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A Comparison of Sectoral Armington Elasticity Estimates in the Trade Literature

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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 methods for estimating Armington elasticities, as well as the main advantages and challenges associated with each approach. 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, have contributed to the wide range of elasticity estimates in the literature.

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I. 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] Under this framework, the Armington elasticity serves as a key model input, since it also determines the quantity response of trade flows to price changes.[2] In general, a higher Armington elasticity means that a given product is more substitutable, or less differentiated, and so the model will predict a larger effect on trade flows for a given policy change affecting that product than in the case of a lower value. A similar effect is seen in traditional computable general equilibrium (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 CGE-based trade policy simulations.[3] Consequently, if a practitioner knows which value of Armington elasticity to use for a particular product, then they will be able to make more accurate predictions about the pattern of trade for any given policy change.

The importance of the Armington elasticity in trade models has generated many empirical studies to provide 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. A number of factors can make it hard to compare Armington elasticities across studies: differences in the estimation framework, differences in the period of analysis and differences in sectoral aggregations. We thus begin in section II 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.

In section III, we develop a concordance to compare Armington elasticity estimates at the sector level for five representative studies: Hertel et al. (2007), Soderbery (2015), Soderbery (2018), Broda and Weinstein (2006), and Ahmad and Riker (2019). We then use density-plot and boxplot graphs to identify certain patterns found within and between studies. We find some common patterns across studies, such as commodities sectors representing high Armington elasticity sectors and differentiated products embodying lower Armington elasticity sectors. Nevertheless, it is hard to conclude definitively the degree to which differences in period of analysis, estimation methods, or choice of product aggregation contribute to the observed

[1] See, for instance, Hertel et al. (2007) and Anderson (1979).
[2] While often used interchangeably, it may be helpful here to distinguish between the Armington elasticity of substitution σ and the trade elasticity ϵ, which captures how a change in the bilateral trade costs changes bilateral trade between two countries. In an Armington trade model, $\epsilon = \sigma - 1$, so that knowledge of the Armington elasticity, along with observed trade shares, is entirely sufficient to quantify the response of trade flows, the changes in consumption, and the overall welfare gains for this class of models (Arkolakis et al., 2012). Our paper specifically focuses on methods developed to estimate σ; see Simonovska and Waugh (2014) for some other approaches that have been developed for estimating ϵ.
[3] Computable general equilibrium (CGE) models are a class of multisector, multiregion economic models that characterize economic behavior in a general equilibrium framework. They are used to understand how a change in an economic policy impacts changes in variables like prices, production, trade, and welfare.

differences across these studies. In section IV, we use a simple model of perfect competition to illustrate how the choice of Armington values can influence model results. Section V summarizes the discussion and identifies several areas for future research.

II. 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, the system of equations estimation, the trade costs method, and the markup method. As discussed in Hillberry and Hummels (2013), the price variation employed to estimate and identify the Armington elasticity from trade data is a key factor in observed differences in Armington elasticity estimates across studies.

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 constant elasticity of substitution (CES) 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:

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

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.[4] Further, quantity measures of imports are themselves quite noisy, so that we have measurement error in both the dependent and independent variable in the

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

regression.[5] 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 movements in observed trade volumes. Finally, these methods do not include supply-side impacts on imports; they treat 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.

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 for any external instruments. The framework assumes that the demand and supply of a good are represented by the following log-linear system of equations:

$$\ln(q_t) = \alpha + \theta \ln(p_t) + \varepsilon_t \qquad (2)$$

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

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

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

Here b is the ordinary least squares (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 indicate 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.[6] 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

[5] As noted in Hillberry and Hummels (2013), if $Q_{hat} = Q.e$ is the observed quantity, then $p_{hat} = \frac{M}{Q_{hat}}$ 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.

[6] As shown in Soderbery (2015), the above framework is compatible under a CES demand with θ being replaced by (1-σ) in the estimation.

generalized method of moments (GMM) estimator can be used over the *N* hyperbolas to obtain the parameters that minimize the sum of square residuals.[7] 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.[8]

Broda and Weinstein (2006) modify the system 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 is computationally intensive and produces large numbers of elasticities with imaginary values. They overcome this problem by using a grid search method so that only a plausible range in the parameter space is available for the GMM estimation. The authors find that more disaggregated sectors appear to produce higher substitution elasticity values, and that median elasticity values decrease over time as goods become more differentiated.

