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Import Demand Elasticities Based on Quantity Data: Theory, Evidence and Implications for the Gains from Trade

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Import Demand Elasticities Based on Quantity Data: Theory, Evidence and Implications for the Gains from Trade *

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Abstract

Correct estimates of import demand elasticities are essential for measuring the gains from trade and predicting the impact of trade policies. We show that estimates of import demand elasticities hinge critically on whether they are derived using trade quantities or trade values, and this difference is due to properties of the estimators. Using partial identification methods, we show theoretically that the upper bound on the set of plausible estimates is lower when using traded quantities, compared to the standard approach using trade values. Our theoretical predictions are confirmed using detailed product-level data on U.S. imports for the years 1993–2006. Our proposed method using traded quantities leads to smaller point estimates of the import demand elasticities for many goods and imply larger gains from trade compared to estimates based on trade values.

JEL Classification Codes: F10, F12, F14, C52.

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1 Introduction

Correct estimates of the elasticity of import demand are crucial to accurately estimate the gains from trade, predict the impact of trade policies and impute the size of trade costs from data on international trade flows. The lower are these estimates, the greater the benefits of international trade and economic integration in most trade models.

Estimations of the elasticity of import demand are traditionally performed using trade value data and "trade unit values" that are constructed by dividing trade values by trade quantities. An alternative approach is to estimate import demand elasticities using data on traded quantities instead of trade values. However, the international economics literature has avoided using import quantity data when estimating import demand elasticities, and authors typically claim that measurement error in the quantity data is at issue. The literature often cites Kemp (1962), who warned of the bias caused by measurement errors when estimating import demand elasticities.

The purpose of this paper is to show that the choice between trade values and traded quantity data for import demand elasticity estimations is not innocuous. We apply the method of partial identification of demand and supply elasticities developed by Leamer (1981) to estimate the upper and lower bounds on the set of possible estimates for the elasticity of import demand. Using detailed product-level data on U.S. imports for the years 1993–2006, we estimate elasticities based on trade value versus trade quantity data. We show that using trade quantities yields estimates of import demand elasticity upper bounds that are substantially *smaller* than if trade values are employed. Since the lower bounds are identical using both approaches, this implies that *the range of plausible estimates is much smaller* when using traded quantities compared to the standard approach of using trade values. The pattern of the upper and lower bounds in both approaches closely matches our theoretical predictions for the asymptotic bias of each bound.

Given earlier authors' concerns regarding measurement error, we also theoretically derive the asymptotic bias of our estimators for the upper and lower bounds in the presence of measurement error in both trade quantities and trade values. We show that our original theoretical results are not overturned unless measurement error is sufficiently more severe in the quantity data than the value data.

The literature typically derives point estimates of import demand elasticities using trade value data, based on the methodology developed by Feenstra (1994). We adapt this methodology in order to derive point estimates using traded quantity data. Taking this new approach to the data, we find that the point estimates based on quantity data are lower on average than the corresponding point estimates using trade value data.

Our results contribute to a recent literature that attemps to quantity the gains from trade for different countries and time periods employing workhorse models of international trade. Using the framework developed by Arkolakis et al. (2012) and Ossa (2015), we show that the demand elasticity point estimates using traded quantity data imply larger gains from trade compared to the traditional approach using point estimates based on trade value data. We also argue that the quantity-based point estimates or the quantity-based upper bounds of the demand elasticities provide an alternative to using value-based point estimates to gauge the gains from trade.

Our results also have important implications for previous studies that measure various impacts of trade using import demand elasticities based on trade values. Prominent examples include previous studies of the gains from increased variety due to imports (Broda and Weinstein, 2006), and the size of trade costs (Jacks et al., 2008, 2011; Chen and Novy, 2011; Novy, 2013) . Import demand elasticities have also been used in the calibration countless applied models of international trade.[1]

While we test and motivate our analysis in the context of international trade, our results are generalizable to any estimation of demand elasticities where price data must be constructed from quantity and value data, and the econometrician must select the most appropriate model. For example, household survey data on expenditures and quantities is used to estimate price elasticities (Deaton, 1987, 1990). Unit values are also prevalent in firm-level datasets, and are used to estimate price elasticities for unit labor costs (Carlsson and Skans, 2012) and electricity unit values (Davis et al., 2013).

The rest of the study proceeds as follows. In section 2 we present the theory behind the partial identification of the import demand elasticities and derive the asymptotic bias associated with the upper and lower bound estimators. Section 3 describes our data and empirical methodology, including how we derive point estimates based on

[1] Import demand elasticities are commonly used to calculate the trade elasticity, and this approach is conceptually distinct from estimates of the trade elasticity using international price differences, (Eaton and Kortum, 2002; Simonovska and Waugh, 2014) tariff fluctuations, (Hummels, 1999; Baier and Bergstrand, 2001; Head and Ries, 2001; Romalis, 2007; Berthou and Fontagne, 2016, Bas et al., 2017) and/or exchange rate fluctuations (Berman et al., 2012; Fitzgerald and Haller, 2018).

traded quantity data. In section 4 we present the results estimating the upper bounds, lower bounds and point estimates of the import demand elasticity using U.S. import data. Given our new estimates, we quantify the impact of these new estimates on the welfare gains from trade in Section 5. Section 6 concludes.

2 Partially Identifying Import Demand Elasticities

We begin by theoretically deriving the difference in asymptotic bias when estimating import demand elasticities using quantity data or value data. The import demand elasticity for a good can be naively estimated by regressing traded quantities on prices:

$$\ln x_{ct} = -\beta \ln p_{ct} + \varepsilon_{ct}, \tag{1}$$

where x_{ct} is the quantity demanded from country c in year t, and p_{ct} is its corresponding price.[2] However, estimating (1) by OLS will lead to biased and inconsistent estimates of β if the errors are correlated with prices, i.e., $E(\varepsilon_{ct} \ln p_{ct}) > 0$. This positive covariance arises if ε_{ct} contains demand shocks — a positive demand shock raises both quantity and price. An IV approach is one potential solution, but the absence of good instruments in this context has lead to alternative approaches in the literature.

The challenge of estimating import demand and supply elasticities in the absence of good instruments has a long tradition in economics. The study of an under-identified supply and demand system was pioneered by Working (1927), who shows that under certain conditions the data trace out the demand curve if the supply curve is more variable than the demand curve. Leamer (1981) shows that in a demand–supply system with zero covariance between the residuals, the set of possible maximum likelihood estimates is defined by a hyperbola.[3] Leamer (1981) also shows that if the demand elasticity is assumed to be negative and the supply elasticity is assumed to be positive, then the set of maximum likelihood estimates for one elasticity is the interval between the direct least-squares estimate (regressing quantities on prices) and the reverse least-squares

[2]Note that we express the elasticity of demand as a positive value. For simplicity and without loss of generality, we omit the constant in the regression equation and assume all variables have mean zero.

[3]Leamer shows this result for a time series on a single good, whereas we work with a cross-country panel. However, there is nothing specific to the nature of the variation that determines the result. Given the specification in (1) and the Leamer assumptions, the result holds whether variation arises over time or across countries.

estimates (regressing prices on quantities). Leamer (1981) furthermore establishes that (1) defines either the upper or the lower bound on the true estimate of the demand elasticity, and that the reverse least square estimate will define the other bound. In what follows, we employ Leamer's (1981) partial identification approach to estimating an upper and a lower bound for the elasticity of import demand.

2.1 Quantity–Price Approach (Leamer, 1981)

The main principle of partial identification is to estimate an interval in which the true parameter lies. Establishing a valid interval requires proving that the upper bound is above the true parameter, and the lower bound is below the true parameter. For these bounds to be informative, the interval should be as narrow as possible, while at the same time ensuring that the bounds bracket the parameter of interest.

We now derive the asymptotic bias of the estimators for the least squares and reverse least squares regressions of import quantities on import prices. The demand equation is given by (1), and the supply equation is given by:

$$\ln x_{ct} = \gamma \ln p_{ct} + \eta_{ct}, \tag{2}$$

which yields the following reduced form:

$$\begin{aligned} \ln x_{ct} &= \frac{\gamma}{\gamma+\beta}\varepsilon_{ct} + \frac{\beta}{\gamma+\beta}\eta_{ct}, \\ \ln p_{ct} &= \frac{1}{\gamma+\beta}\varepsilon_{ct} - \frac{1}{\gamma+\beta}\eta_{ct}. \end{aligned}$$

The probability limit of the OLS estimate of β using (1) is[4]

$$\texttt{plim}\ \hat{\beta} = -\frac{E(\ln x_{ct} \ln p_{ct})}{E\left((\ln p_{ct})^2\right)} = \frac{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 + (\gamma-\beta)\sigma_{\varepsilon\eta}}{\sigma_\varepsilon^2 + \sigma_\eta^2 - 2\sigma_{\varepsilon\eta}},$$

where $\sigma_{\varepsilon\eta} = E(\varepsilon_{ct}\eta_{ct})$, $\sigma_\varepsilon = var(\varepsilon_{ct})$, and $\sigma_\eta = var(\eta_{ct})$. Now, consider the reverse

[4]Throughout, we assume that the data satisfy sufficient moment and dependence conditions for a law of large numbers to hold.

regression of $\ln p_{ct}$ on $\ln x_{ct}$. The probability limit of the OLS estimator is

$$\texttt{plim}\ \hat{\beta}^R = -\frac{E(\ln x_{ct} \ln p_{ct})}{E\left((\ln x_{ct})^2\right)} = \frac{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 + (\gamma - \beta)\sigma_{\varepsilon\eta}}{\gamma^2\sigma_\varepsilon^2 + \beta^2\sigma_\eta^2 + (\beta + \gamma)\sigma_{\varepsilon\eta}}.$$

Assume the supply and demand shocks are uncorrelated, i.e. $\sigma_{\varepsilon\eta} = 0$. This yields the following probability limits for the least squares and reverse least squares estimates:[5]:

$$\texttt{plim}\ \hat{\beta} = \beta - (\gamma + \beta)\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\eta^2} \leq \beta, \tag{3}$$

$$\frac{1}{\texttt{plim}\ \hat{\beta}^R} = \beta + (\gamma + \beta)\frac{\gamma\sigma_\varepsilon^2}{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2} \gtreqless \beta \tag{4}$$

It is clear from (3) that the least squares estimate, which captures the lower bound, brackets the true β from below. With an additional parametric assumption on the sign of the denominator in (4), we obtain the Leamer (1981) result that the least squares and reverse least squares estimates constitute the upper and lower bound on β:

$$0 \leq \texttt{plim}\ \hat{\beta} \leq \beta \leq \frac{1}{\texttt{plim}\ \hat{\beta}^R} \Leftrightarrow \beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 > 0. \tag{5}$$

