Online Appendix for *Exporter Heterogeneity and Price Discrimination: A Quantitative View*

March 2018

1 Quantitative Results for All Directly Additive Non-Homothetic Models

The results reported in this appendix appeared originally in Jung et al. (2015). Notice that in revised versions we have focused solely on the Generalized CES (GCES) case and also switched to Chilean firm-level data. In the previous version we quantified the GCES along with alternative preferences: log-linear generalized CES as used in Simonovska (2015) (SIM), quadratic demand as in Melitz and Ottaviano (2008) (MO) but without the non-separable term (η), and negative exponential demand as in Behrens et al. (2014) (BMMS). Instead of the moments from Chilean data, in this version we targeted moments from the U.S. firm distribution as reported in Bernard et al. (2003). These results provide a useful parameterization of non-homthetic demand preferences with Pareto productivity that matches US firm data. Also, they are useful as a comparison of parameters across the different models.

1.1 Data

The gravity estimation is based on data from 71 countries for the year 2004. This is a slightly larger sample than in our current version where we drop 5 countries. We construct bilateral trade shares, $\lambda_{ij} = \frac{X_{ij}}{Y_j}$, using nominal trade flows X_{ij} and gross output, adjusted for trade imbalances Y_j[1], from UNIDO. To estimate parameters from the gravity equation, we use country-pair gravity variables from CEPII. The Penn World Table (PWT) 8.0 provides our variable L, population.

[1]For each country, this corresponds to gross manufacturing production minus manufacturing exports (in the sample) plus manufacturing imports (in the sample) to j.

We also rely on two moments that characterize firm behavior: US exporter sales advantage in the domestic market, which is 4.8 according to BEJK, and US exporter measured productivity advantage (in logs), which is 33 percent according to BEJK. These two moments serve to identify the two parameters that govern the size and productivity distribution of firms (θ, σ).

1.2 Results

The quantitative results for the generalized CES model verify our claim that adding curvature to the demand function (relative to the SIM benchmark), or allowing σ to be greater than one, is necessary to jointly match the two firm-level moments of interest. Notice that σ affects the size distribution of firms by varying the substitution across goods. As σ increases, the market power of each firm is smaller, and more productive firms gain sales relative to less productive firms as consumers do not value variety as much. The Pareto shape parameter determines the variability in firm productivity, so a lower θ (more variance) raises the measured productivity advantage —- which we call the markup advantage in the current version – of more productive firms.

Table 1: Moments and Parameters

Model	Data/Targets	σ	θ	Simulated Moment
Generalized CES	$M_{sales} = 4.80$, $M_{prod} = 0.33$	1.41	1.92	$M_{sales} = 4.80$, $M_{prod} = 0.33$
SIM (MP)	$M_{prod} = 0.33$	1	2.11	$M_{sales} = 4.16$, $M_{prod} = 0.33$
SIM (SA)	$M_{sales} = 4.80$	1	3.33	$M_{sales} = 4.80$, $M_{prod} = 0.20$
MO ($\eta = 0$) (MP)	$M_{prod} = 0.33$	–	2.44	$M_{sales} = 3.04$, $M_{prod} = 0.33$
MO ($\eta = 0$) (SA)	$M_{sales} = 4.80$	–	6.46	$M_{sales} = 4.80$, $M_{prod} = 0.10$
BMMS (MP)	$M_{prod} = 0.33$	–	2.37	$M_{sales} = 3.47$, $M_{prod} = 0.33$
BMMS (SA)	$M_{sales} = 4.80$	–	5.09	$M_{sales} = 4.80$, $M_{prod} = 0.13$

Table 1 displays the calibrated parameter values for all the separable models. For the existing models, we calibrate θ to match either the measured productivity advantage (MP) or the sales advantage of exporters (SA). We demonstrated theoretically that it is impossible to match both moments with the same value for θ. In the second row of the table, we successfully match only the productivity advantage in the SIM model with a θ close to the general model. In the third row, for a higher value of the Pareto shape parameter, the sales advantage is attainable but at the cost of a very low productivity advantage.

