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Saad Ahmad, Christopher Montgomery,
and Samantha Schreiber

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Abstract

The Armington elasticity is one of the key parameters in quantitative trade models as it determines the level of substitutability between domestic and imported varieties of a good in a country. Estimates of this key parameter have been provided by several empirical studies using different methods and data sources. Our goal in this paper is to summarize and compare Armington elasticity estimates that are available at the sector level. We first discuss some of the most commonly used methodologies for estimating Armington elasticities as well as the main advantages and challenges associated with each method. Using a common concordance, we then compare these Armington elasticity estimates at the sector level and assess if different levels of aggregation are driving the observed differences across studies. We find that the different estimation strategies, in combination with different levels of sectoral aggregation, has contributed to a wide range of estimates in the literature.

Saad Ahmad, Office of Economics
saad.ahmad@usitc.gov

Christopher Montgomery, Office of Economics
christopher.montgomery@usitc.gov

Samantha Schreiber, Office of Economics
samantha.schreiber@usitc.gov

1 Introduction

Following Armington (1969), trade models often assume that products are differentiated by their country of origin, with the Armington elasticity determining how substitutable domestic and imported varieties of a good are from the perspective of domestic buyers (households and firms).¹ The magnitude of the Armington elasticity is an important driver of model predictions—a higher value means the good is more substitutable, or less differentiated, and so leads to larger effects on trade flows in the liberalizing economy than in the case of a lower value.² Moreover, Arkolakis et al. (2012) show that knowledge of the Armington elasticity, along with observed trade shares, are entirely sufficient to quantify the response of trade flows, consumption and the overall welfare gains for a large class of structural trade models, encompassing a number of alternate market structures. A similar effect is seen in traditional CGE models as well, for instance, McDaniel and Balistreri (2003) show that the values of the Armington elasticity can have a significant effect on the welfare gains or losses in trade policy simulations.

The importance of the Armington elasticity in trade models has led to many empirical studies providing their own estimates of this parameter. Our goal in this paper is to summarize and compare Armington elasticity estimates currently available at the sector level. We start by reviewing some prominent approaches for estimating Armington elasticities including the import price method, the system of equations method, the trade costs method, and the markup method. Along with the estimation framework, differences in sectoral aggregations can also make it harder to compare Armington elasticities across studies. Accordingly, we develop a common concordance to compare Armington elasticity estimates at the sector level for five representative studies: Hertel et al. (2007), Soderbery (2015), Soderbery

¹See for instance Hertel et al. (2007) and Anderson (1979).

²Note that within a Constant Elasticity of Substitution (CES) demand framework, the elasticity of substitution approximates the own-price elasticity of demand if the number of varieties is large.

(2018), Broda and Weinstein (2006), and Ahmad and Riker (2019). Using density- and box-plot graphs, we identify certain patterns within and between studies such as commodities representing high Armington elasticity sectors and differentiated products embodying low Armington elasticity sectors. Nevertheless, it is hard to conclude definitively if different levels of aggregation are in fact driving the observed differences across these studies.

In Section 2, we provide an overview of the methods being employed in the literature for estimating and updating Armington elasticities, along with the main advantages and challenges associated with each approach. We also discuss why estimates may differ systematically due to the method of estimation, the time period and data sources used, and the level of aggregation in each study. In Section 3, we summarize estimates from several key studies as well as provide a qualitative analysis of differences at the sector level using a common concordance for a number of studies. In Section 4, we conclude.

2 Review of Methodologies

The trade literature has suggested several approaches for estimating the Armington elasticity. We focus on four prominent methods: the import price method, system of equations estimation, the trade costs method, and the markup method. As discussed in Hillberry and Hummels (2013) the price variation employed in the estimation and identification strategy are key determinants of observed differences in elasticity estimates across studies.

2.1 Import Price Method

The import price method relies on time-series variation in the prices and quantity of imports in each industry to estimate the Armington elasticity. A CES utility function aggregates the home and foreign goods within a sector, with all sources of foreign goods in the sector treated as perfect substitutes. Estimates of the Armington elasticity can then be

obtained from the following equation:

$$\ln\left(\frac{Q_{kFt}}{Q_{kHt}}\right) = \alpha_k - \sigma_k \ln\left(\frac{P_{kFt}}{P_{kHt}}\right) + \mu_{kt} \quad (1)$$

In the equation above, the left-hand side represents the log of the quantity demanded of imports of good k (from all sources) relative to domestic production. The right-hand side includes a constant α_k , the Armington elasticity of substitution σ_k , the log of relative prices, and an error term. Examples of studies that use this approach are Reinert and Roland-Holst (1992) and Gallaway et al. (2003). It is important to note that this method only identifies the elasticity of substitution between home-produced goods and composite imports within each sector, it does not estimate the elasticity of substitution among imported varieties.

The import price method is relatively straightforward to implement in terms of data requirements, while being consistent with the CES demand function often employed in quantitative trade models. However, as discussed in detail in Hillberry and Hummels (2013), this methodology suffers from several econometric issues that can lead to biased estimates. First, import prices based on unit values are likely to suffer from measurement errors as the reported quantity units are often specific to individual product categories and can differ widely across products, even within an industry.³ Further, quantity measures of imports are themselves quite noisy, so that we have measurement error in both the dependent and independent variable in the regression.⁴ Second, the use of fixed weights to construct a composite price for imports can put too much weight on high foreign prices and too little weight on low foreign prices. Higher variation in this composite import price, relative to a CES price index, requires a low elasticity of substitution in order to reconcile with the small

³For example, constructing unit prices for transportation equipment may require aggregating over dissimilar units (numbers of cars plus numbers of trucks plus kilograms of tires).

