Trade Elasticity and Many Zero Flows: Estimates from Product-level Data

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Abstract

This paper estimates trade elasticities using bilateral tariff data at product levels (HS2-digit as well as HS6-digit) for 83 countries from 2001 to 2003. We extend the Helpman *et al.* (2008) approach that controls for self-selection and firm heterogeneity at aggregate level to the product level using the signals from learning in Fernandes and Tang (2014) as exclusion restrictions in two-stage estimation. The empirical results show that there is substantial upward bias in trade elasticities estimated with only positive flows. Proper accounting of zero trade flows and firm heterogeneity at product level yields substantially smaller estimates of trade elasticities (i.e. the magnitude decrease from -3.54 to -0.75), which imply much larger welfare gains from trade. Sector-level estimations also show that accounting for zero is important for various heterogeneous groups.

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1 Introduction

The 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 costs.[1] The import penetration ratio can be easily obtained from national statistics whereas the trade elasticity is not directly observable and needs to be estimated. However, the estimates of trade elasticity could significantly vary due to model specifications and estimation methodologies even after taking into account of data differences in coverage of country and time. For instance, Anderson and van Wincoop (2004) provide a survey using the elasticity estimates in previous studies which range from -5 to -10 and this implies sizable discrepancy in the measured trade frictionsand welfare gains from trade depending upon contexts.

An extensive number of studies in the trade literature have tried to provide improved estimates 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 with the US's import penetration ratio of 0.07 as in the year 2000 to their formula and obtain the US's gains from trade (from autarky to complete removal of tariff) lie between 0.7% and 1.4%, which means that given that the US economy was in equilibrium in 2000, for a representative consumer its real income should be compensated by between 0.7% and 1.4% if it moves to autarky. Given the importance of trade to modern economies, these welfare gain estimates considered as small.

While many studies in earlier period use country-level data mostly due to data limita-

[1] Melitz and Redding (2015) show, however, that the trade elasticity is endogenously determined under heterogeneous firm models and the additional adjustment margin in the 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.

tion, more recent studies have provided product-level estimates with the improved accessibility of disaggregate data. Simonovska and Waugh (2014a) and Caliendo and Parro (2014) which build on Eaton and Kortum (2002) 's model incorporating geographic barriers into a Ricardian model with a continuum of goods in many countries, obtain sector-level elasticity estimates, but their estimates are not much far from those in the literature. Broda *et al.* (2008) and Kee *et al.* (2008) use fairly disaggregate data that cover many countries to structurally estimate the elasticity based on simplified demand and supply functions or GDP functions. Even though they provide much detailed information on the trade elasticity compared to earlier studies, their models have not takein 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) in the sense that incorporating sectoral linkages across industries and shows very small trade elasticities in a few industries could contribute to overall welfare gains significantly. Ossa (2015)'s average trade elasticity estimate across industries (which is equivalent to aggregate trade elasticities), -3.9, is at the lower end of the spectrum of the previous literature. However, this estimate still misses the features of the new trade models with 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 not allowing heterogeneity across products would suffer from systematic downward bias in absolute value (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 heterogeneity and use aggregate 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 the disaggregate tariff (as a variable cost) and trade flow data while accounting for firm heterogeneity which is important in firm's export market entry decision at the product level. Our estimation results show that ignoring zero trade flows causes (upward in absolute magnitude) 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 firm's self-selection out of foreign/export markets and show that not accounting for these heterogeneous firm characteristics could cause bias in the gravity model estimations. Like Simonovska and Waugh (2014b) that provide further evidence that the extensive margin observed in the new trade models reduces trade elasticities and significantly increases welfare gains from trade, we also obtain smaller trade elasticities by accounting for zero trade flows.

HMR suggests a two-stage procedure that account for bias from omitting zero trade flows. Export market entry decision is estimated in the first stage and volume decision conditional on entering the market is estimated 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). However, this method is difficult to implement with product level data mainly due to data limitation. It is because we need exogenous variations (i.e.exclusion restriction variables) which affect the firm's entry decisions at the product level, but not their performance once they entered the exporting market.[2] First of all, very few country-pair-product-time varying variables are available in practice. Up to our knowledge, tariff and trade flows are only two variables that vary over country-pair-product-time. Second, we cannot use raw tariff and trade flows data as exclusion restriction variables because they are the key explanatory and the dependent variables respectively, and must be included in volume/outcome equation.

To circumvent this data issue, we propose new exclusion restriction variables that allow us to extend the HMR approach to sector level while accounting for firm's fixed costs of exporting. The variables of exclusion restriction is obtained by transforming trade flows at the product level. The justification of proposed exclusion restrictions rely upon the recent literature on search and learning in exporting markets as argued in Eaton *et al.* (2007), Eaton

[2]Recent theoretical studies like Chaney (2008) and Krautheim (2012) pay attention to the role of fixed costs in heterogeneous firm's entry decision in new export markets, which is empirically supported by Koenig *et al.* (2010).

et al. (2014), Albornoz *et al.* (2012), Morales *et al.* (2011), Fernandes and Tang (2014) and others (details are provided in Section 3). In these papers, firms can learn about their demand in a potential new export market at least from 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 the potential market's demand positively affects a potential entrant's entry decision. The exclusion restriction is justify only if such learning does not affect their performance once they enter a specific export market (conditional on unobserved factors that are accounted for by fixed effects). As long as we can justify our exclusion restriction, our methodology allows to control firm heterogeneity with product level data. This is progress because it opens up opportunities to apply the highly influential HMR approach to testing various trade theories using much richer existing product level data.