The separable MO and BMMS models behave qualitatively similarly to the SIM model, but there are notable quantitative differences.[2] Having reconciled the productivity advantage, the

[2]The value of the Pareto parameter that we obtain is lower than in Behrens et al. (2014) who calibrate it

two models struggle more to generate a dispersion in sales. Notice that, when the SIM model matches the measured productivity dispersion, it generates a sales dispersion that falls only somewhat short of the moment observed in the data. This is further confirmed by the fact that the generalized CES model requires a value for σ that is only 40% higher than unity to match the sales advantage in the data, conditional on matching the measured productivity with a value for the Pareto shape parameter of 1.92, which is only slightly below the 2.11 value that the SIM model requires.

1.3 Model Predictions and Fit to Data

Given that the general model is consistent with the cross-sectional observations on firm productivity and sales, we also test how the model fits other aspects of the data. Throughout, we maintain a comparison to the fit of the restricted models under the two values for θ reported above. We examine the following moments in the data: i) percentage of US firms that export, ii) the export intensity of exporting firms, iii) the standard deviation in log domestic sales, iv) the elasticity of prices of tradables with respect to per capita income, and v) the average markup.

1.3.1 Exporting Firms

The first prediction that we examine is the fraction of firms that export. Bernard et al. (2012) report that in 2002, 18% of American manufacturing firms exported, and BEJK report this number to be 21% in 1992 data. In our model, there are two determinants of export entry: i) iceberg trade barriers raise the cost to serve foreign markets and ii) destination specific aggregates determine the cutoff cost to sell in each country. The fraction of firms that export is given by the following equation:

$$M^m_{i,ex} = \frac{(\tilde{c}^x_{ii})^\theta}{(\bar{c}_i)^\theta}, \tag{1}$$

where the numerator is the familiar cost cutoff for firms from country i that serve at least one export destination j. We are interested in the relative cutoffs of the US and its easiest exporting destination, which corresponds to Canada in the simulated models.

Table 2 presents the results for the four models along with the data. The generalized CES model and the restricted models, under the MP parameterization, predict a very similar fraction of exporters, which is below 50%—hence, exporters are in the minority as documented

to be 8.5. Our strategies are different in terms of the sample of countries used, wages (they use labor income share for gross output), and, most importantly, trade cost specification: Behrens et al. (2014) posit that trade costs are symmetric.

Table 2: US Exporters, % of Total

Model	Data	σ	θ	% of Firms that Export
Generalized CES	18-21%	1.41	1.92	41.4%
SIM (MP)	18-21%	1	2.11	42.7%
SIM (SA)	18-21%	1	3.33	49.2%
MO ($\eta = 0$) (MP)	18-21%	–	2.44	44.8%
MO ($\eta = 0$) (SA)	18-21%	–	6.46	57.1%
BMMS (MP)	18-21%	–	2.37	44.4%
BMMS (SA)	18-21%	–	5.09	54.5%

in BEJK.[3] The small difference in the values of the last column are solely attributed to the (relatively) small difference in the Pareto shape parameter across the calibrated models. However, when the restricted models fit the sales advantage moment, they severely overpredict the fraction of exporters, which is problematic.

1.3.2 Export Intensity

BEJK report that even the small fraction of firms that do export sell mostly at home. To evaluate the models' predictions along this dimension, for US exporters, we also compute the fraction of total firm sales that are exported and call this the export intensity:

$$EXINT_i(s) = \frac{\sum_{v \neq i} \delta_{iv}(s)\bar{c}_v L_v \bar{q}(t_{iv}^{1-\sigma}(s) - t_{iv}(s))}{\sum_{v=1}^{I} \delta_{iv}(s)\bar{c}_v L_v \bar{q}(t_{iv}^{1-\sigma}(s) - t_{iv}(s))}$$

with firms indexed by s. Then, as in BEJK, we measure the percentage of exporters that fall into certain ranges of export intensity.

