ELSEVIER



Contents lists available at ScienceDirect

journal homepage: www.elsevier.com/locate/jie

Estimating import supply and demand elasticities: Analysis and implications $\stackrel{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}}{\overset{\mbox{}}{\overset{\mbox{}}}{\overset{\mbox{}}}{\overset{\mbox{}}}}{\overset{\mbox{}}}{\overset{\mbox{}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}}$



Anson Soderbery *

Department of Economics, Purdue University, West Lafayette, IN 47907-2056, United States

A R T I C L E I N F O

Article history: Received 22 February 2013 Received in revised form 7 January 2015 Accepted 7 January 2015 Available online 15 January 2015

JEL classification: F10 F12 F14

Keywords: Import elasticity Limited information maximum likelihood Variety gains

1. Introduction

Feenstra (1994)/Broda and Weinstein (2006) estimates (F/BW henceforth) of supply and demand elasticities have been heavily utilized in modern economic research. Studies using these estimates span international trade, open economy macroeconomics and labor economics.¹ Despite its wide use, I show the methodology possesses substantial biases that are rarely acknowledged.

This paper returns to the first principles of the technique, developed by Leamer (1981), to clarify the methodology. Leamer (1981)'s insights allow us to analyze deficiencies in the standard methodology of F/BW and motivate a "hybrid" estimator. The hybrid estimator proposed here combines limited information maximum likelihood (LIML) with a constrained nonlinear LIML routine. LIML addresses small sample bias while the nonlinear routine corrects grid search inefficiencies. Through

Corresponding author.

E-mail address: asoderbe@purdue.edu.

¹ Trade topics range from studies of quality such as Khandelwal (2010), trade in intermediates Goldberg et al. (2010), and optimal tariffs Broda et al. (2008). Macroeconomic studies include Caballero et al. (2008). Labor topics include Iranzo and Peri (2009). This list hardly scratches the surface of the influential works utilizing Broda and Weinstein (2006)'s estimates (a simple count yields around 200 published articles using these estimates off-the-shelf).

ABSTRACT

Feenstra (1994) developed, and Broda and Weinstein (2006) refined, a structural estimator of import demand and supply elasticities. Working through the first principles of the methodology from Leamer (1981), this paper analyzes and improves the technique to provide a unified estimator of import supply and demand elasticities. The proposed LIML routine corrects small sample biases and constrained search inefficiencies. Previously used estimates are shown to overestimate the median elasticity of substitution by over 35%. Applied to US import data from 1993 to 2007, the biases of the standard estimates translate into an understatement of consumer gains from product variety by a factor of 6. To conclude, I investigate the implications of violations to the underlying assumptions of the model.

© 2015 Elsevier B.V. All rights reserved.

Monte Carlo experiments and applications to actual data, I document the sources of bias in F/BW. In conjunction, I develop the intuition behind the improvements associated with the hybrid estimator. All methods of evaluation strongly support the hybrid estimator.

I show that the standard estimator is biased because it overweights outlier observations. The hybrid estimator better accounts for outlier observations, and significantly outperforms the standard method in Monte Carlo experiments. The estimators are then applied to import data. Correcting the biases of the standard estimates yields a 35% lower median demand elasticity for the universe of HS8 products imported by the US from 1993 to 2007. I demonstrate that bias in the standard estimates is responsible for understating consumer gains from product variety by a factor of 6 over the sample, and carries significant implications for a host of prominent studies.

I conclude by investigating the robustness of the methodology. First, I investigate violations to the assumed independence of errors through Monte Carlo experiments. When the supply and demand errors are positively correlated (e.g., endogenous quality), estimates of demand elasticities exhibit moderate bias of 10%–25% regardless of method. However, when errors are negatively correlated (e.g., hidden varieties), the hybrid estimator shows moderate bias while the standard method is significantly upward biased by 50%–125%. Estimates of the supply elasticity suffer regardless of method, but the hybrid estimator consistently outperforms the standard.

Next, I reestimate the model for various cuts of the data determined by income levels of each variety's country of origin in order to examine whether elasticities are feasibly identical across varieties. Hybrid

[☆] This paper has benefited immensely from its editor Dan Trefler, two anonymous referees, and discussions with Bruce Blonigen, Robert Feenstra, David Hummels, Nicholas Sly, Justin Tobias, Chong Xiang, and seminar participants at the Chicago Federal Reserve, Rocky Mountain Empirical Trade Conference, Purdue University and Indiana University. Invaluable research assistance was provided by Andrew Greenland and Marcelo Castillo-Rivas. All errors and omissions are my own.

estimates of the demand elasticity are insensitive to the various specifications. The standard estimator, on the other hand, is extremely sensitive to the data used for estimation.² For the hybrid estimator, narrowing the sample to high income or OECD varieties leads to statistically different distributions only for the supply elasticity. Alleviating the bias of the standard estimator thus provides stronger support for the underlying assumptions of the model, but does suggest potential gains from a structural estimator that allows export supply elasticities to differ across varieties.