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 tariffs changes (Aggregate, HS 2-digit and HS 6 digits covering 83 countries), which representing a variable trade cost changes from tariff changes. This is because, for a given change in import prices, the source of the change should be irrelevant to the demand outcome, and tariff measures suffer less from measurement errors than other sources of variable trade costs such as transportation costs and informational costs.[3]

Our main findings are as follows. The elasticity estimates from the HMR method with and without zero flows are not statistically different when aggregate data used. This is because, with the relatively small portion of zero trade flows (15%), the effects of accounting for zero flows are quantitatively small. However, once we disaggregate our data to HS 2-digit and HS 6-digit where zero trade flows are about 60% and 90%, respectively, the estimate with zero flows significantly smaller than that with the HMR method. As we include zero flows, the elasticity estimate decreases from -3.54 to -0.75 for HS 2-digit data and from

[3]Here we implicitly assume that price changes due to tariff changes represent well any variable trade cost changes.

-1.57 to -1.17 for HS 6 digit data as we are accounting for zero trade flows. We also provide a calculation of welfare gains from trade using US data in 2000 such that trade with foreign countries might increase gains about 9%. [4]

In the HMR model, the main sources of biases are firm heterogeneity and self-selection of export. In particular, the HMR reports serious bias due to firm heterogeneity if zero flows are large. Thus, if zero flows are ignored and product heterogeneity is large, the bias of elasticity estimate is potentially large. We use sector level heterogeneity measures – required skill/technology intensity, pricing information in Rauch (1999) – to quantify the magnitude of bias according to heterogeneity of products within a sector assuming the HMR method account for firm heterogeneity. We find that the bias of ignoring zero flows are particularly large for high skill and technology-intensive products for which the role of productivity is most important.

The rest of the paper is organized as follows. Section 2 extends the HMR model for disaggregate data and explains the new exclusion restriction variables we derive from the learning literature. Section 3 describes the data and provides the estimation results, and Section 4 concludes.

[4]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 elasticities (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. It is paramount to have an unbiased estimate of trade elasticity in the evaluation of the welfare impact of trade liberalization. Our estimates imply that accounting for zero trade flows gives a much larger estimate for the welfare gains from trade compared to those in the previous literature.

2 The HMR Model for Sector Level Data

Firm-level heterogeneity has received attention in recent papers and numerous theoretical as well as empirical studies (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) incorporate firm heterogeneity as an essential feature that explains firm's export market entry decision and other trade patterns.[5] A key features of these papers is an extensive margin of trade which is determined by firm heterogeneity. As trade barriers changes, firms can start to entering export markets and this endogenous selection of firms into the export markets can explain observed patterns of trade flows. Building on Melitz (2003)'s firm heterogeneity model under monopolistic competition, HMR develop an estimation equation considering a truncated Pareto distribution of firms' productivity to account for zero trade flows at the aggregate data. For an estimation approach, they suggest a Heckman (1979)'s type two-stage method in which a second stage gravity equation additionally includes inverse Mills ratio and variables to account for firm heterogeneity obtained from a first-stage Probit estimation.

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 one firm produces only one variety, and each firm produces a slightly different variety which is equivalent to assume a one-to-one mapping between varieties and firms. In our application with HS 6-digit data, this is effectively the same as to assume independence between sectors in broad classification (e.g. sector in HS2 digit classification) but allow substitution and heterogeneity across varieties (e.g. product in HS6 digit classification) within a sector.

In each sector, a firm produces one variety and each variety is slightly different from each other in the monopolistic competition setting. Suppose that each exporting firm (in country)

[5] 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.

j faces the following demand in destination i for its product variety at sector k, q_{ijk}, under the monopolistic competition market:

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

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

where Q_{ik} is the equilibrium market size of importing country i for sector k; c_{jk} is a measure of average product-specific productivity in sector k of firms in country j; τ_{ijk} is the variable trade cost of firm in sector k 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 the HMR, we assume for each sector k that $G(a_k)$ 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 reflects the proportion of country j's exporting firms to country i in sector k; and γ_k is the import demand elasticity (in absolute value) that is specific to sector. Firms in country j take P_{ik} and Q_{ik} as given.[6] 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.

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

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

where for each sector k, λ_j is exporter specific fixed effects (FEs) which subsume $ln(N_j)$ and $ln(c_j)$; ξ_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-level gravity variables such as distance, cultural ties, and colonial relationship, and pair-sector level variables such as tariffs; $\omega_{ij}(= ln(W_{ij}))$ is a function of cut-off productivity that determines the fraction of firms in country j 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 the HMR except 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 determinants of $\mathbf{x}_{1ij}$ and ω_{ij} that are specific to each sector for 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 a 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

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

In eq.(2), the numerator is the operating revenue and the denominator is the fixed cost of exporting. So as long as $Z_{ij} > 1$, export accrues positive operating profits. We assume the fixed costs of exporting are determined as follows:

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

where ψ_j subsumes inherent factors specific to exporter j that could affect their fixed costs of exporting, ψ_i is destination specific factors that could affect the fixed costs, σ_{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 errors (u_{ij}) in the second-stage estimation. We take logarithm on eq.(2), then we have

$$z_{ij} \equiv ln(Z_{ij}) = \beta_0' + \eta_j + w_i + \mathbf{x}_{ij}\delta - \theta\sigma_{ij} + \epsilon_{1ij}$$

where $\mathbf{x}_{ij}$ represents typical observed pair variables included in the gravity model, η_j is exporter FEs, subsuming all j-specific variables including c_j, w_i is importer FEs, subsuming all i-specific variables including P_i and Q_i, σ_{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 assume $\rho_0 = 1$ for the sake of simplicity.

