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Abstract

Since the early 1970s there has been a worldwide upsurge in the price of energy and in particular of gasoline. Therefore, demand functions for energy and its components like gasoline have received much attention. However, since confidence in the estimated demand functions is important for use in policy and forecasting, following Amarawickrama and Hunt (2008), this paper estimates the demand for gasoline is estimated with 6 alternative time series techniques with data from Fiji. Estimates with these 6 alternative techniques are very close and thus increase our confidence in them. We found that gasoline demand is both price and income inelastic.

Keywords: Gasoline Demand, Income and price elasticities, Cointegration.

JEL: Q40, Q41.

1. Introduction

Since the early 1970s there has been a worldwide upsurge in the price of energy and in particular of gasoline. Many researchers, therefore, have estimated demand functions for energy and its components of which the gasoline has received much attention.[1] The main purpose of these studies has been to understand how the demand for gasoline has responded to price changes and whether the income and price elasticities of demand are elastic or inelastic. This information is useful to forecast demand for gasoline and also for determining taxes to reduce demand if necessary. Therefore, it is necessary to have some confidence in the estimates of the parameters and this confidence can be increased if alternative methods of estimation yield similar estimates. This is the main objective of our paper and is similar to the purpose of a recent study by Amarawickrama and Hunt (2008) of the demand for electricity in Sri Lanka.

In this process we also highlight a few neglected issues in estimating the demand for gasoline and energy. One of these issues is endogeniety of the explanatory variables viz., income and price. This may lead to biases in the estimates in the single equation time series methods. A second issue is the reliability of the estimated standard errors in finite samples although they are asymptotically efficient in all methods. Some exceptions in the energy demand studies to these limitations are Polemis (2006) for the demand for gasoline in Greece and Amarawickrama and Hunt (2008) in the demand for electricity in Sri Lanka.

The above two issues are partly methodological in nature and it is worth stating briefly the general conclusions reached by Inder's (1993) Monte Carlo simulation study. Firstly, he found that although the popular Engle and Granger (1987) two-step procedure gives unbiased and efficient estimates in finite samples, these properties can be improved if an over-parameterized dynamic equation is estimated in the first stage to derive the equilibrium or cointegration equation. In the second stage the short run equation can be estimated with the lagged residuals

[1] A quick search for energy demand papers produced 95 references from Science Direct journals alone of which more than half are on the demand for gasoline.

from this first stage cointegrating equation.[2] The modified Engle-Granger method is known as dynamic Engle-Granger method (*DEG*). Secondly, Inder (1993) also found that the Phillips and Hansen (1990) alternative with a semi-parametric correction did not yield unbiased and efficient estimates in finite samples. However, this approach is attractive because it is easy to implement and known as the fully modified *OLS (FMOLS)* approach. Inder (1993) found that the Monte Carlo exercise conducted by Phillips and Hansen is somewhat biased in favour of *FMOLS*.

Amarawickrama and Hunt have provided a useful summary of the relative merits of 6 alternative time series estimation methods: (1) Static Engle and Granger (1987),(*SEG*) method, (2) Dynamic Engle and Granger (1987), (*DEG*) method, (3) Fully modified ordinary least squares (*FMOLS*) method, Pesaran, Shin and Smith's (2001) bounds test (*BT*) method, (5) Johansen's (1988) maximum likelihood method (*JML*), which is a systems method and minimizes endogenous variable bias, and (6) an alternative approach advocated by Harvey (1997), known as the Structured time series method (*STSM*). In this last method trend is treated as stochastic whereas in all other methods trend is deterministic.[3] Two methods not examined by them are the Stock and Watson (1988) dynamic ordinary least squares method (*DOLS*) and the general to specific approach (*GETS*) of the London School of Economics; see footnote 2. Thus there are 8 alternative methods to estimate time series models. In principle all these methods should give similar estimates of the coefficients in large samples i.e., their asymptotic properties should be similar. However, their finite sample properties may differ and the more substantial problems are biases due to endogeneity and lack of power of the cointegrating tests against the null of no cointegration. These issues can only be resolved by undertaking exhaustive Monte Carlo studies similar to Inder (1993) and Banerjee, Dolado, Hendry and Smith (1986).

