GASOLINE, DIESEL FUEL AND JET FUEL DEMAND IN SOUTH AFRICA

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Abstract

The paper investigates the price and income elasticity of gasoline (petrol), diesel and jet fuel demand in South Africa using autoregressive distributed lag (ARDL) models. We compare elasticity estimates for 1982Q1-2010Q4 with estimates for 1998Q1-2010Q4. Price and income elasticity estimates for gasoline remain unchanged compared to previous estimates and robust across smaller sub-periods. Similar to recent findings for other developing countries, income is the dominant driver of South African diesel demand even when controlling for the increased number of diesel vehicles. Similarly, income dominates jet fuel demand, a finding that is robust to controls for international tourist departures and is consistent with international findings.

1. Introduction

South African fuel prices continue to attract media and policy attention, as geopolitical uncertainties, high and variable crude oil prices and a volatile exchange rate generate large changes in fuel prices. These price developments have altered the fuel consumption behaviour of some consumers, yet many producers (including farmers) cannot easily limit fuel demand without reducing production (Fofana, Chitiga and Mabugu, 2009). In contrast, strong economic growth of the past decade has boosted fuel (especially diesel) demand, which has placed significant pressure on South African fuel refineries (Merven, Hughes and Davis, 2010). Therefore, local policymakers and the petroleum industry are keenly interested in understanding the price and income determinants of South African fuel demand.

Interest in fuel demand has grown steadily over the past three years, as price and income elasticity estimates were key inputs in policy decisions (including fuel pipeline tariffs) and long-run planning for large infrastructure projects. Despite their importance, current elasticity estimates tend to rely on long sample periods that underplay structural change, even while policymakers and industry are

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concerned about the effects of more efficient fuel technologies and changing consumer preferences on fuel demand. Current elasticity estimates also focus mostly on gasoline (petrol), with less emphasis on diesel and no analysis of jet fuel. Diesel and jet fuel sales, however, have grown much faster than gasoline sales over the past decade. It is important to study the impact of price and income changes on these new revenue sources of energy companies. Furthermore, the greater use of air transport and diesel-powered vehicles suggest that price and, especially, income changes are likely to have a greater impact on the economy.

Given this background, we study price and income elasticity of gasoline, diesel fuel, and jet fuel demand, and emphasise structural change. A study of structural change in demand patterns requires isolating more recent sample periods, perhaps using higher-frequency data to increase degrees of freedom. The paper identifies structural breaks econometrically and subsequently employs both a shorter (commencing 1998) and a longer (commencing 1982) sample period to detect changes in price and income elasticity.

The paper first explains recent policy and corporate developments related to South African fuel demand, in order to locate the rationale and specific contributions of this paper. This is followed by a review of the South African literature on demand elasticity for fuel, an exposition of the econometric methodology and data, a presentation of the model results, and the conclusions.

2. Rationale

Price and income elasticity feature prominently in energy and competition policy and in corporate planning at petroleum companies and financial institutions. The following sub-sections explore each of these contexts, outlining recent instances where elasticity estimates played an important role.

2.1 Energy policy

The price and income elasticity of fuel demand in South Africa were focal points in the 2009/2010 pipeline tariff determination hearings of the National Energy Regulator of South Africa (NERSA). Transnet, the state-owned transport conglomerate, owns and operates the Durban-Johannesburg pipeline (DJP). The pipeline, constructed in 1965, feeds the so-called “in-land”[1] fuel region of South Africa, which includes Gauteng, North-West, Mpumalanga, Limpopo, the Free State, as well as parts of the Northern Cape and KwaZulu-Natal. While Transnet owns the DJP, as well as other pipelines, the government regulates pipeline tariffs (Swart, 2010). Specifically, since 1 November 2005, NERSA regulates petroleum pipeline tariffs.

[1]The Main Supply Agreement (MSA) of 1954, concluded among South African petroleum companies, divided the country into two main fuel supply regions: the “in-land” region supplied exclusively by Sasol and the “coastal” region supplied by the coastal refineries (Swart 2010). Although the MSA was terminated in 2003, these definitions continue to be used widely in the industry.

In 2007, NERSA granted Transnet a construction license for the New Multi Product Pipeline (NMPP), which will significantly raise future supply capacity to the in-land region. Transnet aimed to fund the construction of the NMPP by applying to NERSA for higher tariffs on the DJP (National Energy Regulator of South Africa, 2010). This resulted in a high-profile legal battle between Transnet and the petroleum companies using the DJP. Petroleum companies with coastal refineries, but wanting to compete in the in-land market, utilize the DJP and pay the pipeline tariffs to move their fuels in-land. Other petroleum companies, including Sasol, with in-land refineries do not face similar costs. Given that retail fuel prices are regulated, pipeline tariff increases would imply a significant comparative disadvantage for the petroleum companies with coastal refineries. Some estimates put the total “windfall” for petroleum companies with in-land facilities at around R1.7 billion (Creamer, 2009). Companies with coastal refineries subsequently disputed whether pipeline tariff setting should account for construction costs of new pipelines.

The size of the tariff adjustment required to fund pipeline construction proved to be contentious. In 2009, Transnet requested a 73,5% average tariff adjustment for the 2010/2011 financial year and also signalled that increases of a similar magnitude would be required for the subsequent four years (Transnet, 2008). These increases sharply deviated from the 8% tariff increases originally projected by Transnet and the company argued that the sharp rise was due to the particularly negative economic outlook at the time. Transnet argued that poor economic growth depressed fuel sales and reduced tariff revenue, and required a rise in the tariff in order to boost revenue. Pipeline tariffs form part of the retail price of fuel and a 73,5% tariff rise would have translated into a 21 cents increase in the per litre retail price (Transnet, 2008).

Petroleum companies with coastal refineries opposed the tariff adjustment requested by Transnet on a number of grounds, including its inconsistency with international pipeline tariff-setting practices. Another source of contention – of importance to this paper – is that petroleum companies questioned Transnet’s overly pessimistic forecasts of future fuel demand: the tariff methodology employed by NERSA allows for a retrospective compensation in future tariffs based on the extent to which projected and actual fuel volumes have diverged. Petroleum companies with coastal refineries argued that Transnet’s volume forecasts are driven by pessimistic economic growth and (to a lesser extent) high oil price assumptions. These companies consequently generated their own volume forecasts, using alternative price and income scenarios, which suggested higher rather than lower fuel demand volumes. NERSA ultimately rejected the Transnet application, although, more recently, it has approved higher tariffs (National Energy Regulator of South Africa, 2010).

2.2 Competition policy

Price and income elasticity also figured prominently in competition policy proceedings in the petroleum industry. In 2005/2006, the Competition Tribunal evaluated a proposed merger between Sasol Oil and Engen to form a new entity called Uhambo. The legal proceedings included testimony by a number of competition economists on behalf of petroleum companies and government. An important part of the proceedings concerned the extent to which Uhambo would enjoy market power in the in-land region and the likelihood of it using this power to foreclose the in-land region to competitors. The foreclosure risk followed from the limited pipeline capacity at the time: petroleum companies without in-land refineries were dependent on Uhambo refineries to supply at least part of their in-land volumes, as they could not easily satisfy all their product needs via pipeline. In fact, depending on the growth rate of their in-land sales, these companies would become increasingly dependent on the Uhambo refineries (Theron, 2008). Therefore, price and income elasticity estimates and forecasts featured centrally in the case: higher future growth rates in in-land volumes would create supply constraints and raise foreclosure risks more quickly, while lower growth rates were favourable to the Uhambo merger.

The various parties involved in the merger proceedings differed significantly in their forecasts of in-land and coastal fuel demand growth. Table 1 presented later contains a summary of the elasticity estimates provided by some of the economists. In its decision, the Tribunal was critical of elasticity estimates and demand projections provided by the merging parties, but also questioned the statistical soundness of the models presented by intervening parties. The Tribunal ultimately rejected the merger (Competition Tribunal, 2006).