2.2 Value-Based Approach

In international trade data, the price is constructed as the average unit value of each trade flow i.e. $p_{ct} = v_{ct}/x_{ct}$, where v_{ct} is the value of trade. Taking logs and rearranging yields

$$\ln v_{ct} = \ln p_{ct} + \ln x_{ct}. \tag{6}$$

This simple relationship between trade values, trade quantities and trade unit values in the data implies that β and γ can be estimated using any two of the components from (6) and then transforming the resulting point estimate. For example, one can use (6) to transform (1) and (2) into regression of trade values on trade unit values, yielding the following expressions for demand and supply:

[5] Leamer (1981) shows that the hyperbola of the maximum likelihood estimates is given by $\hat{\gamma}^2\left(\hat{\beta}s_p^2 - s_{px}\right) + \hat{\beta}^2\left(-\hat{\gamma}s_p^2 + s_{px}\right) = \left(\hat{\beta} - \hat{\gamma}\right)s_x^2$, where s_p^2 and s_x^2 are the sample variances and s_{px} is the sample covariance. Assuming a non–negative supply elasticity, the upper bound for the demand elasticity is found by imposing $\hat{\gamma} = 0$, which yields $\hat{\beta} = \frac{s_x^2}{s_{px}}$, the inverse of the least squares estimate of p on x.

$$\ln v_{ct} = (1-\beta)\ln p_{ct} + \varepsilon_{ct}, \tag{7}$$

$$\ln v_{ct} = (\gamma+1)\ln p_{ct} + \eta_{ct}. \tag{8}$$

Feenstra's (1994) point estimates are based on structural equations similar to (7) and (8), which require using constructed trade unit values. The reduced form of this system of equations is given by:

$$\begin{aligned}\ln v_{ct} &= \frac{1+\gamma}{\gamma+\beta}\varepsilon_{ct} + \frac{\beta-1}{\gamma+\beta}\eta_{ct},\\ \ln p_{ct} &= \frac{1}{\gamma+\beta}\varepsilon_{ct} - \frac{1}{\gamma+\beta}\eta_{ct}.\end{aligned}$$

The probability limit of the lower bound on β using (7) is the OLS regression of trade values on prices, transformed using (6):

$$1 - \texttt{plim}\ \hat{\beta}^{P} = 1 - \frac{E(\ln v_{ct}\ln p_{ct})}{E\left((\ln p_{ct})^2\right)} = \beta - (\gamma+\beta)\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2} \leq \beta. \tag{9}$$

Note that the probability limit of the lower bound in (9) is *identical* to (3). This stems from the fact that price is on the right hand side when estimating the lower bounds, regardless of whether quantities or values are the dependent variable. We can show, however, that the upper bounds are not identical to the quantity–price approach. The probability limit for the upper bound based on the reverse least squares estimation takes the following form:[6]

$$\begin{aligned}\texttt{plim}\ \left(-\frac{1-\hat{\beta}^{R,P}}{\hat{\beta}^{R,P}}\right) &= -\frac{1-\frac{E(\ln v_{ct}\ln p_{ct})}{E((\ln v_{ct})^2)}}{\frac{E(\ln v_{ct}\ln p_{ct})}{E((\ln v_{ct})^2)}}\\ &= \beta + (\beta+\gamma)\frac{(1+\gamma)\sigma_\varepsilon^2}{(\beta-1)\sigma_\eta^2-(1+\gamma)\sigma_\varepsilon^2}.\end{aligned} \tag{10}$$

It is clear from the denominator in (10) that the reverse least squares regression will unambiguously not bound the true β from above if $\beta < 1$. However, $\beta > 1$ is a

[6]Inverting equation (7) without the error term yields the transformed reverse least squares estimate $\hat{\beta}^{R,P} = \frac{1}{1-\hat{\beta}^{P}}$. Rearranging yields $\hat{\beta}^{P} = -\frac{1-\hat{\beta}^{R,P}}{\hat{\beta}^{R,P}}$.

common assumption in the literature and will be satisfied for may imported products. Feenstra (1994) assumes a demand elasticity in excess of unity due to CES preferences, and Scobie and Johnson (1975) argue that the elasticity of demand will be elastic if supplying countries are sufficiently "small" in the sense that there are several suppliers of a similar good to the export market. It is also evident in (10) that the upper bound based on trade value data will hold under in some cases in the presence of a downward-sloping supply curve. The numerator of the bias term in (10) is larger than the numerator in equation (4), which suggests that the upper bound is likely larger using trade value data compared to using trade quantity data.[7]

To illustrate the relationships between the bounds, we plot the predicted asymptotic biases of each estimator for various values of the true import demand elasticity. The results of this exercise are reported in figure 1 where we plot β between 0 and 10, and we hold constant $\gamma = 1$ and $\sigma_\varepsilon^2/\sigma_\eta^2 = 0.5$. It is evident from the figure that the upper bound based on trade value data is *larger* than the Leamer upper bound for most values of β. Figure 1 also illustrates that the upper bound based on trade value data is highly unstable at low values of β, and becomes negative when the true import demand elasticity is below a certain threshold. The quantity-based approach is thus particularly well–suited to situations where the true import demand elasticity is low.

2.3 Measurement Error

Next, we investigate whether our theoretical results hold in the presence of measurement error. Kemp (1962) was the first to warn of the bias caused by measurement errors when using quantity data for the purpose of estimating import demand elasticities. In Kemp's case, the bias was caused by constructing quantity indices from trade value and price index data. In the second paragraph of Kemp (1962), he writes:

> In aggregative studies, however, the quantity variables almost always is constructed by dividing the index of import prices into an index of the total

[7]As suggested by Scobie and Johnson (1975), another way to partially estimate import demand elasticities is to regress $\ln x_{ct}$ on $\ln v_{ct}$ and vice versa, thus avoiding the need to construct price data. We derive the asymptotic bias of the upper and lower bounds using this approach in the Appendix. We find that the quantity–value lower bound is identical to the Leamer upper bound, and that the quantity–value upper bound is identical to the upper bound based on trade value data. Since the lower bound is not likely to bracket the true elasticity in this case, estimating import demand elasticities without constructing trade unit values thus leads to implausibly high estimates.

money value of imports. The quantity variable is subject therefore to a measurement error of its own.

In his derivations, Kemp assumes a measurement error term in the price index data, but not in the money value of imports. Kemp goes on to show that using constructed quantity index data leads to biased and inconsistent estimates of the import demand elasticity, which correspond to our lower bound estimates. In the context of contemporary international trade data, however, the raw Comtrade data reports the value of trade and its quantity (in weight or units). In the raw 10-digit US import data, for example, there are 47 different types of quantity measures. Moreover, one cannot rule out that measurement error exists in the contemporary trade value data. Transfer pricing, for example, can lead to measurement error in the trade value data.

To allow for measurement error, we express the observed data as

$$\ln v_{ct} = \ln \tilde{v}_{ct} + u_{ct}$$
$$\ln x_{ct} = \ln \tilde{x}_{ct} + w_{ct}$$

where $\tilde{v}_{ct}$ and $\tilde{x}_{ct}$ denote the true (unobserved) data. The measurement error variances and covariances are σ_u^2, σ_w^2, and σ_{uw}. Because $\ln p_{ct} = \ln v_{ct} - \ln x_{ct}$, the measurement error in prices is $u_{ct} - w_{ct}$. We assume classical measurement error, i.e., the measurement errors are uncorrelated with the true values.[8]

We first present the probability limits on the bounds in the quantity-based specification. Incorporating measurement error, the probability limit of β using (1) is

$$\begin{aligned}
\texttt{plim}\ \hat{\beta} &= -\frac{E(\ln x_{ct} \ln p_{ct})}{E\left((\ln p_{ct})^2\right)} \\
&= \frac{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 + (\beta+\gamma)^2\left(\sigma_w^2 - \sigma_{uw}\right)}{\sigma_\varepsilon^2 + \sigma_\eta^2 + (\beta+\gamma)^2\left(\sigma_u^2 + \sigma_w^2 - 2\sigma_{uw}\right)} \\
&= \beta - (\beta+\gamma)\frac{\sigma_\varepsilon^2 + \beta(\beta+\gamma)\left(\sigma_u^2 - \sigma_{uw}\right) + (\beta-1)(\beta+\gamma)\left(\sigma_w^2 - \sigma_{uw}\right)}{\sigma_\varepsilon^2 + \sigma_\eta^2 + (\beta+\gamma)^2\left(\sigma_u^2 + \sigma_w^2 - 2\sigma_{uw}\right)} \qquad (11)
\end{aligned}$$

[8] Unobserved quality can also be treated as a component of the measurement error. For example, define the $ln\tilde{v}_{ct}$ to be the value of country c's product if it were of average quality and u_{ct} to be the quality differential. This term would also appear in the price because prices are constructed from unit values, i.e., $p_{ct} = v_{ct}/x_{ct}$.

For the reverse regression, we have

$$
\begin{aligned}
\frac{1}{\texttt{plim}\ \hat{\beta}^R} &= -\frac{E\left((\ln x_{ct})^2\right)}{E(\ln x_{ct} \ln p_{ct})} \\
&= \frac{\gamma^2\sigma_\varepsilon^2 + \beta^2\sigma_\eta^2 + (\beta+\gamma)^2\sigma_w^2}{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 - (\beta+\gamma)^2(\sigma_{uw} - \sigma_w^2)} \\
&= \beta + (\beta+\gamma)\frac{\gamma\sigma_\varepsilon^2 + \beta(\beta+\gamma)(\sigma_{uw} - \sigma_w^2) + (\beta+\gamma)\sigma_w^2}{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 - (\beta+\gamma)^2(\sigma_{uw} - \sigma_w^2)}
\end{aligned} \tag{12}
$$

For the value-based approach, the probability limit of β^P using the direct regression in (7) is identical to (11) in the presence of measurement error. The reverse regression, however, is not identical to (12), and $1/\beta^{RP}$ takes the following form:

$$
\begin{aligned}
\frac{1}{\texttt{plim}\ \hat{\beta}^R} &= \frac{\gamma(1+\gamma)\sigma_\varepsilon^2 + \beta(\beta-1)\sigma_\eta^2 + (\beta+\gamma)^2\sigma_u^2 - (\beta+\gamma)^2(\sigma_u^2 - \sigma_{uw})}{(\beta-1)\sigma_\eta^2 - (1+\gamma)\sigma_\varepsilon^2 - (\beta+\gamma)^2(\sigma_u^2 - \sigma_{uw})} \\
&= \beta + (\beta+\gamma)\frac{(1+\gamma)\sigma_\varepsilon^2 + (\beta+\gamma)\sigma_u^2 + (\beta-1)(\beta+\gamma)(\sigma_u^2 - \sigma_{uw})}{(\beta-1)\sigma_\eta^2 - (1+\gamma)\sigma_\varepsilon^2 - (\beta+\gamma)^2(\sigma_u^2 - \sigma_{uw})}.
\end{aligned} \tag{13}
$$

The parameter restrictions required for the bounds to hold in the presence of measurement error are now more complicated because they also hinge on the magnitudes of the error variance and covariance. We therefore study three specific cases of measurement error. In the first case, we assume that the measurement error variance in traded quantities and trade values, and their covariance, are equal in magnitude, which we call the "quantity and value error" case. This case implies that there is no error in the unit values (prices). In the second and third cases, we assume that there is measurement error in either traded quantities or trade values. The results of this exercise are illustrated in figure 2. In all cases, when a measurement error is non-zero, we set its variance equal to 5% of the variance of the supply shock (σ_η^2).

