

IMPORT DEMAND ELASTICITIES AND TRADE DISTORTIONS^{*}

Hiau Looi Kee[†], Alessandro Nicita[‡], Marcelo Olarreaga[§]

Abstract

This paper provides a systematic estimation of import demand elasticities for a broad group of countries at a very disaggregated level of product detail. We use a semiflexible translog GDP function approach to formally derive import demands and their elasticities, which are estimated with data on prices and endowments. Within a theoretically consistent framework, we use the estimated elasticities to construct Feenstra's (1995) simplification of Anderson and Neary's trade restrictiveness index (TRI). The difference between TRIs and import-weighted tariffs is shown to depend on the tariff variance and the covariance between tariffs and import demand elasticities.

JEL classification numbers: F1, F10, F13

^{*}We are grateful to James Anderson, Erwin Diewert, Robert Feenstra, James Harrigan, Kala Krishna, Peter Neary, David Weinstein and two anonymous referees for very helpful suggestions. We also thank Paul Brenton, Hadi Esfahani, Joe Francois, Kishore Gawande, Catherine Mann, William Martin, Christine McDaniel, Guido Porto, Dave Richardson, Claudio Sfreddo, Clinton Shiells, Dominique Van Der Mensbrugge, Alan Winters, and seminar participants at the ITI program of the NBER Summer Institute 2005, the Center of Global Development, the Econometric Society Meetings 2004 at Brown University, the Empirical Trade Analysis Conference at the Woodrow Wilson International Center, PREM week, and the World Bank for their comments. The views expressed here are those of the authors and do not necessarily reflect those of the institutions to which they are affiliated.

[†]Development Research Group, The World Bank, Washington, DC 20433, USA; Tel. (202) 473-4155; Fax: (202) 522-1159; e-mail: hlkee@worldbank.org.

[‡]Development Research Group, The World Bank.

[§]Development Research Group, The World Bank, and CEPR, London.

1 Introduction

Import demand elasticities are crucial inputs into many ex-ante analysis of trade reform. To evaluate the impact of regional trade agreements on trade flows or customs revenue, one needs to first answer the question of how trade volumes would adjust. To estimate ad-valorem equivalents of quotas or other non-tariff barriers one often needs to transform quantity impacts into their price equivalent, for which import elasticities are necessary. Moreover, trade policy is often determined at much higher levels of disaggregation than existing import demand elasticities.¹ This mismatch can lead to serious aggregation biases when calculating the impact of trade policy interventions that have become surgical procedures. Finally, to evaluate trade restrictiveness and welfare loss across different countries and years, one would need to have a consistent set of trade elasticities, estimated using the same data and methodology. These do not exist. The closest substitute, and the one often used by trade economists, is the survey of the empirical literature put together by Stern et al. (1976). More recent attempts to provide disaggregate estimates of import elasticities have been country specific and have mainly focused on the United States.²

The objective of this paper is threefold. First, to fill in the gap in the literature by providing a systematic estimation of import demand elasticities for a broad range of countries at a fairly disaggregated level of product detail. Second, using the estimated elasticities and within a theoretically consistent framework, we construct measures of trade restrictiveness based on Feenstra's (1995) simplification of Anderson and Neary's trade restrictiveness index (TRI).³ The TRI is the uniform tariff that would maintain welfare at its current level given

the existing tariff structure. Finally, using TRIs the paper analyzes the size and composition of tariff induced trade distortions.

The basic theoretical setup for the estimation of import demand elasticities is the production based GDP function approach as in Kohli (1991) and Harrigan (1997). This GDP function approach is consistent with neoclassical trade theories, and it takes into account general equilibrium effects associated with the reallocation of resources due to exogenous changes in prices and endowments. As in Sanyal and Jones (1982), imports are considered inputs into domestic production, for given exogenous world prices, productivity and endowments. In a world where a significant share of growth in world trade is explained by vertical specialization (Yi, 2003), the fact that imports are treated as inputs into the GDP function—rather than as final consumption goods as in most of the previous literature—seems an attractive feature of this approach. More importantly, even if an imported good is ready for final consumption, before being sold in the domestic market it will incorporate some domestic value added associated with domestic transport and logistics, marketing and retailing (see Sanyal and Jones, 1982). This implies that all imported goods should be treated as inputs into the GDP function.

The estimated import demand elasticities are defined as the percentage change in the quantity of an imported good when the price of this good increases by 1 percent, holding prices of all other goods, productivity and endowments of the economy constant. This is in contrast to the more commonly used price elasticities of demand, which are derived from utility maximization or expenditure minimization holding GDP or national income constant.

As argued by Kohli (1991) it seems that the former approach is more consistent with neo-classical international trade theories, where income is generally considered endogenous, and endowments and productivity are most of the time exogenous.

While Kohli (1991) focuses mainly on aggregate import demand and export supply functions and Harrigan (1997) on industry level export supply functions, this paper modifies the GDP function approach to estimate import demand elasticities at the six digit of the Harmonized System (HS). When estimating elasticities of the 4900 goods at tariff line level, dealing with cross-price effects can become insurmountable. In order to avoid running out of degrees of freedom in the estimation of the structural parameters of the GDP function, we reparametrize the fully flexible translog function to be semiflexible, or flexible of degree one, as in Diewert and Wales (1988). This reparametrization significantly reduces the number of price related translog parameters from $N(N-1)/2 + N$, (around 10 million in our case) to only N , (around 4900), and yet is flexible enough to approximate up to the second order any twice continuously differentiable function at any point. A similar simplification is used in Neary (2004) for the estimation of the AIDS and QUAIDS systems.

Another practical problem we are facing is that the HS classification was only introduced in the late 1980s, so even if we solve the n -good problem, we may still run out of degrees of freedom if we were to estimate the different parameters using only the time variation in the data. Thus, assuming that the structural parameters of the GDP function are common across countries (up to a constant) as in Harrigan (1997), we take advantage of the panel dimension of the data set by applying within estimators.

Finally, we address econometric issues associated with the potential endogeneity and measurement errors of unit values, selection bias due to zero imports, and the sluggish adjustment of imports to changes in prices, and other explanatory variables.

More than 377,000 import demand elasticities have been estimated across 117 countries for 4900 HS 6-digit products. The simple average elasticity across all countries and goods is about -3.12. The overall fit of the import demand elasticities is good. The median of bootstrap t-statistics is 3.3, and more than 70 percent of the estimates are statistically significant.

Using the estimated import demand elasticities, we construct TRIs for 88 countries for which tariff schedules are available. We show that the difference between TRI and import-weighted tariff depends on the variance of tariffs and the covariance between tariffs and import demand elasticities. Results suggest that the contribution of the variance of tariffs and their covariance with import demand elasticities to the overall trade restrictiveness of the countries in our sample is high, as import-weighted average tariffs underestimate the restrictiveness of a country's tariff regime by 64 percent on average. In some countries, such as the U.S., TRI is more than 3 times higher than the import-weighted average tariff. This indicates the presence of disproportionately large tariff variance and covariance with import demand elasticities.

Finally, we study the roles of tariffs' variance and covariance with import demand elasticities in determining the size and composition of the deadweight loss associated with the existing tariff schedules of the 88 countries. The results show that omitting the variance

of tariffs and their covariance with import elasticities leads to the underestimation of the size of the total deadweight loss by 55 percent. In other words, the overall deadweight loss due to tariffs is 2 times higher than average tariffs would imply. Countries that have the largest share of deadweight loss due to tariff variance are Japan, the Philippines, and Egypt. Countries where the covariance between tariffs and import elasticities plays a large role in causing deadweight loss are Sudan, Canada, and the U.S.. In particular, 64 percent of the Canadian deadweight loss of USD 912 million per annum can be attributed to higher tariffs on more elastic imports such as wheat. Given that a high import demand elasticity could be due to close substitution with domestic goods, this result highlights that those industries that lobby for tariff protection are those that face severe import competition –a result that can inform lobbying models.

The rest of the paper is organized as follows. Section 2 provides the theoretical framework to estimate import demand elasticities, whereas section 3 describes the empirical strategy. Section 4 discusses data sources. Section 5 presents the results of the estimation of import demand elasticities. Section 6 applies the estimated import demand elasticities to construct TRIs, as well as deadweight losses associated with existing tariff structures and their determinants. Section 7 concludes.

2 Theoretical Model – GDP Function Approach

The theoretical model follows Kohli's (1991) GDP function approach for the estimation of trade elasticities. We also draw on Harrigan's (1997) treatment of productivity terms in

GDP functions. We will first derive the GDP and import demand functions for one country. However, assuming that the GDP function is common across all countries up to a country specific term –which controls for country productivity differences– it is then easily generalized to a multi-country setting in the next section.

Consider a small open economy in period t .⁴ Let $\mathbf{S}^t \subset \mathbf{R}^{N+M}$ be the strictly convex production set in t of its net output vector $q^t = (q_1^t, q_2^t, \dots, q_N^t)$ and factor endowment vector $v^t = (v_1^t, v_2^t, \dots, v_M^t) \geq 0$. For the elements in the net output vector q^t , we adopt the convention that positive numbers denote outputs, which include exports, and negative numbers denote inputs, which include imported goods. We consider imported goods and competing domestically produced goods as differentiated products. Similarly domestic products sold in the domestic market are differentiated from products sold in foreign markets (i.e., exported).

Given the exogenous world price vector $\tilde{p}^t = (\tilde{p}_1^t, \tilde{p}_2^t, \dots, \tilde{p}_N^t) > 0$, the country specific endowments, v^t , and N -dimensional diagonal Hicks-neutral productivity matrix $\mathbf{A}^t = \text{diag}\{A_1^t, A_2^t, \dots, A_N^t\}$, perfect competition leads firms to choose a mixed of goods that maximizes GDP in each period t :

$$G^t(\tilde{p}^t, \mathbf{A}^t, v^t) \equiv \max_{q^t} \{\tilde{p}^t \cdot \mathbf{A}^t q^t : (q^t, v^t) \in \mathbf{S}^t\} \Rightarrow \quad (1)$$

$$G^t(\tilde{p}^t \mathbf{A}^t, v^t) \equiv \max_{q^t} \{\tilde{p}^t \mathbf{A}^t \cdot q^t : (q^t, v^t) \in \mathbf{S}^t\}, \quad (2)$$

where $G^t(\tilde{p}^t \mathbf{A}^t, v^t)$, is the maximum value of goods the economy can produce given prices, Hicks-neutral productivity and factor endowments in period t . It is equal to the total value of output for exports and final domestic consumption minus the total value of imports ($q_n^t < 0$

for imports). In other words, the optimal net output vector is chosen to maximize GDP, for given prices, productivity and endowments. We shall refer to the optimal net output vector as the GDP maximizing net output vector, which includes GDP maximizing import demands.

As shown in Harrigan (1997), Equation (2) highlights that price and productivity enter multiplicatively in the GDP function, $G^t(\tilde{p}^t \mathbf{A}^t, v^t)$. This property allows us to re-express the GDP function, by defining the productivity inclusive price vector, $p^t = (p_1^t, p_2^t, \dots, p_N^t) > 0$:

$$G^t(p^t, v^t) = \max_{q^t} \{p^t \cdot q^t : (q^t, v^t) \in \mathbf{S}^t\}, \text{ with} \quad (3)$$

$$p^t \equiv \tilde{p}^t \mathbf{A}^t, \text{ and } p_n^t \equiv \tilde{p}_n^t A_n^t, \forall n. \quad (4)$$

Notice that the productivity inclusive price vector, p^t , is no longer common across countries even though the world price vector, \tilde{p}^t , is identical across countries. This allows the model to better fit the data where different world prices are observed for the same good in different countries. In a recent study, Schott (2004) successfully explains variation in unit values within tariff lines with GDP per capita –the higher is GDP per capita, the higher the unit value. To the extent that GDP per capita is a proxy for labor productivity, Schott’s finding provides support for our productivity inclusive price level, p^t .

For $G^t(p^t, v^t)$ to be a well defined GDP function, it is assumed to be homogeneous of degree one with respect to prices. Moreover, strict convexity of \mathbf{S}^t also ensures that the second order sufficient conditions are satisfied, such that $G^t(p^t, v^t)$ is twice differentiable and it is convex in p^t and concave in v^t . To derive import demand function, we apply the

Envelope Theorem, which shows that the gradient of $G^t(p^t, v^t)$ with respect to p^t is the GDP maximizing net output vector, $q^t(p^t, v^t)$:⁵

$$\frac{\partial G^t(p^t, v^t)}{\partial p_n^t} = q_n^t(p^t, v^t), \quad \forall n = 1, \dots, N. \quad (5)$$

Thus if good n is an imported good, Equation (5) is the GDP maximizing import demand function of good n , which is a function of prices and endowments. It also implies that an increase in import prices would reduce GDP (i.e., $q_n^t < 0$ if n is an imported good). Given that $G^t(p^t, v^t)$ is continuous and twice differentiable, and is convex and homogeneous of degree one with respect to prices, the Euler Theorem implies that q_n^t is homogenous of degree zero in prices, has non-negative own price effects, and has symmetric cross price effects:⁶

$$\frac{\partial^2 G^t(p^t, v^t)}{\partial p_n^t \partial p_k^t} = \begin{cases} \frac{\partial q_n^t(p^t, v^t)}{\partial p_n^t} \geq 0, \quad \forall n = k \\ \frac{\partial q_n^t(p^t, v^t)}{\partial p_k^t} = \frac{\partial q_k^t(p^t, v^t)}{\partial p_n^t}, \quad \forall n \neq k \end{cases}. \quad (6)$$

In other words, for every final good, including exports, a price increase *raises* output *supply*; for every input, including imports, an increase in prices *decreases* input *demand*. In addition, if an increase in the price of an imported input causes supply of an exported output to decrease, then an increase in the price of the exported output would increase the demand of the imported input in the same magnitude.