⁴As noted in Hillberry and Hummels (2013), if $\hat{Q} = Q \cdot e$ is the observed quantity, then $\hat{p} = M/\hat{Q}$ will be the constructed unit price and we obtain the following equation: $\ln Q_t + e_t = \beta(\ln p_t + e_t)$. If the only variation comes from the error term, then such estimation would yield an elasticity of 1.

movements in observed trade volumes. Finally, these methods do not include supply-side impacts on imports, treating shocks to prices as uncorrelated with the error term in the demand equation, as if they were exogenously determined. Since this strong assumption is unlikely to hold for most countries, a simultaneity bias will also be present in these estimated elasticities. Given these significant econometric challenges, the import price method is no longer considered a reliable way of estimating the Armington elasticity.

2.2 System of Equations Method

Leamer (1981) introduced a new approach for identifying supply and demand parameters in a system of simultaneous equations without the need of any external instruments. The framework assumes that the demand and supply of a good are represented by the following log-linear system of equations:

$$\ln(q_t) = \alpha + \theta \ln(p_t) + \epsilon_t \quad (2)$$

$$\ln(q_t) = \gamma + \omega \ln(p_t) + \mu_t \quad (3)$$

If the demand error ϵ_t is uncorrelated with the supply error μ_t , then the demand (θ) and supply (ω) elasticity parameters can be related by the following hyperbolic function:

$$(\theta - b)(\omega - b) = \left(\frac{b}{b_r} - 1\right)(b_r * b) \quad (4)$$

Here b is the OLS estimate of the regression between quantity and price, while b_r is the estimate of the reverse regression. In the case of a single good, this approach can provide informative bounds for either the demand elasticity or supply elasticity, but not both (Leamer; 1981). For example, if the data indicates a negative correlation between price and quantity as well as a greater variance in the supply shocks, then equation 4 could be

used to construct a relatively tight bound on the demand elasticity. But we will not be able to get any useful information about the supply elasticity in this instance.

Feenstra (1994) builds on this insight to develop a method for estimating Armington elasticities using trade data.⁵ He notes that for a given importer, we can have N different series on prices and quantities, one for each of the N exporting countries. If these suppliers face different demand and supply shocks, then a different hyperbolic relationship can be constructed for each exporter. A Generalized Method of Moments (GMM) estimator can be used over the N hyperbolas to obtain the parameters that minimize the sum of square residuals.⁶ The key identifying assumptions are that the supply and demand elasticities are identical across countries, and that the supply and demand shocks are all drawn independently.⁷

Broda and Weinstein (2006) modify the systems of equations method to estimate Armington elasticities for U.S. trade data under different aggregations. They point out that the estimation in Feenstra’s method was computationally intensive and produced large numbers of elasticities with imaginary values. They overcome this problem by using a grid search method that minimizes the residual sum of squares in the GMM estimation only over a plausible range in the parameter space. The authors find that more disaggregated sectors appear to produce higher substitution elasticity values, and that median elasticity values were decreasing over time as goods become more differentiated.

Soderbery (2015) determines that the use of a GMM estimator in the Feenstra’s system of equations framework can lead to biased estimates in small samples. He instead proposes the use of a Limited Information Maximum Likelihood (LIML) estimator as it can give more weight to hyperbola which are more precisely estimated and less weight to the impre-

⁵As shown in Soderbery (2015), the above framework is compatible under a CES demand with θ being replaced by $(1-\sigma)$ in the estimation.

⁶To control for measurement error in unit prices, Feenstra (1994) utilizes market shares rather than quantities in the estimation.

⁷The assumption of independent supply and demand shocks may also be violated in practice and produce inconsistent estimates. For example, a recession can cause both firm productivity and consumer spending to fall simultaneously, leading to shifts in both the supply and demand curves.

cisely estimated hyperbolae. In Monte Carlo experiments, he shows that LIML estimator is better able to account for correlations between supply and demand errors and significantly outperforms the GMM estimator.

Feenstra et al. (2018) apply the systems of equations method to estimate both the top-level “macro” elasticity of substitution between domestic and composite foreign imports and the lower-level “micro” elasticity of substitution between alternate foreign suppliers. A unique set of matched production and trade data allows them to add another moment condition that the shock to aggregate demand is uncorrelated with the shock to the aggregate supply equation for each good. This additional moment condition addresses the small sample bias issue identified in Soderbery (2015). They find that for between two-thirds and three-quarters of goods sampled, there is no significant difference between the macro- and micro-elasticities. Lastly, Soderbery (2018) departs from the Feenstra (1994) by using variation in prices and quantities across multiple markets in order to identify heterogenous export supply elasticities.

2.3 Trade Cost Method

Several studies rely on the variation in prices of trading partners due to trade costs as a means of estimating Armington elasticities. By exploiting the price variation induced by trade costs, this method is better able to account for measurement error in trade data as well as control for export supply shocks. Under this approach, Armington elasticities are obtained by estimating a simple gravity equation of trade:

$$\ln(X_{ij}) = \alpha_i + \alpha_j + (1 - \sigma) \ln(\tau_{ij}) + \epsilon_{ij} \quad (5)$$

Here X_{ij} represent the value of bilateral trade from country i to j , α_i and α_j control for origin and destination effects, τ_{ij} are bilateral trade costs, and σ is the Armington elasticity. In practice, different proxies for trade costs like tariffs and transportation costs are employed

in the estimation (Head and Ries (2001), Caliendo and Parro (2015), Hertel et al. (2007)).