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[2] This solution is somewhat similar to Banerjee, Dolado, Hendry and Smith (1986) where they argued that the London School of Economic method, known as the general to specific approach (*GETS*), of which Professor David Hendry is the most ardent exponent, is efficient with good finite sample properties. In *GETS* both the cointegrating equation and the short run dynamics are estimated in one step by estimating an over-parameterized equation at first. Then a parsimonious specification is derived by deleting the insignificant changes in the variables.

[3] An easy to understand exposition of the methodological nature of the controversy on how to model trend see Rao (2009).

The outline of this paper can be stated as follows. Section 2 reviews selected previous works. In Section 3 we present estimates of the demand for gasoline in Fiji with *DEG*, *GETS*, *FMOLS*, *BT* and *JML*.[4] We have neglected the other methods to limit the length of this paper. Comparisons of estimates with these 5 methods should be adequate to reveal any differences that are likely to exist in the estimates of the parameters. Section 4 concludes.

2. Review of Selected Previous Studies

We have selected a few recent studies on the demand for gasoline because most of the earlier studies have been adequately reviewed in some of these recent works like Amarawickrama and Hunt (2008) and Akinboade, Ziramba and Kumo (2008).

Studies on the gasoline demand functions predominantly estimated the price and income elasticities of demand using different methodologies and time series techniques. Most estimates of price and income elasticities do not provide a consensus on the short run and long run elasticity estimates. Sterner and Dahl (1990) surveyed over a hundred past studies on gasoline

[4] We have selected *GETS* for the following reasons. Firstly, the cointegrating equation and the dynamic adjustment equation can be estimated in one step. Secondly, *GETS* can be estimated with the instrumental variables method to minimize the endogenous variables bias. Thirdly, it is possible to estimate by imposing constraints on the coefficients and this is not easy in other methods although one can test for the validity of the constraints on the parameters in JML. This option is especially useful for incorporating structural breaks in trend and the cointegrating vector. Finally, it is not necessary to pretest the variables for unit roots under the original interpretation of GETS. Before the time series econometrics became popular, *GETS* was seen as an alternative to the partial adjustment method of estimating equilibrium relationships with disequilibrium data. Therefore, *GETS* specifications can be estimated with the standard classical methods. However, this has been neglected after the popularity of the time series methods. Belatedly Ericsson and MacKinnon (2002) have developed a cointegrating test giving a time series interpretation to *GETS* . We shall use both approaches noting that pretesting is necessary under the second interpretation.

We have selected *BT* for two reasons. Firstly it is popular in applied work because pretesting is not necessary. Secondly, it does not seem to have been applied correctly in some if not all the applied papers. Although we are not aware of any Monte Carlo study on its finite properties, Turner (2006) has computed the critical values for small samples using the surface response approach of MacKinnon (1991) which is more appropriate than others based on unexplained criteria. Only the asymptotic critical values are tabulated in the Microfit manual.

demand. The models ranged from static to dynamic partial adjustment models to lagged endogenous models with variations in the use of explanatory variables. All studies have used real income and real price of gasoline as the explanatory variables in the model. Some studies have taken stock of vehicles or proxied automobile size for vehicle efficiency in the model. The price elasticity estimates in the short run ranged from -0.12 to -0.41, implying a highly price inelastic demand. The long run estimates are more elastic, ranging from -0.23 to – 0.97. The income elasticity of demand in the short run is insensitive to income, income elasticity coefficients ranging from 0.14 to 0.58. The long run income elasticity coefficients range from 0.6 to 1.31[5]. These results provide estimates with a wide range. After stratifying the models into ten broad categories, Sterner and Dahl were able to provide alternative estimates for the long run and short run. They conclude that there is strong evidence that gasoline consumption is responsive to price and income albeit inelastically.

Wasserfallen and Ghtensperger (1988) estimated the demand for gasoline with the stock of motor vehicles as the explanatory variable for the Swiss economy. They showed that an increase in the stock of cars by 1% increases gasoline consumption by 0.75 %. Sterner and Dahl (1990) report that vehicle elasticity ranges from 0.40 to 0.91 from their survey of gasoline demand functions. Bentzan (1994) reported that the magnitudes of price elasticities in the short and long run are -0.32 and -0.41, respectively. The possible differences in estimates for the income and price elasticities in various studies have been attributed to differences in modeling techniques and different time periods used for estimation.

