ESTIMATING THE KEY PARAMETERS OF THE LESOTHO CGE MODEL

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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 compromises. Estimating key parameters is very crucial since CGE results have been shown to be quite sensitive to the value of parameters. This paper first, uses a seemingly unrelated regressions method to estimate own-price and income elasticities, as well as Frisch parameters for households whose consumption behavior is described by a Linear Expenditure System (LES) demand function. The paper also uses 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); Demand System (LES); Armington; Seemingly Unrelated Regressions (SUR); Lesotho

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Contents

1 Objective and Motivation

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. In fact, 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 compromises to the empirical basis for the parameters used in CGE models. The purpose of this paper is to address some of these issues. More precisely as long as data availability permits, in this paper, we estimate *linear* expenditure system (LES) parameters (elasticities of expenditures, own-price elasticities, and Frisch parameters) and Armington elasticities, all intended for use in the Lesotho CGE model. It has been shown that CGE model conclusions are quite sensitive to the value of those behavioral parameters (Arndt, Robinson, and Tarp 2002).

The remainder of the paper is organized as follows: Section 2 presents a brief economic background of Lesotho; Section 3 deals with the description of the data used in this paper; The estimation of LES parameters, income and own-price elasticities is provided in Section 4; Section 5 presents a brief background of the Armington elasticities of imports as well as the Generalized Maximum Entropy (GME) technique used. The estimation results for Armington elasticities are also provided in Section 5. Finally, Section 6 concludes.

2 Brief Economic Background

Lesotho is a small country with many unique features. Landlocked and entirely surrounded by South Africa, about 60 percent of Lesotho's area (approximately 30,344 square kilometers) is mountainous with limited cultivable and pastoral land. Lesotho is referred to as the "Mountain Kingdom," for it has no lowlands below 1,400 meters in altitude (Chandra, Anderson, Kolavalli, and Nganou 2002). According to government sources, approximately 2.2 million people populated Lesotho in 2000. As one of the smallest countries in the world, the economy of Lesotho is characterized by a severe absence of natural resources. In fact, Lesotho's only important natural resource is fresh water from the mountains. However, despite its apparent abundance, water seems to be in short supply for the drinking, agricultural and industrial water needs of the population.

With a gross national product (GNP) per capita estimated at US$ 500 in 2001 (down from US$ 580 in 2000), Lesotho is a poor country, as approximately more than half the population lives below the poverty line. In a World Bank study, Chandra et al (2002) reported that, based on an absolute poverty line equivalent to the international threshold of 2200 kilograms calories needed for a healthy and active life, approximately 58 percent of the population of Lesotho could be classified as poor in 1986; this proportion was virtually unchanged in 1994.

3 The Data

For the estimation of LES parameters, the 1986/87 Lesotho Household Expenditures Survey (HES) of the Lesotho Bureau of Statistics was used to derive expenditure levels. The commodities for which data were available in the HES were re-categorized to match the commodities classification provided in the Lesotho SAM (STLESAM). Thus, Lesotho households direct most of their spending to the following nine commodities: Agriculture, Food, Beverages and Tobacco, Textiles, Utilities, Private services, Government services, Transport, Other Manufacturing, and Financial services. Table 1 presents the descriptive statistics for commodities expenditures and consumer price indices for each category of household. The data set contains a maximum of 1932 observations for urban households and 2628 observations for rural households. In general, expenditure and price levels are higher for urban households than their rural counterparts. As expected, the average expenditure amounts to 91,721.86 maloti for urban households compared to only 35,185.76 maloti for rural households. Financial services seem to be the most purchased service for urban households (12,000 maloti on average) whereas rural households consumed more textile products (10,160 maloti). It was not useful to break the data set down into several sub-samples according to income and location to agree exactly with the disaggregation provided in the STLESAM because the number of observations was significantly smaller for some sub-samples. In order to estimate LES parameters, the data on prices are also needed. The 2000 Consumer Price Index (CPI) series by commodities and location (rural and urban) provided by the Lesotho Bureau of Statistics are used as price variables (1997 was the base year).

For the estimation of Armington elasticities, the lack of data is very characteristic in developing countries. Available data suggest that consumers choose between the following imported and domestically produced goods: Agriculture, Food, Beverages and Tobacco, Tex-

Table 1: Descriptive Statistics (means) for Commodities Expenditures and Consumer Price Indices by Household type

	Urban			Rural			All Households	
	Obs.	Expend.	CPI	Obs.	Expend.	CPI	Expend.	CPI
Agriculture	1900	6563.45	1.47	2326	4573.57	1.43	5468.22	1.45
Food	1932	7886.18	1.53	2525	3504.49	1.48	5403.84	1.50
Textiles	1932	7780.45	1.33	1077	10159.18	0.57	8631.86	0.89
Utilities	1932	6287.66	1.29	2628	950.726	1.35	3211.9	1.32
Private Services	1932	6155.31	1.30	1503	6073.81	0.74	6119.65	0.98
Govt Services	1932	7856.48	1.20	1374	2529.74	0.63	5642.64	0.87
Transport	1932	6457.14	1.50	799	3768.5	0.44	5670.53	0.89
Other Manufacturing	1932	6476.14	1.37	2449	4602.59	1.30	5428.82	1.33
Financial Services	1932	12007.06	1.30	866	6355.26	0.43	10257.79	0.79
Total Expenditures	1932	91721.86		2628	35185.76		59139.21	