For the lower bound, equal quantity and value error causes the measurement error to drop out of (11), so the quantity and value error case is identical to no measurement error. If $\beta > 1$, then both quantity and value measurement error reduce the lower bound, so the bound remains valid for any parameter values. For $\beta < 1$, however, value measurement error increases the bound and it may become invalid depending on the other parameters. The top panel of figure 2 shows that the lower bound becomes uninformative for large values of β, especially for value measurement error.

For the upper bound, measurement error in quantities only attenuates the quantity-based bound, and measurement error in values only attenuates the value-based bound. The middle panel of figure 2 shows the true import demand elasticity along with the quantity-based upper bound with no measurement error, with measurement error of equal magnitude in quantities and values, and with measurement error in quantities only. Equal quantity and value error unambiguously increases the numerator in the bound formula. Thus, just as for the no measurement error case, the bound remains valid for any value of β above a threshold. Measurement error in quantities only attenuates the quantity-based upper bound, and the bound may be invalid for large values of β.

The bottom panel of figure 2 shows the true import demand elasticity along with the upper bound based on trade value data with no measurement error, with measurement error of equal magnitude in quantities and values, and with measurement error in values only. As for the quantity-based case, equal quantity and value error unambiguously increases the numerator in the bound formula, and the bound is valid for any value of β above a threshold. Measurement error in values only inflates the upper bound based on trade value data and increases the threshold value of β at which it becomes invalid.

Overall, our partial identification theoretical results suggest that it is best to estimate import demand elasticities using traded quantities if there is relatively low measurement error in quantities, relatively low measurement error in general, or if the error is similar in magnitude in the quantity and value data, i.e., there is little measurement error in prices. If measurement error in the data is suspected to be large, then the choice between using traded quantity data or trade value data becomes more pertinent. In this case, if measurement error is a relatively larger problem in the quantity data then it should be avoided, while if measurement error is relatively larger problem in the value data then it should be avoided. In general, quantity data is particularly well-suited to estimating import demand elasticities for goods with an expected low elasticity. With these theoretical predictions in hand, we now describe the trade data and estimate the bounds on the elasticity of substitution and the point estimates using the Leamer (1981) and Feenstra (1994) approaches.

3 Data and Empirical Application to U.S. Imports

We now describe how we estimate the upper and lower bounds using traded quantity and trade value data. We first describe the data, then provide our estimating equations for the bounds, and finally explain how we derive point estimates using the quantity data.

3.1 Data

Our main data source is the U.S. import data available at the Center for International Data, which is based on data from the U.S. Customs Service.[9] The data includes the value of U.S. imports (in USD) and its associated quantity by country of origin at the 10-digit HS level. We focus on the years 1993–2006. From the trade values and trade quantities we compute trade unit values. We thus observe the trade value, trade quantity and trade unit values by HS product, partner country and year. We study the U.S. since it is a large importer that imports from many countries, even within narrowly defined product categories, and also since it allows us to relate our results to those of Feenstra (1994), Broda and Weinstein (2006) and Soderbery (2015).

We perform our estimations at the 8-, 6-, and 4-digit HS levels, which we achieve by aggregating the data across products. There are 47 different types of quantity units in the data. Since it is crucial to use the same quantity unit for each product, we keep only the trade flows that use the most common quantity unit before aggregating the data to more coarse product definitions. The units used to measure quantity are very often the same, even within broad product categories. Approximately 5 percent of trade flow observations are dropped when harmonizing the quantity units at the 8-digit HS level. When harmonizing quantity units at the 8-digit and 6-digit HS level we drop approximately 11 percent and 14 percent of observations. When harmonizing quantity units at the 4-digit HS level, our most aggregated product definition, we drop approximately 18 percent of observations.

As a robustness check we perform our estimations using data from the COMTRADE database, which is administered by the United Nations. We use importer-reported data for U.S. imports at the 6-digit HS level for the years 1991–2015, where both the value

[9] See Feenstra et al. (2002) for a detailed description of the U.S. import data. The data can be found at http://cid.econ.ucdavis.edu/usix.html

of trade (in USD) and the quantity of trade (in kilograms) are reported.

In order to calculate the gains from trade for each imported product, we require data on import penetration ratios for each product, which we take from the U.S. Bureau of Economic Analysis (BEA) 2007 input-output tables, available at the 6-digit level. We collapse the BEA commodity/industry classification to the 4-digit level, then merge it with the Center for International Data U.S. import data at the 4-digit NAICS level.[10]

3.2 Empirical Method

Following Feenstra (1994), we also difference the data with respect to a reference country k. Normalizing the data with respect to a reference country absorbs the origin–product–year fixed effect, which contains the importer's price index term that would arise in a CES demand framework. We do not convert the trade data into import shares, since the differencing with respect to a reference country already controls for total imports.[11] Using logged imports instead of import shares also corresponds more closely with our theoretical framework.

We estimate the lower and upper bounds of the elasticity of import demand for each good at the 3-, 4-, 6- and 8-digit HS level of aggregation, normalizing the variables as described above. Formally, the Leamer lower bound regression for good g is:

$$\Delta^k \ln x_{gct} = -\hat{\beta}_g \Delta^k \ln p_{gct} + \varsigma_{gct}, \tag{14}$$

where

$$\Delta^k \ln x_{gct} \equiv \Delta \ln x_{gct} - \Delta \ln x_{gkt},$$
$$\Delta^k \ln p_{gct} \equiv \Delta \ln p_{gct} - \Delta \ln p_{gkt}$$

The Leamer upper bound regression is:

[10] To assess the extent of measurement error in trade values and traded quantities due to human manipulation of the data, we test whether or not the data deviates from Benford's Law. Benford's Law describes the distribution of first digits in economic or accounting data. The results are reported in figure A.1 in the Appendix. We find that the distribution of first digits is very similar among the quantity and value data, which suggests that measurement error due to manipulation of the data is highly similar between quantities and values.

[11] Total imports in the denominator of the shares cancels out when differencing with respect to a reference country. In the case of quantities, $\ln(x_{gct}/X_{gt}) - \ln(x_{gkt}/X_{gt}) = \ln x_{gct} - \ln x_{gkt}$, where $X_t = \sum_{c \in C_{gt}} x_{gct}$.

$$\Delta^k \ln p_{gct} = -\hat{\beta}_g^R \Delta^k \ln x_{gct} + \upsilon_{gct}, \tag{15}$$

The lower bound regression based on trade values is:

$$\Delta^k \ln v_{gct} = -\hat{\beta}_g^P \Delta^k \ln p_{gct} + \xi_{gct}, \tag{16}$$

where

$$\Delta^k \ln v_{gct} \equiv \Delta \ln v_{gct} - \Delta \ln v_{gkt},$$

The upper bound regression based on trade values is:

$$\Delta^k \ln p_{gct} = -\hat{\beta}_g^{R,P} \Delta^k \ln v_{gct} + \zeta_{gct}, \tag{17}$$

We also develop a method for deriving point estimates of import demand elasticities using data on traded quantities instead of trade values, based on Feenstra's (1994) method. The structural model's "demand" and "supply" equations are as follows:

$$\Delta^k \ln x_{gct} = -\sigma_g^x \Delta^k \ln p_{gct} + \epsilon_{gct}^k \tag{18}$$

$$\Delta^k \ln p_{gct} = \omega_g^x \Delta^k \ln x_{gct} + \delta_{gct}^k \tag{19}$$

where ϵ_{gct}^k and δ_{gct}^k are unobservable demand and supply shocks, respectively and $\omega \geq 0$ is the inverse supply elasticity. Feenstra (1994) derives equations similar to (18) and (19), but using expenditure shares instead of quantity shares, from a model of CES preferences, using the Armington (1969) assumption of product differentiation by country of origin.[12] Note, however, that σ_g^x in (18) is identical to our estimate of the Leamer lower bound, $\hat{\beta}_g^R$, in equation (14). Moreover, ω_g^x in (19) is the reverse least squares estimate, which is the same as our estimate of the Leamer upper bound with the opposite sign, $\hat{\beta}_g^R$, in equation (15). Thus, the structural equations used to establish point estimates of the elasticity of demand are directly related to the estimating equations of the upper and lower bounds.

[12] Harberger (1957) shows that this system yields an elasticity of substitution with more general assumptions on consumer preferences than CES.

Feenstra's innovation is to multiply ϵ_{gct}^{k} and δ_{gct}^{k} together to convert equations (18) and (19) into one estimable equation. Following Feenstra (1994), we assume that ϵ_{gct}^{k} and δ_{gct}^{k} are independent. We define $\rho_g^x = \frac{\sigma_g^x \omega_g^x}{1+\sigma_g^x \omega_g^x} \in [0,1)$, scale by $\frac{1}{\sigma_g^x\left(1-\rho_g^x\right)}$ and rearrange to obtain the analogue of Feenstra's (1994) estimating equation:

$$\left(\Delta^k \ln p_{gct}\right)^2 = \theta_{1g}^x \left(\Delta^k \ln x_{gct}\right)^2 + \theta_{2g}^x \left(\Delta^k \ln p_{gct} \Delta^k \ln x_{gct}\right) + u_{gct}, \tag{20}$$

where

$$\begin{aligned} \theta_{1g}^x &= \frac{\rho_g^x}{\left(\sigma_g^x\right)^2 \left(1-\rho_g^x\right)}, \\ \theta_{2g}^x &= \frac{2\rho_g^x - 1}{\sigma_g^x \left(1-\rho_g^x\right)} \end{aligned} \tag{21}$$

and

$$u_{gct} = \frac{\epsilon_{gct}\delta_{gct}}{\sigma_g^x \left(1-\rho_g^x\right)} \tag{22}$$

Feenstra (1994) shows that estimating (20) by 2SLS, where the instruments are dummy variables across the countries $c \neq k$, leads to consistent estimates of θ_{1g}^x and θ_{2g}^x. We implement the most recent refinement of Feenstra's method, by Soderbery (2015), who applies a limited information maximum likelihood (LIML) estimator to reduce bias and improve constrained search efficiencies.

