A Maximum Entropy Estimation of Armington Elasticities for Mexico.

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**Abstract**: Armington elasticities are a key parameter in applied general equilibrium models, more so in those models used to analyze free trade agreements and other trade related issues. However, frequently only educated guesses, or extrapolated figures, are used to run the models, and Mexico has not been an exception. In this paper, given the quantity and quality of available data from the Mexican Statistics Institute, we consider the Maximum Entropy approach to be a suitable tool to estimate such elasticities for Mexico. Using annual time series from 1988 to 2004, we estimate the Armington elasticities using the 72 Activities disaggregation level of the System of National Accounts of Mexico (SNAM). Specifically, we use three main model specifications to estimate short run and long run elasticities. The first model is just the simplest regression in levels, while the second one is a partial adjustment model, and the third one an error correction mechanism model.

**Keywords**: Armington elasticity, Maximum entropy, Mexico.

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## 1. Introduction

The structure introduced by Armington (1969) has been used to analyze trade policy in partial and general equilibrium models. The Armington Elasticities (AE), which is to say the degree of substitution between domestic and imported goods, are known to be important, but are seldom estimated empirically and, to our knowledge, no AE have been estimated for Mexico, which casts some doubts, for example, on CGE models used to analyze the NAFTA from Mexico's viewpoint.

Armington Elasticities (AE) are a key parameter in applied general equilibrium models, more so in those models used to analyze free trade agreements and other trade related issues. However, frequently only educated guesses, or extrapolated figures, are used to run the models, and Mexico has not been an exception. In this working paper, given the quantity and quality of available data from the Mexican "National Institute of Satitistics, Geography and Informatics" (INEGI), we consider the Maximum Entropy (ME) approach to be a suitable tool to estimate said elasticities. Using time series from 1988 to 2004, we estimate the AE for the main 61 aggregated commodities, according to the classification of the System of National Accounts of Mexico (SNAM). Specifically, we use three main model specifications to estimate short run and long run elasticities. The first model is just the simplest regression in levels, while the second one is a partial adjustment model, and the third one an error correction mechanism model.

## 2. The Armington Elasticity (AE)

Armington (1969) assumed that, besides being differentiated by kind, goods are also differentiated by their place of production, and in this sense he distinguished among "goods" and "products". Therefore, products from one country are not perfect substitutes for the same kind of products from another country.

Then, for each sector *i*, total domestic supply results from a CES aggregation of domestically produced goods and imported goods:

$$Q_i = \bar{Q}_i\left[\rho_i M_i^{-\rho_i} + (1-\delta_i)D_i^{-\rho_i}\right]^{-1/\rho_i} \qquad (2.1)$$

Where $Q_i$, $M_i$, and $D_i$, are respectively, total supply, imports, and domestic production, in sector $i$, $\bar{Q}_i$ the scale parameter, $0<\delta_i<1$ a distribution parameter, and $\rho_i$ accounts for the degree of substitution between imported and domestic goods. Since the CES function is specified with negative powers, then $\rho_i > -1$; and $\sigma_i = 1/(1+\rho_i)$ .

Considering prices $P_{Mi}$ and $P_{Di}$ for imports and domestic goods respectively, and assuming a representative firm, the firm's optimal ratio, $M_i/D_i$, as given by cost minimization is:

$$\frac{M_i}{D_i} = \left(\frac{\delta_i}{1-\delta_i}\frac{P_{Di}}{P_{Mi}}\right)^{\sigma_i} \qquad (2.2)$$

And then, the optimal ratio, $M_i/D_i$, is a function of (variable) prices and (constant) parameters. Note that, for $\rho_i=0$ the CES function collapses to a Cobb-Douglas and the (constant) elasticity of substitution equals 1, then the optimal ratio is a function of prices as given by (2). Else, for $\rho_i > -1$, $\sigma_i \neq 1$ and diverse degrees of substitution will be observed for different sectors.

Therefore, if $\rho_i \to \infty$, then $\sigma_i \to 0$, and there is no substitution between imports and domestic goods, so that the optimal ratio is independent of relative prices. And, if $\rho_i \to -1$, then $\sigma_i \to \infty$, and both goods are said to be perfect substitutes.

Then, we can see that small changes in relative prices, might promote significant changes in the optimal ratio, depending on how big $\sigma_i$ is. To illustrate this, suppose $P_{Mi}$ decreases (while $P_{Di}$ remains unchanged), then the whole expression inside the parenthesis will increase; if $\sigma_i>1$, this will cause an even higher increase in the optimal ratio. However, if transmission mechanisms allow for a full reaction of domestic prices, then the domestic price will increase up to the point, where the optimal ratio will recover its former level.