Table 3: % of Exporting Plants Conditional on Export Intensity

Exp. Intensity (%)	Data (%)	General CES	SIM (MP)	MO ($\eta = 0$) (MP)	BMMS (MP)
0-10	66	88.3	85.9	79.5	82.2
10-20	16	11.4	13.7	20.0	17.3
20-30	7.7	0.1	0.2	0.1	0.2
30-40	4.4	0.1	0.1	0.1	0.1
40-50	2.4	0.1	0.1	0.1	0.1
50-60	1.5	0	0	0.1	0.1
60-100	2.8	0	0	0.1	0

[3] All four models overpredict the fraction of exporters. Similarly, BEJK find that their calibrated model overpredicts the fraction of exporters—the authors obtain a value of 51%.

In Table 3, we report the moments in the data and the models. We condition on only exporting firms and split export intensity into deciles in order to measure the percentage of firms that fall within a certain range of export intensity. For example, the first row shows that in the generalized CES model 88.3% of exporting firms have export revenue that is less than 10% of their total revenue. In the simulated generalized CES model, there are many very small exporting firms, more-so than in the data. Part of this is due to the fact that trade costs are large when θ is only 1.92. This increases the difference between the domestic cutoff cost and the cutoff for exporting. Still, we are able to pick up the small number of exporters that have a very large export intensity in the lower rows. 0.1% of the simulated exporters have an export intensity between 40-50%, and none greater than 50%.

Reducing σ can also reduce the fraction of exporters with very low export intensity because with less substitution there is a lower sales advantage for the very productive firms. When $\sigma = 1$, the value in the first row of the fourth column decreases, although by little. The separable MO and BMMS models show little bit better predictions for the portion of exporters with higher export intensity. All the separable models that match the SA moment yield similar numbers but exhibit higher weight on lower export intensities.

1.3.3 Variability of Domestic Sales

We compute the standard deviation of the log of normalized domestic sales. Log (normalized) domestic sales are firm domestic sales relative to total domestic sales: $\log\left(\frac{r_{ii}(s)}{T_{ii}}\right)$. T_{ii} is constant, so the standard deviation of log domestic sales relative to total domestic sales is equivalent to the standard deviation of log domestic sales, but the normalization allows us to compute the desired statistics without having to calibrate additional parameters from the models.

For the generalized CES model, the value amounts to 1.26, which falls somewhat short of the statistic in the US in 1992 of 1.67, as reported in BEJK. Similarly, BEJK struggle to match this statistic using the model that they develop. As in BEJK, higher values of σ raise the sales variance, but they also raise the sales advantage of exporters relative to non-exporters. To the extent that we discipline the model along the second dimension, we fall short along the first.

In the SIM model, the statistics are comparable and amount to 1.20 (MP) and 1.22 (SA). The values are considerably lower in the remaining separable models. The standard deviations of log domestic sales in the MO model are 1.04 (MP) and 1.17 (SA), whereas in BMMS they are 1.10 (MP) and 1.19 (SA).

1.3.4 Prices and Income

An important aspect of the data that the models analyzed in this paper attempt to explain is price dispersion across markets. A major feature of variable markup models is that they can explain a large portion of the variation in the prices of identical tradable goods (see the discussion in Simonovska (2015)). In particular, as argued in previous sections, the models yield a positive relationship between prices and per-capita income of destinations. Below, we quantify this relationship and we compare the findings to those that we obtain from two commonly-employed price datasets.

To begin, we investigate the relationship between price and income in the data using prices reported by the Economist Intelligence Unit (EIU) and the International Comparison Program (ICP). The EIU reports prices of 110 goods sold in all the countries in our sample. The EIU surveys the prices of individual goods across various cities in two types of retail stores: mid-priced, or branded stores, and supermarkets, or chain stores. The dataset contains the nominal prices of goods and services, reported in local currency, as well as nominal exchange rates relative to the US dollar, which are recorded at the time of the survey. While in the majority of the countries, price surveys are conducted in a single major city, in 17 of the 71 countries multiple cities are surveyed. For these countries, we use the price data from the city which provided the maximum coverage of goods. In most instances, the location that satisfied this requirement was the largest city in the country.

