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Estimates of Armington Parameters for a Landlocked Economy

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Abstract: One of the most debated issues in the Computable General Equilibrium (CGE) literature concerns the validity of the key behavioral parameters used in the calibration process. CGE modelers seldom estimate those parameters, preferring to borrow from the handful of estimates available in the literature. The lack of data is often cited as a reason for this type of modus operandi (technique). Estimating key parameters is very crucial since CGE results are quite sensitive to parameter specification. This paper proposes a new and robust econometric technique, the Generalized Maximum Entropy (GME), to estimate Armington elasticities for selected commodities. All the parameters estimated are intended for use in a Lesotho CGE model.

Keywords: CGE; Maximum Entropy (GME); Armington; Africa; Lesotho

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1. Introduction

One of the most debated issues in the computable general equilibrium (CGE) literature concerns the validity of the key behavioral parameters used in the calibration process. CGE modelers seldom estimate these parameters empirically, preferring to borrow from the handful of estimates available in the literature. These estimates usually are more appropriate for countries other than the ones the CGE model is trying to represent. Moreover, critics argue that the partial equilibrium framework in which these parameters are mostly estimated is inconsistent with CGE analysis. The paucity of data is often cited by CGE modelers as the major reason for considering compromises to the empirical basis for the parameters used in CGE models.

The literature on the estimation of Armington elasticities of substitution has been limited for the context of developing countries.[2] Table 1 below, presents a summary of selected studies on the estimation of Armington elasticities. In several studies, Shiells and his associates applied three econometric methods (generalized least square (GLS), maximum likelihood (ML), and simultaneous equations system) to a large multisectoral U.S. data set (Shiells, Stern, and Deardoff, 1986; Shiells and Reinert, 1993). While their studies suggested that the estimation method does not matter, their results were structurally inconsistent with the general equilibrium analysis, since the formal analysis of the model largely ignored the supply side of the market. Galloway, McDaniel, and Rivera (2000) used time series regressions to estimate long-run Armington elasticities for the U.S, and their findings indicated higher Armington estimates compared to those found by Shiells and associates. Arndt, Robinson, and Tarp (2002) employed a system of simultaneous equations-based generalized maximum entropy (SSE-GME) to estimate Armington parameters for Mozambique. Their methodology is consistent with the general equilibrium framework since they exploit the flexibility of maximum entropy to add a general problem.

[2] McDaniel and Balistreri (2002) provides a comprehensive literature review on Armington elasticities.

Table 1: Selected Empirical literature on Armington Parameters Estimation

Studies	Country	Methodology	Remarks
Shiells, Stern, and Deardoff (1986); Shiells and Reinert (1993	USA	Based on: * generalized least square(GLS),maximum likelihood (ML), system of simultaneous equations. * Large multisectoral data.	Methodology does not matter. Structurally inconsistent with general equilibrium analysis: supply side of the market ignored.
Gallaway, Mc-Daniel and Reinert (2000)	USA	Time series regression (long-run analysis).	*Found higher estimates.
Arndt, Tarp and Robinson (2002)	Mozambique	Simultaneous equations Generalized Maximum Entropy.	Specification consistent with general equilibrium analysis.

Source: Nganou (2005)

The purpose of this paper is to address some of the criticisms leveled against the use of parameters taken from the literature in CGE models. In this paper, we provide an alternative estimation technique to the use of parameters taken from the literature in CGE models. Our methodology on the estimation of the Armington parameter is a variant of the methodology used in Arndt, Robinson, and Tarp (2002), to the extent that it relies on a single equation generalized maximum entropy (GME). However, unlike Arndt, Robinson, and Tarp (2002), we did not include a constraint to account for general equilibrium analysis. More specifically, our estimates of Armington elasticites depend on data availability, intended for use in a Lesotho CGE model. This is primarily to address some of the conceptual problems that would arise in estimating CGE models, as some of earlier studies have shown that results from CGE models are often sensitive to the value of those behavioral parameters (e.g., Arndt, Robinson, and Tarp 2002).