### 3. Traditional Estimation of $\sigma_i$.

Traditional estimation of Armington elasticities departs from the optimal ratio in (2), to estimate $\sigma_i$ from time series for $M_i/D_i$ and $P_{Di}/P_{Mi}$; usually considering that, the relevant price for imports is the CIF price, a function of the foreign price (in foreign or international currency) ($P_{Ei}$), the exchange rate ($e$), and the tariff ($\tau_i$), so that $P_{Mi} = P_{Ei}\, e\, (1+\tau_i)$ .

However this approach has been subject to several problems, which had prevented many researchers from estimating Armington elasticities, leading them to rely on sensitivity analysis instead, or informal adjustment of parameters to meet target observed variables.

One of the main problems has been lack of information, mainly in developing countries. And also data processing, since some variables must suffer several manipulations before they can be used in a traditional econometric estimation.

Second, econometric estimates are almost always obtained using annual data. The elasticities obtained are thus short run. However, most CGE analysis consider much longer periods of adjustment. Short run elasticities are likely to understate the response capacity of agents over longer periods.

Third, given the large number of parameters to be estimated, long time series data for numerous variables are required to provide sufficient degrees of freedom for estimation. In many cases, the economy is likely to have undergone structural changes over the period, which may or may not be appropriately reflected in the estimation procedure.

Finally, even those econometric estimates designed specifically to feed parameter estimates to CGE models undertake estimation without imposition of the full set of general equilibrium constraints. While the estimated parameters might provide a highly plausible description of historical production and consumption data sets, the estimated values will not be fully compatible with the general equilibrium system they are designed to represent.

For this reasons, the so called maximum entropy approach, which presumably overcomes these problems, and has some additional advantages, has been developed to tackle several estimation problems in economics, and particularly, estimation of CGE models parameters.

## 4. (Generalized) Maximum Entropy Estimation

The Maximum Entropy (ME) approach is motivated by "information theory" and a function to measure the uncertainty, or entropy, of a collection of events, and the maximization of that function subject to appropriate consistency relations, such as moment conditions.

In general, information in an estimation problem using the entropy principle comes in two forms: 1) information (theoretical or empirical) about the system that imposes constraints on the values that the various parameters can take; and 2) prior knowledge of likely parameter values.

In the first case, the information is applied by specifying constraint equations in the estimation procedure. In the second, the information is applied by specifying a discrete prior distribution and estimating by minimizing the entropy distance between the estimated and prior distribution –the Minimum Cross-Entropy approach. Since we do not have any prior information on our subject parameters, only the (Generalized) Maximum Entropy principle will be used.

### 4.1 The model.

For each Activity *i*, the optimal ratio $\frac{M}{D} = \left(\frac{\delta}{1-\delta}\frac{P_D}{P_M}\right)^{\sigma}$ can be log-linearized as:

$$log\left(\frac{M}{D}\right) = \sigma ln\left(\frac{\delta}{1-\delta}\right) + \sigma ln\left(\frac{P_D}{P_M}\right) \tag{4.1}$$

And the econometric model (or consistency constraint) specified as:

$$ln\left(\frac{M(t)}{D(t)}\right) = \beta_1 + \beta_2 ln\left(\frac{P_D(t)}{P_M(t)}\right) + e(t) \tag{4.2}$$

Where $t$ $(=1,2,\ldots,T)$ is the number of data points, $\beta_1$ the constant term, $\beta_2$ the Armington elasticity, and $e$ the noise associated to each equation. We call (4.2) the Base Model (BM).

Since no a priori information on the distributions is available, instead of using the more general cross entropy specification, we directly focus on the maximum entropy (ME) specification. In order to specify the (Generalized) ME problem, consider the parametric space supports $\boldsymbol{z}_k=(z_{k1},\ldots,z_{kM})'$, $k=1,2$, $M=5$,[1] with corresponding probabilities $\boldsymbol{p_k}=(p_{k1},\ldots,p_{kM})'$, for the vector of parameters $\boldsymbol{\beta}=(\beta_1,\beta_2)'$, and the support $\boldsymbol{v}_t=(v_1,\ldots,v_J)'$, $J=3$, with corresponding weights $\boldsymbol{w_t}=(w_{1t},\ldots,w_{Jt})'$ for the noise terms $\boldsymbol{e} \in \mathbb{R}^T$. Given this specifications we can re-parameterize as follows:

$$\boldsymbol{\beta} = \boldsymbol{Zp} = \begin{bmatrix} \boldsymbol{z}_1' & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{z}_2' \end{bmatrix} \begin{bmatrix} \boldsymbol{p_1} \\ \boldsymbol{p_2} \end{bmatrix} \tag{4.3}$$

$$\boldsymbol{e} = \boldsymbol{Vw} = \begin{bmatrix} \boldsymbol{v}' & \ldots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \ldots & \boldsymbol{v}' \end{bmatrix} \begin{bmatrix} \boldsymbol{w}_1 \\ \vdots \\ \boldsymbol{w}_T \end{bmatrix} \tag{4.4}$$

