# Trade Elasticity: Estimates from Product-level Data

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**Abstract**

This paper estimates trade elasticity using bilateral tariff data for 64 importing and 137 exporting countries at product levels from 1996 to 2010. We use the Helpman et al. (2008) (HMR) two-stage approach that controls for self-selection and firm heterogeneity with many zero observations of trade flows. To apply the HMR approach at the product level estimation, however, we propose new exclusion restriction variables following the literature of search and learning in exporting markets as in Fernandes and Tang (2014). The empirical results show that there is substantial upward bias in the estimates of trade elasticity in most previous studies that only use positive trade flows. Proper accounting of zero trade flows and firm heterogeneity at the product level yields substantially smaller estimates of trade elasticity (i.e. the magnitude decreases from to ), which imply much larger welfare gains from trade. Also, sector-level estimations show that accounting for zero is important for sectors with higher-level technologies and more heterogeneous products.

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# 1 Introduction

Trade elasticity is a key parameter to quantify welfare gains from trade. As shown in Arkolakis et al. (2012) (denoted as ACR hereafter), for a broad range of trade models encompassing homogeneous and heterogeneous firm models, one can measure welfare gains from trade if two parameters are given: the import penetration ratio (or domestic share out of total expenditure) and the trade elasticity with respect to variable trade costs.[1] The import penetration ratio can be readily obtained from national statistics, whereas the trade elasticity is not directly observable and needs to be estimated. However, estimates of trade elasticity could vary significantly with model specifications and estimation methodologies even after taking into account of data differences in coverage of country and time. For instance, a survey by Anderson and van Wincoop (2004) find that elasticity estimates range from -5 to -10. This large range of elasticity estimates implies sizable discrepancy in the measured trade frictions and welfare gains from trade.

A lot of efforts have been spent on improving the estimation of trade elasticity over several decades (see e.g., Anderson, 1979; Harrigan, 1993; Baier and Bergstrand, 2001; Broda and Weinstein, 2006; Simonovska and Waugh, 2014a; Imbs and Mejean, 2015 and Ossa, 2015). ACR apply these estimates and the US's import penetration ratio of 0.07 as in year 2000 to their formula and obtain the US's gains from trade (from autarky to the then trade regime) lie between 0.7% and 1.4% of real income, assuming that the US economy was in equilibrium in year 2000. Given the importance of trade to modern economies, these welfare gain estimates seem to be rather small.

While many early studies on trade elasticity rely on country-level data, more recent studies are able to provide product-level estimates as disaggregate data have become more accessible. Simonovska and Waugh (2014a) and Caliendo and Parro (2014), which build on the Eaton and Kortum (2002) Ricardian model with geographic barriers, obtain sector-level elasticity estimates, but their estimates are not much different from those in the previous literature. Broda and Weinstein (2006) and Kee et al. (2008)

[1]Melitz and Redding (2015) show, however, that the trade elasticity is endogenously determined under heterogeneous firm models and the additional adjustment margin in heterogeneous firm models is not captured by the trade elasticity, so that the import penetration ratio and the trade elasticity are not sufficient to measure the welfare gains from trade in more general setting.

conduct structural estimations with disaggregate data using simplified demand and supply functions or Gross Domestic Product (GDP) functions. Although they provide much detailed information on the trade elasticity than earlier studies, their models have not taken into account the micro-level margins from firm heterogeneity in the new trade models. Ossa (2015) uses a method similar to Broda et al. (2008) that incorporates sectoral linkages across industries, and he shows that very small trade elasticity in just a few industries could contribute to significant overall welfare gains. Ossa (2015)'s average trade elasticity estimate across industries (which is equivalent to aggregate trade elasticity), -3.9, is at the lower end (in absolute terms, same for the rest of the paper) of the spectrum of the previous literature. However, this estimate still omits firm heterogeneity and implies a rather small welfare gain in overall economy. Imbs and Mejean (2015) show that the trade elasticity estimates from aggregate data would suffer from systematic downward bias (e.g. true estimate is -6 but biased estimate is -3). This indicates that welfare gains from trade should be even smaller if we consider products heterogeneity using disaggregate data. As Ossa (2015) stresses, with all the improvement in estimation techniques and data quality over time, elasticity estimates remain to be large and welfare gains to be small.

The objective of this paper is to provide an improved trade elasticity estimate using disaggregate tariff (as a variable cost) and trade flow data while accounting for firm heterogeneity, which is important in firms' export market entry decision at the product level. Our estimation results show that ignoring zero trade flows causes upward bias in the trade elasticity estimates, and the bias could be substantial if the portion of zero trade flows is large. Helpman et al. (2008) (denoted as HMR hereafter) argue that zero trade flows between countries are the result of heterogeneous firms' self-selection out of export markets and show that not accounting for these heterogeneous firm characteristics could cause bias in the gravity model estimations. Echoing the findings of Simonovska and Waugh (2014b) that the extensive margin observed in the new trade models reduces trade elasticity, we obtain smaller trade elasticity and thus larger welfare gains from trade by accounting for zero trade flows.[2]

HMR suggest a two-stage procedure that corrects for bias from omitting zero trade flows. The export

[2]Using year 2004 cross sectional data covering 30 countries Simonovska and Waugh (2014b) find that trade elasticity estimates in the Melitz model is 30 percent lower than in the Krugman model. The result is attributed to presence of an extensive margin of trade in the former, but not in the latter.

market entry decision is modeled in the first stage and the volume decision conditional on entering the market is modeled in the second stage. Their method has been well adopted in the gravity model literature and used widely in various contexts (e.g., Baier et al., 2014; Dutt et al., 2013; Cheong et al., 2015). The method requires exogenous variations (i.e. ER variables) that affect firms' entry decisions, but not their performance once they entered an foreign market.[3] Previous example of ERs (ERs) for aggregate data includes religion proximity (e.g. Helpman et al. (2008); Dutt et al. (2013); Cheong et al. (2015)), but its theoretical foundations could be questioned. Furthermore, this ER is not applicable for product level data, and finding ones that work at the product level data is even more challenging mainly due to data limitation. Very few country-pair-product-time varying variables are available in practice. To the best of our knowledge, tariff and trade flows are the only two variables that data are publicly available at the country-pair-product-time level covering substantial number of countries . However, we cannot use raw tariff and trade flows data as ER variables because they are the key explanatory and dependent variables, respectively, in the volume equation.

One of key contributions of the current paper is to propose new ER variables that allow us to extend the HMR approach to product level data. The variables of ER are derived based on the recent literature on search and learning in exporting markets as argued in Eaton et al. (2007), Eaton et al. (2014), Albornoz et al. (2012), Morales et al. (2011), Fernandes and Tang (2014), and Holloway (2017). In these papers, firms learn about their prospect in a prospective export market from at least two channels: i) performance of other countries/firms in the same market for the same product, and ii) their own performance in other destinations for the same product. Such learning about a prospective market's demand positively affects a firm's entry decision. But once a firm has entered a new market, it can directly observe the demand for its product and therefore does not need to infer from other firms' experience or their own experience in other markets to decide how much it should export to the market. We show that these variables based on learning past standard tests for exclusion restrictions after controlling for various unobserved factors. This methodological innovation is important because it opens up opportunities to apply the highly influential HMR approach to testing various trade theories using product level data.

[3]Recent theoretical studies like Chaney (2008) and Krautheim (2012) pay attention to the role of fixed costs in heterogeneous firms' decision in entering new export markets. Their conclusions are empirically supported by Koenig et al. (2010).