2. The Data

Lack of data is the most common predicament in developing countries for the estimation of Armington elasticities. Available data suggest that consumers in Lesotho choose between the following imported and domestically produced goods: Agriculture, Food, Beverages and Tobacco, Textiles, Mining and quarrying, and Transport. Disaggregated annual data on imports were obtained from the Lesotho Bureau of Statistics covering 1993-1999. Given that these series were in nominal local currency units, appropriate average annual import price indices (or import prices, base year 1997=100), also from the Bureau of Statistics, were used to evaluate the transaction import prices. Subsequently, real import series were taken to be the physical quantity of imported commodities. Data on the price of domestic output was obtained from the consumer price index (CPI) of the Bureau of Statistics, while real GDP data were used as the physical quantity of domestically produced goods and services. Summary of descriptive statistics for real imports, real domestic outputs, import prices and domestic output prices are presented in Table 2.

Table 2.Descriptive Statistics (means) for Key variables in the Armington Regression

Commodities	Imports[a]	Domestic Production value[a]	Import Price Index[b]	Domestic Price Index[b]
Agriculture	252.63	152.23	0.91	0.89
Food & Bev. & Tobacco	96.05	59.37	0.88	0.93
Textiles	148.40	43.37	0.94	0.95
Mining	50.60	0.63	0.98	0.96
Transport	125.09	31.68	0.94	0.93

Source: Author's Calculations.

Note. a=Imports and domestic production are evaluated at constant prices and measured in million of Maloti.

b=for both price indices, 1997 is the base year.

3. Estimation of Armington Parameters

Given the dearth of data for the variables required for estimating Armington elasticities, GME technique was employed in this analysis. Earlier studies (see for example, Golan, Judge, and Miller 1996) have shown that GME method is more appropriate for ill-posed and limited data problems, as it provides more robust results.

A. A Brief Theoretical Background[3]

The Armington elasticity, which measures the degree of substitution between domestic and imported goods, is a key behavioral parameter that drives the results of interest to policymakers. For instance, trade policy can affect the price of traded goods relative to domestically produced goods. Such price changes will affect a country's trade opportunities, level of income, and employment. The magnitude of these impacts will largely depend on the magnitude of the elasticities, including Armington parameters. Partial and general equilibrium models that rely on the Armington elasticities are usually sensitive to these parameters (McDaniel and Balistreri 2002). Thus, it is important to use the right Armington parameters for the countries of study. Therefore, despite the dearth of data for Lesotho, we used GME technique to estimate Armington parameters.

The Armington assumption states that imported and domestic goods are imperfect substitutes for any traded good.[4] Consequently, the model departs from the neoclassical assumption of perfect substitutability of tradables and the law of one price. Domestic final demand is conceptually comprised of household consumption demand (*QH*), government consumption demand (*QG*), investment demand (*QINV*), and the demand for intermediate inputs (*QINT*) generated by domestic producers. The required demand could be met through either domestic production or imported commodities. It is assumed that, for each commodity, supply from domestic and foreign sources is combined to form a composite commodity (*QQ*) which will be available to domestic consumers. This is achieved through the use of aggregated CES function with a given elasticity of substitution, and it is specified as follows:

$$QQ_c = \alpha_c^q \left[\delta_c^q . QM_c^{\rho_c^q} + (1 - \delta_c^q) . QD_c^{\rho_c^q} \right]^{\frac{1}{\rho_c^q}} \qquad (1)$$

where $\alpha^q{}_c$ is an Armington function shift parameter; δ_c^q is an Armington function share parameter, and $\rho^q{}_c$ is an Armington function exponent.

In the above CES aggregation function, it is analogous to considering QM_c and QD_c to be the inputs generating domestically supplied composite commodity. Equation (1) implies that consumer demand for imports and domestically produced commodities are derived demand,

[3]The theoretical foundations of the Armington demand are also presented in Nganou (2005; chapter 7).