Source: Author's calculations

tiles, Mining and quarrying, Other Manufacturing, and Transport. Disaggregated import series are annual data 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, 1997=base year), also from the Bureau of Statistics, were used to deflate import series. The resulting variables (real import series) were taken to be the physical quantity of imported commodities. The price of domestic output was obtained from the CPI data of the Bureau of Statistics. Real GDP data were used as the physical quantity of domestically produced goods and services.

Descriptive statistics for real imports, real domestic outputs, import prices and domestic output prices are presented in Table 2.

Two methods were used to estimate our parameters of interest: iterated seemingly unrelated regression (ITSUR) and generalized maximum entropy (GME) techniques for LES and

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

Commodities	Imports *value*[a]	Domestic Production *value*[a]	Import Price *Index*[b]	Domestic Price *Index*[b]
Agriculture	252.63	152.23	0.91	0.89
Food	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
Other Manuf.	395.64	24.06	0.98	0.94
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.

Armington parameters respectively. Because efficiency gain can be achieved by combining each demand equation as a system, the Zellner's SUR method was used to estimate LES parameters. Given the dearth of data for the variables required for estimating Armington elasticities, the power of GME techniques was exploited for the purpose of estimation. The robustness of the GME method has been proven for ill-posed, limited and poor data problems (Golan, Judge, and Miller 1996).

4 Estimating LES Parameters and Elasticities

4.1 Theoretical Background and Methodology

The basic theoretical foundations of the *linear* expenditure system (LES) demand were presented in Nganou (2004). The following LES Marshallian demands were derived:

$$\mathrm{QH_{ch}} = \gamma_{\mathrm{ch}} + \frac{\beta_{\mathrm{ch}}}{\mathrm{PQ_c}} \left(\mathrm{EH_h} - \sum_{\mathrm{c'}} \mathrm{PQ_{c'}} \cdot \gamma_{\mathrm{c'h}} \right) \tag{1}$$

where $\mathrm{QH_{ch}}$ is the quantity demanded of commodities c by household h, $\mathrm{EH_h}$ is the total expenditures (or income) of household h, $\mathrm{PQ_c}$ is the price of commodity c, γ_{ch} and β_{ch} are

LES parameters. More precisely, γ_{ch} represents subsistence quantities while β_{ch} reflects the relative contribution of each commodity to utility after subsistence has been achieved.

For estimation purposes, it is common practice to multiply both sides of eq. (1) by $\mathrm{PQ_c}$ to obtain a *linear* expenditure system of equations, so designated because expenditure is a linear function of income and prices. The expenditure system is clearly not linear in the parameters (γ_{ch}, β_{ch}) (see Judge, Hill, Griffiths, Lütkepohl, and Lee (1988)). The corresponding econometric model for the *linear* expenditure system is the following:

$$\mathrm{PQ_c} \cdot \mathrm{QH_{ch}} = \mathrm{PQ_c} \cdot \gamma_{\mathrm{ch}} + \beta_{\mathrm{ch}} \left(\mathrm{EH_h} - \sum_{\mathrm{c'}} \mathrm{PQ_{c'}} \cdot \gamma_{\mathrm{c'h}} \right) + \epsilon_{ch} \tag{2}$$

where ϵ_{ch} is the error term, γ_{ch} and β_{ch} are the parameters to be estimated, c=c' represents the commodities for which sample data on prices, quantities, and income are available for the estimation of parameters (i.e., c= Agriculture, Food, Beverages and Tobacco, Textiles, Utilities, Private Services, Government Services, Transport, Other Manufacturing, and Financial Services). Meanwhile, only two household categories had appropriate data (i.e., h= urban, rural). The system represented by equation (2) can be viewed as a set of nonlinear seemingly unrelated regression equations since it can be shown that the covariance matrix of the system is not diagonal.

Due to the fact that the sum of expenditures should equal the total income (i.e., the sum of the dependent variables is equal to one of the explanatory variables for all observations), the sum of error terms for each equation of the system is equal to 0, leading to the singularity of the covariance matrix. In such conditions, estimation procedure breaks down. To overcome this singularity problem, it is common practice that one equation be omitted for the estimation of the demand system (Judge, Hill, Griffiths, Lütkepohl, and Lee 1988). The adding-up constraint $\mathrm{EH_h} = \sum_c \mathrm{PQ_c} \cdot \mathrm{QH_{ch}}$, ensures that the omitted equation is deducible by difference. The choice of the omitted equation is arbitrary.