Building on the HMR model, we propose an empirical gravity model at the sector level. The trade elasticity is obtained from the response of trade flows to tariff changes using HS 2-digit data from year 1996 to year 2010 covering 64 importing and 137 exporting countries), which constitute changes in variable trade costs. For a given change in import prices, the source of the price change should be irrelevant to the demand outcome. But focusing on tariffs has the advantage that tariff data suffer less from measurement errors than other sources of variable trade costs such as transportation costs and information costs.[4]

Our main findings are as follows. In the case of HS 2-digit data, where zero trade flows are about 56%, the elasticity estimate decreases from -2.56 to -1.45 when accounting for zero flows. We apply the new elasticity estimates to the ACR formula for welfare gains from trade and show that for the US the gains increase substantially. The results imply that in evaluating the welfare effects of trade, it is paramount to consider zero trade flows.[5]

We further analyze heterogeneity of the trade elasticity for several sub-groups including the income level of pair countries, sectors and years. We also provide the trade elasticity estimates for each importing country in our sample. Our results find that the trade elasticity estimates are largest for trade between developing countries and smallest for trade between industrial countries, and the trade elasticity is larger for industrial countries, We also find that the trade elasticity increases over time in our sample. Lastly, we find that theres exist husge heterogeneity across sectors.

The rest of the paper is organized as follows. Section 2 extends the HMR model for disaggregate data and explains the new ER variables we derive from the learning literature. Section 3 describes the data. Section 4 reports the main results and Section 5 provides some extension. The last section concludes.

[4]Here we implicitly assume that price changes due to tariff changes represent any variable trade cost changes of an equal amount.

[5]To compute the total welfare gains with multiple sectors, we need additional data on the share of domestic expenditure, the share of consumption and employment for each sector as well as sectoral trade elasticity (see section 5.1 in ACR). We focus on trade elasticity average across industries, and we provide a simple numerical example to evaluate the welfare impact of trade liberalization.

# 2 The HMR Model for Sector Level Data

Firm-level heterogeneity has received attention in the recent international trade literature. Numerous theoretical and empirical studies, such as Eaton and Kortum (2002); Melitz (2003); Bernard et al. (2003); Das et al. (2007); Helpman et al. (2008); Hallak and Sivadasan (2009); Arkolakis (2010); Baldwin and Harrigan (2011); Roberts et al. (2012); Crozet et al. (2012); Johnson (2012); Kugler and Verhoogen (2012); Manova and Zhang (2012) among others, use firm heterogeneity to explain firms' export market entry decision and other trade patterns.[6] A key features of these papers is that the extensive margin of trade is determined by firm heterogeneity. As trade barriers changes, firms can start to entering export markets and this endogenous selection of firms into export markets can explain observed patterns of trade flows. Building on the Melitz (2003) model of heterogeneous firms under monopolistic competition, HMR develop an estimable equation using a truncated Pareto distribution of firm productivity to account for zero trade flows at the aggregate (i.e. national) level. For the estimation strategy, they suggest a Heckman (1979) type two-stage method, in which an inverse Mills ratio and related variables obtained from the first-stage Probit estimation are used to account for firm heterogeneity in the second-stage estimation of a gravity equation.

In this section, we extend the firm's entry decision model used for aggregate data in HMR to a model for disaggregated sector level data. Without loss of generality, we assume products are distinct across sector, and within each sector each firm produces one slightly different variety in a monopolistic competition environment. Therefore, there is a one-to-one mapping between varieties and firms.

Suppose that an exporting firm in sector $k$ from country $j$ faces the following demand for its product variety in destination $i$, $q_{ijk}$, under the monopolistic competition condition:

$$q_{ijk} = Q_{ik} \left( \frac{c_{jk}\tau_{ijk}}{\alpha_k P_{ik}} \right)^{-\gamma_k} N_{jk} V_{ijk}$$

[6] Firm heterogeneity due to numerous sources such as preference factors, production cost factors, quality factors and export fixed cost factors has been studied. In this paper, we do not distinguish the source of firm heterogeneity but focus on accounting for firm heterogeneity to obtain a consistent trade elasticity estimation.

$$V_{ijk} = \frac{\theta a_{kL}^{\theta+\gamma}}{(\theta+\gamma_k)(a_{kH}^{\theta} - a_{kL}^{\theta})} W_{ijk},\ W_{ijk} = max\{(\frac{a_{ijk}}{a_{kL}})^{\theta+\gamma_k} - 1, 0\}$$

where $Q_{ik}$ is the equilibrium market size of importing country $i$ for products in sector $k$; $c_{jk}$ is a measure of average product-specific productivity in sector $k$ of firms in country $j$; $\tau_{ijk}$ is the variable trade cost of firms in sector $k$ exporting from $j$ to $i$; $P_{ik}$ is the price index for sector $k$ in importing country $i$, determined by domestic producers and existing exporters selling in country $i$; the inverse of $a_k$ (i.e. 1/$a_k$) represents firms' productivity in sector $k$. Productivity is heterogeneous across firms within a sector and $1/a_k$ determines firm-productivity cut-off of exporting (with non-negative profit) in sector $k$. As in HMR, we assume that for each sector $k$, $G(a_k)$ has a truncated Pareto distribution with the support $[a_{kL,}a_{kH}]$, where $a_{kH}$ ($a_{kL}$) implies the lowest (highest) productivity in sector $k$, so that $G(a_k) = (a_k^{\theta} - a_{kL}^{\theta})/(a_{kH}^{\theta} - a_{kL}^{\theta})$, $\theta > \gamma_k$; $N_{jk}$ is the number of firms from country $j$ in sector $k$; $V_{ijk}$ and $W_{ijk}$ are a function of productivity cut-off which determines the proportion of country $j$'s firms in sector $k$ exporting to country $i$; and $\gamma_k$ is the import demand elasticity. Firms in country $j$ take $P_{ik}$ and $Q_{ik}$ as given.[7] Notice that cut-off productivity and demand elasticity is sector-specific and these variables are functions of sector level trade barrier.

Similar to HMR, we can write the volume of trade as follows. Under sector independence assumptions, we suppress $k$ for the sake of simplicity.

$$ln(q_{ij}) = \beta_0 + \lambda_j + \xi_i + \mathbf{x}_{1ij}\delta_1 + w_{ij} + u_{ij} \tag{1}$$

where for each sector $k$, $\lambda_j$ is exporter specific fixed effects (FEs), which subsume $ln(N_j)$ and $ln(c_j)$; $\xi_i$ is destination FEs, which subsume $ln(Q_i)$ and $ln(P_i)$; $\mathbf{x}_{1ij}$ includes all observed variables that could capture trade costs, including pair gravity variables such as distance, cultural ties, and colonial relationship, and pair-sector variables such as tariffs; $w_{ij}(= ln(W_{ij}))$ is a function of cut-off productivity that determines the fraction of firms in country $j$ exporting to destination $i$ for each sector; and $u_{ij}$ is an idiosyncratic error term. Effectively, the obtained equation for the volume of trade in eq.(1) is the same as HMR except

[7]For brevity, we skip the parts to derive a trade flow equation (i.e.$j$'s demand for product $k$ from $i$) from a representative consumer's utility function in $j$. For the details of the model, see Helpman et al. (2008).

that the cut-off productivity due to sector specific trade barriers differ by sector. As a result, we estimate eq.(1) sector by sector, and we need information on $\mathbf{x}_{1ij}$ and $w_{ij}$, which are specific to each sector, for the identification of sector specific parameters.