[4] This was named after its author (Armington ,1969) who came up with the idea of using a CES function for such a purpose.

analogous to demand for factor inputs in a conventional production function. Households choose a mix of QM_c and QD_c according to their relative prices. So given specified prices for domestic and imported goods, the consumer's problem is to find a commodity bundle (aggregate composite commodity) to minimize cost subject to the constraint stated in Equation (1), and this is mathematically presented as follows:

min $PQ_c.QQ_c = (PM_c.QM_c + PD_c.QD_c)$; c = 1,…,6, (2)

subject to equation (1).

The Lagrangian with respect to the consumer choice variables is therefore:

$$\text{Min } L = \left(PM_c.QM_c + PD_c.QD_c\right) + \lambda\left(QQ_c - \alpha_c^q\left[\delta_c^q.QM_c^{\rho_c^q} + (1-\delta_c^q).QD_c^{\rho_c^q}\right]^{\frac{1}{\rho_c^q}}\right) \tag{3}$$

Differentiating the above equation with respect to QM_c and QD_c and rearranging terms yields the following tangency condition:

$$\frac{QM_c}{QD_c} = \left[\frac{PD_c}{PM_c}.\frac{\delta_c^q}{1-\delta_c^q}\right]^{\frac{1}{1+q_c^q}}, \quad \text{c = 1,…,6} \tag{4}$$

The elasticity of substitution between commodities from these two sources is given by

$\sigma_c^q = \dfrac{1}{1+\rho_c^q}$, which is a transformation of ρ_c^q. Equation (4) defines the optimal mix between imports and domestically produced goods. It suggests that an increase in the domestic-import price ratio generates an increase in the import-domestic demand ratio. In this case, the demand shifts away from more expensive sources.

From equation (4), σ_c^q can be derived as follows:

$$\sigma_c^q = \frac{\partial \ln\left(\dfrac{QM_c(t)}{QD_c(t)}\right)}{\partial \ln\left(\dfrac{PD_c(t)}{PM_c(t)}\right)}, \text{ c = 1,…,6; t = 1,…,7} \tag{5}$$

where the numerator is the partial derivative of the logarithm of the ratio of quantity of imports and domestic output, the denominator is the ratio of prices of domestic output and imports, and t represents the time subscript (i.e., 7 years).

Intuitively, σ_c^q is the proportionate change in the ratio of quantities divided by the proportionate change in the marginal rate of technical substitution in the demand between the two sources (i.e., domestic production and imports). The marginal rate of technical substitution is given by their prices ratio.

For the purpose of estimation, the following parsimonious model specification, also common in the empirical literature on Armington elasticity of substitution, was used:

$$\ln\left(\frac{QM_c(t)}{QD_c(t)}\right) = \alpha_c^0 + \sigma_c^q . \ln\left(\frac{PD_c(t)}{PM_c(t)}\right) + \upsilon_c(t), \text{ c=1,…,6; t=1,…,7} \quad (6)$$

where α_c^0 is the constant term, and $\upsilon_c(t)$ is the disturbances term associated to each equation.

B. Maximum Entropy: A Brief Review

As discussed in Golan, Judge, and Miller (1996), the traditional maximum entropy (ME) is based on the entropy-information measure of Shannon (1948). Shannon used entropy to measure the state of knowledge (uncertainty) that we have about the occurrence of a collection of events. ME is a special case of the generalized maximum entropy (GME) where the data are represented in terms of exact moments. The GME proposed by Golan et al. (1996) uses a flexible, dual-loss objective function - a weighted average of the entropy of the deterministic part of the model and the entropy from the disturbance or stochastic part.

A detailed discussion on the properties of GME is provided in Golan, Judge, and Miller (1996), and here we briefly overview these properties. The GME approach uses all the data points and does not require any restrictive moment or distributional error assumptions. Thus, the GME is robust for a general class of error distributions. Additionally, the GME estimator may be used in several circumstances namely, when the sample is small, there are many covariates, and the covariates are highly correlated. Moreover, the GME method is very flexible as it can allow the user to easily impose nonlinear and inequality constraints (Golan, Perloff,and Shen, 2001).