Hertel et al. (2007) uses exports from every country in the world into selected import countries to estimate the Armington elasticities at the GTAP commodity level. The selected import countries (Argentina, Brazil, Chile, Paraguay, USA, Uruguay, and New Zealand) all provide detailed customs information on tariffs and transportation costs. Exporter and importer characteristics, at the commodity level, are controlled for by fixed effects, so the variation in the delivery price across importers is only a function of differences in observed bilateral trade costs. They find considerable sectoral variation in the estimated Armington elasticities, with the largest elasticity of substitution observed for natural gas and the lowest for other mineral products. A limitation of this approach is the higher data requirements. Transportation costs are not readily available, making it a challenge to estimate Armington elasticities for more disaggregated sectors and countries.

Caliendo and Parro (2015) rely on the multiplicative properties of the gravity equation to derive a relationship between bilateral trade and tariffs, eliminating the need to obtain additional information on the other trade costs in the estimation. In particular, they show that the ratio of the cross-product of bilateral trade flows between three countries in one direction (i to j , j to k , and k to i) over the cross-product of the same flows in the other direction (i to k , k to j , and j to i) eliminates all parameters specific to a particular origin or destination along with other iceberg trade costs.⁸ Using data from 1993 for 16 large economies, they are able to estimate Armington elasticities for 20 sectors. It is important to note that their constructed ratio also eliminates MFN tariffs so identification is achieved only from preferential bilateral tariffs. For instance, if the sample countries are all WTO members, then there is just not enough variation in preferential tariffs to achieve meaningful identification and get useful Armington elasticity estimates from this approach (Ossa; 2015).

⁸Caliendo and Parro (2015) show that all the symmetric and asymmetric components of the iceberg trade costs cancel out if the changes in unobserved trade costs are independent of tariff changes.

2.4 Markup Method

Ahmad and Riker (2019) estimate Armington elasticities by leveraging the structural relationship between the price-cost markup and the elasticity of substitution in industries operating under monopolistic competition.⁹ In a monopolistic competition framework, as in Krugman (1980) and Melitz (2003), there is a continuum of firms, each with monopoly power in the differentiated variety it produces. Firms take the industry price as given such that the own-price elasticity of demand of its good is constant and equal to $-\sigma$. Further, firms are assumed to have constant marginal costs that are equal to their average variable costs.

A profit maximizing firm's markup, under these conditions, equals the reciprocal of the substitution elasticity. So for price p and marginal costs c , the elasticity of substitution σ is just:

$$\frac{1}{\sigma} = \frac{p - c}{p} \quad (6)$$

Ahmad and Riker (2019) rely on publicly available data from the 2012 Economic Census for manufacturing industries to compute industry mark-ups at the 4-digit and 6-digit NAICS aggregation. Assuming constant marginal costs, the mark-ups in equation 6 can be expressed in terms of revenues (TR) and total variable costs (TVC):¹⁰

$$\frac{1}{\sigma} = \frac{TR - TVC}{TR} \quad (7)$$

The strength of the mark-up method is its simplicity and ability to generate estimates at the detailed industry level. Another advantage is that the U.S. manufacturing data are from an official census that is publicly available and periodically updated. However, these

⁹This approach is consistent with the differentiated products model in Krugman (1980), Melitz (2003) and Chaney (2008).

¹⁰Two alternative measures of total variable costs are used in the computations: a low estimate that assumes wage payments to production workers are the only part of the payroll that is a variable cost and a high estimate that the entire payroll is a variable cost.

estimates rely on the validity of monopolistic competition and specific functional forms, while common in trade modeling, are nevertheless stylized. Another limitation is that the total variable costs computation is at best approximate given the data constraints.

3 Study-level Comparison

We have discussed some of the common methods used in the literature for estimating Armington elasticities. Our next task is to review the Armington elasticities generated by these studies and compare them across different industries. Since there is a large econometric literature devoted to estimating the Armington elasticity, we restrict our attention to studies that generate Armington elasticities at the sector level and can be used for practical trade policy analysis.

3.1 Study-Level Analysis

Table 1 summarizes estimates from several of the studies discussed in Section 2. For each study, the econometric method, the range of estimated Armington elasticities across sectors (along with the median), and the level of aggregation is provided. As seen from Table 1, these Armington elasticity estimates vary considerably across the literature, reflecting both the differences in underlying trade data and sectoral aggregation as well as the estimation method employed in the analysis.

Table 1: Summary of Armington Elasticity Estimates Across Studies

Study	Method	Armington Interval	Level of Aggregation
Reinert and Roland-Holst (1992)	Import price	σ from [0.1, 3.0], Median=0.97	163 sectors, BEA classification
Gallaway et al. (2003)	Import price	σ from [1.0, 5.0], Median=0.9	4-digit US SIC level
Broda and Weinstein (2006)	System of equations	σ from [1.2,17.1], Median=3.1	10-digit HTS, and 3-5 digit SITC
Hertel et al. (2007)	Trade costs	σ from [1.8,34.4], Median=6.5,	5-digit SITC agg to 40 GTAP sec
Caliendo and Parro (2015)	Trade costs	σ from [0.4,51.0], Median=3.9	2-digit ISIC Rev. 3
Ossa (2015)	System of equations	σ from [1.5,25.1], Median=2.93	SITC Rev 3
Soderbery (2015)	System of equations	σ from [1.0,131], Median=1.9	8 and 10-digit HTS
Soderbery (2018)	System of equations	σ from [1.3,3312.3], Median=2.9	4-digit HS
Ahmad and Riker (2019)	Markup	σ from [1.3,11.6], Median=2.5	4 and 6-digit NAICS