This paper proceeds as follows. Section 2 lays out the method of estimating import elasticities. Section 2.2 describes the first principles of the estimator. Section 3 presents Monte Carlo results supporting the hybrid estimator. Section 4 applies each estimator discussed to actual trade data. Section 5 investigates the robustness of the methodology across estimators, and Section 6 concludes.

2. Estimating import supply and demand

This section first describes the theoretical foundation of the Feenstra (1994)/Broda and Weinstein (2006) (F/BW) method to estimate import demand and export supply elasticities. Next, the econometric underpinnings of the estimator, which are drawn from Leamer (1981), are used to clarify the methodology. Finally, I lay out the steps that map Leamer (1981) to F/BW. Aligning F/BW with Leamer (1981) highlights sources of bias in the standard estimator. This section concludes by leveraging the intuition of the estimator to motivate an improved hybrid methodology.

2.1. Theory: the F/BW framework

We begin with the theoretical framework used by F/BW. The goal is to structurally estimate import demand and export supply elasticities in a common model of international trade. A representative consumer faces nested CES preferences over foreign and domestic goods and varieties. Denote the set of varieties *v* of good *g* available at time *t* by $I_{gt} \subset \{1,.., v,.., V\}$.³ The aggregate quantity of each variety consumed in period *t* is x_{gvt} , and $\sigma_g > 1$ is the good specific constant elasticity of substitution. We also allow demand to contain a variety specific taste shock, denoted by b_{gvt} . Focusing on the variety nest for the imported good *g*, utility is given by,

$$X_{gt} = \left(\sum_{v \in I_{gt}} b_{gvt}^{\frac{1}{\sigma_g}} x_{gvt}^{\frac{\sigma_{g-1}}{\sigma_g}}\right)^{\frac{\sigma_g}{\sigma_g-1}}.$$
(1)

Demand for a given variety v of good g at time t is then $x_{gvt} = p_{gvt}^{-\sigma_g} b_{gvt} \left(\phi_{gt}(\mathbf{b}_{gt}) \right)^{\sigma_g - 1}$, where $\phi_{gt}(\mathbf{b}_{gt}) \equiv \left(\sum_{v \in I_{gt}} b_{gvt} \ p_{gvt}^{1 - \sigma_g} \right)^{1/1 - \sigma_g}$.

 $p_{gvt} \cdot p_{gvt} \left(\varphi_{gt} \left(\mathbf{u}_{gt} \right) \right)$, where $\varphi_{gt} \left(\mathbf{u}_{gt} \right) = \left(\mathcal{L}_{v \in I_{gt}} \cdot p_{gvt} \cdot p_{gvt} \right)$ Hence, the market share is,

$$s_{gvt} \equiv \frac{p_{gvt} x_{gvt}}{\sum_{v \in I_{gt}} p_{gvt} x_{gvt}} = \left(\frac{p_{gvt}}{\Phi_{gt} \left(\mathbf{b}_{gt}\right)}\right)^{1-\sigma_g} b_{gvt}.$$
 (2)

Market share depends upon own price (p_{gvt}) relative to the price index $(\phi_{gt}(\mathbf{b}_{gt}))$, and the variety specific random taste parameter (b_{gvt}) .

Exporters are monopolistically competitive with upward sloping export supply of the form,

$$p_{gvt} = \left(\frac{\sigma_g}{\sigma_g - 1}\right) exp(\eta_{gvt}) \ \left(x_{gvt}\right)^{\omega_g}.$$

The inverse export supply elasticity for good *g* is given by $\omega_g \ge 0$, and η_{gvt} embodies a random technology factor. As with demand, we convert quantities supplied into market shares such that supply is written as,

$$p_{gvt} = \left(\sum_{v \in I_{gt}} exp\left(\frac{-\eta_{gvt}}{\omega_g}\right) p_{gvt}^{\frac{1+\omega_g}{\omega_g}}\right)^{\frac{1+\omega_g}{\omega_g}} exp\left(\frac{\eta_{gvt}}{1+\omega_g}\right) s_{gvt}^{\frac{\omega_g}{1+\omega_g}}$$