C. A GME Estimation of Armington Elasticities

In order to estimate equation (6) above with GME[5] , we need to express all the coefficients and errors in the equation in terms of probabilities. For instance, to re-parameterize σ_c^q , we start by choosing a set of discrete points, called the support space, $\underline{z}_c^{\sigma} = (\underline{z}^{\sigma}_{c1}; \underline{z}^{\sigma}_{c2},\ldots,\underline{z}^{\sigma}_{cD})'$ of dimension D>=2, that are at uniform intervals, symmetric around zero, and span the

[5]To perform the estimation GAMS was employed. Alternatively SAS can be used. Version 9 of SAS includes a specific routine to implement GME.

interval [$\underline{z}^{\sigma}{}_{c1},\ldots,\underline{z}^{\sigma}{}_{cD}$]. The vector of corresponding unknown weights is also introduced as follows:

$\underline{p}_c^{\sigma} = (p^{\sigma}{}_{c1}, p^{\sigma}{}_{c2,\ldots,}p^{\sigma}{}_{cD})'$ such that $\sum_{d=1}^{D} p_{cd}^{\sigma} = 1$ and $\sum_{d=1}^{D} z_{cd}^{\sigma} p_{cd}^{\sigma} = \sigma_c^q$ for all *c*, *d*=1,2,. . . ,*D* is the index used for the number of discrete points (dimension) in the support space for each unknown coefficient. Similarly, the constant term α_c^0 can be re-parameterized using the same approach.

In order to re-parameterize the errors $\upsilon_c(t)$, the definition of a transformation matrix *V* that converts the possible outcomes from the dimensions of discrete points $u_c(t)$ to the interval [0,1] is required. Such a transformation is done by specifying a vector of *M*>=2 discrete points $\underline{v} = (v_1, v_{2,\ldots,}v_M)'$, distributed uniformly about zero, and an associated vector of proper unknown weights $\underline{w} = (w_{c1}(t), w_{c2}(t),\ldots, w_{cM}(t))'$ such that $\sum_m v_m . w_{cm} = u_c(t)$. With GME, there is no need to assume any subjective information on the distribution of the probabilities (Golan, Perloff, and Shen 2001).

Incorporating the above re-parameterized terms into our equation of interest (Eq. 6), we obtain:

$$\ln\left(\frac{QM_c(t)}{QD_c(t)}\right) = \sum_{d=1}^{D} z_{cd}^{0} p_{cd}^{0} + \sum_{d=1}^{D} z_{cd}^{\sigma} p_{cd}^{\sigma} . \ln\left(\frac{PD_c(t)}{PM_c(t)}\right) + \sum_{m=1}^{M} v_m w_{cm}(t) \tag{7}$$

The GME estimator maximizes the entropy of all the probabilities representing the signal (α_c^0, σ_c^q) and the noise ($\upsilon_c(t)$), subject to the data (Equation (7) above) and the adding up constraints of the probabilities.

Letting $\underline{p} = (\underline{p}^{\alpha'}, \underline{p}^{\sigma'})'$, the GME estimator is given by the following optimization problem:

$$\max R\left(\underline{p},\underline{w}\right) = -\underline{p}'.\ln(\underline{p}) - \underline{w}'.\ln(\underline{w})$$

subject to the data (i.e., Eq. (7)) and the GME adding-up conditions,

$$\sum_{d=1}^{D} p_{cd}^{0} = \sum_{d=1}^{D} p_{cd}^{\sigma} = \sum_{m=1}^{M} w_{cd}(t) = 1 \tag{8}$$

The solution to this maximization problem is unique. Forming the Lagrangian and solving for the first-order conditions yields the optimal solution, from which the following point estimates for our econometric model are derived:

$$\hat{\alpha}_c^0 = \sum_{d=1}^{D} z_{cd}^0 \hat{p}_{cd}^0 \tag{9}$$

$$\hat{\sigma}_c^q = \sum_{d=1}^{D} z_{cd}^\sigma \hat{p}_{cd}^\sigma \tag{10}$$

$$\hat{u}_c(t) = \sum_{m=1}^{M} v_m w_{cm}(t) \tag{11}$$

The Choice of Support Spaces

An extensive discussion on the choice and dimension of the support space on parameters and error term is provided in Golan, Judge, and Miller (1996) (Chap. 8). With respect to the dimension or the number of points in the support space for the parameters we will consider 5 (i.e., D = 5). In fact, based on some experiments, Golan, Judge, and Miller (1996) argue that the greatest improvement in precision could be obtained when the support space on the parameters has 5 elements (see page 140).