## 2.1 Model for the entry decision of a firm

For each sector, the selection of country $j$'s firms into market $i$ is determined by $V_{ij}$, which describes the cut-off productivity level for export market entry, $a_{ij}$. Now consider a latent variable $Z_{ij}$ which is defined as

$$Z_{ij} = \frac{(1-\alpha)\left(\frac{c_j \tau_{ij}}{\alpha P_i}\right)^{-\gamma} Q_i a_{ij}^{-\gamma}}{c_j f_{ij}} \tag{2}$$

where the numerator is the operating revenue and the denominator is the fixed costs of exporting. As long as $Z_{ij} > 1$, export accrues positive operating profits. We assume that for each sector the fixed costs of exporting are determined as follows:

$$f_{ij} = exp(\psi_j + \psi_i + \theta\sigma_{ij} - v_{ij})$$

where $\psi_j$ subsumes inherent factors specific to exporter $j$ that could affect their fixed costs of exporting; $\psi_i$ is destination specific factors that could affect the fixed costs; $\sigma_{ij}$ contains information on the fixed costs that are specific to both exporter $j$ and destination $i$; and $v_{ij} \sim N(0, \phi_v^2)$ capture remaining unobserved factors. The fixed exporting costs are stochastic due to unmeasured trade frictions $v_{ij}$ that are assumed to be i.i.d. but correlated with the errors ($u_{ij}$) in the second-stage estimation. We take logarithm of eq.(2) to obtain

$$z_{ij} \equiv ln(Z_{ij}) = \gamma_0 + \eta_j + \omega_i + \mathbf{x}_{ij}\delta - \theta\sigma_{ij} + \epsilon_{1ij}$$

where $\mathbf{x}_{ij}$ represents typical observed pair variables included in the gravity model; $\eta_j$ is exporter FEs, subsuming all $j$-specific variables including $c_j$; $\omega_i$ is importer FEs, subsuming all $i$-specific variables including $P_i$ and $Q_i$; $\sigma_{ij}$ is information on the (sector specific) fixed costs for firms in $j$ to export to $i$; and $\epsilon_{1ij} = \rho_0 u_{ij} + v_{ij} \sim N(0, \phi_u^2 + \phi_v^2)$, and it is assumed that $\rho_0 = 1$ for the sake of simplicity.

As $\sigma_{ij}$ is not present in eq.(1), it could be used as an ER for the identification of parameters in eq.(1). Implementation of the two-stage estimation requires observed factors in $\sigma_{ij}$ that vary with $ij$ and affect the fixed costs of exporting. We need an ER for $\sigma_{ij}$.

Using the Probit model, we could obtain $\rho_{ij} = Prob(q_{ij} > 0 | \eta_j, \omega_i, \mathbf{x}_{1ij}, \sigma_{ij})$ by:

$$\rho_{ij} = \Phi(\gamma_0^* + \eta_j^* + \omega_i^* + \mathbf{x}_{1ij}\delta^* - \theta^* \sigma_{ij}) \tag{3}$$

where $\Phi(\cdot)$ is a standard normal CDF. Let $\hat{\rho}_{ij}$ be the predicted probability from the Probit estimation of eq.(3) and $\hat{z}_{ij}^* = \Phi^{-1}(\hat{\rho}_{ij})$ be the predicted value of $z_{ij}^* = \frac{z_{ij}}{\phi_v}$.

Similar to HMR, we can use the Probit estimation of eq.(3) to obtain consistent estimates in the second stage by controlling for both the endogenous number and self-selection of $j$'s firms exporting to $i$ as in:

$$ln(q_{ij}) = \beta_0 + \lambda_j + \xi_i + \mathbf{x}_{1ij}\delta_1 + w_{ij} + u_{ij}$$

where $\omega_{ij}$ includes factors that determine the fraction of firms in sector $k$ exporting from $j$ to $i$. Therefore, we need the estimates for both $E(w_{ij} | q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$ and $E(u_{ij} | q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$. Both terms depend on $\bar{v}_{ij}^* = E(v_{ij}^* | q_{ij} > 0, \eta_j, \omega_i, \mathbf{x}_{1ij}, \sigma_{ij})$. It should be noted that $E(u_{ij} | q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i) = corr(u_{ij}, v_{ij}) \cdot \frac{\sigma_u}{\sigma_v} \bar{v}_{ij}^*$, and $corr(u_{ij}, v_{ij}) \cdot \frac{\sigma_u}{\sigma_v} = \rho_1$ where $v_{ij}^* = \frac{v_{ij}}{\sigma_v}$. Also, the estimate for $\bar{v}_{ij}^*$ could be obtained from the inverse Mills ratio (IMR), $\hat{\bar{v}}_{ij}^* = \frac{\phi(\hat{z}_{ij}^*)}{\Phi(\hat{z}_{ij}^*)}$. Furthermore, for the consistent estimate of $E(z_{ij} | q_{ij} > 0, \eta_j, \omega_i, \mathbf{x}_{1ij}, \sigma_{ij})$, we could use $\hat{z}_{ij}^* + \hat{\bar{v}}_{ij}^*$ and $\hat{\bar{w}}_{ij}^* = ln[exp(\alpha(\hat{\bar{v}}_{ij}^* + \hat{z}_{ij}^*)) - 1]$ for the consistent estimate for $E(w_{ij} | q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$.

Finally, we could estimate the second stage by using the following equation:

$$ln(q_{ij}) = \beta_0 + \lambda_j + \xi_i + \delta_1 \mathbf{x}_{1ij} + ln[exp(\alpha(\hat{\bar{v}}_{ij}^* + \hat{z}_{ij}^*)) - 1] + \rho_1 \hat{\bar{v}}_{ij}^* + e_{ij} \tag{4}$$

where $\alpha$ is a function of $\gamma$ as well as $\theta$; and $W_{ij} = Z_{ij}^{\alpha} - 1 = exp(\alpha z_{ij}) - 1$ is used to estimate $w_{ij}$ by taking logarithm of both sides of the equation. As long as an ER is available, we can implement eq.(3) to obtain $ln[exp(\delta(\hat{\bar{v}}_{ij}^* + \hat{z}_{ij}^*)) - 1] + \rho_1 \hat{\bar{v}}_{ij}^*$. Here $ln[exp(\delta(\hat{\bar{v}}_{ij}^* + \hat{z}_{ij}^*)) - 1]$ and $\rho_1 \hat{\bar{v}}_{ij}^*$ account for firm heterogeneity and self-selection of exporting at the sector level, respectively.

## 2.2 Exclusion restrictions at the sector level: Learning in exporting markets

The HMR approach requires one or more ERs that: (i) affect the fixed costs of exporting and more broadly entry decision at the sector level; and (ii) do not affect the volume of trade of product once an entrant becomes an incumbent in the export market.[8] Finding variables that meet these strict requirements at the aggregate level is already difficult, doing it at the sector level is imaginably far more challenging. In particular, at the sector level ERs have to be varying over pair-product-time. We are not aware of any readily available variables that are pair-product-time variant and satisfy the two criteria of ERs at the same time. To tackle this problem, we develop a number of new exclusion variables based on the recent literature on export learning.

Fernandes and Tang (2014) argue that a larger number or a faster growth of a country's neighboring exporters in a specific market could provide information about the market's demand for the country in concern. They show that the signal positively affects the country's entry decision. On the other hand, Eaton et al. (2007) and Eaton et al. (2014) show that learning from its previous export success affects a firm's incentive to search for more markets, and also that a firm's geographic expansion path depends on its initial destination markets. Morales et al. (2011) also find that a firm's entry to a new destination is positively affected by its previous export experience in geographically or economically similar markets. Similarly, Albornoz et al. (2012) and Holloway (2017) observe that a firm discovers its profitability as an exporter after actually engaging in exporting and decides whether to enter into new markets.

Based on this export learning literature, we assume that firms can learn about their demand in a potential new export market from three channels: i) their own experience in other markets for the same product; and ii) the performance of other countries in the same market for the same product. As regarding

[8] The first condition can be verified at the first stage of estimations using the Probit model and the F-test of partial correlation, but the second condition cannot be verified.

