Online Appendix to
The Elasticity of Trade: Estimates and Evidence

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A. Data Appendix

1.1. Trade Shares

To construct trade shares, we used bilateral trade flows and production data as follows:

$$\frac{X_{ni}}{X_n} = \frac{\text{Imports}_{ni}}{\text{Gross Mfg. Production}_n - \text{Exports}_n + \text{Imports}_n},$$

$$\frac{X_{nn}}{X_n} = 1 - \sum_{k \neq n}^{N} \frac{X_{ni}}{X_n}.$$

Putting the numerator and denominator together is simply computing an expenditure share by dividing the value of goods country n imported from country i by the total value of goods in country n. The home trade share $\frac{X_{nn}}{X_n}$ is simply constructed as the residual from one minus the sum of all bilateral expenditure shares.

To construct $\frac{X_{ni}}{X_n}$, the numerator is the aggregate value of manufactured goods that country n imports from country i. Bilateral trade-flow data are from UN Comtrade for the year 2004. We obtain all bilateral trade flows for our sample of 123 countries at the four-digit SITC level. We then used concordance tables between four-digit SITC and three-digit ISIC codes provided by the UN and further modified by Muendler (2009).[25] We restrict our analysis to manufacturing bilateral trade flows only—namely, those that correspond with manufacturing as defined in ISIC Rev.#2.

[25] The trade data often report bilateral trade flows from two sources. For example, the exports of country A to country B can appear in the UN Comtrade data as exports reported by country A or as imports reported by country B. In this case, we take the report of bilateral trade flows between countries A and B that yields a higher total volume of trade across the sum of all SITC four-digit categories.

The denominator is gross manufacturing production minus manufactured exports (for only the sample) plus manufactured imports (for only the sample). Gross manufacturing production data are the most serious data constraint we faced. We obtain manufacturing production data for 2004 from UNIDO for a large sub-sample of countries. We then imputed gross manufacturing production for countries for which data are unavailable as follows: We first obtain 2004 data on manufacturing (MVA) and agriculture (AVA) value added, as well as population size (L) and GDP for all countries in the sample. We then impute the gross output (GO) to manufacturing value added ratio for the missing countries using coefficients resulting from the following regression:

$$\log\left(\frac{MVA}{GO}\right) = \beta_0 + \beta_{GDP}C_{GDP} + \beta_L C_L + \beta_{MVA}C_{MVA} + \beta_{AVA}C_{AVA} + \epsilon,$$

where β_x is a 1x3 vector of coefficients corresponding to C_x, an Nx3 matrix which contains $[\log(x), (\log(x))^2, (\log(x))^3]$ for the sub-sample of N countries for which gross output data are available.

1.2. Prices

The ICP price data we employ in our estimation procedure is reported at the basic-heading level. A basic heading represents a narrowly-defined group of goods for which expenditure data are available. For example, basic heading "1101111 Rice" is made up of prices of different types of rice, and the resulting value is an aggregate over these different types of rice. This implies that a typical price observation of "Rice" contains different types of rice, as well as different packaging options that affect the unit price of rice within and across countries.

According to the ICP Handbook, the price of the basic heading "Rice" is constructed using a transitive Jevons index of prices of different varieties of rice. To illustrate this point, suppose that the world economy consists of three countries, A, B, C and ten types of rice, 1-10. Further suppose that consumers in country A have access to all 10 types of rice; those in country B only have access to types 1-5 of rice; and those in country C have access to types 4-6 of rice. Although all types of rice are not found in all three countries, it is sufficient that each pair of countries shares at least one type of rice.

The ICP obtains unit prices for all available types of rice in all three countries and records a price of 0 if the type of rice is not available in a particular country. The relative price of rice between countries A and B, based on goods available in these two countries, $p_{AB}^{A,B}$, is a geometric average of the relative prices of rice of types 1-5

$$p_{AB}^{A,B} = \left[\prod_{j=1}^{5} \frac{p_A(j)}{p_B(j)}\right]^{\frac{1}{5}}.$$

Similarly, one can compute the relative price of rice between countries A and C (B and C) based on varieties available in both A and C (B and C). The price of the basic heading "Rice" reported by the ICP is:

$$p_{AB} = \left[p_{AB}^{A,B} p_{AB}^{A,B} \frac{p_{AC}^{A,C}}{p_{BC}^{B,C}} \right]^{\frac{1}{3}},$$

which is a geometric average that features not only relative prices of rice between countries A and B, but also cross-prices between A and B linked via country C. This procedure ensures that prices of basic headings are transitive across countries and minimizes the impact of missing prices across countries.

Thus, a basic-heading price is a geometric average of prices of varieties that is directly comparable across countries.

B. Proofs

Below, we describe the steps to proving Lemmata 1 and 2. The key part in Lemma 1 is deriving the distribution of the maximal log price difference. We then prove Propositions 1 and 2.

2.1. Proof of Lemma 1, Lemma 2, and Proposition 1

First, we derive the distribution of the maximal log price difference. The key insight is to work with direct comparisons of goods' prices (i.e., do not impose equilibrium and work from the equilibrium price distribution) and to compute the distribution of log price differences and then the distribution of the maximal log price difference.

Having obtained the distribution of the maximum log price difference, we show that the expected value of the maximum log price difference is biased in a finite sample and the estimator $\hat{\beta}$ is biased.

2.1.A. Preliminaries

In deriving the distribution of maximum log price differences, we will work with a relabeling of the production functions and exponential distributions following an argument in Alvarez and Lucas (2007). They relate the pdfs of the exponential and Frèchet distributions. The claim is that if $z_i \sim \exp(T_i)$, then $y_i \equiv z_i^{-\frac{1}{\theta}} \sim \exp(-T_i y_i^{-\theta})$. To see this, notice that since $y_i = h(z_i)$ is a decreasing function, it must be that $f(z_i)dz_i = -g(y_i)dy_i$, where f, g are the pdf's of z_i, y_i, respectively. The result will allow us to characterize moments of the log price difference by invoking properties of the exponential distribution.

2.1.B. Proof of Lemma 1

The proof of Lemma 1 follows.

Let $z_k^{-\frac{1}{\theta}} \sim \exp(-T_k(z_k^{-\frac{1}{\theta}})^{-\theta})$ be the productivity associated with good z, drawn from the Frèchet pdf in country k. By the argument above, the underlying distribution of z_k is exponential. The price for good z produced in country k and supplied to country i is $p_{ik} \equiv w_k \tau_{ik} z_k^{\frac{1}{\theta}}$. The relative price ratio of good z between countries n and i is:

$$v_{ni}(z) = \frac{\min\left\{\min_{k\neq i}[w_k \tau_{nk} z_k^{\frac{1}{\theta}}], w_i \tau_{ni} z_i^{\frac{1}{\theta}}\right\}}{\min\left\{\min_{k\neq n}[w_k \tau_{ik} z_k^{\frac{1}{\theta}}], w_n \tau_{in} z_n^{\frac{1}{\theta}}\right\}}. \tag{b.1}$$

Take this object to the power of θ:

$$(v_{ni}(z))^\theta = \frac{\min\left\{\min_{k\neq i}[w_k^\theta \tau_{nk}^\theta z_k], w_i^\theta \tau_{ni}^\theta z_i\right\}}{\min\left\{\min_{k\neq n}[w_k^\theta \tau_{ik}^\theta z_k], w_n^\theta \tau_{in}^\theta z_n\right\}}. \tag{b.2}$$

We want to characterize the distribution of (b.2), so we will first derive the pdf's of its components. Define $\tilde{z}_{ik} = w_k^\theta \tau_{ik}^\theta z_k$. Since $z_k \sim \exp(T_k)$, it must be that $\tilde{z}_{ik} \sim \exp(T_k w_k^{-\theta} \tau_{ik}^{-\theta})$. Let $\tilde{\lambda}_{ik} \equiv T_k w_k^{-\theta} \tau_{ik}^{-\theta}$.

Next, we derive the distribution of $\tilde{z}_i \equiv \min_{k\neq n}[w_k^\theta \tau_{ik}^\theta z_k] = \min_{k\neq n}[\tilde{z}_{ik}]$. Since each $\tilde{z}_{ik} \sim \exp(\tilde{\lambda}_{ik})$ and independent across countries k, $\tilde{z}_i \sim \exp(\sum_{k\neq n} \tilde{\lambda}_{ik})$. Define $\tilde{\lambda}_i \equiv \sum_{k\neq n} \tilde{\lambda}_{ik}$. Repeat the procedure for importer n in the numerator.