Equation (5) shows that the GDP maximizing import demand function of good n is a function of prices and factor endowments. Thus, the implied own price effects of imports, and the import demand elasticities, are therefore conditioned on prices of other goods and

aggregate endowments being fixed. In other words, the GDP maximizing import demand functions do not depend on income or utility, unlike the expenditure minimizing Hicksian import demand functions or the utility maximizing Marshallian import demand functions. This is because, aggregate factor income and welfare are in fact endogenous to prices and endowments. Such a set up is more relevant for general equilibrium trade models, but may not be relevant for partial equilibrium micro models which often take aggregate income as exogenous. As a result, comparing the GDP maximizing import demand elasticities to the existing Hicksian or Marshallian import demand elasticities in the literature may not be appropriate. Note that we will not be able to derive income elasticities from the GDP maximizing import demand functions, but instead, we would be able to estimate the Rybczynski elasticities from Equation (5), which shows how import demand reacts to changes in factor endowments.⁷

To implement the above GDP function empirically, we first assume that $G^t(p^t, v^t)$ follows a flexible translog functional form with respect to good prices and factor endowments, with n and k index goods, and m and l index factors:

$$\begin{aligned}
\ln G^t(p^t, v^t) &= a_{00}^t + \sum_{n=1}^N a_{0n}^t \ln p_n^t + \frac{1}{2} \sum_{n=1}^N \sum_{k=1}^N a_{nk}^t \ln p_n^t \ln p_k^t \\
&+ \sum_{m=1}^M b_{0m}^t \ln v_m^t + \frac{1}{2} \sum_{m=1}^M \sum_{l=1}^M b_{ml}^t \ln v_m^t \ln v_l^t \\
&+ \sum_{n=1}^N \sum_{m=1}^M c_{nm}^t \ln p_n^t \ln v_m^t,
\end{aligned} \tag{7}$$

where all the translog parameters a , b and c 's are indexed by t to allow for changes over time.

As shown in Kohli (1991) and Harrigan (1997), such a fully flexible translog function can approximate any functional form up to second order without loss of generality. In addition, there are some nice features of the above specification that are absent in the more commonly used CES specification. First, we do not need to assume that the elasticity of substitution between goods is constant. Second, the elasticity of substitution of good i with respect to good j does not need to be equal to the elasticity of substitution of good j with respect to good i . Third, the underlying production function does not need to be weakly separable (Blackbory and Russell, 1981).⁸

In order to make sure that Equation (7) satisfies the homogeneity and symmetry properties of a GDP function, we impose the following restrictions:

$$\sum_{n=1}^N a_{0n}^t = 1, \quad \sum_{k=1}^N a_{nk}^t = \sum_{n=1}^N c_{nm}^t = 0, \quad a_{nk}^t = a_{kn}^t, \quad \forall n, k = 1, \dots, N, \quad \forall m = 1, \dots, M. \quad (8)$$

Furthermore, if we assume that the GDP function is homogeneous of degree one in factor endowments, then we also need to impose the following restrictions:

$$\sum_{n=1}^N b_{0n}^t = 1, \quad \sum_{k=1}^N b_{nk}^t = \sum_{m=1}^M c_{nm}^t = 0, \quad b_{nk}^t = b_{kn}^t, \quad \forall n, k = 1, \dots, N, \quad \forall m = 1, \dots, M. \quad (9)$$

Given the translog functional form and the symmetry and homogeneity restrictions, the derivative of $\ln G^t(p^t, v^t)$ with respect to $\ln p_n^t$ gives the equilibrium share of good n in GDP

at period t :

$$\begin{aligned}
s_n^t(p^t, v^t) &\equiv \frac{p_n^t q_n^t(p^t, v^t)}{G^t(p^t, v^t)} = a_{0n}^t + \sum_{k=1}^N a_{nk}^t \ln p_k^t + \sum_{m=1}^M c_{nm}^t \ln v_m^t \\
&= a_{0n}^t + a_{nn}^t \ln p_n^t + \sum_{k \neq n} a_{nk}^t \ln p_k^t + \sum_{m=1}^M c_{nm}^t \ln v_m^t, \quad \forall n = 1, \dots, N, \quad (10)
\end{aligned}$$

where s_n^t is the share of good n in GDP ($s_n^t < 0$ if good n is an input, as in the case of imports). From Equation (10) it can be shown that, if good n is an imported good, then the import demand elasticity of good n derived from its GDP maximizing demand function is:⁹

$$\varepsilon_{nn}^t \equiv \frac{\partial q_n^t(p^t, v^t)}{\partial p_n^t} \frac{p_n^t}{q_n^t} = \frac{a_{nn}^t}{s_n^t} + s_n^t - 1 \leq 0, \quad \forall s_n^t < 0. \quad (11)$$

Thus we can infer the import demand elasticities once a_{nn} is properly estimated based on Equation (10). Note that the size of the import elasticity, ε_{nn}^t , depends on the sign of a_{nn}^t , which captures the changes in the share of good n in GDP when the price of good n increases by 1 percent:

$$\varepsilon_{nn}^t \begin{cases} < -1 \text{ if } a_{nn}^t > 0, \\ = -1 \text{ if } a_{nn}^t = 0, \\ > -1 \text{ if } a_{nn}^t < 0. \end{cases}$$

The rationale is straightforward. If the share of imports in GDP does not vary with import prices ($a_{nn}^t = 0$), then the implied import demand is unitary elastic such that an increase in import price induces an equi-proportional decrease in import quantities and leaves the value of imports unchanged. If the share of imports in GDP, which is negative by construction,

decreases with import price ($a_{nn}^t < 0$), then the implied import demand is inelastic, so that an increase in import price induces a less than proportionate decrease in import quantities. Finally, if the share of import in GDP increases with import prices ($a_{nn}^t > 0$), then the implied import demand must be elastic such that an increase in the price of import induces a more than proportionate decrease in import quantity.¹⁰

3 Empirical Strategy

With data on output shares, unit values and factor endowments, Equation (10) is the basis for the estimation of import elasticities. In principle, we could first estimate the own price effects, a_{nn}^t , for every good according to Equation (10), and apply Equation (11) to derive the implied estimated elasticities, since the own price elasticity is a linear function of own price effects. There are, however, at least three problems with the estimation of the elasticities using (10). First, there are more than 4900 HS 6 digit goods traded among countries in any given year. Moreover, there is also a large number of non-traded commodities that compete for scarce factor endowments and contribute to GDP in each country. Thus the number of explanatory variables in Equation (10) could easily exhausts our degrees of freedom or introduce serious collinearity problems. Second, even after solving this first problem, we could also run out of degrees of freedom given the short time span of trade data available at the six digit of the HS classification –which was introduced in the late 1980s. Third, there are several econometric issues that may bias our results if they are not addressed. These include the endogeneity and measurement error of unit values, selection bias, and the

sluggish adjustment of imports to changes in prices or any of the other explanatory variables.

We tackle all these problems in turn.

3.1 Estimating the N-good share equations

Estimating the own price and cross price effects, a_{nk}^t , for each of the 4900 HS 6 digit goods is equivalent to estimating the upper triangle of the N by N second order substitution matrix. Thus in total there would be $N(N - 1)/2 + N$ parameters to be estimated, which works out to represent more than 10 million parameters for each time period t ! This is obviously not feasible, even if we restrict all the translog parameters to be time invariant, and the normal system of share equation techniques used in Kohli (1991) or Harrigan (1997) would not have been sufficient. We need a way to legitimately reduce the number of parameter to be estimated and only focus on those parameters that are of interests. In our case, the own price import demand elasticities, and therefore the 4900 diagonal elements of the substitution matrix.

We adopt a *semiflexible functional form* developed in Diewert and Wales (1988) specifically designed to handle translog models with a large number of goods. We first restrict all the translog parameters to be time invariant. Next, rather than allowing the substitution matrix of $[a_{nk}^t]$ to have full rank, we restrict it to be of rank one by imposing the following

constraints:

$$a_{nk}^t = \gamma a_n a_k, \forall n \neq k, \quad (12)$$

$$a_{nn}^t = -\gamma a_n \sum_{k \neq n} a_k \quad (13)$$

where γ , a_n and a_k are constants. Such reparametrization effectively reduce the fully flexible translog function in Equation (7) to be *flexible of degree one*. Diewert and Wales (1988) show that such a semiflexible functional form can still approximate a twice continuously differentiable function at any point up to the second order, even though the matrix of second order partial derivatives with respect to prices is restricted to have rank one instead of the maximum possible rank of $N - 1$.¹¹ They further show that the cost of estimating a semiflexible function, instead of a fully flexible functional form, is that one misses part of the effect of a_{nn} associated with the smallest eigen-values, but in many situations this cost is small.¹²

It could be easily verified that for any good n , the above reparametrization satisfies the homogeneity constraint: $a_{nn} + \sum_{k \neq n} a_{nk} = 0$, as well as the symmetry constraint: $a_{nk} = a_{kn}$. In other words, we approximate the full rank second order substitution matrix by the product of a column vector, $a = [a_1, \dots, a_N]'$, and its transpose, and adjust the diagonal elements to satisfy all homogeneity constraints (13) :

$$[a_{nk}]_{N \times N} = \gamma a_{N \times 1} a'_{1 \times N} - \text{diag} \left[\gamma a_n a_n + \gamma a_n \sum_{k \neq n} a_k \right]_{N \times N} .$$

The resulting share equation for each good n is

$$\begin{aligned}
s_n^t(p^t, v^t) &= a_{0n} - \gamma a_n \sum_{k \neq n} a_k \ln p_n^t + \gamma a_n \sum_{k \neq n} a_k \ln p_k^t + \sum_{m=1}^M c_{nm} \ln v_m^t, \quad \forall n = 1, \dots, N, \\
&= a_{0n} - \gamma a_n \left(\sum_{k \neq n} a_k \right) \ln p_n^t + \gamma a_n \left(\sum_{k \neq n} a_k \right) \sum_{k \neq n} \frac{a_k}{\sum_{k \neq n} a_k} \ln p_k^t + \sum_{m=1}^M c_{nm} \ln v_m^t \\
&= a_{0n} - \gamma a_n \left(\sum_{k \neq n} a_k \right) \left(\ln p_n^t - \overline{\ln p_k^t} \right) + \sum_{m=1}^M c_{nm} \ln v_m^t, \\
&= a_{0n} + a_{nn} \ln \frac{p_n^t}{p_k^t} + \sum_{m=1}^M c_{nm} \ln v_m^t,
\end{aligned}$$

where $\overline{\ln p_k^t} = \sum_{k \neq n} \frac{a_k}{\sum_{k \neq n} a_k} \ln p_k^t$ is a weighted average of the log prices of all non- n goods.

Thus with this reparametrization, the share equation of good n depends linearly on the log price of good n relative to an average price of all non- n goods, and the endowments. This significantly reduces the number of variables on the right-hand side from $N + M$, to $1 + M$.¹³

We further impose homogeneity constraints on endowments, so $\sum_{m=1}^M c_{nm} = 0$, $\forall n = 1, \dots, N$. This reduces the number of right-hand side variables to only M :

$$s_n^t(p^t, v^t) = a_{0n} + a_{nn} \ln \frac{p_n^t}{p_k^t} + \sum_{m \neq l, m=1}^M c_{nm} \ln \frac{v_m^t}{v_l^t}, \quad \forall n = 1, \dots, N.$$

Note that the weights used to construct the average price of all non- n goods are all unknown, so we approximate the average price with the observed Tornqvist price index of all non- n goods, $\ln p_{-n}$, which is the share-weighted average prices of all non- n goods. It is constructed

using the GDP deflator net of the price of good n , adjusted by the share of non- n goods,

$$\ln p_{-n}^t = (\ln p^t - \bar{s}_n^t \ln p_n^t) / (1 - \bar{s}_n^t), \text{ where } \bar{s}_n^t = 0.5 (s_n^t + s_n^{t-1}) \quad (14)$$

due to Caves, Christensen and Diewert (1982).¹⁴ Thus, with data on GDP deflators, the share of good n in GDP, and the price of good n , which is measured using unit values, we can construct the price of the non- n good according to Equation (14). This approximation introduces an additive error term to reflect measurement error in each share equation, κ_n^t :

$$\begin{aligned} \ln p_{-n}^t &\equiv \sum_{k \neq n} \frac{\bar{s}_k^t}{\sum_{k \neq n} \bar{s}_k^t} \ln p_k^t, \text{ where } \bar{s}_k^t = \frac{1}{2} (s_k^t + s_k^{t-1}) \\ \overline{\ln p_k^t} &= \ln p_{-n}^t + \kappa_n^t, \end{aligned} \quad (15)$$

$$s_n^t(p^t, v^t) = a_{0n} + a_{nn} \ln \frac{p_n^t}{p_{-n}^t} + \sum_{m \neq n, m=1}^M c_{nm} \ln \frac{v_m^t}{v_l^t} + \kappa_n^t, \forall n = 1, \dots, N. \quad (16)$$

Equation (16) is the basic expression used to estimate the own price effect, a_{nn} , and hence the own price import elasticity, ε_{nn} .