Following Feenstra (1994), we wish to eliminate any time and good specific unobservables that would convolute the estimation of supply and demand elasticities. We eliminate good specific unobservables by first differencing prices and shares (denote first differences by Δ).⁴ To eliminate time specific unobservables we difference again by a reference country *k* (denote reference differences by superscript *k*). This results in the system of equations,

$$\Delta^{k} lns_{gvt} \equiv \Delta lns_{gvt} - \Delta lns_{gkt} = -(\sigma_{g} - 1)\Delta^{k} ln(p_{gvt}) + \varepsilon_{gvt}^{k}$$
(3)

$$\Delta^{k} lnp_{gvt} \equiv \Delta lnp_{gvt} - \Delta lnp_{gkt} = \left(\frac{\omega_{g}}{1 + \omega_{g}}\right) \Delta^{k} ln\left(s_{gvt}\right) + \delta^{k}_{gvt}, \tag{4}$$

where $\varepsilon_{gvt}^k = \Delta^k ln(b_{gvt})$ and $\delta_{gvt}^k = \Delta^k \left(\frac{\eta_{or}}{1+\omega_s}\right)$ are unobservable demand and supply shocks, respectively. Eqs. (3) and (4) are the structural model's demand and supply curves.

As Feenstra (1994) shows, we can multiply ε_{gvt}^k and δ_{gvt}^k together in order to convert Eqs. (3) and (4) into one estimable equation. Define $\rho_g \equiv \frac{\omega_g(\sigma_g-1)}{1+\omega_g\sigma_g} \in \left[0, \frac{\sigma_g-1}{\sigma_g}\right]$, scale by $\frac{1}{(1-\rho_g)}$, and rearrange to produce Feenstra (1994)'s estimating equation,

$$Y_{gvt} = \theta_{1g} X_{1gvt} + \theta_{2g} X_{2gvt} + u_{gvt}, \text{ where} Y_{gvt} \equiv \left(\Delta^k lnp_{gvt}\right)^2, X_{1gvt} \equiv \left(\Delta^k lns_{gvt}\right)^2, X_{2gvt} \equiv \left(\Delta^k lns_{gvt}\right) \left(\Delta^k lnp_{gvt}\right) \text{ and } u_{gvt} = \frac{\varepsilon_{gvt}^k \delta_{gvt}^k}{\left(1 - \rho_g\right)},$$
(5)

where the coefficients, θ_{1g} and θ_{2g} , are nonlinear functions of σ_{g} and ρ_{g} such that,

$$\theta_{1g} \equiv \frac{\rho_g}{\left(\sigma_g - 1\right)^2 \left(1 - \rho_g\right)} \text{ and } \theta_{2g} \equiv \frac{2\rho_g - 1}{\left(\sigma_g - 1\right) \left(1 - \rho_g\right)}.$$
(6)

$$\Delta ln(s_{gvt}) = \varphi_{gt} - (\sigma_g - 1) \Delta ln(p_{gvt}) + \varepsilon_{gvt}$$

where $\phi_{gt} \equiv (\sigma_g - 1)\Delta ln(\phi_{gt}(\mathbf{b}_{gt}))$ is a time-product specific random shock driven by the vector of random taste parameters \mathbf{b}_{gt} . The variety specific random shock, $\varepsilon_{gvt} = \Delta ln(b_{gvt})$, is driven by the random tastes of consumers across varieties. Second, the underlying supply in logs and first differences can be written as,

$$\Delta ln(p_{gvt}) = \psi_{gt} + \frac{\omega_g}{1 + \omega_g} \Delta ln(s_{gvt}) + \delta_{gvt},$$

where $\psi_{gt} = \frac{\alpha_{b}}{1+\omega_{b}}\Delta ln \left(\sum_{v \in I_{gt}} exp\left(-\eta_{gvt}/\omega_{g}\right) p_{gvt}^{1+\omega_{g}/\omega_{g}}\right)$ captures time-product specific shocks to production. The inverse supply elasticity for each product is $\omega_{g} \geq 0$. Random technology shocks to the production of each variety, η_{gvt} , manifest themselves through $\delta_{gvt} = \Delta(\eta_{gvt}/1 + \omega_{g})$. Third, differencing by a reference variety in Eqs. (3) and (4) serves to eliminate the time-product shocks present in supply and demand (φ_{gt} and ψ_{gt}).

² Kolmogorov–Smirnov tests reject the hypothesis that demand and supply elasticities are identically distributed across each cut of the data.

³ Clarity regarding what is a variety and good is the key to understanding the estimator to follow. We rely on trade flows at the *HS*8 level of aggregation. Each *HS*8 will define a good. Then we employ the Armington (1969) assumption of national differentiation, so that varieties are defined by their country of origin. We can thus define the set {1,....,V} as the set of all potential exporters in the world.

⁴ This footnote makes three points. First, the underlying demand in logs and first differences for each variety can be written as,

Download English Version:

https://daneshyari.com/en/article/962931

Download Persian Version:

https://daneshyari.com/article/962931

Daneshyari.com