Once we have obtained the estimates of $\hat{\theta}_{1g}^x$ and $\hat{\theta}_{2g}^x$, the values of $\hat{\sigma}_g^x$ and $\hat{\rho}_g^x$ can be solved from the quadratic equations in (21). As long as $\hat{\theta}_{1g}^x > 0$, these equations yield two solutions for $\hat{\sigma}_g^x$, one positive and one negative.[13] We restrict attention to the positive solution. Formally:

[13] This system can also be solved in terms of σ_g^x and ω_g^x, where $\theta_{1g}^x = \omega_g^x / \sigma_g^x$ and $\theta_{2g}^x = \left(\sigma_g^q \omega_g^x - 1\right) / \sigma_g^x$. It is clear here that θ_{1g}^x must be positive so that σ_g^x and ω_g^x are both positive.

$$\hat{\rho}_g^x = \frac{1}{2} + \left(\frac{1}{4} - \frac{1}{4 + \left(\hat{\theta}_{2g}^x \right)^2 / \hat{\theta}_{1g}^x} \right)^{1/2} \quad if\ \theta_{2g}^x > 0, \tag{23}$$

$$\hat{\rho}_g^x = \frac{1}{2} - \left(\frac{1}{4} - \frac{1}{4 + \left(\hat{\theta}_{2g}^x \right)^2 / \hat{\theta}_{1g}^x} \right)^{1/2} \quad if\ \theta_{2g}^x < 0, \tag{24}$$

$$\hat{\sigma}_g^x = \left(\frac{2\hat{\rho}_g^x - 1}{1 - \hat{\rho}_g^x} \right) \frac{1}{\hat{\theta}_{2g}^x} > 0. \tag{25}$$

If θ_{1g}^x is negative, then the solution fails to provide estimates of σ_g^x and ρ_g^x that satisfy the restriction that $\sigma_g^x > 0$ and $0 \leq \rho_g^x < 1$. The restriction on ρ_g^x implies that the supply elasticity must be non-negative, i.e. $\omega_g^x > 0$, which falls directly from Leamer's (1981) inequality constraints. In the event that θ_{1g}^x is negative or there is an imaginary solution, then we apply the constrained search algorithm developed by Soderbery (2015).

4 Results

4.1 Partial identification using quantity data

We first estimate the upper and lower bounds using the trade value – trade unit value specification as given by (16) and (17), which produces the bounds on the set of plausible point estimates based on quantity data. We call this set of possible estimates the "value-based bounds". The results for each 4-digit HS import product are illustrated in figure 3. The x-axis ranks each 4-digit HS product by its lower bound (least squares) estimate. While all lower bound estimates are positive and lie close to one, the estimates of the upper bound vary widely. For many products with a small lower bound estimate, the corresponding reverse least squares estimate is negative, which agrees with the predicted asymptotic bias. For several products the upper bound is very high. We thus truncate the figure to display estimates between 0 and 30. We also report all "value-based point estimates" based on trade values that the Soderbery (2015) procedure yields. The vast majority of the point estimates lie within the bounds given by the estimates of equations

(16) and equation (17), with only a few exceptions.

We then estimate the point estimates and the upper and lower bounds using the Leamer trade quantity – trade unit value specification as given by (14) and (15), which we call the "Leamer bounds". We report both the Leamer bounds and the value-based bounds, plus the value-based point estimates, in figure 4. As predicted by the theory, the quantity-basd and value-based lower bounds are identical, while the Leamer upper bound is far below the value-based upper bound. It is also evident that many of the value-based point estimates (around one third) lie above the Leamer upper bound. This suggests that many of the elasticity estimates used in the literature may be implausably large. Finally, it is evident that the Leamer upper bounds are positive and lie above the lower bounds for all products, including those for which the value-based upper bound was negative.

We also check whether our results regarding the difference between the Leamer and value-based bounds are sensitive to the level of product aggregation. Imbs and Mejean (2015) show, for example, that estimates of trade elasticities are smaller in aggregate data than at finer levels of aggregation. In figure A.2 in the Appendix we illustrate the alternative bounds with the original bounds and point estimates at the HS 6-digit level. We find that the difference between the Feenstra and Leamer upper bounds persists at finer levels of product aggregation. We also find that many of the value-based point estimates lie below the Feenstra and Leamer lower bounds even at finer levels of aggregation.

4.2 Point estimates using quantity data

We now turn to our point estimates of the import demand elasticities using quantity data, and compare them with the point estimates derived from using trade value data, which is the standard approach in the literature. In figure 5 we illustrate the point estimates based on traded quantity data for each 4-digit HS import product, which we call the "quantity-based point estimates", as well as the corresponding value-based point estimate using trade value data. We also include the Leamer bounds, which allows us to discern how well the point estimates fit withing the set of plausible estimates. Figure 5 illustrates that nearly all our quantity-based point estimates lie within the bounds. The figure also illustrates that the value-based point estimates tend to be larger on average, especially for those products where the value-based point estimate lies above the Leamer bound. We also calculate the quantity-based point estimates at the 4-digit, 6-digit and 8-digit levels.

Descriptive statistics of all of the bounds and point estimates at the 4-, 6- and 8-digit level are provided in Table 1, where we report the number of products, the raw mean and the median. The mean and median of the Leamer upper bounds are always lower than the corresponding measure of the value-based upper bounds, regardless of the level of product aggregation. The median is lower than the mean in all cases for the upper bounds, which is driven by a small number of products with relatively high upper bounds. The difference between the mean and the median is especially pronounced for the value-based upper bounds. Table 1 also highlights that the quantity-based point estimates are lower than the value-based point estimates in all cases, for all levels of product aggregation. The raw average and median of the point estimates are very stable across product aggregations.

5 Implications for the Gains from Trade

We now quantify the economic importance of our alternative approach to measuring import demand elasticities for the welfare gains from economic integration. We use the framework developed by Arkolakis et al. (2012) and adapted to the multi-sector framework by Ossa (2015) and Costinot and Rodrguez-Clare (2014), which distill the welfare gains from trade compared to autarky across a wide array of trade models into a simple formula:

$$\hat{G}_j = 1 - \prod_{s=1}^{S} \left(\hat{\lambda}_{jj,s} \frac{e_{j,s}}{r_{j,s}} \right)^{\beta_{j,s}/\epsilon_s}, \tag{26}$$

where $\hat{G}_j$ is the percentage change in welfare in destination country j when moving from the status quo to autarky, $\hat{\lambda}_{jj,s}$ equals the percentage change in country j's internal trade in sector s (1 minus the import penetration ratio), $e_{j,s}$ denotes the share of total expenditure in country j allocated to sector s, and $\beta_{j,s} = e_{j,s}$ assuming Cobb-Douglas preferences between sectors. $r_{j,s}$ denotes the share of total revenues in country j generated from sector s, and ϵ_s is the elasticity of imports with respect to variable trade costs in sector s, also known as the "trade elasticity". In the Armington (1969) model, $\epsilon = 1 - \sigma$, where σ is the import demand elasticity.[14] The formula given in (26) thus highlights that estimates of the import demand elasticity play a central roll in measuring the gains from trade.

We first calculate the point estimates at the 4-digit BEA commodity classification level. These estimations yield 50 BEA commodities for which we have viable value-based and quantity-based point estimates, and we report these estimates in figure A.4 in the Appendix. We then combine these point estimates with data on the import penetration ratio from the 2007 BEA input-output tables. We find that the overall gains from trade are 74 percent using point estimates based on traded quantity data versus 25 percent using point estimates based on trade value data.[15]

An alternative approach is to gauge the gains from trade using the upper bounds on the import demand elasticities instead of the point estimates. Using the upper bounds instead of point estimates yields more conservative gains, but the difference between value data or quantity data remains large. Using the quantity-based upper bounds yields a 34 percent overall gain, while using the value-based upper bounds yields a 5 percent overall gain. Overall, the lower import demand elasticities obtained using quantities translate into much larger gains from trade compared to the estimates obtained using trade value data.

6 Conclusion

Accurate estimates of import demand elasticities are essential for measuring the gains from trade and predicting the impact of trade policies. The international economics literature has typically estimated these elasticities using trade value data instead of trade quantities. Using partial identification methods, we show theoretically that the upper bound on the import demand elasticity is more biased upward compared to using traded quantity data. We confirm our theoretical predictions using detailed U.S. import data. We also generate import demand elasticity point estimates based on traded quantity data and compare them with corresponding point estimates using trade value

[14] In the Melitz (2003) model, $\epsilon = 1 - \sigma - \gamma_j$, where γ_j is the extensive margin elasticity. In the Ricardian model, $\epsilon = 1 - \sigma + \gamma^i_{jj} - \gamma^i_{ij}$, where γ^i_{jj} and γ^i_{ij} denote the extensive margin elasticities.

[15] Our 25 percent estimate using trade value data is comparable with Ossa's (2015) estimate of a 19 percent gain from trade for the United States. The differences between our estimates are likely driven by the fact that Ossa (2015) estimates import demand elasticities on a panel of 129 countries using data from GTAP.

data. Our results suggest that import demand elasticities are lower than previously thought for many goods, which implies that the gains from economic integration have been underestimated in earlier studies.

While we test and motivate our analysis in the context of international trade, our results are generalizable to any estimation of demand elasticities where price data must be constructed from quantity and value data, and the econometrician must select the most appropriate model. Our derivations of the asymptotic bias suggest that using quantity data is superior to value data in cases where measurement error is of similar magnitude in the quantity and value data.

Our results have many implications in international economics that we leave for further research, such as analyzing the impact on the variety gains from trade or the magnitude of trade costs implied by trade flow data. Given that these elasticities are so important for understanding the gains from trade, it is hoped that our study encourages discussion on the pros and cons of using quantity versus value data when estimating demand elasticities.