While Sterner and Dahl (1990) surveyed several important studies prior to 1990's, Polemis (2006) has provided an overview a number of studies during the 1990s to early 2000[6]. Most of the studies have been on either the OECD countries or some developed countries. We review two studies here on the developing countries.

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[5] Akinboade, Ziramba and Kumo (2008) also find long run estimates of price elasticities ranging from -0.12 to -0.464 and income elasticity ranging from 0.12 to 2.68.

[6] For example, Bentzen (1994), Ramanathan (1999), Nicol (2003), Fouquet et al (1997) and Alves and Bueno (2003), quoted in Sterner and Dahl (1990).

Alves and Bueno (2003) estimated the elasticities for gasoline demand for Brazil. In their study they extended the previous studies by estimating the cross price elasticity of demand between gasoline and alcohol. They found that gasoline and alcohol are imperfect substitutes. Their estimates of price elasticities are close to the estimates by Eltony and Al-Mutairi (1995) in Kuwait (-0.463) and Ramanathan (1999) in India (-0.319). But they find low long and short income elasticities for Brazil (0.122 and 0.122 respectively) when compared to Kuwait (1.617 and 0.319) respectively) and India (2.682 and 1.178 respectively). Alves and Bueno (2003) and Ramanthan have used the two step Engle and Granger (1987).

Akinboade and Kumo (2008) applied the Autoregressive Distributed Lag (*ARDL*) bounds testing approach to cointegration to analyze the gasoline demand for South Africa. They analyzed the long run relationship between the variables in the gasoline demand function over the period 1978-2005. Their study confirms the existence of a cointegrating relationship and the estimated long run price and income elasticities were, respectively, -0.47 and 0.36, implying that the gasoline demand in South Africa is price and income inelastic.

3. Empirical Estimates with Alternative Methods

As stated earlier we shall use data from Fiji for the period 1970-2005 to estimate the demand for gasoline with 5 alternative methods viz., *DEG, FMOLS, GETS, BT* and *JML*. Our procedure is easy to replicate for other countries and where necessary we shall quote some results with data from a recent study by Akinboade, Ziramba and Kumo (2008) on South Africa for the period 1978-2005.[7]

Fiji is a small island country with a population of less than a million. Its per capita vehicle ratio is high compared to other developing countries and this has increased from 3 per 100 in 1970 to 17 by 2005. The trend rate of growth is about 4% per year. Private cars, taxies, rental and hire cars and motorcycles, which use gasoline, are more than 60% of total of vehicles. Some commercial vehicles and coaches also use gasoline. Since Fiji has no oil fields and oil refineries, 100% of its

[7] We thank Dr Akinboade for supplying these data,

gasoline needs are imported from the refineries in Singapore. The import bill of gasoline is FJ$70.1 million in 2005 and this is slightly above 9.0% of its total mineral fuel imports.[8] The demand for gasoline in Fiji has steadily increased over time as incomes grew and due to policy changes which enabled traders to import pre-used vehicles from December 1986. This helped the lower middle income groups to own vehicles. Table-1 below shows the annual average imports of gasoline.

Table 1

Gasoline Imports into Fiji: 1970-2005[9]

Years	Gasoline Imports (Million liters)
1971- 1975	48.42
1976 - 1980	69.82
1981 - 1985	70.92
1986 - 1990	71.76
1991 - 1995	89.7
1996 - 2000	93.46
2001 - 2005	83.58

While the current retail prices of gasoline have risen over the period 1970 to 2005, the real retail prices (retail price/CPI) have marginally declined and in 2005 the real retail gasoline prices are lower than prior to 1980's.

3.1 Specification, Unit Roots and Block Non-causality

We have used a variant of the standard specification for the long run demand from a recent works of Akinboade, Ziramba and Kumo (2008) and Amarawickrama and Hunt (2008) which is:

$$gas = \alpha_0 + \beta_1 y + \beta_2 p + u \qquad (1)$$

[8] The mineral fuel import is valued at F$781 million which is 28.9% of total imports and 18.4% of GDP of Fiji in 2005.