As σ_{ij} is not present in the eq.(1), it could be used as an exclusion restriction for identification of parameters in eq.(1). Implementation of two-stage estimation requires observed factors in σ_{ij} that vary at ij and affect the fixed cost of exporting. We need an exclusion restriction for σ_{ij}.

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

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

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 endogenous number and self-selection of j's firms exporting to i (w_{ij}).

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

where ω_{ij} include factors that determine the fraction of firms exporting from j to i in sector k. Therefore, we need the estimates for both $E(\omega_{ij}|q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$ and $E(u_{ij}|q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$. Both terms depend on $\bar{v}_{ij}^* = E(v_{ij}^*|q_{ij} > 0, \eta_j, w_i, \mathbf{x}_{1ij}, \sigma_{ij})$ and note that

$E(u_{ij}|q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i) = corr(u_{ij}, v_{ij}) \cdot \frac{\sigma_u}{\sigma_v} \bar{v}^*_{ij}$, $corr(u_{ij}, v_{ij}) \cdot \frac{\sigma_u}{\sigma_v} = \rho_1$ where $v^*_{ij} = \frac{v_{ij}}{\sigma_v}$. Also note that 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 $E(z_{ij}|q_{ij} > 0, \eta_j, w_i, \mathbf{x}_{1ij}, \sigma_{ij})$, we could use $\hat{z}^*_{ij} + \hat{\bar{v}}^*_{ij}$and $\hat{\bar{\omega}}^*_{ij} = ln[exp(\alpha(\hat{\bar{v}}^*_{ij} + \hat{z}^*_{ij})) - 1]$ for the consistent estimate for $E(\omega_{ij}|q_{ij} > 0, \mathbf{x}_{1ij}, \lambda_j, \xi_i)$.

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 α is a function of γ as well as θ and in the eq.(4), $W_{ij} = Z^{\alpha}_{ij} - 1 = exp(\alpha z_{ij}) - 1$ is used to estimate ω_{ij} by taking log both sides of the equation. As long as exclusion restriction is available, we can easily 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

In order to extend the HMR approach to sector level, the estimation requires an exclusion restriction variables that affects firm's export market entry decision but not their trade volumes once they have already entered. These are factors that have the effect on the fixed cost of exporting. However, finding a readily-available exclusion restriction that varies over pair-product-time is difficult not only due to data limitation but also due to conceptual constraints.

Following recent studies in export learning literature, we propose a potential candidate for exclusion restriction variables that allow us to apply the HMR approach to accounting for firm's fixed costs of exporting to the sector-level estimations. Exclusion restriction requires that: (i) it affects the fixed costs of exporting and more broadly entry decision but; (ii) does not affect the volume of trade of product once an entrant becomes an incumbent in the export market.[7] For this purpose, we assume that firms can learn about their demand in a potential new export market from two channels: i) performance of other countries in the same market for the same product, and ii) their own experience in other markets for the same product. Such learning about the potential market's demand positively affects a potential entrant's entry decision, but not their performance once they enter a specific export market. These assumptions are supported by export learning literature. On the one hand, Fernandes and Tang (2014) examine which neighborhood countries' export performance to a specific market would be a signal to infer the potential market's demand and show that it positively affects a potential entrant's entry decision and initial export volume to the market. It implies that the larger number or faster export growth of an exporter's neighborhood could signal information about market demand as well as product demand. B On the other hand, other studies examine learning from exporter's own experience in other markets to explain its export performance in a specific exporting market using firm-level data. For instance, Eaton *et al.* (2007) and Eaton *et al.* (2014) show that learning from its success in foreign markets affects a firm's incentive to search for more markets and also that a firm's geographic expansion paths depends on its initial destination market. Likewise, Albornoz *et al.* (2012) observe that a firm discovers its profitability as an exporter after actually engaging in exporting and adjusts quantities and decides whether to enter into or exit from new markets. Furthermore, Morales *et al.* (2011) find that a firm's entry to a new destination is positively affected by its previous export experience in similar (geographically or economically) market. By definition of signal, once firms enter new export markets based on a decision from these channels, information from exporter's neighborhood or its experience from other markets has no additional information on the demand for new entrant as entrant firms can directly observe their product demand in a specific market.

In the construction of signals of market demand of product, we follow the specification of Fernandes and Tang (2014). Two variables are used as the signal of new market demand for

[7] 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.

each channel: i) average export growth, and ii) the number of incumbents (or destinations). As we consider learning in two dimensions (learning from other countries' performance at the same market and from its own performance at different market), we have four exclusion restriction variables in total.

We estimate the following specification in firm's new entry market decision:

$$\begin{aligned} 1(export_{ijkt} > 0) = \Phi(&\gamma_1 ln(\overline{export}_{ikt}) + \gamma_2 ln(\overline{export}_{jkt}) \\ &+ \gamma_3 ln(n_{ikt}) + \gamma_4 ln(n_{jkt}) + \mathbf{Z}_{ijt}\delta + \alpha_0 + e_{ijkt} \geq 0) \end{aligned} \tag{5}$$