Soderbery (2015) determines that the use of a GMM estimator in this 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 hyperbolas which are more precisely estimated and less weight to the imprecisely estimated hyperbolas. In Monte Carlo experiments, he shows that an LIML estimator is better able to account for correlations between supply and demand errors and significantly outperforms the GMM estimator. Using variation in prices and quantities across multiple markets, Soderbery (2018) is also able to identify heterogenous export supply elasticities.

Feenstra et al. (2018) modify the system of equations method to estimate both a top-level "macro" elasticity of substitution between domestic and composite foreign imports and a lower-level "micro" elasticity of substitution between alternate foreign importers. They are able to estimate both these elasticities with a unique set of matched production and trade data which allows them to add another moment condition: that the shock to aggregate demand is uncorrelated with the shock to the aggregate supply for each good.[9]. They find that for between two-thirds and three-quarters of goods sampled, there is no significant difference between the macro- and micro-elasticities, indicating less need for researchers, in general, to account for nested substitution elasticities in policy applications. Moreover, given the granular level of data needed for this particular methodology, trade practitioners are likely to continue to rely on the ad hoc Rule of Two to distinguish between "micro" and "macro" elasticities in their models, rather than estimating it themselves.[10]

[7] To control for measurement error in unit prices, Feenstra (1994) uses market shares rather than quantities in the estimation.
[8] The 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.
[9] Feenstra et al. (2018) also show that this additional moment condition helps address the issue of biased estimates in small samples that was first pointed by Soderbery (2015).
[10] Feenstra et al. (2018) find some support for the Rule of Two, as they are unable to reject that the hypothesis that the micro-elasticity is twice as large as the macro-elasticity for about four-fifths of the goods in their sample.

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. The approach obtains Armington elasticities by estimating a simple gravity equation of trade:

$$ln(X_{ij}) = \alpha_i + \alpha_j + (1 - \sigma)\, ln(\tau_{ij}) + \varepsilon_{ij} \qquad (5)$$

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) use exports from every country in the world into selected import countries to estimate the Armington elasticities at the Global Trade Analysis Project (GTAP) commodity level.[11] The selected import countries (Argentina, Brazil, Chile, Paraguay, the United States, 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, including all other trade costs.[12] 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 most-favored-nation (MFN) tariffs, so that the identification of the trade elasticity is achieved only from preferential bilateral tariffs. For instance, if the sample countries are all WTO members,

[11] GTAP produces a global database that describes bilateral trade patterns, production, consumption, and intermediate use of commodities and services. Hertel et al. (2007) estimate substitution elasticities for 40 commodity groups in the GTAP database.
[12] Caliendo and Parro (2015) show that if the other trade costs are modeled as an ad valorem tax equivalent, then the symmetric and asymmetric components of the trade costs will cancel out as long as the changes in unobserved trade costs are independent of tariff changes.

then there is not enough variation in preferential tariffs to get useful Armington elasticity estimates from this approach (Ossa (2015)).

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.[13] 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 for their 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:

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

Ahmad and Riker (2019) rely on publicly available data from the U.S. Census Bureau's 2012 Economic Census for manufacturing industries to compute industry markups, aggregated at the 4-digit and 6-digit North American Industry Classification System (NAICS) level. Assuming constant marginal costs, the markups in equation (6) can be expressed in terms of revenues (TR) and total variable costs (TVC):[14]

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

Two strengths of the markup method are its simplicity and its 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 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 computation of total variable costs is at best approximate, given the data constraints.

III. 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

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

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

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.

Study-Level Analysis

Table 1 summarizes estimates from several of the studies discussed in section II. 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 in table 1, these Armington elasticity estimates vary considerably across the literature, reflecting not only the different estimation methods employed in the analyses, but also the differences in underlying trade data and sectoral aggregation.

Table 1: Summary of Armington elasticity estimates across studies

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

Note: There are different product nomenclatures used across studies listed in this table. BEA refers to the U.S. Bureau of Economic Analysis (BEA) sectors. SIC refers to the Standard Industrial Classification. The HTS classification is the Harmonized Tariff Schedule at 4-, 6-, 8-, and 10-digit levels. SITC refers to the Standard International Trade Classification. Finally, NAICS refers to the North American Industry Classification System.

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 than do studies using other methods, with estimates often close to or less than 1.[15] 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. On the

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

other hand, 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 between studies within the same estimation approach. For example, the system of equations 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 HS-6 product category within that sector. Broda and Weinstein (2006), Imbs and Méjean (2015), Bajzik et al. (2020), 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)).