[9] Source: Overseas Trade Reports, Fiji Islands Bureau of Statistics, Suva, various issues.

where gas is the log of total gasoline demand converted into mega-joules (MJ) equivalent, y is the log of real GDP, p is the log of real gasoline price computed by dividing retail gasoline price with CPI and u is the error term with the usual classical properties $N \sim (0, \sigma_u)$. Instead of per capita demand and per capita income, we have used their total values because annual estimates of population are generally not accurate since they are extrapolated from the census data. Note that we have excluded the trend variable from (3) because inclusion of trend gave some implausible empirical results. A similar problem has been also encountered by Amarawickrama and Hunt and Akinboade, Ziramba and Kumo. However, at appropriate places we shall also report some results with trend.

We address 3 issues at the outset concerning the 3 variables in equation (1). These are (a) the order of integration of these 3 variables (b) the optimal order for VAR with these 3 variables and (c) whether y and p are weakly exogenous with respect to gas. Results with unit root tests are given in Table-2. We have used the standard *ADF* and *KPSS* tests for the variables. The results indicate that while gas and p are *I(1)* in levels and *I(0)* in their first differences, both tests have shown that the level of y is stationary at the 5% level. However, the more powerful *DFGLS* test showed that y is *I(1)* in its level and *I(0)* in first differences. The results in Table-2 are self explanatory.

To determine the order of the *VAR* the standard *AIC* and *SBC* criteria are used starting with an order of 4. *AIC* indicated a second order but *SBC* indicated only a first order. Since our sample size is small we decided to use first order for the *VAR*.

Using a first order *VAR* we conducted the block non-causality test to find out if y and p are weakly exogenous to gas. We included the intercept and then the intercept and trend. When the trend is excluded the null that both explanatory variables are weakly exogenous could not be rejected at the 1% level and only marginally at the 5% level. The computed test statistic with the p-value in the square brackets is $\chi^2(2) = 5.954$ [0.051].[10] This is useful because the likely endogeneity bias with the single equation methods would be small and *JML* estimate of the cointegrating equation can be normalized on *gas*.

Table-2: Unit Root Tests

	ADF	KPSS	DFGLS
gas	-3.544 (9) [-2.948]	0.153 [0.146]	---
Δgas	-10.159 (9) [-2.951]	0.247 [0.463]	---
y	-3.895 (9) [-3.544] [[-4.244]]	0.117 [0.146]	-2.869 (9) [-3.190]
Δy	-7.569 (9) [-2.951]	0.257 [0.463]	-7.178 (9) [-1.951]
p	-0.806 (9) [-3.544]	0.199 [0.146]	---
Δp	-3.902 (9) [-2.951]	0.368 [0.463]	---

Notes: EViews 6 has been used for the tests. The number of lags used are in the parentheses. Test statistics for the 5 % and 10% are reported in single square brackets and double square brackets respectively. ADGLS test for output is conducted it has more power against the null of no cointegration.

[10] When trend is included the result is more conclusive because the null could be rejected at the 5% level. The computed test statistic is $\chi^2(2) =$ 2.506 [0.286].

3.2 Estimates of the Cointegrating Equations

Estimates of the cointegrating equations with the 5 selected alternative methods viz., *DEG*, *FMOLS*, *GETS*, *BT* and *JML* are shown in Table-3. We shall report the short run dynamic equations later.

Estimates with *DEG* are reported in column1 of Table-3. We have introduced an intercept dummy *DUM8798* because without this dummy, tests for both serial correlation and non-normality of residuals were poor.[11] This dummy variable is 1 from 1987 to 1998 and zero at all other times. This was a period of political instability in Fiji. The issues surrounding the Fiji constitution were being challenged in the courts and subsequently a new constitution was drafted. The simple *ADF* test on the computed residuals with trend has been used as the cointegration test for all countries for uniformity, but where a technique specific test for cointegration is available it is shown in the last row of Table-3. The absolute value of the *ADF* test statistic (4.84) exceeds the absolute critical value (3.56) at the 5 % level and rejects the null of no cointegration. The estimates of income and price elasticities, which are all significant, are highly plausible and have the expected signs and within the range of estimates for various other countries summarized by Akinboade, Ziramba and Kumo (2008) in their Table-2. However, our estimates are closer to the estimates for South Africa by Cloete and Smit (1988). Gasoline demand in Fiji is inelastic with respect to income and relative price since the estimated elasticities are 0.429 and -0.244 respectively.