Table 1 shows that the chosen estimation method plays a prominent role in the observed differences in the median Armington elasticities and ranges across the studies. Studies relying on the import price method generally produce smaller Armington elasticities at the industry-level with estimates often close to or less than 1.¹¹ As noted in Hillberry and Hummels (2013), econometric issues due to measurement error and simultaneity bias may cause the estimates generated in these studies to be biased towards negative 1. Further, studies that use the trade cost method have higher estimates than either the markup method or the system of equations method. Head and Mayer (2014) suggest that compared to the system of equations method, trade cost estimation tends to produce higher estimates, irrespective of the level of disaggregation used in the study. Differences can also exist across studies within the same estimation strategy. For example, the systems of equations (Feenstra) approach has evolved over time—Soderbery (2015) implemented a LIML estimator instead of GMM to account for a small sample bias, resulting in lower estimates than what was found by Broda and Weinstein (2006). Lastly, the estimates in Ahmad and Riker (2019) are concentrated within the lower end of the range of the elasticity estimates found in Table 1.

Along with estimation methods, Table 1 shows that Armington elasticities are estimated at different sectoral aggregations. It is reasonable to expect differences in estimates as a result of the chosen aggregation. For example, an estimated Armington elasticity for an entire GTAP metal products sector should probably not be the same value as the estimated elasticity for a given HS6 product category within that sector. Broda and Weinstein (2006), Imbs and Méjean (2015), Bajzik et al. (2019) and others have provided evidence that more finely disaggregated data generate higher Armington elasticities, indicating that trade is more responsive to relative price changes. However, other studies have found no difference in estimates across aggregation levels (Soderbery (2015); Ahmad and Riker (2019)). It

¹¹Reinert and Roland-Holst (1992) find that only 6 of their 163 sectors had an Armington elasticity greater than 2.

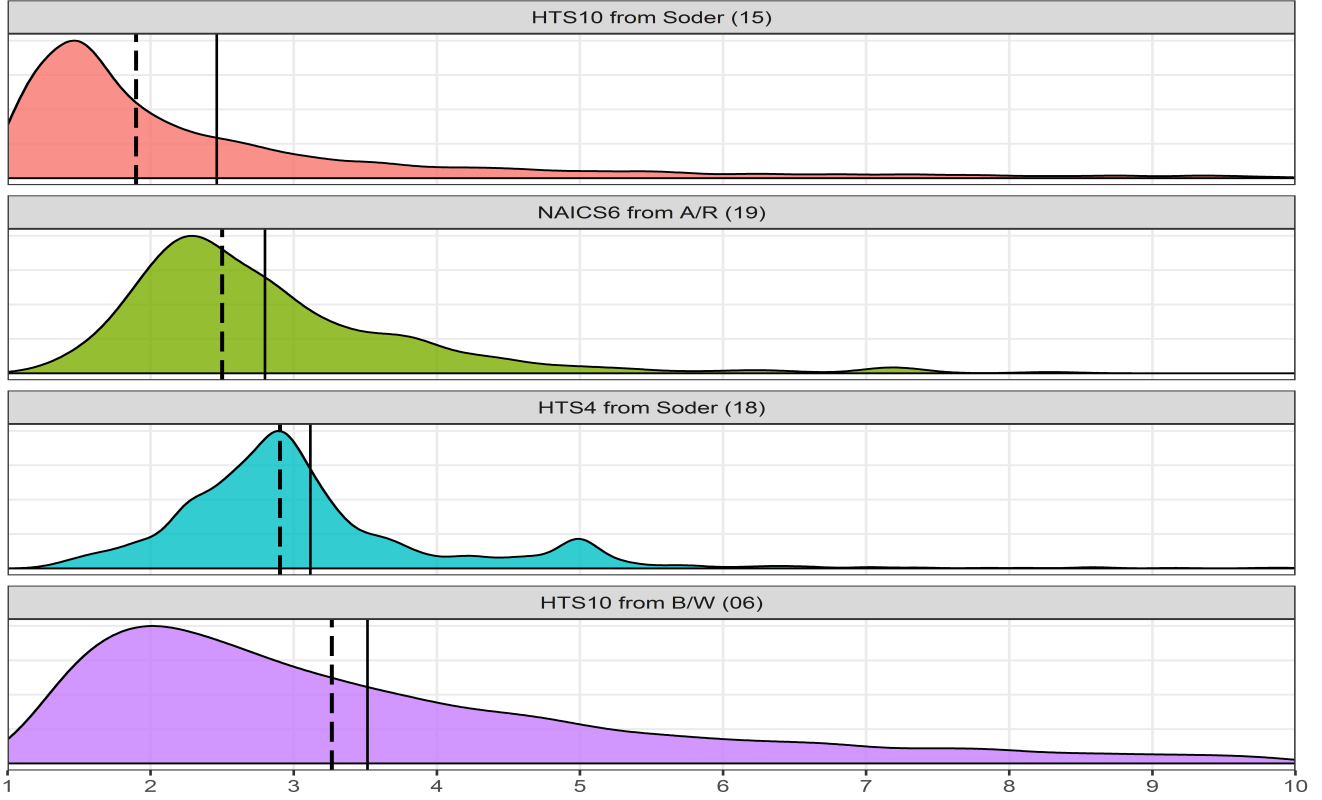
is important to note that having the same Armington elasticity for different aggregations implies that the ability to substitute between domestic and foreign varieties is not affected by the level of aggregation. For some products and sectors this may be a reasonable assumption. For instance, if U.S. consumers don't think Japanese meat products are substitutable with American meat products, then they probably don't view Japanese beef as substitutable with American beef either.