For comparison, we also examine prices from the ICP. The ICP collects price data on goods with identical characteristics across retail locations in 123 countries during the 2003-2005 period. The basic-heading level represents a narrowly-defined group of goods for which expenditure data are available. The data set contains a total of 129 basic headings, which include goods and services. We employ a subsample of 62 tradable categories in order to maintain consistency with the models' assumption that all products are potentially tradable.[4] For both datasets, we construct price indices by taking a geometric average across goods within a country, where all individual good prices are normalized relative to the US.

We follow a similar strategy to generate price indices from the models. However, before constructing price indices, we need to simulate individual good prices. We proceed by following a simulation and sampling methodology introduced by Simonovska and Waugh (2014), which aims to replicate steps taken to construct the ICP database. In particular, we construct a set of "common" goods and then we draw 100 random samples of 110 products from the set. We compute relative prices and geometric average price indices for each sample and we plot the mean index across all 100 samples for each country. What remains is to discuss the definition of

[4]For more detailed information about the ICP data, see the discussions in Simonovska and Waugh (2014) and Deaton and Heston (2010).

a "common" good. We define a good to be "common" if it appears in at least 30 destinations—nearly half the destinations used in our analysis. Since each good is produced by a single firm, this rule implies that we consider firms that serve at least 30 destinations. The motivation to follow this rule is that Eaton et al. (2004) report that only 1.5% of exporters serve more than 50 destinations but many exporters (20%) serve at least 10 destinations. We choose a value in the middle that would still include a significant number of exporters.