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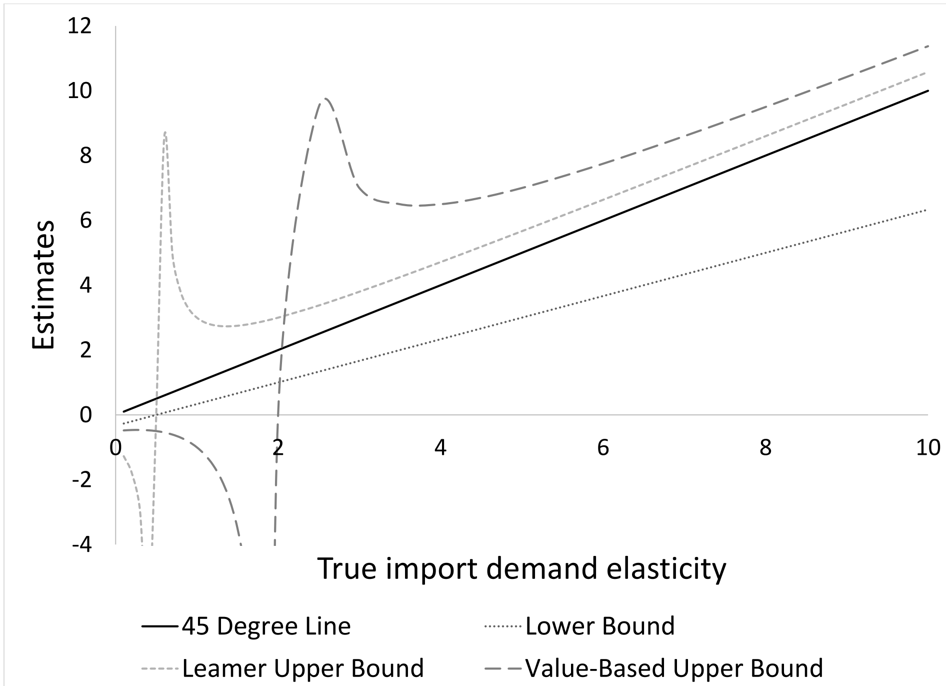

Figure 1: Theoretically predicted upper and lower bounds as function of true import demand elasticity, no measurement error.
Notes: $\gamma = 1, \sigma_{\varepsilon}^2/\sigma_{\eta}^2 = 0.5$ in all cases. Source: authors' calculations

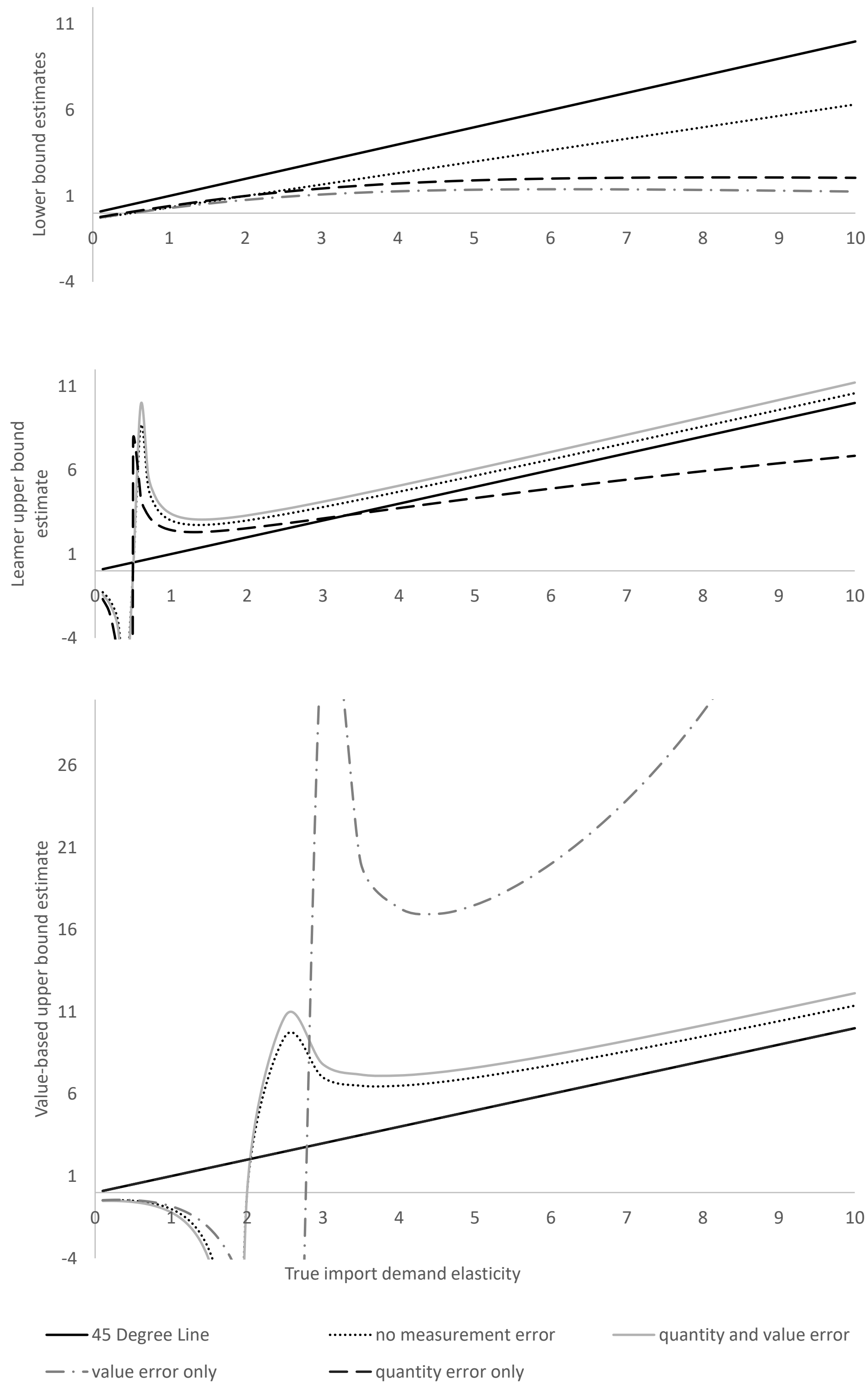

Figure 2: Theoretically predicted lower and upper bounds with measurement error.
Notes: $\gamma = 1, \sigma_\varepsilon^2/\sigma_\eta^2 = 0.5$ in all cases. $\sigma_u^2/\sigma_\eta^2 = 0, \sigma_w^2/\sigma_\eta^2 = 0.05$ in quantity measurement error case. $\sigma_u^2/\sigma_\eta^2 = 0.05, \sigma_w^2/\sigma_\eta^2 = 0$ in value measurement error case. $\sigma_u^2/\sigma_\eta^2 = \sigma_w^2/\sigma_\eta^2 = \sigma_{uw}/\sigma_\eta^2 = 0.05$ in quantity and value error case. Source: authors' calculations

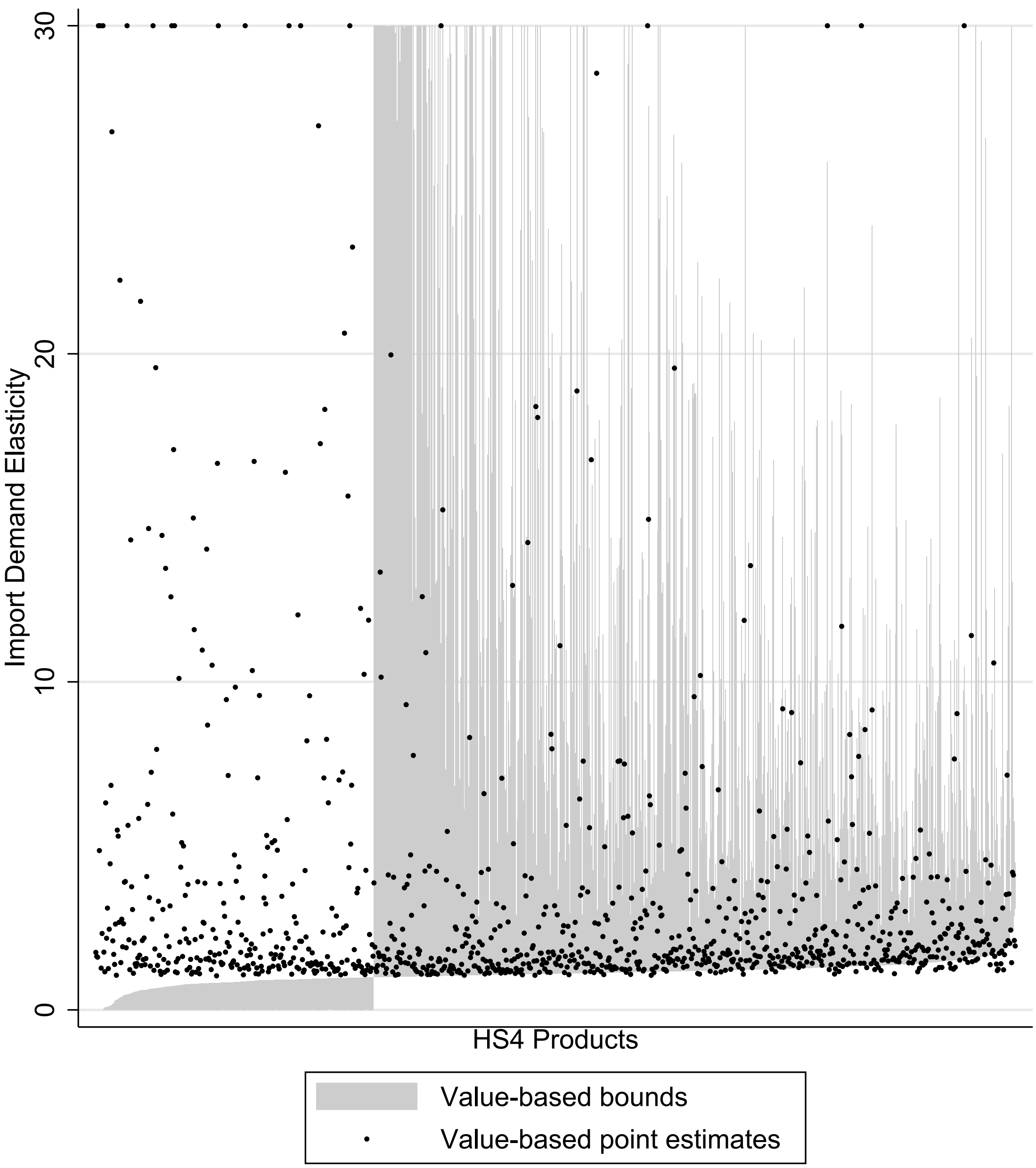

Figure 3: Value-based bounds and point estimates, by 4-digit HS, U.S., 1993-2006.
Source: UC Davis Center for International Data, authors' calculations