Finally, Table 1 shows that different data sources and time periods have been used in the estimation, and this may contribute to differences across studies as well. Some studies focus only on U.S. trade data while others use global trade flows in their estimations. Changes in Armington elasticities over time makes it harder to compare studies that focus on different time periods, ranging from 1993 to 2019. The frequency of the data may also matter. Bajzik et al. (2019) point out that annual data generate substantially smaller estimates than monthly and quarterly data. Ruhl (2005) shows that elasticities estimated using cross-sectional data are naturally higher than time-series data because they implicitly embed firm dynamics.¹²

We next focus on the distribution of elasticity estimates for some of the studies referenced in Table 1. Specifically, Figure 1 depicts elasticity distributions for four studies: Soderbery (2015); Ahmad and Riker (2019); Soderbery (2018); and Broda and Weinstein (2006). Visual inspection of each distribution leads to several findings. To begin, elasticity estimates are consistently skewed to the right. Each distribution exhibits long right tails with varying proportions of elasticity estimates extending beyond the value of 5. This appears to be especially true for the estimates in Broda and Weinstein (2006). The estimates in Soderbery (2015) comprise the lowest median elasticity value, 1.9, and appear considerably lower than estimates from Broda and Weinstein (2006), with median elasticity 3.1. In addition to

¹²Imbs and Méjean (2015) point out that in practice, disaggregated datasets tend to be cross-sectional, whereas aggregated datasets are usually time-series, so that the differences in Armington elasticity values may be more related to the level of aggregation than the time structure of the dataset.

Figure 1: Armington Elasticity Estimate Distributions by Study



*Vertical dashed lines denote study-specific median elasticity estimates. Solid lines denote study-specific means. Elasticity values greater than 10 were dropped to promote ease of graphical interpretation

having a higher median elasticity value, the modal value of the Broda and Weinstein (2006) distribution is higher than the modal value of the Soderbery (2015) distribution. Ahmad and Riker (2019) (NAICS6) and Soderbery (2018) (HS4) median elasticity values fall between these two studies with values of 2.5 and 2.9 respectively. While not featured in Figure 1, GTAP sector elasticity estimates from Hertel et al. (2007) were highest among the studies reviewed, with a median elasticity of 6.5.

Overall, the comparison across studies does not provide much insight into the relationship between level of aggregation and product substitutability. With the exception of Broda and

Weinstein (2006), Figure 1 suggests that higher levels of aggregation yield higher elasticity estimates than those with more disaggregated sectors like Soderbery (2015). However, such comparisons should be avoided as additional factors, including differences across studies in estimation methods and sample periods, are likely to influence elasticity estimates across studies as well.

3.2 Sector-Level Analysis

To better compare Armington elasticity estimates across studies, we create a common concordance for each classification system used in the following studies: Hertel et al. (2007), Soderbery (2015), Soderbery (2018), Broda and Weinstein (2006), and Ahmad and Riker (2019). A mapping of different Harmonized Tariff Schedule (HTS) codes, 6-digit NAICS and GTAP sectors was constructed and then grouped at the 3-digit NAICS classification. To systematically analyze differences at the sector level within and between studies, we produced density and boxplots focusing on different features of each study’s Armington elasticity distributions.

Figure 2 shows the Armington elasticity distributions of each study for each of the three-digit NAICS manufacturing sectors.¹³ The figure further reinforces several of the patterns identified in section 3.1. For example, median elasticity estimates from Hertel et al. (2007) are highest in magnitude for each of the 20 NAICS-3 manufacturing sectors considered. Furthermore, sectoral estimates from Soderbery (2015) consistently fall below the other distributions depicted in Figure 2. Distributions from Ahmad and Riker (2019); Broda and Weinstein (2006); and Soderbery (2018) regularly fall between these two studies. Sector-specific boxplots show that Broda and Weinstein (2006) estimates are consistently larger than Soderbery (2015) estimates at the same level of aggregation.

¹³The NAICS sector for Miscellaneous manufacturing (339) is excluded from the analysis since it consists of a several diverse industries which may lead to greater heterogeneity in Armington elasticity estimates.

