariff rates in the two countries, we find that China has a more stringent tariff requirement than Mexico, especially for wheat, corn, rice and cotton (using out-of-quota tariff rates). However, the tariff schedule for soybeans, cheese, apples, beef and pork imports are relatively lower in China compared to Mexico on an MFN basis. On the other hand, the RPM indices for most U.S. products in China are almost always negative, implying that U.S. exports face a relative tariff disadvantage compared to other competing suppliers in the Chinese market. Conversely, in Mexico, the RPM index for all products are positive, indicating a strong relative preferential margin for U.S. agricultural products as a result of NAFTA compared to other suppliers in the Mexican market. The largest positive RPM values (exclusive of any retaliatory tariffs), in Mexico's import market are for cheese and wheat, reflecting relatively high MFN tariffs faced by competing exporters that do not enjoy any preferential tariff advantages in the Mexican market.

In column 6 of Table 1 we report the post-retaliatory RPM the U.S. would face after the implementation of China's 25% tariff on all selected products and Mexico's 20% tariff on pork. As expected, the U.S. RPM in China worsens, implying a more severe competitive price disadvantage for all products exported from the U.S. to China. Similarly, Mexico's imposition of a 20% retaliatory tariff on U.S. pork exports essentially erases all preferential advantage the U.S. has enjoyed under NAFTA.

In the final column we report the HHI index of market concentration in China and Mexico for each product impacted by retaliatory tariffs. In China, the average HHI for corn and sorghum imports are relatively high, meaning that China's imports of these two commodities are concentrated with fewer but larger export suppliers. The average HHIs for soybean, wheat, rice and beef imports are moderately concentrated while that for cotton, cheese, apples, and pork imports are relatively lower. Different from China, the average HHIs for all products except wheat are considerably higher in Mexico, implying a highly concentrated market environment given its proximity to the U.S. Given the diverse market structure and concentration levels in China and Mexico, we might expect the estimated trade elasticities for China and Mexico will be different, depending on their specific HHI. In other words, HHI

[11] https://comtrade.un.org/db
[12] http://www.macmap.org/QuickSearch/FindTariff/FindTariff.aspx?subsite=open_access
[13] http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.asp

will be one of the factors that may affect the estimated import demand elasticities and substitution possibilities.

Table 1: Summary statistics for China and Mexico imports and tariff details (2012-2016)

	Global Imports ($ million)	Imports from U.S. ($ million)	Avg. MFN Tariff (%)	Avg. Applied Tariff (%)	U.S. RPM (%)	U.S. RPM after Tariff Retaliation (%)	Avg. HHI (%)
				China			
Soybean	36,450	14,250	3.0	2.3	-0.62	-25.04	36.97
Wheat	1,123	434	65.0	1.0	-0.03	-24.79	41.33
Corn	1,020	595	42.5	0.5	0.00	-22.62	75.71
Rice	1,293	0.037	65.0	0.9	-0.11	-24.89	42.17
Sorghum	1,286	1,068	2.0	0.9	-0.07	-24.84	80.00
Cotton	5,874	1,775	16.1	15.2	-0.76	-22.51	26.67
Cheese	305	46	12.0	10.8	-0.01	-24.13	26.42
Apple	104	31	10.0	9.1	-0.02	-25.19	32.92
Beef	1,539	0.021	15.9	13.0	-3.15	-25.31	48.19
Pork	1,556	280	15.3	14.0	-2.20	-22.83	28.38
				Mexico			
Soybean	1,865	1,654	5.0	2.1	2.43	2.43	81.92
Wheat	1,237	844	45.0	42.3	30.29	30.29	51.39
Corn	2,519	2,376	3.0	2.4	2.39	2.39	90.02
Rice	371	317	2.5	2.2	2.24	2.24	74.33
Sorghum	224	191	0.0	0.0	0.00	0.00	87.56
Cotton	404	402	3.3	1.1	1.37	1.37	99.13
Cheese	481	375	71.7	62.5	39.90	39.90	52.70
Apple	393	275	20.0	10.0	5.42	5.42	90.71
Beef	856	739	22.9	10.6	10.66	10.66	64.23
Pork	1,273	1,126	16.7	6.1	5.95	-11.88	78.65

Notes: Most of listed products are reported in HS 4-digit codes, including soybeans – HS 1201, wheat – HS1001, corn – HS 1005, rice – HS 1006, sorghum – HS 1007, cotton – HS 5201, cheese – HS 0406, fresh apples – HS 080810, and fresh and frozen beef – HS 0201 & 0202 and select bovine products from 0206. Since Mexico imposed retaliatory tariffs on U.S. pork products consisting of HS 0203, 160241 & 160242, we report the trade and tariff details of these three HS codes. Average MFN tariff and average applied tariff are reported in HS 4-digit that aggregated from products in HS 6-digit codes where specified. For average MFN tariff on wheat, corn and rice imports in China, we report the average out-of-quota tariff rate. For average applied tariff on wheat, corn and rice imports in China, we report the average applied in-quota tariff rate. The calculation of U.S. RPM after retaliation is based on an additional tariff of 25% that China will impose on U.S. soybeans, wheat, corn, rice, sorghum, cotton and pork, and an additional tariff of 20% that Mexico will impose on U.S. pork products due to trade retaliation.

5. Discussion

The results are organized as follows. In the first sub-section we present the global commodity import demand elasticity results using direct and relative preferential tariff margins. The results are first presented without considering market concentration levels or possible interaction effects between tariffs and market concentration. These are contained in Table 2 along with robust standard errors to clustering on country-pairs. Tables 3 and 4 present the results with explicit controls for market concentration using the HHI index and the interaction of market concentration with tariffs and relative preferential margins. In subsection two, we use the tariff elasticity marginal effects to evaluate the predicted trade effects from changes in relative prices as they relate to tariff changes.

