EUROPEAN CENTRAL BANK

EUROSYSTEM

WORKING PAPER SERIES

NO 1482 / OCTOBER 2012

OPTIMISM BIAS? THE ELASTICITY PUZZLE IN INTERNATIONAL ECONOMICS REVISITED

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Acknowledgements
The authors wish to thank Alexander Chudik, Alistair Dieppe, Nils Gottfries, Jean Imbs, Per Johansson, Johan Lyhagen, Filippo di Mauro, Andreas Westermark, seminar participants at the European Central Bank and Uppsala University, and the participants at the National Meeting of Swedish Economists 2011. Vesna Corbo thanks the ECB for the hospitality and financial support during part of this project. The opinions expressed in this paper are the authors' only and do not reflect those of the ECB or of the Eurosystem.

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ISSN 1725-2806 (online)

Abstract

The elasticity of substitution between domestic and imported goods is a central parameter in macroeconomic models, but after decades of empirical studies there is no consensus on its magnitude. Earlier literature using time series arrives at low values, while more recent studies using panel-based econometric methods on disaggregated data find higher values. We examine the econometric methodology of this more recent literature, which follows the seminal work by Feenstra (1994), looking in more detail at the effect on the results of the non-linear mapping between reduced-form and structural parameters. Our main contribution is the use of bootstrap methods, which offer more insight into the Feenstra method and can explain why researchers applying it may tend to find high estimates. The bootstrap not only allows us to obtain considerably less biased estimates of the structural elasticity parameter, but also to better characterize their accuracy, a point vastly overlooked by the literature.

Keywords: Trade Elasticities, Elasticity of Substitution, Heterogeneity, Bootstrap
JEL classification: C14, C23, F14

Non-Technical Summary

The elasticity of substitution between domestic and imported goods has been the object of intense empirical study since the middle of last century. Decades of empirical studies have however not delivered a consensus on its magnitude. The literature is divided between "elasticity pessimism" stemming from the earlier literature based on time series, and the "elasticity optimism" of the more recent studies that use panel-based econometric methods on disaggregated data. In other words, studies in the earlier literature usually find very low elasticity estimates, while studies pertaining to the latter arrive at much higher ones. We discuss the econometric methodology of this more recent literature, looking in more detail at the sensitivity of the results to the non-linear mapping between reduced-form and structural parameters used since the seminal work by Feenstra (1994).

Feenstra proposed a method based on panel regressions on disaggregated (sector level) data. The estimation equation, derived from economic theory is a function of two estimable coefficients, which in turn are non-linear functions of the structural elasticity parameter of interest. The theoretical derivation imposes restrictions on the regression parameters, rendering a mapping function that is non-linear and discontinuous. The irregular shape of this mapping function causes the elasticity estimates in some regions of the parameter space to be biased. In particular, the higher the elasticity estimate, the more likely it is to be biased. This bias stems from the parameter mapping itself, and not from the estimates of the reduced-form parameters being biased – in other words, it may be present even if the reduced-form estimator is consistent.

Applying bootstrap methods, we are able to identify, quantify and partly correct for the aforementioned bias. We present results based on Monte Carlo experiments, as well as estimation results based on bilateral sector-level trade data, finding that the resulting bootstrap distributions can be very irregular as a consequence of the non-linearity inherent in the estimation. The main insight provided by the bootstrap is that the Feenstra method is likely to lead to high, and highly unstable, estimates for the elasticity of substitution in some regions of the parameter space. If the sector level elasticities are subsequently aggregated, this will jack up the resulting aggregate. In this sense, we find that the method itself may lead to "elasticity overoptimism". Furthermore, the previous literature uses the delta method to derive the variance of the estimates, but given the discontinuity in the mapping function, this method is not applicable. We find that, indeed, it provides vastly underestimated measures of the variance of the elasticity of substitution, thus leading also to overoptimism on the significance of results.

Based on the outcome of our Monte Carlo experiments, we can discriminate between alternative measures of the elasticity of substitution. We find that, using robust measures of central tendency of the bootstrap distributions, we are able to obtain considerably less biased estimates in the problematic regions of the parameter space, where the majority of the estimates are located. We tend to obtain the same estimates as those that would be produced by the standard application of the Feenstra (1994) method (and smaller standard deviations) in cases where the bootstrap-based diagnostics do not indicate restrictions violations, but smaller ones in the cases where they do. Finally, we also provide alternative measures of dispersion based on the bootstrap distribution. Our proposed bias correction and improved characterization of the standard errors may support "elasticity realism", leading to estimates that, though higher than those based on time series, are distinctly lower than the more recent ones.

1 Introduction

Empirical economists have tried to estimate the elasticity of substitution between domestic and imported goods since the middle of the last century (see e.g. Tinbergen (1946), Polak (1950), and in particular Orcutt (1950), Streeten (1954) and Preeg (1967) for early uses of the terms “elasticity pessimism” and “elasticity optimism”). After decades of empirical studies, however, no consensus has been reached on what magnitude should be used for this central parameter in the calibration of macroeconomic models. Earlier literature, based on time series, mainly arrives at low values, leading to “elasticity pessimism”. More recent studies that use panel-based econometric methods on disaggregated data find higher values, hence the recent “elasticity optimism” (see e.g. Feenstra (1994), Broda and Weinstein (2006), Broda, Greenfield, and Weinstein (2006) and more recently Imbs and Méjean (2009, 2011)). We examine the econometric methodology of this more recent literature, which, following the seminal work by Feenstra (1994), relies on the estimation of reduced-form parameters which are subsequently mapped into the structural elasticity parameter of interest using a non-linear mapping function. In particular, our focus is on the sensitivity of the results to this non-linear mapping between reduced-form and structural parameters, which generates a, sometimes considerable, bias even in the case of consistently estimated reduced-form parameters.

The Feenstra method is based on panel regressions on disaggregated (sector level) data. The estimation equation, derived from theory, is a linear function of two reduced-form parameters, which in turn are some non-linear functions of the structural elasticities of interest. Having obtained estimates of the reduced-form parameters, one can then compute the elasticity of substitution. The theoretical restrictions on the elasticities impose restrictions on the regression parameters, which in come cases may be violated. In particular, in the case of a highly competitive market, and hence a high elasticity of substitution, we face a risk of obtaining theory-inconsistent estimates. Moreover, in these same cases, even if we do obtain a theory-consistent estimate, it is likely to be biased due to the convexity of the mapping function in this particular part of the parameter space. The bias we have in mind here stems from the parameter mapping itself, and not from the reduced-form parameters being biased – in other words, it may be present even in the case of consistent estimation.

Applying bootstrap methods, we are able to identify, quantify and partly correct for the bias induced by the non-linearity of the function mapping the estimated reduced-form coefficients into structural parameters. We present results based on Monte Carlo experiments, as well as estimation results based on actual trade data. The results we present are obtained from estimations on German import data at the 4-digit ISIC level covering the years 1995-2009. Our analysis leads to two main insights. First, the Feenstra method is likely to lead to too high and unstable estimates for the elasticity of substitution in some frequently visited regions of the parameter space. If the sector-level elasticities are subsequently aggregated, this will jack up the resulting aggregate. Second, the previous literature uses the delta method to derive the variance of the estimates, but given the functional form of the mapping function, which has a discontinuity, this method is not applicable. We find that, indeed, it provides vastly underestimated measures of the variance of the elasticity of substitution, thus leading to the significance of results being overestimated.

Guided by our simulation results, we then propose alternative measures of the elasticity estimate and an alternative measure of dispersion based on the bootstrap distribution. Our preferred measures of central tendency, the median and the mode of the bootstrapped distribution, are on average less biased than the estimates obtained from original two-stage least squares (2SLS) estimator proposed by Feenstra (1994).

The rest of the paper is organized as follows. Sections 2 and 3 are devoted to overviews of the literature and of the Feenstra method, respectively. In Section 4, we discuss the estimation procedure. Section 5 contains the results of Monte Carlo experiments, quantifying the bias of the alternative measures we test against each other, and formally affirming the advantages of the bootstrap in our context. In Section 6, the estimation results are discussed. Finally, Section 7 concludes.

2 Overview of related literature

Following the seminal paper by Feenstra (1994), a literature employing panel data methods for the estimation of elasticities of international substitution has emerged. It makes use of the increasingly available sources of disaggregated trade data to produce structural estimates of elasticities, at the good and at the macroeconomic level. Unlike the earlier literature, dating as far back as the 1940s, the more recent literature applying panel data estimation methods is able to address the endogeneity problem present whenever quantities or volumes are regressed on prices. Furthermore, the use of disaggregated data significantly reduces the aggregation bias problems related to the use of macro time series. For a full discussion of the earlier literature employing macroeconomic time series for the estimation of trade elasticities and elasticities of substitution, see the summary in McDaniel and Balistreri (2003) who discuss some of the main references in the field. Other relevant references include Orcutt (1950), Houthakker and Magee (1969), Marquez (1990), and Gallaway, McDaniel, and Rivera (2003).

Feenstra (1994) introduced a way of structurally estimating the elasticity of substitution, by explicitly modeling both the supply side and the demand side of each market. Under the assumption of equal substitutability of all varieties independently of their origin, as in Armington (1969), the resulting system of equations can be estimated using trade data only. Broda and Weinstein (2006) made the methodological contribution of extending the Feenstra method to deal with estimates that do not yield theory-consistent elasticities of substitution. Whenever the estimation generates a value which is inconsistent with the theoretical model, a grid search is performed over the range of admissible values, and the best among these is chosen.[1]

Mohler (2009) evaluates the sensitivity of estimates based on the Feenstra methodology to changes in the estimation specification. He finds that the elasticities are estimated quite robustly, using the original Feenstra (1994) estimator. However, as we will further elaborate on below, Mohler uses a linear approximation to compute standard deviations of the estimates, which in some cases can yield highly underestimated variance estimates. Indeed, he does point out that the estimates sometimes react very sensitively to different specifications, while at the same time exhibiting very low variances, without however investigating the reason for this directly.

3 The Feenstra (1994) method

The main advantage of the Feenstra approach is that it explicitly models the supply side of the economy in addition to the standard demand side specification which is traditionally used when estimating elasticities of substitution. It exploits the panel structure of the data to address the simultaneity issues present whenever quantities are regressed on prices, since each is co-determined with the other. This is a clear advantage compared to using IV methods, since instruments for prices and quantities at the good level are hard to find.[2] The identification strategy that the Feenstra method hinges on stems from Armington (1969), who assumed that the substitutability between two imported varieties of the same good is the same as the substitutability between an imported variety and a domestic one. This assumption is what allows us to use trade data only for the estimation of the elasticities of our interest; this is of crucial

[1]We discuss the advantages and drawbacks of this approach in Section 4 below.