Figure 2: Elasticities by Sector and Study

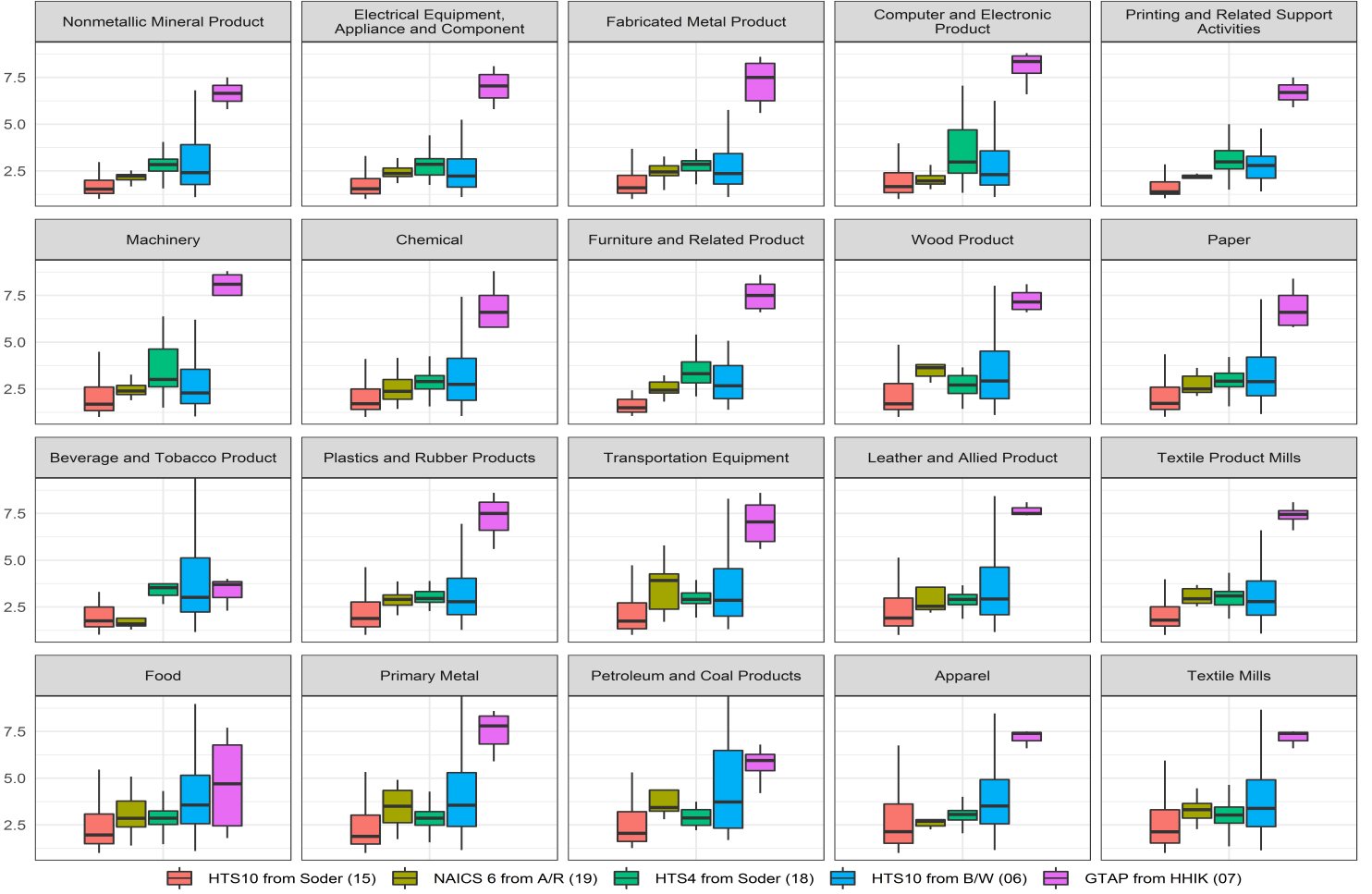
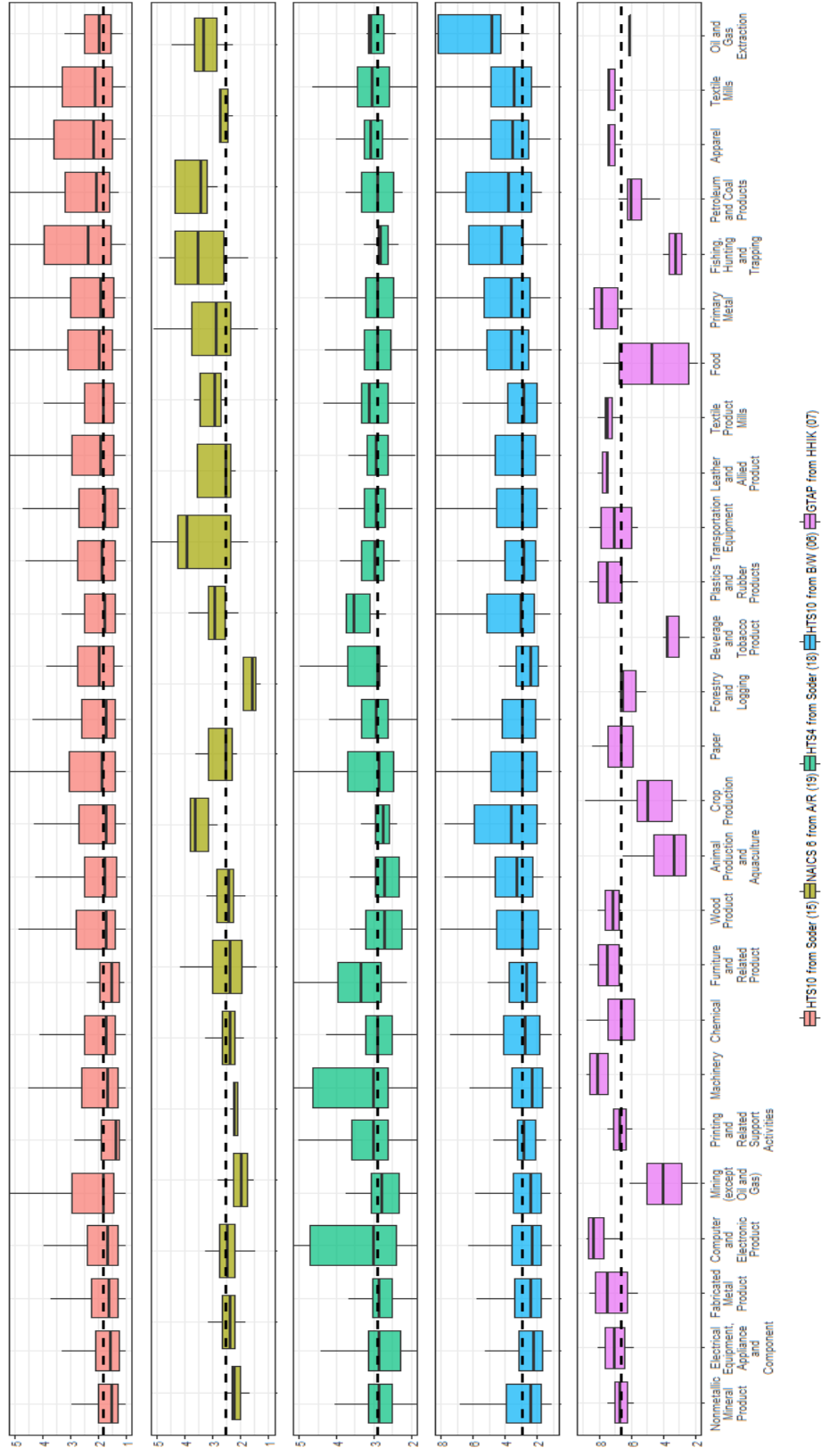