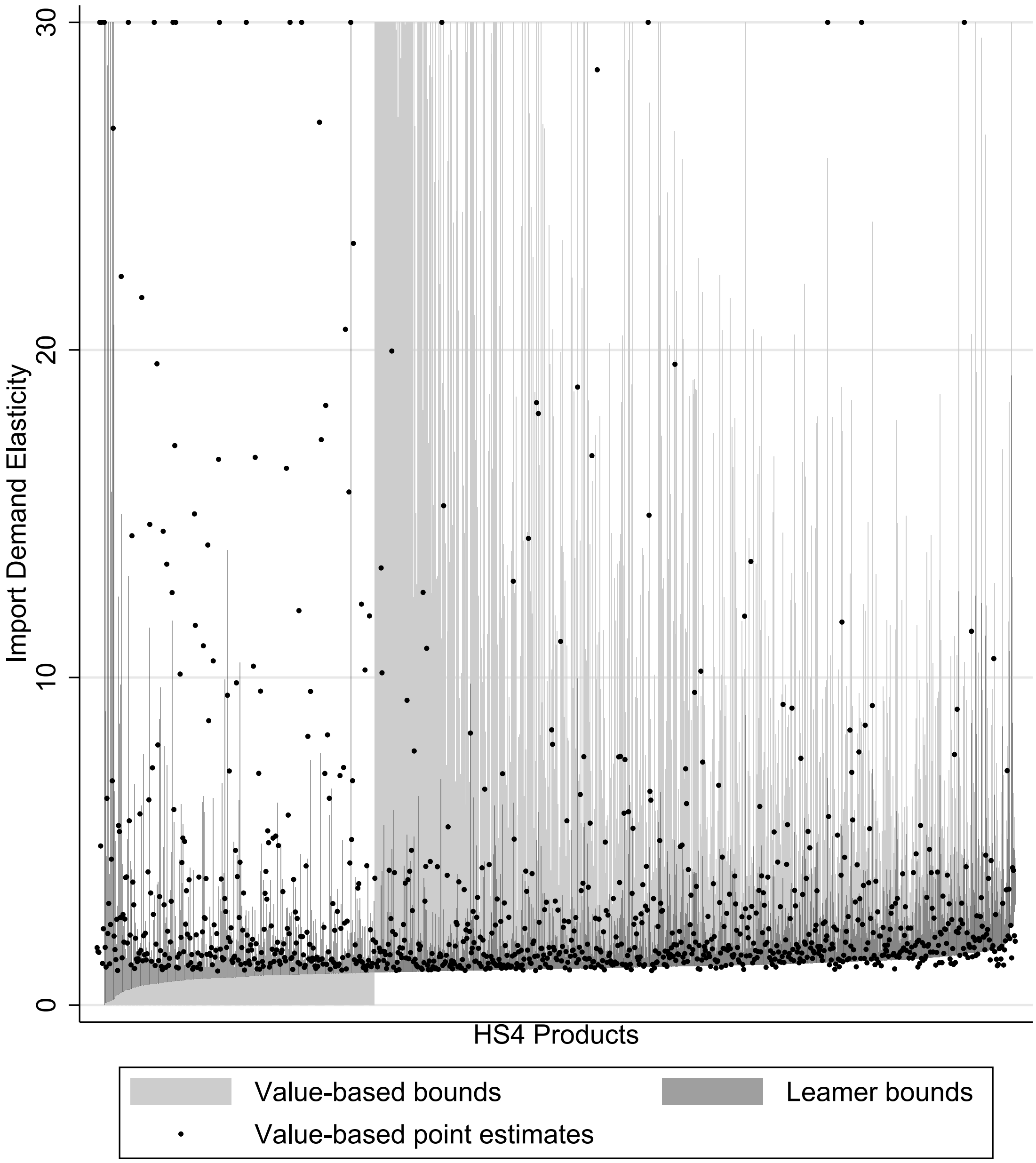

Figure 4: Leamer bounds, value-based bounds and point estimates, by 4-digit HS, U.S., 1993-2006.
Source: UC Davis Center for International Data, authors' calculations

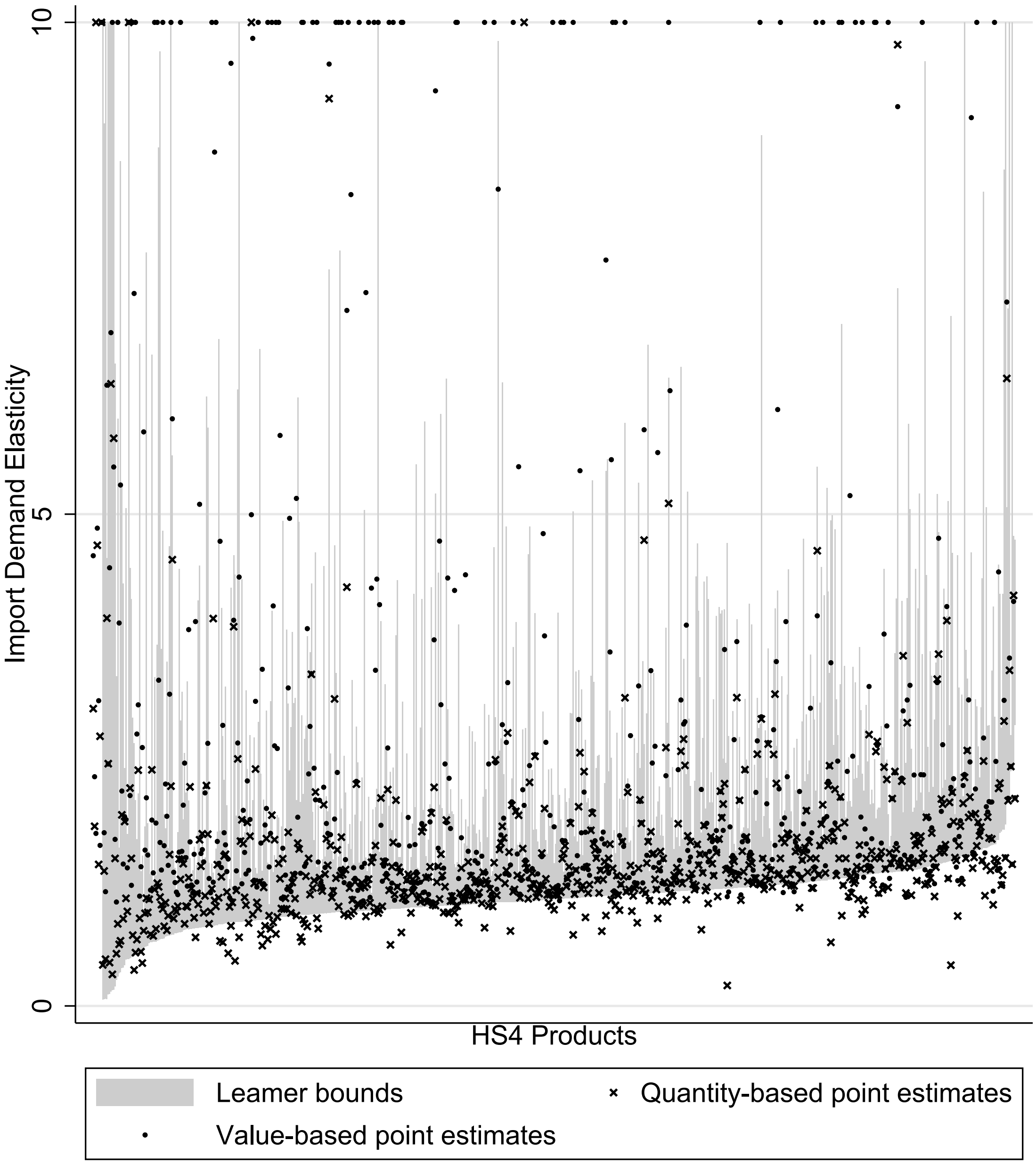

Figure 5: Value-based point estimates, quantity-based point estimates and Leamer bounds by 4-digit HS, U.S., 1993-2006.
Source: UC Davis Center for International Data, authors' calculations

Table 1: U.S. Import Elasticity Descriptive Statistics

	Quantity-Based Point Estimate	Leamer Lower Bound	Leamer Upper Bound	Value-Based Point Estimate	Value-Based Lower Bound	Value-Based Upper Bound
Panel A: 4-digit HS						
count	645	645	645	645	645	431
mean	1.56	1.09	3.59	7.36	1.09	40.1
median	1.33	1.09	2.36	1.63	1.09	10.3
Panel B: 6-digit HS						
count	2734	2734	2734	2734	2734	1765
mean	2.20	1.14	6.02	6.15	1.14	98.0
median	1.43	1.11	3.01	1.75	1.11	10.4
Panel C: 8-digit HS						
count	4847	4847	4847	4847	4847	3012
mean	2.64	1.14	13.9	6.24	1.14	82.7
median	1.47	1.09	3.40	1.82	1.09	10.9

Notes: the sample is restricted to those products for which value- and quantity-based point estimates exist. Source: UC Davis Center for International Data, authors' calculations.

A Appendix

A.1 Deviations from Benford's Law in the Traded Quantity and Trade Value Data

In order to access the extent of measurement error in trade values and traded quantities due to human manipulation of the data, we test whether or not the data deviates from Benford's Law. Benford's Law describes the distribution of first digits in economic or accounting data. For each 10-digit product, the goodness-of-fit test statistic is calculated using product-level export data according to the following formula:

$$N \sum_{d=1}^{9} \frac{\left(f^d - \hat{f}^d\right)^2}{f^d},$$

where $\hat{f}^d$ is the fraction of digit d in the data and f^d is the fraction predicted by Benford's law. The test statistic converges to a χ^2 distribution with eight degrees of freedom as N approaches infinity. The corresponding 10%, 5% and 1% critical values are 13.4, 15.5, and 20.1.

The distributions of the χ^2 goodness-of-fit test statistic values for the U.S. import value and import quantity are illustrated in figure A.1. We find that the distribution of first digits is very similar among the quantity and value data, which suggests that measurement error due to manipulation of the data is highly similar between quantities and values.