Given that the estimation method used here is iterative, the choice of starting values is also crucial. There is no clear rule on these values. But as stated in Judge, Hill, Griffiths, Lütkepohl, and Lee (1988), "the nature of the model provides some guide as to what might be good starting values for an iterative algorithm." For each commodity they suggest the minimum value of the quantity demanded as a reasonable starting value for the associated γ_c. Also, they proposed the average budget shares to be good starting values for the β_c.

Consequently for our purposes, the starting values used are summarized in table 3.

Table 3: Starting values for the iterative process of estimation of LES parameters

	Urban		Rural		All Households	
	γ_c^0	β_c^0	γ_c^0	β_c^0	γ_c^0	β_c^0
Agriculture	33.380	0.072	0.000	0.130	7.440	0.092
Food	0.000	0.086	0.000	0.100	0.000	0.091
Textiles	0.000	0.085	0.000	0.289	0.000	0.146
Utilities	0.000	0.069	0.000	0.027	0.000	0.054
Private Services	0.000	0.067	0.000	0.173	0.000	0.103
Govt Services	0.000	0.086	0.000	0.072	0.000	0.095
Transport	0.000	0.070	0.000	0.107	0.000	0.096
Other Manufacturing	0.000	0.071	0.000	0.131	0.000	0.092
Financial Services	0.000	0.131	0.000	0.181	0.000	0.173
Total		1		1		1

Source: Author's Calculations

The ITSUR method available in SAS (version 9.0) was employed in the estimation of eq. (2) with restrictions of non-negativity of coefficients imposed (i.e., $\gamma_\mathrm{c} \geq 0$, and $0 < \beta_\mathrm{c} < 1$). Zellner (1962) came up with the notion of seemingly unrelated regression equations (SURE) for systems whose equations, at first examination unrelated, are in reality related through the correlation in the errors. In short, a set of equations that has contemporaneous correlation between the disturbances in different equations is a seemingly unrelated regression system. ITSUR procedure adjusts for cross-equation contemporaneous correlation and consequently takes into account the optimization process underlying the demand system. The iterative process of the ITSUR ensures that the obtained estimates approach asymptotically those of the maximum likelihood method. Moreover, ITSUR unlike Seemingly Unrelated Regression (SUR) is insensitive to the excluded equation (in our case the financial services equation) (Judge, Hill, Griffiths, Lütkepohl, and Lee 1980).[1] Breusch-Pagan and White tests for heteroskedasticity were performed for separate equations of the system in this study. Both tests significantly rejected the null hypothesis, indicating the presence of cross-equation contemporaneous correlation.[2] Thus, the set of demand equations to be estimated is a seemingly unrelated system. Therefore, the Zellner's estimation approach (SUR) is appropriate for this purpose.

4.2 Estimation Results

The results of estimation are presented in table 4 below. Interestingly, findings suggest that the subsistence requirement parameter (γ) is higher for urban households compared to that for their rural counterparts in the following commodities: Agriculture, Food, Utilities, Government services, and Other Manufacturing. In most of those commodities, the value of those parameters is double the value for rural households. The subsistence parameter for

[1]ITSUR iterates from initial guesstimates specified.
[2]Tests results are not reported in this paper but are available upon request from the author.

Transport is relatively larger among rural households (M2739.90 compared to M128.68 for urban households). This makes sense since in rural areas, given the scarcity of transport and communication infrastructure, the subsistence levels should be higher. Financial services is estimated to be zero among urban households while it is around M2900 for their rural counterparts. In fact, in rural areas, given that funeral homes also provide some financial services (informal), households do not have many options compared to urban households. Findings also reveal that for urban households, the share of supernumerary income (β) is important toward Financial Services (38 percent), Transport (23 percent) and Private services (12 percent). Meanwhile, rural households spend 26 percent of their supernumerary income on Other Manufacturing commodities, 22 percent on Private Services (personal care, etc.), and 20 percent on Financial Services. These results suggest that for each household group, the commodities mentioned are luxuries since the supernumerary income is also interpreted as luxuries expenditures. This is confirmed by income elasticities greater than unity (see table 4 below). Interestingly, urban households spend more of their supernumerary income on Transport than do rural households (4 percent), which simply means that transport and communication is a luxury in urban areas whereas it is a necessity in rural zones.

In CGE models that adopt LES demand systems to represent the consumption behavior of households, income elasticity of each commodity and Frisch parameters for each household category are crucial in the calibration process. The Frisch parameter is the substitution parameter measuring the sensitivity of the marginal utility of income to income/total expenditures. The Frisch parameter, also called money flexibility, establishes a relationship

Table 4: Estimation Results of parameters of the LES Demand System

	Urban		Rural		All Households	
	γ_c	β_c	γ_c	β_c	γ_c	β_c
Agriculture	6115.67^a	0.014^a	3696.41^a	0.089^a	4745.30^a	0.025^a
Food	6993.31^a	0.031^a	2864.39^a	0.072^a	4446.53^a	0.041^a
Textiles	6415.99^a	0.042^a	7919.98^a	0.09^a	6307.41^a	0.048^a
Utilities	4345.50^a	0.06^a	782.58^a	0.02^a	1903.72^a	0.058^a
Private Services	2126.28^b	0.123^a	2192.90^a	0.216^a	1436.41^a	0.133^a
Govt Services	5046.26^a	0.080^a	2103.88^a	0.020^a	2610.10^a	0.075^a
Transport	128.68	0.230^a	2739.90^a	0.040^a	0.00	0.201^a
Other Manufacturing	4966.32^a	0.050^a	2020.60^a	0.261^a	3586.74^a	0.074^a
Financial Services.	0	0.38	2916.91^a	0.20	0.00	0.35