Estimates with *FMOLS*, which is easy to implement with Microfit, are in column 3 of Table-3. There does not seem to be any specific test for cointegration. However, the *ADF* test on the residuals, with trend, shows that the null of no cointegration is rejected at the 5% level. The estimated coefficients are all significant at the 5% level and have the expected signs. Estimates of

[11] Without the intercept dummy the estimated coefficients are close to those in column 1 of this table. These estimates for the intercept income and price, respectively, are 18.092, 0.476 and -0.187. All are significant.

intercept and income elasticity at 0.433 are close to the estimates with *DEG* method. However, price elasticity at -0.203 is slightly lower.

Estimates with *GETS* are in column 3 of Table-3. These estimates are made with the two stage nonlinear instrumental variables method. Lagged values of the variables are used as instruments and the Sargan χ^2 test (not shown) validated the choice of instrumental variables. Its specification also includes the short run dynamic terms, which will be shortly discussed. Both the residual based *ADF* and a specifically developed test for cointegration in *GETS* specifications by Ericsson and MacKinnon (2002) show that the null of no cointegration can be rejected at the 5% level. The income and price coefficients have the expected signs. While the coefficient of income is significant at the 5% level, the coefficient of price is significant at the 10% level. The estimate of price elasticity at -0.159 is lower compared to the estimates with *DEG* and *FMOLS*. When *DUM8798* was included into the specification of the error correction term, the income and price coefficients became insignificant. This is not shown to conserve space.

Estimates with the popular bounds test (*BT*) are somewhat disappointing. In a good number of empirical works with this method, some arbitrary changes seem to have been made and they depart from the procedure explained in the Microfit 4.0 manual in pages 302-308. For convenience these steps are stated as follows with a couple of additional suggestions for selecting the order of the *VAR* and testing for weak exogeneity. First, test for the order selection of the underlying *VAR* of the selected variables using *AIC* and *SBC* criteria. Second, test for deleting the deterministic variables viz., trend and intercept. Third, use the test for block non-causality to determine the choice of the dependent variable. This test can also be conducted with *BT*. Suppose the optimal order of the *VAR* is 2 in a model $F(y, x, z)$, and x and *z* are also found to be weakly exogenous, then the following model can be estimated with *OLS* in the fourth step.

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$$\Delta y_t = f(\Delta x_{t-1}, \Delta z_{t-1}, \Delta y_{t-1}, C, T) \qquad (2)$$

where C and *T* are intercept and trend respectively. The earlier deletion test for these deterministic terms determines whether one or both should be included in the *OLS* estimates. The summary statistics for this *OLS* equation can be ignored. In the fifth step the variable addition test for including the one period lagged values of the 3 variables is conducted. The F-statistic of this test is the test statistic for cointegration and should be compared with the critical values in the Microfit manual. If the null of no cointegration is rejected, in the final step the long run and short run relationships can be estimated with the univariate option 6 in the Microfit or with other software by computing the *ECM*.

Table-3: Cointegrating Equations

	DEG	*FMOLS*	*GETS*	*BT*	*JML*
Intercept	18.482 [0.00]	18.452 [0.00]	18.495 [0.00]	18.399 [0.00]	18.085 [0.00]
% DEVIATION FROM JML	2.2%	2.0%	2.2%	2.1%	
*Dum*8798	-0.097 [0.01]	--	--		--
y	0.429 [0.00]	0.433 [0.041]	0.427 [0.040]	0.439 [0.058]	0.462 [0.04]
% DEVIATION FROM JML	-7.4%	-6.7%	-7.9%	-7.2%	
p	-0.244 [0.00]	-0.203 [0.034]	-0.159 [0.092]	-0.162 [0.118]	-0.190 [0.06]
% DEVIATION FROM JML	25.0%	6.6%	-17.8%	-23.0%	
ADF (5% cv) LAG TREND	-4.835* (-3.556) [0] YES	-4.837* (-3.556) [0] YES	-4.797* (-3.556) [0] YES	-4.785* (-3.556) [0] YES	-4.829* (-3.556) [0] YES
SPECIFIC TESTS FOR CI			-4.604* [-3.627]	F(3, 27) = 2.363 [LB: 3.219 UB: 4.378]	--

Notes: Probability values are below the coefficients in the square brackets. Asterisk in row 8 for *ADF* test for the residuals indicates rejection of the null of no cointegration at the 5% level. We are not aware of technique specific CI tests for *DEG* and *FMOLS*.