[2]Erkel-Rousse and Mirza (2002) estimate elasticities for 27 ISIC sectors in 13 importing countries, instrumenting the prices by relative wage and relative exchange rate indices. Their estimation requires a panel, just as ours. The wage series they use are, however, much less detailed and comprehensive, and less easily accessible than the data on trade flows.

importance, since data on domestic production and consumption are not available at the same level of disaggregation as trade data for a wide set of countries. Here we only present a summary containing the main equations and underlying assumptions of the Feenstra method. For details, see Appendix A.

3.1 Deriving the estimated equation

We begin by clarifying some concepts and definitions. The disaggregation level at which we compute and estimate the elasticity of substitution will be the good level. We use the terms *sector* and *good* interchangeably; in other words, the sector grouping is what determines the definition of a good. A good, in turn, contains a number of varieties. By *variety*, we refer to a good produced in a specific country. Hence, the definition of good is based on some product characteristics other than its origin, and variety refers to products of a specific origin belonging to some category of goods. This implies that we have as many varieties of each good as there are trading partners in the specific sector. The exact empirical definitions of goods and varieties will depend on the disaggregation level and availability of the data.

A few words on notation are in place here; to make the formulas easy to read, we have set all indices to the first letter of what they are meant to index. Hence, we denote the country under study by c, the good (or sector) by g, the variety (or country producing good g) by v, and the time period by t. If a variable denotes the aggregate across some of the indices, a dot will appear in the place of the index across which we are aggregating. In the case of parameters being assumed constant across some dimension, they will only be denoted by the indices across which they vary.

Assuming a standard CES setting, we have the following demand function:

$$C_{cgvt} = \beta_{cgvt}^{\sigma_{cg}-1} \left(\frac{P_{cgvt}}{P_{cg.t}} \right)^{-\sigma_{cg}} C_{cg.t} \,, \tag{1}$$

where C_{cgvt} denotes the consumption of variety v, pertaining to good g, in country c at time t and $C_{cg.t}$ the total consumption of good g in country c at time t, and P_{cgvt} and $P_{cg.t}$ are the corresponding prices. The parameter β_{cgvt} is a taste parameter specific to each variety, good and country at each point in time. Finally, σ_{cg} denotes the elasticity of substitution of good g in country c. This is our parameter of interest and it is assumed to be equal over all varieties of good g, imported as well as domestically produced.[3]

[3]This is the Armington (1969) assumption, discussed above, upon which Feenstra's identification strategy hinges.

Rewriting in terms of expenditure shares, taking logs and differencing, we can rewrite (1) as

$$\Delta \ln \tilde{s}_{cgvt} = (1 - \sigma_{cg})\Delta \ln \tilde{P}_{cgvt} + \Phi_{cg.t} + \varepsilon_{cgvt}\,. \tag{2}$$

Here, Δ denotes the difference over time or, in other words, the growth rate of a variable; $\tilde{s}_{cgvt} \equiv \frac{P_{cgvt}C_{cgvt}}{\sum_{v \neq c} P_{cgvt}C_{cgvt}}$ denotes the observed expenditure share of variety v in country c's total imports of good g at time t; $\tilde{P}_{cgvt}$ is the observed price; $\Phi_{cg.t}$ is a term containing the variables that are common to all varieties; and ε_{cgvt} is an error-term capturing unobserved trade costs and taste variables.[4] Note that the error term is assumed idiosyncratic, allowing each variety to exhibit some characteristics specific to it alone. In other words, it is assumed to be identically and independently distributed across time, countries, sectors and varieties.

The supply equation is assumed to take on the following simple structure:

$$P_{cgvt} = \tau_{cgvt} \exp(v_{cgvt}) C_{cgvt}^{\omega_{cg}}\,, \tag{3}$$

where τ_{cgvt} is a measure of variety-specific multiplicative trade costs, v_{cgvt} is a sector- and country-specific technology shock, and $\omega_{cg} \geq 0$ is the inverse of the price elasticity of supply of good g in country c, assumed equal across varieties but allowed to differ between goods. The assumption of equality across varieties is crucial for identification, as this is what allows us to eliminate all terms common across varieties and thus express the estimation equation in term of observable variables only. Rewriting in a similar fashion as with demand above, the final supply equation becomes

$$\Delta \ln \tilde{P}_{cgvt} = \Psi_{cg.t} + \frac{\omega_{cg}}{1 + \omega_{cg}\sigma_{cg}}\,\varepsilon_{cgvt} + \delta_{cgvt}\,. \tag{4}$$

The term containing variables common to all varieties is now denoted $\Psi_{cg.t}$, while the idiosyncratic error term is given by δ_{cgvt}, also assumed to be i.i.d. across all dimensions.

In order to make identification of the system of equations given by (2) and (4) possible, we need to make the assumption of no correlation between the error terms,[5]

[4]Note that the observed expenditure share differs from the true expenditure share due to the availability of data. As we only have data on international trade, and not on domestic consumption, the observed share is expressed as a fraction of imports expenditures on good g instead of total expenditures on good g. The import prices we observe are measured CIF (Cost, Insurance and Freight). This implies that insurance, handling and shipping costs are all included; customs charges, however, are not (Radelet and Sachs, 1998). For further details on the distinction between theoretical and observed prices and shares, see Section A.1.1 in the Appendix.

[5]As discussed also in Feenstra (1994), Leamer (1981) demonstrates that this assumption in a time series setting yields elasticity estimates that lie on a hyperbola defined by the second moments of the

i.e.

$$\mathrm{E}(\varepsilon_{cgvt}\delta_{cgvt}) = 0\,. \tag{5}$$

Next, we eliminate the terms common to all varieties by subtracting from each equation indexed v the same equation for some reference variety v_r, obtaining

$$\begin{aligned}
\breve{\varepsilon}_{cgvt} &\equiv \varepsilon_{cgvt} - \varepsilon_{cgv_rt} \qquad (6)\\
&= [\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}] + (\sigma_{cg} - 1)\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right]\\
\breve{\delta}_{cgvt} &\equiv \delta_{cgvt} - \delta_{cgv_rt} \qquad (7)\\
&= \frac{1+\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right] \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}} [\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}]\,.
\end{aligned}$$

By assumption (5), $\breve{\varepsilon}_{cgvt}$ and $\breve{\delta}_{cgvt}$ are independent. We can hence multiply the above equations for the differenced error terms, obtaining an expression for the i.i.d. variable u_{cgvt} in terms of combinations of expenditure shares and prices only – both variables that we can observe. Rearranging, we arrive at the estimation equation

$$Y_{cgvt} = \theta_{1cg}X_{1cgvt} + \theta_{2cg}X_{2cgvt} + u_{cgvt}\,, \tag{8}$$

where we have defined:

$$Y_{cgvt} \equiv \left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right]^2\,, \tag{9}$$

$$X_{1cgvt} \equiv [\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}]^2\,, \tag{10}$$

$$X_{2cgvt} \equiv [\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}] \cdot \left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right]\,, \tag{11}$$

$$u_{cgvt} \equiv \frac{1+\omega_{cg}\sigma_{cg}}{(1+\omega_{cg})(\sigma_{cg}-1)}\,\breve{\varepsilon}_{cgvt}\breve{\delta}_{cgvt}\,, \tag{12}$$

$$\theta_{1cg} \equiv \frac{\omega_{cg}}{(1+\omega_{cg})(\sigma_{cg}-1)}\,, \tag{13}$$

and

$$\theta_{2cg} \equiv \frac{\omega_{cg}\sigma_{cg} - 2\omega_{cg} - 1}{(1+\omega_{cg})(\sigma_{cg}-1)}\,. \tag{14}$$

To sum up, our regression variables are the second moments of expenditure shares and prices, once they have been differenced over time and with respect to a reference variety in

data. Using time series data, the estimate is not unique. With a panel, however, we are able to obtain multiple hyperbolas – one for each trading partner, the intersection of which will yield a unique set of elasticity estimates.

order to eliminate any level dependence and good-specific shocks common to all varieties. Based on the estimates from a regression on those variables, we are able to compute the structural parameter of interest.

3.2 Consistency

Equation (8), estimated by OLS, will not yield consistent estimates since prices and expenditure shares are correlated with the error terms, as discussed in Feenstra (1991, 1994). To deal with this problem, Feenstra suggests including country-specific fixed effects as instruments, a method we also pursue. Denoting by $\mathbf{Z}_{cg}$ the block-diagonal matrix of instruments for good g imported to country c, and by $\mathbf{X}_{cg}$ the matrix containing the regressors X_{1cg} and X_{2cg}, we estimate the coefficients $\hat{\boldsymbol{\theta}}_{cg}$ from the following equation[6]

$$\hat{\boldsymbol{\theta}}_{cg} = \left[\mathbf{X}'_{cg}\mathbf{Z}_{cg}\left(\mathbf{Z}'_{cg}\mathbf{Z}_{cg}\right)^{-1}\mathbf{Z}'_{cg}\mathbf{X}_{cg}\right]^{-1}\mathbf{X}'_{cg}\mathbf{Z}_{cg}\left(\mathbf{Z}'_{cg}\mathbf{Z}_{cg}\right)^{-1}\mathbf{Z}'_{cg}\mathbf{X}_{cg}\,. \tag{15}$$

Our estimator yields consistent estimates of θ_{1cg} and θ_{2cg}, but not all such estimates are *theory-consistent*, due to the restrictions imposed by the structural model on σ_{cg}. We next discuss these theory-imposed restrictions.

Combining expressions (13) and (14), we obtain an expression for σ_{cg} in terms of θ_{1cg} and θ_{2cg}. In order to derive the restrictions on the parameters, Feenstra (1994) rewrites the above expressions in terms of the parameter ρ_{cg}, defined as

$$\rho_{cg} = \frac{\omega_{cg}(\sigma_{cg}-1)}{1+\omega_{cg}\sigma_{cg}}\,, \tag{16}$$

instead of ω_{cg}. This simplifies the derivations since both an upper and a lower restriction can be obtained for ρ_{cg}, while ω_{cg} is only bounded below by zero. Noting that ρ_{cg} is increasing in ω_{cg}, we obtain the lower bound $\rho_{cg} = 0$ by letting $\omega_{cg} = 0$. On the other extreme, we have

$$\rho_{cg}\big|_{\omega_{cg}\to\infty} = \left.\frac{1}{\frac{1}{\rho_{cg}}}\right|_{\omega_{cg}\to\infty} = \left.\frac{1}{\frac{1+\omega_{cg}\sigma_{cg}}{\omega_{cg}(\sigma_{cg}-1)}}\right|_{\omega_{cg}\to\infty} = \frac{1}{0+\frac{\sigma_{cg}}{\sigma_{cg}-1}} = \frac{\sigma_{cg}-1}{\sigma_{cg}} < 1\,. \tag{17}$$

Hence, it holds that $0 \leq \rho_{cg} < \frac{\sigma_{cg}-1}{\sigma_{cg}} < 1$. Rewriting the expressions for $\hat{\theta}_{1cg}$ and $\hat{\theta}_{2cg}$ in terms of $\hat{\rho}_{cg}$, next, yields

$$\hat{\theta}_{1cg} = \frac{\hat{\rho}_{cg}}{(\hat{\sigma}_{cg}-1)^2(1-\hat{\rho}_{cg})} \tag{18}$$