Source: Author's Calculations

Note. a = significant at 1 percent level, b= significant at 5 percent level; γ_c is the subsistence requirement parameter on commodity c; β_c is the supernumerary income share parameter on commodity c.

between own-price and income elasticities. It is important for cases (such as cross sectional studies) where reliable price data are difficult to be obtained to provide good estimates of own-price elasticities. Consequently, the relationship for directly additive preferences proposed by Frisch (1959) and embodied in the Linear Expenditure System (LES) is often used to derive own- and cross-price elasticities. In fact, price elasticities of demand are determined simply by the income elasticity in conjunction with the Frisch parameter.

It is worth noting that although own-price elasticities are estimated, in practice CGE modelers prefer using the income and Frisch parameters. Using Frisch parameters prevent us from using own-price elasticities with positive signs in the CGE model. Also, given the huge number of cross-price elasticities (i.e., n(n-1)) to be estimated, there is an enormous saving in statistical investigation if the Frisch parameters were used to derived those elasticities instead of making a separate analysis for each of the cross-price elasticities (Frisch 1959).

However, in the context of this paper, the estimation of own-price elasticities was not useless since it provides us with significant insights into the consumption behavior of the people of Lesotho.

The formula used to derive Frisch parameters is simply the negative ratio between household's total expenditures and the supernumerary income (i.e., the difference between household income and total expenditures on subsistence requirements) at the sample means (indicated by a bar over a variable). Frisch parameters are

$$\mathrm{Frisch_h} = -\frac{\overline{\mathrm{EH}}_\mathrm{h}}{\left(\overline{\mathrm{EH}}_\mathrm{h} - \sum_{\mathrm{c'}} \overline{\mathrm{PQ}}_{\mathrm{c'}} \cdot \gamma_{\mathrm{c'h}}\right)} \tag{3}$$

Similarly, we calculate Marshallian own-price and expenditures elasticities at the sample means. The Marshallian own-price elasticities are

$$\epsilon_{\mathrm{ch}} = \frac{\overline{\gamma}_{\mathrm{ch}} \cdot (1 - \beta_{\mathrm{ch}})}{\overline{\mathrm{QH}}_{\mathrm{ch}}} - 1 \tag{4}$$

The expenditure/income elasticities are

$$\eta_{\mathrm{ch}} = \frac{\beta_{\mathrm{ch}} \cdot \overline{\mathrm{EH}}_\mathrm{h}}{\overline{\mathrm{PQ}}_\mathrm{c} \cdot \overline{\mathrm{QH}}_{\mathrm{ch}}} \tag{5}$$

After estimating the LES parameters, we use a feature of the SAS software (i.e., "Estimate") to compute/derive own-price, income/expenditures elasticities, as well as Frisch parameters for the two household subcategories and the entire sample. These results are presented in Table 5 along with associated standard errors.

With regard to own-price elasticities, we observe that the demand for the majority of commodities listed is either price inelastic or unitary elastic in some cases. There are some commodities whose price elasticities have the wrong sign (positive). More specifically, for urban households, findings indicate negative own-price elasticities for all commodities, with few exceptions (Agriculture, Food, and Textiles), as predicted by the neoclassical consumer theory. While the demand for Financial Services is unitary elastic, the price elasticity of demand for Transport nears unity. Other Manufacturing and Utilities sectors have the lowest own-price elasticities (-0.004 and -0.160) for urban households. It is worth mentioning that Textiles and Other Manufacturing are the only commodities for urban households whose price elasticities are not statistically significant. Among rural households, Agriculture, Textiles, and Transport have statistically significant unitary elastic demands, which means that a unit increase in the price of those commodities leads to a unit reduction in their respective quantities demanded. Meanwhile, rural households' demand for Government Services and Financial Services have own-price elasticities with a positive sign, which contradicts the neoclassical consumer theory predictions. However, while the latter is not statistically significant, the former certainly is, which seems to suggest that Government services is a Giffen "good" for rural households. It could also be the case that the estimated model is misspecified or incorrect in the sense that it is not appropriate to describe the consumption behavior of Basotho Households.[3] Given that the own-price elasticity for Financial Services and Textiles is not statistically significant among rural and urban households respectively, it suggests that the demand for those commodities is vertical for both household groups. This finding indicates that a marginal increase in the price of those commodities leaves its

[3] These remarks also apply to incorrectly signed urban households demand elasticities.

demand unchanged. For the entire sample (across all households), the demands for Agricultural commodities and Food have statistically significant positive own-price elasticities (wrong sign).