Where $\boldsymbol{Z}$ is the $(K\times KM)$ matrix of parameter supports, $\boldsymbol{p} \in \mathbb{R}^{KM}$ is the vector of unknown parameters, $\boldsymbol{V}$ is the $(T\times JT)$ matrix of error supports, and $\boldsymbol{w} \in \mathbb{R}^{JT}$ the vector of unknown errors. Then (following Golan et al. 1996, and Golan 2008) we can state the ME problem as:

$$max_{\boldsymbol{p},\boldsymbol{w}}\ H(\boldsymbol{p},\boldsymbol{w}) = \boldsymbol{p}'\,ln(\boldsymbol{p}) - \boldsymbol{w}'ln(\boldsymbol{w}) \tag{4.5}$$

Subject to

[1] According to Golan, et al. (1996).

$$ln\left(\frac{M(t)}{D(t)}\right) = \sum_{m=1}^{5} z_{1m} p_{1m} + \sum_{m=1}^{5} z_{2m} p_{2m} \left(\frac{P_D(t)}{P_M(t)}\right) + \sum_{j=1}^{3} v_j w_{jt} \ , \forall t \qquad (4.6)$$[2]

$$\mathbf{1}_{\boldsymbol{K}} = (\boldsymbol{I}_{\boldsymbol{K}} \otimes \mathbf{1}_{\boldsymbol{M}}^{'})\boldsymbol{p} \qquad (4.7)$$

$$\mathbf{1}_{\boldsymbol{T}} = \left(\boldsymbol{I}_{\boldsymbol{T}} \otimes \mathbf{1}_{\boldsymbol{J}}^{'}\right)\boldsymbol{w} \qquad (4.8)$$

## 5. The data

We use four data sets provided by the National Institute of Statistics, Geography and Informatics (INEGI), all four sets containing yearly information from 1988 to 2004 for i) Domestic Production in current pesos, ii) Domestic Production in Constant Pesos of 1993, iii) Imports in current pesos and iv) Imports in constant pesos of 1993, at the 72 industries or activities disaggregation level. Therefore we have 17 yearly observations for each variable. Also, these data sets do not include *maquila*.

To build the series used for the ME estimation of Armington Elasticities, we begin by dividing domestic production in current pesos by domestic production in constant pesos to obtain price indexes for domestic production, the same applies to imports. Then we divide Imports in constant pesos by domestic Production in constant pesos, and take the natural logarithm, to obtain the series for the ratio *ln(M/D)*; and finally, we divide domestic prices by imports prices, and take de natural logarithm to obtain the series for the ratio $ln(P_D/P_M)$.

## 6. Results

In the first place we estimate the base model (BM) in levels to obtain annually based (short run) Armington elasticities. According to the above specifications, a typical output

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[2] In matrix form: $\boldsymbol{\alpha} = \boldsymbol{\Gamma Z p} + \boldsymbol{V w},$ where $\boldsymbol{\alpha} = \begin{bmatrix} ln\left(\frac{M(1)}{D(1)}\right) \\ \vdots \\ ln\left(\frac{M(T)}{D(T)}\right) \end{bmatrix}$, and $\boldsymbol{\Gamma} = \begin{bmatrix} 1 & ln\left(\frac{p_D(1)}{p_M(1)}\right) \\ \vdots & \vdots \\ 1 & ln\left(\frac{p_D(T)}{p_M(T)}\right) \end{bmatrix}$.

for an activity results as Table 6.1 shows. In this table the first column specifies the parameters support set, second column shows the ME estimated AE for each support set, and the third column the corresponding normalized entropy.

**Table 6.1** Output for Activity 2 (Livestock) from Maximum Entropy estimation of Base Model

| **A2 Livestock** | $\beta$2 COEFF | NORMALIZED ENTROPY |
|---|---|---|
| PARAMETERS SUPPORT | (SRAE*) | |
| (-10, -5, 0, 5, 10) | 2.684 | 0.934 |
| (-20, -10, 0, 10, 20) | 2.870 | 0.983 |
| (-40 -20, 0, 20, 40) | 2.921 | 0.996 |
| (-80, -40 0, 40, 80) | 2.934 | 0.999 |
| (-160, -80, -40 0, 40, 80, 160) | 2.938 | 1.000 |

SRAE*: Short Run Armington Elasticity

According to Golan, *et al*. (1996), we use the normalized entropy measure as the "model selection" rule, then as a general rule we select the estimate from support with normalized entropy nearest to 0.999 (Although we do not use any prior info, it is sensible to consider that, usually, elasticities will not go beyond a value of 50 for example).