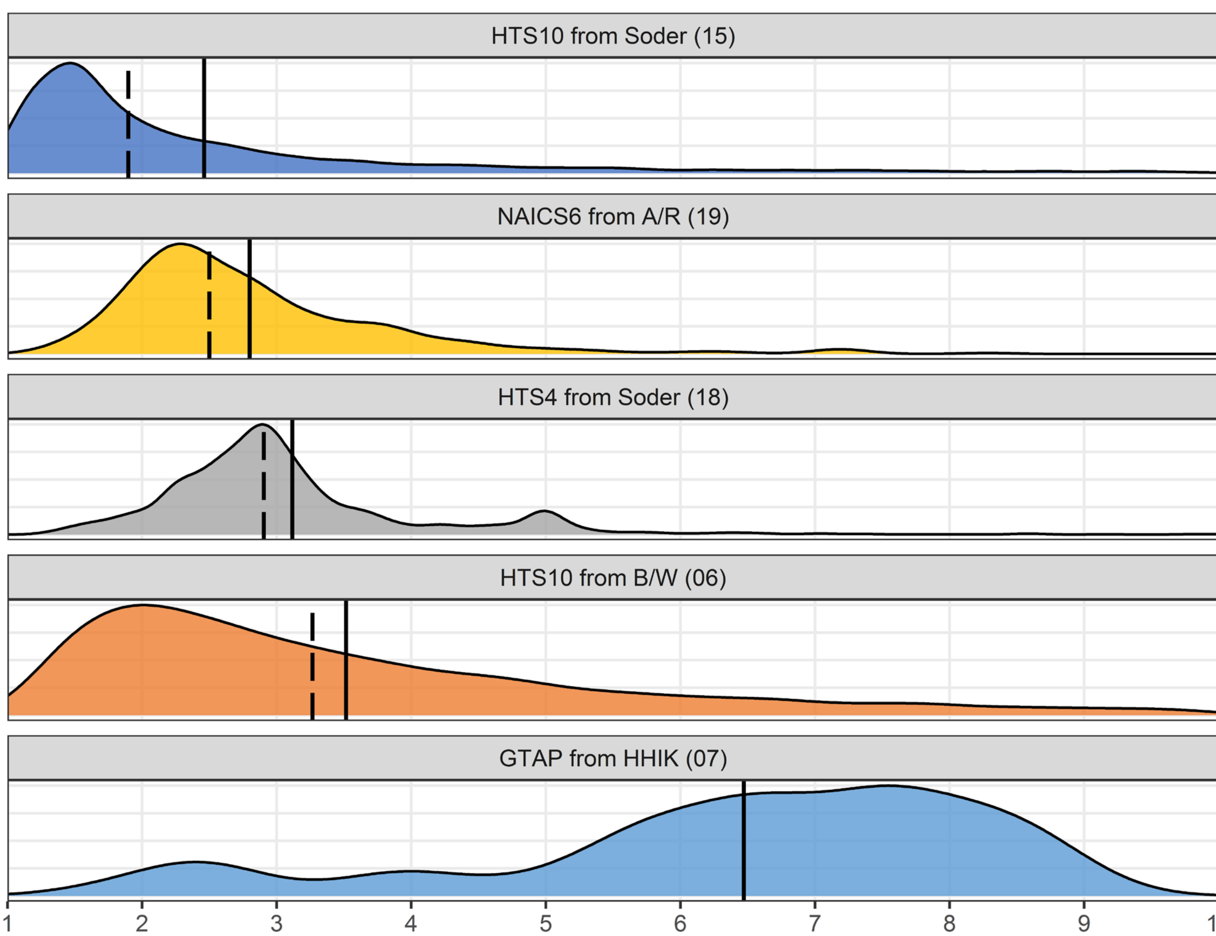
It is important to note that having the same Armington elasticity for different aggregations within a sector only implies that the ability to substitute between domestic and foreign varieties is not affected by the level of aggregation. For some products and sectors this may be a reasonable assumption. 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. Conversely, if the aggregation is broad enough, then individual products may be more likely to be more substitutable across foreign and domestic producers than are industry-level product baskets. For example, we could have less substitutability between Japanese and U.S. products for all manufacturing goods but see higher elasticities of substitution in a narrower sector like automobiles.

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; the studies used in this paper, for example, range from 1993 to 2019. The frequency of the data used in the estimation 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.[16]

[16] However, Imbs and Méjean (2015) note that differences in Armington elasticities may be related to the level of aggregation than the structure of the data as disaggregated datasets tend to have more cross-sectional observations.