2.3 Corporate planning

Estimates of price and income elasticity of fuel demand have also been important in corporate planning. Corporate planners at petroleum companies and banks generate future fuel scenarios for South Africa and these scenarios depend on income and price elasticity. In recent years, two corporate developments have highlighted the need for accurate price and income elasticity estimates. Firstly, the development of further pipelines from Durban to Gauteng requires significant storage infrastructure investment to house the transported fuel in Gauteng. Informal estimates, based on the author’s involvement in some of these projects, suggest capital values exceeding R1 billion. Similarly, refinery infrastructure investments at the coast also depend critically on estimates of future price and income elasticity. Demand models – and elasticity estimates – are therefore critical inputs into investment planning processes at petroleum and related companies[2]. Secondly, efficiency changes and new technologies also affect price and income elasticity and therefore alter corporate projections. In this regard, South African-specific issues related to the taxi-recapitalization programme and to the question surrounding the gasoline/diesel split (diesel volumes have grown relatively stronger than gasoline volumes in recent years) have received corporate and media attention.

[2] Recent supply problems at fuel pump stations (especially in the in-land region) are, at least in part, also the result of insufficient planning – although inertia in energy policymaking was probably the main underlying driver.

2.4 Jet fuel issues

The price and income elasticities of gasoline and diesel demand often dominate policy and corporate discussions because of their economy-wide impact. But the price elasticity and income elasticity of jet fuel demand have also received corporate attention in recent years. Jet fuel sales in South Africa nearly doubled during the 1990s, although subsequent growth has been sluggish. This is confirmed by the intense competition among South African airlines for passengers – given that the demand for air transport determines the demand for jet fuel.

Air travel demand is affected by the price of air tickets and the income of travellers. The price elasticity of air travellers offers one explanation of financial underperformance in the South African airline industry in recent years. The oil price increases of 2007/2008 prompted increases in ticket prices, which affected passenger volumes. Local airlines attempted to absorb some of these price increases, but found their profitability significantly reduced. The addition of the Lanseria private airport in Gauteng has also supported volumes, especially for the low-cost airline Kulula. It is not yet clear to what extent Lanseria ticket prices are lower, but costs at Lanseria (of which jet fuel costs represent an important part) appear to be lower compared to ACSA airports. However, an industry source also suggests to the author that the price elasticity of jet fuel demand from international airlines may be quite low, as some airlines appear to be buying minimum volumes of jet fuel in South Africa – choosing to refuel elsewhere on the continent.

Income seems to have been an important driver of jet fuel demand. The number of domestic and foreign travellers reduced significantly in the global slowdown of 2002 and, more recently, in the aftermath of the financial crisis. Many business passengers chose to switch to low-cost airlines (also explaining the success of the Lanseria venture) and this substitution may have reduced the impact on overall jet fuel volumes. In addition, many South African airlines are now shifting to more fuel-efficient aeroplanes, which will affect future jet fuel consumption. While efficiency data is difficult to obtain, it is vital to energy companies, airlines and airport operators to understand the behaviour of jet fuel demand in recent years, including its stability over shorter sample periods.

The examples above demonstrate the need for more accurate estimates of the income and price elasticity of demand for gasoline, diesel fuel and jet fuel. The following section summarizes research on South African fuel demand and discusses why existing estimates are less useful to policymakers and corporate planners.

3. Literature review

Energy demand models can be classified along a continuum ranging from fully theory-driven at the one extreme to fully data-driven at the other extreme. Data-driven approaches cover a range of statistical and econometric models. Statistical models include autoregressive specifications and crude smoothing procedures and appear to outperform more sophisticated econometric and theoretical models in forecasting (Li, Rose and Hensher, 2010). However, econometric models are useful for policy and retrospective analysis. Econometric models of energy demand boast a range of cointegration and related dynamic models. One technique that has gained popularity over the past decade is the autoregressive distributed lag (ARDL) bounds-testing approach developed by Pesaran, Shin and Smith (2001). In Southern African context, ARDL energy demand applications (usually in electricity, but also in fuel demand) include De Vita, Endresen and Hunt (2006), Akinboade, Ziramba and Kumo (2008), Amusa, Amusa and Mabuga (2009) and Ziramba (2008; 2009). Nevertheless, even the newer econometric models face challenges in dealing with structural change. Theoretical approaches, such as the partial adjustment model, allow for changes in habits and structural breaks (Breunig and Gisz, 2009). Despite this promising feature, these new theoretical models are less successful in forecasting.

Data-driven approaches dominate research on fuel demand in South Africa. Academic research is surprisingly scarce and Theron (2008) provides a summary of recent private-sector estimates, to which one can add estimates from two academic papers, as shown in Table 1. Price elasticity estimates for South African gasoline demand are generally around -0,5 and around -0,1 for diesel demand. Income elasticity of gasoline demand are estimated at 0,4 (with the exception of one estimate of 1,0), while income elasticity of diesel appears to be above 1,0.

Table 1: Estimates of price and income elasticity of South African fuel demand

Authors	**Sample period**	**Price elasticity**		**Income elasticity**	
		Gasoline	**Diesel**	**Gasoline**	**Diesel**
Cloete and Smit (1988)	1970-1983	-0,24 (short-term) -0,37 (long-term)		0,43	
Bureau for Economic Research (BER) (2003)	n.a.-2003	-0,21 (short-term) -0,51 (long-term)	-0,18 (short-term) -0,06 (long-term)		
Akinboade *et al.* (2008)	1978-2005	-0,47 (long-term)		0,36 (long-term)	
Theron (2008) summary of BER model	1984-2004	-0,19 (short-term) -0,62 (long-term)	-0,1 (long-term)	0,1 (short-term) 1,0 (long-term)	1,36 (long-term)
Theron (2008) summary of Econometrix model	n.a.	-0,24	-0,14	0,38	1,47

The more recent estimates reported in Table 1 do not differ significantly from the earlier estimates of Cloete and Smit (1988). However, three factors suggest that South African fuel consumption behaviour has changed significantly over the past two decades. First and foremost, gasoline volumes grew rapidly up to the mid-

1990s but then growth slowed down significantly; in turn, diesel volume growth accelerated significantly from the late 1990s (refer to the data discussion presented later). Secondly, consumers become more price-sensitive over time: even price-inelastic demand will, over time, become more elastic. Modelling fuel demand over a very long period, and obtaining an average long-run relationship over this period, may not yield accurate estimates. Econometrically speaking, it is possible to find an average relationship (especially if change occurs slowly), but such a relationship does not reflect current behaviour. Thirdly, technological change and efficiency improvements may have supported a switch to more diesel-powered vehicles. More recently, electricity problems have boosted demand for alternative power sources, including diesel generators, which could affect the relationship between income and fuel volumes (see Spalding-Fecher and Matibe (2003) for an earlier summary). These factors support the re-assessment of price and income elasticity of fuel demand in South Africa. In particular, they suggest that one should control for additional variables when modelling fuel demand.

A potentially relevant study in this regard is the work by De Vita *et al*. (2006), who control for institutional changes (as well as substitution and temperature) when modelling gasoline and diesel demand in Namibia. More important, however, is the need to control for technological change – especially as far as modelling the demand for diesel fuel is concerned (Schipper and Fulton, 2009). A simple way of accounting for such technological change is by including lagged dependent variables in the demand function: technological change affects fuel consumption over a longer period rather than instantaneously and lagged consumption variables offer one way of dealing with this slow change (see Li *et al.* (2010) for a summary of research on such functional forms). Such an approach is clearly problematic when dealing with high-frequency data, where it will be difficult to including enough lagged variables to sufficiently capture this slow adjustment process. Therefore, research over the past decades has attempted to formally model technological change by including measures of fuel efficiency. Fuel efficiency, however, are strongly influenced by price and income drivers (see overview and estimates in Bonilla (2009)). This implies potential bias in income elasticity estimates. Furthermore, we do not have access to data on South African fuel efficiency, which forces an alternative approach to dealing with technological change in fuel demand. One way to control for this change is to consider the stock of diesel-powered vehicles as an additional regressor in diesel demand equations (see Baltagi and Griffin (1997) and, for a recent application, Breunig and Gisz (2009)). Again, however, strong linkages between the stock of vehicles and income may bias the income elasticity estimate (Pock, 2010). An alternative way is to account for the relative importance of diesel-powered and gasoline-powered vehicles. We therefore consider both the stock of diesel vehicles as well as the ratio of diesel to total vehicle sales as additional variables in our specifications for diesel demand.