5.1 Estimated Trade Elasticities

Table 2 presents the estimated trade elasticities using direct applied tariffs and the RPM. All estimated coefficients are negative in the case of tariffs, as expected since higher tariffs reduce trade, all else constant, and significant at the level of 5% level. Conversely, the RPM coefficients are positive, as expected, and indicate that more advantages preferential margins in a given import market lead to higher levels of bilateral trade in each commodity holding all else constant. Recall that the trade elasticity, σ, equals one minus the estimated coefficient of tariff.

Table 2: Estimated trade elasticities using tariff or RPM

	Trade elasticities using tariff		Tariff elasticities using RPM		Obs.
	Est.	Std err.	Est.	Std err.	
Soybean	6.537*	(2.419)	6.643*	(2.733)	4512
Wheat	7.979***	(0.859)	8.983***	(1.044)	4884
Corn	13.005***	(3.502)	17.046***	(3.908)	7131
Rice	16.559***	(1.110)	17.026***	(1.166)	8402
Sorghum	29.170**	(8.582)	38.351***	(10.066)	1976
Cotton	4.738***	(1.114)	30.752***	(6.552)	4865
Cheese	8.683***	(0.599)	7.554***	(0.496)	10598
Apple	13.042***	(1.287)	14.168***	(1.043)	7607
Beef	8.865***	(0.366)	7.279***	(0.319)	8503
Pork	5.416***	(0.403)	5.107***	(0.417)	26052

Note: Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001. The model estimation includes HS 4-digit codes, mainly HS 1201, 1001, 1005, 1006, 1007, 5201, 0406, 080810, and 0201, 0202, 0203, and 0206.

In terms of commodity specific differences in trade elasticities, sorghum import demand is the most price elastic, suggesting that imports are the most sensitive to changes in import prices as they relate to tariffs. For example, a 1% change in the price of sorghum imports could lead to a 29.2% change on average in sorghum imports, which could be substituted by products from other importing sources. Corn, rice and apple import demand is also very elastic to changes in tariffs, with an elasticity of 13, 16.6 and 13, respectively. Soybeans, wheat, rice, cheese, beef and pork import demand are relatively less elastic ranging from 4.7 to 8.9 by exploiting variation

in applied tariffs, meaning that competition across sources of supply is not as "tough". Given the relatively large standard errors, the 95% confidence intervals suggest that the trade elasticity for soybeans could be as high as 8.9 or as low as 4.1 with a mean of 6.5, representing the large variation in our data sample.

Note that in order to draw policy implications from the estimated elasticities and possible tariff increases by 20-25% on U.S. products, we have to know something about the final relative price changes of U.S. products in China and Mexico which are likely significantly less than the initial tariff increase. This is because higher tariffs imposed by China and Mexico will lead to lower demand for U.S. products and thus lower origin prices. Further, as importing countries substitute away from US products and toward competing suppliers, demand for non-U.S. products increase effectively raising origin prices in competing suppliers. Thus, in the end, the tariff induced relative price increase on U.S. products will likely be much lower than the full 25% retaliatory tariff increase[14]. If, for example, the effective tariff-induced relative price of U.S. soybeans increases by 5% in the long run, China's demand for soybeans from the U.S. could drop by 32.7% (the 95% confidence intervals lie between 20.59% and 44.78%), suggesting a significant shift in China's soybean import profile.

As the tariffs faced by a given exporter increase, the RPM for that exporter relative to other sources decreases, making it less price competitive (i.e., a relative tariff disadvantage). Using RPM variation, we find that corn, rice, sorghum and cotton imports are quite sensitive to changes of relative tariff preferences. Recall from the discussion of equation (4), the RPM is a proxy for the tariff component of relative prices. The estimated relative trade elasticities in Table 2 range from 5.1 to 38.4 at the mean. Soybean, beef, pork and cheese imports are less sensitive to RPM changes, compared to the other commodities, with estimated trade elasticities ranging from 5.1 to 7.5. On average, there is more sectoral variation (and larger standard errors) in these estimated trade elasticities using RPMs than those using tariff, which is reasonable as a change in one tariff can lead to relatively larger changes in the RPM.

In Hummels (1999), they find significant estimates for over 90 percent of the products in 62 GTAP categories with an average value of 5.6, with most falling in range from 3 to 8 using ordinary least squares (OLS) estimates, and an average value of 9.3 using nonlinear least

[14] Taheripour and Tyner (2018) find that the price impacts of the 25% Chinese tariff on the U.S. agricultural products are limited, according to the simulation results obtained from the GTAP-BIO model. The U.S. producer price for soybeans drops by about 4% to 5% in response to the 25% Chinese tariff. The destination price for U.S. soybean exports to China thus increase by about 20%, less than the increase of the retaliatory tariff.

squares (NLS) estimates (GTAP 5 Database). The most recent release of GTAP (GTAP v9) the OLS estimated elasticities for oilseeds (osd), cereals (gro), wheat, rice, bovine meat products (ctl), vegetables fruits and nuts and dairy are 4.9, 2.6, 8.9, 10.1, 4.0, 3.7, 7.3, respectively. Using the same data while exploiting within-sector variation in tariffs and freight/transport costs in each of the 40 GTAP categories, Hertel et al. (2007) find the simple average of the 40 GTAP categories is 7.0 (GTAP 9 Database). Kee et al. (2008) use a semi-flexible translog GDP function approach to estimate the import demand elasticities over 4,900 HS 6-digit goods traded among 117 countries for the period 1988-2001. They find an average import demand elasticity of -3.12 (thus the elasticity of substitution would be 3.12) for a broad group of countries. Tokarick (2010) uses a general equilibrium model from international trade theory, which is similar to the GDP function approach in Kee et al. (2008), to estimate import demand and export supply elasticities for a large number of low, middle, and upper income countries in both short-run and long-run analysis (GTAP 6 and 7 Database for the year 2001 and 2004). He finds the overall import demand elasticity at the mean is -0.8 in the short-run and -1.1 in the long run. Our methodology follows closely Hummels (1999) and Hertel et al. (2007) using more detailed product descriptions. Our results are consistent with these studies although the elasticity estimates presented here are often much larger in absolute value compared to previous findings given the more disaggregated commodity specific focus of this study.