[6]For details on the consistency of the estimator, see Feenstra (1991).

and

$$\hat{\theta}_{2cg} = \frac{2\hat{\rho}_{cg} - 1}{(\hat{\sigma}_{cg} - 1)(1 - \hat{\rho}_{cg})} \,. \tag{19}$$

Dividing the square of (19) by (18), and solving the resulting equation, yields the following expression for $\hat{\rho}_{cg}$

$$\hat{\rho}_{cg} = \frac{1}{2} \pm \left[\frac{1}{4} - \frac{1}{4 + \left(\hat{\theta}^2_{2cg} / \hat{\theta}_{1cg} \right)} \right]^{\frac{1}{2}} , \tag{20}$$

while from (19) we have

$$\hat{\sigma}_{cg} = 1 + \frac{2\hat{\rho}_{cg} - 1}{\hat{\theta}_{2cg}(1 - \hat{\rho}_{cg})} \,. \tag{21}$$

In order to insure that $\hat{\sigma}_{cg} > 1$,[7] we must choose a value of $\hat{\rho}_{cg} > \frac{1}{2}$ when $\hat{\theta}_{2cg} > 0$, and a value of $\hat{\rho}_{cg} < \frac{1}{2}$ when $\hat{\theta}_{2cg} < 0$. Knowing that $\hat{\rho}_{1cg}$ and $(1 - \hat{\rho}_{1cg})$ must both be positive, it follows from equation (18) that the restrictions on $\hat{\sigma}_{cg}$ and $\hat{\rho}_{cg}$ will be fulfilled whenever $\hat{\theta}_{1cg} > 0$ holds.[8] Finally, if $\hat{\theta}_{2cg} \to 0$, then $\hat{\rho}_{cg} \to \frac{1}{2}$ and $\hat{\sigma}_{cg} \to 1 + \hat{\theta}_{1cg}^{-\frac{1}{2}}$.

These parameter restrictions imply that a negative value of $\hat{\theta}_{1cg}$ will generally not yield theory-consistent estimates of the elasticity of substitution. In Feenstra's original paper, the sectors that yield theory-inconsistent estimates are discarded. More recent papers applying the Feenstra (1994) method usually follow Broda and Weinstein (2006) and perform a grid search over the interval of admissible parameter values.[9] Specifically, whenever a theory-inconsistent estimate is obtained, a search algorithm is used to locate the best fit over the interval of admissible values of $\hat{\rho}_{kj}$ and $\hat{\sigma}_{kj}$. However, there are potential problems associated with this method, as one needs to limit the grid from below and above, and determine its fineness in some arbitrary fashion. The possibility of corner solutions then makes the estimates arbitrary as well, since they will depend on the

[7]An elasticity below unity is theoretically unappealing, as it would imply that all varieties are essential for the consumer to achieve positive utility. This would also imply that no existing varieties could disappear from the market, nor new ones be introduced. Hence, in line with previous literature, we consider any estimate of $\hat{\sigma}_{cg} < 1$ to be theory-inconsistent.

[8]Note that it is possible that a slightly negative value of $\hat{\theta}_{1cg}$ yields a theory-consistent estimate if

$$\hat{\theta}_{1cg} > -\frac{\hat{\theta}^2_{2cg}}{4} \,,$$

even though the restriction on $\hat{\rho}_{cg}$ will not be fulfilled. See Feenstra (1994) for derivations. This case does occur from time to time in our estimations. In Feenstra (1994), it occurs for one out of the eight sectors for which theory-consistent estimates are obtained.

[9]See Broda and Weinstein (2006) for a description of the method, and Imbs and Méjean (2009, 2011) for examples of applications.

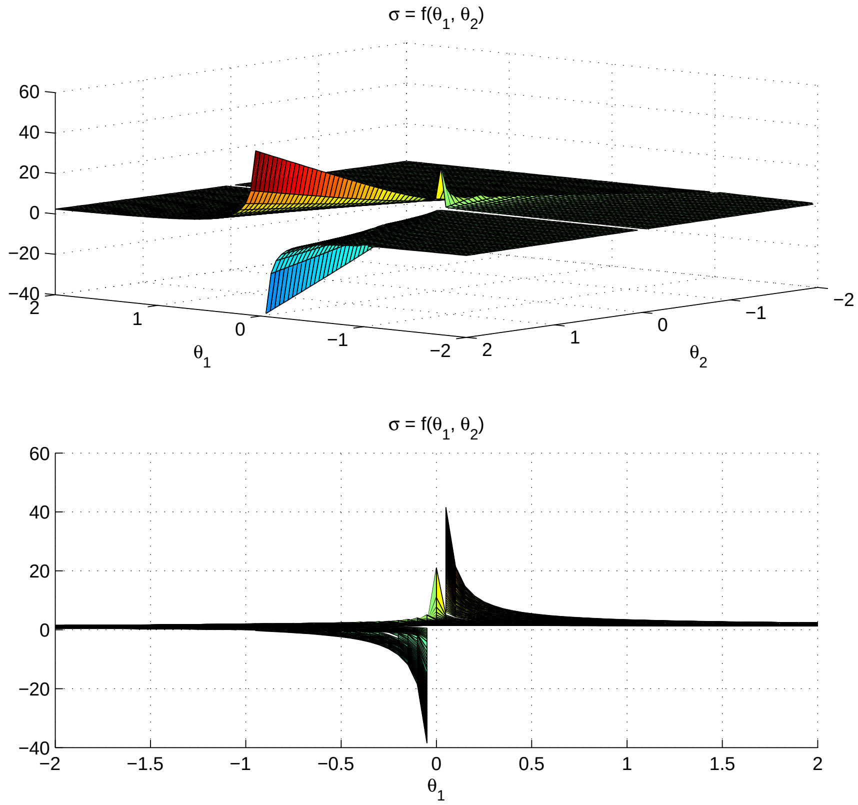

Figure 1: A graphical representation of the functional form of the mapping from θ_1 and θ_2 to σ.

specific choice of grid employed. Another important issue that, to our knowledge, has not been debated in earlier work is the computation of standard deviations of the estimates. The procedure proposed by Feenstra is to use a first-order Taylor approximation of the expression for the elasticity of substitution around the coefficient estimates $\hat{\theta}_{1cg}$ and $\hat{\theta}_{2cg}$, and to use the variances and covariances of those to compute the variance of the elasticity estimate. However, for an approximation of this sort to be appropriate, the function mapping $\hat{\theta}_{1cg}$ and $\hat{\theta}_{2cg}$ into $\hat{\sigma}_{cg}$ needs to be infinitely differentiable in the neighborhood of the estimate. In our setting, this is not the case. This is best shown graphically, as in Figure 1, which shows the function $\sigma = f(\theta_1, \theta_2)$ in the relevant space of θ_1 and θ_2. Moreover, as the approximation is of first order, it is likely to be inadequate even in the parts of the parameter space where the function is continuous but has a high curvature.

It is easily seen from the figure that the mapping function is discontinuous and that it explodes in some regions of the parameter space. Applying a linear approximation despite this fact implies the risk of seriously overestimating the accuracy of the elasticity estimates. This may also explain the apparent contrast between the non-robustness of the point estimates and the low estimated standard errors observed by Mohler (2009).

4 Estimation procedure

In order to avoid the above mentioned problems, we propose a different method of estimating the elasticity of substitution under the theory-imposed constraint, and of assessing the accuracy of the estimates. We apply a bootstrap procedure to get a characterization of the full distribution of the estimates for all of the country-sector combinations for which we perform estimation. From this we can then obtain various measures of central tendency and dispersion. As we expect the mean of the bootstrapped distribution to be sensitive to outliers, we also consider the median and mode of the distribution as measures of central tendency. Moreover, we consider the interquartile range as an additional measure of dispersion, expecting the same instability in the variance as in the mean of the distribution.

In the well-behaved region of the mapping function, the robust central-tendency measures (median and mode) of the coefficient estimates generated by our bootstrap procedure are practically the same as the point estimates obtained from the original estimation. As will become clear from the results presented in Section 6, the results differ substantially when the point estimate is located near the discontinuous region of the mapping function. This is the case not only for theory-inconsistent estimates, but also for high and mid-range estimates that are theory-consistent. Given the highly non-linear form of the mapping function between the estimated coefficients and the parameters of interest, we suspect that the bootstrapped distributions may be very irregular. For this reason we take particular care in choosing measures of central tendency and dispersion. We find that, while in some country-sector pairs the bootstrap distributions are quite regular, very irregular ones do arise in a non-negligible fraction of cases. This yields highly distorted measures of the standard deviations of the elasticity estimates, especially in those cases where restricted estimation is necessary, but also in case the point estimate is high. As discussed above, this feature tends to severely overestimate the true accuracy of the obtained estimates. Thanks to the increased transparency that the bootstrap offers, we can provide a more complete and consistent picture of the information contained in the data. We next describe our bootstrapping procedure in more detail.

4.1 The bootstrapping procedure

We use a wild bootstrap resampling procedure to estimate the empirical distribution of our estimates of the sectoral elasticities of substitution. The wild bootstrap is meant to address the problem of heteroskedastic errors and was popularized by Liu (1988), who in turn took the main idea from Wu (1986) and Beran (1986). The implementation we use was proposed by Mammen (1993). Other studies discussing the properties of the wild bootstrap are Flachaire (2005) and Davidson and Flachaire (2008). It was used, among others, by Davidson and MacKinnon (2010) for instrumental variables regressions, and by Cavaliere, Rahbek, and Taylor (2010a) and Cavaliere, Rahbek, and Taylor (2010b) for cointegration regressions in the presence of conditional heteroskedasticity and non-stationary volatility.