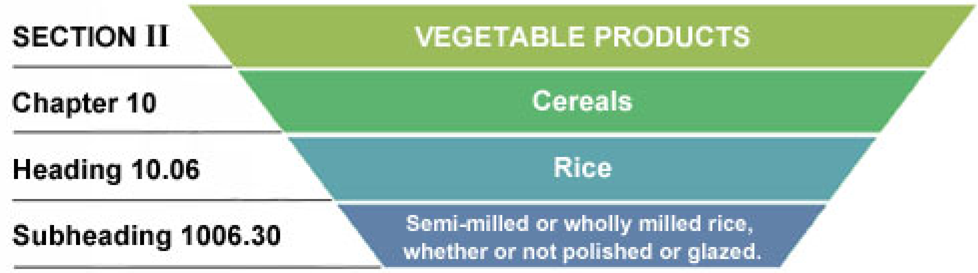
where $\overline{export}_{ikt}$ is average export volume at the destination i at product k in time t (e.g. this is a measure to capture other exporter's average performance for the same product in the same sector and destination) ; $\overline{export}_{jkt}$ is average export volume across all destinations for exporter j at product k in time t (e.g. this is a measure to capture firms average performance in all destinations for the same product); n_{ikt} is the number of exporters at destination i for product k at time t with positive flows; n_{jkt} is the number of destinations for exporter j and product k at year t. Thus, γ_s captures the effect of learning on the probability of entering into the potential new export market. $\mathbf{Z}_{ijt}$ includes gravity variables.

3 Empirical Analysis

3.1 Data

The dependent variable is bilateral trade flows, and the main explanatory variable is bilateral tariffs averaged at the HS6 digit as well as the HS2 digit from 2001 to 2003 for 83 countries which are all WTO member countries. Our sample coverage for 83 countries is determined mainly by tariff data availability. The use of panel data of three years allows us to account for pair-year unobserved factors using fixed effects. Trade flows are obtained from the UN-

Figure 1: Example of the hierarchical structure of the Harmonized System (HS)



Note: A source of the figure is https://en.wikipedia.org/wiki/Harmonized_System. HS2 classification contains 96 chapters/sectors and HS6 classification contains about 5500 subheadings/products.

COMTRADE, and time-variant bilateral tariffs at HS6 digit are obtained from the World Integrated Trade Solution (WITS).

Our bilateral tariff data at HS6 digit as well as HS2 digit are obtained from World Integrated Trade Solution (WITS) from World Bank. Original sources of tariff data are from UNCTAD TRAINS and WTO IDB CTS. We use applied tariff data for the entries with positive flows. However, for entry with zero flow, we use preferential tariffs from UNCTAD TRAINS if available and for the rest of entries we use MFN tariffs. Thus, for HS6 digit, more than 80% of entries, tariff data are filled with MFN tariffs.

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. PTA data are constructed from Regional Trade Agreements Information System (RTA-IS) of the World Trade Organization (WTO), 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 from CEPII.

Table 3.1 shows that the proportion of zero trade flows for aggregate data in our sample which is as low as 15%. For aggregate data, the percentage of zero flows is relatively small because we restrict our sample countries to 83 which has bilateral tariff data. Most of those countries with bilateral tariff data at HS6 digit are relatively advanced countries with better record system. However, for disaggregate data, for those pair-product-time units with available tariff data, the proportions of no trade flows are as high as 64% and 90% for HS2 digit

Table 1: Sample statistics: Positive and zero trade flows

	Aggregate, 1996-2008	HS2, 2001-2003*	HS6, 2001-2003*
Positive value only	75,107	555,470	8,652,510
Zero + positive value	88,478	1,542,470	79,861,650
Proportion of zero	15.11%	63.99%	90.22%

Note: For disaggregate data analyses, we restrict the sample to manufacturing sectors that are more closely aline with the HMR model. Among HS2 chapters, we exclude first 14 chapters including Section 1(Live animals and Animal products) and Section 2 (Vegetable products) and the six following chapters: the mineral products (chapters 25, 26 and 27); others chapters that contain various products (chapters 68, 81); the works of art, collectors' pieces and antiques (chapter 97) and the two last chapters, 98 and 99, devoted to special classifications or transactions. We further restrict the sample to use only three annual data to minimize computational problems caused by high dimensional dummy variables (i.e. fixed effects) accounting for unobserved heterogeneity.

and HS6 digit classifications, respectively. For instance, among chapters for all pair-time, 90% of these units have no trade flows. As pointed out in HMR, accounting for zero trade flows is crucial for the obtained estimated to be unbiased. Given that the proportion of zero flows are much higher in product level data than that of the aggregate level, it should be more important in practice to account for zero flows with disaggregate data.

For disaggregate data in Table 3.1, we restrict the sample to 76 out of 98 chapters as we believe that the HMR model for firm heterogeneity under monopolistic competition in fits better with manufacturing sectors. The note at Table 3.1 provides details on which chapters are excluded in our analysis.

3.2 Estimation Results

Table 3.2 presents basic statistics for outcome and main explanatory variables – tariff and trade liberalization policy dummy variables. Three dummy variables according to the depth of liberalization are included in all regressions. The first two columns show unconditional mean and standard deviation while the last two columns show the mean and standard deviation of variables conditional on positive trade flows. For those units (pair-product) with positive flows have lower tariff rates and those pair of countries with positive flows are more likely to form a stronger form of trade liberalization agreement such as FTA and CU.

Table 2: Simple statistics: Trade flows, tariff, and trade agreement dummy variables

	Mean	SD	Mean|Flow>0	SD|Flow>0
Trade Flows(Import)	136.13	10,909	1392.58	34,868
tariff	9.68	19.93	8.85	14.09
PSA (Partial Scope Agreement)	.144	.351	.087	.281
FTA (Free Trade Agreement)	.059	.235	.145	.352
CU (Custom Union)	.042	.200	.141	.348

Note: Basic statistics are obtained for disaggregate observations by HS6 sub-heading classification from 2001 to 2003 for 83 countries pair.