Table 3 presents the estimated trade elasticities using RPM variation interacted with HHI. Higher HHI scores implies lower market competitiveness (less competing suppliers) in the destination market while a lower HHI means high market competitiveness (more competing suppliers). In this section, we are able to consider how and to what extent the estimated trade elasticities vary at different market concentration levels in each destination market.

The results in Table 3 suggest that market concentration plays an important role in determining some of the trade elasticities, particularly in the estimation of soybean, wheat, cheese and beef trade elasticities where the interaction coefficient of RPM and the HHI index is statistically significant. In general, the more concentrated is the destination market (i.e., fewer suppliers competing in a given market reflecting a higher HHI value), the higher is the estimated trade elasticities of substitution (Table 3).

5.2 Predicted Trade Analysis

Interpretation of the coefficient of a dichromatic interaction term is straightforward while that of a continuous interaction term needs further examination. To better interpret the interaction terms and understand how market concentration affects trade elasticities, we plot the predictive margins at a given range of RPM with respect to different HHI levels in each product estimation (Figure 1 to 8 in the Appendix)[15]. The panel on the left depicts the average predictive margins of RPM change across all 75 agricultural exporting countries in the WTO. The panel on the right depicts the average predictive margins of RPM change

[15] Notably, the confidence intervals are omitted in these figures as our data sample exhibit very large confidence intervals given the large cross-sectional variation. Moreover, the variation of RPM (and tariff) are much smaller as compared to the variation of bilateral trade imports, thus, the predictive margins with extreme values of RPM are out of sample prediction very large confidence intervals.

over the top five exporting countries.

Table 3: Estimated trade elasticities using RPM interacted with HHI

	RPM		HHI		RPM # HHI		Obs.
	Coef.	Std err.	Coef.	Std err.	Coef.	Std err.	
Soybean	-7.361	(5.39)	0.426	(0.489)	21.661*	(9.406)	4512
Wheat	3.875	(2.474)	-0.15	(0.538)	11.794*	(4.873)	4884
Corn	14.591	(7.584)	0.254	(0.441)	3.842	(14.02)	7131
Rice	19.250***	(1.198)	0.111	(0.499)	-7.228	(5.467)	8402
Sorghum	46.545	(26.862)	-0.301	(1.079)	-10.274	(28.478)	1976
Cotton	30.703*	(13.276)	0.94	(0.694)	-0.318	(20.447)	4865
Cheese	3.694**	(1.177)	0.858	(0.806)	15.996***	(3.801)	10598
Apple	14.148***	(1.852)	0.152	(0.571)	0.033	(3.207)	7607
Beef	5.979***	(0.482)	-0.584*	(0.265)	5.775***	(1.733)	8503
Pork	6.380***	(0.85)	-1.149***	(0.236)	-3.213	(1.999)	26052

Note: Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001. The model estimation includes HS 4-digit codes, mainly HS 1201, 1001, 1005, 1006, 1007, 5201, 0406, 080810, and 0201, 0202, 0203, and 0206.

On average, the predictive margins of these imports are increasing in the RPM at all levels of HHI. When comparing the two panels in each figure, it is important to note that the magnitudes of predictive margins on the vertical axis are much greater for all graphs that only consider the top 5 exporters. For example, the average predicted imports for top 5 exporting countries are 2 to 10 times larger than the average predicted imports for top 75 country-pairs for a given change in the RPM and HHI.

At lower levels of the HHI, the change in the predictive trade margins are more stable for all listed products except rice and sorghum. As the importing market becomes more concentrated, however, the change in the predictive import margins become more significant. Looking closer, we find that there is a threshold RPM level for which the effect of market concentration on the predictive trade margins of soybean, wheat, rice, beef, apples and cheese imports reverses (i.e., the point of intersection). For example, when RPM is above the threshold, soybean, wheat, rice, cheese, apple and beef imports decline faster for a given decrease in the RPM for the average country-pair the higher is the market concentration in the importer market. For rice, sorghum, and apple imports, the predictive trade margins decline faster for a given fall in the RPM the less concentrated the importer's market is. Generally, as the destination market is more concentrated with fewer but larger suppliers, the predictive import margins will change more drastically for a given change in the RPM value provided the RPM is above the threshold. When RPM is below the threshold, for example in cheese imports, the predictive import margins are higher the less concentrated the destination market is.

From these figures we can see that, on average, trade declines quite rapidly for countries that enjoy positive RPM tariff preferences. For example, when the MFN tariff of 3% on soybeans is applied to U.S. soybean exports to China, the RPM for U.S. soybean exports to China exclusive of any retaliatory tariffs is -0.68%. However, once the retaliation is enforced and the tariff is increased to 28%, the corresponding RPM for U.S. soybean exports to China becomes -25.12%, which is an extreme disadvantage for U.S. soybean suppliers when compared to its competitors in China.

Figure 9 and 10 (in the Appendix) display the predictive margins of beef and pork imports with respect to different values of the RPM and HHI. Both the predictive margins of beef and pork imports in response to RPM changes tend to be larger if the importer's market is more concentrated. As the RPM decreases, the predictive beef and pork imports tend to decrease irrespective of the change in HHI. But the rate of decrease is declining. In other words, when the tariff becomes prohibitive, the predicted imports due to change of tariff (and RPM) will be small irrespective of the market concentration index. For example, when U.S. pork product exports to Mexico are duty free under NAFTA, the RPM for U.S. pork products is positive 5.95%, much greater than its competing suppliers in the Mexican market. However, if the retaliatory tariff of 20% is added, the corresponding U.S. pork exports to Mexico drops to a negative value of -14.45%, erasing the preferential advantage the U.S. enjoys in the Mexican market. In this case, predictive trade marginal effects of pork imports is significant as the RPM decreases from a positive value to a negative value.

To see how the Mexican tariff on U.S. pork could possibly wipe out the NAFTA benefit, we also plot the predictive margins of pork imports with respect to country adjacent status (ADJ=1 if the importer and exporter share a common border, otherwise zero) and regional trade agreement status (RTA=1 if they share a common regional trade agreement, otherwise zero).