The basic idea of the wild bootstrap is to replicate a heteroskedastic structure in resampling the residuals. Our chosen procedure works as follows. We estimate our reduced-form parameters $\hat{\theta}_{1cg}$ and $\hat{\theta}_{2cg}$ once, using 2SLS as discussed above. We bootstrap the residuals from equation (15), and then we reconstruct the dependent variable applying the following transformation:

$$\breve{Y}_{cgvt} = \hat{\theta}_{1cg} X_{1cgvt} + \hat{\theta}_{2cg} X_{2cgvt} + \hat{u}_{cgvt} \breve{\varepsilon}_t \,, \tag{22}$$

where $\hat{u}_{cgvt}$ is the residual from the 2SLS regression and $\breve{\varepsilon}_t$ is white noise following a distribution that is chosen to have expectation $E(\breve{\varepsilon}_t) = 0$ and variance $E(\breve{\varepsilon}_t^2) = 1$. We use the following two-point distribution for $\breve{\varepsilon}_t$:

$$\breve{\varepsilon}_t = \begin{cases} -(\sqrt{5}-1)/2 & \text{with probability } p = (\sqrt{5}+1)/(2\sqrt{5})) \\ (\sqrt{5}+1)/2 & \text{with probability } 1-p \end{cases} \tag{23}$$

To reconstruct the dependent variable, we use the initial point estimates and the data for the regressors (treating them as fixed) and we re-estimate the equation 5 000 times. Out of the 5 000 obtained combinations of estimated parameters, we only keep those for which $\hat{\theta}_{1cg} > 0$, and which hence yield theory-consistent elasticity estimates.[10] The rest are replaced by continuing the bootstrapping procedure until we have obtained a total of 5 000 admissible estimates, keeping track of the required number of draws as a measure of plausibility of the imposed modeling assumptions for each country-sector pair. When a very large number of draws is needed to generate our obtained final estimate, we take

[10] We also keep the combinations containing some negative value of $\hat{\theta}_{1cg}$ such that $\hat{\theta}_{1cg} > -\hat{\theta}_{2cg}^2/4$, as these also provide us with theory-consistent estimates. The great bulk of the draws that we keep, however, contain a positive $\hat{\theta}_{1cg}$.

it as an indication that the model does not match the data for the country and sector in question. Due to the discontinuity of the mapping function, however, we do expect the total number of draws to exceed 5 000 somewhat for very high elasticity estimates, even when the model assumptions are appropriate. The 5 000 draws that we keep form a distribution of each of the parameters contained in $\boldsymbol{\theta}_{cg}$ as well as σ_{cg}, the moments of which can be used to measure the elasticity of substitution and of the accuracy with which it is measured. We use the inter-quartile range of the bootstrap distribution as our estimate of the dispersion of the elasticity of substitution (see Section 6).[11] From the bootstrap distribution, we also obtain various measures of central tendency that could be used as estimates of the elasticity; specifically, we measure the mean, the median and the mode of each generated distribution. With such irregular shapes as the ones we encounter here, however, it is not obvious what the best measure of central tendency for distributions is. Given the occurrence of outliers, sometimes even very extreme ones, the mean is not a stable, nor a representative measure of the distribution, and the point estimate not a particularly informative one. The median is more robust than the mean to outliers, but can lie in a part of the distribution with relatively little probability mass. To shed some light on these issues, we devote the following section to a more thorough evaluation of the alternative measures of central tendency, based on which we choose our preferred estimate of the elasticity of substitution.

5 Monte Carlo experiment

Before selecting our preferred measure of the elasticity of our interest, we wish to determine the accuracy of the different alternatives. In order to assess the severeness of the presumed bias, however, we need to know the true value of σ in the data we are dealing with, i.e. we need to know the underlying data generating process of our sample. To be able to control this, we construct a Monte Carlo experiment, simulating the data and running the exact same procedure as we do in our estimation.

We start by characterizing the joint distribution of our estimation data. Specifically, using the moments from the data on trade shares and unit values which are used to create the regressors X_1 and X_2, we generate data series of a sample size representative for our data.[12] We then pick a value of θ_1, keeping θ_2 fixed, and compute the true value

[11] For comparison purposes, we also report the estimates obtained using the standard 2SLS procedure. The standard errors reported with these estimates are obtained following the linear-approximation method used by Feenstra (1994), Imbs and Méjean (2009), and others.

[12] The results presented here are all based on a sample size of 72. We have, however, experimented with other sample sizes as well. For markedly larger sample sizes, all measures perform better, just as

of σ. For the results we present here, we have always used $\theta_2 = 0.4$, which approximately equals the mean value of θ_2 in our estimations.[13] Using the residual moments from the German import data estimations, the results of which are presented in the following section, we generate a vector of residuals which, together with the regressor data and the selected parameter values, is used to construct the data for Y. Using the data for X_1, X_2 and Y, we then first estimate the $\boldsymbol{\theta}$ coefficients and compute the implied elasticity estimate, and then run the bootstrap exactly as we do in our actual estimations. Having generated all of our candidate measures of central tendency, we use the true value of σ to assess the bias in each of them. This procedure is then repeated 2 000 times for each set of chosen parameter values; the results we report are averages over the 2 000 repetitions. In Figures 2 and 3, we present a summary of the results from the Monte Carlo simulations, with the graphs corresponding to the bootstrap shown as dotted and dashed lines, and the one corresponding to 2SLS as a solid line.

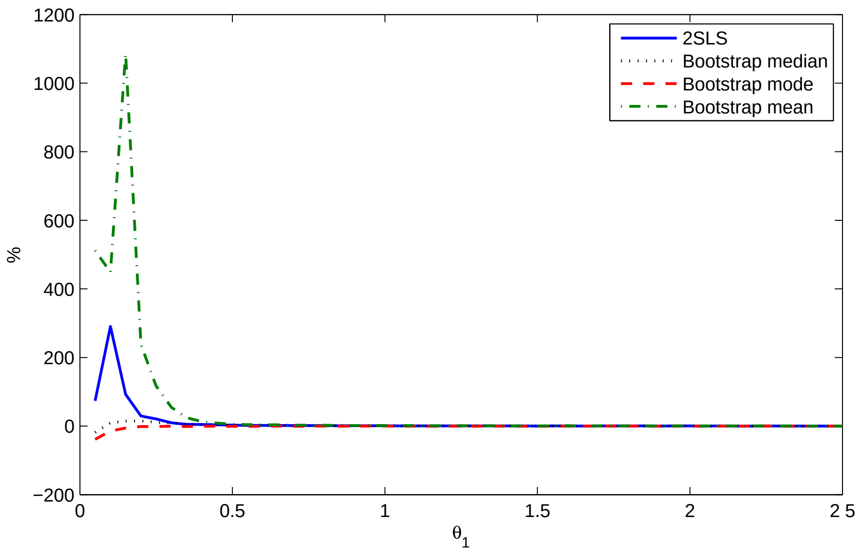

Figure 2: Bias as percent of the true value of σ (entire space of θ_1)

we expect them to. As the sample size in our estimations has an average of 82 for Germany and 60 for the cross-section of countries, and it very rarely goes above 100, we choose a sample size of 72 as representative for our data.

[13]This is the case both when looking across German import data estimates, and across a larger sample of countries with all sectors included. Note that the most critical measure for the size of the bias is the magnitude of θ_1, more specifically its proximity to 0. We have performed simulations for a grid of values of θ_2, spanning over the entire interval of encountered θ_2 estimates in our data. The conclusions however remain largely the same, why, in the interest of brevity, we choose not to present them here.

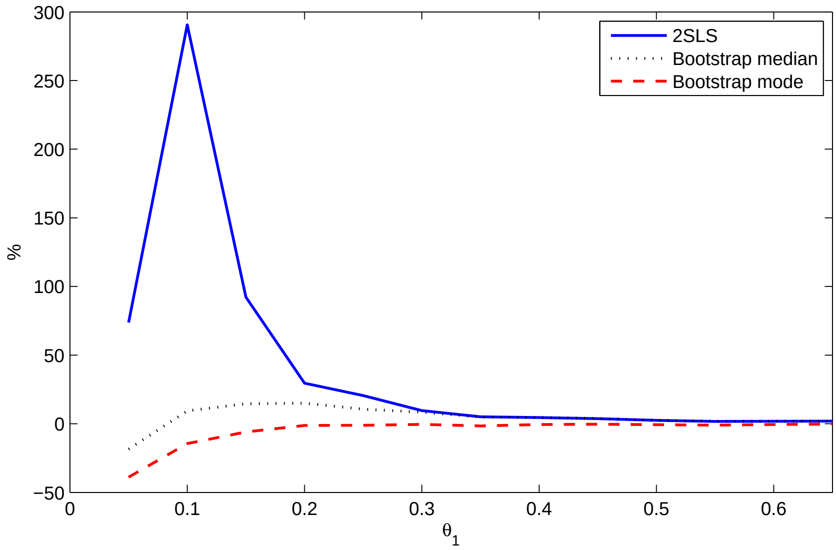

Figure 3: Bias as percent of the true value of σ (problematic region)

Figure 2, first, plots the bias, for the entire span of θ_1, expressed in percent of the true value of σ, so that a bias of say 50 % when $\sigma = 4$ means that the obtained estimate was equal to 6. From the figure, it is clear that for a high value of θ_1 or, equally, a low value of σ, all of the analyzed measures perform well, just as expected as the mapping function in this region of the parameter space displays no irregularities. Moving further to the left in the figure, the bias of the bootstrap mean becomes quite volatile and often extremely high, due to the sensitivity of the measure to extreme outliers. In what follows, for visual clarity and since the measure performs too poorly to be interesting for our purposes, we exclude the bootstrap mean from the graphs. Turning now to the lowest part of the range of θ_1, we see that the biases of the three remaining measures also diverge. We next focus on this region of the parameter space, more clearly presented in Figure 3. The figure shows that the bootstrap produces notably less biased measures of the elasticity of substitution than the original 2SLS estimates. We further note that none of the measures performs particulary well for extremely low θ_1, i.e. extremely high σ which is unsurprising in the light of the pronounced non-linearity of the mapping function in that precise region.

These plots indicate that the bootstrap measures perform at least as well as the 2SLS estimate – they are as good as or better in all of the parameter space. To be sure that this difference is relevant in practice, using a large number of sector level estimates, we count how frequently we visit the regions in which the bootstrap and the 2SLS perform equally well, the bootstrap performs better, or both measures perform poorly. We choose the mid range of estimates conservatively; in order not to risk overstating the performance of the bootstrap, we define the mid range to be $0.15 \leq \theta_1 \leq 0.4$. Correcting for the bias based on the Monte Carlo results, this yields the approximate elasticity interval of $3.16 \leq \sigma \leq 10$. We find elasticities in this interval in just above 56 % of the cases, elasticities higher than 10 in approximately 6 % of the cases, and elasticities lower than 3.16 in the remainder of the cases.[14] Indeed, the mid-range elasticities make up the largest fraction of estimated elasticities, while, at the same time, we observe a large bias in the 2SLS estimates of these. This leads us to conclude that the bootstrapped estimates are preferable to the 2SLS point estimates, and that the difference in their performance is non-negligible.

Finally, when comparing the bootstrap median and the bootstrap mode, we find that the mode performs as well as or slightly better than the median in the bulk of the parameter space. In the lowest region of θ_1, where none of the measures is satisfactory, we note that the mode performs slightly worse. As the mode is better for all but the very lowest θ_1, which we know do not occur very frequently, we propose to use the mode, or to compare the median and the mode when they are very different.[15]

6 Estimation results

For each sector separately, we estimate the elasticity of substitution for imports, using (8) as estimating equation. As the main point of this paper is methodological, we only present estimates for the 106 manufacturing sectors in Germany, highlighting in practice the point made above on the instability of the high estimates generated with the 2-stage least squares (2SLS) estimator. The results are obtained using disaggregated 4-digit ISIC data from the Eurostat COMEXT database, covering the years 1995-2009. The same set of results for other EU countries are available upon request.[16] Details on data

[14]The numbers presented here are based on the estimates for all available sectors in the EU15. For Germany, the corresponding shares of the mid-range and high elasticity intervals are 60 % and 5 %, respectively.