3.2.1 Estimation with Aggregate Data

For both aggregate and sector data, we use the following trade flow equation derived from eq.(4):

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

where $\mathbf{Z}_{ij}$ is subsumed when including pair FEs, w_{ij} and MRTs using country-time FEs, λ_{it} and ξ_{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 $\rho_1\hat{\bar{\eta}}^*_{ijt} + \rho_2\hat{\bar{z}}^*_{ijt} + \rho_3\hat{\bar{z}}^{*2}_{ijt} + \rho_4\hat{\bar{z}}^{*3}_{ijt}$, where $\hat{\bar{\eta}}^*_{ij} = \frac{\varphi(\hat{z}^*_{ij})}{\Phi(\hat{z}^*_{ij})}$ obtained from eq. (5) to account for selection bias and firm heterogeneity. In the first stage estimation, we need exclusion restriction factors that affect entry decision but not affecting volume decision once firm enter the market. In HMR, they consider the bilateral regulation costs measure as the exclusion restriction variable. Besides strong assumption of excludability in the model for trade volume, a practical limitation of exclusion restriction is data availability, which prompts HMR to consider an alternative variable of an index of common religion (between any pair) which is relatively easier to obtain. As suggested in Section 2, following Fernandes and Tang (2014) and other related literature we use variables used for learning about market demand as exclusion restriction in implementing HMR method at both aggregate and sector level.

The regression results with the aggregate data are shown in Table 3.2.1. Column (1) presents the results from the log-linear OLS estimator. Column (2) includes additional pair FEs and country-time FEs to controlling for the multilateral resistance terms (MRTs). The estimation results from HMR method controlling for self-selection and firm heterogeneity are presented in Column (3). .

The trade elasticity estimates are not statistically different between the OLS estimate with fixed effects and one from the HMR method. Given that missing proportion is only 15% of total observations, it could be possible that HMR correction terms do not affect the trade elasticity estimate much.

3.2.2 Estimation with Sectoral Data

With product level panel data (HS2 digit or HS6 digit), our main estimation equation for pooled data (e.g. pooling over all sectors) is as follows:

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

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

It should be noted that in eq.(7), besides HMR terms, $\rho_1 \hat{\bar{\eta}}^*_{ijkt} + \rho_2 \hat{\bar{z}}^*_{ijkt} + \rho_3 \hat{\bar{z}}^{*2}_{ijkt} + \rho_4 \hat{\bar{z}}^{*3}_{ijkt}$, it has two distinct unobserved factors, λ_{ijt} which accounts for typical gravity variables as well as MRTs and u_k which accounts for the product-specific unobserved heterogeneity. Thus, firm heterogeneity factors that vary at ijt and k levels are controlled for by fixed effects but heterogeneity factors that vary over $ijkt$ are controlled for by the terms, $\rho_1 \hat{\bar{\eta}}^*_{ijkt} + \rho_2 \hat{\bar{z}}^*_{ijkt} + \rho_3 \hat{\bar{z}}^{*2}_{ijkt} + \rho_4 \hat{\bar{z}}^{*3}_{ijkt}$.

Table 3.2.2 reports the main estimation results. The first three columns and the last three

Table 3: Trade elasticity from aggregate data, 1996-2008

	(1)	(2)	(3)
	Aggregate, 1996-2008		
Elasticity (1-σ)	-1.288***	-1.125**	-1.203**
	(0.348)	(0.500)	(0.526)
GDP_i	1.024***		
	(0.013)		
GDP_j	1.198***		
	(0.013)		
$Distance$	-1.203***		
	(0.037)		
PSA	0.121*		
	(0.067)		
FTA	0.513***		
	(0.079)		
CU	0.543***		
	(0.142)		
$\hat{\bar{\eta}}^*_{ijt}$			1.120***
			(0.526)
$\hat{\bar{z}}^*_{ijt}$			1.533***
			(0.487)
$\hat{\bar{z}}^{*2}_{ijt}$			-0.420***
			(0.124)
$\hat{\bar{z}}^{*3}_{ijt}$			0.034***
			(0.011)
Gravity vars.	Yes	Yes	Yes
Pair (ij) FEs	No	Yes	Yes
MRTs (it, jt FEs)	No	Yes	Yes
R^2	0.719	0.922	0.923
Model	log-linear		HMR
Number of Obs		75,107	

Notes: Gravity variables additionally include dummy variables for sharing border, common legal origin, common colony, and log of GDP per capita for importer as well as exporter. MRTs are accounted for by importer-year and exporter-year fixed effects. Cluster (pair) robust standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively.

columns show results from HS2 digit and HS6 digit data, respectively. The proportion of zero trade flows for HS2 and HS6 digit data are about 64% and 90%, respectively. This must be too large to be ignored so that accounting for zero trade flows from self-selection and firm heterogeneity could be very important especially if the response from zero flows to positive flows due to tariff change is different from the response from one positive flows to another positive flows.

As for HS2 digit data, Column (1) is the results from baseline OLS with gravity variables and Column (2) is different in terms of controlling for FEs. The two trade elasticity estimates are not statistically different. In Column (3) additionally including HMR terms to account for zero trade flows, the trade elasticity estimate decreases from -3.5 to -0.75, which implies that the trade elasticity is overestimated in absolute value by 79% (=$\frac{3.5-0.75}{3.5}$) when we ignore zero trade flows. The qualitative results are not different when we use HS6 digit data. Our results indicate that with a new shock in tariffs and, if units with no trade flow engage in trade, the trade elasticity for these units will be very small compared to those are already in the sample with positive trade flows.