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), labeled in figures as Soder (15); Ahmad and Riker (2019), labeled as A/R (19); Soderbery (2018), labeled as Soder (18); Broda and Weinstein (2006), labeled as B/W (06); and Hertel et al. (2007), labeled as HHIK (07). The level of aggregation is listed in the figure, where the 4-digit Harmonized Tariff Schedule (HTS) is labeled as HTS4, 10-digit level as HTS10, and 6-digit NAICS codes as NAICS6. Visual inspection of each distribution leads to several findings. To begin, elasticity estimates are consistently skewed to the right. Apart from Hertel et al. (2007), the distributions exhibit 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 a median elasticity of 3.1.

Figure 1: Distribution of Armington elasticity estimates 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.

In addition to 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. 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, such as Soderbery (2015). However, such comparisons should be avoided, given that additional factors, including differences across studies in estimation methods and sample periods, are likely to influence elasticity estimates across studies.

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 HTS codes, NAICS 6-digit codes, and GTAP sectors was constructed and then grouped at the NAICS 3-digit (NAICS-3) classification level. To systematically analyze differences at the sector level within and between studies, we produced density plots and boxplots focusing on different features of each study's Armington elasticity distributions.

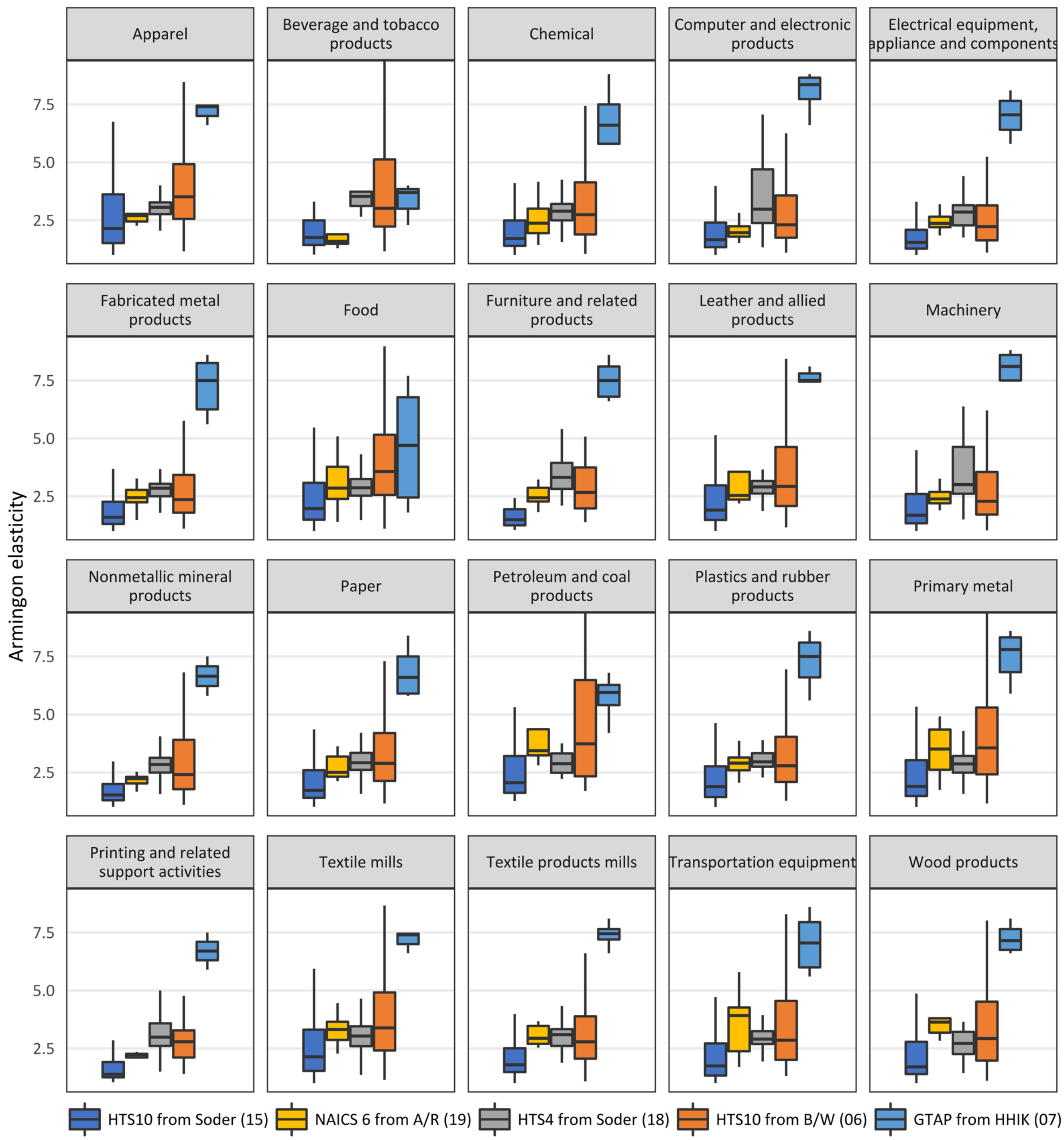
Figure 2 shows the Armington elasticity distributions of each study for each of the NAICS-3 manufacturing sectors.[17] The figure further reinforces several of the patterns identified in section 3.1. For example, median elasticity estimates from Hertel et al. (2007) are highest in magnitude for each of the 20 NAICS-3 manufacturing sectors considered. Meanwhile, sectoral estimates from Soderbery (2015) consistently fall below the other distributions. 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.