In Figure 11 (in the Appendix) we can see that the predicted pork imports are significantly higher for the bilateral pairs that share a common border and those that share a common RTA. Typically, given zero tariff rate, the average predicted imports of pork products will be $135 million ($74.2 million) for bilateral pairs with a RTA (a common border), as compared to $28.5 million ($19.5 million) for those without a RTA (a common border). The benefits from having a common border and a common RTA gradually fade out as the tariff increases (RPM decreases). For instance, at the RPM of -14.45%, the average predicted imports of pork products become $24.4 million ($23.4 million) for bilateral pairs with a RTA (a common border), as compared to $8.9 million ($8.4 million) for those without a RTA (a common border). The retaliatory tariff imposed by Mexico on U.S. pork products will likely eliminate the benefits that the U.S. enjoys under NAFTA.

V. Conclusion

Trade elasticities are a significant determinant of the size and nature of trade adjustments to policy shocks that can influence a nation's terms-of-trade, welfare distribution, and productivity growth. Previous studies have examined the diverse methods and data coverage for estimating trade elasticities. However, many of them have not been updated to more recent trade data and more disaggregated product levels. In this report, we use recently collected tariff data to estimate trade elasticities of grains, oilseeds, cotton, pork, beef, apples and cheese which face tariff retaliation by China and Mexico against U.S. Section 232 and 301 of U.S. trade law.

Our results show that most of these crop and meat imports are significantly price elastic, and generally larger than what has been estimated previously. Thus, in today's trade environment for which China and Mexico are large players, the results suggest that products from different countries are quite substitutable with higher substitution effects among foreign sources in the destination markets as relative prices change. Further for some products, as the destination market becomes more concentrated reflecting fewer competing suppliers, their trade elasticities tend to be even higher and competition for market share increases.

Generally, the predictive margins of soybean, wheat, corn, rice, sorghum, cotton, cheese, apples, beef and pork imports decrease with increases in tariffs and decrease with less advantageous preferential margins at all levels of market concentration. Overall, trade declines quite rapidly for countries that enjoy positive RPM tariff preferences. Thereafter moving from smaller negative to larger negative RPM values results in less severe trade flow changes. At a given RPM, the average predictive margins of these imports are higher the more concentrated the destination market is. This means that market concentration affects our interpretation of trade elasticities and predicted trade changes and ignoring competition in market structure may lead to biased and inconsistent policy implications.

To put the above analysis in policy context, we also discussed how China's and Mexico's retaliatory tariff would impact their imports from the U.S. in the long run and how free trade agreements and country adjacent land border status can significantly affect trade as in the case of U.S.-Mexico relationship. Given the increase of China's tariff on U.S. grains, oilseeds, cotton, cheese, apple, beef and pork products, the corresponding RPM of U.S. product exports to China will decrease from marginally negative value to a more significant negative value, putting the U.S. in a much worse position in the Chinese soybean import market relative to its competing suppliers. Pairwise, given the increase of Mexico's tariff on U.S. pork products, the corresponding RPM of U.S. products will decrease from a large positive value to a negative value, leads to a significant drop in predicted trade between Mexico and the U.S. as relative prices change due to retaliatory tariffs. Moreover, due to the retaliation, the duty free benefit between Mexico and the U.S. under NAFTA would be eliminated.

In conclusion, our results are consistent and significant in accordance with the trade and import demand literature. Micro-based trade elasticities provide instructive policy implications for agricultural farmers and policymakers, and closely connects to the current debate of tariff retaliation. However, the estimated trade elasticities are not without some caveats. First, by utilizing the cross sectional tariff variation, we are able to estimate import demand elasticities on a global average. Second, in this analysis, we only consider the direct effect of tariff change without recognizing the indirect effect that may affect the trade value through other channels. For example, given the increase of tariff imposed on U.S. products, the market concentrations of these products in China and Mexico are likely to change as they may look for other importing sources to fulfill their large import demand. Instead, we simply hold the HHI fixed when calculating the predictions. Third, the RPM for all competing suppliers in a destination market will change as tariffs imposed by the importer changes. For simplicity, we hold the RPM fixed for all other competing suppliers and assume only the RPM for the U.S. as an exporter of interest is changing. However, this assumption should not alter the main conclusions of our results as the direction and trend of the predicted trade changes for a given change in the RPM are consistent.

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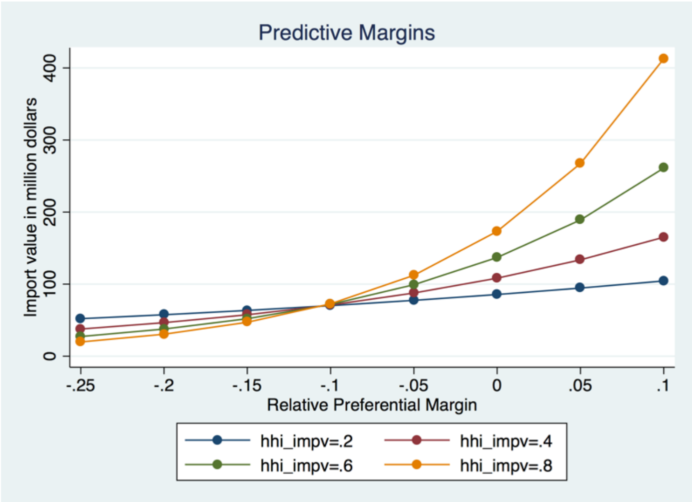
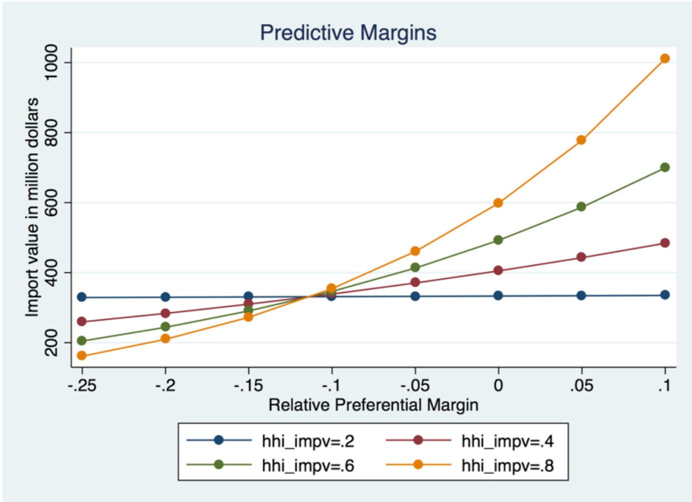
Appendix