3.2 Using the panel variation in the data

Due to the limited time variation in the data and to take advantage of the panel nature of the sample, Equation (16) is pooled across countries and years for each good n , while allowing for country and year fixed effects to capture any systematic shift in the share equation that

is country or year specific (c indexes countries):

$$\begin{aligned}
s_{nc}^t(p_{nc}^t, p_{-nc}^t, v_c^t) &= a_{0n} + a_{nn} \ln \frac{p_{nc}^t}{p_{-nc}^t} + \sum_{m \neq l, m=1}^M c_{nm} \ln \frac{v_{mc}^t}{v_{lc}^t} + \kappa_{nc}^t, \quad \forall n, c, \text{ with} \\
\kappa_{nc}^t &= a_{nc} + a_n^t + u_{nc}^t, \quad u_{nc}^t \sim \mathcal{N}(0, \sigma_n^2), \quad \Rightarrow \\
s_{nc}^t(p_{nc}^t, p_{-nc}^t, v_c^t) &= a_{0n} + a_{nc} + a_n^t + a_{nn} \ln \frac{p_{nc}^t}{p_{-nc}^t} + \sum_{m \neq l, m=1}^M c_{nm} \ln \frac{v_{mc}^t}{v_{lc}^t} + u_{nc}^t, \quad \forall n. \quad (17)
\end{aligned}$$

We therefore assume that the structural parameters of the semiflexible translog GDP function are common across countries (up to a constant) as in Harrigan (1997). Let's \hat{a}_{nn} denote the consistent estimate of a_{nn} . The consistent estimate of import demand elasticity of good n in country c , $\hat{\varepsilon}_{nnc}$, is constructed using the average import shares of each country c , \bar{s}_{nc} , and \hat{a}_{nn} :

$$\hat{\varepsilon}_{nnc} = \frac{\hat{a}_{nn}}{\bar{s}_{nc}} + \bar{s}_{nc} - 1. \quad (18)$$

The fixed effect (FE) estimates of a_{nn} according to Equation (17) provide our baseline estimates for ε_{nnc} .

3.3 Econometric issues

For Equation (17) to provide a consistent estimate of a_{nn} , the regression error needs to be well behaved and in particular it should not be correlated with relative prices. There are three reasons why this may not be the case in practice. First is the endogeneity and measurement errors in prices –countries may face an upward sloping supply curve which cause prices to increase with imports; and unit values may measure prices with errors. Both problems

contaminate the regression errors and cause the FE estimate of a_{nn} to be bias. Second is selection bias due to zero imports –some countries in some years may *choose* not to import, and their decision could be driven by factors that are correlated with relative prices. Third is the partial adjustment of imports –import shares may take more than one year to respond to price changes which leads to serial correlation in error terms and inconsistency in the FE estimate of a_{nn} . We address each of these issues sequentially. We will also provide bootstrap standard errors for the elasticity estimates taking into account the estimation errors in \hat{a}_{nn} and the sampling errors in \bar{s}_{nc} .

3.3.1 Endogeneity and measurement errors

The relative price of good n is likely to be correlated with the regression error in Equation (17). Increases in import demand may increase import prices if countries face upward sloping supply curves. This may bias the FE estimate of a_{nn} towards zero and reduces the size of the estimated import elasticities. Moreover, due to data limitation, prices of goods are measured by the unit values of imports. Any measurement errors in unit values would also bias the FE estimate of a_{nn} towards zero. We address these two problems by instrumenting unit values using the simple and inverse-distance weighted averages of the unit values of the rest of the world, as well as the trade-weighted average distance of country c to all the exporting countries of good n . We also instrument for price of non- n good in a similar fashion to form the average relative price of the rest of the world. Specifically, the two average relative prices of the rest of the world are constructed as follows (recall that price of non- n good

is the GDP deflator $\ln p^t$ net of the price of good n , adjusted by the share of non- n good,

$$\ln p_{-n}^t = (\ln p^t - \bar{s}_n^t \ln p_n^t) / (1 - \bar{s}_n^t):$$

$$z_{nc}^t = \ln \frac{\bar{p}_{n-c}^t}{\bar{p}_{-n-c}^t} = \ln \left(\sum_{k \neq c} w_k p_{nk}^t \right) - \left(\frac{\ln \sum_{k \neq c} w_k \bar{p}_k^t - \left(\sum_{k \neq c} w_k \bar{s}_{nk}^t \right) \ln \left(\sum_{k \neq c} w_k p_{nk}^t \right)}{1 - \left(\sum_{k \neq c} w_k \bar{s}_{nk}^t \right)} \right),$$

$$w_k = \begin{cases} 1/(C-1), & \text{for the simple average} \\ 1/(\text{distance in kilometer between country } c \text{ and } k), & \text{for the weighted average} \end{cases} \quad (19)$$

where C is the total number of countries in the sample of good n . Trade-weighted distance is calculated as

$$z_{nc}^t = \sum_k w_k^t \text{distance}_{kc}, \quad (20)$$

with k indices all exporting countries of good n ; distance between k and c is measured in kilometers, and w_k^t is the share of k in world exports of good n in year t . We expect the relative price of good n in the rest of the world to be positively correlated with the relative price of n in c , while it is not necessarily correlated with the share of n in the GDP of c . Similarly, the price of good n in c should increase with the distance between c to any exporting country of good n while the latter may not be correlated with the share of n in the GDP of c . These three instruments therefore pick up the exogenous relationship between the relative price of good n and the dependent variable, while bypassing measurement error and endogeneity of prices.

We estimate Equation (17) with fixed effect instrumental variable (FEIV) regression. Correcting for endogeneity and measurement error should increase the magnitude of the

elasticity estimates, relative to the baseline fixed effect specification of Equation (17).

3.3.2 Selection bias

For each good n , we rely on a country-year panel data set to estimate Equation (17). These data sets are not balanced as we don't observe positive import values in all countries and years. Helpman, Melitz and Rubinstein (2007) show that omitting countries with zero or missing import volume in a gravity setup explaining bilateral trade may lead to potentially large selection bias in the event zero or missing imports are systematically driven by some unobserved fixed trade costs that are also correlated with the observed trade barriers. However, they found that their theoretical result has little empirical support, as the change in estimates is negligible after they controlled for selection bias. Nevertheless, this may be different in our sample.

Given that we cannot construct unit value unless import volume is positive, our sample consists mainly of observations with low unobserved fixed trade costs. When the relative price of good n increases, the share of good n in GDP may not change as much if the unobserved fixed costs remain low. This leads to an upward bias (less negative) of the FEIV estimate of a_{nn} , which will under-estimate the magnitude of import demand elasticities.

While country and year fixed effects may help control for part of the unobserved fixed costs that are country and year specific, the part of fixed costs that varies within country or within year will still affect our FEIV estimate of a_{nn} . To control for such selection bias, it is necessary to estimate a selection model to control for the propensity of being an importer.

Given that importer status is likely to persist over time and may be country specific, we would need to estimate a selection model in a panel data set with unobserved country effects. Wooldridge (2002) details an estimation strategy to deal with panel selection model with no endogenous right hand side variables. In our case, given that we have an endogenous right hand side variable (price of good n), we use a procedure developed in Semykina and Wooldridge (2005), which is an extension of the textbook treatment of Wooldridge (2002) to allow for instrumental variables.

Specifically, we have the following selection model for the importer status of each country c in each good n (index n is omitted for simplicity):

$$I_c^t = 1 \left[\tilde{I}_c^t > 0 \right] = 1 \left[z_c^t \delta + c_c + \zeta_c^t > 0 \right], \quad (21)$$

where I_c^t denotes the importer status which equals 1 when country c imports some positive amount of good n in year t . It is determined by a latent variable, \tilde{I}_c^t , whose realization depends on the vector of exogenous variables and instruments, z_c^t , unobserved country effects, c_c and a classical error term, ζ_c^t . Variables in z_c^t include $\ln \frac{v_{mc}^t}{v_{ic}^t}$, the average relative prices of good n in the rest of the world, and trade weighted distance as mentioned above.

Estimating Equation (21) with probit in the presence of country fixed effect yields inconsistent estimates due to the incidental parameter problems when the year dimension is shorter than the country dimension. Instead, Semykina and Wooldridge (2005) assume that the unobserved country effect, c_c , can be modeled as a linear function of the time averages

of the exogenous variables and instruments, \bar{z}_c :

$$c_c = \eta + \bar{z}_c \xi + \omega_c, \quad (22)$$

where ω_c is a well behaved error term. Given that the selection equation is just a reduced form equation, it is less restrictive to have time varying coefficients:

$$I_c^t = 1 [\eta_t + z_c^t \delta_t + \bar{z}_c \xi_t + \nu_c^t > 0], \quad (23)$$

$$\nu_c^t = \zeta_c^t + \omega_c. \quad (24)$$

Thus to test for selection bias in this unbalanced panel data set, we first use the probit model to estimate this equation for each period t :

$$P(I_c^t = 1 | z_c) = \Phi(\eta_t + z_c^t \delta_t + \bar{z}_c \xi_t). \quad (25)$$

The inverse Mills ratios, $\hat{\lambda}_c^t = \lambda(\hat{\eta}_t + z_c^t \hat{\delta}_t + \bar{z}_c \hat{\xi}_t)$ is then constructed from the estimated coefficients of the above period specific probit regression, where $\lambda(\alpha) = \phi(\alpha) / \Phi(\alpha)$. $\hat{\lambda}_c^t$ is consistent under the assumption that unobserved country effects in the selection equation is controlled by the time averages of the exogenous and instrumental variables, \bar{z}_c . We include $\hat{\lambda}_c^t$ in the FEIV regression as an additional right-hand side variable. Selection bias cannot be rejected if $\hat{\lambda}_c^t$ is statistically significant, with serial correlation and heteroscedasticity robust standard errors being used for the construction of the t -statistic.

To correct for selection bias when $\hat{\lambda}_c^t$ is statistically significant in the FEIV regression of Equation (17), we estimate the following regression with pooled two stage least squares (2SLS) without country fixed effects, using a constant term, z_c^t , \bar{z}_c and $\hat{\lambda}_c^t$ as instruments for $\ln \frac{p_{nc}^t}{p_{-nc}^t}$ (good index n is reintroduced for clarity):

$$s_c^t = a_n^t + a_{nn} \ln \frac{p_{nc}^t}{p_{-nc}^t} + \sum_{m \neq l, m=1}^M c_{nm} \ln \frac{v_{mc}^t}{v_{lc}^t} + \eta_{1n} + \bar{z}_{nc} \xi_{1n} + \gamma_n \hat{\lambda}_{nc}^t + \tilde{u}_{nc}^t, \quad \forall n, \quad (26)$$

The above pooled 2SLS estimate of a_{nn} is consistent in the presence of selection bias, as well as endogeneity and measurement errors in prices. With only one endogenous variable on the right hand side, we have three additional instruments to help us identify both the selection equation and the share equation. We will be able to test for the validity of instruments with an overidentifying restriction test. In short, Equation (26) replaces country fixed effects with a linear function of the time averages of the exogenous variables and instruments and is estimated with pooled 2SLS. We expect the selection bias corrected elasticity estimates to be larger in magnitude.

3.3.3 Serial correlation and partial adjustment in import shares

Equation (26) is correctly specified if import shares respond to changes in prices and endowments within a year. If import shares are sticky, and it takes more than one year to fully adjust to changes in any of the right hand side variable, then the error term in Equation (26) may be serially correlated, which makes the pooled 2SLS estimate of a_{nn} to be inefficient. At a minimum, as suggested in Wooldridge (2002, p. 275), robust standard errors should be

used when the year dimension is small relative to the cross section, which is the case in our sample. Alternatively, one may include a lagged dependent variable in the right hand side and estimate a dynamic panel regression of partial adjustment:

$$s_{nc}^t = a_n^t + a_{nc} + \mu_n s_{nc}^{t-1} + a_{nm} \ln \frac{p_{nc}^t}{p^{-nc}^t} + \sum_{m \neq l, m=1}^M c_{nm} \ln \frac{v_{mc}^t}{v_{lc}^t} + \gamma_n \hat{\lambda}_{nc}^t + \tilde{u}_{nc}^t, \quad \forall n. \quad (27)$$

When serial correlation is present, Equation (27) is estimated using Arellano and Bover (1995) system GMM estimators, which is Arellano and Bond (1991) difference GMM estimators with a level equation added to the system to improve efficiency.¹⁵ $\hat{\lambda}_{nc}^t$ is included whenever selection bias is detected in the FEIV regressions. We will use serial correlation and heteroscedasticity robust standard errors with the GMM estimates. We will also be able to test for overidentifying restrictions.