In the second place we estimate the partial adjustment model (PAM) (Reinert, et al. 1992, Hernández 1998, Kapuscinsky 1999), with the following specification for each Activity:

$$y(t) = \beta_1 + \beta_2\, x(t) + \beta_3\, y(t-1) + e(t)$$

Where $\beta_2$ is the short run elasticity, and $\beta_2/(1- \beta_3)$ the long run elasticity, if $0< \beta_3<1$, else $\beta_2$ is it.

According to the above specifications, a typical output for an activity results as Table 6.2 shows. In this table the first column specifies the parameters support set, second column shows the Maximum Entropy (ME) estimated short run Armington Elasticity (AE) for each support set, the third column the $\beta_3$ coefficient, fourth column the long run elasticity, and the fifth column the corresponding normalized entropy.

**Table 6.2** Output for Activity 2 (Livestock) from Maximum Entropy estimation of Partial Adjustment Model.

| PARAMETERS SUPPORT | β2 Coeff (SRAE*) | β3 Coeff | β2 / (1-β3) (LRAE*) | Normalized Entropy |
|---|---|---|---|---|
| (-10, -5, 0, 5, 10) | 2.963 | 0.178 | 3.604 | 0.963 |
| (-20, -10, 0, 10, 20) | 3.315 | 0.068 | 3.556 | 0.988 |
| (-40 -20, 0, 20, 40) | 3.413 | 0.037 | 3.543 | 0.997 |
| (-80, -40 0, 40, 80) | <u>3.439</u> | <u>0.028</u> | <u>3.539</u> | <u>0.999</u> |
| (-160, -80, -40 0, 40, 80, 160) | 3.445 | 0.026 | 3.539 | 1.000 |

SRAE*: Short Run Armington Elasticity
LRAE*: Long Run Armington Elasticity

In the third place we estimate the Error Correction Mechanism model (ECM) (Gallaway *et al*. 2003, Kapuscinsky 1999), with the following specification for each Activity:

$$\Delta y(t) = \beta_1 + \beta_2 \Delta x(t) + \beta_3 y(t\text{-}1) + \beta_4 x(t\text{-}1) + e(t)$$

Where $\beta_2$ is the short run Armington elasticity (SRAE), and $(-\beta_4 / \beta_3)$ the long run Armington Elasticity (LRAE).

According to the above specifications, a typical output for an activity results as table 6.3 shows. In this table the first column specifies the parameters support set, second column shows the $\beta_2$ coefficient (short run AE) for each support set, the third column the $\beta_3$ coefficient, the fourth column the $\beta_4$, the fifth column the long run AE, and the sixth column the corresponding normalized entropy.

**Table 6.3** Output for Activity 2 (Livestock) from Maximum Entropy estimation of Error Correction Mechanism model.

| **A2 Livestock** | $\beta$2 COEFF | $\beta$3 COEFF | $\beta$4 COEFF | $-\beta4 / \beta3$ | NORMALIZED |
|---|---|---|---|---|---|
| PARAMETERS SUPPORT | (SRAE*) | | | (LRAE*) | ENTROPY |
| (-10, -5, 0, 5, 10) | 2.745 | -0.596 | 1.587 | 2.664 | 0.963 |
| (-20, -10, 0, 10, 20) | 3.263 | -0.803 | 2.594 | 3.230 | 0.988 |
| (-40 -20, 0, 20, 40) | 3.444 | -0.885 | 2.998 | 3.388 | 0.997 |
| (-80, -40 0, 40, 80) | <u>3.494</u> | <u>-0.908</u> | <u>3.114</u> | <u>3.428</u> | <u>0.999</u> |
| (-160, -80, -40 0, 40, 80, 160) | 3.507 | -0.914 | 3.144 | 3.438 | 1.000 |

SRAE*: Short Run Armington Elasticity
LRAE*: Long Run Armington Elasticity

To begin with, Table 6.4 presents the estimates for the 13 main aggregated Activities of the Mexican economy for which we have imports. Out of 17 main aggregates, four of them do not have any imports: 4 Construction, 6 Commerce, Restaurants, and Hotels, 7 transport, Storage, and Communications, and 8 Financial Services, Insurance, and Real Estate.