[15]In principle, choosing the best measure should depend on one's purposes. The ultimate goal of our estimations is to produce reliable measures of country-specific aggregate elasticities that are useful for policy experiments. The mode is a good candidate because it is related to a high probability of realization in the markets of interest. This is true for single-modal distributions. In cases of multi-modality, however, the median is likely to produce a more representative measure, as it is not clear which of the multiple modes to choose.

[16]In a companion paper, Corbo and Osbat (2012), we present estimation and aggregation results for each of the 27 EU countries' imports. In addition, we derive and estimate an analogous equation for

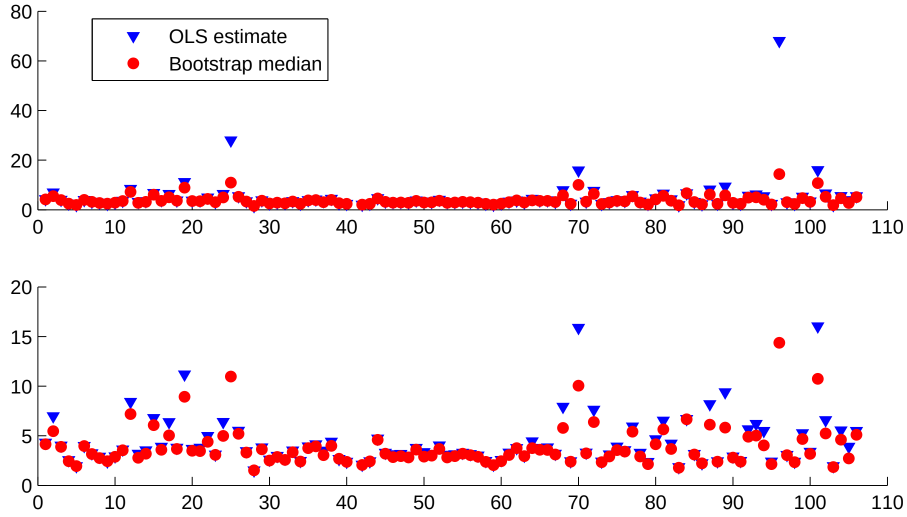

Figure 4: Import elasticity estimates for Germany: the top panel includes all estimates, the bottom panel excludes estimates larger than 20 to facilitate comparison.

and outlier cleaning are summarized in Appendix B.

We find that for Germany in our sample, the 2SLS and bootstrap estimates are generally very close. The difference arises in a few sectors; for those sectors, however, the implied estimate of σ will be very high, which will in turn lead to a high macro-level estimate for Germany if the sector-level elasticities are aggregated (see Figure 4). The problem here does not arise from high elasticities being implausible as such, but rather from the shape of the mapping function which causes the very high estimates to be also highly unstable, as discussed in Sections 4 and 5. The high values of $\hat{\sigma}$ vary considerably with even minor changes to $\hat{\boldsymbol{\theta}}$, such as the ones caused by the resampling of residuals in our bootstrapping procedure. Hence, and as confirmed by the Monte Carlo experiment, applying the Feenstra method, high and imprecise estimates go hand in hand. The higher the estimate of $\hat{\sigma}$, the more imprecise it is, irrespective of the precision with which $\hat{\boldsymbol{\theta}}$ is estimated.

The bootstrap results make it very transparent that the extreme values shown in Figure 4 do not come from problems in estimating the regression in equation (15), but from the functional form itself. This conclusion is supported by comparing Figures 5 and 6. Figure 5 shows the bootstrap distribution for a sector (*Food processing machinery*)

exports, which however requires an additional assumption and a third level of differencing.

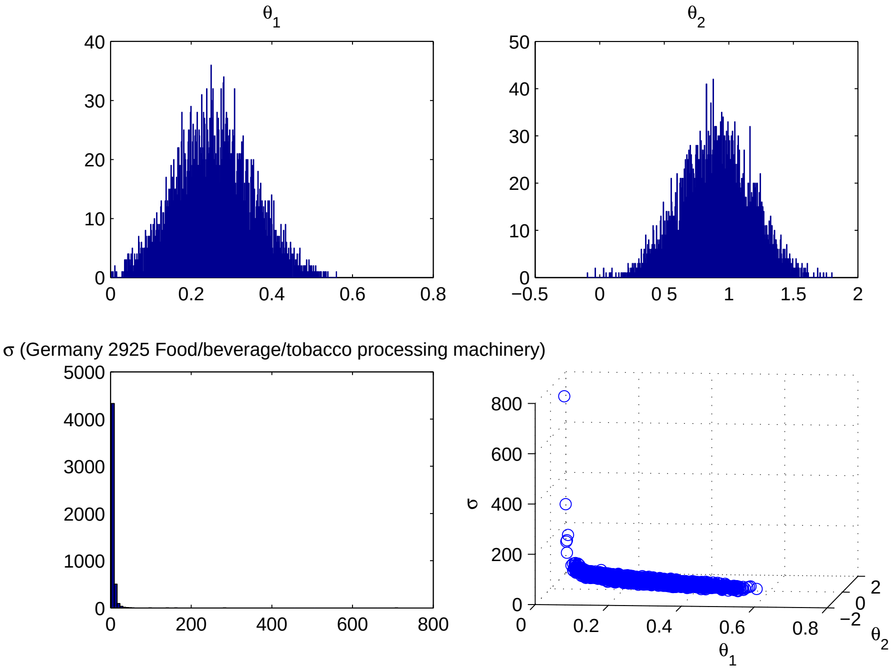

Figure 5: Bootstrap distributions of $\hat{\theta}_1$, $\hat{\theta}_2$ and $\hat{\sigma}$ for German food processing machinery, ISIC code 2925.

where the restriction $\theta_1 > 0$ bites, while Figure 6 shows the same picture for a sector (*Starches*) where none of the 5 000 replications generates an estimate that violates the theoretical restrictions. The regression estimates have regular distributions for both sectors, but the resulting distribution for σ is regular only for the *Starches* sector, where the bootstrap distribution of the θ_1 estimates is comfortably larger than zero (see Figure 6). Moreover, in comparison with the grid search proposed in Broda and Weinstein (2006), our proposed bootstrap-based approach to incorporating the theoretical restriction in the estimation of the elasticity of substitution has a twofold advantage: it avoids relying on ad hoc specifications of the grid and it provides a measure of dispersion that does not rely on the (violated) assumption of continuity of the mapping function. Furthermore, the simple count of instances of rejection of replications where the theoretical restrictions are violated gives us an indication of the extent to which the data for each sector are compatible with that restriction. The deviation from normality mostly manifests itself in the form of very long tails. This is shown graphically in Figure 7. It displays the box plots of the sectoral estimates for Germany, which are all strongly affected by outliers

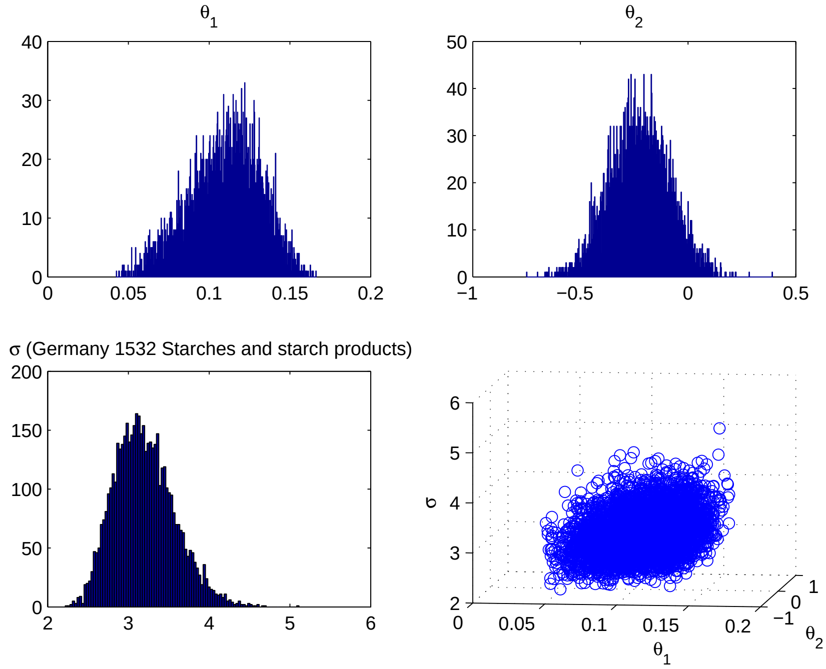

Figure 6: Bootstrap distributions of $\hat{\theta}_1$, $\hat{\theta}_2$ and σ for German starches, ISIC code 1532.

(indicated as red-colored tails in the charts). Figure 7 again shows that although the largest 1% of observations was excluded from the plots in order to have legible charts, it is clear, from the quantity of extreme outliers, that it is not appropriate to use the mean as a measure of central tendency for many of them.

Whatever the choice of measure of central tendency, the point that is made clear by looking at the full bootstrap distribution is that one must take into account very large deviations from the normality assumption. The same applies to choosing a measure of dispersion: the variance is very strongly affected by outliers. As discussed in Section 4, we suggest using the interquartile range (IQR), but any quantile intervals can be used.

Detailed results are reported in Table 1, where the columns, in order, contain the sector ISIC code, the size of the cross-section, the 2SLS point estimate, its standard deviation, the number of replications needed to obtain 5 000 sets of estimates that yield theoretically admissible values, the mean, median and mode of the bootstrap distribution and its IQR.[17] In the Gaussian distribution it holds that $IQR = 1.349\sigma$, so we also

[17]The mode is calculated using a kernel density estimator with positive support and a smoothing parameter of 0.05. Experimentation has shown that in some cases, where multimodality prevails, the choice of smoothing parameter makes a large difference on the position of the mode.