3.3.4 Bootstrap standard errors for elasticity estimates

To obtain the bootstrap standard errors of the elasticity estimates, we apply the following procedure.

First, for each good n , we randomly draw 50 values of \ddot{a}_{nn} from a normal distribution according to our preferred estimate, \hat{a}_{nn} and its robust standard error. Note that \hat{a}_{nn} is a consistent estimator, and it has an asymptotic normal distribution (see Wooldridge, 2002, p. 423). Thus, by constructing a sample normal distribution base on \hat{a}_{nn} , we are able to save computing time to obtain the bootstrap sample of \ddot{a}_{nn} in a reasonable way.¹⁶

Next, for each good n , we construct a random sample of import shares for each country

based on repeated draws from the regression data set. The size of the random sample is identical to the actual data set. Based on this random sample we construct the average share of each country. This procedure is repeated 50 times to construct the 50 average shares, \bar{s}_{nc} , for each good in each country. Finally, we construct 50 elasticity estimates, $\bar{\epsilon}_{nnc}$, using \bar{a}_{nn} and \bar{s}_{nc} according to (18). The standard deviation of the 50 $\bar{\epsilon}_{nnc}$ is the bootstrap standard error of $\hat{\epsilon}_{nnc}$ for each good in each country.

4 Data

The data consists of import values and quantities reported by different countries to the UN Comtrade system at the six digit of the HS (around 4900 products). The HS was introduced in 1988, but a wide use of this classification system only started in the early 1990s. The basic data set consists of an unbalanced panel of imports for 117 countries at the six digit level of the HS for the period 1988-2001. The number of countries obviously varies across products depending on the presence of import flows and on the availability of trade statistics at the HS level.¹⁷

There are three factor endowments included in the regression: labor, capital stock and agriculture land. Data on labor force and agriculture land are from the World Bank's World Development Indicators (World Bank, 2003). Data on capital endowments is constructed using the perpetual inventory method based on real investment data in the World Development Indicators.

5 Empirical Results

For our baseline FE estimates, we fit Equation (17) for each good using available data from all countries and years. Using the FE estimate for a_{nn} , we construct import demand elasticity according to Equation (18). After excluding outliers (elasticity estimates that are more than 2 standard deviations away from the mean) and observations with positive import demand elasticities (about 5 percent of the estimates), the average elasticity is -1.60. However, these FE estimates are likely to be biased due to endogeneity and measurement issues.

To correct for endogeneity and measurement errors in prices, we estimate Equation (17) using FEIV regression with the simple and inverse-distance weighted average price of the rest of world and the trade weighted distance to exporters as the additional instruments. These instruments are constructed according to Equations (19) and (20). Such correction yields an average elasticity of -3.23. This is in line with our expectation that endogeneity and measurement errors cause the elasticity estimates to be smaller in magnitude. The overall fit of the regressions is good, with an average partial R^2 on the three excluded instruments equals 0.17, an average p-value of the first stage F-statistics on the three excluded instruments equal to 0.09, and the instruments being jointly significant in 75 percent of the regressions.

To test for selection bias, we first run the probit regressions based on Equation (25) for every good in every year. The overall fit of the probit regressions is very good with an average pseudo R^2 of 0.36 and an average $\chi^2_{(10)}$ of 45.98 which is statistically significant for almost all goods.¹⁸ The inverse Mills ratio, $\hat{\lambda}_{nc}^t$, is then constructed for the selected sample with positive import values. We include $\hat{\lambda}_{nc}^t$ in the FEIV regressions. The null hypothesis

that there is selection bias cannot be rejected if $\hat{\lambda}_{nc}^t$ is statistically significant. This occurs in 12 percent of the regressions. To correct for selection bias, we estimate Equation (26) for this subset of goods using pooled 2SLS. With the selection bias correction, the overall average elasticity is -3.32, which again is in line with our expectation that selection bias cause elasticity estimates to be smaller in magnitude.

Finally, tests for serial correlation based on the regression errors of the FEIV regressions show that almost 40 percent of the regression errors have serial correlation.¹⁹ For this subset of goods, we allow for partial adjustment in import shares. Two versions of Equation (27) are estimated with the system GMM estimators depending on whether selection bias was rejected in the FEIV regressions. For about 30 percent of goods where there is serial correlation but no selection bias, we exclude $\hat{\lambda}_{nc}^t$ from Equation (27). With such correction, the overall average elasticity is -3.03. Thus, not surprisingly, allowing for partial adjustment significantly reduces the magnitude of the demand elasticity even after taking into account the “long-run” effect of prices on import shares by dividing a_{nn} by $1 - \mu_n$ (the coefficient in front of the lagged depended variable).²⁰ For about 5 percent of the goods where both selection bias and serial correlation are detected, we estimate Equation (27) with $\hat{\lambda}_{nc}^t$ as an additional explanatory variable. The overall average elasticity using this final correction is -3.12. This is our final and preferred estimates of import demand elasticities.

Based on these estimates, we evaluate the validity of the instruments taking into account selection bias and partial adjustment. About 85 percent of the regressions pass the over-identifying restriction tests, with an average p-value of 0.45. Thus overall the instruments

perform reasonably well and the specification of the regression is accepted most of the time.

In summary, we estimate more than 377,000 import demand elasticities. While all these elasticities are robust to endogeneity and measurement errors using instrumental variables, 7 percent of the estimates are further corrected for selection bias only, 29 percent are corrected for serial correlation only and 5 percent are corrected for both selection bias and serial correlation. The simple average elasticity across all countries and goods is -3.12 and the standard deviation is 14.05 suggesting quite a bit of variance in the estimates, as shown in the kernel density distribution plot in Figure 1.

Table 1 presents the sample moments of the elasticity estimates by country. It also provides the average of industry level estimates by country, which were estimated using the same methodology, but with data at the ISIC 3-digit industry level. As expected, import demands tend to be less elastic when estimated using more aggregated data.²¹

Finally, we construct the bootstrap standard errors of these elasticity estimates, taking into account the estimation uncertainty in \hat{a}_{nn} , the sampling errors in average shares, and, when applicable, the estimation errors in $\hat{\mu}_n$, and its covariance with \hat{a}_{nn} . Most of the import demand elasticities are quite precisely estimated. The median t-statistics is around 3.3. Around 57 percent of the elasticities are significant at the 1 percent level; 66 percent at the 5 percent level and 71 percent at the 10 percent level.

6 Calculating TRIs and Deadweight Losses

The estimated import demand elasticities allow us to examine the trade restrictiveness and welfare losses associated with the existing tariff structure in 88 countries for which tariff schedules are available.²² More importantly, this can be done within a theoretically-sound framework. Simple and import-weighted average tariffs have been used in the literature as the conventional measures of trade restrictiveness.²³ As argued by Anderson and Neary (1994, 1996, 2007) these have little theoretical foundations. Import-weighted averages tend to be downward bias, as for example, they put zero weight on prohibitive tariffs and simple average tariffs put identical weights on tariffs that may have very different economic significance. Anderson and Neary (1994, 1996) propose a trade restrictiveness index (TRI), which has a theoretically sound averaging procedure. TRI is defined as the uniform tariff that yields the same real income, and therefore national welfare, as the existing tariff structure. Deadweight loss measures can also be constructed using TRIs and theoretically consistent estimates of import demand elasticities, which in turn allows for comparisons of welfare distortions associated with each country's tariff structure.

To calculate the TRI, one would ideally need to solve a full-fledged general equilibrium model for the uniform tariff that could keep welfare constant given the observed tariff structure. Taking a partial equilibrium approach, Feenstra (1995) provides a simplification for the calculation of TRI, which only requires information on import demand elasticities, share of imports and tariff schedules:²⁴

$$\text{TRI}_c = \left[\frac{\frac{1}{2} \sum_n (\partial q_{nc} / \partial p_{nc}) t_{nc}^2}{\frac{1}{2} \sum_n (\partial q_{nc} / \partial p_{nc})} \right]^{1/2} = \left[\frac{\sum_n s_{nc} \varepsilon_{nnc} t_{nc}^2}{\sum_n s_{nc} \varepsilon_{nnc}} \right]^{1/2}, \quad (28)$$

with t_{nc} is the tariff on good n in country c . Thus, the partial equilibrium TRI is the square root of a weighted average of square tariffs, where weights are determined by the import demand elasticities in each country. Given that we are using GDP maximizing import demand elasticities instead of Hicksian elasticities as in Feenstra (1995), our measures of TRI and DWL are consistent with GDP maximization.²⁵

It is clear from Equation (28) that when tariffs are uniform, the TRI equals both import-weighted and simple average tariffs. When tariffs are not uniform, this is not longer the case, except under very unlikely conditions. To see this, let \bar{t}_c denote the import-weighted average tariff of country c , σ_c^2 the import-weighted variance of the tariff schedule, $\bar{\varepsilon}_c$ the import-weighted average elasticities of c , $\tilde{\varepsilon}_{nc}$ the import demand elasticity of good n in c re-scaled by $\bar{\varepsilon}_c$, and ρ_c the import-weighted covariance between tariff square and import demand elasticities:

$$\begin{aligned} \bar{t}_c &\equiv \sum_n s_{nc} t_{nc}, \quad \sigma_c^2 \equiv \sum_n s_{nc} (t_{nc} - \bar{t}_c)^2 > 0, \\ \bar{\varepsilon}_c &\equiv \sum_n s_{nc} \varepsilon_{nnc}, \quad \tilde{\varepsilon}_{nc} \equiv \frac{\varepsilon_{nnc}}{\bar{\varepsilon}_c} > 0, \quad \rho_c \equiv \text{Cov}(\tilde{\varepsilon}_{nc}, t_{nc}^2). \end{aligned}$$

Then using Equation (28) it can be shown that:²⁶

$$\text{TRI}_c = \left[\sum_n s_{nc} \tilde{\varepsilon}_{nc} t_{nc}^2 \right]^{1/2} = [E(\tilde{\varepsilon}_{nc} t_{nc}^2)]^{1/2} = [\bar{t}_c^2 + \sigma_c^2 + \rho_c]^{1/2}. \quad (29)$$

Thus, according to Equation (29), TRI increases with import-weighted tariffs, their variance and their covariance with import demand elasticities. As in Feenstra (1995) and Anderson and Neary (2007), everything else equal, the larger the tariff variance, the larger is TRI_c relative to \bar{t}_c . More interestingly, TRI_c will be larger than \bar{t}_c , if high tariffs are levied on more elastic imported goods so that the covariance between elasticities and tariff squared is positive. In short, the ratio and difference between TRI and \bar{t}_c reflects both the variance of tariffs and the correlation between tariffs and import demand elasticities:

$$\ln \frac{\text{TRI}_c}{\bar{t}_c} = \frac{1}{2} \ln \left(1 + \frac{\sigma_c^2}{\bar{t}_c^2} + \frac{\rho_c}{\bar{t}_c} \right), \quad (30)$$

$$\text{TRI}_c - \bar{t}_c = \frac{\sigma_c^2 + \rho_c}{\text{TRI}_c + \bar{t}_c}. \quad (31)$$

Using Equations (28) and (29), one can further compute the linear approximation to the deadweight losses (DWL) associated with the existing tariff structure as:

$$\text{DWL}_c \equiv \frac{1}{2} \text{GDP}_c \sum_n s_{nc} \varepsilon_{nnc} t_{nc}^2 \quad (32)$$

$$= \frac{1}{2} (\text{TRI}_c)^2 \text{GDP}_c \sum_n s_{nc} \varepsilon_{nnc} \quad (33)$$

$$= \underbrace{\frac{1}{2} \bar{t}_c^2 \text{GDP}_c \bar{\varepsilon}_c}_{\text{Tariff average}} + \underbrace{\frac{1}{2} \sigma_c^2 \text{GDP}_c \bar{\varepsilon}_c}_{\text{Tariff variance}} + \underbrace{\frac{1}{2} \rho_c \text{GDP}_c \bar{\varepsilon}_c}_{\text{Tariff-elasticity covariance}}. \quad (34)$$

Equation (33) shows how we can infer the deadweight loss associated with the existing tariff regime using the constructed TRI_c . Equation (34) shows how the deadweight loss can be divided into the three elements that define TRI_c .