Figure 2 also demonstrates considerable differences in the variation of estimates across studies. Apart from a few manufacturing sectors, interquartile ranges from Ahmad and Riker (2019) and Soderbery (2018) are considerably smaller than ranges produced by other studies featured in Figure 2. On the other hand, boxplots from Broda and Weinstein (2006) consistently show large interquartile ranges across sectors. In general, few individual sectors show consistent patterns regarding the variation or size of interquartile ranges across all of the studies. However, several of the boxes within some individual sectors, such as Food,

Transportation Equipment, and Primary Metals, appear to exhibit above average interquartile ranges. Conversely, Printing, Electrical Equipment, and Nonmetallic Mineral Products generally exhibit lower levels of variance across studies.

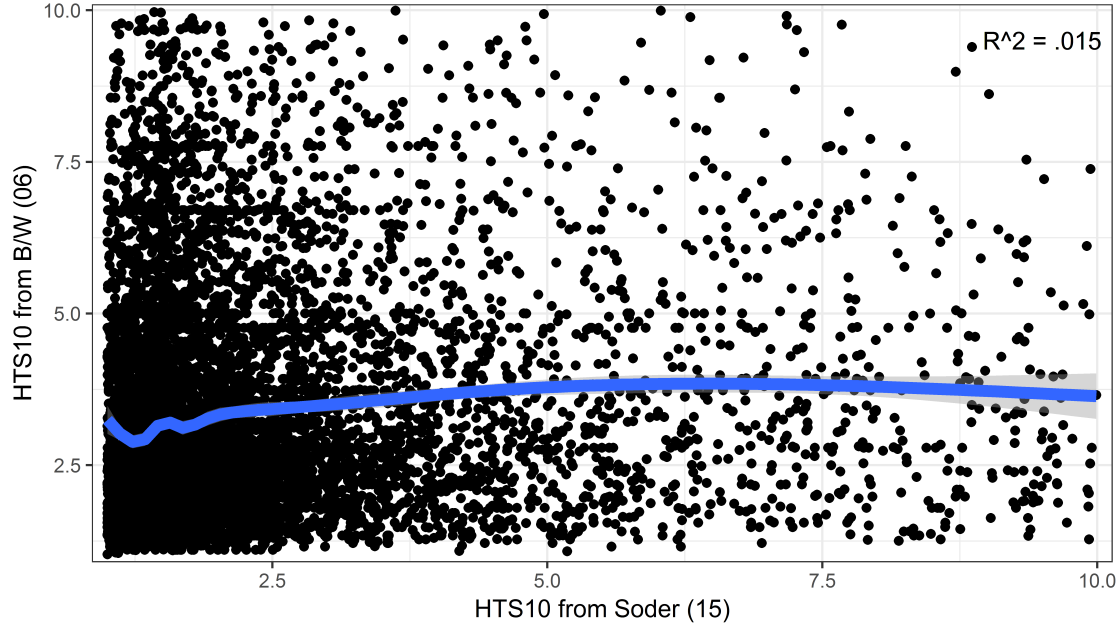
Figure 3 looks at the variation in Armington elasticity estimates across sectors for each of these studies. We generally find that across studies, Nonmetallic Mineral Products (327), Electrical Equipment (335), and Fabricated Metal Products (339) exhibit lower median Armington elasticities compared to their within-study averages. On the other hand, Apparel (315), Textile Mills (313), and Primary Metals (331) were consistently found to be on the high end of Armington elasticity estimates. These findings are supported by basic economic theory. Non-differentiated products and commodities, such as apparel or metals, trend towards the high end of Armington elasticity estimates, while more differentiated sectors like Electrical Equipment exhibit lower Armington elasticity estimates across studies. Figure 3 also shows that few sectors deviate considerably from their study-specific median elasticity. This finding is especially true for both Soderbery studies, which show strong clustering of median sectoral elasticities on or around the study-specific median. Estimates from Hertel et al. (2007) represent an exception to these general trends, with several sectors appear to differ substantially from the study wide median Armington elasticity value of 6.5.

Figure 3: Sectoral Armington Elasticity Distributions Ordered by Magnitude



*Dashed lines represent study-specific median elasticity values. To present estimates on a more observable scale, elasticity estimates above 10 are not graphed, and outlier observations are hidden.

Figure 4: Soderbery and Broda Weinstein Armington Estimates



*Scatter points represent elasticity estimates at the HTS10 level.