Table 5: Own-Price and Income/Expenditures Elasticities of the LES Demand

	Urban		Rural		All Households	
	ϵ_c	η_c	ϵ_c	η_c	ϵ_c	η_c
Agriculture	0.376^a	0.198^a	-1.00^a	0.480^a	0.267^a	0.271^a
	(0.033)	(0.015)	(0.000)	(0.016)	(0.026)	(0.012)
Food	0.313^a	0.364^a	-0.212^a	0.490^a	0.206^a	0.444^a
	(0.043)	(0.019)	(0.030)	(0.016)	(0.031)	(0.013)
Textiles	0.05	0.497^a	-1.00^a	0.539^a	-0.074^b	0.325^a
	(0.066)	(0.03)	(0.000)	(0.023)	(0.034)	(0.013)
Utilities	-0.160^b	0.871^a	-0.198^a	0.500^a	-0.279^a	1.066^a
	(0.065)	(0.032)	(0.049)	(0.029)	(0.054)	(0.025)
Private Services	-0.608^b	1.836^a	-0.508^a	1.688^a	-0.736^a	1.282^a
	(0.197)	(0.091)	(0.120)	(0.051)	(0.101)	(0.040)
Govt Services	-0.288^a	0.930^a	0.559^a	0.428^a	-0.485^a	0.787^a
	(0.106)	(0.048)	(0.079)	(0.035)	(0.07)	(0.027)
Transport	-0.977^a	3.21^a	-1.00^a	0.852^a	-1.00^a	2.092^a
	(0.254)	(0.118)	(0.000)	(0.063)	(0.00)	(0.052)
Other Manufacturing	-0.004	0.687^a	-0.654^a	1.534^a	-0.165^a	0.807^a
	(0.074)	(0.034)	(0.079)	(0.042)	(0.062)	(0.028)
Financial Services	-1.00^a	2.867^a	0.069	2.537^a	-1.00^a	2.513^a
	(0.00)	(0.069)	(0.235)	(0.085)	(0.00)	(0.033)
Frisch Parameter	-2.188^a		-1.634^a		-2.415^a	
	(0.224)		(0.092)		(0.132)	

Source: Author's Calculations.
Note. a = significant at 1 percent level, b= significant at 5 percent level; standard errors are in the parenthesis; ϵ represents own-price elasticity; η is the income elasticity.

On the other hand, findings suggest that all the commodities listed are normal goods, given that their income elasticity is positive in sign. For urban households, Agriculture has the lowest income elasticity, followed by Food, Textiles, Other Manufacturing (0.198-0.687). Also, given that the income elasticity for all other commodities, except Private Services, Transport, and Financial Services, is positive but less than one, those commodities are necessities for urban households. Meanwhile, among rural households, the income elasticity for Private Services, Other Manufacturing and Financial Services is greater than one, suggesting that those commodities are luxuries. Other Manufacturing is a luxury for rural households whereas it is a necessity for urban households. This makes sense since household appliances, which constitute part of Other Manufacturing, can be thought of as luxury goods in rural areas. In fact, rural households in general do not use modern household appliances; rather, they resort to rudimentary methods/tools. The same contrast can be drawn for Transport and Communication, which is a luxury for urban households and a necessity for rural households. Interestingly, the income elasticities on Agriculture, Food, and Textiles are larger for rural households. For instance, an increase of 100 units in the income of urban households leads to an increase of 20 units in their demand for Agriculture. A similar increase in the income of rural households causes an increase of 48 units in their demand for Agriculture. In sum, Agriculture, Food, and Textiles are more necessities for rural households than they are for their urban counterparts.

5 Estimating Armington Parameters

5.1 A Brief Theoretical Background

The Armington elasticity, 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 a price change 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 true Armington parameters for the countries of study. Consequently, despite the dearth of data for Lesotho, GME technique is used here to estimate Armington parameters.

The theoretical foundations of the Armington demand were presented in Nganou (2004). The following equation is the first order condition of the Armington's consumer problem:

$$\frac{\mathrm{QM_c}}{\mathrm{QD_c}} = \left[\frac{\mathrm{PDD_c}}{\mathrm{PM_c}} \cdot \frac{\delta_\mathrm{c}^\mathrm{q}}{1-\delta_\mathrm{c}^\mathrm{q}}\right]^{\sigma_\mathrm{c}^\mathrm{q}}, \quad c = 1, \ldots, 6 \tag{6}$$

where the elasticity of substitution between commodities from these two sources is given by $\sigma_c^q = \frac{1}{1+\rho_c^q}$. Equation 6 defines the optimal mix between imports and domestic output. It suggests that an increase in the domestic-import price ratio generates an increase in the import-domestic demand ratio. As a result, the demand shifts away from the source that becomes more expensive.