Figure 1: Predictive Margins of Soybean Imports

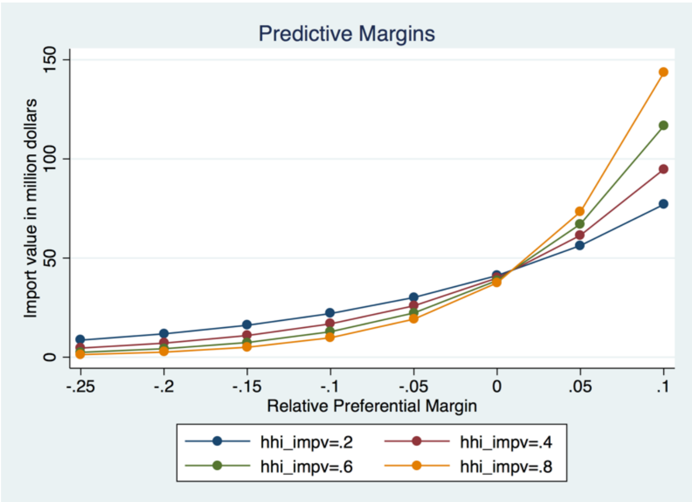


For top 75 countries



For top 5 exporters

Figure 2: Predictive Margins of Wheat Imports



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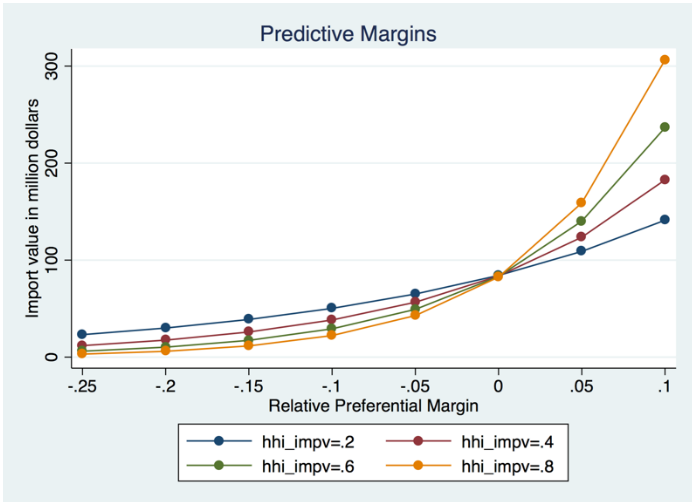
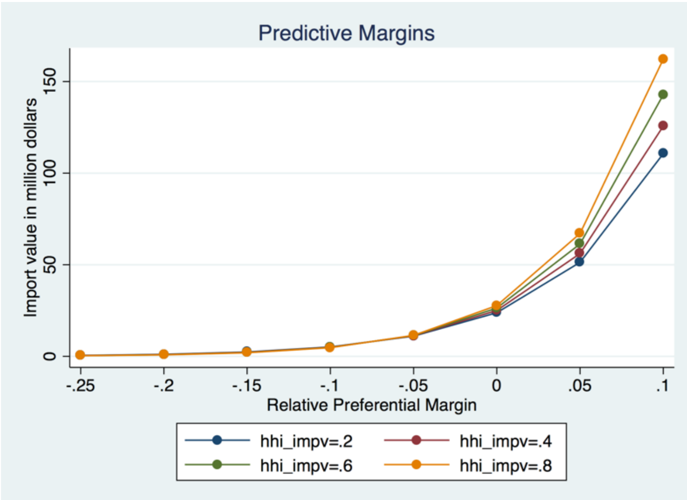


For top 5 exporters

Figure 3: Predictive Margins of Corn Imports



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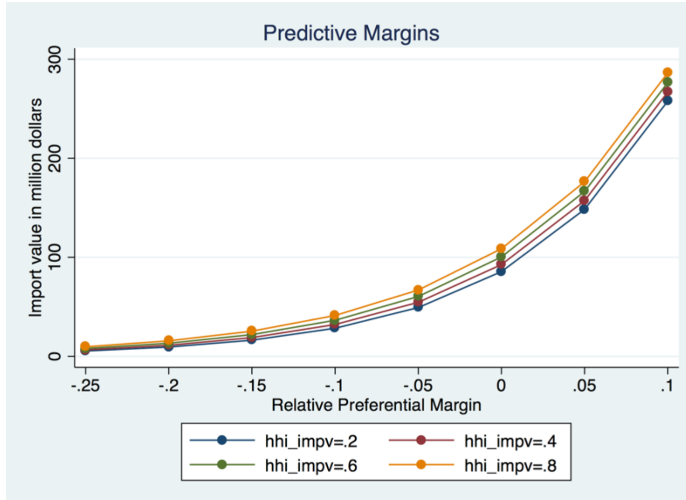
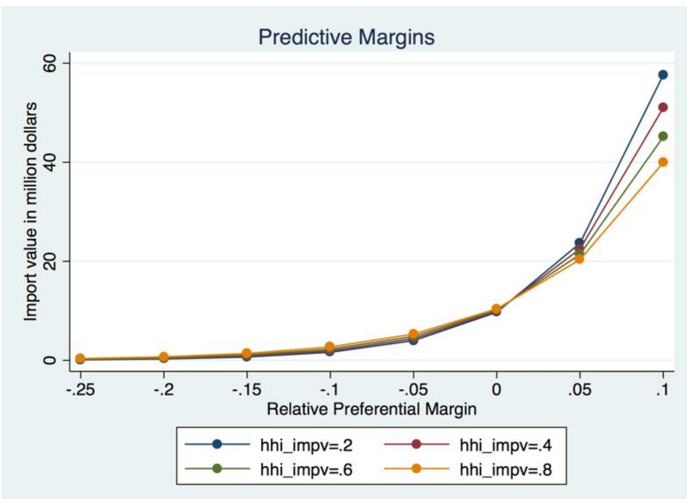