Given these definitions, (b.2) can be rewritten as:

$$(v_{ni}(z))^\theta = \frac{\min\left\{\tilde{z}_n, w_i^\theta \tau_{ni}^\theta z_i\right\}}{\min\left\{\tilde{z}_i, w_n^\theta \tau_{in}^\theta z_n\right\}}. \tag{b.3}$$

Define $\epsilon_{ni}(z) = \log(v_{ni}(z))$. Taking logs of expression (b.3) gives:

$$\begin{aligned} \theta\epsilon_{ni}(z) = \quad & \min\left\{\log(\tilde{z}_n), [\theta\log(w_i) + \theta\log(\tau_{ni}) + \log(z_i)]\right\} \\ - \quad & \min\left\{\log(\tilde{z}_i), [\theta\log(w_n) + \theta\log(\tau_{in}) + \log(z_n)]\right\}. \end{aligned} \tag{b.4}$$

Next, we argue that $\theta\epsilon_{ni}(z) \in [-\theta\log(\tau_{in}), \theta\log(\tau_{ni})]$. For any good z, $\theta\epsilon_{ni}(z)$ can satisfy one and only one of the following three cases:

1. Countries n and i buy good z from two different sources. Then,

$$\theta\epsilon_{ni}(z) = \log(\tilde{z}_n) - \log(\tilde{z}_i) \tag{b.5}$$

2. Country n buys good z from country i. Assuming that trade barriers don't violate the triangle inequality, it must be that i buys the good from itself. Then,

$$\theta\epsilon_{ni}(z) = \theta\log(w_i) + \theta\log(\tau_{ni}) + \log(z_i) - \theta\log(w_i) - \log(z_i) = \theta\log(\tau_{ni}). \tag{b.6}$$

3. Country i buys good z from n. Then it must be that n buys the good from itself, so:

$$\theta\epsilon_{ni}(z) = \theta\log(w_n) + \log(z_n) - \theta\log(w_n) - \theta\log(\tau_{in}) - \log(z_n) = -\theta\log(\tau_{in}). \tag{b.7}$$

We claim that the following ordering occurs: $-\theta\log(\tau_{in}) \leq \log(\tilde{z}_n) - \log(\tilde{z}_i) \leq \theta\log(\tau_{ni})$. To show this, we need to consider the following two scenarios:

1. Countries n and i buy good z from the same source k. Then,

$$\begin{aligned}\log(\tilde{z}_n) - \log(\tilde{z}_i) &= \log(w_k^\theta\tau_{nk}^\theta z_k) - \log(w_k^\theta\tau_{ik}^\theta z_k)\\ &= \theta(\log(\tau_{nk}) - \log(\tau_{ik})).\end{aligned} \tag{b.8}$$

   Clearly,

$$\theta(\log(\tau_{nk}) - \log(\tau_{ik})) \geq -\theta\log(\tau_{in}) \iff \tau_{in}\tau_{nk} \geq \tau_{ik},$$

   where the latter inequality is true under the triangle inequality assumption.

   Similarly,

$$\theta(\log(\tau_{nk}) - \log(\tau_{ik})) \leq \theta\log(\tau_{ni}) \iff \tau_{nk} \leq \tau_{ni}\tau_{ik},$$

   again true by triangle inequality.

2. Country n buys good z from source a and country i from source b, $a \neq b$. We want to show that $-\theta\log(\tau_{in}) \leq \log(w_a^\theta\tau_{na}^\theta z_a) - \log(w_b^\theta\tau_{ib}^\theta z_b) \leq \theta\log(\tau_{ni})$.

   Since n imported from a over b, it must be that:

$$w_a^\theta\tau_{na}^\theta z_a \leq w_b^\theta\tau_{nb}^\theta z_b \tag{b.9}$$

   Similarly, since i imported from b over a, it must be that:

$$w_b^\theta\tau_{ib}^\theta z_b \leq w_a^\theta\tau_{ia}^\theta z_a \tag{b.10}$$

To find the upper bound, take logs of (b.9) and subtract $\log(w_b^\theta \tau_{ib}^\theta z_b)$ from both sides:

$$\log(w_a^\theta \tau_{na}^\theta z_a) - \log(w_b^\theta \tau_{ib}^\theta z_b) \le \log(w_b^\theta \tau_{nb}^\theta z_b) - \log(w_b^\theta \tau_{ib}^\theta z_b) \tag{b.11}$$

It suffices to show that the right-hand side is itself below the upper bound since, by transitivity, so is the left-hand side (which is the object of interest).

$$\begin{aligned} &\log(w_b^\theta \tau_{nb}^\theta z_b) - \log(w_b^\theta \tau_{ib}^\theta z_b) \le \theta \log(\tau_{ni}) \\ \iff &\theta \log(\tau_{nb}) - \theta \log(\tau_{ib}) \le \theta \log(\tau_{ni}) \\ \iff &\tau_{nb} \le \tau_{ni}\tau_{ib}, \end{aligned} \tag{b.12}$$

which is true by triangle inequality.

The argument for the lower bound is similar. Take logs of (b.10), multiply by -1 (and reverse inequality) and add $\log(w_a^\theta \tau_{na}^\theta z_a)$ to both sides:

$$\log(w_a^\theta \tau_{na}^\theta z_a) - \log(w_b^\theta \tau_{ib}^\theta z_b) \ge \log(w_a^\theta \tau_{na}^\theta z_a) - \log(w_a^\theta \tau_{ia}^\theta z_a) \tag{b.13}$$

It suffices to show that the right-hand side is itself above the lower bound since, by transitivity, so is the left-hand side (which is the object of interest).

$$\begin{aligned} &\log(w_a^\theta \tau_{na}^\theta z_a) - \log(w_a^\theta \tau_{ia}^\theta z_a) \ge -\theta \log(\tau_{in}) \\ \iff &\theta \log(\tau_{na}) - \theta \log(\tau_{ia}) \ge -\theta \log(\tau_{in}) \\ \iff &\tau_{in}\tau_{na} \ge \tau_{ia}, \end{aligned} \tag{b.14}$$

which is true by triangle inequality.

Hence, $\theta\epsilon_{ni}(z) \in [-\theta \log(\tau_{in}), \theta \log(\tau_{ni})]$.

Next, we proceed to derive the distribution of $\theta\epsilon_{ni}(z) = \log(\tilde{z}_n) - \log(\tilde{z}_i)$. First, we derive the pdfs of its two components.

Let $y_i \equiv \log(\tilde{z}_i)$. Then $\tilde{z}_i = \exp(y_i)$. The pdf of y_i must satisfy:

$$\begin{aligned} f(y_i)dy_i = g(\tilde{z}_i)d\tilde{z}_i \;\Rightarrow\; & \quad f(y_i) = \tilde{\lambda}_i \exp(-\tilde{\lambda}_i \tilde{z}_i)\frac{d\tilde{z}_i}{dy_i} \\ \Rightarrow\; & \quad f(y_i) = \tilde{\lambda}_i \exp(-\tilde{\lambda}_i \exp(y_i)) \exp(y_i) \\ \Rightarrow\; & \quad F(y_i) = 1 - \exp(-\tilde{\lambda}_i \exp(y_i)) \end{aligned} \tag{b.15}$$

The same holds for n.

Now that we have the pdf's of the two components, we can define the pdf of $\epsilon \equiv \theta\epsilon_{ni}(z) \in$

$[-\theta \log(\tau_{in}), \theta \log(\tau_{ni})]$ as follows:

$$f(\epsilon) \equiv f_{y_n - y_i}(x) = \int_{-\infty}^{\infty} f_{y_n}(y) f_{y_i}(y - x) dy, \tag{b.16}$$

where we have used the fact that y_n and y_i are independently distributed hence, the pdf of their difference is the convolution of the pdfs of the two random variables.