From equation 6, it can be shown that, σ_c^q is derived as follows:

$$\sigma_\mathrm{c}^\mathrm{q} = \frac{\partial \mathrm{Ln}\left(\frac{\mathrm{QM_c(t)}}{\mathrm{QD_c(t)}}\right)}{\partial \mathrm{Ln}\left(\frac{\mathrm{PDD_c(t)}}{\mathrm{PM_c(t)}}\right)}, \quad c = 1, \ldots, 6; \quad t = 1, \ldots, 7 \tag{7}$$

where the numerator is the partial derivative of the logarithm of the ratio of quantity of imports and domestic output, and the denominator is that for the ratio of prices of domestic output and imports. 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. The marginal rate of technical substitution is given by their prices ratio. t represents the time subscript (i.e., 7 years).

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

$$\mathrm{Ln}\left(\frac{\mathrm{QM_c(t)}}{\mathrm{QD_c(t)}}\right) = \alpha_{\mathrm{c}}^{0} + \sigma_{\mathrm{c}}^{\mathrm{q}} \cdot \mathrm{Ln}\left(\frac{\mathrm{PDD_c(t)}}{\mathrm{PM_c(t)}}\right) + u_c(t), \quad c = 1, \ldots, 6; \quad t = 1, \ldots, 24 \tag{8}$$

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

5.2 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) we have about the occurrence of a collection of events. ME is a special case of the GME where no weight is placed on the entropy of the error terms and 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 (Golan, Perloff, and Shen 2001).

The desirable properties of GME are described in details in Golan, Judge, and Miller (1996). Some of these properties are briefly mentioned here. 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).

5.3 A GME Estimation of Armington Elasticities

In order to estimate equation (8) above with GME[4], 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, $\underline{z}_c^\sigma = (z_{c1}^\sigma, z_{c2}^\sigma, \ldots, z_{cD}^\sigma)'$ of dimension $D \geq 2$, that are at uniform intervals, symmetric around zero, and span the interval $[z_{c1}^\sigma, z_{cD}^\sigma]$. The vector of corresponding unknown weights is also introduced as follows: $\underline{p}_c^\sigma = (p_{c1}^\sigma, p_{c2}^\sigma, \ldots, p_{cD}^\sigma)'$ such that $\sum_{d=1}^{D} p_{cd}^\sigma = 1$ and $\sum_{d=1}^{D} z_{cd}^\sigma \cdot p_{cd}^\sigma = \sigma_c^q$ 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 $u_c(t)$, 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 $M \geq 2$ discrete points $\underline{v} = (v_1, v_2, \ldots, v_M)'$, distributed uniformly about zero, and an associated

[4]To perform the estimation GAMS was employed. Alternatively SAS can be used. Version 9 of SAS includes a specific routine to implement GME, albeit it remains experimental.

vector of proper unknown weights $\underline{w} = (w_{c1}(t), w_{c2}(t), \ldots, w_{cM}(t))'$ such that $\sum_m v_m \cdot w_{cm}(t)$ $= u_c(t)$. 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. 8), we obtain:

$$\mathrm{Ln}\left(\frac{\mathrm{QM_c(t)}}{\mathrm{QD_c(t)}}\right) = \sum_{\mathrm{d=1}}^{\mathrm{D}} \mathrm{z}_{\mathrm{cd}}^{0} \cdot \mathrm{p}_{\mathrm{cd}}^{0} + \sum_{\mathrm{d=1}}^{\mathrm{D}} \mathrm{z}_{\mathrm{cd}}^{\sigma} \cdot \mathrm{p}_{\mathrm{cd}}^{\sigma} \cdot \mathrm{Ln}\left(\frac{\mathrm{PDD_c(t)}}{\mathrm{PM_c(t)}}\right) + \sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{v_m} \cdot \mathrm{w_{cm}(t)}$$
$$c = 1, \ldots, 6; \quad t = 1, \ldots, 7 \tag{9}$$

The GME estimator maximizes the entropy of all the probabilities representing the signal (α_c^0, σ_c^q) and the noise ($u_c(t)$), subject to the data (equation (9) 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:

$$\max R(\underline{p}, \underline{w}) = -\underline{p}' \cdot Ln(\underline{p}) - \underline{w}' \cdot Ln(\underline{w}), \tag{10}$$

subject to the data (i.e., Eq. (9)) and the GME adding-up conditions,

$$\sum_{d=1}^{D} p_{cd}^{0} = \sum_{d=1}^{D} p_{cd}^{\sigma} = \sum_{m=1}^{M} w_{cd}(t) = 1 \tag{11}$$

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:

$$\widehat{\alpha}_c^0 = \sum_{d=1}^{D} z_{cd}^0 \cdot \widehat{p}_{cd}^0 \tag{12}$$

$$\widehat{\sigma}_c^q = \sum_{d=1}^{D} z_{cd}^\sigma \cdot \widehat{p}_{cd}^\sigma \tag{13}$$

$$\widehat{u}_c(t) = \sum_{m=1}^{M} v_m \cdot \widehat{w}_{cm}(t) \tag{14}$$

5.3.1 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). The dimension or the number of points in the support space for the parameters we will consider is 5 (*i.e.*, $D = 5$). In fact, based on some experiments, Golan, Judge, and Miller (1996) argue that the greatest improvement in precision[5] could be obtained when the support space on the parameters has 5 elements (see page 140).