Note that effects of various trade agreements become insignificant when we use HS6 digit data while they are both economically and statistically significant with less disaggregate data. The main objective and achievement of trade agreements is to reduce or eliminate tariffs among members. However, as the coefficient of trade elasticity captures the effects of tariff changes, the estimates of trade agreements represent effects of trade agreements due to changes in other trade barriers but tariff changes. Supposing such non-tariff related effects are not significant in our data, our results might be attributed to the fact that the accuracy of the effects of tariff changes deteriorates with tariff data aggregation so that they appear as positive and significant coefficients of trade agreement variables under less disaggregate data.

Table 4: Trade elasticity from HS2 digit and HS6 digit data, 2001-2003

	(1)	(2)	(3)	(4)	(5)	(6)
	HS2, 2001-2003			HS6, 2001-2003		
Elasticity (1-σ)	-3.599***	-3.544***	-0.748***	-2.352***	-1.574***	-1.169***
	(0.169)	(0.139)	(0.127)	(0.123)	(0.078)	(0.072)
GDP_i	0.675***			0.438***		
	(0.011)			(0.000)		
GDP_j	0.889***			0.062***		
	(0.012)			(0.008)		
$Distance$	-0.824***			-0.420***		
	(0.031)			(0.025)		
PSA	0.143**			0.011		
	(0.055)			(0.044)		
FTA	0.318***			-0.016		
	(0.079)			(0.058)		
CU	0.640***			0.064		
	(0.083)			(0.065)		
$\hat{\bar{\eta}}^*_{ijt}$			1.396***			0.476***
			(0.060)			(0.053)
$\hat{\bar{z}}^*_{ijt}$			9.607***			4.127***
			(0.243)			(0.376)
$\hat{\bar{z}}^{*2}_{ijt}$			-1.930***			-0.074
			(0.091)			(0.199)
$\hat{\bar{z}}^{*3}_{ijt}$			0.155***			-0.039
			(0.010)			(0.31)
Gravity vars	Yes	Yes	Yes	Yes	Yes	Yes
Pair-year (ijt) FEs	No	Yes	Yes	No	Yes	Yes
Sector (k) FEs	No	Yes	Yes	No	Yes	Yes
HMR controls	No	No	Yes	No	No	Yes
No. of obs.		555,470			8,652,510	

Notes: Gravity variables additionally include dummy variables for sharing border, common legal origin, common colony, and log of GDP per capita for importer as well as exporter. Country-level MRTs are subsumed by pair-year FEs. Cluster (pair) robust standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively.

3.3 Sector Heterogeneity

Our extension of HMR to sector level allows the parameters in the outcome differ by sector. According to the model specification, accounting for zero is more important if a sector has more heterogeneous products. We can rewrite the estimation equation that allows parameter heterogeneity using sector-by-sector specification as in eq. 8. For each sector k, a specification for sector-by-sector estimation can be rewritten as:

$$ln(q_{ijt}) = \beta_0 + \lambda_{ij} + u_{it} + v_{jt} + \mathbf{x}_{ijt}\delta + \beta_1(1 + tariff_{ijt}) + \rho_1\hat{\hat{\eta}}^*_{ijt} + \rho_2\hat{\hat{z}}^*_{ijt} + \rho_3\hat{\hat{z}}^{*2}_{ijt} + \rho_4\hat{\hat{z}}^{*3}_{ijt} + e_{ijt}. \tag{8}$$

3.3.1 Heterogeneity in Products of Different Skill and Technology Intensity

On the one hand, firms' markups depend on trade elasticity. Higher trade elasticity yields lower markups. Skill intensity of products may indicate the firms' market power, where greater skill intensity and market power set higher markups. Firms produce higher skill intensity products, for example, say contact lenses, may have more market power compared firms producing lower skill intensity products, say toilet papers. On the other hand, goods produced with high skill intensity are less likely to be substitutable (more variety is likely to be observed for products in the same sector) so accounting for zero flows (i.e. account for firm heterogeneity or productivity cutoff) is important to avoid the bias of trade elasticity estimate, and thus the effects of using HMR might be the largest for these products.

We examine these hypotheses using the classification of products at HS6 digit according to average technological skill content appearing in Basu (2011). It classifies all HS6 digit products into seven groups – Non-fuel Primary Commodities, Resource-intensive Commodities, Low Skill-Technology intensive, Medium Skill-Technology intensive, High Skill-Technology intensive, Mineral Fuels, and Other transactions. Table 3.3.1 presents sample products for each of seven groups.

Table 5: Classification of HS6 sub-heading products using technical level classification

	Sample Products
Non-fuel Primary Commodities	Fresh Fruit, Meal, Rice, Cocoa, Tea, Coffee
Resource-intensive	Plywood, Knitted wool or fine animal hair skirts, Glass
Low Skill- And Technology-intensive	Toilet paper, Stainless steel wire, Handbag hooks
Medium Skill- And Technology Intensive	Air conditioner, Bakery ovens, Bulldozers
High Skill- And Technology Intensive	Microscope, Tissue adhesive pharmaceutical goods, Explosives propellent powders
Mineral Fuels	Ore Concentrates, Petroleum/Rubber Products, Cement, Cut Gems
Others Transactions	Data/graphic display tubes,Optical instruments and appliances; for inspecting semiconductor wafers or devices

Notes: The classification of sectors according to the technological content appears in Basu (2011). The data can be downloaded at http://www.unctad.info/en/Trade-Analysis- Branch/Data-And-Statistics/Other-Databases/ .