ER criterion (i), the signal firms refer from these sources can affect their entry decision into a potential export market. As regarding condition (ii), once a firm enters the new market, it can directly observe the demand for its product in this market, and therefore the indirect signal it obtained from other markets,or other countries could be irrelevant for its decision of the supply quantity for this market.

To capture the signal of the market demand for a product, we follow the specification of Fernandes and Tang (2014) to focus on the average export growth and the number of incumbents (or destinations). As such, we use the following information to generate sets of ER variables:

i. $\overline{q}_{jkt}$ (the average GDP-weighted export volume of product $k$ across all destinations excluding $i$ by country $j$)[9] and $N_{jkt}$ (the number of destinations excluding $i$ for country $j$ and product $k$);

ii. $\overline{q}_{ikt}$ (the average export volume of product $k$ by all countries excluding $j$ to destination $i$) and $N_{ikt}$ (the number of countries excluding $j$ exporting product $k$ to destination $i$).

Thus, we estimate the following specification in firm's new entry market decision:

$$\begin{aligned} 1(q_{ijkt} > 0) \quad = \quad & \Phi(\beta_1 ln(\overline{q}_{jkt}) + \beta_2 ln(N_{jkt}) + \gamma_1 ln(\overline{q}_{ikt}) + \gamma_2 ln(N_{ikt}) \\ & + \mathbf{Z}_{ijkt}\delta + \alpha_0 + e_{ijkt} \geq 0) \end{aligned} \tag{5}$$

where $\mathbf{Z}_{ijt}$ is a set of gravity variables and $e_{ijkt}$ is an error term. $\beta_s$ captures the effect from the signals from $j$'s own performance from other destinations for product $k$ at time $t$ and $\gamma_s$ captures the effect from the signals from performance of other countries in destination $i$ for product $k$ at time $t$.

# 3 Data

The dependent variable in our empirical analysis is bilateral trade flows, and the main explanatory variable is bilateral tariffs averaged at the HS 2 levels, respectively, from year 1996 to 2010 for 64 importing and 137 exporting countries, all of which are World Trade Organization (WTO) members. Our sample

[9] We first obtain the ratio of export volume of product $k$ by firm $j$ to a given destination $h$ as a proportion of the 1999 GDP of destination $h$, and then compute the average of the export to GDP ratio across all destinations excluding $i$.

Table 1: Sample statistics: Positive and zero trade flows

| | Aggregate, 1996-2010 | HS 2-digit,1996-2010* |
|---|---|---|
| Positive value only | 99,456 | 5,003,927 |
| Zero + positive value | 124,927 | 11,412,444 |
| Proportion of zero | 20.39% | 55.94% |

coverage, especially for importing countries is determined mainly by substantial tariff data availability. We use the HS 2 digit level data despite availability of the HS 6 digit level data to minimize computational problems caused by high dimensional FEs accounting for unobserved heterogeneity.

Trade flows are obtained from the UNCOMTRADE, and time-variant bilateral tariffs are obtained from the World Integrated Trade Solution (WITS). The sources of original tariff data are the UNCTAD Trade Analysis Information System (TRAINS) and WTO's Integrated Data base (IDB) and Consolidated Tariff Schedules (CTS) database. We use applied tariff data for entries with positive flows. However, for entries with zero trade flows, we use preferential tariffs from the UNCTAD TRAINS if available and Most Favoured Nation (MFN) tariffs for the rest. At the HS 6-digit level, MFN tariffs are used for more than 80% of the entries.

Data on nominal GDP and GDP per capita are drawn from the Penn World Table (PWT) 7.0, and data on GDP deflator are drawn from the U.S. Department of Commerce's Bureau of Economic Analysis. Preferential Trade Agreement (PTA) data are obtained from WTO's Regional Trade Agreements Information System (RTA-IS), and data on GATT/WTO membership are also drawn from the WTO website. Data on gravity variables such as distance, common language, common colony, common legal origin, and adjacency are sourced from the CEPII.

Table 3 shows that the proportion of zero trade flows for aggregate data in our sample is about 20%.[10] However, for for the HS 2-digit datafor those pair-product-time units with available tariff data, the proportions of zero trade flows is about 56% . If the omission of zero trade flows is a source of estimation bias, then it should be more important in practice to account for zero flows for estimations using disaggregate data than for those using aggregate data.

[10]The percentage of zero trade flows is relatively small partly because we restrict our sample to 64 importing and 137 exporting countries that have bilateral tariff data. Most of the countries with bilateral tariff data are relatively advanced countries with good records of trade statistics.

Table 2: Basic statistics: Trade flows, tariffs, and trade agreement dummy variables

| | Mean | SD | Mean\|Flow>0 | SD\|Flow>0 |
|---|---|---|---|---|
| Trade Flows (Imports) | 38,542.76 | 825,294.9 | 86,720.20 | 1,236,247 |
| Tariffs | 8.32 | 13.33 | 6.76 | 9.68 |
| Partial Scope Agreement (PSA) | 0.080 | 0.272 | 0.085 | 0.279 |
| Free Trade Agreement (FTA) | 0.093 | 0.290 | 0.080 | 0.272 |
| Custom Union (CU) | 0.016 | 0.124 | 0.033 | 0.178 |

Note: Basic statistics for trade flows and tariffs are obtained for disaggregate observations by HS2 sub-heading classification from 1996 to 2010 for 64 importers and 132 exporter countries pair. PSA, FTA, and CU statistics are obtained from aggregate observations.

Table 3 presents basic statistics for a few key variables. Three dummy variables are used to capture trade liberalization of various depth. The first two columns show the unconditional mean and standard deviation while the last two columns show the mean and standard deviation of variables conditional on positive trade flows. The statistics indicate that country pairs with positive flows tend to have lower tariff rates and are more likely to form stronger trade agreements such as free trade agrees (FTAs) and custom unions (CUs).

# 4 Estimations

## 4.1 Estimation with Aggregate Data

The first stage estimation with aggregate data follows eq. (3). For the second stage estimation to account for self selection and firm heterogeneity, we use the following trade flow equation derived from eq.(4):

$$ln(q_{ijt}) = \beta_0 + \lambda_{it} + \xi_{jt} + \mu_{ij} + \beta_1 ln(1 + tariff_{ijt}) + \mathbf{Z}_{ij}\delta + ln[exp(\delta(\hat{\bar{v}}^*_{ijt} + \hat{z}^*_{ijt})) - 1] + \rho_1 \hat{\bar{v}}^*_{ijt} + e_{ijt} \quad (6)$$

where $\mathbf{Z}_{ij}$ is subsumed when pair FEs, $\mu_{ij}$, are used; and the multilateral resistance terms (MRTs) are counted for using country-time FEs, $\lambda_{it}$ and $\xi_{jt}$. As in HMR, for $q_{ijt} > 0$ observations, we approximate $ln[exp(\delta(\hat{\bar{v}}^*_{ijt} + \hat{z}^*_{ijt})) - 1] + \rho_1 \hat{\bar{v}}^*_{ijt}$ using $\rho_1 \hat{\bar{\eta}}^*_{ijt} + \rho_2 \hat{\bar{z}}^*_{ijt} + \rho_3 \hat{\bar{z}}^{*2}_{ijt} + \rho_4 \hat{\bar{z}}^{*3}_{ijt} + \rho_5 \hat{\bar{z}}^{*4}_{ijt}$, where $\hat{\bar{\eta}}^*_{ij} = \frac{\varphi(\hat{z}^*_{ij})}{\Phi(\hat{z}^*_{ij})}$ is obtained from eq.(5). As for the ER, HMR first consider the bilateral regulation costs. However, besides a strong assumption of excludability in the model for trade volume, data availability is a problem. As a result, HMR resort to an index of religion proximity (between any pair), which is relatively easier to obtain, as a proxy for fixed trade costs.Following HMR, to construct an ER for the estimation for aggregate data we use four most popular religions, Christianity, Judaism, Islam and Buddhism using the data obtained from Maoz and Henderson (2013).[11] As the religion data are available only for every 5 years, we use the data from the closest previous year for a year where data is unavailable. For example, we use the year 2000 data for years 2001–2004. Because the ER changes only four times between pair countries in our sample period with not much variation of religion proximity per se,

The first and second-stage regression results with the aggregate data are shown in Tables 3 and 4, respectively. Column (1) in Table 4 presents the results from the log-linear estimator, column (2) presents the results from the HMR method. Both regressions include pair FEs and country-time FEs. The trade elasticity estimates of the two models are around -2.6 and not statistically different. These figures are smaller than those from the literature. It is worth mentioning that the coefficient estimate of the variable to control for self selection is not statistically significant. It may attribute to the fact that the ER changes only four times between pair countries in our sample period with not much variation of religion proximity per se. With relatively small missing proportion out of total observations (20%), it is possible that accounting for zero trade flows does not affect the trade elasticity estimate much.