**Table 6.4** Maximum Entropy estimation of Armington Elasticities (AE) for 13 main aggregated Activities of the Mexican economy. Base Model (BM), Partial Adjustment Model (PAM), and Error Correction Mechanism Model (ECM).

| | **SHORT RUN AE** | | | **LONG RUN AE** | |
|---|---|---|---|---|---|
| Activity | BM | PAM | ECM | PAM | ECM |
| 1 Agriculture, Livestock, Forestry, and Fishing | 0.47 | 0.11 | 0.35 | 0.51 | -0.52 |
| 2 Mining | -0.36 | -0.16 | -0.35 | -1.95 | -1.92 |
| **3 Manufacturing Industries** | | | | | |
| I Food, Beberages, and Tobacco | 1.54 | 1.00 | 1.09 | 1.46 | 1.31 |
| II Textiles, Clothing, and Leather | 0.37 | 0.62 | 1.38 | 3.15 | -0.18 |
| III Wood, and Wood Products | 2.50 | 1.35 | 1.70 | 3.71 | 3.77 |
| IV Paper, Paper Products, Printing and Editing | 0.00 | 0.67 | 1.08 | 6.62 | 28.88 |
| V Chemicals, Crude Oil Derivatives, and Rubber and Plastic Products | 2.89 | 0.32 | 0.74 | 2.16 | -4.42 |
| VI Products from Non-metallic Minerals, except Crude Oil and Carbon Derivatives | 1.90 | 0.27 | 0.57 | 1.09 | -0.08 |
| VII Basic Metal Industries | -0.95 | 0.32 | 1.15 | 1.84 | -1.00 |
| VIII Metal Products, Machinery, and Equipment | 2.88 | 0.91 | 1.25 | 2.74 | 1.91 |
| IX Other Manufacturing Industries | 2.89 | 0.03 | 0.25 | 0.15 | -2.75 |
| 5 Electricity, Gas, and Water | 2.85 | 1.19 | 1.19 | 2.37 | 2.37 |
| 9 Communal, Social, and Personal Services* | 0.00 | -0.07 | -0.03 | -0.08 | -0.10 |

*Only includes Activities 68 (Professional Services) and 71 (Entertainment Services).

In what follows we present results for Activities disaggregated to a more detailed level, using the 72 Activities disaggregation level of the SNAM. Table 6.5 presents the estimates for the 61 Activities in which the previous 13 more aggregated are disaggregated.

**Table 6.5** Maximum Entropy estimation of Armington Elasticities (AE) for Base Model (BM), Partial Adjustment Model (PAM), and Error Correction Mechanism Model (ECM). 61 Activities

| Activity | SHORT RUN AE | | | LONG RUN AE | |
|---|---|---|---|---|---|
| **AGRICULTURE, LIVESTOCK, FORESTRY, AND FISHING** | BM | PAM | ECM | PAM | ECM |
| 1 Agriculture | 0.44 | 0.07 | 0.26 | 0.31 | -0.35 |
| 2 Livestock | 2.93 | 3.44 | 3.49 | 3.54 | 3.43 |
| 3 Forestry | -0.19 | -0.07 | -0.08 | -0.30 | -0.27 |
| 4 Fishing | 2.01 | 0.80 | 1.26 | 14.62 | 11.06 |
| **MINING** | | | | | |
| 5 Carbon and graphite | -1.11 | -0.18 | 0.15 | -0.86 | -0.99 |
| 7 Ferrous mineral | -2.59 | -1.74 | -2.75 | -1.75 | -1.20 |
| 8 Non-ferrous Metalic Minerals | 0.46 | 0.51 | 1.06 | 1.26 | 0.92 |
| 9 Sand and Clay | -0.40 | -0.32 | -0.21 | -0.48 | -0.49 |
| 10 Other Non-metallic Minerals | -0.28 | -0.21 | 0.53 | -0.30 | -0.86 |
| **FOOD, BEBERAGES, AND TOBACCO** | | | | | |
| 11 Meat and dairy products | 0.58 | 0.56 | 1.01 | 1.63 | -2.16 |
| 12 Fruits and vegetables | 1.17 | 0.95 | 1.47 | 2.47 | 1.77 |
| 13 Wheat | 4.78 | 1.80 | 1.79 | 3.49 | 3.96 |
| 14 Maize | 0.87 | 0.03 | 0.14 | 0.05 | 0.03 |
| 15 Coffe | -1.95 | -0.26 | -0.20 | -0.49 | -1.24 |
| 16 Sugar | -0.14 | -2.71 | -0.52 | -5.26 | -7.61 |
| 17 Edible oils and fats | 2.00 | 0.76 | 0.84 | 1.68 | 1.66 |
| 18 Food for animals | 0.71 | 0.09 | 0.94 | 0.41 | -1.57 |
| 19 Other food | 2.66 | 1.26 | 1.44 | 2.32 | 1.94 |
| 20 Alcoholic beberages | 1.82 | 1.03 | 1.08 | 2.70 | 2.76 |
| 21 Beer and malt | 1.93 | 0.55 | 0.74 | 0.82 | 0.57 |
| 22 Non-alcoholic beberages and water | 1.98 | 1.06 | 1.14 | 1.25 | 1.23 |
| 23 Tobacco | 2.44 | 0.37 | 0.72 | 0.86 | -0.05 |