Since there is no theoretical justification that illuminates the true Armington parameters, the value of elasticities remains entirely an empirical issue. While some "structural" economists have argued that most often the trade elasticities used in CGE models are too large and do not sufficiently reflect institutional rigidities in trade (e.g. import quotas, or other protectionist trade policies), while other market-leaning economists have argued to the contrary (Liu, Arndt, and Hertel 2001). In such conditions, it is always recommended to choose a wider support space for the parameters. Also, in so doing, the impact of the support space on the parameters is reduced while that of the data is increased (Golan, Judge, and Miller 1996). Moreover, entertaining a variety of plausible bounds constitutes a check for the robustness of the estimated parameters to the support space.

As for the support space on the error term, for each equation we used the three-sigma rule symmetric around zero, as recommended in Golan, Judge, and Miller (1996). The dimension of the support space on the disturbance terms is 3 (i.e., 3 elements). The support space for the errors is therefore: [-3.*stdev*, 0, 3.*stdev*], where *stdev* is the empirical (data) standard deviation of the dependent variable.

Estimation Evaluation and Inference Issues

A simple way to evaluate the estimated coefficients could be based upon the a priori (from theory) expectations in terms of their signs and magnitude. However, the computation of asymptotic standard errors for estimated coefficients (and therefore *t*-tests) is also possible, and may facilitate a more conventional inference approach (Mittelhammer and Cardell 1997). Mittelhammer, Judge, and Miller (2000) show that under some regularity conditions (e.g., the true error values and parameters should be contained in their respective support bounds) defined by Mittelhammer and Cardell (1997) the GME estimator is consistent and asymptotically normal (also see Golan, Judge, and Miller (1996)). Fraser (2000) provides an application of Mittelhammer et al's inference approach.

Another evaluation tool is the normalized entropy on the GME coefficients, obtained by dividing the Shannon objective function by the natural log of *M*, the number of points in the parameter support. The normalized entropy rule proposed in Golan et al (1996) can be used in the selection of variables in a regression model. A variable is extraneous in a regression model if its normalized entropy statistic is lower than 0.99 (Golan, Judge, and Miller 1996).

Additionally, it is possible to use the overall degree of fit (R^2) in estimated equations as a diagnostic tool. This overall goodness of fit measure remains a useful summary statistic, although it is said to be biased downward in GME cases[6] as it uses out of sample information (Fraser 2000). This is also supported by our findings (see Tables 3-8).

In our analysis, the above-mentioned diagnostic tools were computed and reported for each regression. They also served as a guide in the selection of the "best model specification" (i.e., the support specification that would produce the final estimated elasticities to be included in the CGE model).

D. GME Estimation Results

Given the lack of precise knowledge about the bounds of Armington elasticities from economic theory as mentioned before, it was useful, as recommended in Golan, Judge, and Miller (1996), to specify various support spaces on the parameters (intercept and elasticity estimates) and to measure the sensitivity of results across support space specifications. Estimation results of coefficients along with associated standard errors are presented in Tables 3-8.

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[6]The R-square derived in the GME case will tend to be lower than that derived by the OLS estimator.

A sensitivity analysis of the GME estimates: While the sign of all estimated elasticities seems consistent across various support spaces, their magnitude is sensitive to the choice of support values, except for commodities for which estimated elasticities were statistically significant (i.e., Agriculture, and Food).