While current research focuses mostly on gasoline volumes and, to a lesser extent, diesel volumes, there is also a need for an assessment of the demand elasticities for jet fuel. The latter has not received research attention in South Africa, despite the implications of inadequate jet fuel supplies for air travel, as illustrated by the

August 2009 supply problems at O.R. Tambo International Airport (South African Petroleum Industry Association, 2010). Jet fuel demand has attracted some attention in the international literature, given the diverging price elasticities of demand for so-called ‘transport’ and ‘non-transport’ fuels: in recent years, transport fuels (comprising gasoline, diesel and jet fuel) have exhibited low price elasticity and high income elasticity compared to heating or residual fuels (Dargay and Gately, 2010). This has focused attention on the individual transport fuels, including jet fuel. In their analysis of a panel of developed and developing countries, Mazraati and Alyousif (2009) finds income elasticity for jet fuel demand in excess of 0,5 and low estimates of price elasticity. The developing countries in their panel cover Pacific-Rim countries: China, India, Indonesia, Malaysia, Philippines, Singapore, Thailand and Vietnam. In a comparative paper, Mazraati and Faquih (2008) find corroborating evidence that China, as a growing market for jet fuel, experiences significantly lower price-sensitivity than the US, which represents a mature market. At the same time, these authors find strong evidence that income is the dominant driver of jet fuel demand in both markets. It would therefore be important to consider the extent to which these results are replicated for South African fuel demand.

Similar to demand for diesel fuel, the demand for jet fuel is likely to have been affected by technological changes (for example, more fuel efficient aircraft). Arguably more important, however, is that the process by which income influences jet fuel demand is complex. The demand for jet fuel is derived from the demand for air transport, which can be split into demand for domestic transport and international transport. Domestic transport demand is likely to be affected by local economic conditions, while international transport demand from tourists is likely to be affected by international economic conditions. This suggests that a jet fuel demand model should, in addition to domestic income (in the form of GDP), include a measure of international demand for air transport. The cross-country panel models mentioned above do not account for these features and it may be important to consider how these will alter the results for price and income elasticity.

The limits of current research are also partially attributable to the use of annual fuel data. Only twelve or so data points are available since the start of structural change in the late 1990s. Higher frequency data increases the available degrees of freedom and this paper uses quarterly data to re-investigate fuel demand. The petroleum industry is also interested in an analysis of quarterly data, as it allows an assessment of the impact of seasonal spikes (such as the Easter and Christmas holiday seasons) on fuel demand, which affect fuel supply logistics. For example, in December 2010 selected in-land refineries were shut down unexpectedly, which reduced in-land supply. At the same time, abnormal weather changes prompted an unusually late ploughing season, which saw in-land diesel demand rise beyond the already high holiday levels. This created fuel shortages in some in-land areas (South African Press Association, 2010).

By increasing the number of observations, quarterly data allows the use of a shorter sample period – which reduces the dominance of pre-structural change data.

Despite this benefit, there is an econometric cost to a short sample period with higher frequency data: unit root and cointegration tests require a sample period of sufficient time span in order to accurately detect stochastic trends and mean reversion (Maddala and Kim, 1998). For example, the asymptotic consistency of unit root test statistics are violated if the time span does not grow with the number of observations (Perron, 1991). This risk is less important to this study, as the results suggest rapid mean reversion for all of the models, i.e. the speed of adjustment towards long-run equilibrium is quick for all models and the sample period therefore allows ample time for full adjustment. Nevertheless, as discussed later, the paper uses both a shorter and a longer sample period of high-frequency data. This responds to the econometric risks, but is also generally useful as it enables a study of the nature and extent of structural change in South African fuel demand.

4. Methodology

An economic agent i has to solve a random utility maximization problem when choosing the optimal volume of fuel Q_i^*:

$$q_i^* = \mathrm{argmax}(u_i(q))$$

Let the utility from consuming a particular quantity q of a homogeneous product depend on the price of the product p, the income of the agent y_i and some idiosyncratic error term ε_i. Then, at the optimal volume, the following equilibrium relationship will hold (assuming linear utility functions and log-transformation):

$$Q_i^* = \beta_{i,1}P + \beta_{i,2}Y_i + \varepsilon_i$$

Assuming a representative agent model[3], one can derive a 'social' utility function and show that society will choose Q^* such that:

$$Q^* = \beta_1 P + \beta_2 Y + \varepsilon$$

This represents the long-run equilibrium relationship between quantity, price and income for a particular fuel. The coefficients of this relationship and the adjustment following a disturbance of equilibrium can then be determined using an empirical time-series model. The empirical analogue of the theoretical relationship above is:

$$Q_t = \beta_1 P_t + \beta_2 Y_t + \varepsilon_t$$

where

in period t, Q_t is the natural logarithm (log) of fuel sales, P_t is the log of fuel price, and Y_t is the log of income, and $\{\varepsilon_t\}$ are assumed a serially uncorrelated series.

[3] Discrete choice models have become popular in recent decades, but the data requirements of these models prevent their application in the current context and most fuel demand studies follow our approach.

This paper employs the ARDL model proposed by Pesaran *et al.* (2001). The ARDL model is a single-equation approach to modelling short- and long-run relationships among variables (Pesaran, Shin and Smith., 1996; Pesaran, 1997). Endogeneity problems traditionally lead econometricians to favour a multivariate systems approach over single-equation approaches when studying long-run relationships. However, estimation and inference from the single-equation ARDL model is still valid if a sufficient lag structure is employed.

Consider an unrestricted ARDL model of lag order p:

$$\Delta Q_t = \beta_0 + \sum_{i=1}^{p} \beta_{1,i}\Delta Q_{t-i} + \sum_{i=0}^{p} \beta_{2,i}\Delta P_{t-i} + \sum_{i=0}^{p} \beta_{3,i}\Delta Y_{t-i} + \alpha_1 Q_{t-1} + \alpha_2 P_{t-1} + \alpha_3 Y_{t-1} + \boldsymbol{\gamma}'\mathbf{Z}_t + \varepsilon_t$$

where

Z_t is a vector of dummy variables dealing with data outliers.

A fundamental assumption of an ARDL model is that of a *unique* long-run relationship among Q, P and Y. The ARDL model offers a way of testing whether such a unique long-run relationship exists. While other tests for long-run relationships – such as cointegration tests – are also available, a benefit of the ARDL model is that it can be applied regardless of the order of integration of the variables. The model therefore avoids the pre-testing problem faced by conventional cointegration tests.

After the initial ARDL model is formulated, the analyst can assess the congruency of the model with both data and theory. The analyst investigates theory congruency by considering whether the signs of the different parameter estimates are consistent with predictions from theory. For example, the analyst checks for an overall negative sign for price elasticity and positive sign for income elasticity. The analyst then considers data congruency by running a batch of misspecification and diagnostic tests on the residuals $\hat{\varepsilon}_t$ (including tests for normality, heteroscedasticity, remaining autocorrelation and the Ramsey RESET test for specification error). If the model passes these tests, the analyst labels it the general unrestricted model (GUM).

The GUM is not a parsimonious model and may contain irrelevant variables that could contaminate the long-run parameter estimates and lead to a less robust model. Consequently, we employ an automated general-to-specific (GETS) search algorithm to reduce the GUM to a specific model (Campos, Ericsson and Hendry, 2005). The algorithm chooses a number of starting points and, for each path, employs a step-wise reduction strategy to omit statistically insignificant variables provided information loss is limited (information loss is measured by change in the maximized log-likelihood value). The results of the multiple paths are then unified in a single model, on which the same step-wise reduction procedure is repeated until the model arrives at a single parsimonious model – known as the specific model (Hendry and Krolzig, 2001).