**Table 6.5** Continues.

| | SHORT RUN AE | | | LONG RUN AE | |
|---|---|---|---|---|---|
| Activity | BM | PAM | ECM | PAM | ECM |
| **TEXTILES, CLOTHING, AND LEATHER** | | | | | |
| 24 Soft fibers textiles | -0.75 | 0.46 | 1.60 | 3.60 | -0.39 |
| 25 Hard fibers textiles | -3.01 | 0.42 | 1.36 | 3.65 | -1.10 |
| 26 Other textiles | -0.23 | 0.66 | 1.26 | 3.35 | 1.22 |
| 27 Clothing | 2.16 | 0.77 | 1.20 | 2.22 | 0.18 |
| 28 Leather and shoes | 2.73 | 1.86 | 2.16 | 6.57 | 5.37 |
| **WOOD AND WOOD PRODUCTS** | | | | | |
| 29 Wood, plywood and the like | 2.47 | 1.43 | 1.69 | 3.20 | 3.31 |
| 30 Other wood and cork products | 1.51 | 1.07 | 1.62 | 4.33 | 3.95 |
| **PAPER, PRINTING AND EDITING** | | | | | |
| 31 Paper and cardboard | -0.20 | 0.58 | 1.19 | 4.48 | 27.00 |
| 32 Printing and editing | 1.15 | 0.68 | 1.20 | 2.04 | 1.74 |
| **CHEMICALS, CRUDE OIL DERIVATIVES, RUBBER AND PLASTIC PRODUCTS** | | | | | |
| 33 Crude oil and derivatives | 1.90 | 0.46 | 0.86 | 1.23 | 0.63 |
| 34 Basic petrochemicals | 2.02 | 0.18 | 0.45 | 55.73 | 0.58 |
| 35 Basic chemicals | -3.43 | -0.67 | -0.77 | -2.61 | -2.67 |
| 36 Fertilizers | -1.31 | 1.71 | 2.16 | 157.94 | 181.50 |
| 37 Sinthetic resinas | -2.51 | -0.04 | 0.38 | -0.30 | -1.80 |
| 38 Pharmaceutical products | 1.48 | 0.62 | 0.76 | 1.45 | 1.43 |
| 39 Soaps, detergents, and cosmetics | 2.71 | 0.79 | 1.00 | 2.71 | 2.09 |
| 40 Other chemical products | 0.38 | 0.19 | 0.35 | 3.35 | 3.39 |
| 41 Rubber products | -3.65 | 0.09 | 1.31 | 0.59 | -2.64 |
| 42 Plastic products | 3.12 | 0.41 | 0.47 | 2.07 | 2.38 |
| **PRODUCTS FROM NON-METALLIC MINERALS, EXCEPT CRUDE OIL AND CARBON DERIVATIVES** | | | | | |
| 43 Glass and derivatives | 1.01 | 0.43 | 0.99 | 1.92 | -1.86 |
| 44 Hydraulic cement | 1.20 | 0.01 | 0.04 | 0.08 | 0.06 |
| 45 Non-metallic minerals products | 1.58 | 0.34 | 0.57 | 1.28 | 0.69 |
| **BASIC METAL INDUSTRIES** | | | | | |
| 46 Basic ferrous and steel industries | -0.23 | 0.37 | 1.34 | 1.05 | 0.36 |
| 47 Basic non-ferrous metals industries | 1.38 | 0.08 | 0.56 | 0.65 | -0.45 |

**Table 6.5** Ends.

| | SHORT RUN AE | | | LONG RUN AE | |
|---|---|---|---|---|---|
| **METAL PRODUCTS, MACHINERY, AND EQUIPMENT** | BM | PAM | ECM | PAM | ECM |
| 48 Metal furniture | 2.21 | 1.22 | 1.33 | 2.00 | 1.85 |
| 49 Structural metal products | 1.56 | 0.25 | -0.17 | 1.24 | 0.64 |
| 50 Other Metal Products, except Machinery | -1.19 | 0.27 | 0.58 | 1.43 | 1.28 |
| 51 Machinery and Non-Electrical Equipment | 1.69 | 0.17 | 0.69 | 1.00 | -1.53 |
| 52 Machinery and Electrical Devices | 1.65 | 0.86 | 1.00 | 1.97 | 1.86 |
| 53 Electrodomestic Devices | 0.87 | 0.28 | 0.59 | 0.74 | 0.71 |
| 54 Electronic Devices | -0.18 | -0.14 | 0.81 | -0.32 | -2.65 |
| 55 Electric Devices | -3.48 | 0.25 | 0.62 | 1.62 | -0.09 |
| 56 Automotive Vehicles | 6.92 | -0.08 | -0.64 | -0.81 | 6.01 |
| 57 Bodyworks, Motors, Spare parts and Accesories for Automotive Vehicles | 1.09 | 0.12 | 1.03 | 0.31 | 0.36 |
| 58 Transport Equipment and Material | 1.47 | 1.42 | 0.44 | 1.76 | 1.71 |
| **OTHER MANUFACTURING INDUSTRIES** | | | | | |
| 59 Other Manufacturing Industries | 2.85 | 0.03 | 0.25 | 0.15 | -2.75 |
| **ELECTRICITY, GAS, AND WATER** | | | | | |
| 61 Electricity, Gas, and Water | 2.85 | 1.19 | 1.19 | 2.37 | 2.37 |
| COMMUNAL, SOCIAL, AND PERSONAL SERVICES | | | | | |
| 68 Professional services | -0.48 | -0.40 | -0.11 | -0.49 | -0.49 |
| 71 Entertainment Services | 0.51 | 0.08 | 0.17 | 0.16 | 0.15 |