Table 2 presents TRIs computed using Equation (28) for a sample of 88 countries where tariff schedules are available in the UNCTAD's TRAINS database.²⁷ While this is the most complete cross country database on tariff data, there are some missing data. On average, about 93 percent of the tariff lines at HS 6-digit level (about 4,900 lines) are available which covers about 87 percent of the total import of these countries. After taking into account outliers and observations that violate curvature conditions in the estimation of elasticities (i.e., that yield positive import demand elasticities), the calculation of TRIs covers 85 percent of tariff lines and 87 percent of the imports of these 88 countries.²⁸ Bootstrap standard errors of TRIs are also presented in Table 2, together with simple and import weighted average tariffs to facilitate comparisons.²⁹ All TRIs are very precisely estimated, with a minimum t-statistics of 2.14. Simple t-tests further reveal that in 84 countries, the TRI is statistically greater than the import weighted average tariff. Among the remaining four countries, there are three with uniform tariffs (Hong Kong, Singapore and Chile), which explains why TRI equals the import weighted average tariff. The only country that has a non-uniform tariff schedule and yet the TRI is not statistically different from the import weighted average tariff are Uruguay, where TRI is 13 percent while import weighted average tariff is 12 percent. On average, the TRI is about 80 percent higher than the import-weighted tariffs and 57 percent higher than the simple average tariff in the sample. This implies that import-weighted average tariff underestimates the trade restrictiveness of the sampled countries by 64 percent on average. The sample mean average tariffs, import-weighted tariffs, and TRI are 9.52, 8.12 and 13 percent, respectively.

Countries with the highest TRIs include Egypt (53.46%), Ghana (34.26%), India (33.11%), Tunisia (31.37%), and Morocco (29.68%). The lowest TRIs are found in Hong Kong (0%), Singapore (0%), Australia (4.97%), Hungary (5.60%), and New Zealand (5.72%). While TRIs, simple and import weighted average tariffs are highly correlated –the correlation coefficient between TRIs and simple average tariffs is 0.79 and between TRIs and import weighted tariffs is 0.75– pair-wise comparisons yield some interesting results. For example, Egypt has the highest TRI but its average tariff is only 9.62 percent, which is about 1.5 percentage point higher than the sample average. On the other hand, while Norway’s average and import-weighted tariffs are only about 1/6 of that of Chile, Norway’s TRI is nearly 60 percent higher. These examples indicate that tariffs’ variance and their covariance with import demand elasticities create an important wedge between TRI and import weighted average tariff in some countries.

Table 2 highlights countries where TRI is larger than the import-weighted average tariff by at least 20, 50 and 100 percent with *, ** and ***, respectively. More than 80 percent of the countries in the sample fall into these 3 categories. Among the countries where the TRI is at least twice as large as the import-weighted tariffs, Sudan, Turkey, Malaysia and Saudi also have higher than average TRIs, ranging from 26 to 15 percent, despite relatively low average tariffs. To illustrate the differences between TRIs and import-weighted average tariffs, Figure 2 plots these two for the 88 countries in our sample, along with the 45 degree line. For each country, the distance above the 45 degree line indicates the wedge between TRI and import-weighted tariff as shown in Equation (31). Countries that have large differences

between TRI and import-weighted tariff are located close to the upper-right corner.

What causes import-weighted tariff to hugely underestimate TRI for these countries? Equation (29) indicates that tariffs' variance and their (positive) covariance with import demand elasticities are the two forces behind this difference. To assess the role played by the former, Table 2 also provides the import-weighted variance of tariffs and their import-weighted covariance with import demand elasticities. For most countries in the sample, tariff variance is the major driving force behind the spread between TRI and import-weighted tariffs. However, disproportionately large positive covariances are observed in Sudan, Canada, and the U.S. among other countries. In fact 80 percent of the sample countries have positive covariances between tariffs and import demand elasticities.

The relative contribution of the tariff average, variance and covariance in distorting trade is most clear when we use TRI to construct and divide total DWL into its three components, according to Equation (34). The total DWL and its components in millions of US dollars are presented in Table 3. Bootstrap standard errors of the DWL estimates are also presented in this table. The DWL estimates of 78 countries are statistically significant. In terms of total DWL, the U.S., China and Mexico, have the largest losses associated with their existing tariff structure. On the other hand, relative to the size of the economy, Egypt, Ghana and Tunisia face the largest losses, which are 2 to 3 percent of their GDP.

The division of DWL into its three components shows that, average tariffs can explain more than 86 percent of total DWL in Chile, Uruguay, and Bolivia. These countries have relatively small tariff variance and covariance with import demand elasticities and thus are

located very close to the 45 degree line in Figure 2. Countries where the variance of tariffs is the largest element contributing to the overall DWL include Japan, the Philippines, and Egypt. More than 90 percent of the total DWL can be attributed to the variance of tariffs in these countries.

The last component of DWL is the covariance between tariffs and import demand elasticities. Covariance between tariffs and import demand elasticities lowers DWL when negative, and rises DWL when positive. As shown in Table 2, 17 countries in the sample have negative covariance between tariffs and import demand elasticities indicating that higher tariffs are levied on more inelastic imports. This happens in countries such as Japan, Uruguay and the Phillipines, which have a negative covariance between tariffs and elasticities which lowers their DWL by 15 to 30 percent. However, for the rest of the countries, positive covariances between tariff and import demand elasticities not only create the wedge between TRIs and import-weighted average tariff, they also increase the size of DWL. This is most important in Sudan, Canada, and the U.S., where more than 60 percent of the DWL is due to the positive covariance between tariffs and import demand elasticities. In particular, in Canada, the covariance between tariffs and elasticities contributes to USD 582 million in DWL, which is nearly two third of its total DWL. A closer look into the Canadian tariff schedule reveals that the highest tariffs, which are 50 and 76 percent, are levied on wheat (HS 100190 and HS 100110) which has very elastic import demand in Canada due to the close substitution with the vast production of domestic wheat. Given that imports that are close substitutes with domestic products tend to have higher import demand elasticities, the positive covariance

between tariffs and import elasticities could be explained by the fact that incentives to lobby for tariff protection are higher when facing stronger import competition.

Finally, some words of caution regarding the TRI and deadweight loss calculations. First, Feenstra (1995) simplification of Anderson and Neary's TRI only takes into account the direct own price effects of tariffs. It ignores the cross price effects of other tariffs on import demand as well as income effects due to the redistribution of tariff revenue. Thus, it reflects the first order impact of tariffs on welfare.³⁰ Second, the calculations of TRI and DWL ignore the existence of non-tariff barriers, such as quotas. To the extent that non-tariff barriers are the more binding constraints, TRI and DWL presented here may only capture a lower bound estimate of trade protection and welfare distortions. Third, we have only focused on Most Favored Nation's tariffs, ignoring the numerous preferential agreements that may erode trade restrictiveness. Finally, given the static nature of the analysis, dynamics effects of tariffs on welfare are also ignored.

7 Concluding Remarks

This paper provides a more systematic estimation of import demand price elasticities than those existing in the previous literature for a broad group of countries and at a fairly disaggregated level of product detail. We use a GDP function approach that is consistent with neoclassical trade theories to derive import demand functions and elasticities. Import demand depends on prices of domestic and imported goods, as well as factor endowments, and can be estimated with existing data sets. The overall fit of the estimation of import

demand elasticities is good. The sample average import demand elasticities is -3.12, with wide variation across countries and products.

We use the elasticity estimates to study the trade restrictiveness and the size and composition of trade distortions in 88 countries for which tariff schedules are available. Instead of relying on simple average or import-weighted tariffs, we construct Feenstra's (1995) simplification of Anderson and Neary's TRI. A major obstacle in the past to calculate the TRI for a wide range of countries was the absence of consistently estimated import demand elasticities. Our estimates overcome this problem.

We then show that the TRI, and the deadweight loss associated with the existing trade regime can be divided into three elements: the import-weighted average tariff, the tariff variance, and the covariance between tariffs and import demand elasticities. Both, a large tariff variance and a high covariance between tariffs and elasticities can drive a large wedge between TRI and the import-weighted tariff, causing the latter to underestimate the restrictiveness of tariff regimes and the deadweight losses associated with them.

Results suggest that import-weighted tariffs underestimate the restrictiveness of trade by 64 percent on average. While the variance of tariffs explains most of the trade distortions in Japan, the Philippines, and Egypt, the covariance between tariffs and import demand elasticities explains more than 60 percent of the trade distortions in Sudan, Canada, and the U.S.. In the case of Canada, about two third of the deadweight loss are due to high tariffs levied on more elastic imported goods. Given that high import demand elasticities partly signals close substitution between domestically produced and imported goods, this

result may be explained by the fact that industries that face stronger import competition are more likely to get organized, and lobby for tariffs. This empirical observation may help inform the design of lobbying models.

References

- [1] Anderson, James and J. Peter Neary, “Measuring the restrictiveness of trade policies,” *World Bank Economic Review* 8 (May 1994), 151-169.
- [2] Anderson, James and J. Peter Neary, “A new approach to evaluating trade policy,” *Review of Economic Studies* 63 (January 1996), 107-125.
- [3] Anderson, James and J. Peter Neary, “The Mercantilist index of trade policy,” *International Economic Review* 44 (May 2003), 627-649.
- [4] Anderson, James and J. Peter Neary, “Welfare versus market access: the implications of tariff structure for tariff reform,” *Journal of International Economics* 71 (March 2007), 187-205.
- [5] Arellano, Manuel and Stephen Bond, “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies* 58 (April 1991), 277-297.
- [6] Arellano, Manuel and Olympia Bover, “Female labour force participation in the 1980s: the case of Spain,” *Investigaciones Economicas* 19 (May 1995), 171-194.

- [7] Blackorby, Charles and Robert Russell, “The Morishima Elasticity of Substitution; Symmetry, Constancy, Separability, and its Relationship to the Hicks and Allen Elasticities,” *Review of Economic Studies* 48 (January 1981), 147-158.
- [8] Blackorby, Charles and Robert Russell, “Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen/Uzawa and Morishima Elasticities),” *American Economic Review* 79 (September 1989), 882-888.
- [9] Broda, Christian and David Weinstein, “Globalization and the gains from variety,” *Quarterly Journal of Economics* 112 (May 2006), 541-585.
- [10] Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert, “Multilateral Comparisons of Output, Input, and Productivity using Superlative Index Numbers,” *Economic Journal* 92 (March 1982), 73-86.
- [11] Diewert, W. Erwin, “Applications of Duality Theory,” in Intriligator, M.D. and D.A. Kendrick, eds., *Frontiers of Quantitative Economics II* (1974), North-Holland, Amsterdam.
- [12] Diewert, W. Erwin and Terence J. Wales, “A Normalized Quadratic Semiflexible Function Form,” *Journal of Econometrics* 37 (March 1988), 327-342.
- [13] Feenstra, Robert, “New Product Varieties and the Measurement of International Prices,” *American Economic Review* 84 (March 1994), 157-177.

- [14] Feenstra, Robert, “Estimating the effects of trade policy,” in Gene Grossman and Kenneth Rogoff, eds., *Handbook of International Economics*, vol. 3 (1995), Elsevier, Amsterdam.
- [15] Feenstra, Robert, “A Homothetic Utility Function for Monopolistic Competition Models, Without Constant Price Elasticity,” *Economics Letters* 78 (January 2003), 79-86.
- [16] Gallaway, Michael, Christine McDaniel and Sandra Rivera, “Short-run and long-run industry-level estimates of US Armington elasticities,” *North American Journal of Economics and Finance* 14 (March 2003), 49-68.
- [17] Harrigan, James, “Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model,” *American Economic Review* 87 (September 1997), 475-494.
- [18] Helpman, Elhanan, Marc Melitz and Yona Rubinstein, “Estimating Trade Flows: Trading Partners and Trading Volumes,” NBER Working Paper No. W12927 (2007).
- [19] Kee, Hiau Looi, Alessandro Nicita and Marcelo Olarreaga, “Estimating Ad-valorem equivalents of Non-Tariff Barriers, The World Bank, Policy Research Working Paper No. 3840 (2006).
- [20] Kohli, Ulrich, *Technology, Duality, and Foreign Trade: The GNP Function Approach to Modeling Imports and Exports* (1991), The University of Michigan Press, Ann Arbor.

- [21] Marquez, Jaime, “Long-period stable trade elasticities for Canada, Japan, and the United States,” *Review of International Economics* 7 (February 1999), 102-116.
- [22] Neary, J. Peter, “Rationalising the Penn World Table: True Multilateral Indices for International Comparisons of Real Incomes,” *American Economic Review* 94 (December 2004), 1411-1428 .
- [23] Panagariya, Arvind, Shekhar Shah and Deepak Mishra, “Demand elasticities in international trade: are they really low?” *Journal of Development Economics* 64 (April 2001), 313-342.
- [24] Rauch, James, “Network versus markets in international trade,” *Journal of International Economics* 48 (June 1999), 7-35.
- [25] Riedel, James, “The demand for LDC exports of manufactures: estimates for Hong Kong,” *Economic Journal* 98 (March 1988), 138-148.
- [26] Roodman, David, “xtabond2: Stata module to extend xtabond dynamic panel data estimator,” Center for Global Development (2005).
- [27] Sanyal, Kalyan and Ronald W. Jones, “The theory of trade in middle products,” *American Economic Review* 72 (March 1982), 16-31.
- [28] Schott, Peter, “Across-Product versus Within-Product Specialization in International Trade,” *Quarterly Journal of Economics* 119 (May 2004), 647-678.