Of the studies analyzed in this paper, only Broda and Weinstein (2006) and Soderbery (2015) estimate Armington elasticities at the same level of sectoral aggregation (HTS10). Figure 4, plots Broda and Weinstein (2006) against Soderbery (2015) Armington elasticity estimates and shows a near horizontal best fit line, implying a near zero relationship between elasticity estimates from each study.¹⁴ As discussed in Section 2.2, while both Soderbery (2015) and Broda and Weinstein (2006) employ the system of equations framework to estimate Armington elasticities, differences in the choice of estimator may be one source of divergence between these two studies.¹⁵ Additionally, a small number of HTS10 codes may not map between studies due to revisions to the tariff schedule.¹⁶ Still, it is notable that estimates from the two studies have such little correlation with one another, given that they

¹⁴The pairwise correlation coefficient of estimates between studies corresponds to an R^2 value of .015.

¹⁵Soderbery (2015) relies on a LIML estimator while Broda and Weinstein (2006) use a GMM estimator.

¹⁶Aggregating estimates up to the HS6 level, which is more stable across HTS revisions, does not improve the correlation between study estimates.

examine largely overlapping time periods and identical products in their analysis.

4 Conclusion

The Armington elasticity plays an essential role in trade policy analysis. Yet, there is still no consensus in the literature on the best way to estimate these elasticities, with different empirical methods generating different estimates. We provide an overview of the main empirical methods employed in the literature, highlighting the main features and shortcoming of each approach. Visual inspection of distributions of Armington elasticity estimates show heterogeneity across studies. Still, there are some common patterns exhibited at the sectoral level across studies, with commodities representing high Armington elasticity sectors and differentiated products embodying low Armington elasticity sectors. Future research could include additional studies in the comparison and could further explore the extent to which Armington elasticity estimates at the same levels of aggregation are correlated across studies.

References

- Ahmad, S. and Riker, D. (2019). A Method for Estimating the Elasticity of Substitution and Import Sensitivity by Industry, *USITC Staff Research Paper Series* **2019–05–B**.
- Anderson, J. E. (1979). A Theoretical Foundation for the Gravity Equation, *American Economic Review* **69**: 106–116.
- Arkolakis, C., Costinot, A. and Rodriguez-Clare, A. (2012). New Trade Models, Same Old Gains?, *American Economic Review* **102**: 94–130.
- Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production, *IMF Staff Papers* **16**: 159–78.

- Bajzik, J., Havranek, T., Irsova, Z. and Schwarz, J. (2019). The Elasticity of Substitution between Domestic and Foreign Goods: A Quantitative Survey, *ZBW–Leibniz Information Center for Economics* .
- Broda, C. and Weinstein, D. (2006). Globalization and the Gains from Variety, *Quarterly Journal of Economics* **121**: 541–585.
- Caliendo, L. and Parro, F. (2015). Estimates of the Trade and Welfare Effects of NAFTA, *The Review of Economic Studies* **82**: 1–44.
- Chaney, T. (2008). Distorted Gravity: The Intensive and Extensive Margins of International Trade, *American Economic Review* **98**: 1707–21.
- Feenstra, R. C. (1994). New Product Varieties and the Measurement of International Prices, *American Economic Review* **84**: 157–177.
- Feenstra, R., Luck, P., Obstfeld, M. and Russ, K. (2018). In Search of the Armington Elasticity, *The Review of Economics and Statistics* **100**: 135–150.
- Gallaway, M. P., McDaniel, C. A. and Rivera, S. A. (2003). Short-Run and Long-Run Industry-Level Estimates of U.S. Armington Elasticities, *The North American Journal of Economics and Finance* **14**: 49–68.
- Head, K. and Mayer, T. (2014). Chapter 3 - Gravity Equations: Workhorse, Toolkit, and Cookbook, *Handbook of International Economics* **4**: 131–195.
- Head, K. and Ries, J. (2001). Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade, *American Economic Review* **91**: 858–876.
- Hertel, T., Hummels, D., Ivanic, M. and Keeney, R. (2007). How Confident can we be of CGE-based Assessments of Free Trade Agreements?, *Economic Modelling* **24**: 611–635.

- Hillberry, R. and Hummels, D. (2013). Chapter 18—Trade Elasticity Parameters for a Computable General Equilibrium Model, *Handbook of Computable General Equilibrium Modeling* **1**: 1213–1269.
- Imbs, J. and Méjean, I. (2015). Elasticity Optimism, *American Economic Journal: Macroeconomics* **7**: 43–83.
- Krugman, P. (1980). Scale Economies, Product Differentiation, and the Pattern of Trade, *American Economic Review* **70**: 950–959.
- Leamer, E. (1981). Is it a Demand Curve, or is it a Supply Curve? Partial Identification through Inequality Constraints, *The Review of Economics and Statistics* **63**: 319–27.
- McDaniel, C. A. and Balistreri, E. J. (2003). A Discussion on Armington Trade Substitution Elasticities, *Economie Internationale* **94-95**: 301–313.
- Melitz, M. J. (2003). The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity, *Econometrica* **71**: 1695–1725.
- Ossa, R. (2015). Why Trade Matters After All, *Journal of International Economics* **97**: 266–277.
- Reinert, K. and Roland-Holst, D. (1992). Armington Elasticities for United States Manufacturing Sectors, *Journal of Policy Modeling* **14**: 631–639.
- Ruhl, K. (2005). Solving the Elasticity Puzzle in International Economics, *Working paper* .
- Soderbery, A. (2015). Estimating Import Supply and Demand Elasticities: Analysis and Implications, *Journal of International Economics* **96**: 1–17.
- Soderbery, A. (2018). Trade Elasticities, Heterogeneity, and Optimal Tariffs, *Journal of International Economics* **114**: 44–62.