Since there is no theory 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), other market-leaning economists have argued the contrary (Liu, Arndt, and

[5]This is due to the fact that the variance of a uniform discrete distribution supported on the support space drops significantly.

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 of 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: $[-3 \cdot stdev, 0, 3 \cdot stdev]$, where $stdev$ is the empirical (data) standard deviation of the dependent variable.

5.3.2 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 and Adjusted 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] due to its use of out of sample information (Fraser 2000). This is also supported by our findings (see Tables 6–11).

For our purpose, 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).

5.4 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.

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

Estimation results of coefficients along with associated standard errors are presented in the Tables 6 - 11.

5.4.1 A Sensitivity Analysis of the GME Estimates

Overall, the estimated elasticities appear to be relatively robust in terms of signs, although the magnitude is, in some cases, variable to the choice of support values.

Table 6: Sensitivity Tests of GME Estimates of Armington Elasticity for Agriculture

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	0.898^a (0.135)	10.86	0.999	0.879	0.899
[-100, -50, 0, 50, 100]	0.898^a (0.135)	10.86	0.999	0.879	0.899
[-50, -25, 0, 25, 50]	0.897^a (0.135)	10.86	0.999	0.879	0.899
[-20, -10, 0, 10, 20]	0.894^a (0.135)	10.86	0.997	0.879	0.899
[-10, -5, 0, 5, 10]	0.882^a (0.135)	10.85	0.995	0.879	0.899

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 parameters '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 6 and 7). The elasticity estimate for Textiles was marginally significant (at 11 percent) in

Table 7: Sensitivity Tests of GME Estimates of Armington Elasticity for Food

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	1.371^b (0.596)	10.66	0.999	0.42	0.51
[-100, -50, 0, 50, 100]	1.37^b (0.596)	10.66	0.999	0.42	0.51
[-50, -25, 0, 25, 50]	1.367^b (0.596)	10.66	0.999	0.41	0.51
[-20, -10, 0, 10, 20]	1.348^b (0.596)	10.66	0.997	0.41	0.51
[-10, -5, 0, 5, 10]	1.282^b (0.597)	10.64	0.989	0.41	0.51

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 's asymptotic standard errors are provided in the parentheses.
See Table 6 for the definition of $S(P_k)$.

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 8).

It is worth mentioning that the estimated Armington elasticity for Other Manufacturing was statistically significant and insensitive across support space specifications, but with a negative sign (contrary to the theory predictions). This could be due to a model misspecification. Estimated Armington elasticities with wrong signs are also common in the literature.

Further efforts were undertaken in order to see whether we can get robust estimates on Other Manufacturing with the correct sign. Thus, we restricted the support space on the parameters (not the intercept term) to be non-negative. The restricted specifications results

Table 8: Sensitivity Tests of GME Estimates of Armington Elasticity for Textiles

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	7.752^d (4.73)	10.58	0.998	0.227	0.356
[-100, -50, 0, 50, 100]	7.613 (4.735)	10.57	0.996	0.226	0.355
[-50, -25, 0, 25, 50]	6.91 (4.754)	10.56	0.988	0.221	0.351
[-20, -10, 0, 10, 20]	4.232 (5.01)	10.49	0.972	0.136	0.28
[-10, -5, 0, 5, 10]	1.825 (5.45)	10.43	0.979	-0.025	0.146

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 's asymptotic standard errors are provided in the parentheses.
See Table 6 for the definition of $S(P_k)$.

are appended in Table 9. The results reveal a severe sensitivity of the parameters to the support space. Moreover, although the estimates are of the right sign (imposed), they are no more statistically significant. We also tried several specifications with (unweighted as well as weighted priors) generalized cross entropy (GCE). The estimated coefficients were very small in size (close to 0) and statistically insignificant.[7]

The estimated coefficients for the remaining commodities (Mining and Transport), although with the correct sign, were both not statistically significant (see Tables 10 and 11). 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 specifi-

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

Table 9: Sensitivity Tests of GME Estimates of Armington Elasticity for Other Manufacturing

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	-1.288^c (0.686)	10.61	0.999	0.294	0.412
[-100, -50, 0, 50, 100]	-1.288^c (0.686)	10.61	0.999	0.294	0.412
[-50, -25, 0, 25, 50]	-1.285^c (0.686)	10.61	0.999	0.294	0.412
[-20, -10, 0, 10, 20]	-1.268^c (0.686)	10.59	0.997	0.294	0.412
[-10, -5, 0, 5, 10]	-1.21^c (0.686)	10.53	0.991	0.294	0.41
[0, 5, 10, 15, 20]	0.486 (1.047)	8.9	0.204	-0.646	-0.371
[0, 10, 25, 30, 50]	0.193 (0.952)	8.8	0.059	-0.36	-0.13
[0, 25, 50, 75, 100]	0.026 (0.902)	8.77	0.003	-0.22	-0.02

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 6 for the definition of $S(P_k)$.

cations).