Figure 1: Geometric Mean of Relative Prices versus Income per Capita

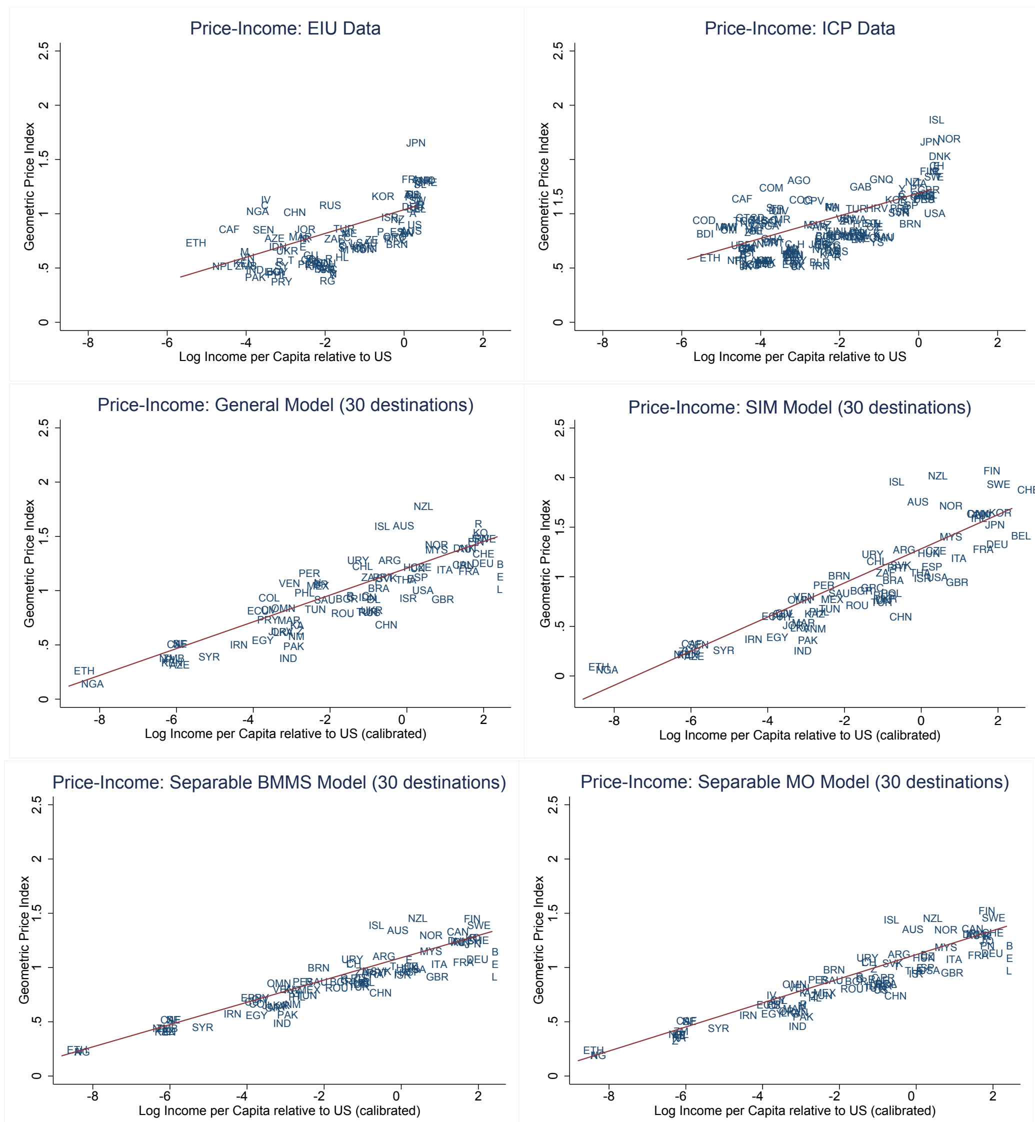


Figure 1 illustrates the geometric price index, plotted against per capita income, in the data and in the four simulated models, when the Pareto shape parameter is calibrated to match the measured productivity moment. In the EIU data (with 71 countries), the slope of the best fit line is a statistically significant 0.11 (standard deviation, 0.015). For robustness, in the top right plot, we show results obtained from the ICP database, which samples a different set of goods than the EIU one and covers a broader set of countries (123 in total). The price-income relationship is almost identical to the one in the EIU data, with the slope of the line of best fit being equal to 0.10 (standard deviation, 0.011). We simulate the models and compute price indices for the set of countries covered in the EIU database. The generalized CES model yields a (statistically significant) slope of 0.12 (standard deviation, 0.009), while its more restricted counterpart yields a coefficient of 0.17 (standard deviation, 0.011), under the calibration that targets measured-productivity. Similarly, the BMMS model yields a slope of 0.10 (standard deviation, 0.006), while the separable MO model yields a slope of 0.11 (standard deviation, 0.006).[5] Hence, the models behave similarly along this dimension and are quantitatively in line with the data.

1.3.5 Average Markups

The average markup is another important price statistic emphasized by the empirical trade and macro literature. Jaimovich and Floetotto (2008) conduct a survey of the literature and document that the average markup found using value added data is in the range of 20-40%. We compute the average markup on domestic sales for domestic firms in our simulation as $\int_0^{\bar{c}_i} \frac{p_{ii}(c_{ii})}{c_{ii}} d\mu_{ii}(c)$. Although we use only domestic firms[6], the average is not source-specific so this number would not change if foreign firms were included.

In the generalized CES model, the average markup of producers selling domestically amounts to 31%, which lies in the middle of the range provided by Jaimovich and Floetotto (2008). In the restricted counterpart, the average markups are 31% and 18% for the MP and SA calibrations, respectively. Hence, when the restricted model's parameters are calibrated to match the measured-productivity advantage of exporters, the model yields a comparable average mark-up to the generalized counterpart. As in De Loecker and Warzynski (2012), exporters have higher markups than non-exporters. The relative markups of exporters to non-exporters amount to 5.7 in the generalized CES model and in the restricted model they amount to roughly 6.4 between the two calibration strategies.