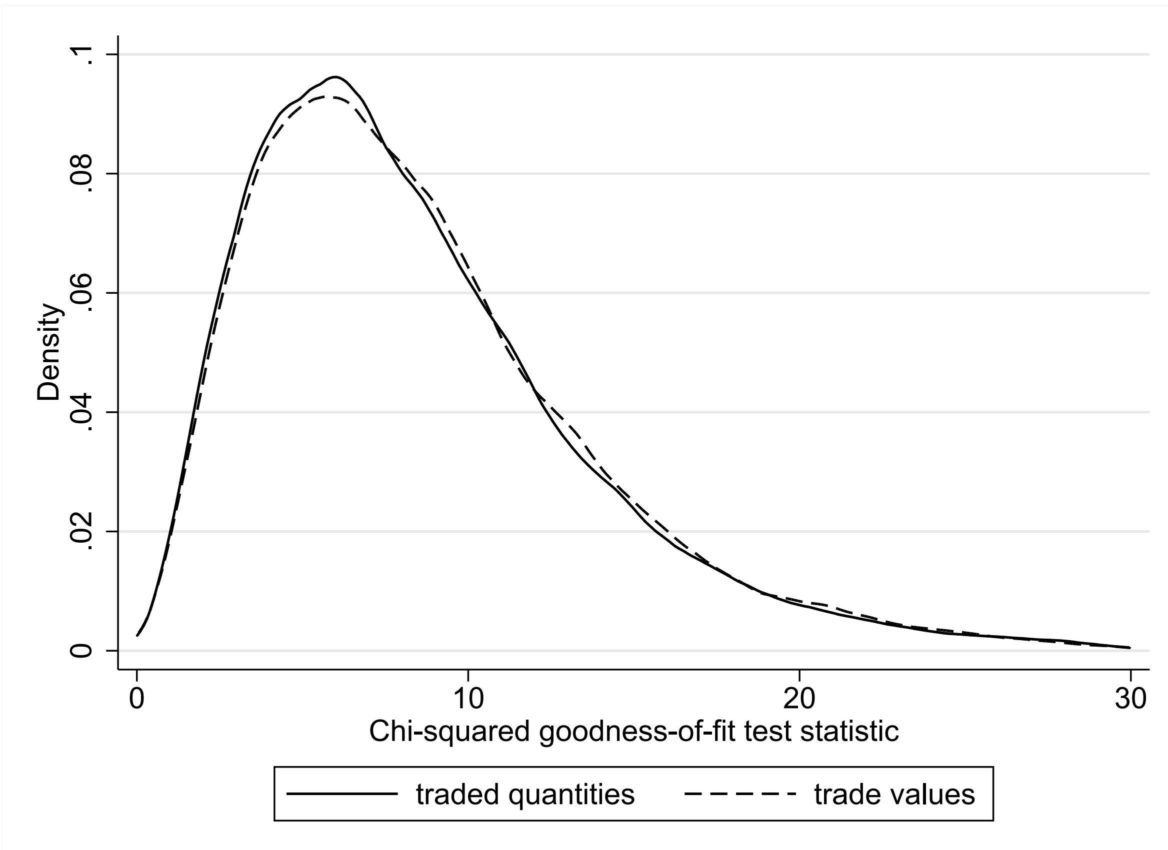

Figure A.1: Deviations from Benford's Law in Traded Quantity and Trade Value Data, by 10-digit HS, U.S., 1993-2006.
Source: UC Davis Center for International Data, authors' calculations

A.2 Partial Identification using the Quantity–Value Approach

As suggested by Scobie and Johnson (1975), another way to estimate import demand elasticities is regress $\ln x_{ct}$ on $\ln v_{ct}$, thus avoiding the need to construct price data. We again use (6) to transform (1) and (2) into a regression of trade quantities on trade values. The regression equation is

$$\ln x_{ct} = \frac{-\beta}{1-\beta} \ln v_{ct} + \frac{1}{1-\beta} \varepsilon_{ct}, \tag{27}$$

where we denote the OLS coefficient $\hat{\delta}^X$. We define $\hat{\delta}^V$ as the coefficient from the reverse regression of $\ln v_{ct}$ on $\ln x_{ct}$:

$$\ln x_{ct} = \frac{\gamma}{1+\gamma} \ln v_{ct} + \frac{1}{1+\gamma} \eta_{ct}. \tag{28}$$

The corresponding estimates of β are

$$\hat{\beta}^X = \frac{\hat{\delta}^X}{\hat{\delta}^X - 1}, \tag{29}$$

$$\hat{\beta}^V = \frac{1}{1 - \hat{\delta}^V}. \tag{30}$$

The reduced form is given by

$$\ln v_{ct} = \frac{1+\gamma}{\gamma+\beta} \varepsilon_{ct} - \frac{1-\beta}{\gamma+\beta} \eta_{ct},$$

$$\ln x_{ct} = \frac{\gamma}{\gamma+\beta} \varepsilon_{ct} + \frac{\beta}{\gamma+\beta} \eta_{ct}.$$

The probability limit of the OLS estimates of δ^X abd δ^V are thus

$$\texttt{plim}\ \hat{\delta}^X = \frac{\beta(\beta-1)\sigma_\eta^2 + \gamma(1+\gamma)\sigma_\varepsilon^2}{(1+\gamma)^2\sigma_\varepsilon^2 + (1-\beta)^2\sigma_\eta^2}, \tag{31}$$

$$\texttt{plim}\ \hat{\delta}^V = \frac{\beta(\beta-1)\sigma_\eta^2 + \gamma(1+\gamma)\sigma_\varepsilon^2}{\gamma^2\sigma_\varepsilon^2 + \beta^2\sigma_\eta^2}. \tag{32}$$

These direct OLS estimates, when expressed in terms of β^X and β^V, are:

$$\texttt{plim}\ \hat{\beta}^X = \beta + (\beta+\gamma)\frac{(1+\gamma)\sigma_\varepsilon^2}{(\beta-1)\sigma_\eta^2 - (1+\gamma)\sigma_\varepsilon^2}, \tag{33}$$

$$\texttt{plim}\ \hat{\beta}^V = \beta + (\gamma+\beta)\frac{\gamma\sigma_\varepsilon^2}{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2} \gtreqless \beta. \tag{34}$$

The probability limit of the lower bound in this case is equivalent to the Leamer upper bound, while the probability limit of the upper bound is equivalent to the value-based upper bound. It follows that the quantity-value lower bound will not hold if the Leamer upper bound holds. It also follows that the union of the Leamer and quantity-value bounds is equal to the value-based bounds.

Regressing trade quantities on trade values tends to overestimate the lower bound. In the vast majority of cases where the Leamer upper bound parameter restrictions are met, this implies that the parameter assumptions required for the quantity–value lower bound to hold are unlikely to be met.

A.2.1 Quantity–Value Approach with Measurement Error

When regressing traded quantities on trade values, the probability limit of the OLS estimates of δ^X abd δ^V are

$$\texttt{plim}\ \hat{\delta}^X = \frac{\beta(\beta-1)\sigma_\eta^2 + \gamma(1+\gamma)\sigma_\varepsilon^2 + (\gamma+\beta)^2\sigma_{uw}}{(1+\gamma)^2\sigma_\varepsilon^2 + (1-\beta)^2\sigma_\eta^2 + (\gamma+\beta)^2\sigma_u^2},$$

$$\texttt{plim}\ \hat{\delta}^V = \frac{\beta(\beta-1)\sigma_\eta^2 + \gamma(1+\gamma)\sigma_\varepsilon^2 + (\gamma+\beta)^2\sigma_{uw}}{\gamma^2\sigma_\varepsilon^2 + \beta^2\sigma_\eta^2 + (\gamma+\beta)^2\sigma_w^2}.$$

These direct OLS estimates, when expressed in terms of β^X abd β^V, yield probability limits equal to equations (13) and (12) respectively

$$\texttt{plim}\ \hat{\beta}^X = \beta + (\beta+\gamma)\frac{(1+\gamma)\,\sigma_\varepsilon^2 + (\beta+\gamma)\,\sigma_u^2 + (\beta-1)\,(\beta+\gamma)\,(\sigma_u^2 - \sigma_{uw})}{(\beta-1)\,\sigma_\eta^2 - (1+\gamma)\,\sigma_\varepsilon^2 - (\beta+\gamma)^2\,(\sigma_u^2 - \sigma_{uw})}., \tag{35}$$

$$\texttt{plim}\ \hat{\beta}^V = \beta + (\beta+\gamma)\frac{\gamma\sigma_\varepsilon^2 + \beta\,(\beta+\gamma)\,(\sigma_{uw} - \sigma_w^2) + (\beta+\gamma)\,\sigma_w^2}{\beta\sigma_\eta^2 - \gamma\sigma_\varepsilon^2 - (\beta+\gamma)^2\,(\sigma_{uw} - \sigma_w^2)}. \tag{36}$$