5.4.2 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[8] described earlier, as well as our knowledge of the country. Given that Lesotho is an import-dependent economy, one might expect the Armington elas-

[8]For our purpose in this study, an extraneous variable is one whose coefficient's associated normalized entropy index is above 0.999.

Table 10: Sensitivity Tests of GME Estimates of Armington Elasticity for Mining

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	7.3 (16.52)	10.4	0.998	-0.148	0.044
[-100, -50, 0, 50, 100]	6.478 (16.53)	10.39	0.997	-0.149	0.042
[-50, -25, 0, 25, 50]	4.01 (16.62)	10.39	0.996	-0.16	0.032
[-20, -10, 0, 10, 20]	1.042 (16.83)	10.35	0.998	-0.19	0.006
[-10, -5, 0, 5, 10]	0.232 (17.04)	10.26	0.999	-0.22	-0.018

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 6 for the definition of $S(P_k)$.

ticity to be relatively high. It is worth mentioning that in our determination of final estimates, we will lean towards those with both wider support space and lower associated normalized entropy statistics. This accounts for our lack of prior knowledge about the parameter bounds as mentioned before, as well as our efforts to let the data speak.

As mentioned before 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)

Table 11: Sensitivity Tests of GME Estimates of Armington Elasticity for Transport

Parameters Support	Estimated Elasticity	Entropy value	Normalized Entropy Ratio $S(P_k)$	Adjusted R-Square	R-Square
[-150, -75, 0, 75, 150]	2.78 (5.054)	10.41	0.999	-0.14	0.05
[-100, -50, 0, 50, 100]	2.741 (5.076)	10.41	0.999	-0.14	0.05
[-50, -25, 0, 25, 50]	2.546 (5.092)	10.41	0.998	-0.14	0.05
[-20, -10, 0, 10, 20]	1.696 (5.093)	10.4	0.996	-0.15	0.043
[-10, -5, 0, 5, 10]	0.774 (5.16)	10.38	0.996	-0.17	0.025

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 6 for the definition of $S(P_k)$.

on the estimated coefficient. Also, its R^2, although low, is similar to that of the first two specifications. 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, the Armington estimate for Transport is 1.696. We could have chosen 0.774 but we leaned towards the estimated coefficient with a wider support space and whose 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 the Armington elasticity for Other Manufacturing will be based only on the restricted regressions, although the ones with the wrong signs were statistically significant and robust across support specifications. The widest non-negative support space yielding the coefficient estimate with the lowest normalized entropy ratio is the last one. But an elasticity of 0.026 for Other Manufacturing does not seem realistic for Lesotho, a very open economy. Here our common sense will play in the selection of the elasticity for Other Manufacturing. Thus, an elasticity of 0.486 seems more realistic for Other Manufacturing. It is the lowest among the six elasticities estimated. The final estimates considered are summarized in Tables 12 and 13.

Table 12: Summary Table of GME Armington Elasticity Estimates for the Lesotho CGE

	Armington Elasticity	Normalized Entropy	R^2
Agriculture	0.898^a (0.135)	0.999	0.899
Food	1.37^b (0.596)	0.999	0.51
Mining	4.01 (16.62)	0.996	0.032
Textiles	4.232 (5.01)	0.972	0.28
Transport	1.696 (5.093)	0.996	0.043
Other Manufacturing	0.486 (1.047)	0.003	-0.02

Source: Author's Calculations.
Note. a = significant at 1 percent level, b= significant at 5 percent level, c= significant at 10 percent level. The parameters 's asymptotic standard errors are provided in the parentheses.

5.4.3 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.[9] We believe that parameters

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

should be country specific, but the 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. A comparison of the estimated Armington elasticities with those used in selected studies is presented in Table 13.

Table 13: A Comparison of Selected Armington Elasticities

	Our estimates	GTAP	de Janvry et al. 01	Lofgren (Egypt's CGE)	South Africa
Agriculture	0.898	2.44	0.40	0.56	1.60
Food	1.37	2.40	0.50	1.65	1.53
Textiles	4.232	3.32	0.50	0.30	4.13
Mining	4.01	2.41	0.50	2.00	0.76
Other Manufacturing	0.486	2.81	0.50	0.30	1.64
Transport	1.696	3.10	0.50	0.30	1.14

Source: Compiled by the Author

First, the table reveals that the majority of Lesotho's estimates are higher than those provided by de Janvry and Sadoulet (2001). However, except for Mining and Textiles, the parameters are below those provided by GTAP. 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 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.

Comparison also reveals that, except for Food, Lesotho estimates for elasticities are higher than those of Egypt. 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.

6 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) argue, 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 in this paper, GME econometrics is possible for developing countries (whose economic data are generally scarce and considered poor in quality). On the other hand, using Household Expenditures Survey (HES) data, ITSUR methods were utilized in the estimation of own-price and income elasticities, and the derivation of Frisch parameters. The estimated coefficients were generally robust. Finally, it is worth noting that the partial equilibrium framework used in this paper for the estimation of parameters may be inconsistent with CGE analysis as argued by critics.

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