In the remaining two models, the average level of mark-ups is more sensitive to the calibration of choice. In the BMMS model, the mark-ups are 32% (MP) and 12% (SA), respectively. In the separable MO model that matches the productivity advantage moment the mark-up is 35%, however the mark-up drops to a mere 9% in the alternative calibration. Hence, the three

[5]When the models' parameters are calibrated to match the sales advantage moment, the price elasticities are 0.13 (0.005), 0.06 (0.002), and 0.06 (0.002) for the SIM, MO, and BMMS models, respectively, where standard deviations are in parentheses.

[6]Domestic firms are the basis for the markup estimates in Basu and Fernald (1997), Hall (1988), Roeger (1995), Norrbin (1993) (US), and Martins et al. (1996) (OECD).

separable models yield average mark-ups that are in line with data when their parameters are calibrated to match the measured-productivity moments, but they predict significantly lower mark-ups under the alternative calibration strategy. The sensitivity of the average mark-up to the calibration strategy of choice appears to be lowest for the SIM model.

1.4 Melitz Ottaviano (2008) with non-separable preferences: Quantitative Analysis

In the Appendix of the main text, we show that like the generalized CES one, Melitz and Ottaviano (2008) can potentially match both the sales and the measured productivity advantage of exporters. It does so via a very different channel: the (normalized) sales distribution is still fixed by θ in this model, but the value of K allows for a flexible cost cutoff, which is not the case in the separable models. In this model, the relative cost cutoffs are not fixed by wages and gravity variables, but shift according to the parameter values of K.

Below, we compare the quantitative predictions of this model to the generalized CES. The calibration results are in Table 4. We calibrate θ and K to match the two moments derived above.

Table 4: Moments and Parameters

Model	Data/Targets	σ	θ	K	Simulated Moment
Generalized CES	$M_{sales} = 4.80$, $M_{prod} = 0.33$	1.41	1.92	–	$M_{sales} = 4.80$, $M_{prod} = 0.33$
Melitz and Ottaviano (2008)	$M_{sales} = 4.80$, $M_{prod} = 0.33$	–	2.01	1.21	$M_{sales} = 4.80$, $M_{prod} = 0.33$

While the model matches the two moments, its out of sample predictions stray widely from the data and from the predictions of the calibrated non-separable MO model. First, exporters are now the majority of firms. Table 5 reports that 74% of firms export in the MO model compared to 41% in the generalized CES (and their calibrated θ are similar). Second, the non-separable MO model displays counterfactual predictions of export intensity. Table 6 compares the results for both models. In the MO model, only a minority of firms are in the 0-10% decile of export intensity.

Further, the standard deviation of log domestic sales is 1.0 in the model, compared to a value of 1.26 in the generalized CES model and a value of 1.67 in the 1992 US Census data as reported by BEJK.

Price discrimination across countries in the model is quite high and amounts to three times more than in the data. The model yields a slope coefficient of 0.35 (standard deviation is 0.04), which is high compared to the generalized CES case (0.12 with standard deviation of 0.009)

Table 5: US Exporters, % of Total

Model	Data	σ	θ	% of Firms that Export
Generalized CES	18-21%	1.41	1.92	41.4%
Melitz and Ottaviano (2008)	18-21%	–	2.01	73.6%