For top 5 exporters

Figure 4: Predictive Margins of Rice Imports



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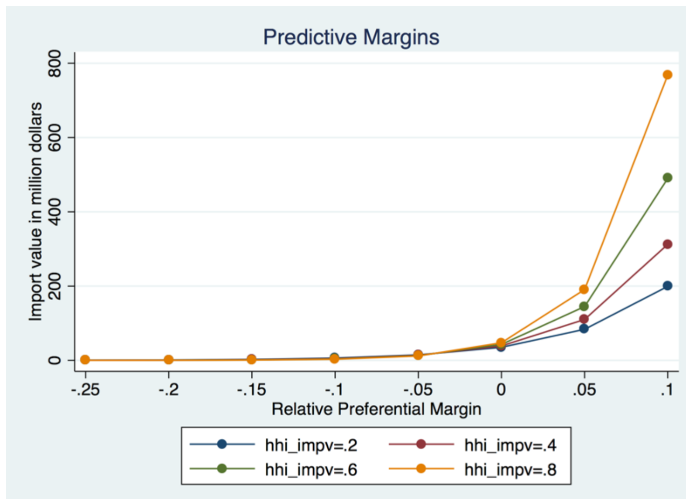
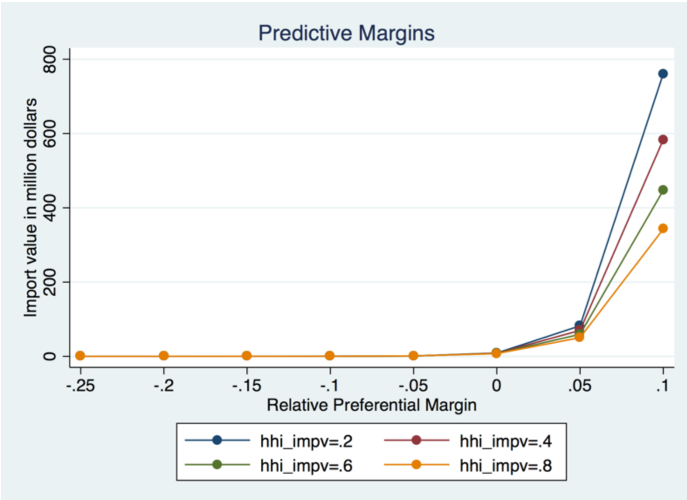
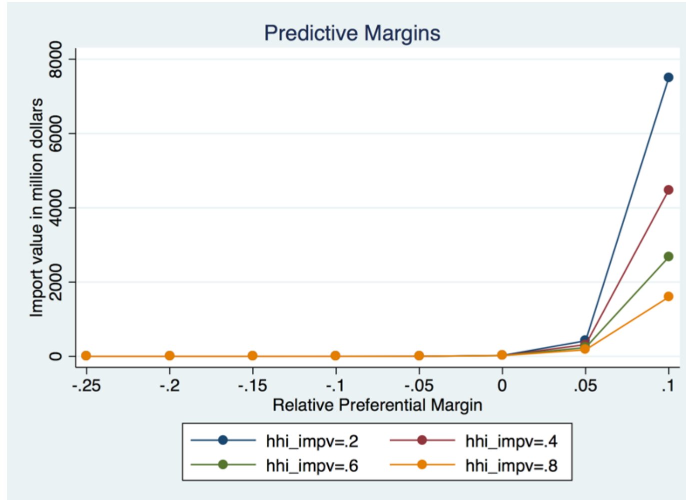