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. By contrast, boxplots from Broda and Weinstein (2006) consistently show large interquartile ranges across sectors. In general, few individual sectors

[17] The NAICS sector for miscellaneous manufacturing (339) is excluded from the analysis, since it consists of several diverse industries; this trait may lead to greater heterogeneity in Armington elasticity estimates.

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 2: Study-specific Armington elasticity estimates concorded to NAICS 3-digit sectors

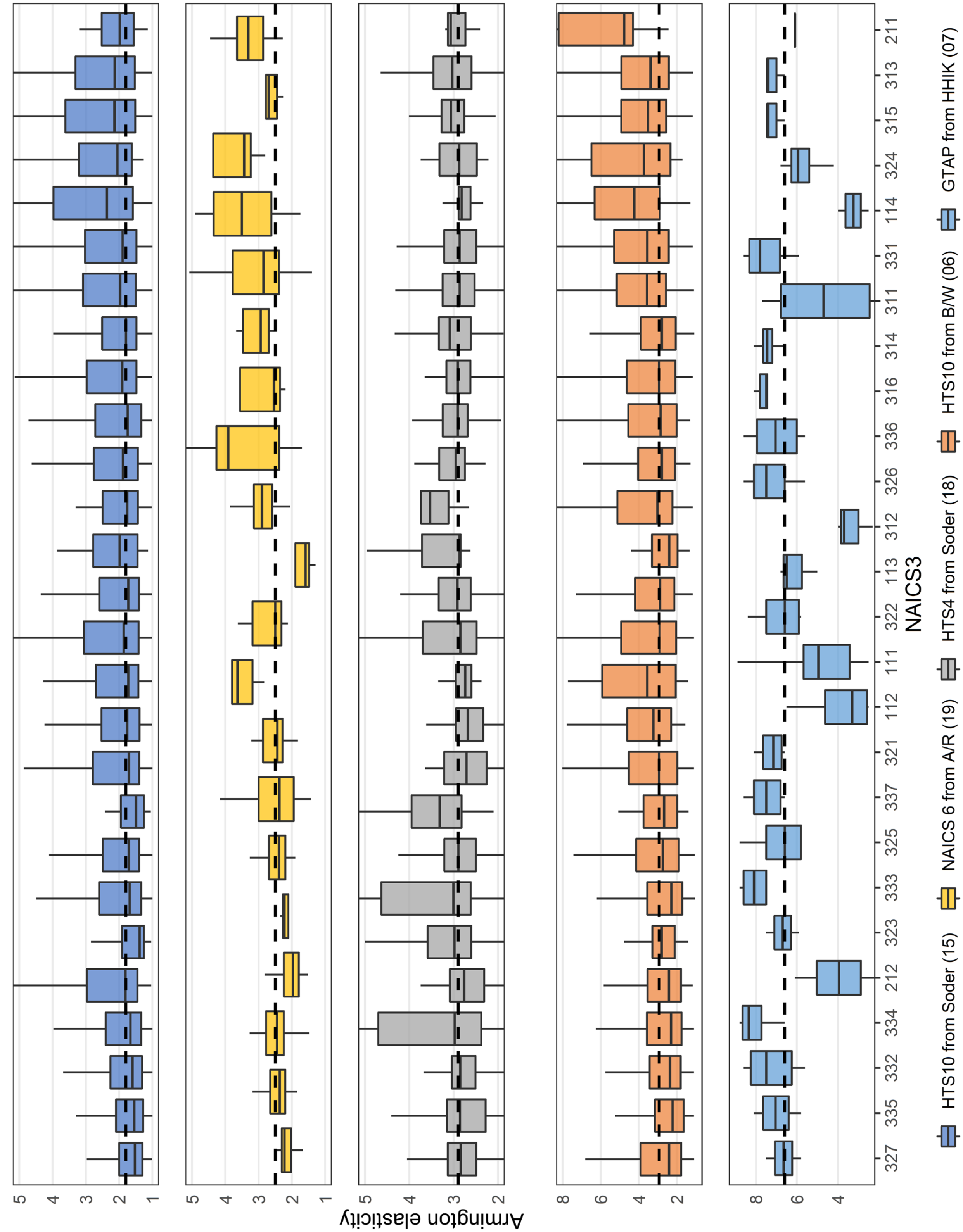


Sector-level boxes featured in this figure are composed of elasticity estimates made at the level of product classification featured in each study, concorded to the corresponding NAICS-3 sector.

Figure 3 displays 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 median Armington elasticities that are lower than 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 within studies, while more differentiated sectors like electrical equipment show lower Armington elasticity estimates across studies.

Nevertheless, figure 3 demonstrates that differences across studies, rather than sectors, drive variation in elasticity estimates, as median estimates for most sectors remain close to their study-specific median elasticities. This finding holds especially true for both Soderbery studies (2015 and 2018), 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, as several sectors appear to differ substantially from the study-wide median Armington elasticity value of 6.5. The higher Armington elasticity estimates found in Hertel et al. (2007) stem from a combination of two factors. One is the estimation method used: trade cost methods generally generate higher Armington elasticity estimates than other estimation methods. The other is the fact that the GTAP aggregation is employed for certain sectors, such as energy and agricultural products, that exhibit greater substitutivity across import sources.