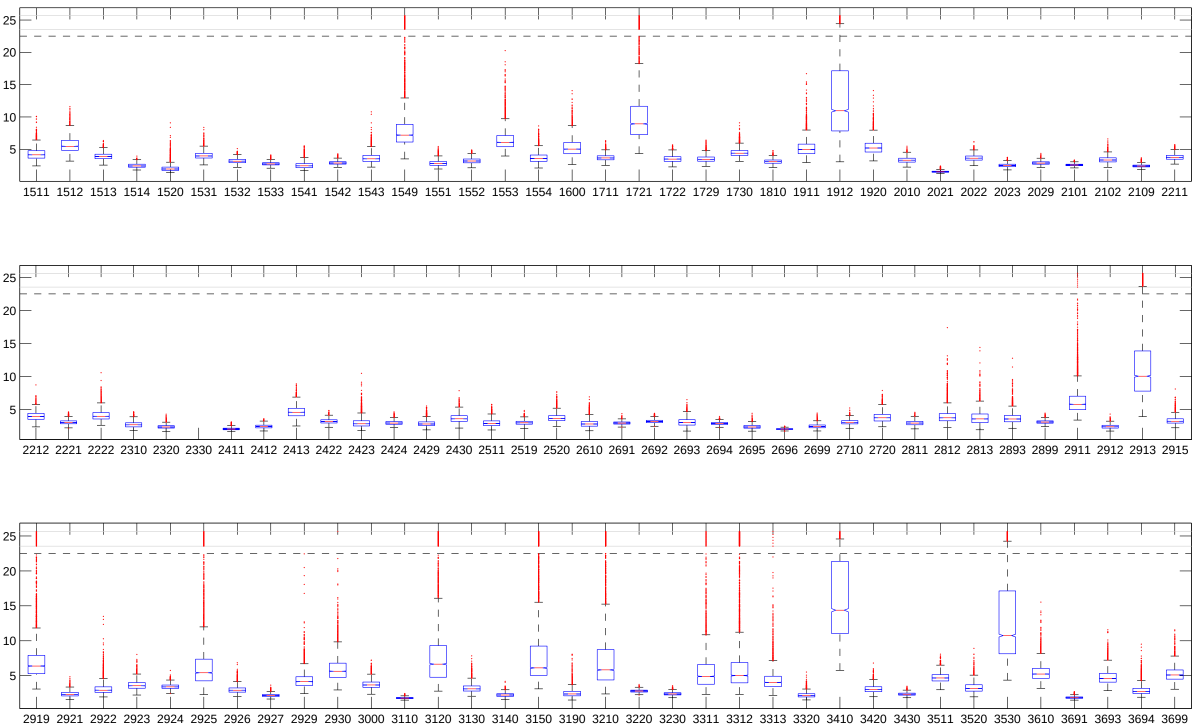

Figure 7: Box plots of sectoral estimates for Germany

show the ratio $IQR/1.349\sigma$ ($IQRnorm$ in Table 1). For comparison, we further include the standard deviation of the bootstrap distribution. Finally, the last two columns contain the 25^{th} and 75^{th} percentiles. For sector 2330 (*Processing of nuclear fuel*), no results are reported due to the sample size being too small. The presented results show that the 2SLS estimation can yield very extreme results, but the Feenstra method can be "robustified" by using the bootstrap and choosing the median or mode as point estimates instead of the mean. Looking for example at sector 1721 (*Made-up textile articles, except apparel*), whose 2SLS estimate is quite high (11.2) and estimated very imprecisely, we see that in order to reach 5 000 theory-consistent estimate sets it was necessary to run 5 010 replications altogether. The mean and standard deviation of the resulting bootstrap distribution are also very high, but in the light of the above discussion it is preferable to consider the median and the mode as measures of central tendency (8.9 and 7.7 respectively). Furthermore, the IQR is also rather wide, with

50% of the distribution included between 7.3 and 11.7. By contrast, looking at sectors where none of the 5 000 replications is rejected, such as 1542 (*Sugar*), the 2SLS estimate (2.9) coincides with the mean, median and mode of the bootstrap distribution. However, while the standard deviation of the 2SLS estimate is 1.1, that of the bootstrap is only 0.3. This signals that our proposed procedure not only robustifies the estimation of the elasticity of substitution using the Feenstra method, but it also reduces the estimated variance in those cases where the 2SLS and bootstrap estimates coincide, which in turn are the cases where the theoretical restrictions hold comfortably. Our proposed bias correction and improved characterization of the standard errors may support "elasticity realism", leading to estimates that, though higher than those based on time series, are distinctly lower than the more recent ones.

Table 1: Sector level results for the German economy

		2SLS		**Bootstrap**								
Sec	**#Partn**	$\hat{\sigma}$	**Std**($\hat{\sigma}$)	**#Reps**	**Mean**	**Median**	**Mode**	**IQR**	**IQRnorm**	**Std**	**25%**	**75%**
1511	68	4.3	5.3	5000	4.3	4.2	3.9	1.1	0.9	0.9	3.6	4.8
1512	103	7.0	12.8	5000	5.7	5.5	5.2	1.5	1.0	1.2	4.8	6.4
1513	118	4.0	4.1	5000	3.9	3.9	3.8	0.7	1.0	0.5	3.6	4.2
1514	91	2.6	1.6	5000	2.5	2.4	2.4	0.5	1.1	0.3	2.2	2.7
1520	48	1.9	1.1	5003	2.1	2.0	1.9	0.5	0.7	0.5	1.7	2.3
1531	77	4.0	4.0	5000	4.1	4.0	3.9	0.7	0.9	0.6	3.6	4.4
1532	46	3.2	2.0	5000	3.2	3.2	3.1	0.5	1.0	0.4	2.9	3.4
1533	49	2.9	1.6	5000	2.8	2.8	2.7	0.3	1.0	0.3	2.6	2.9
1541	69	2.4	1.4	5000	2.5	2.4	2.3	0.6	0.9	0.5	2.2	2.8
1542	46	2.9	1.1	5000	2.9	2.9	2.9	0.4	0.9	0.3	2.7	3.1
1543	84	3.6	3.7	5000	3.7	3.5	3.4	0.9	0.9	0.8	3.1	4.1
1549	96	8.4	18.9	5000	9.2	7.2	6.7	2.7	0.0	73.5	6.1	8.9
1551	81	3.2	3.3	5000	2.9	2.8	2.7	0.6	0.9	0.5	2.5	3.1
1552	73	3.5	3.0	5000	3.2	3.2	3.1	0.6	1.0	0.4	2.9	3.5
1553	61	6.8	8.3	5000	6.6	6.1	6.0	1.7	0.7	1.7	5.4	7.1
1554	75	3.9	6.6	5000	3.7	3.6	3.4	1.0	0.9	0.8	3.2	4.1
1600	52	6.4	10.9	5000	5.3	5.0	4.6	1.7	0.9	1.5	4.3	6.1
1711	107	3.8	3.6	5000	3.7	3.7	3.6	0.6	0.9	0.5	3.4	4.0
1721	109	11.2	27.1	5010	11.7	8.9	7.7	4.4	0.1	30.8	7.3	11.7
1722	86	3.7	3.4	5000	3.5	3.5	3.5	0.7	1.0	0.5	3.2	3.9
1729	77	3.8	3.8	5000	3.5	3.5	3.3	0.7	0.9	0.5	3.2	3.8
1730	103	5.0	0.4	5000	4.5	4.4	4.3	0.8	0.9	0.6	4.1	4.8
1810	147	3.1	2.3	5000	3.1	3.1	3.1	0.5	1.0	0.4	2.9	3.3
1911	75	6.4	12.1	5000	5.2	5.0	4.6	1.5	0.8	1.3	4.3	5.8
1912	97	27.9	280.2	5164	26.4	11.0	8.5	9.3	0.0	17.0	7.8	17.2
1920	91	5.5	6.5	5000	5.4	5.2	5.0	1.4	0.9	1.1	4.6	5.9
2010	93	3.5	2.6	5000	3.3	3.3	3.3	0.6	1.0	0.5	3.0	3.6
2021	68	1.5	0.4	5000	1.6	1.5	1.5	0.2	0.8	0.2	1.4	1.6
2022	80	3.8	3.7	5000	3.7	3.6	3.5	0.6	1.0	0.5	3.3	4.0
2023	91	2.6	2.1	5000	2.5	2.5	2.5	0.4	1.0	0.3	2.3	2.7
2029	122	3.0	2.1	5000	2.9	2.9	2.9	0.4	1.0	0.3	2.7	3.1
2101	72	2.7	1.3	5000	2.6	2.6	2.6	0.2	1.0	0.2	2.5	2.7
2102	85	3.5	3.3	5000	3.4	3.3	3.3	0.6	0.9	0.5	3.1	3.7
2109	82	2.5	1.4	5000	2.4	2.4	2.4	0.3	0.9	0.2	2.3	2.6
2211	98	3.9	3.1	5000	3.8	3.8	3.7	0.6	1.0	0.5	3.5	4.1
2212	71	4.1	3.4	5000	4.0	3.9	3.9	0.9	1.0	0.7	3.5	4.4
2221	94	3.5	3.7	5000	3.1	3.1	3.0	0.4	1.0	0.3	2.8	3.3
2222	67	4.4	6.4	5000	4.1	4.0	3.8	1.0	0.9	0.8	3.6	4.5
2310	19	2.7	0.3	5000	2.7	2.7	2.7	0.6	1.0	0.4	2.4	3.0
2320	40	2.4	0.1	5000	2.4	2.4	2.3	0.4	0.9	0.3	2.2	2.6
2330	8	-	-	-	-	-	-	-	-	-	-	-
2411	105	2.1	1.0	5000	2.1	2.1	2.0	0.2	0.9	0.2	1.9	2.2
2412	41	2.4	1.4	5000	2.5	2.4	2.4	0.4	1.0	0.3	2.2	2.6
2413	78	4.7	0.6	5000	4.7	4.6	4.5	1.1	1.0	0.9	4.1	5.2
2422	63	3.3	2.9	5000	3.2	3.2	3.2	0.5	1.0	0.4	3.0	3.4
2423	76	3.1	3.7	5000	3.0	2.9	2.7	0.8	0.8	0.7	2.5	3.3
2424	92	3.2	2.0	5000	3.0	3.0	2.9	0.4	0.9	0.3	2.8	3.2
2429	103	3.0	0.3	5000	2.9	2.8	2.7	0.5	0.9	0.4	2.6	3.1
2430	63	3.8	3.6	5000	3.7	3.6	3.4	0.9	1.0	0.7	3.2	4.1
2511	74	3.4	4.1	5000	3.0	2.9	2.9	0.7	0.9	0.6	2.6	3.3