Substituting the pdfs of y_n and y_i into (b.16) yields:

$$\begin{aligned} f(\epsilon) =& \int_{-\infty}^{\infty} \tilde{\lambda}_n \exp(-\tilde{\lambda}_n \exp(y)) \exp(y) \tilde{\lambda}_i \exp(-\tilde{\lambda}_i \exp(y - \epsilon)) \exp(y - \epsilon) dy \\ =& \frac{-\tilde{\lambda}_n \tilde{\lambda}_i}{(\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i)^2} \left[\frac{\tilde{\lambda}_n \exp(y + \epsilon) + \tilde{\lambda}_i \exp(y) + \exp(\epsilon)}{\exp\left\{\exp(y)(\tilde{\lambda}_n + \tilde{\lambda}_i \exp(-\epsilon))\right\}} \right]_{y=-\infty}^{y=+\infty} \end{aligned} \tag{b.17}$$

Let $v(y)$ be the expression in the bracket.

$$\lim_{y \to -\infty} v(y) = \frac{0 + 0 + \exp(\epsilon)}{\exp\{0\}} = \exp(\epsilon) \tag{b.18}$$

For the upper bound, we use l'Hopital rule:

$$\begin{aligned} \lim_{y \to \infty} v(y) =& \lim_{y \to \infty} \frac{\tilde{\lambda}_n \exp(y + \epsilon) + \tilde{\lambda}_i \exp(y)}{\exp\left\{\exp(y)(\tilde{\lambda}_n + \tilde{\lambda}_i \exp(-\epsilon))\right\} \exp(y)(\tilde{\lambda}_n + \tilde{\lambda}_i \exp(-\epsilon))} \\ =& \lim_{y \to \infty} \frac{\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i}{\exp\left\{\exp(y)(\tilde{\lambda}_n + \tilde{\lambda}_i \exp(-\epsilon))\right\} (\tilde{\lambda}_n + \tilde{\lambda}_i \exp(-\epsilon))} \\ =& 0 \end{aligned} \tag{b.19}$$

Thus, (b.17) becomes:

$$f(\epsilon) = \frac{\tilde{\lambda}_n \tilde{\lambda}_i \exp(\epsilon)}{(\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i)^2} \tag{b.20}$$

The corresponding cdf is:

$$F(\epsilon) = 1 - \frac{\tilde{\lambda}_i}{\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i} \tag{b.21}$$

Given that ϵ is bounded, we can compute the truncated pdf as:

$$\begin{aligned} f_T(\epsilon) =& \frac{f(\epsilon)}{F(\theta \log(\tau_{ni})) - F(-\theta \log(\tau_{in}))} \\ =& \gamma^{-1} \frac{\tilde{\lambda}_n \tilde{\lambda}_i \exp(\epsilon)}{(\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i)^2}, \end{aligned} \tag{b.22}$$

where:

$$\gamma = -\frac{\tilde{\lambda}_i}{\tilde{\lambda}_n \exp(\theta \log(\tau_{ni})) + \tilde{\lambda}_i} + \frac{\tilde{\lambda}_i}{\tilde{\lambda}_n \exp(-\theta \log(\tau_{in})) + \tilde{\lambda}_i} \tag{b.23}$$

Similarly, the truncated cdf is:

$$F_T(\epsilon) = \gamma^{-1} \int_{-\theta \log(\tau_{in})}^{\epsilon} f(t) dt \tag{b.24}$$

Now that we have these distributions, we compute order statistics from them, which allow us to characterize the trade barriers estimated from price data. We use the following result: Given L observations drawn from pdf $h(x)$, the pdf of the r-th order statistic (where $r = L$ is the max and $r = 1$ is the min) is:

$$h_r(x) = \frac{L!}{(r-1)!(L-r)!} H(x)^{r-1} (1 - H(x))^{L-r} h(x) \tag{b.25}$$

The pdf of the max reduces to:

$$h_{\max}(x, L) = L H(x)^{L-1} h(x)$$

With this pdf defined, we can compute the expectation of the maximum statistic:

$$E[\max_{z \in L}(x_z)] = \int_{-\infty}^{\infty} x h_{\max}(x, L) dx \tag{b.26}$$

Recall that we are interested in computing the expectation of the maximum logged price difference between countries n and i. But, so far, we have derived the truncated pdf and cdf of $\epsilon = \theta \log(v_{ni}(z))$. Our object of interest is actually $\log(v_{ni}(z)) = \frac{1}{\theta}\epsilon$. The expectation of this object, which represents the maximum log price difference, for L draws, is given by:

$$E[\max_{z \in L}(\log(p_n(z)) - \log(p_i(z)))] = \frac{1}{\theta} \int_{-\theta \log(\tau_{in})}^{\theta \log(\tau_{ni})} \epsilon f_{\max}(\epsilon, L) d\epsilon, \tag{b.27}$$

where:

$$
\begin{aligned}
f_{\max}(\epsilon, L) =& L F_T(\epsilon)^{L-1} f_T(\epsilon) \\
=& L \left[\gamma^{-1} \int_{-\theta \log(\tau_{in})}^{\epsilon} f(t) dt \right]^{L-1} \gamma^{-1} \frac{\tilde{\lambda}_n \tilde{\lambda}_i \exp(\epsilon)}{(\tilde{\lambda}_n \exp(\epsilon) + \tilde{\lambda}_i)^2}
\end{aligned} \tag{b.28}
$$

Hence, the expectation of the maximum of the log price difference is proportional to $1/\theta$, where the proportionality object comes from gravity,

$$
E[\max_{z \in L}(\log(p_n(z)) - \log(p_i(z)))] = \Psi_{ni}(L; \mathbf{S}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{i}}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{n}}), \tag{b.29}
$$

where:

$$
\Psi_{ni}(L; \mathbf{S}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{i}}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{n}}) \equiv \frac{1}{\theta} \int_{-\theta \log(\tau_{in})}^{\theta \log(\tau_{ni})} \epsilon f_{\max}(\epsilon, L) d\epsilon, \tag{b.30}
$$

and the values $\mathbf{S}$ and $\tilde{\boldsymbol{\tau}}_{\boldsymbol{n}}$ correspond with the definitions outlined in Definition 1. It is worth emphasizing the nature of this integral: Other than the scalar in the front, it depends completely on objects that can be recovered from the standard gravity equation in (22).

Finally, one can rewrite equation (b.30) via integration by parts as:

$$
E[\max_{z \in L}(\log(p_n(z)) - \log(p_i(z)))] = \log \tau_{ni} - \frac{1}{\theta} \int_{-\theta \log(\tau_{in})}^{\theta \log(\tau_{ni})} F_{\max}(\epsilon, L) d\epsilon \tag{b.31}
$$

$$
\log \tau_{ni} = E[\max_{z \in L}(\log(p_n(z)) - \log(p_i(z)))] + \frac{1}{\theta} \int_{-\theta \log(\tau_{in})}^{\theta \log(\tau_{ni})} F_{\max}(\epsilon, L) d\epsilon, \tag{b.32}
$$

which implies the following strict inequality:

$$
\log \tau_{ni} > E[\max_{z \in L}(\log(p_n(z)) - \log(p_i(z)))] = \Psi_{ni}(L; \mathbf{S}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{i}}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{n}}), \tag{b.33}
$$

where the strict inequality simply follows from the inspection of the CDF $F_{\max}(\epsilon, L)$ which has positive mass below the point $\theta \log(\tau_{ni})$. This then proves claim 1. in Lemma 1.

To prove claim 2. in Lemma 1, we compute the difference in the expected values of log prices between two countries. We show that they are equal to the (scaled) difference in the price parameters Φ.

Rather than working with the distribution described above, it is more convenient to directly compute the expectation of log prices using the equilibrium price distribution. Note that EK show that the cdf and pdf of prices in country i are $G(p) = 1 - \exp(-\Phi_i p^\theta)$ and $g(p) = p^{\theta-1} \theta \Phi_i \exp(-\Phi_i p^\theta)$, respectively.

For any country i, define the expectation of logged prices as

$$E[\log(p_i(z))] = \int_0^\infty \log(p)g(p)dp \tag{b.34}$$

Substituting the pdf of prices and then utilizing some algebra to find an appropriate change in variables, expression (b.34) yields

$$\begin{aligned} E[\log(p_i(z))] &= \int_0^\infty \log(p)p^{\theta-1}\theta\Phi_i \exp(-\Phi_i p^\theta)dp \\ &= \int_0^\infty \log(p)\theta\Phi_i \exp(\theta\log(p))\exp(-\Phi_i \exp(\theta\log(p)))\frac{dp}{p} \end{aligned}$$

Our change of variables will set $x = \log(p)$, which yields $dx/dp = 1/p$. Then, integration by change of variables allows us to rewrite the above as

$$\begin{aligned} E[\log(p_i(z))] &= \int_0^\infty \log(p)\theta\Phi_i \exp(\theta\log(p))\exp(-\Phi_i \exp(\theta\log(p)))\frac{dp}{p} \\ &= \int_0^\infty x\theta\Phi_i \exp(\theta x)\exp(-\Phi_i \exp(\theta x))\frac{\theta}{\theta}dx \end{aligned}$$

Let $y = \theta x$, so that $dy/dx = \theta$; then, another change of variables gives

$$E[\log(p_i(z))] = \frac{1}{\theta}\int_0^\infty y\Phi_i \exp(y)\exp(-\Phi_i \exp(y))dy$$

Let $t = \Phi_i \exp(y)$, so that $dt/dy = \Phi_i \exp(y)$ and $y = \log(t/\Phi_i)$. Then,

$$\begin{aligned} E[\log(p_i(z))] &= \frac{1}{\theta}\int_0^\infty \log\left(\frac{t}{\Phi_i}\right)\exp(-t)dt \\ &= \frac{1}{\theta}\left\{\int_0^\infty \log(t)\exp(-t)dt - \int_0^\infty \log(\Phi_i)\exp(-t)dt\right\} \\ &= -\frac{1}{\theta}\left\{\tilde{\gamma} + \log(\Phi_i)\right\}, \end{aligned} \tag{b.35}$$

where $\tilde{\gamma}$ is the Euler-Mascheroni constant. Finally, using (b.35) and taking the expected difference in log prices between country n and country i, the scaled Euler-Mascheroni constant cancels between the two countries and leaves the following expression

$$\begin{aligned} E[\log(p_n(z))] - E[\log(p_i(z))] &= -\frac{1}{\theta}\left\{\log(\Phi_n) - \log(\Phi_i)\right\} \\ &\equiv \Omega_{ni}(\mathbf{S}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{n}}, \tilde{\boldsymbol{\tau}}_{\boldsymbol{i}}), \end{aligned} \tag{b.36}$$

which then proves claim 2. in Lemma 1.