The specific model allows testing for the existence of a unique long-run relationship and provides long-run elasticity estimates. Pesaran *et al*. (2001) show that a test for the existence of a long-run relationship involves testing the hypothesis that $\alpha_1 = \alpha_2 = \alpha_3 = 0$ against two-sided alternatives. These authors suggests a bounds test approach, according to which the F-statistic is compared to two critical bounds, an upper value associated with the condition where all of P, Q and Y are $I(1)$, i.e. contain unit roots, and a lower value where all of P, Q and Y are $I(0)$, i.e. are stationary. Values below the lower boundary indicate the absence of a systematic relationship, while values that exceed the upper boundary confirm such a relationship. Where the test statistic falls between the two critical values, it is necessary to test for unit roots in the individual series. If the series are all integrated, the upper bound is the critical value. Where all series are found stationary, the lower bound is the critical value. For a combination of stationary and non-stationary variables the test is inconclusive if the test statistic falls between the critical bounds. The latter is not common and the bounds test approach therefore avoids (or, at least, significantly reduces) the need for pre-testing the series for unit roots.

Pesaran *et al.* (2001) report asymptotic critical values for the bounds test, but Turner (2006) shows that finite-sample critical values are necessary in practice as asymptotic critical values can be biased even for relatively large samples of 300 observations. Using an approach similar to that employed by Pesaran *et al.*, Narayan (2005) generates finite-sample critical values for sample sizes of 30 to 80. This paper compares results for the Pesaran *et al.* and Narayan critical values, given the relatively small number of observations.

Once the existence of a long-run relationship is established, it is straightforward to calculate estimates for the long-run price and income elasticity of fuel demand:

$$\hat{\theta}_{\text{price}} = \frac{\widehat{\alpha_2}}{\widehat{\alpha_1}}$$
$$\hat{\theta}_{\text{income}} = \frac{\widehat{\alpha_3}}{\widehat{\alpha_1}}$$

The parameter estimate $\hat{\alpha}_1$ is the so-called speed-of-adjustment parameter if all series are non-stationary. It shows the speed at which the ΔQ_t will respond to any long-run disequilibria. For example, if the speed-of-adjustment parameter is small, equilibrium adjustment plays a less important role in the quarter-to-quarter behaviour of fuel consumption: short-run factors are more important than the adjustment process towards long-run equilibrium. Under these conditions, it takes the disequilibrium errors a long time to work through the system.

5. Data description

5.1 Variables and data sources

The first step in economic modelling is the identification of the parameters of interest and the collection of data on variables that will enable estimates of these parameters. This paper focuses on own price and income elasticity as central drivers of fuel demand. The literature also emphasizes the importance of substitute prices as well as a plethora of additional demand-shift factors, including preferences, technology and institutional change. While all these variables would ensure a rich model of fuel demand, the empirical estimation of such a function is challenging. Accounting for changes in the underlying tastes and preferences of consumers as well as for changes in the institutional environment is a difficult task. This paper attempts to account for some of these changes by comparing results for a shorter and longer sample period, while continuing to focus on price and income forces due to data constraints.

Table 2 reports the data sources used in the econometric models. Note that the South African Petroleum Industry Association (SAPIA) only provides sales volume data until 2008. This followed competition concerns relating to the exchange of volume data among petroleum companies (see, for example, Das Nair and Mncube (2009)). Sales volumes for the last two years were obtained from an independent expert, who has collated information from various oil companies for other purposes. The technique used to construct the data for the last two years follows the same methodology employed by SAPIA.

The models use the real retail price of gasoline and diesel fuel and the real oil price in South African currency (rand) for jet fuel (actual jet fuel prices are not available). For income, the gasoline models rely on real disposable income and the diesel fuel and jet fuel models rely on real gross domestic product (GDP)[4]. The difference is motivated from previous South African research, which finds that disposable income offers a better fit than GDP in gasoline demand functions (Theron, 2008).

For some specifications of the diesel models, we also require a measure of the stock of diesel vehicles in South Africa. Data on the stock of vehicles is not available. However, the National Association of Automobile Manufacturers of South Africa (NAAMSA) provided data on diesel vehicles sales, one of light commercial vehicles and another of passenger vehicles. We cumulate the sales data to construct quasi stock variables. Some specifications of the jet fuel models also include as variable the number of international departures of tourists, obtained from Statistics South Africa.

[4]Some studies have considered demand for transport fuels by sector (Dimitropoulos, Hunt and Judge, 2005). We focus on aggregate demand, as our fuel sales data cannot be disaggregated by sector. Also, we do not include sector-specific variables in our aggregate demand functions. For example, we do not include agricultural production as an independent variable: income is likely to be closely related to agricultural production, biasing the aggregate income elasticity estimates.

Table 2: Variables and data sources

Variable	Source	Description
Gasoline sales	South African Petroleum Industry Association (SAPIA) (up to 2008), industry sources (2008 to 2010)	Petrol sales in millions of litre, 1982Q1-2010Q4
Diesel fuel sales	SAPIA (up to 2008), industry sources	Diesel sales in millions of litre, 1982Q1-2010Q4
Jet fuel sales	SAPIA (up to 2008), industry sources	Jet fuel sales in millions of litre, 1994Q1-2009Q3
Gasoline price	SAPIA	Retail coastal pump price of 95 octane petrol in Rand, 1982Q1-2010Q4
Diesel price	SAPIA	Retail coastal pump price of 0.05% sulphur diesel in Rand, 1982Q1-2010Q4
Oil price	South African Reserve Bank (SARB)	Quarterly Brent crude oil (spot) in US dollars (data series KBP5344M), 1980Q3-2010Q4
General price level	SARB	Private consumption deflator, base year 2005, 1982Q1-2010Q4, calculated from nominal and real private consumption expenditure (data series KBP6007D and KBP6007L)
Income	SARB	Household disposable income in millions of Rand (data series KBP6246L), 1982Q1-2010Q4, deflated to base year 2005 using the private consumption deflator above Real gross domestic product in millions of Rand, base year 2005 (data series KBP6006D), 1982Q1-2010Q4
Rand dollar exchange rate	SARB	Rand dollar exchange rate (data series KBP5339M), 1982Q1-2010Q4
Commercial diesel vehicle sales	National Association of Automobile Manufacturers of South Africa (NAAMSA)	Sales of diesel-powered light commercial vehicles, 1994Q1-2009Q1
Passenger diesel vehicle sales	NAAMSA	Sales of diesel-powered passenger vehicles, 1994Q1-2009Q1
International tourist departures	Statistics South Africa	Number of departures by foreign citizens to international destinations (monthly report P0351), 2001Q1-2009Q3

5.2 Seasonality

Prior to modelling the various demand functions, we investigate the seasonal features of the data. Figure 1 reports the unadjusted and seasonally-adjusted gasoline and diesel fuel sales for the period 1982 to 2010[5].

[5] Seasonal adjustment technique is the X12 procedure developed by the U.S. Census Bureau. The literature suggests that alternative techniques perform equally well.

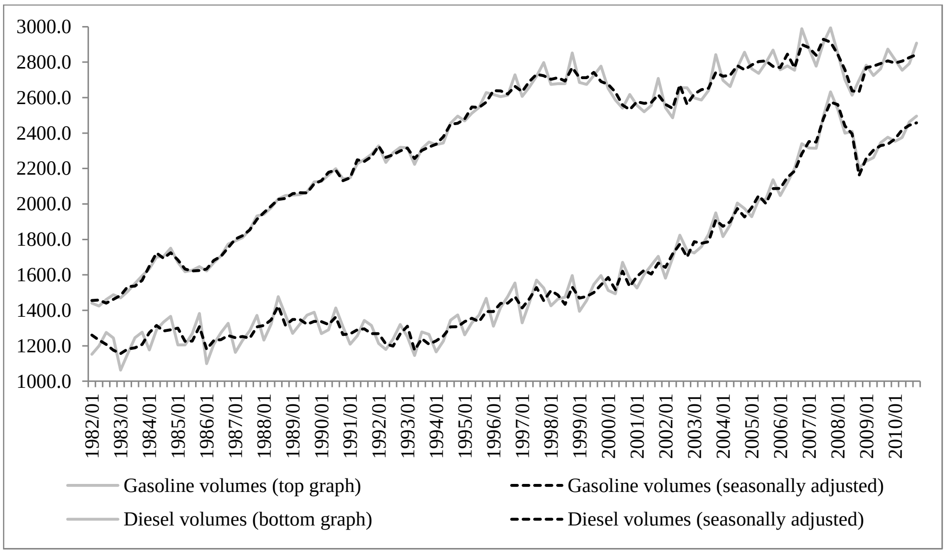

Figure 1: Unadjusted and seasonally-adjusted gasoline and diesel fuel sales in South Africa (millions of litre), 1982Q1-2010Q4