The estimation results are reported in Table 3.3.1. The missing proportion of all seven groups is very high around 88% up to 94%. In all estimations, we use the most exhaustive fixed effects as in Columns (2) and (5) of Table 3.2.2. In Table 3.3.1, Column (1) reports the results without accounting for zero flows while Columns (2) accounts for zero flows using learning for the signal as exclusion restriction. The estimates from all groups except for Medium skill-and technology intensive product group decrease when we account for zero trade flows. The results also show that the differences of the estimates from OLS and HMR method are largest for groups, “High skill- and technology intensive” and “Other transactions”. These two groups are more likely to have firms which have productivity are potentially most heterogeneous. It confirms that when zero flows are dominant, controlling for firm heterogeneity is especially important in sectors with high productivity heterogeneity.

The results from the HMR method (Column 2) also show that among manufacturing products (Resource-intensive and Low, Medium and High-skill-and technology intensive) Resource intensive manufacturing products have the highest trade elasticity while High-skill- and intensive manufacturing products have the lowest.

3.3.2 Heterogeneity in Products of Different Pricing Information

The more homogeneous a product is, the higher the substitutability amongst its varieties should be. Rauch (1999) tests this hypothesis by classifying goods into three groups: commodities, reference priced goods and differentiated goods, where commodities are goods that traded on organized exchange, reference priced goods are the goods that reference prices of

Table 6: Trade elasticity: 7 sub-sample estimations according to technical level classification

	HS6, technical level heterogeneity		positive flows	missing proportion
	(1)	(2)	(3)	(4)
Non-fuel primary commodities	-0.804***	-0.182**	566,084	94%
	(0.085)	(0.085)		
Resource-intensive	-2.276***	-1.907***	2,224,514	90%
	(0.127)	(0.121)		
Low skill- and technology-intensive	-1.261***	-0.622***	912,989	89%
	(0.105)	(0.100)		
Medium skill- and technology intensive	-0.648***	-0.926***	1,945,729	87%
	(0.097)	(0.090)		
High skill- and technology intensive	-2.418***	-0.624***	1,857,095	91%
	(0.128)	(0.094)		
Mineral fuels	-0.475***	-0.463***	389,598	88%
	(0.114)	(0.107)		
Others Transactions	-3.037***	-1.073***	567,555	91%
	(0.142)	(0.099)		
All FEs	Yes	Yes	8,463,564#	
HMR	No	Yes		

Notes: Cluster (pair) robust standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. # indicates total sum of seven sub-samples. 188,946 observations were not used in any of sub-samples estimation because some sectors cannot be assigned to any sub-sample by classification. In "Others Transactions", for HS2 classification, chapters 29 (Organic chemicals), 72 (Iron and steel), 84 (Nuclear reactors, boilers, machinery and mechanical appliances), 85 (Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles), and 90 (Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus) have observations more than 5% of total observations.

them being published in trade journals, and the rest are differentiated goods. He finds that the trade elasticity of commodities is the largest and that of differentiated goods the smallest. Broda and Weinstein (2006), using a model of import demand and supply equations, also find the commodities have a higher elasticity of substitution than the other goods. However, Broda and Weinstein (2006) caution that commodities are not necessarily perfectly substitutable goods, as demonstrated in the example that tea products, despite highly differentiated, are traded in organized exchange and thus classified as a commodity by Rauch (1999). They further argue that such product classifications may not truly reflect the homogeneity of a product with the example that "dried, salted, or smoked fish" is classified as a commodity, while "fresh fish" a reference priced good and "frozen fish" a differentiated good.

In this section, we reexamine this hypothesis by applying the classification of Rauch (1999) to our data. In our sample, 1.9%, 18.7% and 79.4% of HS-6 product classifications are composed of commodities, reference priced and differentiated products, respectively. Table 3.3.2 shows the results. In Column (1), trade elasticity estimates are not statistically different among three sub-sample estimations. In Column (2), once we account for zero, all trade elasticity estimates decrease (in absolute terms) as expected, and differentiated products now have the largest elasticity, while commodities products have the smallest one. The results in Table 7 show that the main implication – trade elasticity is overestimated if ignoring zero and firm heterogeneity – is not driven by one group of products. The importance of accounting for zeros are important all product groups we consider here.

3.3.3 Pair Heterogeneity by Income Level

We provide another example for the use of HMR approach to sector level. The idea is that, even for the product in the same HS classification, variety quality from a rich exporter to a poor importer may be different from those from a poor exporter to a rich importer. For instance, rich importers and rich exporters may engage in markets where more variety of products compete. Thus, firm heterogeneity as emphasized in HMR is more important in this

Table 7: Trade elasticity: Three sub-sample estimations according to different pricing information

	HS6 digit, different pricing information					
	(1)	(2)	(3)	(4)	(5)	(6)
	Conservative classification		(1)-(2)	Liberal classification		(4)-(5)
Differentiated products	-1.288***	-0.925**	-0.363	-1.288***	-0.855**	-0.433
	(0.088)	(0.080)		(0.089)	(0.081)	
Reference priced products	-1.501***	-0.842***	-0.659	-1.503***	-0.656***	-0.847
	(0.116)	(0.114)		(0.107)	(0.096)	
Commodity products	-1.270***	-0.498***	-0.772	-1.115***	-0.637***	-0.478
	(0.268)	(0.241)		(0.224)	(0.209)	
All FEs	Yes	Yes		Yes	Yes	
HMR	No	Yes		No	Yes	

Notes: Cluster (pair) robust standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Source: Product classification according to homogeneity of products is from Rauch (1999). As we connect HS6 digit with SITC2 4 digit, the number of unmatched observations is 7,957,019 while the number of matched observations is 80,557,141.

market with various variety. To test this idea, in Table 3.3.3, we classify countries by three groups according to their income level according to WITS. Further, we denote "developed" for countries in high income group and "developing" for countries in middle and low income group. Table 3.3.3 shows the estimation results. Columns (1) and (2) uses OLS and HMR method, respectively. As in previous estimations, trade elasticity estimate from HMR method decrease in absolute term. Although the difference between two estimates are largest if the importers are developing countries, the differences are quite large for all groups compared to standard error estimates.[8] Similarly to previous section, for all four pairs from developed and developing countries, the estimates from HMR method are significantly smaller in absolute term.