Table 3. Sensitivity Tests of GME Estimates of Armington Elasticity for Agriculture

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	0.898[a]	10.86	0.999	0.899
	(0.135)			
[-100, -50, 0, 50, 100]	0.898[a]	10.86	0.999	0.899
	(0.135)			
[-50, -25, 0, 25, 50]	0.897[a]	10.86	0.999	0.899
	(0.135)			
[-20, -10, 0, 10, 20]	0.894[a]	10.86	0.997	0.899
	(0.135)			
[-10, -5, 0, 5, 10]	0.882[a]	10.85	0.995	0.899
	(0.135)			

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level. The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-1.721, 0, 1.721] as error support. The parameter's asymptotic standard errors are provided in the parentheses. $S(P_k)$ is the normalized entropy statistic on the estimated parameter (here the Armington elasticities). It measures the informational content of the estimates with 1 reflecting uniformity (complete ignorance) of the estimates and 0 reflecting perfect knowledge.

More precisely, the Armington elasticity estimates for Agriculture and Food are statistically significant at 5 percent and 10 percent, respectively, and have the correct sign. They are also very robust in the sense that they do not vary with the support space specified (Tables 3 and 4). The elasticity estimate for Textiles was marginally significant (at 11 percent) in the first and second support space specifications. However, in terms of robustness, it can be noticed that with a tight support space (support specifications 3 and 4) the estimated coefficient for Textiles is shrinking significantly (Table 5).

Table 4. Sensitivity Tests of GME Estimates of Armington Elasticity for Food

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	1.371[b]	10.66	0.999	0.42
	(0.596)			
[-100, -50, 0, 50, 100]	1.37[b]	10.66	0.999	0.42
	(0.596)			
[-50, -25, 0, 25, 50]	1.367[b]	10.66	0.999	0.41
	(0.596)			
[-20, -10, 0, 10, 20]	1.348[b]	10.66	0.997	0.41
	(0.596)			
[-10, -5, 0, 5, 10]	1.282[b]	10.64	0.989	0.41
	(0.597)			

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level. The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-1.82, 0, 1.82] as error support. The parameters' asymptotic standard errors are provided in the parentheses; See Table 7 for the definition of $S(P_k)$.

It is worth mentioning that the estimated Armington elasticity for Other Manufacturing was statistically significant, insensitive across support space specifications, but with a negative sign (contrary to the theory predictions). This could be due to a model inaccurate (Table 6). Estimated Armington elasticities with wrong signs are also common in the literature. Further efforts, such as, using several specifications with (unweighted as well as weighted priors) generalized cross entropy (GCE) were undertaken in order to see whether we can get robust estimates on Other Manufacturing with the correct sign. The estimated coefficients were very small in size (close to 0) and statistically insignificant.[7]

[7] Results are not reported here but are available from the author.

Table 5. Sensitivity Tests of GME Estimates of Armington Elasticity for Textiles

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	7.752[c]	10.58	0.998	0.227
	(4.73)			
[-100, -50, 0, 50, 100]	7.613	10.57	0.996	0.226
	(4.735)			
[-50, -25, 0, 25, 50]	6.91	10.56	0.988	0.221
	(4.754)			
[-20, -10, 0, 10, 20]	4.232	10.49	0.972	0.136
	(5.01)			
[-10, -5, 0, 5, 10]	1.825	10.43	0.979	-0.025
	(5.45)			

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level, d = significant at 11 percent level. The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-1.65, 0, 1.65] as error support. The parameters' asymptotic standard errors are provided in the parentheses; See Table 7 for the definition of $S(P_k)$.

The estimated coefficients for the remaining commodities (Mining and Transport), although with the correct sign, were both not statistically significant (see Tables 7 and 8). Additionally, the Armington elasticities for Mining and Transport are sensitive to tighter support space of the parameters (especially in the [-20,...,20] and [-10,…,10] support specifications).