## 7. Final Comments

In this working paper three alternative models were used to estimate short run and long run Armington Elasticities for 61 Activities of the Mexican economy, considering data for imports and domestic production. Which elasticities are to be selected as those reflecting the best estimates, is a task that in principle can be undertaken following two main criteria: the normalized entropy measure to assess extraneous variables, and the time series analysis to test for unitary roots and cointegration.

## 8. References


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**Appendix 1** Base gams code

```
$title 1

$ontext

maximum entropy estimation of base, pa, and ecm models
Armington elasticity

$offtext

set a   b variables     /lnMD, lnPDPM/
    t     b index        /1988*2004/
    k    b  index       /1*2/

    apa  pa variables    /lnMD, lnPDPM, lnMDL1/
    tpa  pa index        /1989*2004/
    kpa  pa index        /1*3/

    aec  ec variables    /DlnMD, DlnPDPM, lnMDL1, lnPDPML1/
    tec  ec index        /1989*2004/
    kec  ec index        /1*4/

    m       index       /1*5/
    j       index       /1*3/
;

parameters
data(t,a)
datapa(tpa,apa)
dataec(tec,aec)
;
$LIBINCLUDE XLIMPORT data   datbysA72.XLS d1!H2:J19
$LIBINCLUDE XLIMPORT datapa datbysA72.XLS d1!L3:O19
$LIBINCLUDE XLIMPORT dataec datbysA72.XLS d1!Q3:U19

parameters
y(t)       dependent variable series
ybar       average dep var
sampvar    sample variance
sigma3     three times sigma
;
y(t)      = (DATA(t,'lnMD') ) ;
ybar      = sum(t, y(t)) / 17       ;
```

```
sampvar   = sum(t, (y(t)-ybar)*(y(t)-ybar) ) / 16 ;
sigma3    = (sampvar**0.5)*3      ;

parameters
ypa(tpa)     pa dependent variable series
ybarpa       average dep var
sampvarpa    sample variance
sigma3pa     three times sigma
;
ypa(tpa)    = (datapa(tpa,'lnMD') ) ;
ybarpa      = sum(tpa, ypa(tpa)) / 16       ;
sampvarpa   = sum(tpa, (ypa(tpa)-ybarpa)*(ypa(tpa)-ybarpa) ) / 15 ;
sigma3pa    = (sampvarpa**0.5)*3      ;

parameters
yec(tec)     ec dependent variable series
ybarec       average dep var
sampvarec    sample variance
sigma3ec     three times sigma
;
yec(tec)    = (dataec(tec,'DlnMD') ) ;
ybarec      = sum(tec, yec(tec)) / 16       ;
sampvarec   = sum(tec, (yec(tec)-ybarec)*(yec(tec)-ybarec) ) / 15 ;
sigma3ec    = (sampvarec**0.5)*3      ;

PARAMETERS
Z(m) parameters support
/1 -10.0
 2 -5.00
 3  0
 4  5.00
 5  10.0/

V(j)      errors support
x(t,k)     independent variables

Vpa(j)          pam error support
xpa(tpa,kpa) independent variables

Vec(j)          ecm error support
xec(tec,kec)  ecm independent variables

LB     lower bounds
;
V('1') = -sigma3 ;
V('2') =  0.0    ;
```

```
V('3') =  sigma3 ;

x(t,'1') = 1                  ;
x(t,'2') = (DATA(t,'lnPDPM') ) ;

Vpa('1') = -sigma3pa ;
Vpa('2') =  0.0      ;
Vpa('3') =  sigma3pa ;

xpa(tpa,'1') = 1                      ;