[8]When zero trade flows are accounted for, the trade elasticity become positive if importers are industrial countries. It implies that developed countries are not sensitive to change in price due to tariffs or even reduce imports if tariffs decrease. On the other hand, developing countries are sensitive to changes in tariffs and their imports rise if tariffs decrease. As expected, the trade elasticity is highest (in absolute term) if developing countries import from developing countries where the market could be most price-competitive.

Table 8: Three income groups in the sample: High, middle, and low

	Countries
High	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States
Middle	Antigua and Barbuda, Botswana, Brazil, Cameroon, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Cuba, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Jamaica, Kenya, Malaysia, Mauritius, Mexico, Morocco, Namibia, Nicaragua, Nigeria, Pakistan, Paraguay, Peru, Philippines, South Africa, Sri Lanka, Thailand, Tunisia, Turkey, Uruguay, Venezuela, Zimbabwe
Low	Bangladesh, Burkina Faso, Madagascar, Malawi, Mali, Mozambique, Senegal, Tanzania, Togo, Uganda, Zambia

Notes: The classification of countries income level is based on WITS website. Only 81 countries are used for the estimations in this section and observations for Barbados and Trinidad Tobago are not used as they are not classified in any of three income groups. We denote "developed" for countries in high income group and "developing" for countries in middle and low income group.

Table 9: Trade elasticity: Four sub-sample estimations according to income level

Importer	Exporter	HS2		Differences of estimates (1)-(2)	total obs (% of zero)
		(1)	(2)	(3)	(4)
Developed	Developed	-0.943**	0.144	-1.087	146,065
		(0.447)	(0.392)		(21%)
Developed	Developing	-0.875*	1.109***	-1.984	332,574
		(0.459)	(0.328)		(65%)
Developing	Developed	-2.711***	-1.295***	-1.416	337,350
		(0.187)	(0.172)		(50%)
Developing	Developing	-3.223***	-1.893***	-1.330	726,615
		(0.227)	(0.208)		(79%)
FEs		Yes	Yes		
HMR		No	Yes		

Notes: Cluster (pair) robust standard errors are reported in parentheses. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively.

3.4 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 measured using two statistics, the share of expenditure on domestic products, λ and the elasticity of imports with respect to variable trade cost, ϕ.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 3.4, we provide a rough calculation for welfare gains from trade using an example of US in 2000 following Arkolakis *et al.* (2012). In year 2000, the share of expenditure devoted to domestic products for US is 0.93 (i.e. $\lambda_{us} = 0.93$). Using the welfare change formula in Arkolakis *et al.* (2012) to evaluate the welfare change in US's year 2000 compared to Autarky, which is $(1 - \lambda^{-1/\phi})$ where $\lambda = 0.93$, they illustrate that the percentage change in real income needed to compensate a representative consumer for going back to autarky is 0.7 percent to 1.8 percent depending if the trade elasticity are ranged from -10 to -4 as found in the literature.

As we replace the estimates obtained from our estimations that account for zero flows in Table 3.2.2, US' gains from trade in year 2000 is implied to be 10.2 percent (the estimate based on HS2-digit data) and 6.2 percent (the estimate based on HS2-digit data), substantially higher than the figures from the literature.

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 elasticities (see section 5.1 in Arkolakis *et al.* (2012)). To deliver the main objective of this paper, however, we focus on trade elasticity average across industries and this simple numerical example serves the purpose that, to evaluate the welfare impact of trade liberalization, it is paramount to have an unbiased estimate of trade elasticity. In-

Table 10: Welfare calculation: Gains from trade

Source	Trade elasticity	Gains from trade (trade in 2000$\longrightarrow$Autarky)
Literature lower bound	-10	0.73%
Literature upper bound	-4	1.83%
HS 2 digit with OLS	-3.6	2.04%
HS 2 digit with HMR	-0.75	10.16%
HS 6 digit with OLS	-2.4	3.07%
HS 6 digit with HMR	-1.2	6.23%

{}

{Notes: In 2000, λ was 0.93 for the US.}

cluding zero trade flows and accounting for firm heterogeneity reduce the trade elasticity substantially so much higher welfare gains from trade.

4 Conclusion

In this paper, we estimates trade elasticities at the product level. We adopt HMR approach to account for large portion of zeros controlling for self-selection and firm heterogeneity. In our estimations, exclusion restrictions are constructed using pair-time-product level trade data to extract the information on the signal from learning as in Fernandes and Tang (2014).

We find upward biases in the estimates of trade elasticities if the positive trade flows are used only. Proper accounting of zero trade flows and firm heterogeneity at product level yields substantially smaller estimates of trade elasticities (i.e. the magnitude decrease from -3.54 to -0.75), which imply much larger welfare gains from trade.

As documented in Anderson and van Wincoop (2004), the literature usually find 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 1.4%. 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 10% of welfare gains from trade compared to Autarky, which are much higher than figures provided in the literature.

We also provide the trade elasticities of heterogeneous groups of products regarding skill and technology-intensity, pricing information and income level of country pairs. Our results show that the bias of ignoring zero flows are particularly large for high skill and technology-intensive products. As for the income level of importers, the estimates with HS2 digit data show that the lower are importing countries' income, the larger the bias from ignoring zero trade flows.

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