Figure 3: Sectoral Armington elasticity distributions ordered by magnitude

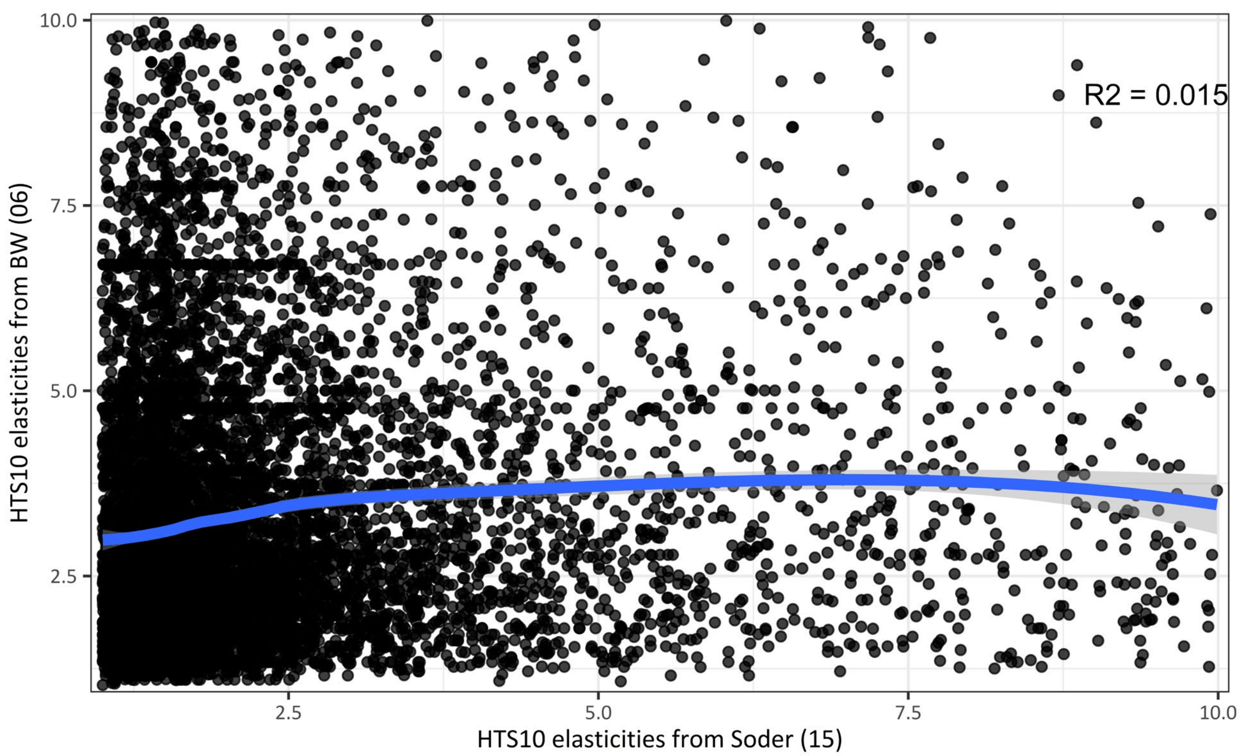


Dashed lines represent study-specific median elasticity values. To present estimates on a more observable scale, elasticity estimates above 10 are not graphed, and outlier observations are hidden. NAICS-3 sector-level boxes for each study are composed of estimates made at the level of product classification featured in each study concorded to the corresponding NAICS-3 sector.

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 (HTS-10). One would expect some degree of correlation in estimates between Broda and Weinstein (2006) and Soderbery (2015), as both studies aim to center their estimates around the true elasticity values for like products during overlapping time frames. To explore further, we plot Armington elasticity estimates by Broda and Weinstein (2006) against those of Soderbery (2015) in figure 4. We find a nearly horizontal best-fit line, implying a near-zero relationship between elasticity estimates from each study.[18] 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.[19] Additionally, a small number of HTS-10 codes may not map between studies due to revisions to the tariff schedule.[20] Still, it is notable that estimates from the two studies correlate so little with one another, given that they generate estimates during largely overlapping time periods on near-identical products in their analysis.

Figure 4: Soderbery (2015) and Broda and Weinstein (2006) HTS-10 product-level elasticities



Heterogeneity in the estimates shown in figure 4 show similarities to findings from a recent meta-analysis performed by Bajzik et al. (2020). In their analysis of more than 3,500 elasticity estimates, the authors attribute significant disparities in Armington estimates within and across

[18] The pairwise correlation coefficient of estimates between studies corresponds to an R^2 value of 0.015.
[19] Soderbery (2015) relies on a LIML estimator, while Broda and Weinstein (2006) use a GMM estimator.
[20] Aggregating estimates up to the HS6 level, which is more stable across HTS revisions, does not improve the correlation between study estimates.

countries to differences in study design and publication biases.[21] At a minimum, both our own findings and those of Bajzik et al. (2020) imply applied modelers should exercise caution when selecting empirically estimated elasticities, as significant differences can exist across methodologies. Future analysis should further investigate the degree to which methodologies yield different elasticity estimates for identical products from the same time periods.