- [29] Semykina, Anastasia and Jeffrey Wooldridge, “Estimating Panel Data Models in the Presence of Endogeneity and Selection: Theory and Application,” Department of Economics, Michigan State University (2005).
- [30] Shiells, Clinton, Robert Stern and Alan Deardorff, “Estimates of the elasticities of substitution between imports and home goods for the United States,” *Weltwirtschaftliches Archiv* 122 (June 1986), 497-519.
- [31] Shiells, Clinton, David Roland-Holst and Kenneth Reinert, “Modeling a North American Free Trade Area: Estimation of flexible functional forms,” *Weltwirtschaftliches Archiv* 129 (February 1993), 55-77.
- [32] Stern, Robert, Jonathan Francis and Bruce Schumacher, *Price elasticities in international trade : an annotated bibliography* (1976), Macmillan, London.
- [33] Wooldridge, Jeffrey, *Econometric Analysis of Cross Section and Panel Data* (2002), MIT Press, Cambridge, Massachusetts.
- [34] World Bank, *World Development Indicators* (2003), Washington, DC.
- [35] Yi, Kei-Mu, “Can vertical specialization explain the growth of world trade?” *Journal of Political Economy* 111 (February 2003), 52-102.

Notes

¹Trade policy is (almost by definition) often determined at the tariff line level. To our knowledge the only set of estimates of import demand elasticities at the six digit level of the Harmonized System (HS) that exist in the literature are the ones provided by Panagariya *et al.* (2001) for the import demand elasticity faced by Bangladesh exporters of apparel and the elasticities of substitution across exporters to the US by Broda and Weinstein (2006).

²These include Shiells, Stern and Deardorff (1986), Shiells, Roland-Holst and Reinert (1993), Marquez (1999), Broda and Weinstein (2006) and Gallaway, McDaniel and Rivera (2003). Note that some of these studies focus on elasticities of substitution or income elasticities rather than price elasticities. As shown in Blackbory and Russell (1989) the elasticity of substitution equals the cross price elasticity minus the own price elasticity. Thus, only when the cross price elasticity is zero, as in the case of a Cobb Douglas utility function, the elasticity of substitution is equal to the price elasticity, which in this case is equal to 1.

³See Anderson and Neary (1994, 1996 and 2007).

⁴For a discussion of the relevance of the small country assumption when estimating trade elasticities, see Riedel (1988) and Panagariya *et al.* (2001).

⁵To ensure that the GDP function is differentiable and the gradient of $G^t(p^t, v^t)$ with respect to p^t is the net output vector, we assume that there are at least as many factors as goods, $M \geq N$. If there are more goods than factors, then the output vector is not unique,

and the gradients need to be reinterpreted as a set of subgradient vectors (see Harrigan, 1997). In the empirical section, we have 3 aggregate factors, which are assumed to be composite factors consistently aggregated from as many disaggregate factors as necessary to satisfy the assumption that there exist more factors than goods. See Kohli (1991) for details.

⁶The latter by Young's Theorem.

⁷See Section 5.3 of Kohli (1991) for a thorough discussion on the various import demand specifications.

⁸The only CES function that is compatible with a translog GDP function is a Cobb-Douglas function which has constant shares. The fact that we can estimate the share equations signals that good shares are not constant and do depend on relative prices and endowments which contradict the Cobb-Douglas production function.

⁹Cross-price elasticities of import demand are given by: $\varepsilon_{nk}^t \equiv \frac{\partial q_n^t(p^t, v^t)}{\partial p_k^t} \frac{p_k^t}{q_n^t} = \frac{a_{nk}^t}{s_n^t} + s_k^t, \forall n \neq k$.

¹⁰Kohli (1991) found an inelastic demand for the aggregate US imports with $a_{nn} < 0$, while highly elastic demand for durables and services imports, with the corresponding $a_{nn} > 0$, when aggregate imports is broken down into 3 groups.

¹¹Neary (2004) uses this approach to estimate the AIDS or QUAIDS systems from an expenditure function. He starts with rank 1, then uses the maximum likelihood estimates as the starting values for the estimation of a rank 2 matrix. With each iteration, one more

column is added, and so is the rank of the matrix. Due to the number of goods involved, we stop at rank 1, in view of the enormous complexity of going to higher ranks.

¹²Diewert and Wales (1988) use Canadian data for ten consumer expenditure categories to illustrate that when the rank is small, semiflexible functional forms may lead to inelastic demand estimates. In our sample, as shown in the result section, the average estimated import elasticity is -2.46, and more than 80 percent of the elasticity estimates are significant at the 10 percent level. Thus the issue of inelastic demand may not be a severe problem in our sample.

¹³We are not the first in the literature to reparametrize the translog revenue function in order to reduce the number of parameters to be estimated. Recently, Feenstra (2003) explores the “symmetric” translog indirect expenditure function where he found that with symmetry, $a_{0n} = 1/N$, $a_{nk} = \gamma/N$ and $a_{nn} = -\gamma(1 - 1/N)$. Feenstra shows that such a reparametrization is very convenient, especially when it comes to introduce new variety of goods into the expenditure function –increase in the number of goods, increases N , which decreases a_{nk} and a_{nn} . The decrease in a_{nn} due to an increase in number goods will further increases own price elasticity of good n in magnitude, and reduces the markups of each existing good, which represents the pro-competitive effect of entry of new goods in a monopolistic competition model. In our current setting, increases in new goods increases $\sum_{k \neq n} K_k$ for each good n , which also decreases a_{nn} for all existing good n , and increases demand elasticities of all existing good n in magnitude. Thus without imposing complete symmetry as in Feenstra (2003), our current setting is also capable of capturing the effects of new goods in the GDP

function, via its effects on the reparametrized slope coefficients of the share equations.

¹⁴Caves, Christensen and Diewert (1982) show that the GDP deflator of a translog GDP function with time invariant parameters is a Tornqvist price index. Thus, we can derive the aggregate price of all non- n goods by using the GDP deflator, $\ln p^t$, net of the price of good n , adjusted by the share of all non- n goods:

$$\begin{aligned}\ln p^t &\equiv \sum_k \bar{s}_k^t \ln p_k^t = \bar{s}_n^t \ln p_n^t + (1 - \bar{s}_n^t) \ln p_{-n}^t \implies \\ \ln p_{-n}^t &= (\ln p^t - \bar{s}_n^t \ln p_n^t) / (1 - \bar{s}_n^t)\end{aligned}$$

¹⁵This is done using the STATA `xtabond2` command. See Roodman (2005) for details.

¹⁶Alternatively, we can re-sample our data set and re-estimate the FE, FEIV, pooled 2SLS and system GMM regressions 50 times for all 4,800 goods in order to obtain the bootstrap distribution of \hat{a}_{nn} . This will take several weeks of computing time.

¹⁷The estimation sample did not include tariff lines where the recorded trade value at the six digit level of the HS was below USD 50,000. This eliminated less than 0.1 percent of imports in the sample, and it is necessary in order to avoid biasing our results with economically meaningless imports.

¹⁸According to Equation (25), we have 2 relative endowment variables and 3 instruments, together with the country averages of these 5 variables which are used in place of country

fixed effects, we have 10 variables on the right hand side of the probit regression, which explains why the χ^2 distribution has 10 degree of freedom.

¹⁹To test for AR(1), we follow Wooldridge (2002, p. 275). We regress the fixed effect error term on its one period lag in a pooled OLS starting from period 3. We evaluate the coefficient of the lagged error based on the fully robust standard error. Under the null hypothesis of no serial correlation, the fixed effect error term is negatively correlated. Thus, if the lagged error term is statistically negative, we do not reject the null hypothesis. Conversely, if the lagged error term is statistically positive, then we reject the null hypothesis in favor of serial correlation.

²⁰Arguably, dividing a_{nn} by $(1 - \mu_n)$ to measure the long run effect of relative prices on the import share of good n may be seen as ad-hoc. Ideally, to estimate the long run elasticities, we would need to start with a dynamic theoretical setup that explicitly allows for such mechanisms. This is beyond the scope of the current paper.

²¹When we restrict the sample to only those goods that are included in the ISIC 3-digit classification, the simple average HS 6-digit elasticity is -2.48, while the average ISIC 3-digit elasticity is -1.10.

²²Data sources for tariff data are United Nations' Comtrade and the Integrated Database of the WTO. In this paper, we abstract from measuring the trade restrictiveness of non-tariff barriers, as well as the role of tariff preferences in eroding trade restrictiveness. For an attempt to do so, see Kee, Nicita and Olarreaga (2006).

²³If NTB measures are to be considered, trade economist often use simple or import-weighted coverage ratios of NTBs.

²⁴See Equation (3.5) in Feenstra (1995). Note that given our setup, the derivation in Feenstra (1995) is equivalent to deriving the TRI that would keep GDP at its maximum level given the existing tariff structure.

²⁵See Kohli (1991), Equations 18.27 to 18.31.

²⁶In the third equality note that the expected value of $\tilde{\varepsilon}_{nc}$ equals 1 by construction.

²⁷Out of the 88 countries, 49 have tariff schedules available for 2004, 25 for 2003, 8 for 2005, 4 for 2002 and 2 for 2001.

²⁸For the 7 percent of tariff lines that are missing which represents 13 percent of imports, we have elasticity estimates for 5.6 percent of the products or 12 percent of the imports.

²⁹Bootstrap standard errors for TRIs are calculated using the same repeated sampling described in the elasticity section, taking into account estimation errors in elasticity and the sample errors in average import shares. Using the 50 random samples of elasticities for all goods, we construct the 50 TRIs for each country. The standard deviation of the 50 TRIs gives us the bootstrap standard errors.

³⁰The main difference between this partial equilibrium TRI and the general equilibrium TRI is that cross price effects and income effects stemming from the redistribution of tariff revenue are missing. While ignoring cross price effects have an ambiguous effects on TRIs,

ignoring tariff revenue will unambiguously decrease TRIs. This is because without tariff revenue the welfare of the representative consumer is lower as total disposable income falls. To keep the consumer indifferent, the average tariff will need to decline. Indeed, when we remove tariff revenue from the CGE model of Anderson and Neary (2003), the average TRI of the countries drops from 17.5 percent to 11.9 percent. Nevertheless, the TRI without tariff revenue redistribution is highly correlated with the TRI with tariff revenue redistribution, with a correlation coefficient equal to 0.845.