## 4.2 Estimation with Product Level Data

Recall that the proportion of zero trade flows for HS 2-digit data is about 56%. Accounting for zero trade flows from self-selection and firm heterogeneity is particularly important if the response from zero flows to positive flows (i.e. at the extensive margin) due to tariff change is different from the response from one volume of positive flows to another volume of positive flows (i.e. at the intensive margin).

With product level panel data, our main estimation equation for pooled data (i.e. pooling over all sectors) is as follows:

[11] See HMR for the details on how to construct the variable.

Table 3: Aggregate data: 1st stage

| | (1)<br>HMR |
|---|---|
| $Contig$ | 0.806*** |
| | (0.079) |
| $Lang$ | 0.508*** |
| | (0.032) |
| $Com\_col$ | -0.588*** |
| | (0.040) |
| $lnDist$ | -0.126*** |
| | (0.016) |
| $lnGDP_i$ | 0.377*** |
| | (0.007) |
| $lnGDP_j$ | 0.200*** |
| | (0.005) |
| $lnGDPPC_i$ | 0.821*** |
| | (0.010) |
| $lnGDPPC_j$ | -0.025*** |
| | (0.008) |
| $PSA$ | -0.224*** |
| | (0.031) |
| $FTA$ | 0.099** |
| | (0.046) |
| $CU$ | -3.334*** |
| | (0.053) |
| $Religion$ | 0.689*** |
| | (0.031) |
| $Constant$ | -12.324 *** |
| | (0.194) |
| Num of Obs | 97,982 |

Notes: Time fixed effects are used. Cluster (pair) robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Aggregate data: 2nd stage

| | (1) Log-liner | (2) HMR |
|---|---|---|
| $ln(1+Tariff)$ | -2.633*** | -2.620*** |
| | (0.418) | (0.458) |
| $PSA$ | -0.204** | -0.300 |
| | (0.103) | (0.265) |
| $FTA$ | -0.019 | 0.030 |
| | (0.037) | (0.115) |
| $CU$ | -0.911*** | -1.985 |
| | (0.172) | (3.651) |
| $\hat{\bar{\eta}}^{*}_{ijt}$ | | 0.554 |
| | | (1.091) |
| $\hat{\bar{z}}^{*}_{ijt}$ | | 0.873 |
| | | (1.214) |
| $\hat{\bar{z}}^{*2}_{ijt}$ | | -0.483*** |
| | | (0.182) |
| $\hat{\bar{z}}^{*3}_{ijt}$ | | 0.080** |
| | | (0.033) |
| $\hat{\bar{z}}^{*4}_{ijt}$ | | -0.005** |
| | | (0.002) |
| $Constant$ | -20.073 | -25.164 |
| | (23.803) | (26.166) |
| Fixed Effects | $ij$, $it$, $jt$ | $ij$, $it$, $jt$ |
| Num of Obs | 86,320 | 77,674 |
| $R^2$ | 0.580 | 0.596 |

Notes: Cluster (pair) robust standard errors are reported in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

$$ln(q_{ijkt}) = \beta_0 + \lambda_{ijt} + \mathbf{x}_{ijt}\delta + \beta_1 ln(1 + tariff_{ijkt}) + \rho_1 \hat{\bar{\eta}}^*_{ijkt} + \rho_2 \hat{\bar{z}}^*_{ijkt} + \rho_3 \hat{\bar{z}}^{*2}_{ijkt} + \rho_4 \hat{\bar{z}}^{*3}_{ijkt} + \rho_5 \hat{\bar{z}}^{*4}_{ijkt} + u_{ijkt} \quad (7)$$

where we use only positive trade flows, i.e. $q_{ijkt} > 0$; $\mathbf{x}_{ijt}$ includes gravity variables as in the previous section but is subsumed when we include pair-year FEs, $\lambda_{ijt}$; and $\hat{\bar{\eta}}^*_{ijkt}$, $\hat{\bar{z}}^*_{ijkt}$, $\hat{\bar{z}}^{*2}_{ijkt}$, $\hat{\bar{z}}^{*3}_{ijkt}$ and $\hat{\bar{z}}^{*4}_{ijkt}$ are obtained from the first stage estimation of eq.(5) using the learning variables defined in Section 2.

In eq.(7), there is a distinct unobserved factor, $\lambda_{ijt}$ . It accounts for not only country level MRTs and pair fixed effects, but also any unobserved pair-time varying heterogeneity. Thus, firm heterogeneity factors that vary at $ijt$ levels are controlled for by FEs but heterogeneity factors that vary over $ijkt$ are controlled for by the HMR terms, $\hat{\bar{z}}^*_{ijkt}$, $\hat{\bar{z}}^{*2}_{ijkt}$, $\hat{\bar{z}}^{*3}_{ijkt}$ and $\hat{\bar{z}}^{*4}_{ijkt}$ .

For product level estimations, despite availability of more disaggregated HS 6-digit data, we use HS 2-digit data due to computational difficulties to control for FEs. Because our main objectives are to emphasize the importance of accounting for self selection and firm heterogeneity when zero trade flows are substantial and to introduce new ERs applied to the product-level estimations, using HS 2-digit data deliver both purposes.

Tables 5 presents the results from the first-stage estimation. In eq. (5) we construct additional ERs, similar to $\overline{q}_{ikt}$, $\overline{q}_{jkt}$ , $N_{ikt}$ and $N_{jkt}$ but those between pairs that share border and they are named as each ER_Contig. The estimates of all ERs are statistically significant and especially, the estimates of $\overline{q}_{ikt}$, $\overline{q}_{jkt}$ , $N_{ikt}$ and $N_{jkt}$ are all positive and statistically significant. It implies that the learning variables we have introduced increase the probability of trade between pair-countries for the specific product, $k$.

The estimation results from the second-stage are reported in Table 6. Columns (1) is the Log-linear estimation with In column (2), wherein HMR terms are included to account for zero trade flows. Both estimations include $ijt$ FEs. The trade elasticity estimate decreases from -2.6 to -1.5 and the HMR terms are statistically significant, indicating that the learning variables have explanatory power in the product level trade flow equationThe result implies that the trade elasticity is overestimated when zero trade flows, especially firm heterogeneity are ignored.