IV. Implications for Applied Modeling

We next use a simple partial equilibrium (PE) modeling application to illustrate the implications of the wide variance in Armington elasticity estimates observed in section III. As previously shown in McDaniel and Balistreri (2003), the Armington elasticity is a key parameter in modern trade models, and changing its value can significantly alter model findings. To illustrate the importance of this parameter, we report differences in economic outcomes from a simple three-source PE model featuring CES demand and perfect competition, as described in the U.S. International Trade Commission's Trade Policy PE Modeling Portal.[22] In these model simulations, we introduce a hypothetical 25 percent tariff for beer imported from the subject country. All market conditions, except for the Armington elasticity parameter value, are kept fixed (table 2).

Table 2: Market conditions for illustrative simulations

Parameter	**Value**
Market share of domestic producer	50%
Market share of subject foreign producer	30%
Market share of non-subject foreign producer	20%
Initial tariff rate for subject producers	0%
New tariff rate for subject producers	25%
Domestic producer supply elasticity	1
Subject foreign producer supply elasticity	5
Non-subject foreign producer supply elasticity	5

Table 3 describes the various Armington elasticity values available to the practitioner for the beer industry, the sector subject to the increase in tariffs in our model simulations. Table 3 also lists the classification system that is relied upon to obtain Armington elasticity estimates for the beer industry from these different empirical studies. To begin, significant variation exists regarding Armington elasticity values across these studies. Ahmad and Riker (2019), Soderbery (2015), and Hertel et al. (2007) estimate low Armington elasticity values for beer-related industries, indicating a product that is not easily substitutable across different sources.[23]

[22] Riker and Schreiber, "Trade Policy PE Modeling Portal," 2020. https://www.usitc.gov/data/pe_modeling/index.htm
[23] One of the relevant HTS-10 sectors (2203.00.00.60) in Soderbery (2015) has an unusually high Armington elasticity estimate of 97.1. This indicates that the estimate is an outlier, and it is thus ignored in our subsequent analysis.