2.1.C. Proof of Lemma 2 and Proposition 1

To prove Lemma 2 and Proposition 1, we invert EK's estimator for the elasticity of trade:

$$\frac{1}{\hat{\beta}} = -\frac{\sum_n \sum_i \left(\log \hat{\tau}_{ni} + \log \hat{P}_i - \log \hat{P}_n\right)}{\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)} \tag{b.37}$$

Given the assumption that the trade data are fixed, equation (b.37) is linear in the random variables $\log \hat{\tau}_{ni}$ and $(\log \hat{P}_n - \log \hat{P}_i)$. With this observation, taking expectations of these random variables yields

$$E\left(\frac{1}{\hat{\beta}}\right) = \frac{1}{\theta}\left\{-\frac{\sum_n \sum_i (\theta \Psi_{ni}(L) - (\log \Phi_i - \log \Phi_n))}{\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}\right\} < \frac{1}{\theta}, \tag{b.38}$$

by substituting in for the expectation of the maximum log price difference using (b.30), and the difference in expectations of log prices using (b.36). Inspection of the bracketed term above implies that the following strict inequality must hold,

$$1 \; > \; \left\{-\frac{\sum_n \sum_i (\theta \Psi_{ni}(L) - (\log \Phi_i - \log \Phi_n))}{\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}\right\} \; > \; 0, \tag{b.39}$$

with the reason being that $\Psi_{ni}(L) < \log \tau_{ni}$ from Lemma 1; otherwise, the bracketed term would correspond exactly with equation (5) in logs and, thus, equal one. Now, inverting the expression above and applying Jensen's inequality results in the following:

$$E(\hat{\beta}) \; \geq \; \left[E\left(\frac{1}{\hat{\beta}}\right)\right]^{-1} = \theta \left\{-\frac{\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}{\sum_n \sum_i (\theta \Psi_{ni}(L) - (\log \Phi_i - \log \Phi_n))}\right\} > \theta, \tag{b.40}$$

with the strict inequality following from (b.38) and (b.39). This proves Proposition 1.

2.2. Proof of Proposition 2

In this subsection, we prove Proposition 2. To prove the claims in Proposition 2, we start with claim 1.

To prove claim 1., we argue that the sample maximum of scaled log price differences is a consistent estimator of the scaled trade cost. In particular, we argue that as the sample size becomes infinite, the probability that the sample scaled trade cost is arbitrarily close to the true scaled trade cost is one.

To see this, consider an estimate of the scaled trade barrier, given a sample of L goods' prices,

$$\theta \log \hat{\tau}_{ni}^{L} = \theta \left\{ \max_{\ell=1,\ldots,L} (\log p_n(\ell) - \log p_i(\ell)) \right\}. \tag{b.41}$$

The cdf of this random variable is the integral of its pdf, which is given in expression (b.28), over the compact interval in which the scaled logged price difference lies, $[-\theta \log \tau_{in}, \theta \log \tau_{ni}]$. Denote this cdf by F_{max}^{L}. From (b.28), $F_{max}^{L} \equiv (F_T)^L$, where F_T is the truncated distribution of the scaled log price difference over the domain $[-\theta \log \tau_{in}, \theta \log \tau_{ni}]$. By definition, F_T and F_{max}^{L} take on values between zero and one, as they are cdfs. In particular, for any realization $x < \theta \log \tau_{ni}$, $F_T(x) < 1$. For any $L > 1$, $F_{max}^{L}(x) = (F_T(x))^L \leq F_T(x) < 1$.

Take $L \to \infty$. Then, for any $x \in [-\theta \log \tau_{in}, \theta \log \tau_{ni})$, $F_{max}^{L} = (F_T)^L$ becomes arbitrarily close to zero since $F_T < 1$. Hence, all the mass of the cdf F_{max}^{L} becomes concentrated at $\theta \log \tau_{ni}$. Thus, as the sample size becomes infinite, the estimated scaled trade barrier converges to the true scaled trade barrier, in probability. Rescaling everything by $\frac{1}{\theta}$ then implies

$$\operatorname*{plim}_{L\to\infty} \log \hat{\tau}_{ni}^{L} = \operatorname*{plim}_{L\to\infty} \max_{\ell=1,\ldots,L} (\log p_n(\ell) - \log p_i(\ell)) = \log \tau_{ni}. \tag{b.42}$$

This proves claim 1. of Proposition 2.

To show consistency of the estimator $\hat{\beta}$, we argue that

$$\operatorname*{plim}_{L\to\infty} \hat{\beta}\,(L; \mathbf{S}, \tilde{\boldsymbol{\tau}}, \mathbb{X}) = \theta, \tag{b.43}$$

or, equivalently, that $\forall \delta > 0$,

$$\lim_{L\to\infty} \Pr\left[\parallel \hat{\beta}\,(L; \mathbf{S}, \tilde{\boldsymbol{\tau}}, \mathbb{X}) - \theta \parallel < \delta\right] = 1. \tag{b.44}$$

Basically, we will argue that, by sampling the prices of an ever-increasing set of goods and applying the estimator β over these prices, with probability one, we will obtain estimates that are arbitrarily close to θ.

Inverting the expression for the estimator $\hat{\beta}$ in expression (12), rearranging, and multiplying and dividing by the scalar θ yields

$$\frac{1}{\hat{\beta}} = \frac{1}{\theta} \frac{\sum_n \sum_i \left(\theta \log \hat{\tau}_{ni}^{L} - \theta[\log \hat{P}_n - \log \hat{P}_i]\right)}{-\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}. \tag{b.45}$$

By assumption, the denominator is trade data and is not a random variable.

In the numerator, $\log \hat{P}_n - \log \hat{P}_i$ is the difference in the average of logged prices for countries n and i, given a sample of L goods. In particular,

$$\log \hat{P}_n - \log \hat{P}_i \equiv \frac{1}{L}\sum_{\ell=1}^{L} \log p_n(\ell) - \frac{1}{L}\sum_{\ell=1}^{L} \log p_i(\ell) \tag{b.46}$$

We refer the reader to Davidson and MacKinnon (2004) for a proof of the well known result that the sample average is both an unbiased and consistent estimator of the mean. Since the difference operator is continuous, the difference in the sample average of logged price is an unbiased and consistent estimator of the difference in mean logged prices. Finally, multiplying these sample averages by a scalar θ, a continuous operation, ensures convergence to true difference in the price terms Φ.

We have argued that the two components in the numerator converge in probability to their true parameter counterparts, as the sample size becomes infinite. Taking the difference of these two components, summing over all country pairs (n, i), and dividing by the scalar $\left[-\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)\right]$, all of which are continuous operations, allows us to conclude that

$$\operatorname*{plim}_{L\to\infty} \frac{\sum_n \sum_i \left(\theta \log \hat{\tau}_{ni}^L - \theta[\log \hat{P}_n - \log \hat{P}_i]\right)}{-\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}$$

$$= \operatorname*{plim}_{L\to\infty} \frac{\sum_n \sum_i \left(\theta \max_{\ell=1,\ldots,L}(\log p_n(\ell) - \log p_i(\ell)) - \theta\left[\frac{1}{L}\sum_{\ell=1}^{L} \log p_n(\ell) - \frac{1}{L}\sum_{\ell=1}^{L} \log p_i(\ell)\right]\right)}{-\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}$$

$$= \frac{-\sum_n \sum_i (\theta \log \tau_{ni} - [\log \Phi_i - \log \Phi_n])}{\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right)}. \tag{b.47}$$

To complete the argument, consider the log of expression (5), which involves Φ. Summing this expression over all (n, i) country pairs gives:

$$\sum_n \sum_i \log\left(\frac{X_{ni}/X_n}{X_{ii}/X_i}\right) = -\sum_n \sum_i (\theta \log \tau_{ni} - [\log \Phi_i - \log \Phi_n]). \tag{b.48}$$

Substituting expression (b.48) in the denominator of (b.47) above makes the fraction in that expression equal to unity. Hence, $1/\hat{\beta}$ converges to $1/\theta$ in probability. Since, for $\beta \in (0, \infty)$, $1/\hat{\beta}$ is a continuous function of $\hat{\beta}$, $\hat{\beta}$ converges to θ in probability. This proves claim 2. of Proposition 2.