Table 1: *Estimated elasticities: sample moments by country*

Country code	Country name	Simple average	Standard deviation	Weighted average	ISIC-3 average	Country code	Country name	Simple average	Standard deviation	Weighted average	ISIC-3 average
ALB	Albania	-1.39	3.21	-1.14	-1.04	KGZ	Kyrgyzstan	-1.05	0.47	-1.03	-1.14
ARE	U. Arab E.	-2.59	7.93	-1.38	-1.40	KIR	Kiribati	-1.01	0.19	-1.01	-1.05
ARG	Argentina	-7.92	28.68	-1.86	-1.32	KNA	St. Kitts & N.	-1.04	0.42	-1.02	-1.07
ARM	Armenia	-1.42	5.37	-1.07	-1.14	KOR	Korea, Rep.	-5.51	22.48	-1.24	-1.21
ATG	Antigua	-1.08	0.69	-1.08	-1.15	LBN	Lebanon	-1.84	7.17	-1.13	-1.15
AUS	Australia	-6.78	24.57	-1.46	-1.14	LCA	St. Lucia	-1.16	2.63	-1.07	-1.12
AUT	Austria	-3.93	17.42	-1.25	-1.07	LKA	Sri Lanka	-1.70	5.53	-1.14	-1.08
AZE	Azerbaijan	-1.44	3.04	-1.12	-1.19	LSO	Lesotho	-1.10	0.93	-1.02	-1.06
BDI	Burundi	-1.19	1.77	-1.10	-1.20	LTU	Lithuania	-1.37	2.24	-1.17	-1.06
BEL	Belgium	-2.51	10.63	-1.14	-1.09	LUX	Luxembourg	-1.83	5.17	-1.05	-1.05
BEN	Benin	-1.22	1.23	-1.08	-1.07	LVA	Latvia	-1.31	2.07	-1.11	-1.07
BFA	Burkina F.	-1.24	1.74	-1.06	-1.08	MAC	Macau	-1.67	7.12	-1.11	-1.03
BGD	Bangladesh	-3.23	11.55	-1.61	-1.23	MAR	Morocco	-2.61	10.08	-1.21	-1.14
BGR	Bulgaria	-1.48	4.77	-1.12	-1.08	MDA	Moldova	-1.24	2.71	-1.07	-1.05
BHR	Bahrain	-1.72	9.07	-1.09	-1.05	MDG	Madagascar	-1.39	2.57	-1.17	-1.09
BHS	Bahamas	-1.36	2.92	-1.09	-1.08	MDV	Maldives	-1.05	0.77	-1.03	-1.18
BLR	Belarus	-1.48	4.60	-1.10	-1.05	MEX	Mexico	-5.65	23.01	-1.34	-1.19
BLZ	Belize	-1.07	0.73	-1.07	-1.13	MKD	Macedonia	-1.38	4.60	-1.12	-1.06
BMU	Bermuda	-1.06	0.63	-1.06	-1.10	MLI	Mali	-1.41	3.07	-1.08	-1.29
BOL	Bolivia	-1.53	3.28	-1.15	-1.03	MLT	Malta	-1.26	2.51	-1.11	-1.09
BRA	Brazil	-12.65	36.75	-2.17	-1.31	MNG	Mongolia	-1.08	0.82	-1.03	-1.09
BRB	Barbados	-1.19	1.26	-1.12	-1.13	MUS	Mauritius	-1.26	2.29	-1.08	-1.11
BRN	Brunei	-1.41	3.64	-1.08	-1.04	MWI	Malawi	-1.17	2.01	-1.07	-1.06
BWA	Botswana	-1.43	6.33	-1.04	-1.05	MYS	Malaysia	-2.42	8.22	-1.08	-1.09
CAF	C. African R.	-1.12	1.21	-1.04	-1.22	NAM	Namibia	-1.24	2.42	-1.06	-1.04
CAN	Canada	-5.75	24.06	-1.28	-1.13	NCL	N. Caledonia	-1.24	3.60	-1.07	-1.07
CHE	Switzerland	-4.42	17.98	-1.32	-1.15	NER	Niger	-1.26	1.52	-1.09	-1.26
CHL	Chile	-2.94	10.16	-1.27	-1.28	NGA	Nigeria	-3.00	11.40	-1.32	-1.16
CHN	China	-7.26	25.86	-1.44	-1.12	NIC	Nicaragua	-1.18	3.15	-1.06	-1.03
CIV	Cote d'I.	-2.18	7.92	-1.16	-1.06	NLD	Netherlands	-3.53	16.50	-1.15	-1.12
CMR	Cameroon	-2.16	7.93	-1.25	-1.19	NOR	Norway	-4.24	14.96	-1.41	-1.23
COG	Congo	-1.28	2.84	-1.05	-1.14	NPL	Nepal	-1.62	5.09	-1.13	-1.13
COL	Colombia	-3.74	14.17	-1.45	-1.34	NZL	New Zealand	-3.02	13.12	-1.27	-1.12
COM	Comoros	-1.04	0.33	-1.08	-1.19	OMN	Oman	-2.38	10.83	-1.11	-1.06
CPV	Cape Verde	-1.04	0.47	-1.02	-1.05	PAN	Panama	-1.89	8.45	-1.19	-1.04
CRI	Costa Rica	-1.74	4.60	-1.10	-1.01	PER	Peru	-3.41	10.23	-1.50	-1.08
CYP	Cyprus	-1.43	3.16	-1.13	-1.12	PHL	Philippines	-3.44	13.01	-1.15	-1.24
CZE	Czech R.	-1.96	6.97	-1.15	-1.08	PNG	Papua N. Guin.	-1.50	4.33	-1.15	-1.09
DEU	Germany	-5.33	21.28	-1.43	-1.21	POL	Poland	-3.21	13.17	-1.32	-1.08
DMA	Dominica	-1.07	0.69	-1.06	-1.10	PRT	Portugal	-2.80	12.02	-1.25	-1.04
DNK	Denmark	-3.65	14.85	-1.38	-1.06	PRY	Paraguay	-1.49	2.53	-1.15	-1.08
DZA	Algeria	-2.83	9.12	-1.24	-1.16	PYF	French Poly.	-1.20	1.27	-1.06	-1.07
EGY	Egypt	-4.32	17.89	-1.31	-1.17	ROM	Romania	-2.14	8.62	-1.19	-1.13
ESP	Spain	-4.60	19.28	-1.33	-1.11	RUS	Russia	-6.23	19.13	-1.57	-1.24
EST	Estonia	-1.21	1.81	-1.05	-1.05	RWA	Rwanda	-1.24	1.21	-1.07	-1.18
ETH	Ethiopia	-1.48	3.74	-1.15	-1.12	SAU	Saudi Arabia	-4.16	15.79	-1.30	-1.19
FIN	Finland	-3.70	13.39	-1.37	-1.20	SDN	Sudan	-2.36	11.81	-1.39	-1.16
FRA	France	-5.26	21.78	-1.47	-1.09	SEN	Senegal	-1.48	3.62	-1.09	-1.09
GAB	Gabon	-1.49	3.83	-1.16	-1.07	SGP	Singapore	-2.07	8.71	-1.05	-1.08
GBR	G. Britain	-5.13	20.47	-1.42	-1.08	SLV	El Salvador	-1.97	8.27	-1.20	-1.04
GEO	Georgia	-1.45	3.86	-1.14	-1.11	SUR	Suriname	-1.04	0.65	-1.04	-1.04
GHA	Ghana	-1.54	4.32	-1.09	-1.07	SVK	Slovakia	-1.60	4.71	-1.09	-1.07
GIN	Guinea	-1.34	2.29	-1.10	-1.29	SVN	Slovenia	-1.73	7.34	-1.10	-1.10
GMB	Gambia	-1.07	0.71	-1.07	-1.06	SWE	Sweden	-4.74	18.89	-1.37	-1.17
GRC	Greece	-3.52	13.46	-1.37	-1.05	SWZ	Swaziland	-1.13	1.05	-1.05	-1.04
GRD	Grenada	-1.05	0.47	-1.03	-1.11	SYC	Seychelles	-1.04	0.42	-1.06	-1.05
GRL	Greenland	-1.14	0.99	-1.04	-1.08	TCD	Chad	-1.16	1.23	-1.02	-1.25
GTM	Guatemala	-2.07	6.59	-1.22	-1.02	TGO	Togo	-1.13	0.91	-1.09	-1.09
GUY	Guyana	-1.03	0.40	-1.05	-1.04	THA	Thailand	-3.74	13.76	-1.18	-1.17
HKG	Hong Kong	-3.10	13.50	-1.05	-1.06	TKM	Turkmenistan	-1.27	1.75	-1.04	-1.09
HND	Honduras	-1.29	2.00	-1.07	-1.01	TTO	Trinidad & T.	-1.36	1.94	-1.15	-1.11
HRV	Croatia	-1.64	4.59	-1.19	-1.08	TUN	Tunisia	-1.66	4.65	-1.11	-1.12
HUN	Hungary	-2.09	8.63	-1.11	-1.11	TUR	Turkey	-4.70	19.29	-1.32	-1.12
IDN	Indonesia	-4.90	17.67	-1.38	-1.21	TWN	Taiwan	-4.93	21.10	-1.17	-1.14
IND	India	-12.07	33.56	-1.74	-1.33	TZA	Tanzania	-1.63	3.69	-1.31	-1.10
IRL	Ireland	-2.86	12.40	-1.20	-1.17	UGA	Uganda	-1.87	6.79	-1.26	-1.10
IRN	Iran	-4.98	19.03	-1.32	-1.43	UKR	Ukraine	-2.53	7.38	-1.19	-1.15
ISL	Iceland	-1.52	4.28	-1.20	-1.08	URY	Uruguay	-2.38	8.47	-1.44	-1.16
ISR	Israel	-3.84	15.97	-1.20	-1.23	USA	United States	-12.26	37.42	-2.09	-1.22
ITA	Italy	-5.69	22.17	-1.35	-1.17	VCT	St. Vincent & G.	-1.03	0.36	-1.02	-1.11
JAM	Jamaica	-1.54	5.30	-1.14	-1.15	VEN	Venezuela	-4.49	18.20	-1.48	-1.17
JOR	Jordan	-1.52	5.19	-1.08	-1.07	ZAF	South Africa	-4.56	15.54	-1.43	-1.20
JPN	Japan	-17.39	45.26	-1.83	-1.19	ZMB	Zambia	-1.33	2.53	-1.11	-1.20
KAZ	Kazakhstan	-2.03	5.33	-1.12	-1.17	ZWE	Zimbabwe	-1.67	8.69	-1.11	-1.04
KEN	Kenya	-1.89	6.77	-1.14	-1.13						

Table 2: Tariffs and trade restrictiveness indices^a

Country code	Trade restrictiveness index			MFN tariff			Trade restrictiveness index			MFN tariff		
	simple average	import-weighted variance	covariance	Country code	restrictiveness index	simple average	import-weighted variance	covariance	simple average	import-weighted variance	covariance	
ALB	13.08	(0.24)	11.60	40.46	-3.89	KOR	8.86	(0.70)**	8.52	5.75	27.18	18.27
ARG	15.36	(0.32)	12.32	83.69	-23.99	LBN	12.52	(0.57)**	6.37	7.30	107.59	-4.25
AUS	4.97	(0.12)**	3.42	13.00	0.67	LKA	15.50	(2.75)**	9.97	7.52	129.48	54.16
AUT	6.36	(0.60)**	4.13	3.98	6.01	LTU	7.40	(0.76)**	4.13	4.07	37.12	1.11
BEL	6.73	(0.67)**	4.13	2.22	24.83	LVA	7.01	(0.79)**	4.13	4.15	26.55	5.43
BFA	13.68	(0.19)	11.97	46.74	2.56	MAR	29.68	(1.80)**	26.11	20.47	441.19	20.66
BGD	21.47	(0.55)*	18.38	17.20	46.87	MDG	14.95	(0.42)	15.84	13.19	47.58	2.08
BLR	11.48	(0.37)*	10.76	36.77	3.61	MEX	24.57	(1.01)**	17.69	15.95	291.08	58.27
BOL	8.95	(0.07)	9.40	11.62	-0.42	MLI	13.35	(0.16)	11.97	11.46	46.01	0.80
BRA	14.54	(0.84)*	13.38	10.69	27.26	MUS	24.20	(1.27)**	18.97	11.39	433.10	22.91
CAF	19.24	(0.46)	18.03	16.36	8.25	MWI	14.72	(0.27)*	13.08	10.65	93.58	9.02
CAN	7.54	(1.05)**	3.75	2.92	-0.04	MYS	15.42	(0.90)**	8.30	5.55	195.32	11.71
CHL	5.98	(0.01)	6.01	5.98	0.10	NGA	24.23	(2.52)*	24.16	16.82	277.90	26.26
CHN	16.16	(0.81)**	10.46	9.18	45.61	NIC	12.34	(0.57)**	5.16	6.58	122.82	-13.97
CIV	10.81	(0.44)*	11.97	8.09	8.91	NLD	6.37	(0.88)**	4.13	3.61	21.32	6.24
CMR	16.31	(0.58)	18.03	13.72	14.57	NOR	9.35	(0.51)**	1.18	0.97	74.46	11.93
COL	14.22	(0.68)**	12.38	11.05	20.06	NZL	5.72	(0.12)**	3.08	3.57	21.41	-1.39
CRI	9.66	(0.61)**	5.84	6.06	9.48	OMN	25.76	(2.14)**	7.64	11.43	487.70	45.53
CZE	5.91	(0.78)**	4.13	3.33	4.41	PER	10.97	(0.22)	10.71	9.70	18.12	7.96
DEU	7.67	(1.28)**	4.56	4.67	13.40	PHL	6.81	(0.87)**	4.78	3.33	42.14	-6.90
DNK	6.61	(1.14)**	4.13	3.98	6.75	POL	5.91	(0.71)**	4.13	3.46	15.04	7.90
DZA	17.12	(0.33)*	18.68	13.12	20.33	PRT	6.52	(0.89)**	4.13	4.14	20.18	5.15
EGY	53.46	(24.95)**	19.61	9.62	174.54	PRY	13.65	(0.60)	11.84	12.09	44.27	-4.23
ESP	6.94	(1.28)**	4.13	20.90	11.91	ROM	20.71	(1.19)**	16.51	13.13	196.83	59.96
EST	6.33	(0.49)**	3.95	3.75	2.14	RWA	12.12	(0.26)**	9.83	9.47	55.09	2.14
ETH	19.29	(0.47)*	17.88	14.97	8.02	SAU	14.61	(2.36)**	6.10	6.70	81.82	86.62
FIN	6.19	(1.15)**	4.13	3.38	17.96	SDN	26.19	(8.74)**	4.98	4.32	92.42	575.00
FRA	7.05	(1.16)**	4.13	4.17	26.50	SEN	11.66	(0.31)*	11.97	9.47	44.36	1.84
GAB	18.08	(0.35)	18.03	15.46	2.53	SGP	0.00	(0.00)	0.00	0.00	0.00	0.00
GBR	6.61	(0.73)**	4.13	4.03	6.85	SLV	10.49	(0.33)**	7.20	6.49	60.61	7.34
GHA	34.26	(5.59)**	13.09	16.97	849.82	SVN	6.39	(0.44)**	4.13	4.16	18.56	4.91
GRC	6.72	(1.08)**	4.13	3.94	6.09	SWE	6.17	(1.08)**	4.13	3.55	17.73	7.81
GTM	8.47	(0.28)**	5.65	5.48	40.04	THA	18.56	(0.95)**	15.35	10.95	176.48	47.92
HKG	0.00	(0.00)	0.00	0.00	0.00	TTO	10.22	(0.65)**	7.91	5.30	75.54	0.78
HND	9.36	(0.54)**	5.85	6.05	39.86	TUN	31.37	(0.49)*	28.09	23.07	439.30	12.60
HUN	5.60	(0.49)**	4.13	3.23	14.44	TUR	15.54	(1.57)**	10.01	4.97	102.62	54.11
IDN	9.81	(1.09)**	6.95	52.22	22.17	TZA	14.42	(0.24)*	13.56	11.22	94.92	-12.77
IND	33.11	(2.12)*	29.16	24.82	163.96	UGA	8.99	(0.15)*	7.82	6.92	37.80	-4.91
IRL	6.16	(0.86)**	4.13	3.24	23.05	UKR	8.04	(0.67)**	6.57	3.82	55.45	-5.46
ISL	6.86	(0.31)**	3.50	38.32	-1.63	URY	13.01	(0.46)	12.82	12.28	48.11	-29.65
ITA	7.22	(0.86)**	4.13	4.04	11.24	USA	10.72	(3.63)**	3.39	2.97	35.73	70.25
JOR	16.63	(1.23)**	13.05	152.09	18.56	VEN	15.22	(0.38)	12.38	13.41	65.20	-13.28
JPN	5.97	(0.54)**	3.10	2.80	-10.89	ZAF	12.79	(0.77)**	8.02	6.20	89.93	35.25
KEN	19.67	(0.68)**	16.73	12.16	228.93	ZMB	13.89	(0.34)*	13.27	10.59	81.64	-0.88