Conversely, Broda and Weinstein (2006) and Soderbery (2018) assign higher values for their corresponding Armington elasticity estimates. Consistent with figure 4, significant disagreement exists between estimates of the same HTS-10 sectors between Soderbery (2015) and Broda and Weinstein (2006).

Table 3: Armington elasticity estimates for beer-related industries across studies

Paper	**Classification**	**Description**	**Armington value**
Ahmad and Riker (2019)	NAICS-6	• Breweries (312120)	• 1.6
Soderbery (2015)	HTS-10	Beer made from malt: • In glass containers (2203.00.00.30) • In containers holding over 4 liters (2203.00.00.90)	 • 1.1 • 1.2
Broda and Weinstein (2006)	HTS-10	Beer made from malt: • In glass containers (2203.00.00.30) • Other (2203.00.00.60) • In containers holding over 4 liters (2203.00.00.90)	 • 5.6 • 5.7 • 5.1
Soderbery (2018)	HTS-4	• Beer made from malt (2203)	• 4.9
Hertel et al. (2012)	GTAP	• Beverages/tobacco	• 2.3

The Armington elasticity estimates in table 3 allows us to select a range of low and high elasticity values for our three-source PE model exercise and determine the extent to which the choice of Armington value drives model results. With few exceptions, table 4 shows that the magnitudes of economic effects substantially increase as Armington elasticity values increase. Substituting an Armington value of 1.1 (the lowest estimate from table 3) with 5.7 (the highest) results in large increases in the magnitudes of domestic and non-subject producer price changes, quantities shipped, and overall consumer price. We note that the direction of the economic effects of introducing a tariff remains consistent across simulated elasticity values; only the magnitude is affected by changes in the Armington elasticity parameter. In summary, table 4 shows the importance of ensuring that the selected Armington elasticity from a given empirical study matches the policy experiment at hand, since small deviations in methodology and data can lead to sharp differences in Armington elasticity values and overall economic effects.

Table 4: Simulation outcomes from selected Armington elasticity values

	Armington elasticity of 1.1	Armington elasticity of 2.3	Armington elasticity of 5.7
Percentage change in prices			
Domestic producers	0.3	2.4	4.6
Subject imports	20.2	17.8	14.1
Non-subject imports	0.1	1.1	2.8
Percentage change in quantity			
Domestic producers	0.3	2.4	4.6
Subject imports	−17.9	−25.8	−36.6
Non-subject imports	0.5	5.5	14.9
Percentage change in price index	6.2	6.8	7.0

V. Conclusion

The Armington elasticity plays an essential role in trade policy analysis. Unfortunately, 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 shortcomings of each approach. Visual inspection of distributions of Armington elasticity estimates show a fair bit of heterogeneity across studies. Still, we do observe some common patterns at the sectoral level across studies, with commodities representing high Armington elasticity sectors and differentiated products embodying low Armington elasticity sectors. A set of simple illustrative simulations are further used to quantify the impact of different Armington elasticity estimates found in the literature on predicted economic outcomes.

Given the impact Armington elasticity values can have on model estimates, we recommend practitioners exhibit caution when relying solely on the literature as a source for this parameter. We concur with Hillberry and Hummels (2013) that the framework used to estimate the elasticity should match the model used for the trade policy simulation. Moreover, modelers should verify if the data used in the Armington elasticity estimation are a good match for the time period and level of product aggregation in the simulation exercise. These steps will help ensure that the selected Armington elasticity estimate best fits the application at hand.

Future research on this topic should consider applying the different estimation strategies to the same dataset. Using the same data would help the researcher determine, for example, if estimates based on the trade cost method are higher on average than those based on the system-of-equations approach. It would also be useful to explore the extent to which Armington elasticity estimates at the same levels of aggregation and/or same estimation strategies are correlated across studies. Fontagné et al. (2020) estimate trade elasticities using the trade cost method and compare them with estimates from other studies. They find strong correlation with Caliendo and Parro (2015) estimates that also use the trade cost method, and weak correlation with Broda and Weinstein (2006) estimates that use the system of equations method. A similar exercise with a more comprehensive set of empirical studies would be a welcome addition to the literature.

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