Both gasoline and diesel fuel sales experience significant seasonal fluctuations. The seasonal fluctuations appear to become more accentuated for gasoline from the mid-1990s, while the same for diesel seems to become less accentuated towards the 2000s. Seasonal sales patterns are similar for the two fuels: volumes are generally lowest in the first quarter, followed by the second quarter. Volumes in both the third and fourth quarters are highest and differ only marginally from one another. Econometric models should account for these seasonal features, but also to do so in a manner that accounts for the change in seasonal behaviour. In fact, as argued earlier, the data covers a period of significant structural change. The graph suggests a structural break around 1998 in gasoline volumes: before 1998 a strong time trend is visible, but none after 1998. At around the same time, diesel fuel volumes appear to accelerate strongly relative to the previous sideways movement.

Jet fuel volumes can be investigated in similar fashion, bearing in mind that we have data only from 1994 onwards. Figure 2 suggests that jet fuel sales are higher in the first and fourth quarters compared to the second and third quarters. As far as structural features are concerned, volumes experience strong growth up to around 1998 after which growth is slower.

Seasonal patterns in the data for the three fuel volume series suggest that models should incorporate seasonal dummy variables. Seasonal dummy variables allow more accurate estimation of seasonal effects compared to the statistical X-12 procedure. This is of particular concern to corporate planners. As noted, current in-land capacity constraints create logistical pressures during peak holiday seasons. Given the rise of tourism-related travel in South Africa, it may be useful to compare how seasonal variation has changed from the longer to the shorter sample period.

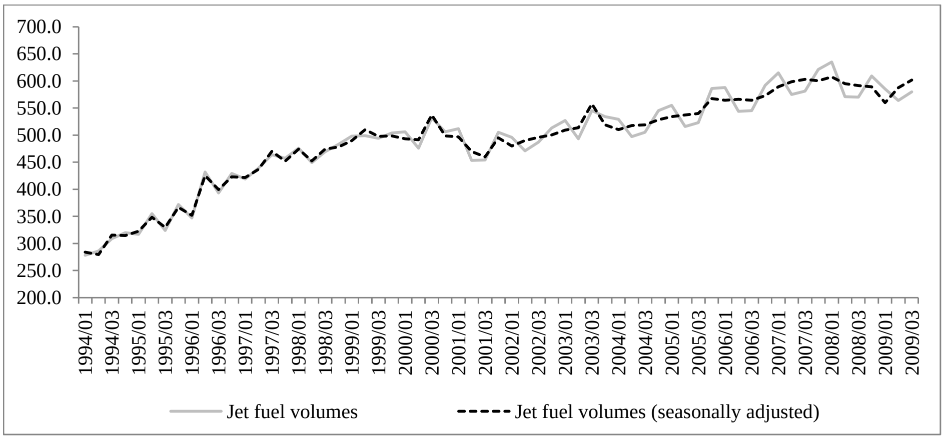

Figure 2: Unadjusted and seasonally-adjusted jet fuel sales in South Africa (millions of litre), 1994Q1-2009Q3

Table 3 reports the size of the seasonal dummy coefficients (with the fourth quarter as reference period) based on the specific models for gasoline, diesel and jet fuel demand (the models are formally presented and discussed in the following section). Seasonal effects are more accentuated in the shorter sample period than the longer period for diesel demand (and, to a lesser extent, for gasoline demand). Consistent with the graphical impression of earlier, both gasoline and diesel volumes are generally lowest in the first quarter, followed by the second quarter. Volumes in the third quarter are marginally lower than the fourth for gasoline and there is little difference in the case of diesel.

Seasonal effects in jet fuel demand suggest lower volumes in the second and third quarters, consistent with the data on air travel from Statistics South Africa, which report significantly higher volumes in the holiday season.

Table 3: Seasonal effects

Seasonal dummy	1982Q1-2010Q4	1998Q1-2010Q4
Gasoline		
Quarter 1	-0,04 (0,01)	-0,08 (0,01)
Quarter 2	-0,04 (0,01)	-0,04 (0,01)
Quarter 3	-0,02 (0,00)	-0,02 (0,01)
Diesel		
Quarter 1	-0,09 (0,01)	-0,12 (0,01)
Quarter 2	-0,07 (0,01)	-0,04 (0,01)
Quarter 3	-	-
Jet fuel		
Quarter 2	n,a,	-0,08 (0,01)
Quarter 3	n,a,	-0,06 (0,01)

5.3 Structural breaks

Appendix A presents scatterplots of gasoline, diesel and jet fuel volumes and the real price of each fuel. While price and fuel volumes appear to be negatively related for the first two decades, the relationship becomes quite murky from 2000 onwards: the black boxes in each scatterplot suggest that the relationship between price and volume may have changed significantly from the late 1990s.

Similarly, Appendix B presents scatterplots of fuel volumes and real income. These figures all suggest a positive relationship between fuel volumes and real disposable income, although the behaviour from the late 1990s is again different from that of the first two decades (a similar graph is obtained when using real GDP).

The structural changes motivate demand models for gasoline and diesel fuel based on both the entire sample period from 1982Q1-2010Q4 and a shorter sample period of 1998Q1-2010Q4. Jet fuel is modelled only for 1998Q1-2009Q3 due to data constraints. The longer sample period provides a standard against which to assess earlier estimates for gasoline and diesel, while the shorter recent sample period provides an indication of how elasticity estimates may have changed in recent years. The graphical impressions of structural change are merely indicative and in the discussion of the model results Chow breakpoint tests are used to formally detect structural breaks.

6. Results

The ARDL results depend critically on the choice of lag structure and the optimal lag length is selected on the basis of the Akaike and Schwarz information criteria. These metrics suggest initial lag length of four quarters for the gasoline and jet fuel models, twelve for the diesel model based on the longer sample period and seven for the diesel model over the shorter sample period. The specific models that emerge from the GETS reduction process usually contain lags of a first or second order, which suggests that the initial lag lengths are not restrictive.

As discussed, the modelling approach starts with a GUM, which is then reduced to a parsimonious specific model. The sub-sections below focus mostly on the specific model results and the GUM results are available on request. In each case, the GUM passes all data misspecification tests and is congruent with theory.

Each sub-section applies the bounds test to test for the existence of a unique long-run relationship. Thereafter, we report the regression results, misspecification tests and long-run estimates of price and income elasticity. Each section ends with recursive graphs for the specific models, to test the robustness of the estimates.

6.1 Gasoline

The GUM over the longer sample period can be used to detect structural change, as Chow (1960) tests on the GUM can highlight parameter non-constancy (see, for example, Hendry and Nielsen (2007: 195-197)). The breakpoint Chow test aims to test whether the model specification fitted on a sample period ending at $t = m$ correctly predicts all of the remaining data points, for every feasible m. The graphical Chow tests results for the gasoline GUM are reported in Appendix C. The p-values for the test range from 4.85% to 8.8% for the period 1996-1998. These values suggest significant structural change during this period, confirming the need for a separate model based on a shorter sample period.

Assuming the adequate of the specific models (tested below), we proceed to the bounds test. Table 4 shows the results, confirming a significant long-run relationship between gasoline sales, price and income for both sample periods.