For top 5 exporters

Figure 5: Predictive Margins of Sorghum Imports

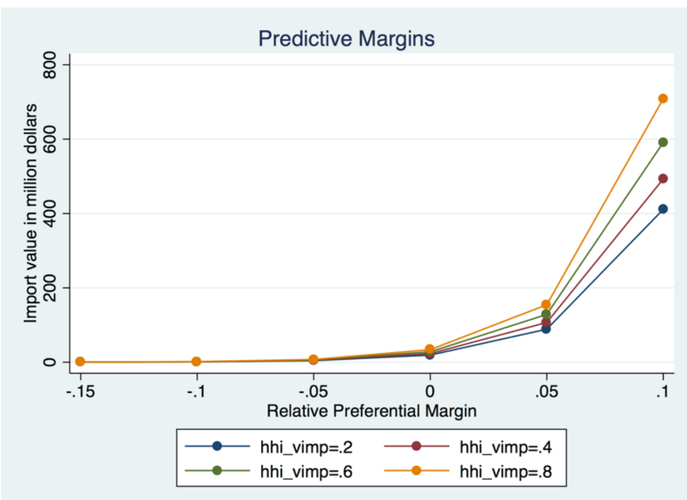


For top 75 countries



For top 5 exporters

Figure 6: Predictive Margins of Cotton Imports



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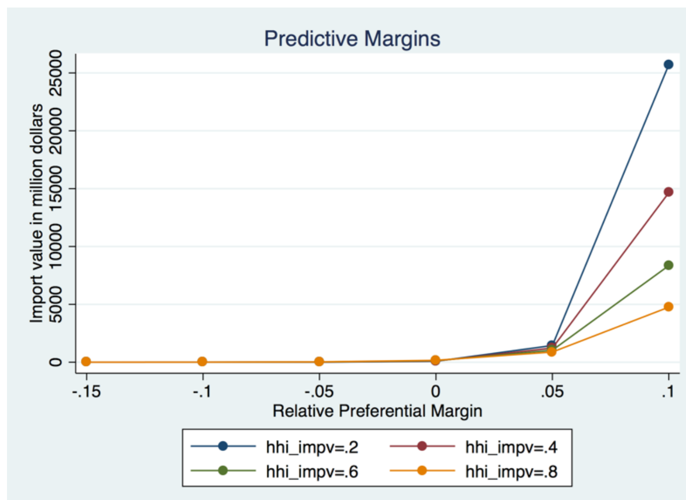
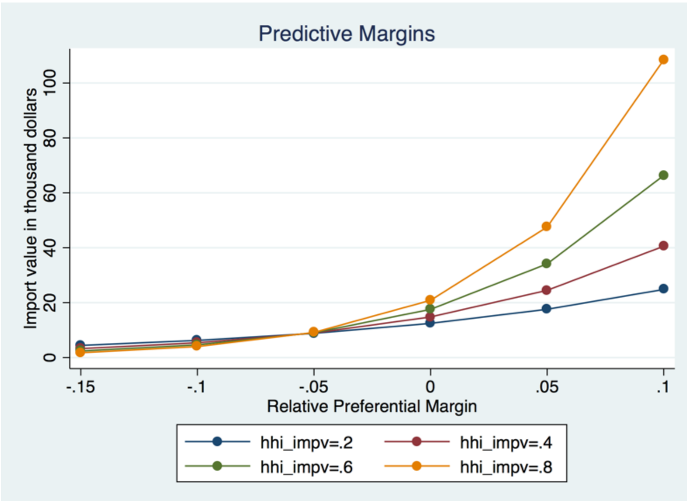


For top 5 exporters

Figure 7: Predictive Margins of Cheese Imports



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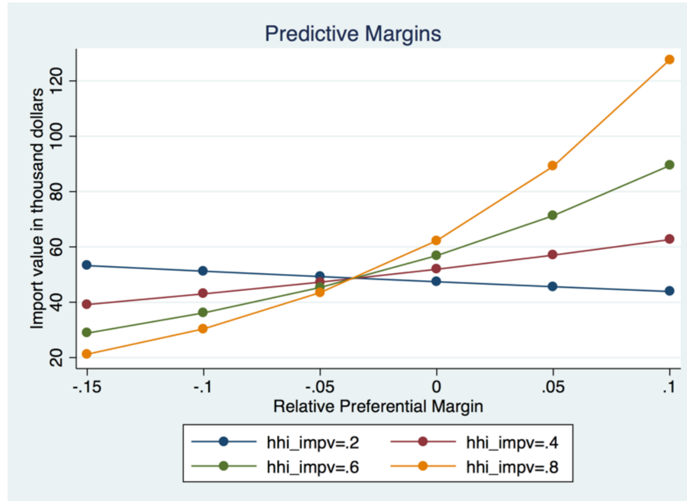
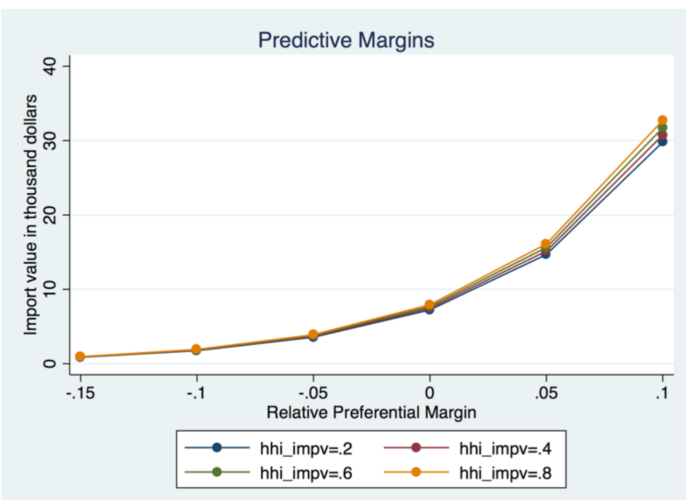


For top 5 exporters

Figure 8: Predictive Margins of Apple Imports



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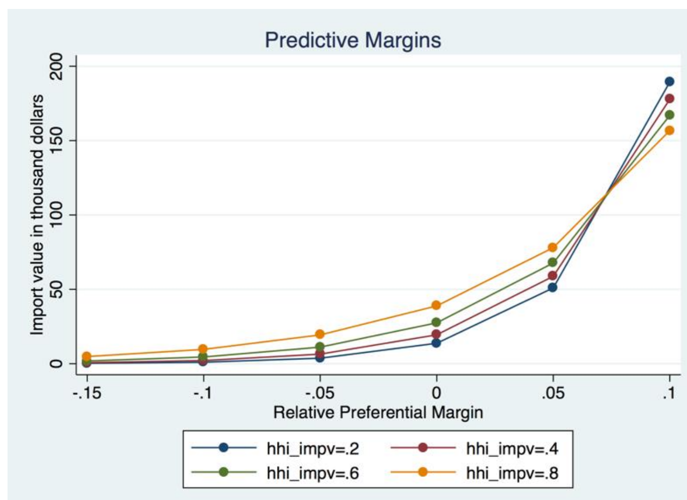
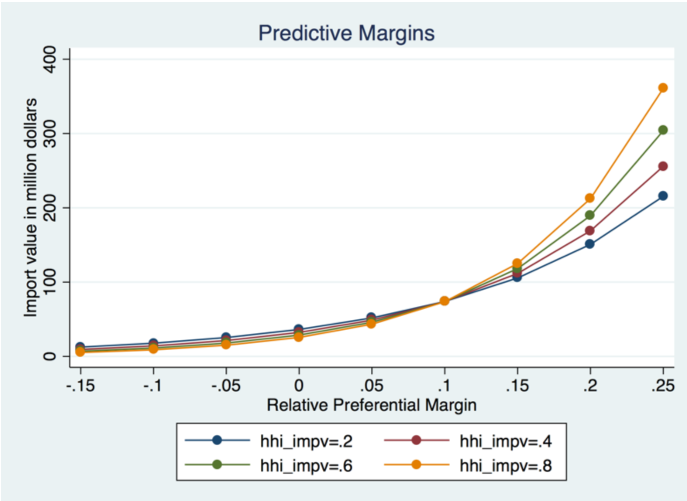