Table 5: HS 2-digit data: 1st stage

| | (1) |
|---|---|
| $Contig$ | 2.169*** |
| | (0.011) |
| $Lang$ | 0.599*** |
| | (0.003) |
| $Com\_col$ | 0.026*** |
| | (0.006) |
| $lnDist$ | -1.038*** |
| | (0.002) |
| $lnGDP_i$ | 0.057*** |
| | (0.001) |
| $lnGDP_j$ | 0.581*** |
| | (0.001) |
| $lnGDPPC_i$ | 0.255*** |
| | (0.001) |
| $lnGDPPC_j$ | 0.108*** |
| | (0.001) |
| $PSA$ | -0.552*** |
| | (0.004) |
| $FTA$ | 0.643*** |
| | (0.005) |
| $CU$ | -0.886*** |
| | (0.007) |
| $lnN_{ikt}$ | 2.566*** |
| | (0.003) |
| $lnN_{ikt}\_Contig$ | -0.278*** |
| | (0.002) |
| $ln\overline{q}_{ikt}$ | 0.074*** |
| | (0.000) |
| $ln\overline{q}_{ikt}\_Contig$ | -0.022*** |
| | (0.000) |
| $lnN_{jkt}$ | 1.407*** |
| | (0.002) |
| $lnN_{jkt}\_Contig$ | -0.714*** |
| | (0.003) |
| $ln\overline{q}_{jkt}$ | 0.059*** |
| | (0.000) |
| $ln\overline{q}_{jkt}\_Contig$ | 0.044*** |
| | (0.000) |
| $Constant$ | -16.181*** |
| | (0.025) |
| Num of Obs | 10,789,339 |

Notes: Time fixed effects are used. Cluster (pair) robust standard errors are reported in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 6: HS 2-digit data: 2nd stage

| | (1) Log-linear | (2) HMR |
|---|---|---|
| $ln(1 + Tariff)$ | -2.558$^{***}$ | -1.454$^{***}$ |
| | (0.106) | (0.102) |
| $\hat{\bar{\eta}}^{*}_{ijt}$ | | 0.004 |
| | | (0.017) |
| $\hat{\bar{z}}^{*}_{ijt}$ | | 1.658$^{***}$ |
| | | (0.052) |
| $\hat{\bar{z}}^{*2}_{ijt}$ | | 0.125$^{***}$ |
| | | (0.012) |
| $\hat{\bar{z}}^{*3}_{ijt}$ | | -0.022$^{***}$ |
| | | (0.001) |
| $\hat{\bar{z}}^{*4}_{ijt}$ | | 0.001$^{***}$ |
| | | (0.000) |
| $Constant$ | 5.890$^{***}$ | 0.660$^{***}$ |
| | (0.007) | (0.060) |
| Fixed Effects | $ijt$ | $ijt$ |
| Num of Obs | 4,203,747 | 4,203,747 |
| $R^2$ | 0.451 | 0.615 |

Notes: Cluster (pair) robust standard errors are reported in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

### 4.3 Senstivity Tests

In this section, we perform the sensitivity tests applying alternative ERs. Instead of using both sets of ERs from two channels; i) learning from exporter's own performance from other destinations; and ii) learning variables from exporter's own performance from other destination, we use only one set of ERs in the estimation. As long as one of them is valid ERs, our method can be justified thus accounting for zero trade flows using the HMR approach should reduce the trade elasticity estimate.

Table 7 reports the results of the first-stage estimation. Column (1) uses sets of ERs obtained from the signals from performance of other competing countries in the destination country for the exporting product and column (2) uses those from exporter's own performance from other destinations for the exporting product. Each set of ERs in both columns are statistically significant, indicating that the learning variables from both channels increase probability of exporting of the product.

The second-stage estimation results are presented in Table 8. Qualitatively the results remain the same as in that accounting for zero flows using the HMR approach reduce the trade elasticity estimates in both cases and they are statistically different from the Log-linear estimate in column (1), Table 6. One can also notice that the magnitude of the trade elasticity estimates decrease as the explantory power of sets of ERs are stronger at the first-stage estimation so that the trade elasticity estimate is the smallest when we consider signals from both channels. The estimate from column (2), Table 6 is the smallest where ERs are controlled for using the learning variables from both channels. .

## 5 Heterogeneity

In this section, we examine heterogeneity of the trade elasticity across various dimensions including income level by country-pairs, sectors and time. For the estimations following the HMR approach, we use ERs from both channels as in eq. (5).

Table 7: Senstivity Test, HS2-digit data:1st stage

| | (1)<br>Signals from $ikt$ | (2)<br>Signals from $jkt$ |
|---|---|---|
| $Contig$ | 1.710*** | 1.237*** |
| | (0.009) | (0.010) |
| $Lang$ | 0.636*** | 0.210*** |
| | (0.003) | (0.003) |
| $Com\_col$ | 0.136*** | -0.153*** |
| | (0.005) | (0.005) |
| $lnDist$ | -0.778*** | -0.959*** |
| | (0.002) | (0.002) |
| $lnGDP_i$ | -0.016*** | 0.233*** |
| | (0.001) | (0.001) |
| $lnGDP_j$ | 0.887*** | 0.262*** |
| | (0.001) | (0.001) |
| $lnGDPPC_i$ | 0.028*** | 0.913*** |
| | (0.001) | (0.001) |
| $lnGDPPC_j$ | 0.160*** | 0.006*** |
| | (0.001) | (0.001) |
| $PSA$ | -0.235*** | -0.923*** |
| | (0.003) | (0.003) |
| $FTA$ | 0.599*** | 0.577*** |
| | (0.004) | (0.004) |
| $CU$ | -0.989*** | -0.270*** |
| | (0.006) | (0.006) |
| $lnN_{ikt}$ | 3.060*** | |
| | (0.003) | |
| $lnN_{ikt}\_Contig$ | -0.170*** | |
| | (0.002) | |
| $ln\overline{q}_{ikt}$ | 0.035*** | |
| | (0.000) | |
| $ln\overline{q}_{ikt}\_Contig$ | -0.004*** | |
| | (0.000) | |
| $lnN_{jkt}$ | | 1.708*** |
| | | (0.002) |
| $lnN_{ikt}\_Contig$ | | -0.575*** |
| | | (0.003) |
| $ln\overline{q}_{jkt}$ | | 0.068*** |
| | | (0.000) |
| $ln\overline{q}_{jkt}\_Contig$ | | 0.041*** |
| | | (0.000) |
| $Constant$ | -16.095*** | -11.823*** |
| | (0.022) | (0.020) |
| N$umofObs$ | 10,789,339 | 10,789,339 |

Notes: Time fixed effects are used. Cluster (pair) robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Senstivity Test, HS2-digit data:2nd stage

| | (1) Signals from $ikt$ | (2) Signals from $jkt$ |
|---|---|---|
| $ln(1+Tariff)$ | -1.764$^{***}$ | -2.013$^{***}$ |
| | (0.111) | (0.089) |
| $\hat{\hat{\eta}}^{*}_{ijt}$-$ikt$ | 0.116$^{***}$ | |
| | (0.030) | |
| $\hat{\hat{z}}^{*}_{ijt}$-$ikt$ | 1.766$^{***}$ | |
| | (0.081) | |
| $\hat{\hat{z}}^{*2}_{ijt}$-$ikt$ | 0.083$^{***}$ | |
| | (0.023) | |
| $\hat{\hat{z}}^{*3}_{ijt}$-$ikt$ | -0.024$^{***}$ | |
| | (0.002) | |
| $\hat{\hat{z}}^{*4}_{ijt}$-$ikt$ | 0.001$^{***}$ | |
| | (0.000) | |
| $\hat{\hat{\eta}}^{*}_{ijt}$-$jkt$ | | 0.786$^{***}$ |
| | | (0.046) |
| $\hat{\hat{z}}^{*}_{ijt}$-$jkt$ | | 9.085$^{***}$ |
| | | (0.327) |
| $\hat{\hat{z}}^{*2}_{ijt}$-$jkt$ | | -1.054$^{***}$ |
| | | (0.119) |
| $\hat{\hat{z}}^{*3}_{ijt}$-$jkt$ | | 0.016 |
| | | (0.016) |
| $\hat{\hat{z}}^{*4}_{ijt}$-$jkt$ | | 0.002$^{**}$ |
| | | (0.001) |
| $Constant$ | 1.713$^{***}$ | -7.256$^{***}$ |
| | (0.082) | (0.267) |
| Fixed Effects | $ijt$ | $ijt$ |
| Num of Obs | 4,203,747 | 4,203,747 |
| $R^2$ | 0.537 | 0.644 |

Notes: Cluster (pair) robust standard errors are reported in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 5.1 Pair Heterogeneity by Income Level

High income households are in general less sensitive to price changes as compared to their low income counterparts. As such the trade elasticity of developed countries is likely to be smaller as compared to that from developing countries. Furthermore, products from the developed countries are likely to be more sensitive to price change as they are usually more expensive. To test these hypotheses, we classify countries by two groups, industrial and developing countries based on the membership of OECD in year 2010.