Table 4: Bounds test results for gasoline demand models

Sample period	F-statistic	10% critical bounds	
		Lower bound ($\boldsymbol{I(0)}$)	Upper bound ($\boldsymbol{I(1)}$)
1982Q1-2010Q4	11,25**	3,17 (asymptotic)	4,14 (asymptotic)
1998Q1-2010Q4	5,00** #	3,17 (asymptotic)	4,14 (asymptotic)
		3,33 (finite)	4,31 (finite)

** Reject at 5% asymptotic significance level # Reject at 10% finite-sample significance level

Table 5 therefore presents the gasoline demand models for both the longer and shorter sample periods:

Table 5: Specific models for gasoline demand (dependent variable ΔG_t)

1982Q1-2010Q4		1998Q1-2010Q4	
Regressor	**Coefficient (standard error)**	**Regressor**	**Coefficient (standard error)**
$\Delta \boldsymbol{G}_{t-1}$	-0,29 (0,07)		
$\Delta \boldsymbol{G}_{t-4}$	0,14 (0,06)		
$\Delta \boldsymbol{P}_{G,t}$	-0,23 (0,02)	$\Delta P_{G,t}$	-0,22 (0,04)
$\Delta \boldsymbol{Y}_{DispInc,t}$	0,21 (0,06)	$\Delta Y_{DispInc,t}$	0,52 (0,24)
$\boldsymbol{G}_{t-1}$	-0,19 (0,04)	G_{t-1}	-0,30 (0,11)
$\boldsymbol{P}_{G,t-1}$	-0,11 (0,02)	$P_{G,t-1}$	-0,13 (0,03)
$\boldsymbol{Y}_{DispInc,t-1}$	0,16 (0,03)	$Y_{DispInc,t-1}$	0,20 (0,06)
$\boldsymbol{R}^2$	0,74	$\boldsymbol{R}^2$	0,84

Misspecification tests, reported in Table 6, confirm the adequacy of both models at a 5% significance level.

Table 6: Misspecification tests for gasoline demand models

	1982Q1-2010Q4	1998Q1-2010Q4
Test name	**Test statistic (probability)**	**Test statistic (probability)**
AR (1-4) test	1,69 (0,14)	1,56 (0,21)
ARCH (1-4) test	0,96 (0,43)	0,82 (0,52)
Normality test	1,16 (0,56)	0,67 (0,72)
Heteroscedasticity test	0,71 (0,79)	0,79 (0,67)
Ramsey RESET	1,96 (0,15)	1,16 (0,33)

Given confirmation of a long-run relationship, Table 7 reports estimates for the parameters in the long-run relationship. Following Akinboade *et al.* (2008), standard errors are estimated using Bardsen (1989). The suggested long-run price elasticity estimates for the model based on the longer sample period is -0,44 and for the shorter sample period -0,55. However, the confidence intervals of these estimates overlap, which suggest no statistically significant difference between the two models. Similarly, the long-run income elasticity is estimated at around 0,8 for the shorter sample period and 0,67 for the longer period. Again, overlapping confidence intervals suggest no statistically significant difference.

Table 7: Long-run elasticities of gasoline demand

Sample period	Price elasticity (standard error)	Income elasticity (standard error)
1982Q1-2010Q4	-0,44 (0,04)	0,67 (0,04)
1998Q1-2010Q4	-0,59 (0,13)	0,82 (0,16)

Although the price elasticity estimates for gasoline demand correspond with earlier estimates, it is not clear whether the result indicates unchanged consumer behaviour or whether the correspondence is due to chance because of parameter instability. Furthermore, income elasticity is found to be much higher in both sample periods, which suggests that consumption of gasoline is more sensitive to consumer income. While some previous studies also find high income elasticity, none of these studies look closely at the problem of structural change and the problem of relying on a long sample period.

Finally, the speed-of-adjustment parameter for both demand models is around 0,2 (refer back to Table 5), which implies that long-run disequilibrium is corrected within five quarters. This speed is different from the speed suggested by previous annual data models (Akinboade *et al*., 2008), which suggest a protracted response of around five years – a response that is not consistent with the intuition offered by the (albeit simplistic) graphical comparison of quarterly fuel consumption and price.

It is possible to further investigate the stability of the two gasoline demand models using recursive estimation, where parameter estimates are derived using data from sub-periods within the larger sample period. Figure 3 reports recursive parameter estimates for price and income elasticity for the model based on the longer sample period. Figure 3 suggests significant instability in price elasticity and, especially, income elasticity for models based on data from the 1980s and 1990s only. In fact, long-run income elasticity seems insignificant until around 2001, while models incorporating data from more recent times suggest a more stable and positive income elasticity. This is consistent with recent findings for other countries that suggest that income has become a more important driver of transport fuel demand compared to price.

Figure 4 replicates the exercise for the gasoline model based on the shorter, more recent, sample period. The recursive results are similar for the two models for the period 2008-2010. However, this similarity does not imply that the model for the longer sample period necessarily encompasses the shorter-period model. As noted above, the results for the longer-period model are driven strongly by more recent data. It is not clear that the long-run relationship suggested by Figure 3 applies to the entire period, given the uncertainty about income elasticity and, to a lesser extent, price elasticity in earlier periods. For this reason, the results support a focus on two sample periods.

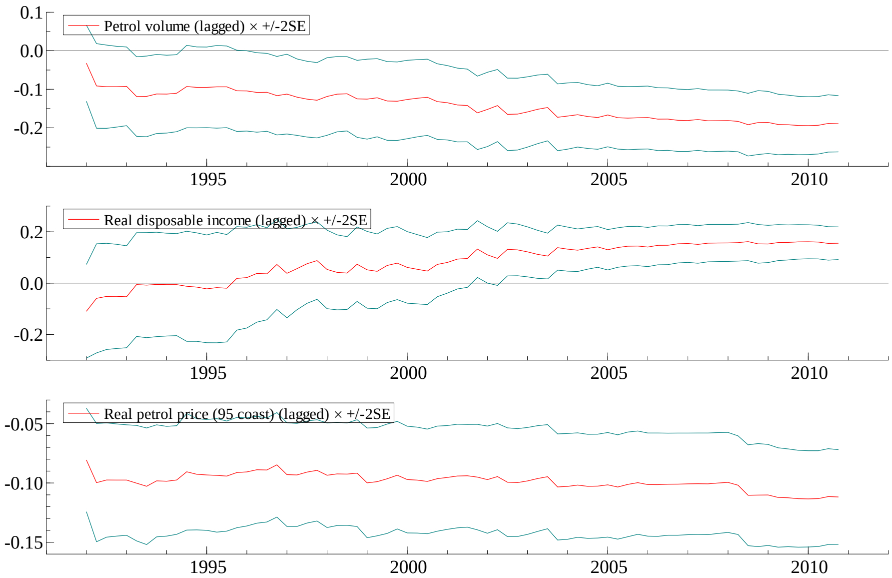

Figure 3: Recursive estimates for long-run price and income elasticity parameters in gasoline demand models (1982Q1-2010Q4) (initial sample size 40 data points)

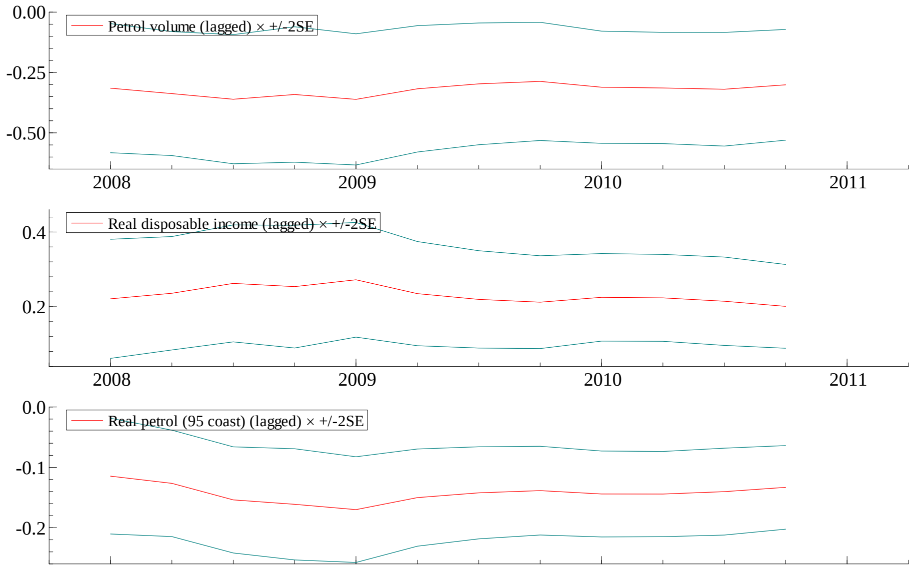

Figure 4: Recursive estimates for long-run price and income elasticity parameter in gasoline demand models (1998Q1-2010Q4) (initial sample size 40 data points)