Claim 3. of Proposition 2 follows from the fact that $\hat{\beta}$ is a consistent estimator of θ (see Hayashi

(2000) for a discussion).

2.3. Deriving the Inverse Marginal Cost Distribution

To simulate the model, we argue that by using the coefficients **S** estimated from the gravity regression (22), we have enough information to simulate prices and trade flows. The key insight is that the S's are sufficient to characterize the inverse marginal cost distribution. Thus, we can sample from this distribution and then compute equilibrium prices and trade flows.

To see this argument, let $z_i \sim F_i(z_i) = \exp(-T_i z_i^{-\theta})$ and define $u_i \equiv z_i/w_i$. The pdf of z_i is $f_i(z_i) = \exp(-T_i z_i^{-\theta})\theta T_i z_i^{-\theta-1}$. To find the pdf of the transformation u_i, $m_i(u_i)$, use the fact that $f_i(z_i)dz_i = m_i(u_i)du_i$, or $m_i(u_i) = f_i(z_i)(du_i/dz_i)^{-1}$. Let $\tilde{S}_i = T_i w_i^{-\theta}$. Using $f_i(z_i)$, $\tilde{S}_i$, and the fact that $du_i/dz_i = 1/w_i$, we obtain:

$$
\begin{aligned}
m_i(u_i) = f_i(z_i)\left(\frac{du_i}{dz_i}\right)^{-1} &= \exp(-T_i z_i^{-\theta})\theta T_i z_i^{-\theta-1}\left(\frac{1}{w_i}\right)^{-1} \\
&= \exp\left(-T_i z_i^{-\theta}\frac{w_i^{-\theta}}{w_i^{-\theta}}\right)\theta T_i z_i^{-\theta-1}\left(\frac{1}{w_i}\right)^{-1}\frac{w_i^{-\theta}}{w_i^{-\theta}} \\
&= \exp\left(-\tilde{S}_i\frac{z_i^{-\theta}}{w_i^{-\theta}}\right)\theta\tilde{S}_i\frac{z_i^{-\theta-1}}{w_i^{-\theta-1}} \\
&= \exp\left(-\tilde{S}_i u_i^{-\theta}\right)\theta\tilde{S}_i u_i^{-\theta-1}
\end{aligned}
$$

Clearly $m_i(u_i)$ is the pdf that corresponds to the cdf $M_i(u_i) = \exp(-\tilde{S}_i u_i^{-\theta})$, which concludes the argument.

C. EK's Alternative Estimators of θ

EK use two other alternative methods to estimate θ than the one described in the main body of the paper. Through these alternative methods they are able to establish a range from 3.6 to 12.86. In this section, we explore the properties of one of these alternative estimators. We show that the estimator associated with the estimate of 12.86 is biased by economically meaningful magnitudes for the same reasons as the estimator discussed in the paper. Similar to our earlier arguments, we then use the moments associated with the biased estimator as the basis for our estimation. Doing so allows us to establish a range from 3.6 to 4.3 with EK's data rather than the range between 3.6 and 12.86.

Before proceeding, we should note that we have little to say about EK's estimation approach that leads to an estimate of 3.6. To arrive at this estimate, they use wage data and proxies for the productivity parameters, T, and find a value of 3.6.[26] While one may have objections to the

[26]Similarly, Costinot et al. (2012) estimate θ using trade data and proxies for productivity at the industry level for

particular statistics that they employ, the resulting estimate is in line with the estimates that we obtain, which we view as reassuring.

3.1. EK's 2SLS Approach

EK propose an alternative estimator for θ that uses the same variation in price data discussed in the text. First, they use the object D_{ni} defined as

$$D_{ni} = \log\left(\frac{\hat{P}_i \hat{\tau}_{ni}}{\hat{P}_n}\right) \tag{b.49}$$

$$\text{where} \quad \log \hat{\tau}_{ni}(L) = \max_{\ell \in L} \left\{ \log p_n(\ell) - \log p_i(\ell) \right\},$$

$$\text{and} \quad \log \hat{P}_i = \frac{1}{L} \sum_{\ell=1}^{L} \log(p_i(\ell)),$$

to proxy trade costs in the gravity equation (22). By using this measure in the gravity equation (rather than using distance and fixed effects), they can then interpret the coefficient on D_{ni} as an estimate of the trade elasticity.

When using (22) and (b.49) to approximate trade costs, EK are concerned about measurement error, so they employ instrumental variables to alleviate this concern. Specifically, they use the geography variables (distance, border, language) in (23) as instruments for D_{ni}. The resulting two stage least squares (2SLS) estimate of θ is 12.86.

3.2. A Monte Carlo Study of EK's 2SLS Approach

Here we apply the same experiment described in Section 4: we simulate trade flows and samples of micro-level prices under a known θ. Then, we apply EK's 2SLS estimator to the artificial data. We employ the same simulation procedure described in Steps 1-3 in Section 5.2 and we estimate all parameters (except for θ) using the trade data from EK. We set the true value of θ equal to 8.28. The sample size of prices is set to $L = 50$, which is the number of prices EK had access to in their data set.

Table 13 presents the results. The first row shows that the estimates using EK's 2SLS approach are almost 100 percent larger than the true θ of 8.28. Comparing theses results with the study of the method of moment estimator in Table 1, the bias takes the same form, but in the 2SLS approach the bias is significantly larger (12.5 vs. 15.9). This suggests (and our estimation below confirms) that any difference between EK's original results using method of moments vs. 2SLS

21 developed countries. They provide a wide range of estimates depending on the specification, with a preferred estimate of 6.53.

Table 13: Monte Carlo Results, EK's 2SLS Approach, True θ = 8.28

Approach = 2SLS, Gravity	Mean Estimate of θ (S.E.)	Median Estimate of θ
50 sampled prices	15.9 (0.24)	15.6
500 sampled prices	10.5 (0.05)	10.4
5,000 sampled prices	8.72 (0.02)	8.73
50,000 sampled prices	8.33 (0.01)	8.33

Note: S.E. is the standard error of the mean. In each simulation there are 19 countries and 500,000 goods. 100 simulations performed.

arises because of how the particular estimator interacts with the bias in the approximation of the trade friction.

The next three rows show how these results change as the number of sampled prices increases. Here increasing the sample size systematically reduces the bias similar to the method of moment results in Table 2. This shows that the key problem with EK's approach is not the estimator per se, but, instead, the poor approximation of the trade costs. Once the sample size of prices becomes large enough, trade costs are better approximated and the bias in the estimate of θ is reduced.

Recall that the purpose of EK's 2SLS estimator was to alleviate an error-in-variables problem. However, 2SLS only works if the error-in-variables problem is classical in the sense that the measurement error is mean zero. The issue identified in this paper is a situation where the measurement error is not classical. The approximated trade friction always underestimates the true trade friction and the approximation error is never mean zero, thus it is not obvious that 2SLS corrects the problem. In fact, the results in Table 13 suggest that 2SLS makes the bias in θ worse when compared to alternative estimators.

3.3. Using EK's 2SLS Estimates as a Basis For Estimation

The estimates from EK's 2SLS approach can be used as the basis for our estimation rather than the estimates from EK's method of moments approach. Specifically, in the exactly identified case, we compare the empirical moment from EK's 2SLS estimation to the averaged simulation moment, which yields the following zero function:

$$y(\theta) = \left[\beta_{2SLS} - \frac{1}{S}\sum_{s=1}^{S}\beta_{2SLS}(\theta, u_s)\right]. \tag{b.50}$$

Our estimation procedure is based on the same moment condition described in the main text:

$$E\left[y(\theta_o)\right] = 0,$$

where θ_o is the true value of θ. Thus, our simulated method of moments estimator is

$$\hat{\theta} = \arg\min_{\theta}\left[y(\theta)'y(\theta)\right], \tag{b.51}$$

where we abstract from the weighting matrix since we focus on the exactly identified case in this section.

Table 14: Estimation Results: 2SLS Moments, EK Data

	Estimate of θ (S.E.)	β_{2SLS}
Data Moments	—	8.03
2SLS Moments, Exactly Identified	4.39 (0.86)	8.03

Table 14 presents the result using EK's data. The first row presents the data moments. Here the estimate of β_{2SLS} is 8.03. This differs from EK's number of 12.86 only because we are using the maximum price difference rather than the second order statistic used in EK. The second row presents the estimate of θ which is 4.39, the standard error, and the model-implied moment.