xpa(tpa,'2') = (DATApa(tpa,'lnPDPM') ) ;
xpa(tpa,'3') = (DATApa(tpa,'lnMDL1') ) ;

Vec('1') = -sigma3ec ;
Vec('2') =  0.0      ;
Vec('3') =  sigma3ec ;

xec(tec,'1') = 1                  ;
xec(tec,'2') = (dataec(tec,'DlnPDPM') ) ;
xec(tec,'3') = (dataec(tec,'lnMDL1') ) ;
xec(tec,'4') = (dataec(tec,'lnPDPML1') ) ;

LB = 0.0000001 ;


VARIABLES
p(k,m) parameter probabilities
w(t,j) error probabilities

ppa(kpa,m) parameter probabilities
wpa(tpa,j) error probabilities

pec(kec,m) parameter probabilities
wec(tec,j) error probabilities

OBJ   bm OBJECTIVE
OBJpa pam OBJECTIVE
OBJec ecm  OBJECTIVE
;
*lower bounds for p and w
p.lo(k,m) = LB ;
w.lo(t,j) = LB ;

ppa.lo(kpa,m) = LB ;
wpa.lo(tpa,j) = LB ;
```

```
pec.lo(kec,m) = LB ;
wec.lo(tec,j) = LB ;

EQUATIONS
OBJECTIVE b objective
AD1(k)    parameter add up constraint
AD2(t)    error add up constraint
CON(t)    consistency constraint
;
OBJECTIVE.. OBJ =E= -SUM(k, SUM(m, p(k,m)*LOG( p(k,m) ) ) )
                -SUM(t, SUM(j, w(t,j)*LOG( w(t,j) ) ) ) ;

AD1(k)..  SUM(m, p(k,m) ) =e= 1 ;

AD2(t)..  SUM(j, w(t,j) ) =e= 1 ;

CON(t)..  y(t) =e= SUM(k, x(t,k)*SUM(m, p(k,m)*z(m) ) )
              + SUM(j, w(t,j)*v(j) )  ;

EQUATIONS
OBJECTIVEpa   pa objective
AD1pa(kpa)    parameter add up constraint
AD2pa(tpa)    error add up constraint
CONpa(tpa)    consistency constraint
;
OBJECTIVEpa.. OBJpa =E= -SUM(kpa, SUM(m, ppa(kpa,m)*LOG( ppa(kpa,m) )
) )
                -SUM(tpa, SUM(j, wpa(tpa,j)*LOG( wpa(tpa,j) ) ) ) ;

AD1pa(kpa)..  SUM(m, ppa(kpa,m) ) =e= 1 ;

AD2pa(tpa)..  SUM(j, wpa(tpa,j) ) =e= 1 ;

CONpa(tpa)..  ypa(tpa) =e= SUM(kpa, xpa(tpa,kpa)*SUM(m, ppa(kpa,m)*z(m) ) )
              + SUM(j, wpa(tpa,j)*vpa(j) )  ;

EQUATIONS
OBJECTIVEec   ec objective
AD1ec(kec)    parameter add up constraint
AD2ec(tec)    error add up constraint
CONec(tec)    consistency constraint
;
OBJECTIVEec.. OBJec =E= -SUM(kec, SUM(m, pec(kec,m)*LOG( pec(kec,m) ) )
)
                -SUM(tec, SUM(j, wec(tec,j)*LOG( wec(tec,j) ) ) ) ;
```

```
AD1ec(kec)..  SUM(m, pec(kec,m) ) =e= 1 ;

AD2ec(tec)..  SUM(j, wec(tec,j) ) =e= 1 ;

CONec(tec)..  yec(tec) =e= SUM(kec, xec(tec,kec)*SUM(m, pec(kec,m)*z(m) ) )
              + SUM(j, wec(tec,j)*vec(j) )  ;

MODEL armington   /objective,   ad1,   ad2,   con  / ;
MODEL armingtonpa /objectivepa, ad1pa, ad2pa, conpa/ ;
MODEL armingtonec /objectiveec, ad1ec, ad2ec, conec/ ;

SOLVE armington MAXIMIZING OBJ USING NLP ;

parameter
bhat1(k)   parameter estimates
ehat1(t)   error estimates
bentr1     parameter entropy (the double sum)
sp1        normalized entropy for parameters
sse1       sum of squared errors
beta12     elast armington
;
bhat1(k) = SUM(m, p.l(k,m)*z(m) )   ;

beta12 = bhat1('2') ;

ehat1(t) = sum(j, w.l(t,j)*v(j) )  ;

sse1  =  sum(t, ehat1(t)*ehat1(t))  ;

bentr1 = -sum(k, sum(m, p.l(k,m)*log(p.l(k,m) ) ) );

*NORMALIZED ENTROPY (ME)
sp1 = bentr1 / (2*LOG(5)) ;
```