Continued on next page

		2SLS		Bootstrap								
Sec	**#Partn**	$\hat{\sigma}$	**Std**($\hat{\sigma}$)	**#Reps**	**Mean**	**Median**	**Mode**	**IQR**	**IQRnorm**	**Std**	**25%**	**75%**
2519	79	3.2	2.4	5000	3.0	3.0	3.0	0.4	1.0	0.3	2.8	3.2
2520	122	4.0	5.3	5000	3.8	3.7	3.6	0.7	0.9	0.6	3.3	4.1
2610	99	3.1	3.8	5000	2.9	2.8	2.7	0.7	0.9	0.6	2.5	3.2
2691	100	3.2	2.2	5000	3.0	3.0	2.9	0.3	1.0	0.2	2.8	3.1
2692	57	3.3	1.6	5000	3.2	3.2	3.2	0.4	1.0	0.3	3.0	3.4
2693	55	3.2	3.0	5000	3.1	3.0	2.8	0.8	1.0	0.6	2.7	3.5
2694	38	3.0	1.3	5000	2.9	2.9	2.9	0.3	1.0	0.2	2.7	3.0
2695	54	2.5	1.7	5000	2.4	2.4	2.4	0.4	0.9	0.3	2.2	2.6
2696	81	2.1	0.9	5000	2.1	2.0	2.0	0.1	1.0	0.1	2.0	2.1
2699	75	2.6	1.7	5000	2.5	2.4	2.4	0.4	0.9	0.3	2.3	2.7
2710	87	3.3	2.8	5000	3.1	3.1	3.0	0.5	1.0	0.4	2.8	3.3
2720	102	3.8	3.2	5000	3.8	3.8	3.8	1.0	1.0	0.7	3.3	4.3
2811	81	3.0	2.5	5000	3.0	3.0	2.9	0.5	1.0	0.4	2.7	3.2
2812	62	4.5	7.7	5000	4.0	3.8	3.5	1.1	0.7	1.1	3.3	4.4
2813	38	3.8	5.4	5000	3.8	3.6	3.3	1.3	0.9	1.1	3.0	4.3
2893	109	3.8	5.0	5000	3.7	3.6	3.5	1.0	0.8	0.8	3.2	4.1
2899	122	3.2	2.0	5000	3.1	3.1	3.1	0.4	1.0	0.3	2.9	3.3
2911	84	7.9	25.7	5000	6.4	5.8	5.3	2.0	0.6	2.4	5.0	7.0
2912	113	2.4	1.9	5000	2.4	2.4	2.4	0.4	1.0	0.3	2.2	2.6
2913	99	15.9	93.9	5032	14.3	10.0	8.3	6.1	0.1	30.1	7.8	13.9
2915	73	3.3	2.8	5000	3.3	3.2	3.1	0.7	0.9	0.5	3.0	3.6
2919	107	7.6	20.7	5002	7.3	6.4	5.9	2.6	0.4	4.5	5.3	7.9
2921	64	2.4	1.8	5000	2.4	2.3	2.3	0.5	1.0	0.4	2.1	2.6
2922	76	3.1	3.6	5000	3.1	2.9	2.7	0.8	0.7	0.8	2.6	3.4
2923	54	3.9	4.6	5000	3.7	3.6	3.4	0.8	0.9	0.7	3.2	4.0
2924	88	3.6	3.3	5000	3.4	3.4	3.4	0.5	1.0	0.4	3.2	3.7
2925	75	5.9	1.6	5011	6.9	5.4	4.5	3.1	0.2	12.2	4.3	7.4
2926	81	3.3	3.8	5000	3.0	2.9	2.8	0.6	0.9	0.5	2.6	3.2
2927	48	2.4	2.1	5000	2.2	2.2	2.1	0.3	0.9	0.2	2.0	2.3
2929	105	4.7	8.9	5000	4.4	4.1	3.9	1.2	0.8	1.2	3.6	4.9
2930	72	6.5	16.3	5000	6.0	5.6	5.3	2.0	0.8	1.8	4.8	6.8
3000	132	4.2	8.0	5000	3.8	3.7	3.6	0.8	0.9	0.6	3.3	4.1
3110	117	1.9	0.1	5000	1.8	1.8	1.8	0.2	0.9	0.1	1.7	1.9
3120	100	6.7	12.7	5014	9.1	6.7	5.4	4.5	0.1	22.6	4.8	9.3
3130	71	3.2	0.2	5000	3.2	3.1	3.0	0.7	0.9	0.6	2.8	3.5
3140	39	2.2	2.2	5000	2.2	2.2	2.2	0.4	1.0	0.3	2.0	2.4
3150	83	8.2	2.9	5036	10.9	6.1	5.5	4.2	0.1	27.3	5.1	9.2
3190	77	2.4	2.6	5000	2.5	2.4	2.3	0.6	0.7	0.7	2.1	2.8
3210	71	9.4	4.1	5716	21.0	5.8	4.6	4.3	0.0	25.7	4.4	8.7
3220	100	2.9	2.0	5000	2.8	2.8	2.8	0.3	1.0	0.2	2.7	2.9
3230	84	2.5	2.7	5000	2.4	2.4	2.4	0.3	1.0	0.2	2.3	2.6
3311	93	5.7	15.3	5005	6.1	4.9	4.0	2.8	0.2	10.0	3.8	6.6
3312	115	6.2	22.1	5056	8.7	5.0	4.2	2.9	0.0	77.1	4.0	6.9
3313	62	5.5	13.8	5000	4.5	4.0	3.6	1.5	0.5	2.4	3.4	4.9
3320	92	2.4	2.4	5000	2.2	2.1	2.1	0.5	0.9	0.4	2.0	2.4
3410	102	68.1	1599.8	6114	35.7	14.4	12.2	10.3	0.0	77.6	11.0	21.4
3420	67	3.1	2.8	5000	3.1	3.1	3.0	0.7	1.0	0.5	2.7	3.4
3430	123	2.4	2.1	5000	2.4	2.3	2.3	0.3	1.0	0.2	2.2	2.5
3511	44	5.3	4.9	5000	4.7	4.7	4.6	0.9	1.0	0.7	4.3	5.2
3520	52	3.4	0.5	5000	3.3	3.2	3.0	0.9	0.9	0.7	2.8	3.7
3530	86	16.0	63.9	5293	27.7	10.7	8.5	9.0	0.0	93.1	8.1	17.1
3610	128	6.6	12.7	5000	5.5	5.2	4.9	1.4	0.8	1.2	4.6	6.1
3691	136	2.0	1.4	5000	1.9	1.8	1.8	0.2	0.9	0.2	1.8	2.0
3693	69	5.5	8.0	5000	4.8	4.6	4.3	1.3	0.9	1.1	4.1	5.3
3694	89	3.9	7.3	5000	2.9	2.7	2.6	0.7	0.7	0.7	2.5	3.2
3699	116	5.5	8.1	5000	5.2	5.1	4.9	1.3	0.9	1.0	4.5	5.8

7 Conclusions

The elasticity of substitution plays a central role in the calibration of open-economy macro models designed to analyze the response of international trade to changes in relative prices. However, the empirical evidence on the magnitude of the elasticity of substitution is polarized between “elasticity pessimism” and “elasticity optimism”. The latter is mostly related to studies that apply a structural sectoral estimation method initially proposed by Feenstra (1994) and refined by Broda and Weinstein (2006), which tend to find much higher estimates than previous studies based on time series estimation. We propose a modification of the Feenstra (1994) method based on the bootstrap, which sheds light on some “built-in” problems with the usual structural estimation. The bootstrap-based estimation produces more robust central estimates whenever the estimated elasticity is in the mid range, i.e. whenever it is higher than 3 and lower than 10, approximately, which it is in the majority of cases. For estimates of around 3 and lower both estimation procedures perform well, and for estimates higher than 10, which are rarely found, none of them performs entirely satisfactorily. The bootstrap also yields better measures of dispersion, and gives an indication of the extent to which the data do not seem to conform to the the theoretical restrictions embedded in the Feenstra (1994) method. In terms of magnitude, we partially reconcile the two poles of the empirical literature, in that our bootstrap-based analysis shows that the application of the Feenstra (1994) 2SLS structural estimation tends to produce upward-biased estimates in country-sector pairs where the elasticities are not in the lowest range, thus leading to high and unstable aggregate elasticities. In fact, we tend to obtain the same estimates as 2SLS (and much smaller standard deviations, obtained by a method appropriate to the nonlinear estimation) in cases where the true elasticities are low, but smaller ones in the cases of higher true elasticities.

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A Computational appendix

A.1 The Feenstra (1994) method

A.1.1 Demand side

Assuming a CES setting, demand at time t is obtained by maximizing the consumption index

$$C_{cg.t} = \left[\sum_{v \in V_{cg.t}} (\beta_{cgvt} C_{cgvt})^{\frac{\sigma_{cg}-1}{\sigma_{cg}}} \right]^{\frac{\sigma_{cg}}{\sigma_{cg}-1}} \tag{A.1}$$

with respect to C_{cgvt}, subject to expenditures

$$\sum_{v \in V_{cg.t}} P_{cgvt} C_{cgvt} = Z_{cg.t} \,. \tag{A.2}$$

Note that we denote by V the entire set of varieties v imported by c. Rearranging the first-order condition, we obtain the following demand function for variety v of good g in country c at time t:

$$C_{cgvt} = \beta_{cgvt}^{\sigma_{cg}-1} \left(\frac{P_{cgvt}}{P_{cg.t}} \right)^{-\sigma_{cg}} C_{cg.t} \,. \tag{A.3}$$

Defining the expenditure share of variety v in country c's total consumption of good g at time t as

$$s_{cgvt} \equiv \frac{P_{cgvt} C_{cgvt}}{P_{cg.t} C_{cg.t}} = \frac{P_{cgvt} C_{cgvt}}{\sum_{i \in I_{cg}} P_{cgvt} C_{cgvt}} \,, \tag{A.4}$$

we can rewrite demand equation (A.3) as

$$s_{cgvt} = \beta_{cgvt}^{\sigma_{cg}-1} \left(\frac{P_{cgvt}}{P_{cg.t}} \right)^{1-\sigma_{cg}} \,. \tag{A.5}$$

As discussed in Feenstra (1994), it is convenient to express demand in terms of expenditure shares instead of volumes since this reduces the problem of correlated measurement pointed out by Kemp (1962). The import prices we observe are measured CIF (Cost, Insurance and Freight), i.e.

$$\tilde{P}_{cgvt} = P_{cgvt}^{CIF} = P_{cgvt} \,, \tag{A.6}$$

where $\tilde{P}_{cgvt}$ is the observed price. The price of our interest is the model-implied price, which is the destination or consumer price,[18] and which here coincides with the price we

[18] The destination and the consumer price may not exactly coincide, due to distribution costs in the importing country etc. Here we take the two prices to be the same, which however does not change

observe due to the prices being measured CIF. Since our data set offers us no information on domestically produced goods but only imported ones, observed expenditure shares are given by

$$\tilde{s}_{cgvt} \equiv \frac{\tilde{P}_{cgvt} C_{cgvt}}{\sum_{v \neq c} \tilde{P}_{cgvt} C_{cgvt}} = \frac{P_{cgvt} C_{cgvt}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} \,. \tag{A.7}$$

In terms of true expenditure shares s_{cgvt}, this can be written as

$$\begin{aligned} \tilde{s}_{cgvt} &= \frac{P_{cgvt} C_{cgvt}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} \cdot \frac{\sum_{v \neq c} P_{cgvt} C_{cgvt}}{\sum_{v \in V_{cg}} P_{cgvt} C_{cgvt}} \cdot \frac{\sum_{v \in V_{cg}} P_{cgvt} C_{cgvt}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} \\ &= \frac{P_{cgvt} C_{cgvt}}{\sum_{v \in V_{cg}} P_{cgvt} C_{cgvt}} \cdot \frac{\sum_{v \in V_{cg}} P_{cgvt} C_{cgvt}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} \\ &= s_{cgvt} \cdot \frac{P_{cg.t} C_{cg.t}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} \\ &= s_{cgvt} \, \mu_{cgt} \\ &= \beta_{cgvt}^{\sigma_{cg}-1} \left(\frac{P_{cgvt}}{P_{cg.t}} \right)^{1-\sigma_{cg}} \mu_{cgt} \,. \end{aligned} \tag{A.8}$$

Note that

$$\mu_{cgt} \equiv \frac{P_{cg.t} C_{cg.t}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} = 1 + \frac{P_{cgct} C_{cgct}}{\sum_{v \neq c} P_{cgvt} C_{cgvt}} > 1 \tag{A.9}$$

is just a fraction of two sums that do not vary with v, and is hence common across all varieties. Taking logs of equation (A.8), yields

$$\ln \tilde{s}_{cgvt} = (\sigma_{cg} - 1) \ln \beta_{cgvt} + (1 - \sigma_{cg}) \ln P_{cgvt} - (1 - \sigma_{cg}) \ln P_{cg.t} + \ln \mu_{cgt} \,. \tag{A.10}$$

Letting

$$\Delta \ln \tilde{s}_{cgvt} = \ln \left(\frac{\tilde{s}_{cgvt}}{\tilde{s}_{cgv,t-1}} \right) = \ln \tilde{s}_{cgvt} - \ln \tilde{s}_{cgv,t-1} \,, \tag{A.11}$$

we can rewrite demand as follows:

$$\begin{aligned} \Delta \ln \tilde{s}_{cgvt} &= (1 - \sigma_{cg}) \Delta \ln \tilde{P}_{cgvt} + (\sigma_{cg} - 1) \Delta \ln \, .P_{cg.t} \\ &\quad + \ln \Delta \mu_{cgt} + (\sigma_{cg} - 1) \ln \Delta \beta_{cgvt} \end{aligned} \tag{A.12}$$

our estimated equation in any way. Given that the trade costs are variety specific, they will not be identifiable, and hence any multiplicative trade cost term will end up in the residual of the estimated equation.