Note that, while a very different moment is the basis of our estimation, the estimate is nearly identical to the exactly identified results in Table 6, i.e. 4.39 vs. 4.42. On its own, this is a reassuring result because it shows that alternative moments are giving similar answers. Moreover, it suggests that any difference between the results using method of moments vs. 2SLS in EK arises primarily because of how the particular estimator interacts with the bias in the approximation of the trade friction. Yet once this bias is corrected for, we find similar results independent of the particular moment used.

D. Feenstra's 1994 Methodology in the Ricardian Model

In this section we analyze Feenstra's (1994) method to estimate the elasticity of substitution from cross-country data in the context of the Ricardian model. We show that Feenstra's (1994) method recovers the *elasticity of substitution across goods*, i.e. the ρ parameter in CES preferences. *It does not recover the θ parameter controlling the trade elasticity*, i.e. how trade flows change in response to changes in trade costs and the welfare gains from trade. Thus, using the estimates from Feenstra (1994) or Broda and Weinsten (2006) to calibrate the θ parameter in the Ricardian model is inappropriate.

We show this result by asking the following question: given prices and shares generated from the Ricardian model, what would Feenstra's (1994) method recover — the θ or the ρ? To answer this question we will briefly describe Feenstra's (1994) method and its application to simulated data from the Ricardian model. In the description, we will mainly follow Feenstra (2010).

First, we will define an individual variety in Feenstra's (1994) language as a specific good j on the zero-one interval. In the Ricardian model, the expenditure share for good j in country k at date t is given by the following formula:

$$s(j)_{kt} = \frac{p(j)_{kt}^{1-\rho}}{\left\{ \int_0^1 p(\ell)_{kt}^{\frac{1}{1-\rho}} d\ell \right\}^{1-\rho}} \tag{b.52}$$

which is the standard formula for expenditure shares from CES demand structures. Recall that the prices $p(j)$ and $p(\ell)$ are optimal, i.e. they correspond to the lowest cost producer. Aggregate expenditure shares in (4) come from integrating (b.52) over country pair combinations.

Taking logs, differencing, and expressing the denominator (b.52) as a time fixed effect yields

$$\Delta \log s(j)_{kt} = \phi_t - (\rho - 1)\Delta \log p(j)_{kt} + \epsilon(j)_{kt}. \tag{b.53}$$

The final term $\epsilon(j)_{kt}$ represents both trade cost shocks and productivity shocks that will generate variation in shares and prices across time/simulations. Equation (b.53) is the same equation that Feenstra's (1994) methodology exploits.

Feenstra (1994) introduces an upward sloping log-linear supply curve into the estimation of (b.53). Define the "reduced form" supply elasticity as η. By differencing the supply and demand equations with respect to a reference county i and then multiplying these equations together (see Feenstra (2010)) he arrives at the following equations:

$$Y_{kt} = \theta_1 X_{kt} + \theta_2 X_{2kt} + u_{kt}, \tag{b.54}$$

where

$$Y_{kt} = (\Delta \log p(j)_{kt} - \Delta \log p(j)_{it})^2, \tag{b.55}$$

$$X_{1kt} = (\Delta \log s(j)_{kt} - \Delta \log s(j)_{it})^2, \tag{b.56}$$

$$X_{1kt} = (\Delta \log p(j)_{kt} - \Delta \log p(j)_{it})(\Delta \log s(j)_{kt} - \Delta \log s(j)_{it}), \tag{b.57}$$

$$\theta_1 = \frac{\eta}{(\rho-1)^2(1-\eta)}, \quad \theta_2 = \frac{2\eta - 1}{(\rho-1)^2(1-\eta)} \tag{b.58}$$

u_{kt} is an error term composed of the shocks to the demand curve and the supply curve. Then averaging these equations across time yields:

$$\bar{Y}_k \;=\; \theta_1 \bar{X}_{1k} + \theta_2 \bar{X}_{2k} + \bar{u}_k. \tag{b.59}$$

Equation (b.59) relates second moments of price and share changes that linearly depend on demand and supply elasticities. Given the appropriate assumptions on the variances of the error terms across countries and across demand and supply shocks, least squares estimates of (b.59) are consistent. Finally, given the estimates of θ_1 and θ_2 one can recover the demand and supply elasticity by using (b.58).

There is an important point to note here. First — and this should be clear from equations (b.58) and (b.59) — Feenstra's (1994) method can only speak to and recover the parameter ρ, which our Monte-Carlo experiment confirms below. This is an important observation because the parameter ρ does not affect aggregate trade flows or measures of the welfare gains from trade in the Ricardian model.[27]

4.1. Monte-Carlo Study of Feenstra's Method in the Ricardian Model

To further illustrate what Feenstra's (1994) method recovers, we performed the following exercise: We simulated prices and expenditure shares for individual varieties from the Ricardian model when calibrated as in Section 4. To generate time series variation we introduced trade cost shocks, cost shocks, and measurement error in the prices. These shocks are independent across time and countries. All the shocks are multiplicative and log normally distributed with the mean of the associated normal distribution set equal to zero and a standard deviation parameter picked by us.

[27] We suspect that a similar result can be derived for the Melitz (2003) model as articulated in Chaney (2008) because the aggregate trade elasticity there relates to the underlying shape parameter of the Pareto distribution of firm productivity.

Table 15: **Estimates of Demand Elasticity, Feenstra's Method**

	Mean Estimate	Median Estimate
Model, $\theta = 4, \rho = 1.5$	1.51 (0.001)	1.51
Model, $\theta = 4, \rho = 2.5$	2.52 (0.003)	2.52
Model, $\theta = 8, \rho = 1.5$	1.51 (0.001)	1.51
Model, $\theta = 8, \rho = 2.5$	2.51 (0.004)	2.51

Note: In the simulation there are 19 countries with trade frictions and productivity parameters calibrated to fit Eaton and Kortum's (2002) data. 29 periods of data were generated and used, which is consistent with the time series in Broda and Weinsten (2006). Means and medians are over 100 simulations.

Given a sequence of prices and shares as described above we apply Feenstra's (1994) method. Mechanically we implement Feenstra's (1994) method by estimating (b.59) by least-squares while constraining $\theta_1 > 0$. This constraint ensures that the recovered demand elasticity is a real number.

Table 15 presents the results for different θ's and ρ's. In all cases, the mean and median elasticity correspond essentially with the ρ parameter in the calibrated model. In no case does Feenstra's (1994) method correspond with the θ parameter in the model. Thus, Feenstra's (1994) method can only speak to and recover the parameter ρ.