Table 9 shows the estimation results for trade among and between these two groups of countries. First four columns are the results from the Log-linear estimations and the last four columns are those from the HMR approach. As for the group names, the first represents the income category of the importing country and the second represents that of the exporting country. For example, Ind-Ind in coumn (1) indicates that the importing country is an industrial country and the exporting country is a developing country.

As found in the previous section, the trade elasticity estimates are overestimated (in absolute terms) in the Log-linear for all groups except for the case from the developing to the industrial. Among three groups with the negative trade elasticity, the trade elasticity estimate is smallest for trade between importers in developed countries and exporters from developed countries as shown in coumn (5), and largest for trade beween importers in developing countries and exporters from developed countries as shown in column (8). Also, as expected the trade elasticity estimates are larger if exporting countries are industrial countries.

The trade elasticity estimates from the developing to the industrials are of the wrong sign as shown in columns (3) and (7). These results imply that developed countries are not sensitive to change in price due to tariffs for the products from developing countries. It may happen if the consumers in industrial countries care product quality more, rather than small changes in prices if the imports are from developing countries.

Table 9: Heterogeneity by Income between country-pairs: HS 2-digit, 2nd stage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Log-liner | | | | HMR | | | |
| | Ind-Ind | Dev-Dev | Ind-Dev | Dev-Ind | Ind-Ind | Dev-Dev | Ind-Dev | Dev-Ind |
| $ln(1+Tariff)$ | -3.908*** | -4.023*** | 0.500*** | -7.660*** | -2.351*** | -3.177*** | 1.472*** | -6.309*** |
| | (0.234) | (0.219) | (0.160) | (0.225) | (0.237) | (0.209) | (0.137) | (0.240) |
| $\hat{\bar{\eta}}^*_{ijt}$ | | | | | -0.834*** | -0.028 | 0.198*** | -0.299*** |
| | | | | | (0.062) | (0.032) | (0.032) | (0.039) |
| $\hat{\bar{z}}^*_{ijt}$ | | | | | 0.174** | 1.103*** | 2.512*** | 1.429*** |
| | | | | | (0.079) | (0.159) | (0.078) | (0.113) |
| $\hat{\bar{z}}^{*2}_{ijt}$ | | | | | 0.371*** | 0.201*** | -0.013 | 0.168*** |
| | | | | | (0.017) | (0.048) | (0.019) | (0.030) |
| $\hat{\bar{z}}^{*3}_{ijt}$ | | | | | -0.034*** | -0.031*** | -0.014*** | -0.031*** |
| | | | | | (0.001) | (0.005) | (0.002) | (0.003) |
| $\hat{\bar{z}}^{*4}_{ijt}$ | | | | | 0.001*** | 0.001*** | 0.000*** | 0.001*** |
| | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Fixed Effects | $ijt$ | $ijt$ | $ijt$ | $ijt$ | $ijt$ | $ijt$ | $ijt$ | $ijt$ |
| Num of Obs | 758,689 | 706,673 | 2,178,637 | 559,748 | 758,689 | 706,673 | 2,178,637 | 559,748 |
| $R^2$ | 0.444 | 0.397 | 0.406 | 0.389 | 0.680 | 0.520 | 0.587 | 0.592 |

Notes: Cluster (pair) robust standard errors are reported in parentheses. $^*p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 5.2 Heterogeneity in Sectors

Although we use product-level data for our analysis, the results presented in Tables 6 and 8 are average effects over all products and therefore silent on any potential heterogeneous effects across sectors. As we use HS 2-digit data, in principle, we can estimate the trade elasticity for 97 HS 2-digit sectors which are known as ‘chapters’. However, due to burden to present the results for all 97 chapters, we use the category of ‘section’ in which each section may include multiple chapters. For HS data, products are categorized as 20 sections. The simple descriptions of each section are presented in Table 13 in Appendix..

Table 10 reports the results. Because several sections include only one chapter which represents ‘product $k$’ in our estimations, we use $ij, it$ and $jt$ FEs, instead of $ijt$ FEs. Our results show that heterogeneity across sectors are substantial. The trade elasticity estimates for Sections VIII and IX, and XV are among largest. These sectors include raw hides, skins, leather, wood, and base metals. The products included in these categories seem to commonly used as intermediate goods and relatively homogeneous products. The trade elasticity estimates for Sections I and XII are of wrong signs and statistically significant. They include animal products and footware. The result from the footware sector may in line with that from in columns (7), Table 9, the positive trade elasticty of the industrial importing countries from the developing exporting countries. Among the statitically significant and negative trade elasticity estmates, Sections IV, VI and XX are found smallest. They include prepared food, chemical products, furniture and toys, which are exported and imported mainly by industrial countries and relatively more differentiated products.

### 5.3 Heterogeneity by Years

We also provide the trade elasticity estimates for every year in our sample.In these estimations we use $ij$ FEs in order not to inclue time FEs. The results are presented in Table 11. It finds that the trade elasticity estimates are relatively very low and sometimes statistically not significant before year 2000. It also shows that the trade elasticity estimates are around 2 between years 2001 and 2006 with small fluctuations and have increased since years 2007 when the global financial crisis begun and are kept high until year 2010.

### 5.4 Welfare Implication

Arkolakis et al. (2012) show that for a range of trade models, including the Armington model and new trade models with micro-foundation like Eaton and Kortum (2002) and Melitz and Ottaviano (2008), the welfare gains from trade (compared to autarky) can be simply computed as $(1 - \lambda^{-1/\phi})$, where $\lambda$ is the share of expenditure on domestic products and $\phi$ is the elasticity of imports with respect to variable trade cost. According to Anderson and van Wincoop (2004), the trade elasticity estimates range from -5 to -10. More recent studies using disaggregate data such as Ossa (2015) and Simonovska and Waugh (2014a) find the trade elasticity slightly lower than the upper bound of those in the literature, close to -4.