For top 5 exporters

Figure 9: Predictive Margins of Beef Imports



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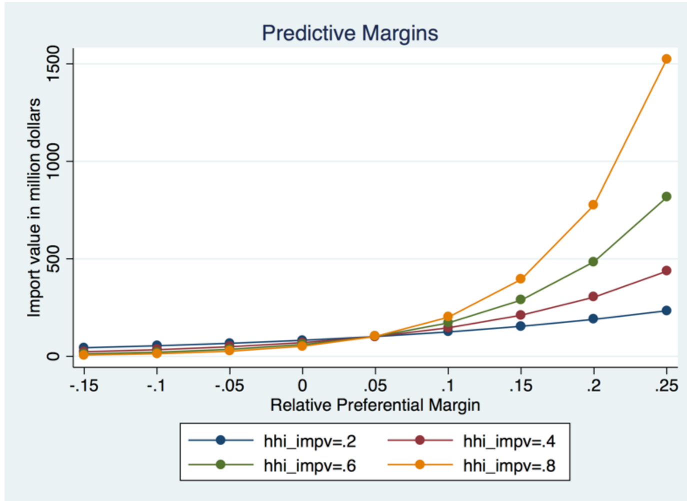
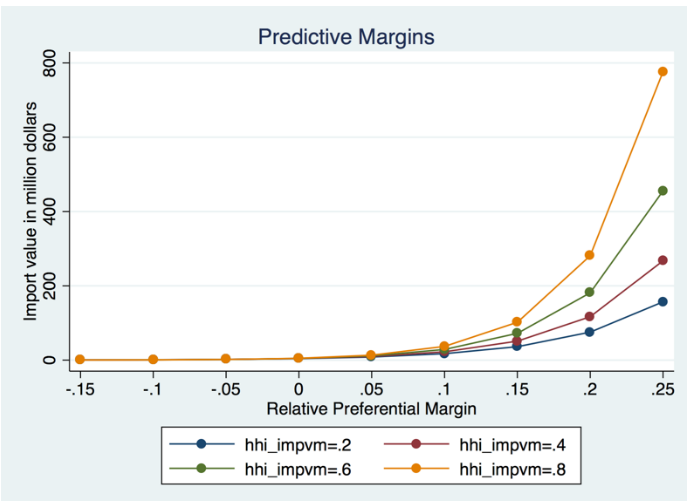


For top 5 exporters

Figure 10: Predictive Margins of Pork Imports



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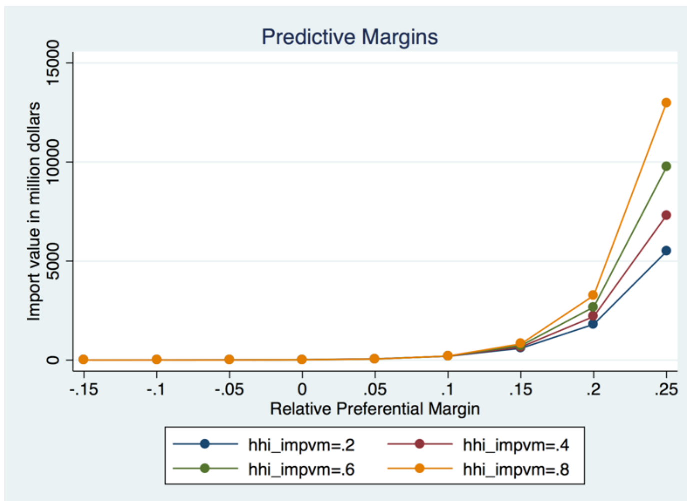
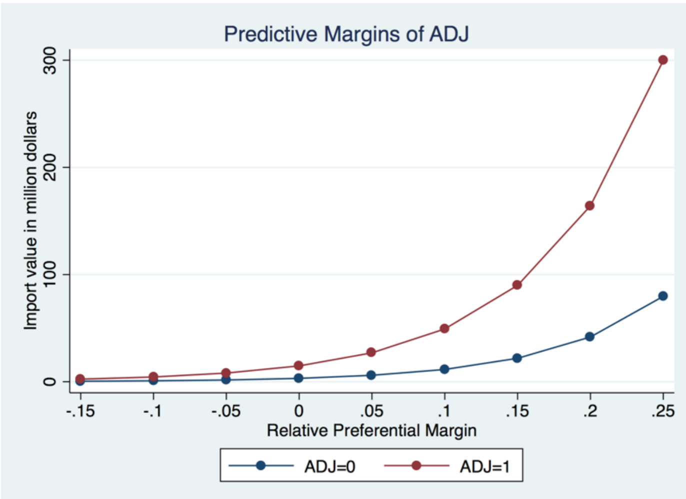


For top 5 exporters

Figure 11: Predictive Margins of Pork Imports based on ADJ and RTA



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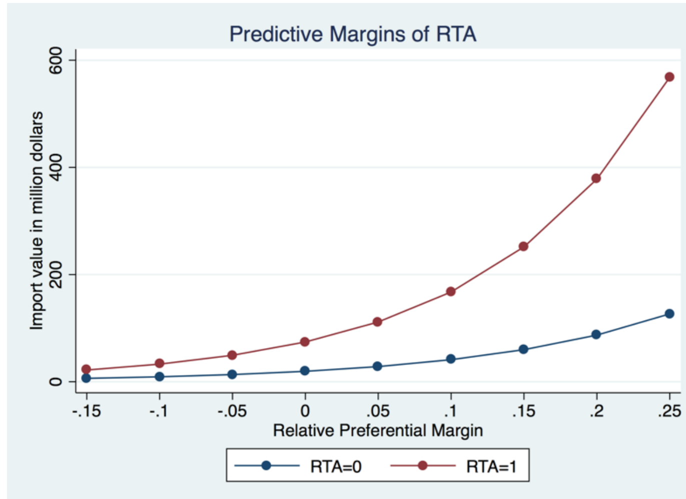

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