Table 16: 2004 ICP Data, Step 1 Country-Specific Estimates

Country	$\hat{S}_i$	S.E.	ex_i	S.E.	Country	$\hat{S}_i$	S.E.	ex_i	S.E.	Country	$\hat{S}_i$	S.E.	ex_i	S.E.
Angola	−1.04	0.21	−2.67	0.35	Fiji	−0.58	0.20	−2.06	0.31	Nepal	0.48	0.24	−3.00	0.32
Argentina	1.13	0.18	2.34	0.25	Finland	1.09	0.17	2.15	0.23	New Zealand	−0.25	0.30	3.17	0.24
Armenia	0.83	0.20	−3.91	0.29	France	0.39	0.16	5.09	0.22	Nigeria	−0.85	0.25	−1.00	0.29
Australia	0.24	0.16	3.59	0.23	Gabon	−1.07	0.18	−1.52	0.27	Norway	0.33	0.37	1.88	0.23
Austria	0.39	0.16	2.71	0.22	Gambia, The	−2.40	0.22	−2.32	0.34	Oman	−0.19	0.36	−0.74	0.26
Azerbaijan	−0.03	0.20	−2.76	0.28	Georgia	−2.78	0.19	0.70	0.27	Pakistan	0.55	0.29	2.03	0.23
Bangladesh	0.76	0.18	0.46	0.24	Germany	0.40	0.16	5.57	0.22	Paraguay	0.04	0.36	−0.74	0.28
Belarus	1.27	0.18	−0.98	0.25	Ghana	−1.32	0.21	0.44	0.29	Peru	0.47	0.24	1.10	0.25
Belgium	−2.75	0.16	8.26	0.22	Greece	0.78	0.16	0.58	0.23	Philippines	−0.34	0.39	2.64	0.24
Benin	−0.62	0.22	−3.66	0.36	Guinea	−1.76	0.22	−2.16	0.33	Poland	0.84	0.34	1.76	0.23
Bhutan	0.37	0.30	−5.45	0.43	Guinea-Bissau	−0.40	0.28	−5.77	0.48	Portugal	−0.20	0.24	2.71	0.23
Bolivia	0.28	0.19	−1.65	0.29	Hungary	0.86	0.17	0.98	0.23	Romania	0.60	0.25	0.75	0.23
Bosnia and Herzegovina	1.14	0.23	−3.68	0.32	Iceland	−0.26	0.18	−0.55	0.26	Russian Federation	1.32	0.34	2.12	0.23
Botswana	0.97	0.25	−3.73	0.37	India	0.94	0.16	3.53	0.25	Rwanda	0.09	0.27	−5.05	0.36
Brazil	1.30	0.16	3.67	0.23	Indonesia	1.34	0.16	3.07	0.23	Sierra Leone	−0.97	0.25	−3.61	0.41
Brunei Darussalam	1.68	0.25	−5.15	0.37	Iran, Islamic Rep.	1.02	0.21	−0.85	0.28	Saudi Arabia	0.70	0.30	0.70	0.28
Bulgaria	0.30	0.17	0.39	0.24	Ireland	−3.21	0.16	6.39	0.22	Senegal	−0.86	0.27	−0.63	0.25
Burkina Faso	0.32	0.20	−4.07	0.31	Israel	0.59	0.17	1.70	0.24	Slovak Republic	−0.31	0.26	1.34	0.23
Burundi	−1.52	0.20	−3.12	0.34	Italy	0.58	0.16	4.56	0.22	Slovenia	1.02	0.38	−0.20	0.24
Cameroon	1.54	0.21	−3.34	0.30	Japan	1.51	0.16	4.89	0.23	South Africa	0.41	0.25	3.61	0.23
Canada	−0.27	0.16	4.59	0.22	Jordan	−0.25	0.18	−0.65	0.25	Spain	0.29	0.31	4.09	0.22
Cape Verde	−0.37	0.21	−4.86	0.38	Kazakhstan	0.28	0.18	−0.03	0.26	Sri Lanka	−0.14	0.42	0.65	0.25
Central African Republic	0.55	0.25	−4.67	0.36	Kenya	−0.53	0.16	−0.07	0.23	Sudan	−0.12	0.33	−3.47	0.32
Chad	0.54	0.24	−6.49	0.40	Korea, Rep.	1.04	0.16	4.38	0.22	Swaziland	2.10	0.38	−3.30	0.33
Chile	0.27	0.18	1.96	0.25	Kyrgyz Republic	0.03	0.20	−2.86	0.30	Sweden	0.75	0.31	3.34	0.22
China	1.13	0.16	5.74	0.23	Lao PDR	1.43	0.27	−3.92	0.35	Switzerland	0.10	0.25	3.69	0.27
Colombia	0.38	0.17	0.50	0.24	Latvia	−0.46	0.19	−0.10	0.26	Syrian Arab Republic	−0.34	0.31	−0.86	0.26
Comoros	−0.84	0.27	−4.54	0.42	Lebanon	0.60	0.20	−2.29	0.28	Tajikistan	1.10	0.37	−3.19	0.34
Congo, Dem. Rep.	−0.65	0.24	−2.31	0.34	Lesotho	1.09	0.30	−5.44	0.44	Tanzania	−1.01	0.26	−1.41	0.31
Congo, Rep.	−0.95	0.21	−1.08	0.30	Lithuania	0.67	0.21	−0.88	0.29	Thailand	0.86	0.29	3.57	0.28
Cte d'Ivoire	0.78	0.21	−1.22	0.30	Macedonia, FYR	0.41	0.18	−2.71	0.27	Togo	−1.40	0.25	−1.34	0.27
Croatia	1.08	0.16	−1.29	0.24	Malawi	−0.63	0.19	−2.59	0.28	Tunisia	0.34	0.36	−0.30	0.24
Cyprus	−0.86	0.17	0.45	0.24	Malaysia	−1.43	0.16	6.58	0.22	Turkey	0.93	0.28	2.38	0.23
Czech Republic	0.43	0.16	2.02	0.23	Mali	−1.03	0.23	−2.66	0.32	Uganda	−0.71	0.29	−2.30	0.26
Denmark	−0.24	0.16	3.63	0.23	Mauritania	−1.97	0.23	−1.79	0.33	Ukraine	1.41	0.24	0.88	0.28
Djibouti	−2.04	0.24	−2.37	0.38	Mauritius	−1.63	0.17	1.44	0.24	United Kingdom	−0.29	0.32	5.59	0.22
Ecuador	−0.24	0.18	0.12	0.26	Mexico	0.21	0.16	2.61	0.24	United States	0.06	0.34	6.87	0.22
Egypt, Arab Rep.	0.44	0.17	0.62	0.23	Moldova	−0.47	0.19	−2.12	0.29	Uruguay	−0.51	0.29	1.40	0.27
Equatorial Guinea	0.47	0.24	−4.24	0.39	Morocco	−0.39	0.17	1.32	0.23	Venezuela, RB	0.72	0.29	−0.60	0.26
Estonia	−1.74	0.17	1.61	0.24	Mozambique	−0.16	0.22	−2.06	0.33	Vietnam	−0.44	0.24	2.69	0.28
Ethiopia	−0.66	0.21	−2.15	0.31	Namibia	1.09	0.23	−3.64	0.33	Zambia	−3.99	0.30	2.59	0.27

Table 17: EK Data, Step 1 Country-Specific Estimates

Country	$\hat{S}_i$	S.E.	ex_i	S.E.	Country	$\hat{S}_i$	S.E.	ex_i	S.E.
Australia	−0.20	0.15	0.54	0.24	Japan	2.54	0.13	1.74	0.21
Austria	0.50	0.12	−1.65	0.18	Netherlands	−3.09	0.12	0.80	0.18
Belgium	−4.38	0.12	0.98	0.18	New Zealand	−1.42	0.15	0.37	0.24
Canada	−0.46	0.13	1.06	0.22	Norway	−0.34	0.12	−1.01	0.18
Denmark	−1.16	0.12	−0.67	0.18	Portugal	−0.28	0.12	−1.38	0.19
Finland	0.82	0.12	−1.33	0.18	Spain	1.56	0.12	−1.35	0.18
France	1.15	0.12	0.05	0.18	Sweden	0.05	0.12	−0.06	0.18
Germany	1.44	0.12	0.82	0.18	United Kingdom	0.52	0.12	0.89	0.18
Greece	−0.38	0.12	−2.51	0.18	United States	1.34	0.13	2.83	0.22
Italy	1.81	0.12	−0.12	0.18					

Table 18: EIU Data, Step 1 Country-Specific Estimates

Country	$\hat{S}_i$	S.E.	ex_i	S.E.	Country	$\hat{S}_i$	S.E.	ex_i	S.E.	Country	$\hat{S}_i$	S.E.	ex_i	S.E.
Argentina	0.71	0.17	0.74	0.24	Iceland	−0.06	0.17	−3.09	0.24	Poland	0.56	0.16	0.26	0.23
Australia	−0.23	0.16	2.19	0.24	India	0.54	0.16	1.76	0.24	Portugal	−0.03	0.16	0.31	0.23
Austria	0.11	0.16	1.31	0.23	Indonesia	1.01	0.16	1.39	0.23	Romania	0.13	0.16	−0.42	0.23
Azerbaijan	0.06	0.17	−5.28	0.25	Iran, Islamic Rep.	0.75	0.18	−2.71	0.26	Russian Federation	1.17	0.16	0.55	0.24
Belgium	−2.79	0.16	6.16	0.23	Ireland	−3.13	0.16	4.65	0.23	Saudi Arabia	0.22	0.18	−0.59	0.26
Brazil	0.59	0.16	2.33	0.23	Israel	0.08	0.17	0.37	0.24	Senegal	−0.70	0.17	−3.76	0.25
Brunei Darussalam	1.59	0.21	−7.49	0.32	Italy	0.35	0.16	2.93	0.23	Slovak Republic	−0.45	0.16	−0.21	0.23
Bulgaria	0.03	0.17	−1.23	0.24	Japan	1.09	0.16	3.49	0.23	South Africa	0.00	0.16	1.76	0.23
Canada	−0.44	0.16	2.89	0.23	Jordan	−0.81	0.17	−1.88	0.24	Spain	0.03	0.16	2.48	0.23
Central African Republic	0.69	0.21	−7.07	0.31	Kazakhstan	0.55	0.17	−2.45	0.24	Sri Lanka	−0.25	0.17	−1.06	0.24
Chile	−0.04	0.17	0.56	0.24	Kenya	−0.65	0.16	−2.69	0.24	Sweden	0.42	0.16	1.86	0.23
China	0.71	0.16	4.04	0.23	Korea, Rep.	0.58	0.16	3.06	0.23	Switzerland	−0.04	0.18	2.05	0.25
Colombia	0.11	0.16	−1.18	0.24	Malaysia	−1.93	0.16	5.33	0.23	Syrian Arab Republic	−0.41	0.17	−3.04	0.24
Cote d'Ivoire	0.80	0.18	−3.42	0.27	Mexico	−0.23	0.16	1.43	0.24	Thailand	0.51	0.18	1.87	0.25
Czech Republic	0.05	0.16	0.68	0.23	Morocco	−0.47	0.16	−0.65	0.23	Tunisia	0.10	0.16	−2.02	0.24
Denmark	−0.37	0.16	1.74	0.23	Nepal	0.43	0.21	−5.07	0.28	Turkey	0.71	0.16	0.51	0.23
Ecuador	−0.32	0.17	−1.84	0.24	New Zealand	−0.62	0.17	1.75	0.24	Ukraine	1.52	0.18	−1.21	0.26
Egypt, Arab Rep.	0.29	0.16	−1.30	0.23	Nigeria	−1.02	0.18	−2.98	0.26	United Kingdom	−0.38	0.16	3.71	0.23
Ethiopia	−0.68	0.18	−4.15	0.27	Norway	0.35	0.16	0.00	0.23	United States	−0.25	0.16	5.19	0.23
Finland	0.60	0.16	0.93	0.23	Oman	−0.36	0.17	−2.94	0.25	Uruguay	−0.53	0.18	−0.59	0.25
France	0.38	0.16	3.04	0.23	Pakistan	0.30	0.16	0.09	0.23	Venezuela, RB	0.85	0.17	−2.51	0.24
Germany	0.11	0.16	3.95	0.23	Paraguay	−0.03	0.18	−3.03	0.26	Vietnam	−0.37	0.18	0.63	0.26
Greece	0.33	0.16	−0.92	0.23	Peru	0.22	0.17	−0.73	0.24	Zambia	−1.91	0.17	−1.84	0.26
Hungary	0.59	0.16	−0.17	0.23	Philippines	−0.72	0.16	1.50	0.23					