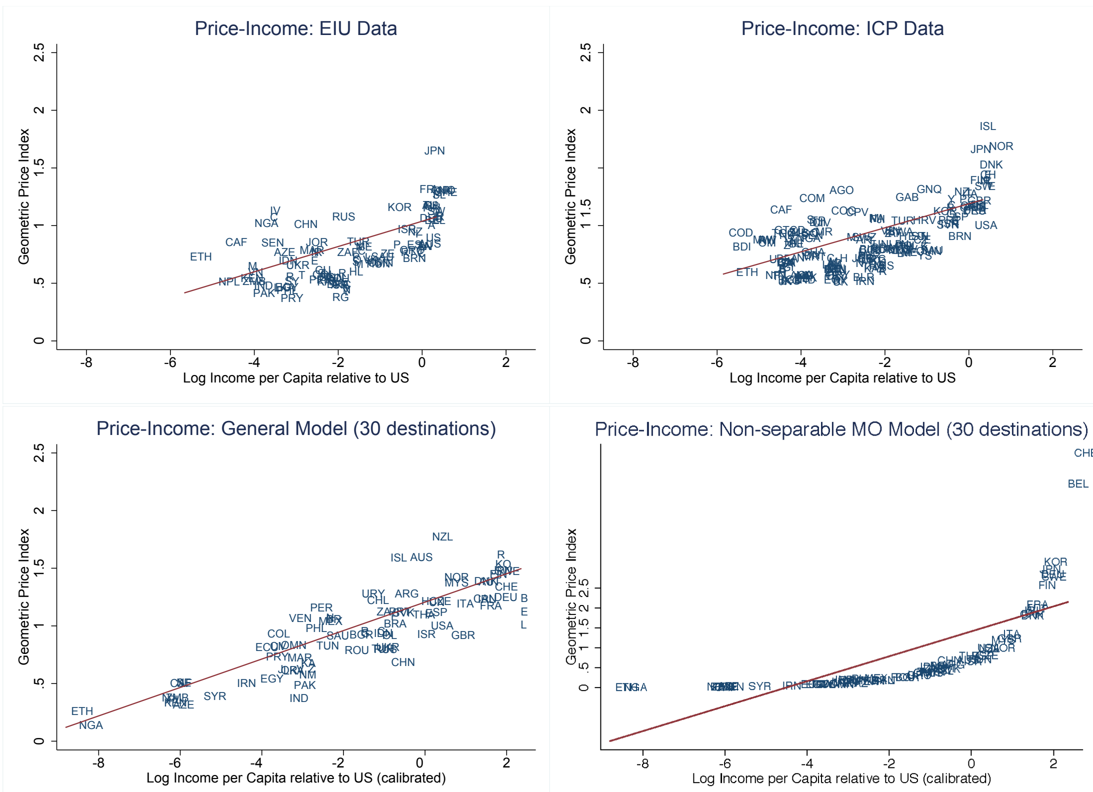
Table 6: % of Exporting Plants Conditional on Export Intensity

Exp. Intensity (%)	Data (%)	General CES	Melitz and Ottaviano (2008)
0-10	66	88.3	39.8
10-20	16	11.4	51.4
20-30	7.7	0.1	2.6
30-40	4.4	0.1	2.2
40-50	2.4	0.1	2.1
50-60	1.5	0	0.5
60-100	2.8	0	1.4

Conditioning on only exporting firms, the export intensity (first column) is the export revenue over total revenue, and we split firms into deciles. For example the first row shows that in the generalized CES model 88.3% of exporting firms have export revenue that is less than 10% of their total revenue. The data is also reported in Bernard et al. (2003) (using 1992 data for the US).

and to the data (0.11 for EIU data and 0.10 for ICP data). The fourth plot in figure 2 shows the predicted price indices in the MO model. As it can be seen, the model yields a very skewed distribution of prices across countries. The implication is an average markup on domestic sales of 50%, which exceeds values reported in the data.

Figure 2: Geometric Mean of Relative Prices versus Income per Capita



Relative prices in the data are taken from EIU. In the model, we simulate firms in each calibrated model and capture firm prices to each destination. In model and data we define relative prices as the price of a good relative to the price in the US, and then take a geometric average of 110 relative prices for each country. For the simulated model, common goods are such that they are sold in at least 30 destinations. There are more than 110 common goods available in the sample, so to reduce sampling error we have 100 draws of 110 random goods. For the simulation we can report the average price-income slope after having computed it for 100 draws.

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