6.2 Diesel fuel

Estimation of the demand function for diesel fuel in South Africa proceeds analogous to that of the gasoline demand function, with models for both the longer and shorter sample period. As with gasoline, the use of a longer and shorter sample period is based on Chow (1960) breakpoint tests, reported in Appendix C. The break in diesel demand appears to be more pronounced than that for gasoline demand. Even after including dummy variables to account for extreme outliers, we do not identify a unique long-run relationship for the 1982Q1-2010Q4 sample period. As argued earlier, the ARDL only allows for a single long-run relationship: finding none may yet imply that there are two relationships – perhaps due to structural change. In fact, we find a significant long-run relationship for the 1998Q1-2010Q4 period; the GUM for this period is congruent with data and theory, showing signs consistent with theory and passing all misspecification tests.

As noted, only the model based on the more recent sample period passes the bounds test, as shown in Table 8, suggesting a significant long-run relationship between diesel fuel price, income and diesel fuel consumption over this period.

Table 8: Bounds test results for diesel fuel demand models

Sample period	F-statistic	10% critical bounds	
		Lower bound ($I(0)$)	Upper bound ($I(1)$)
1983Q2-2010Q4	0,88	3,17 (asymptotic)	4,14 (asymptotic)
1998Q1-2010Q4	9,17	3,17 (asymptotic)	4,14 (asymptotic)
		3,33 (finite)	4,31 (finite)

However, the particularly strong growth in diesel fuel sales merits further attention. It may be important to formally account for improvements in diesel technology and increased take-up of diesel power as alternative transport fuel. Below we discuss two ways of doing so.

One way to control for technological change is to include a variable capturing the ratio of sales of diesel-powered vehicles to that of all vehicles. This should provide a signal of the extent to which there is consumer switching towards diesel technology. Figure 5 reports the ratio of diesel to total passengers and light commercial vehicle sales. The graph shows that the shift to diesel-powered LCVs already occurred during the late 1990s rather than in recent years. In other words, it is unlikely that the acceleration in diesel fuel sales in the past decade was due to proportionally more diesel-powered trucks (than gasoline-powered trucks) on South African roads. The shift to diesel-powered passenger vehicles seems to have been more gradual.

Second, one may include a variable on the stock of diesel vehicles: a significant rise in the sale of diesel vehicles in recent years would help to explain the strong growth in diesel sales. Both of these modelling options are limited, due to data constraints. No data is available on the stock of vehicles in South Africa. While data on the sales of vehicles are available, these start only in 1994 and restrict our focus to the model for the shorter sample period. Data is also limited to passenger and light commercial vehicles (LCVs), which is problematic given that heavy commercial vehicles are mostly powered by diesel. Figure 6 reports the cumulated LCV and passenger vehicle sales from 1994 onwards. These provide quasi-measures of the stock of diesel vehicles, ignoring depreciation and the stock of diesel vehicles as at the start of 1994.

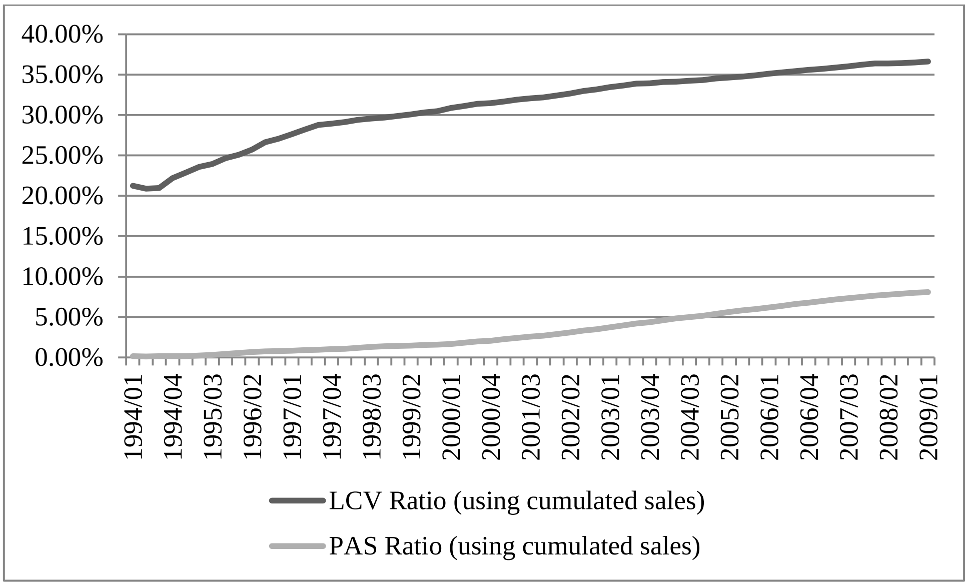

Figure 5: Ratio of diesel sales to total sales of passenger vehicles (PAS) and light commercial vehicles (LCV) (1994Q1-2009Q1)

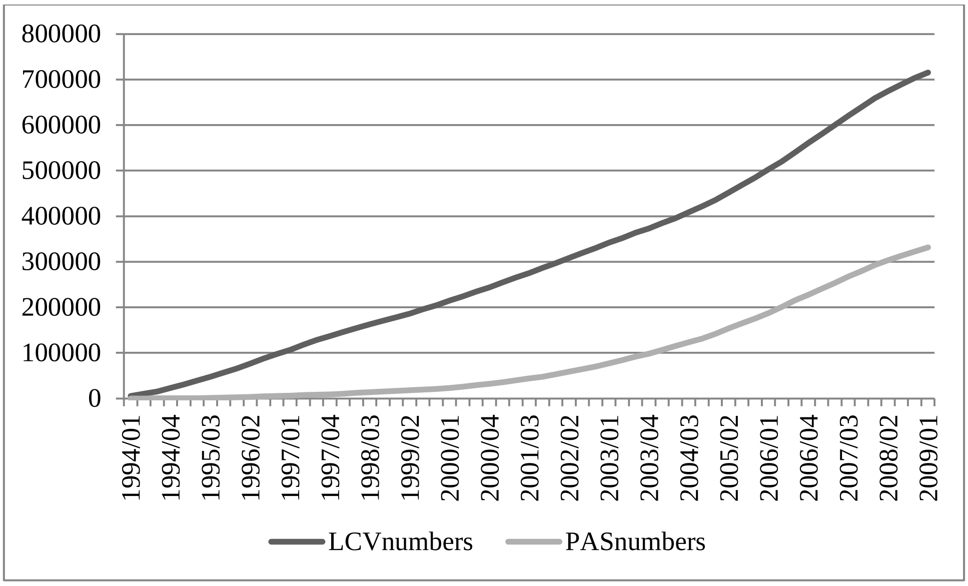

Figure 6: Cumulated number of passenger vehicle (PAS) and light commercial vehicle (LCV) sales (1994Q1-2009Q1)

We do not dispute that technological change or changes in consumer preferences may have altered diesel demand. However, the control variables for these processes do not perform well. The general unrestricted models that include these control variables consistently suggest negative relationships for these variables, which is counter-intuitive. While this suggests that the GUMs are not congruent with theory, one can proceed to apply a GETS procedure and obtain specific models. Surprisingly, the GETS procedure removes all of the control variables from the final specification, such that the results are very similar to a GUM which did not contain any of the technology variables. Of course, one would want to further explore this further (trying, for example, to obtain further data from industry). However, in the current paper, the focus is on the price and income elasticities of diesel fuel demand and it is clear that elasticity estimates are not significantly altered when including the above variables. In fact, the long-run income elasticity implied by those incongruent GUMs mentioned above are *close* to the ones suggested by specific models derived from (congruent) GUMs excluding the technology control variables. We are therefore reasonably confident of the accuracy of the income elasticity estimate.