Table 6. Sensitivity Tests of GME Estimates of Armington Elasticity for Other Manufacturing

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	-1.288c	10.61	0.999	0.412
	(0.686)			
[-100, -50, 0, 50, 100]	-1.288c	10.61	0.999	0.412
	(0.686)			
[-50, -25, 0, 25, 50]	-1.285c	10.61	0.999	0.412

	(0.686)			
[-20, -10, 0, 10, 20]	-1.268c	10.59	0.997	0.412
	(0.686)			
[-10, -5, 0, 5, 10]	-1.21c	10.53	0.991	0.41
	(0.686)			

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level. For the 3 last regressions, only the support space on the estimated elasticity was further restricted to be positive. The constant's support was maintained at [-150, -75, 0, 75, 150].

The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-0.976, 0, 0.976] as error support. The parameters's asymptotic standard errors are provided in the parentheses. See Table 7.7 for the definition of $S(P_k)$.

Table 7. Sensitivity Tests of GME Estimates of Armington Elasticity for Mining

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	7.3	10.4	0.998	0.044
	(16.52)			
[-100, -50, 0, 50, 100]	6.478	10.39	0.997	0.042
	(16.53)			
[-50, -25, 0, 25, 50]	4.01	10.39	0.996	0.032
	(16.62)			
[-20, -10, 0, 10, 20]	1.042	10.35	0.998	0.006
	(16.83)			
[-10, -5, 0, 5, 10]	0.232	10.26	0.999	-0.018
	(17.04)			0.044

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level.

The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-5.52, 0, 5.52] as error support. The parameters's asymptotic standard errors are provided in the parentheses; See Table 7 for the definition of $S(P_k)$.

Table 8. Sensitivity Tests of GME Estimates of Armington Elasticity for Transport

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(p_k)$	R^2
[-150, -75, 0, 75, 150]	2.78	10.41	0.999	0.05
	(5.054)			
[-100, -50, 0, 50, 100]	2.741	10.41	0.999	0.05
	(5.076)			
[-50, -25, 0, 25, 50]	2.546	10.41	0.998	0.05
	(5.092)			
[-20, -10, 0, 10, 20]	1.696	10.4	0.996	0.043
	(5.093)			
[-10, -5, 0, 5, 10]	0.774	10.38	0.996	0.025
	(5.16)			

Source: Author's Calculations.

Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level. The support on errors is based on a 3-sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variable. Here we used [-2.27, 0, 2.27] as error support. The parameters's asymptotic standard errors are provided in the parentheses; See Table 7 for the definition of $S(P_k)$.

The Choice of the final Armington elasticities: In order to choose the Armington elasticity estimates that will be used in the CGE model, we make use of the diagnostic tools described earlier, as well as our knowledge of the country. Given that Lesotho is an import-dependent economy, one might expect the Armington elasticity to be relatively high. It is worth mentioning that in determining the final estimates, we will lean towards those with both wider support space and lower associated normalized entropy statistics. In so doing, our lack of prior knowledge about the parameter bounds, as mentioned before, will be accounted for, as well as our efforts to let the data speak.

As mentioned before, estimates for Agriculture and Food are robust across support specifications. Therefore, the choice of a support specification does not make a difference. The specification chosen for both commodities is the one with the widest support, given the lack of prior knowledge of the support bounds for the estimates. Thus, the Armington elasticity for Agriculture is 0.898 while that for Food is 1.37. For Mining and quarrying, specification 3 (i.e., [-50,...,50]) is chosen since it has the lowest normalized entropy statistic (0.996) on the estimated coefficient. Also, its R^2, although low, is similar to that for the first two specifications. Moreover, Lesotho does not impose any trade barriers on mining products imported from South Africa. The Armington elasticity for Mining is therefore 4.01.

The Armington elasticity for Textiles is 4.232, since it displays the lowest normalized entropy statistic. Based on the same criterion, Armington estimate for Transport is 1.696. We could have chosen 0.774 but, instead, we leaned towards the estimated coefficient with a wider support space and for which R^2 does not change drastically, reflecting the limited impact of non-sample information. Finally, since Armington elasticity could not be negative, our choice of Armington elasticity for Other Manufacturing was not based on its econometric estimation, rather we used its value (i.e., 0.5) proposed by de Janvry and Sadoulet (2001) in their archetypal CGE model for Africa, which also seems plausible for Lesotho where handicrafts industry is protected.