Defining the term that contains all variables that are common across varieties as

$$\Phi_{cgt} \equiv (\sigma_{cg} - 1)\Delta \ln P_{cg.t} + \ln \Delta\mu_{cgt} \,, \tag{A.13}$$

and the error term of the equation that captures the unobserved trade-cost and taste variables as

$$\varepsilon_{cgvt} \equiv (\sigma_{cg} - 1) \ln \Delta\beta_{cgvt} \,, \tag{A.14}$$

we finally arrive at demand equation (2) in the main text.

A.1.2 Supply side

Following Feenstra (1994), we adopt the following simple supply structure:

$$P_{cgvt} = \tau_{cgvt} \exp(v_{cgvt}) C_{cgvt}^{\omega_{cg}} \tag{A.15}$$

where τ_{cgvt} is a measure of variety-specific multiplicative trade costs, v_{cgvt} is a sector- and country-specific technology shock, and $\omega_{cg} \geq 0$ is the inverse of the price elasticity of supply, assumed equal over exporters but allowed to differ between sectors.[19] Inserting equation (A.3) into equation (A.15), and rewriting in terms of observed prices, yields

$$\tilde{P}_{cgvt} = \tau_{cgvt} \exp(v_{cgvt}) \beta_{cgvt}^{\omega_{cg}(\sigma_{cg}-1)} \left(\frac{\tilde{P}_{cgvt}}{P_{cg.t}} \right)^{-\omega_{cg}\sigma_{cg}} C_{cg.t}^{\omega_{cg}} \,. \tag{A.16}$$

Taking logs and rearranging,

$$\begin{aligned} \ln \tilde{P}_{cgvt} &= \ln \tau_{cgvt} + v_{cgvt} + \omega_{cg}(\sigma_{cg} - 1) \ln \beta_{cgvt} \\ &\quad - \omega_{cg}\sigma_{cg} \ln \tilde{P}_{cgvt} + \omega_{cg}\sigma_{cg} \ln P_{cg.t} + \omega_{cg} \ln C_{cg.t} \\ &= \frac{1}{1 + \omega_{cg}\sigma_{cg}} \Bigg[\ln \tau_{cgvt} v_{cgvt} + \omega_{cg}(\sigma_{cg} - 1) \ln \beta_{cgvt} \\ &\qquad + \omega_{cg}\sigma_{cg} \ln P_{cg.t} + \omega_{cg} \ln C_{cg.t} \Bigg] \,. \end{aligned} \tag{A.17}$$

[19] As can be seen from the below derivations, the assumption of equality is crucial for identification.

Differencing,

$$
\begin{aligned}
\Delta \ln \tilde{P}_{cgvt} &= \frac{1}{1+\omega_{cg}\sigma_{cg}}\Big[\omega_{cg}\sigma_{cg}\Delta \ln P_{cg.t} + \omega_{cg}(\sigma_{cg}-1)\Delta \ln \beta_{cgvt} \\
&\qquad + \omega_{cg}\Delta \ln C_{cg.t} + \Delta \ln \tau_{cgvt} + \Delta v_{cgvt}\Big] \\
&= \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}[\sigma_{cg}\Delta \ln P_{cg.t} + \Delta \ln C_{cg.t}] + \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}\varepsilon_{cgvt} \qquad \text{(A.18)} \\
&\qquad + \frac{1}{1+\omega_{cg}\sigma_{cg}}[\Delta \ln \tau_{cgvt} + \Delta v_{cgvt}] \, .
\end{aligned}
$$

Letting

$$\Psi_{cgt} \equiv \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}[\sigma_{cg}\Delta \ln P_{cg.t} + \Delta \ln C_{cg.t}] \qquad \text{(A.19)}$$

denote the term containing the variables that are common across varieties, and

$$\delta_{cgvt} \equiv \frac{1}{1+\omega_{cg}\sigma_{cg}}[\Delta \ln \tau_{cgvt} + \Delta v_{cgvt}] \qquad \text{(A.20)}$$

denote the error term of the equation, capturing the unobserved trade-cost and technology variables, we get the final supply equation as given by equation (4) in the main text.

A.1.3 Deriving the estimated regression

Following section *IV* in Feenstra (1994), we start by eliminating the terms common across all varieties from equations (2) and (4) in the main text, by subtracting from each of them the same equation for a source of reference v_r.

$$
\begin{aligned}
\check{\varepsilon}_{cgvt} &\equiv \varepsilon_{cgvt} - \varepsilon_{cgv_rt} \\
&= [\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}] + (\sigma_{cg}-1)\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right] \qquad \text{(A.21)} \\
\check{\delta}_{cgvt} &\equiv \delta_{cgvt} - \delta_{cgv_rt} \\
&= \left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right] - \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}[\varepsilon_{cgvt} - \varepsilon_{cgv_rt}] \qquad \text{(A.22)} \\
&= \frac{1+\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_rt}\right] - \frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}[\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_rt}]
\end{aligned}
$$

Since, $\breve{\varepsilon}_{cgvt}$ and $\breve{\delta}_{cgvt}$ are independent, we can multiply equations (A.21) and (A.22) to obtain

$$\begin{aligned}\breve{\varepsilon}_{cgvt}\breve{\delta}_{cgvt} = & -\frac{\omega_{cg}}{1+\omega_{cg}\sigma_{cg}}\left[\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_r t}\right]^2 \\ & + \frac{(1+\omega_{cg})(\sigma_{cg}-1)}{1+\omega_{cg}\sigma_{cg}}\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_r t}\right]^2 \\ + \left(\frac{1+\omega_{cg}}{1+\omega_{cg}\sigma_{cg}} - \frac{\omega_{cg}(\sigma_{cg}-1)}{1+\omega_{cg}\sigma_{cg}}\right) & \left[\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_r t}\right] \cdot \left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_r t}\right] .\end{aligned} \tag{A.23}$$

Dividing through by $\frac{(1+\omega_{cg})(\sigma_{cg}-1)}{1+\omega_{cg}\sigma_{cg}}$ and rearranging,

$$\begin{aligned}\left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_r t}\right]^2 = & \frac{\omega_{cg}}{(1+\omega_{cg})(\sigma_{cg}-1)}\left[\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_r t}\right]^2 \\ + \frac{\omega_{cg}\sigma_{cg} - 2\omega_{cg} - 1}{(1+\omega_{cg})(\sigma_{cg}-1)} & \left[\Delta \ln \tilde{s}_{cgvt} - \Delta \ln \tilde{s}_{cgv_r t}\right] \cdot \left[\Delta \ln \tilde{P}_{cgvt} - \Delta \ln \tilde{P}_{cgv_r t}\right] \\ & + \frac{1+\omega_{cg}\sigma_{cg}}{(1+\omega_{cg})(\sigma_{cg}-1)}\breve{\varepsilon}_{cgvt}\breve{\delta}_{cgvt}\end{aligned} \tag{A.24}$$

Finally, defining Y_{cgvt}, X_{1cgvt}, X_{2cgvt}, u_{cgvt}, θ_{1cg}, and θ_{2cg} as in equations (9)-(14) in the main text, we can write expression (A.24) as expression (8) in the main text.

B Data Appendix

Our data is obtained from the Eurostat's COMEXT database, which contains monthly observations on values and quantities of imports and exports reported by all EU countries from and to up to 270 trading partners. The full database is available at a disaggregation level of 8 digits in the *Combined nomenclature* (CN), based on the Harmonized System, which however only goes up to 6 digits (HS-6). For each country-partner-sector triplet at each point in time, COMEXT provides information on the value of each monthly transaction in ECU-EUR, the quantity in 1 000 Kg and, if available, the corresponding Special Units (which vary by sector and can be items, liters, meters, etc). The reporting of quantities is not always consistent, so that often values without a corresponding quantity are observed. These end up as missing values in our sample, because one of our main variables is the unit value of imports, which we obtain by dividing the value by the quantity. The unit values at the 8-digit level of disaggregation are the variable we use to clean the data from outliers, which are an endemic feature of this database.

We use a cross-sectional benchmark to identify outliers in the data. For each sector, we take all observations on import unit values of all 27 declarants from all partners; the outliers are those observations that lie "too far" from the median of this cross-section. Note that this procedure can only make sense at a very disaggregated level, when the unit values refer to goods that are as similar as it gets when dealing with trade data. As a metric of distance we use the absolute deviation from the median (*mad*), which is much more robust to outliers than the standard deviation around the mean. We aim at eliminating a small percentage of observations, so that we progressively increase the number of *mad* around the median if we see that the procedure tends to eliminate too many observations. We start off with a distance of $(2 * 1.4785 * mad)$, but if more than 3 percent of observations are classified as outliers, we increase the cutoff from $(2 * 1.4785 * mad)$ to $(3 * 1.4785 * mad)$ and so on. We alternate between raising and lowering the cutoff by fractions of $(\text{cutoff} * 1.4785 * mad)$ for at most 100 times. If after 100 runs the percentage of classified outliers is still very high, we accept this as a sign of high variability and accept the algorithm's decision, keeping track, for every sector-year pair, of the percentage of outliers. Note that these extreme cases tend to occur in sector-year pairs with very few observations, which will in any case drop out of our analysis due to a low number of bilateral transactions.

We choose not to use the highest level of disaggregation, facing a tradeoff between high disaggregation and low data availability, and the opposite. Taking into account both aspects, we choose to aggregate our data into 4-digit ISIC sectors yearly observations.