^aNumbers in parentheses are bootstrapped standard errors. *, **, and *** indicate that the TRI is greater than import weighted average tariff by at least 20, 50 and 100 percent, respectively.

Table 3: Decomposition of deadweight loss due to the existing tariff regime.^a

Country code	Total dead weight loss (Million of US\$)		% of GDP		Dead weight loss due to tariff		Dead weight loss due to tariff	
	average	variance	average	covariance	average	variance	average	covariance
ALB	10.58	(1.69)***	0.24	8.32	2.50	-0.24	0.09	222.89
ARG	218.41	(100.83)**	0.14	163.18	77.42	-22.19	0.28	19.00
AUS	148.82	(57.08)***	0.07	66.51	78.31	4.01	0.43	20.24
AUT	203.08	(73.08)***	0.21	79.71	93.15	30.21	0.15	8.21
BEL	479.96	(145.59)***	0.14	193.38	263.08	23.50	0.10	2.86
BFA	12.62	(1.99)***	0.26	9.29	3.15	0.17	1.36	283.79
BGD	263.63	(110.46)**	0.47	169.27	67.54	26.81	0.21	7.45
BLR	43.04	(8.61)***	0.29	29.86	12.01	1.18	0.73	2114.84
BOL	9.25	(2.29)***	0.11	7.95	1.34	-0.05	0.23	8.14
BRA	700.53	(397.55)**	0.12	378.28	231.93	90.31	1.23	12.38
CAF	5.25	(0.89)***	0.38	3.80	1.34	0.12	0.32	2.86
CAN	911.94	(413.34)**	0.08	136.42	193.20	582.33	0.93	125.09
CHL	42.70	(11.42)***	0.04	42.63	0.12	-0.05	0.42	118.31
CHN	5329.76	(1977.36)***	0.28	1721.44	2677.19	931.13	0.50	6.38
CIV	23.53	(6.82)***	0.15	13.17	8.56	1.79	0.08	151.10
CMR	45.33	(14.44)***	0.27	32.08	10.77	2.48	0.12	2.77
COL	168.25	(77.34)**	0.17	101.65	49.92	16.69	0.04	15.79
CRI	30.90	(9.76)***	0.17	12.15	15.61	3.14	0.91	36.33
CZE	82.76	(36.43)**	0.09	26.31	46.01	10.44	0.10	54.03
DEU	1584.92	(1129.33)	0.06	588.74	634.63	361.54	0.11	21.89
DNK	146.50	(97.75)	0.06	53.08	70.80	22.62	0.05	40.48
DZA	243.82	(69.59)***	0.36	143.20	83.71	16.91	0.08	51.90
EGY	2404.18	(5688.29)	3.05	77.81	2179.54	146.83	0.29	16.72
ESP	551.78	(402.72)	0.05	175.44	239.71	136.63	0.75	228.40
EST	16.24	(3.79)***	0.18	5.72	9.65	0.87	0.13	1.35
ETH	26.47	(5.90)***	0.33	15.94	9.95	0.37	0.25	131.76
FIN	95.11	(73.90)	0.05	28.34	44.61	22.17	0.48	2.31
FRA	1190.25	(841.09)	0.06	415.33	633.92	141.00	0.27	13.46
GAB	28.03	(7.55)***	0.35	20.50	7.31	0.22	0.00	0.00
GBR	1168.74	(510.11)**	0.06	434.34	551.02	183.39	0.16	9.83
GHA	246.30	(86.51)***	2.78	60.47	178.37	7.46	0.10	12.09
GRC	124.84	(81.64)	0.06	42.97	65.04	16.82	0.06	63.64
GTM	25.57	(8.33)***	0.09	10.69	14.27	0.61	0.71	352.64
HKG	0.00	(0.00)	0.00	0.00	0.00	0.00	0.25	7.12
HND	15.18	(3.68)***	0.21	6.34	6.90	1.93	0.28	69.02
HUN	59.33	(17.21)***	0.07	19.66	27.28	12.39	2.16	329.26
IDN	274.27	(151.17)**	0.11	62.19	148.88	63.20	0.28	69.02
IND	4286.24	(2407.86)*	0.62	2407.28	1238.00	640.97	0.08	3.29
IRL	155.25	(74.10)**	0.09	42.94	94.24	18.08	0.11	12.51
ISL	7.42	(2.31)***	0.07	1.63	6.05	-0.26	0.17	20.54
ITA	861.08	(389.78)**	0.05	270.47	405.22	185.99	0.09	851.52
JOR	78.87	(25.27)***	0.78	30.19	43.38	5.29	0.22	183.69
JPN	805.73	(317.18)**	0.02	177.93	874.44	-246.64	0.14	53.62
KEN	89.59	(23.69)***	0.56	34.25	53.03	2.30	0.33	13.92
KOR	529.36	(179.61)***	0.24	8.32	2.50	-0.24	0.09	222.89
LBN	55.85	(9.09)***	0.14	163.18	77.42	-22.19	0.28	19.00
LKA	86.04	(52.31)**	0.07	66.51	78.31	4.01	0.43	20.24
LTU	27.11	(7.82)***	0.21	79.71	93.15	30.21	0.15	8.21
LVA	8.19	(3.31)**	0.14	193.38	263.08	23.50	0.10	2.86
MAR	596.68	(210.55)***	0.26	9.29	3.15	0.17	1.36	283.79
MDG	9.58	(3.06)***	0.47	169.27	67.54	26.81	0.21	7.45
MEX	5019.52	(1807.67)***	0.29	29.86	12.01	1.18	0.73	2114.84
MLI	11.04	(1.48)***	0.11	7.95	1.34	-0.05	0.23	8.14
MUS	55.86	(13.11)***	0.12	378.28	231.93	90.31	1.23	12.38
MWI	5.46	(0.56)***	0.38	3.80	1.34	0.12	0.32	2.86
MYS	966.49	(213.84)***	0.08	136.42	193.20	582.33	0.93	125.09
NGA	245.47	(116.46)**	0.04	42.63	0.12	-0.05	0.42	118.31
NIC	22.40	(3.68)***	0.28	1721.44	2677.19	931.13	0.50	6.38
NLD	469.86	(235.53)**	0.15	13.17	8.56	1.79	0.08	151.10
NOR	255.33	(97.10)***	0.27	32.08	10.77	2.48	0.12	2.77
NZL	40.66	(11.31)***	0.17	101.65	49.92	16.69	0.04	15.79
OMN	184.75	(26.45)***	0.17	12.15	15.61	3.14	0.91	36.33
PER	69.00	(26.59)***	0.09	26.31	46.01	10.44	0.10	54.03
PHL	91.60	(35.98)**	0.06	588.74	634.63	361.54	0.11	21.89
POL	118.24	(50.71)**	0.06	53.08	70.80	22.62	0.05	40.48
PRT	128.61	(66.99)**	0.36	143.20	83.71	16.91	0.08	51.90
PRY	21.30	(4.12)***	3.05	77.81	2179.54	146.83	0.29	16.72
ROM	568.78	(176.10)***	0.05	175.44	239.71	136.63	0.75	228.40
RWA	2.21	(0.40)***	0.18	5.72	9.65	0.87	0.13	1.35
SAU	625.46	(246.88)**	0.33	15.94	9.95	0.37	0.25	131.76
SDN	84.90	(58.59)	0.05	28.34	44.61	22.17	0.48	2.31
SEN	20.39	(4.01)***	0.06	415.33	633.92	141.00	0.27	13.46
SGP	0.00	(0.00)	0.35	20.50	7.31	0.22	0.00	0.00
SLV	25.68	(7.08)***	0.06	434.34	551.02	183.39	0.16	9.83
SVN	28.46	(6.89)***	2.78	60.47	178.37	7.46	0.10	12.09
SWE	192.96	(138.99)	0.06	42.97	65.04	16.82	0.06	63.64
THA	1012.53	(321.21)***	0.09	10.69	14.27	0.61	0.71	352.64
TTO	26.45	(7.68)***	0.00	0.00	0.00	0.00	0.25	7.12
TUN	608.77	(112.64)***	0.21	6.34	6.90	1.93	0.28	69.02
TUR	675.07	(343.30)**	0.07	19.66	27.28	12.39	2.16	329.26
TZA	27.38	(7.55)***	0.11	62.19	148.88	63.20	0.28	69.02
UGA	5.54	(1.51)***	0.62	2407.28	1238.00	640.97	0.08	3.29
UKR	55.43	(18.64)***	0.09	42.94	94.24	18.08	0.11	12.51
URY	23.05	(7.65)***	0.07	1.63	6.05	-0.26	0.17	20.54
USA	11060.84	(10254.86)	0.05	270.47	405.22	185.99	0.09	851.52
VEN	236.75	(75.44)***	0.78	30.19	43.38	5.29	0.22	183.69
ZAF	227.99	(94.93)**	0.02	177.93	874.44	-246.64	0.14	53.62
ZMB	23.93	(5.33)***	0.56	34.25	53.03	2.30	0.33	13.92

^aCalculation based on TRI and the estimated import demand elasticities. DWL can be divided into three components associated with the contributions of import-weighted tariff, tariff variance, and the covariance between tariffs and import demand elasticities. A positive contribution of the covariance indicates that countries impose higher tariffs on more elastic imports. Numbers in parentheses are bootstrapped standard errors. *, **, and *** indicate that the DWL is statistically different from 0 with 90, 95 and 99 percent significance, respectively.

Figure 1: Distribution of the import demand elasticity estimates at HS 6-digit level

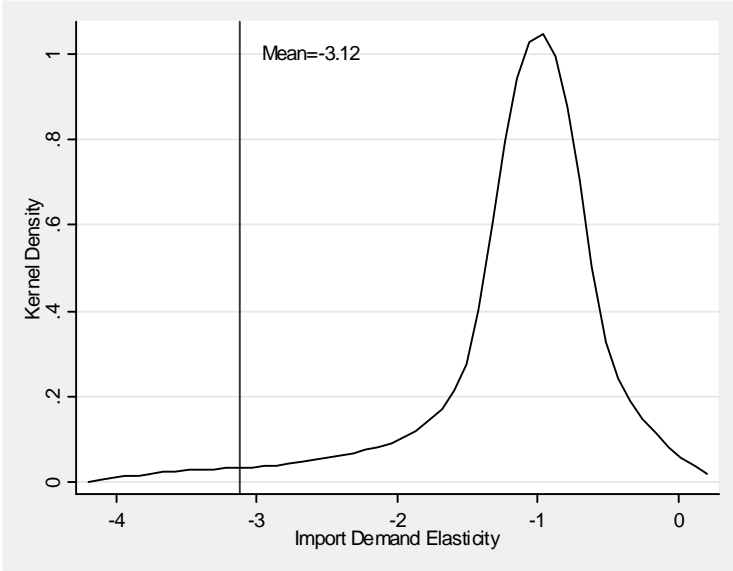


Figure 2: Trade Restrictiveness Index vs. Import Weighted Average Tariff