Comparing Armington Elasticities from Selected Sources: There is no consensus on the value of the parameters used in CGE models. Although many approaches to econometric estimation of these elasticities have been offered for the last 30 years, many trade economists view the estimates as fairly small[8]. We believe that parameters should be country-specific, but lack of data seldom allows their estimation for each country. Nevertheless, we can compare our Armington estimates to those of a selected literature, although we cannot provide any evidence of the statistical significance of the difference between the estimates[9].

A comparison of the estimated Armington elasticities with those used in selected studies is presented in Table 9. First, the table reveals that the majority of Lesotho's estimates are higher than the Armington elasticities used in de Janvry and Sadoulet (2001). However, except for Mining and Textiles, the parameters are below those provided by GTAP (Global Trade Analysis Project of Purdue University). For Textiles, the Armington parameter (2.69) is apparently not far from the 3.3 used in the GTAP studies. In comparison, only Mining and Transport have an elasticity of substitution between imports and domestic output that is

[8]McDaniel and Balistreri (2002) provide a comprehensive review of literature on the estimation of Armington elasticities.

[9]Obviously, such a comparison is not a perfect one, given that the commodity classification used in selected studies was not identical.

greater in magnitude than the South African parameters. Interestingly, our estimates for Textiles and Food are very close in size to those for South Africa.

Table 9. A Comparison of Selected Armington Elasticities

	Our estimates	GTAP	Janvry et al. 2001	Lofgren (Egypt's CGE)	South Africa (Thurlow et al)	Mozambique (Arndt et al (2002))
Agriculture	0.898	2.44	0.4	0.56	1.596	0.69
Food	1.37	2.4	0.5	1.65	1.53	0.57
Textiles	4.232	3.32	0.5	0.3	4.13	NA
Mining	4.01	2.41	0.5	2	0.76	NA
Transport	1.696	3.1	0.5	0.3	1.14	1.85

Source: Compiled by the Author.

Note. GTAP: Global Trade Analysis Project of Purdue University

Comparison also reveals that, except for Food, Lesotho estimates for elasticities are higher than those of Egypt. Finally, because Arndt et al. (2002) use a GME approach in their estimation of trade parameters for Mozambique, a country with some similar features (e.g., very poor, small dependent economy) as Lesotho, we found it useful to compare our estimates to theirs. In general, estimated coefficients are not very distant across the two studies (e.g., Transport services and Agriculture). But the advantage of our approach compared to that of Arndt et al. (2002) is that it is simpler since it is based on the single regression equations.

In sum, since there is a divergence of parameter values across studies, it might not be a good idea to use results of cross-country estimations in a country's CGE model. Using country-specific elasticities should be the way to go.

4. Conclusion

The objective of this paper was to estimate some key parameters intended for use in the CGE model for Lesotho. Given the poor quality of data available, we employed GME techniques to estimate Armington elasticities. Using only 7 years of data, we were able to obtain some interesting and sensible estimates. Although we found that many of the

Armington estimates were not statistically significant (based on asymptotic standard errors), they were generally of the correct sign. However, as Mittelhammer and Cardell (1997) argued, asymptotic standard errors need to be interpreted cautiously in the GME/GCE context. Sensitivity tests of parameters to the support space undertaken in this paper were also proven to be an important check for the robustness of GME estimates.

In sum, the excuse of the lack of data usually advanced by CGE modelers for not using country-specific parameters may not hold anymore. As was shown earlier in this paper, GME econometrics is possible for developing countries (whose economic data are generally scarce and considered poor in quality). It is worth noting that the partial equilibrium framework used for the estimation of parameters, although inconsistent with CGE analysis as argued by critics, offers a computational advantage for its simplicity. Overall, we found that estimates from Arndt et al (2002) were very close to those provided in this paper using single equation GME regressions.

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