In some applications of *BT*, some investigators have removed the insignificant changes in the variables from the *OLS* estimates in the fourth step. It is not clear if this is a valid procedure because arbitrary removal of insignificant variables causes path dependence biases and changes the computed value of F statistic. A second practice is to estimate both the long run and short run specifications in one step as in *GETS*. However, using the estimated F value of this equation, which will be much higher compared to its value from the variables addition test, is not a valid test statistic for cointegration.[12]

We have followed the procedure described in the Microfit manual and estimated with OLS a specification similar to (3) without the trend variable i.e., the following specification.

$$\Delta gas_t = f(\Delta y_{t-1}, \Delta p_{t-1}, \Delta gas_{t-1}, C) \qquad (3)$$

The variable addition test gave a low F value of 2.363 which is lower than the upper bound 5% *CV* of 4.368 implying that the null of no cointegration cannot be rejected. However, our somewhat *ad hoc ADF* test on the residuals show that these are *I(0)*. When we increased the order of the *VAR* and included the trend the value of the F test did not increase. Although the cointegration test based on the F test failed, we have estimated the long run equation to see how it differs from the estimates with other methods. It can be seen from column 4 that the estimates of all the parameters are good and close to those of other estimates. However, the elasticity of price at -0.162 is significant at a slightly higher level than the 10% level. Since *BT* is a popular

[12] These errors were found by the first author while refereeing papers based on the bounds test. The first doubtful procedures has been recently used by Akinboade, Ziramba and Kumo (2008). This not to pillory these authors since a few others may have also used such procedures. Akinboade, Ziramba and Kumo (2008) has some merits although their procedure can be interpreted as estimation with *GETS* and not with the bounds test. When their model is reestimated, using the data they have kindly supplied, with the *GETS* approach described in our paper, their results stand with minor changes. The Ericsson and MacKinnon test for cointegration rejected the null of no cointegration at the 10% but not at the 5% level. The computed test statistic is -3.575 and the 10% CV is -3.250. However, the Wald test did not reject the null that the absolute values of the income and price elasticities are equal at 0.385.

technique, it would be useful if others, with a sound knowledge of estimation theory, clarify some confusions in applying this method.[13]

Estimates with *JML* are in the last column of Table-3. A first order *VAR* is used as in the other methods. Both the eigenvalue and trace tests showed that with restricted intercept and without the trend there is a single cointegrating vector.[14] The estimated coefficients of the cointegrating equation show that while income elasticity at 0.462 is significant at the 5% level the price elasticity at -0.196 is significant at a slightly higher level of 6%. The residual based *ADF* test is reported only for comparisons but it is not a valid test for *JML*. Since this is a systems method and the endogeneity biases will be minimal, it is worth comparing estimates with other methods to those with *JML*. The percentage deviations of other estimates from *JML* are shown below the coefficient estimates. In general the deviation of the intercept is minimal at about 2%. Income elasticity seems to be overestimated in other methods ranging from 6.7% in *FMOLS* to high value of 7.9% in *GETS*. Price elasticity is over estimated ranging from a low of 6.6% in *FMOLS* to a high of 25% in *DEG*. Surprisingly estimates with *BT*, though these failed the cointegration test, are not bad at all. All in all *FMOLS* estimates seem to have performed better than the other single equation methods. Since this method is easy to implement with Microfit, it is an attractive alternative single equation method. However, we do not recommend only one method of

[13] Some confusions are as follows. First, pretesting for the order of the variables has now become simpler. If all variables are *I(0)*, then there is no need to use time series methods. Second, the finite sample properties of the estimates and the *CVs* are not clear and well known. This would be useful because some have been claiming that they have computed these small sample *CVs* without an adequate explanation of how they are computed. It is a reasonable guess that these *CVs* are computed by simply replacing the value of T with lower numbers in the GAUSS programme of the original authors which has been used to compute the asymptotic *CVs* in the Microfit manual. Third, are some deviations from the procedures in the Microfit manual, e.g., use of parsimonious versions of *VAR* by deleting the insignificant variables, valid? This is important because the F statistics differ considerably in these two procedures.

[14] To conserve space we are not reporting results with the trace test. The following is the result of the eigenvalue test.