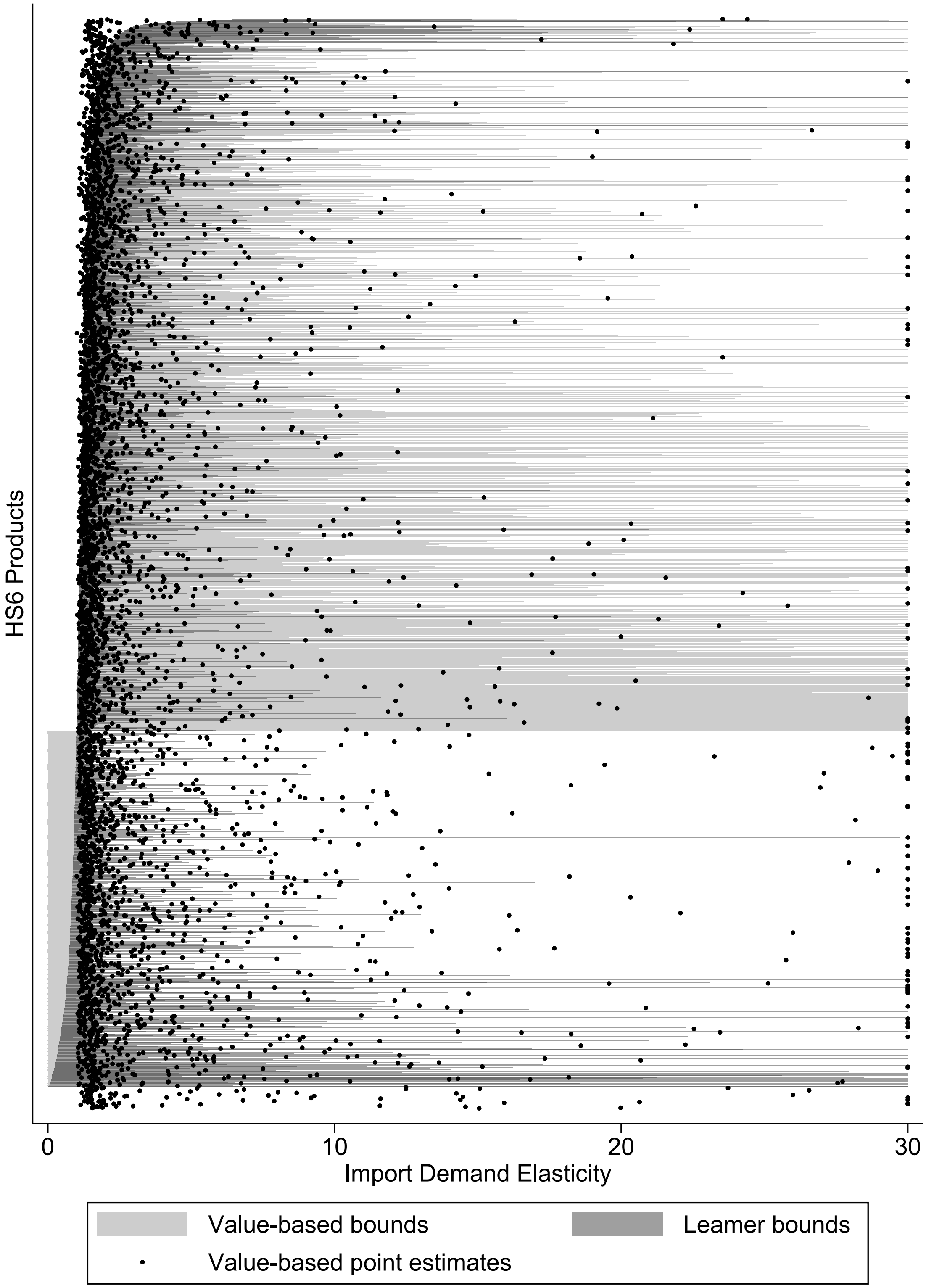

Figure A.2: Leamer bounds, Feenstra bounds and point estimates, by 6-digit HS, U.S., 1993-2006.
Source: UC Davis Center for International Data, authors' calculations

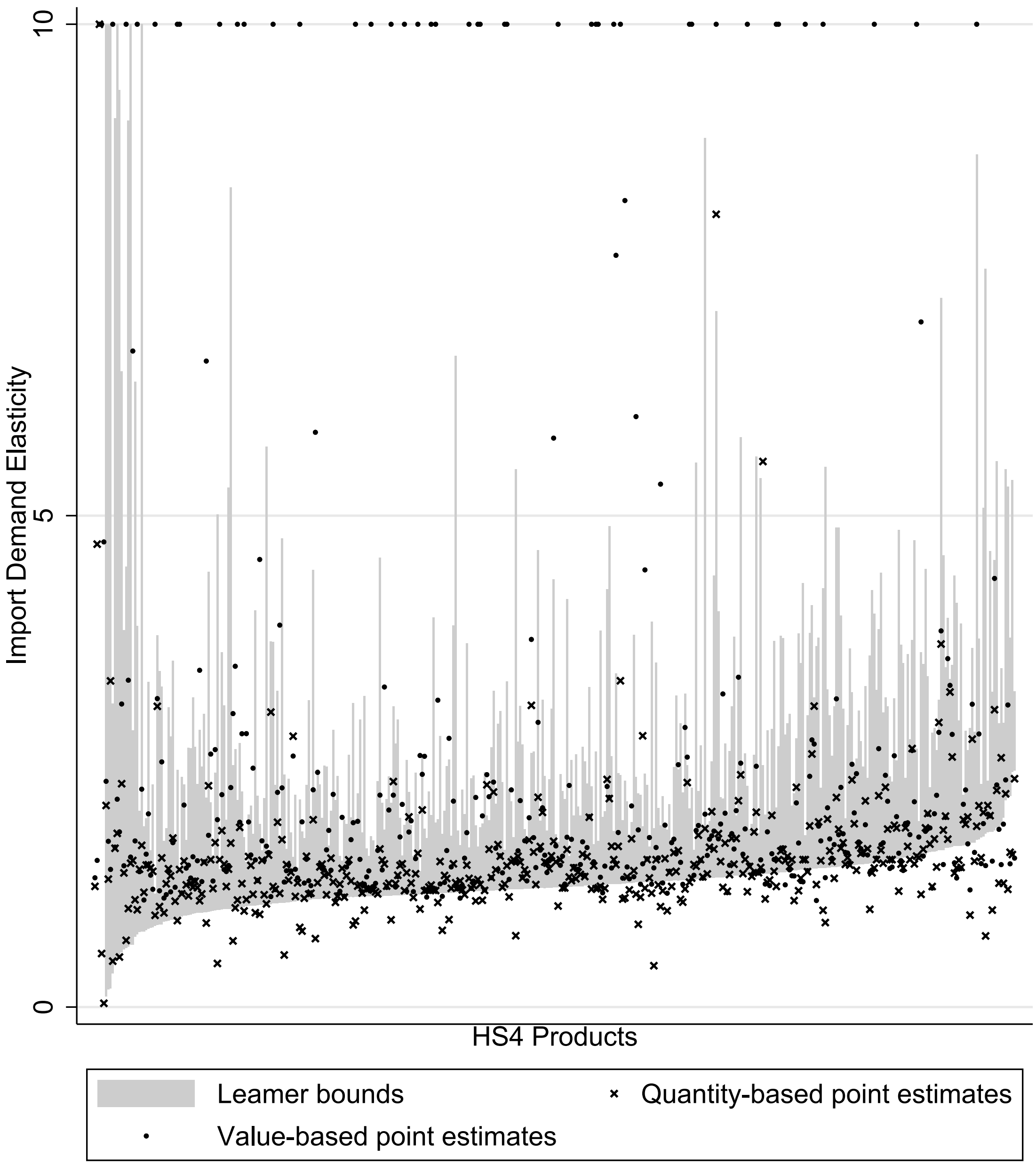

Figure A.3: Value-based point estimates, quantity-based point estimates and Leamer bounds by 4-digit HS, U.S., 1991-2015.
Source: Comtrade, authors' calculations

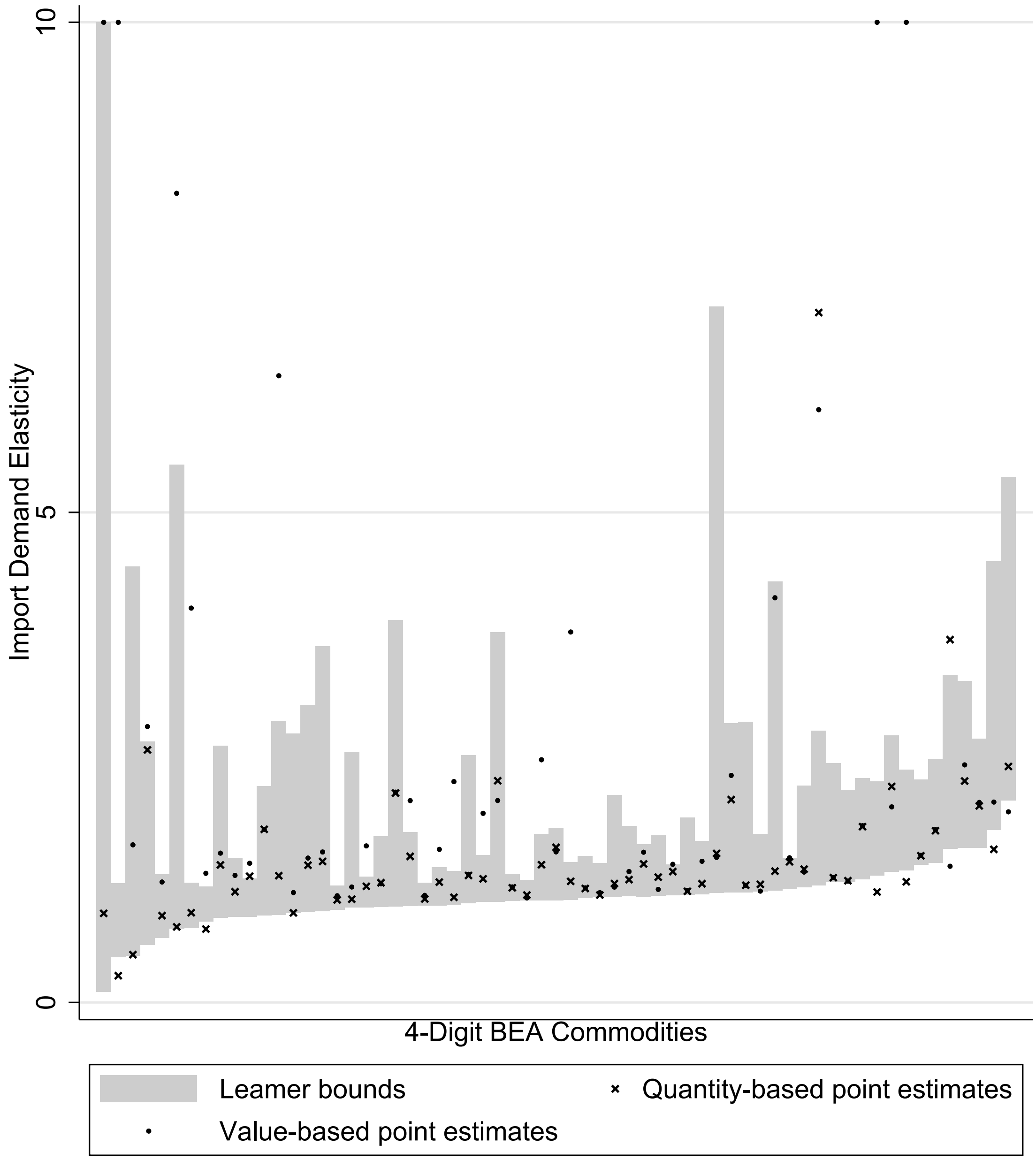

Figure A.4: Value-based point estimates, quantity-based point estimates and Leamer bounds by 4-digit BEA commodity, U.S., 1993-2006.
Source: UC Davis Center for International Data and BEA, authors' calculations