In Table 5.4, we provide calculations for welfare gains from trade using an example of the US in year 2000 following Arkolakis et al. (2012). In year 2000, the share of expenditure devoted to domestic products for the US is 0.93. Using this value for $\lambda$, Arkolakis et al. (2012) illustrate that the percentage

Table 10: Heterogeneity by Sectors: HS 2-digit, 2nd stage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sec I | Sec II | Sec III | Sec IV | Sec V | Sec VI | Sec VII | Sec VIII | Sec IX | Sec X |
| $ln(1 + Tariff)$ | 3.621*** | -0.040 | 0.369 | -1.593*** | -10.621*** | -2.652*** | -19.083*** | -25.712*** | -17.104*** | 0.580 |
| | (0.181) | (0.182) | (0.529) | (0.169) | (2.071) | (0.323) | (1.418) | (1.034) | (1.522) | (0.933) |
| Fixed Effects | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ |
| Num of Obs | 173,115 | 351,599 | 43,163 | 352,356 | 126,233 | 468,951 | 121,347 | 124,343 | 112,544 | 143,074 |
| $R^2$ | 0.709 | 0.694 | 0.924 | 0.650 | 0.731 | 0.737 | 0.928 | 0.824 | 0.835 | 0.842 |
| | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
| | Sec XI | Sec XII | Sec XIII | Sec XIV | Sec XV | Sec XVI | Sec XVII | Sec XVIII | Sec XIX | Sec XX |
| $ln(1 + Tariff)$ | -13.604*** | 6.740*** | -6.099*** | -6.814*** | -15.518*** | -4.688*** | -5.727*** | -5.149*** | -0.167 | -3.669*** |
| | (0.326) | (0.538) | (0.530) | (0.673) | (0.421) | (0.793) | (0.629) | (0.847) | (1.101) | (0.668) |
| Fixed Effects | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ | $ij, it, jt$ |
| Num of Obs | 569,358 | 151,260 | 152,597 | 55,559 | 445,286 | 146,315 | 165,494 | 147,765 | 25,425 | 169,018 |
| $R^2$ | 0.753 | 0.849 | 0.899 | 0.940 | 0.737 | 0.964 | 0.816 | 0.901 | 0.919 | 0.907 |

Notes: Cluster (pair) robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 11: Heterogeneity by Years: HS 2-digit, 2nd stage

| | (1) 1996 | (2) 1997 | (3) 1998 | (4) 1999 | (5) 2000 | (6) 2001 | (7) 2002 | (8) 2003 |
|---|---|---|---|---|---|---|---|---|
| $ln(1+Tariff)$ | 0.107 | 0.125 | -0.227* | -0.133 | -0.143 | -2.399*** | -2.125*** | -1.918*** |
| | (0.109) | (0.106) | (0.120) | (0.106) | (0.115) | (0.149) | (0.166) | (0.156) |
| Fixed Effects | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ |
| Num of Obs | 168,481 | 204,876 | 218,115 | 258,824 | 266,865 | 294,784 | 258,239 | 278,708 |
| $R^2$ | 0.607 | 0.605 | 0.611 | 0.619 | 0.615 | 0.626 | 0.637 | 0.640 |
| | (9) 2004 | (10) 2005 | (11) 2006 | (12) 2007 | (13) 2008 | (14) 2009 | (15) 2010 | |
| $ln(1+Tariff)$ | -1.857*** | -2.236*** | -2.185*** | -2.615*** | -2.700*** | -2.666*** | -3.187*** | |
| | (0.161) | (0.160) | (0.167) | (0.174) | (0.147) | (0.144) | (0.160) | |
| Fixed Effects | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | $ij$ | |
| Num of Obs | 302,211 | 290,894 | 291,628 | 295,923 | 322,158 | 316,196 | 435,845 | |
| $R^2$ | 0.626 | 0.623 | 0.617 | 0.617 | 0.613 | 0.615 | 0.632 | |

Notes: Cluster (pair) robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

change in real income needed to compensate a representative consumer in the US for going from year 2000 back to autarky is 0.7% to 1.8%, based on the trade elasticity estimates found in the literature.

As we replace the trade elasticity estimates obtained from our estimation that account for zero flows in Table 6 , the US's gains from trade in year 2000 is revised to 4.72%(based on HS 2-digit data) substantially higher than the figures from the literature. Given that the estimates from the product level data tend to be larger as found in the literature (e.g. Broda and Weinstein (2006); Imbs and Mejean (2015) ), our results imply much higher welfare improvement compared to those from aggregate data in the literature. Unfortunately, our results from the aggregate data fail to verify this due to lack of good quality ERs.

It should be pointed out that in order to compute the total welfare gains with multiple sectors we need additional data on share of domestic expenditure, share of consumption and employment for each sector as well as sectoral trade elasticity (see section 5.1 in Arkolakis et al. (2012)). To deliver the main objective of this paper, we however focus on the average trade elasticity across sectors. The simplified numerical example serves to deliver the message that, to evaluate the welfare impact of trade liberalization, it is paramount to have an unbiased estimate of trade elasticity. Including zero trade flows and accounting for firm heterogeneity reduce the trade elasticity substantially and therefore lead to a much larger estimate of welfare gains from trade.

Table 12: Welfare calculation: Gains from trade

| Source | Trade elasticity | Gains from trade (trade in year 2000 back to autarky) |
|---|---|---|
| Literature lower bound | -10 | 0.72% |
| Literature upper bound | -4 | 1.80% |
| Aggregate with Log-liner | -2.6 | 2.75% |
| Aggregate with HMR | -2.6 | 2.75% |
| HS 2-digit with Log-liner | -2.6 | 2.75% |
| HS 2-digit with HMR | -1.5 | 4.72% |

Notes: In year 2000, $\lambda$ was 0.93 for the US.

# 6 Conclusion

In this paper, we estimates the trade elasticity at the product level. We adopt the HMR approach to account for a large portion of zeros controlling for self-selection and firm heterogeneity while introducing new ERs that are constructed using pair-time-product level trade data to extract the information on the signal from learning as in Fernandes and Tang (2014) and other search and learning literature.

We find upward bias in the estimates of the trade elasticity if the positive trade flows are used only. Proper accounting of zero trade flows and firm heterogeneity at the product level yields substantially smaller estimates of the trade elasticity (the magnitude decrease from -2.6 to -1.5), which imply much larger welfare gains from trade.

As documented in Anderson and van Wincoop (2004), the literature usually finds the trade elasticity estimates ranging from -4 to -10. With the US's import penetration ratio of 0.07 in 2000, a formula for gains from trade (from autarky) provided in Arkolakis et al. (2012) gives welfare gain between 0.7% and 1.8%. Given the importance of trade to modern economies, these welfare gain estimates considered as small. Our estimates with proper control for self-selection and firm heterogeneity implies roughly 4.7% of welfare gains from trade compared to autarky, which are much higher than figures previously provided in the literature.

We also provide the trade elasticity of heterogeneous groups across income level of country-pairs, sectors and time. As for the income level of importers, the estimates with HS 2-digit data show that bias from ignoring zero trade flows are substantial for every group. Our results also suggest that the trade elasticity is larger for developing countries, thus smaller welfare gains from trade compard to industrial countries. In addition, the trade elasticity is larger for imported products from the industrial countries. We further find that there is huge heteretogeneity across sectors. The products which are relatively homogeneous and more likely to be used as intermediates oberseve high trade elasticity while the products more likely to be traded between industrials countries and relatively more differential products observe small trade elasticity. We also find that the trade elasticity has increased since years 2007 when the global financial crisis begun and are kept high until year 2010.

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Table 13: HS Classification by Section

| HS Sections | HS 2-digit Codes | Simple Descriptions |
|---|---|---|
| Sections I | 01-05 | Animal Products |
| Sections II | 06-14 | Vegetable Products |
| Sections III | 15 | Animal or Vegetable Fats and Oils |
| Section IV | 16-24 | Prepared Foodstuffs |
| Section V | 25-27 | Mineral Products |
| Sections VI | 28-38 | Chemical Products |
| Sections VII | 39-40 | Plastic, Rubber |
| Sections VIII | 41-43 | Raw hides, Skins, Leather |
| Sections IX | 44-46 | Wood |
| Sections X | 47-49 | Pulp of Wood, Paper |
| Section XI | 50-63 | Textiles |
| Sections XII | 64-67 | Footwear |
| Sections XIII | 68-70 | Plaster, Glass |
| Sections XIV | 71 | Pearls, Precious stones |
| Sections XV | 72-83 | Base Metals |
| Section XVI | 84-85 | Machinery, Appliances |
| Section XVII | 86-89 | Vehicles |
| Section XVIII | 90-92 | Optical, Watches |
| Section XIX | 93 | Arms |
| Section XX | 94-96 | Furniture, Toys |