Null	Alternative	Statistic	95% CVs	90% CVs
r = 0	r = 1	23.2904*	21.1200	19.0200
r<= 1	r = 2	7.7530	14.8800	12.9800

estimation and strongly support the view of Amarawickrama and Hunt that estimates with alternative methods are desirable.

So, what are the more reliable estimates of the income and price elasticities of demand for gasoline in Fiji? Using an average of the estimates with *FMOLS* and *JML* we conjecture that broadly these elasticities, respectively, are about 0.45 and -0.20. It is also note worthy that estimates of these parameter, with other methods, are not far from these values and needless to say these close results thus increase our confidence in the estimate.

To conserve space we do not report all the estimates of the short run dynamic equations. These dynamic equations are estimated with the lagged error terms implied in Table-3 and by including 3 lagged values of the changes in the variables. To obtain the parsimonious versions *PcGETS* has been used since its search procedures are free from the path dependence biases. The estimated adjustment coefficients are similar at about unity in all but in *JML* where it is about 0.7. This implies that adjustment towards equilibrium is quick which is plausible in a small country like Fiji. The summary statistics of all these equations are also similar with $\bar{R}^2$ *s* ranging from 0.40 to 0.45. However, the χ^2 tests for the normality of the residuals were only marginally insignificant at the 5% level. Since *GETS* (equation 4 below) is a one step procedure and *JML* (equation 5 below) is a systems procedure, estimates of the short run dynamic equations with these two methods are reported below.

$$\Delta gas_t = -1.083(gas_{t-1} - (18.495 + 0.427 y_{t-1} - 0.159 p_{t-1})) - 0.355\Delta p_t \qquad (4)$$

[0.00] [0.00] [0.04] [0.09] [0.13]

$\bar{R}^2 = 0.400$; $\chi^2_{Sargan} = 0.245$ [0.970]; χ^2_{sc} =0.010 [0.920]; χ^2_n =5.967 [0.053]

$$\Delta gas_t = -0.677 ECM_{t-1} + 2.559\Delta y_t + 0.194\Delta gas_{t-2} \qquad (5)$$

[0.00] [0.00] [0.02]

$\bar{R}^2 = 0.437$; χ^2_{sc} =3.147 [0.076]; χ^2_n =4.034 [0.133]

It seems that the *GETS* dynamics is more plausible because consumers generally respond in the short run to price changes than changes in income.

4. Conclusions

This study has estimated the gasoline demand function for Fiji using five alternative time series methods. Estimates of the long run parameters are close in all the five selected methods. Among the single equation methods *FMOLS* estimates are closer to the estimates of the systems *JML* method. Using rounded values from the estimates with *FMOLS* and *JML* we conjecture that broadly income and price elasticities, respectively, are about 0.45 and -0.20. It is also note worthy that estimates of these elasticities with other methods are also similar increasing the confidence in them and to draw the conclusion that gasoline demand in Fiji in long run is price and income inelastic.

Further we find that the *GETS* dynamics is more plausible than the *JML* estimates as consumers generally respond in the short run to price changes than changes in income. The adjustment coefficient of about unity, in all but in *JML* where it is about 0.7, implies that adjustment towards equilibrium is quick and this is plausible in a small country like Fiji. From a fiscal policy point of view we may conclude that taxation to limit gasoline demand either to contain the import bill or for the containment of environmental degradation may not be a good policy option.

A limitation in this paper is that the popular bounds test approach could not reject the null of no cointegration. However, we pointed that this technique is used in some modified and unsubstantiated forms to produce a high test statistics to reject the null of no cointegration. It is not known if these ad hoc procedures are valid and we hope that other investigators will develop some solutions.

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Data Appendix

gas = log of total gasoline demand converted to mega-joules (MJ) equivalent.
Conversion key: one liter of gasoline = 34.2 MJ. Data extracted from Overseas Trade Reports, Fiji Islands Bureau of Statistics, Suva.

p = log of real price of gasoline. Real price of gasoline = $\frac{retail\ price\ of\ gasoline}{\text{CPI}}$
Data supplied by Prices and Incomes Board, Fiji.

CPI = Consumer price index. Data extracted from Key Statistics, Fiji Islands Bureau of Statistics, Reserve Bank of Fiji Statistical Appendix and calculations by the authors. Base period: 1993.

y = Real GDP. Data extracted from Key Statistics, Fiji Islands Bureau of Statistics and authors calculations. Base period: 1995.