Table 19: Step 1 Trade Cost Estimates and Summary Statistics

Geographic Barriers	**ICP 2004 Data**		**EK Data**		**EIU Data**	
Barrier	Parameter Estimate	S.E.	Parameter Estimate	S.E.	Parameter Estimate	S.E.
$[0, 375)$	-5.30	0.21	-2.89	0.14	-5.02	0.19
$[375, 750)$	-6.29	0.14	-3.56	0.10	-5.28	0.11
$[750, 1500)$	-7.27	0.09	-3.87	0.07	-5.71	0.07
$[1500, 3000)$	-8.50	0.06	-4.10	0.15	-6.63	0.05
$[3000, 6000)$	-9.65	0.04	-6.15	0.09	-7.70	0.04
$[6000, \text{maximum}]$	-10.35	0.05	-6.60	0.10	-8.41	0.04
Shared border	1.25	0.12	0.44	0.14	1.04	0.16

Summary Statistics

	ICP 2004 Data	**EK Data**	**EIU Data**
No. Obs	10,513	342	4,607
TSS	152,660	2,936	47,110
SSR	30,054	76.56	8,208
σ_ν^2	2.93	0.25	1.84

Table 20: 2003-2005 ICP Data, List of 62 Tradable Basic Headings

Product Name	Product Name
Rice	Glassware, tableware and household utensils
Other cereals and flour	Major tools and equipment
Bread	Small tools and miscellaneous accessories
Other bakery products	Non-durable household goods
Pasta products	Pharmaceutical products
Beef and veal	Other medical products
Pork	Therapeutical appliances and equipment
Lamb, mutton and goat	Motor cars
Poultry	Motor cycles
Other meats and preparations	Bicycles
Fresh or frozen fish and seafood	Fuels and lubricants for personal transport equipment
Preserved fish and seafood	Telephone and telefax equipment
Fresh milk	Audio-visual, photographic and information processing equipment
Preserved milk and milk products	Recording media
Cheese	Major durables for outdoor and indoor recreation
Eggs and egg-based products	Other recreational items and equipment
Butter and margarine	Newspapers, books and stationery
Other edible oils and fats	Appliances, articles and products for personal care
Fresh or chilled fruit	Jewellery, clocks and watches
Frozen, preserved or processed fruits	Metal products and equipment
Fresh or chilled vegetables	Transport equipment
Fresh or chilled potatoes	
Frozen or preserved vegetables	
Sugar	
Jams, marmalades and honey	
Confectionery, chocolate and ice cream	
Food products n.e.c.	
Coffee, tea and cocoa	
Mineral waters, soft drinks, fruit and vegetable juices	
Spirits	
Wine	
Beer	
Tobacco	
Clothing materials and accessories	
Garments	
Footwear	
Furniture and furnishings	
Carpets and other floor coverings	
Household textiles	
Major household appliances whether electric or not	
Small electric household appliances	

Table 21: 2004 EIU Data, List of 110 Tradable Goods

Product Name	Product Name	Product Name
White bread, 1 kg	Ham: whole (1 kg)	Business shirt, white
Butter, 500 g	Chicken: frozen (1 kg)	Men's shoes, business wear
Margarine, 500g	Chicken: fresh (1 kg)	Bacon (1 kg)
White rice, 1 kg	Frozen fish fingers (1 kg)	Men's raincoat, Burberry type
Spaghetti (1 kg)	Fresh fish (1 kg)	Socks, wool mixture
Flour, white (1 kg)	Instant coffee (125 g)	Dress, ready to wear, daytime
Sugar, white (1 kg)	Ground coffee (500 g)	Women's shoes, town
Cheese, imported (500 g)	Tea bags (25 bags)	Women's cardigan sweater
Cornflakes (375 g)	Cocoa (250 g)	Women's raincoat, Burberry type
Yoghurt, natural (150 g)	Drinking chocolate (500 g)	Tights, panty hose
Milk, pasteurized (1 l)	Coca-Cola (1 l)	Child's jeans
Olive oil (1 l)	Tonic water (200 ml)	Child's shoes, dresswear
Peanut or corn oil (1 l)	Mineral water (1 l)	Child' s shoes, sportswear
Potatoes (2 kg)	Orange juice (1 l)	Girl's dress
Onions (1 kg)	Wine, common table (1 l)	Boy's jacket, smart
Mushrooms (1 kg)	Wine, superior quality (700 ml)	Compact disc album
Tomatoes (1 kg)	Wine, fine quality (700 ml)	Television, colour (66 cm)
Carrots (1 kg)	Beer, top quality (330 ml)	Kodak colour film (36 exposures)
Oranges (1 kg)	Scotch whisky, six years old (700 ml)	International foreign daily newspaper
Apples (1 kg)	Gin, Gilbey's or equivalent (700 ml)	International weekly news magazine (Time)
Lemons (1 kg)	Vermouth, Martini & Rossi (1 l)	Paperback novel (at bookstore)
Bananas (1 kg)	Cognac, French VSOP (700 ml)	Personal computer (64 MB)
Lettuce (one)	Liqueur, Cointreau (700 ml)	Low priced car (900-1299 cc)
Eggs (12)	Soap (100 g)	Compact car (1300-1799 cc)
Peas, canned (250 g)	Laundry detergent (3 l)	Family car (1800-2499 cc)
Tomatoes, canned (250 g)	Toilet tissue (two rolls)	Deluxe car (2500 cc upwards)
Peaches, canned (500 g)	Dishwashing liquid (750 ml)	Regular unleaded petrol (1 l)
Sliced pineapples, canned (500 g)	Insect-killer spray (330 g)	Cost of six tennis balls eg Dunlop, Wilson
Beef: filet mignon (1 kg)	Light bulbs (two, 60 watts)	
Beef: steak, entrecote (1 kg)	Batteries (two, size D/LR20)	
Beef: stewing, shoulder (1 kg)	Frying pan (Teflon or good equivalent)	
Beef: roast (1 kg)	Electric toaster (for two slices)	
Beef: ground or minced (1 kg)	Aspirins (100 tablets)	
Veal: chops (1 kg)	Razor blades (five pieces)	
Veal: fillet (1 kg)	Toothpaste with fluoride (120 g)	
Veal: roast (1 kg)	Facial tissues (box of 100)	
Lamb: leg (1 kg)	Hand lotion (125 ml)	
Lamb: chops (1 kg)	Shampoo & conditioner in one (400 ml)	
Lamb: Stewing (1 kg)	Lipstick (deluxe type)	
Pork: chops (1 kg)	Cigarettes, Marlboro (pack of 20)	
Pork: loin (1 kg)	Business suit, two piece, medium weight	

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