Table 10 reports the specific diesel demand models for the shorter and longer sample period. Despite the unsatisfactory results for the longer-sample GUM, we report the specific model derived from this GUM. As noted, the longer-period GUM's problems carry over into its specific model, which includes no long-run component. We therefore focus mostly on the 1998Q1-2010Q4 specific model.

Table 9 confirms the adequacy of the specific model for 1998Q1-2010Q4 and highlights some of the problems of the longer period specific model (notice, for example, the p-value for the RESET test, which is an indicator of structural change). The problems may be the result of significant change in diesel fuel consumption behaviour during the mid-1990s – a period included in the longer sample period.

Table 9: Misspecification tests for diesel fuel demand specific models

	1983Q2-2010Q4	1998Q1-2010Q4
Test name	**Test statistic (probability)**	**Test statistic (probability)**
AR (1-4) test	1,46 (0,21)	0,97 (0,44)
ARCH (1-4) test	1,17 (0,33)	0,47 (0,76)
Normality test	3,61 (0,16)	3,27 (0,20)
Heteroscedasticity test	1,14 (0,32)	0,58 (0,91)
Ramsey RESET	2,72 (0,07)	0,04 (0,96)

Table 10: Specific models for diesel fuel demand (dependent variable ΔD_t)

1983Q2-2010Q4		1998Q1-2010Q4	
Regressor	**Coefficient (standard error)**	**Regressor**	**Coefficient (standard error)**
ΔD_{t-1}	-0,66 (0,07)	ΔD_{t-1}	-0,40 (0,09)
ΔD_{t-2}	-0,31 (0,05)		
		ΔD_{t-5}	0,09 (0,06)
ΔD_{t-7}	-0,09 (0,04)		
ΔD_{t-12}	0,11 (0,04)		
$\Delta P_{D,t}$	-0,13 (0,04)	$\Delta P_{D,t}$	-0,26 (0,04)
$\Delta P_{D,t-1}$	-0,17 (0,03)		
$\Delta P_{D,t-5}$	-0,08 (0,03)		
		$\Delta P_{D,t-7}$	0,21 (0,03)
$\Delta Y_{GDP,t}$	3,26 (0,32)	$\Delta Y_{GDP,t}$	5,61 (0,79)
		$\Delta Y_{GDP,t-1}$	-2,99 (0,75)
		$\Delta Y_{GDP,t-3}$	3,10 (0,60)
$\Delta Y_{GDP,t-4}$	1,36 (0,29)		
		$\Delta Y_{GDP,t-5}$	-1,35 (0,51)
$\Delta Y_{GDP,t-8}$	1,35 (0,34)		
$\Delta Y_{GDP,t-9}$	-1,16 (0,35)		
		D_{t-1}	-0,48 (0,11)
		$P_{D,t-1}$	-0,10 (0,03)
		$Y_{GDP,t-1}$	0,75 (0,16)
R^2	0,90	R^2	0,93

Figure 7 reports recursive estimation results for the specific model based on the shorter sample period and suggests that the estimates are fairly stable:

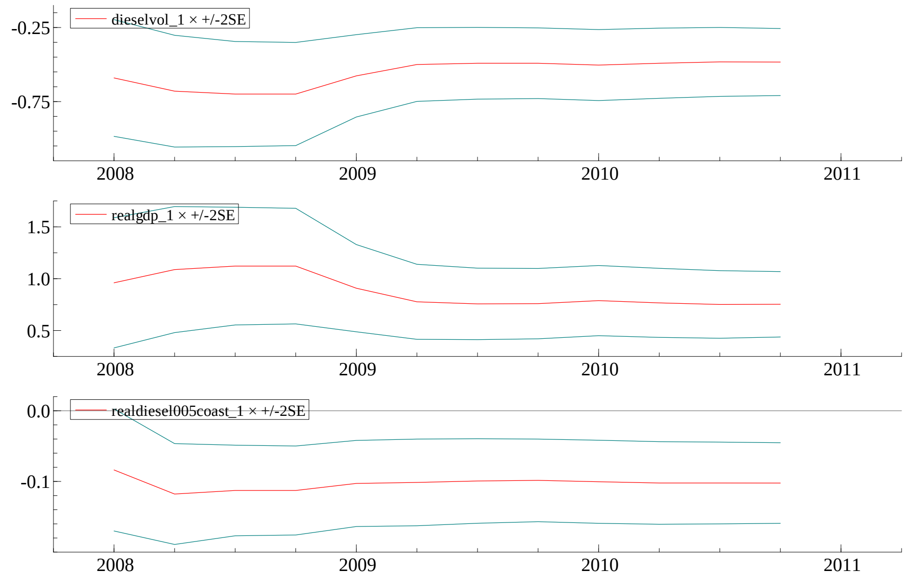

Figure 7: Recursive estimates for long-run income elasticity parameter in diesel fuel demand model (1998Q1-2010Q4) (initial sample size 40 data points)

Table 11 reports the long-run elasticity estimates suggested by the shorter sample period. Demand elasticity for the shorter period specific model is estimated at around -0.2 for price and 1.5 for income.

Table 11: Long-run elasticities of diesel fuel demand

Sample period	Price elasticity (standard error)	Income elasticity (standard error)
1998Q1-2010Q4	-0,21 (0,08)	1,56 (0,11)

These results are consistent with previous diesel fuel demand estimates for South Africa of about -0,1 for price and 1,4 for income (refer to Table 1). It is also consistent and in the same range as the De Vita *et al.* (2006) findings for Namibia, which suggests that price elasticity of diesel fuel demand are significantly lower than that of gasoline demand. It is also intuitively plausible: we may expect diesel demand to be less responsive to price than gasoline demand, as diesel fuel is used by freight vehicles, whose owners are price-inelastic (Goodwin, Dargay and Hanly, 2004). Given South Africa's poorly functioning rail network, the need for freight transport via road may well explain this low price elasticity.

The results confirm the significant role of economic growth in driving demand for diesel fuel in South Africa, much stronger than for gasoline. Furthermore, even if one takes the diesel model over the longer period to be merely indicative, a case can be made that economic growth remains the most important driver of diesel fuel consumption.

The speed-of-adjustment parameter is around 0.48 (refer back to Table 7), which implies that long-run disequilibrium is corrected within about two quarters. This response is quite rapid and, given the importance of economic growth in diesel demand, suggests that diesel volumes quickly respond to changes in economic conditions.

6.3 Jet fuel

Estimation of the jet fuel demand model is slightly more complicated, given that both local and international income conditions play a role. We are interested in the elasticity of fuel demand with respect to domestic income, but elasticity estimates may be biased if the model does not account for international demand drivers as well. We therefore include both domestic income (in the form of GDP) and, as a measure of international demand for South African air transport, the number of international departures by foreign citizens. We use departures, rather than arrivals, as departing aeroplanes will require South African jet fuel (although, of course, the departures and arrivals data behave quite similarly). We do not include domestic departures with income in our reduced-form model, as income is already a determinant of domestic departures (see the discussion of the results below). An alternative specification that excludes the income variable but includes domestic departures performs well, though it cannot provide the income elasticity estimate we are looking for.

Jet fuel consumption data is more limited than gasoline or diesel fuel data and are only available from 1994Q1-2009Q3. We therefore report first the standard model of jet fuel demand without international departures as control variable for the period 1998Q1-2009Q3, in order to retain comparability with the other demand models. Secondly, we report the model with the international departures control variable included. Unfortunately, data on international departures of foreign citizens and domestic departures commence only in January 2000, so that this model runs from 2001Q2-2009Q3. This reduces the sample period further, which suggests that one should be careful when interpreting the results.

We derive the specific models using a GETS procedure analogous to that employed for the gasoline and diesel models (after confirming that the GUMs are congruent with the data and theory). Given the stability of the specific models (see results that follow), we perform the bounds test and find evidence of a statistically significant long-run relationship for both sample periods, as shown in Table 12.

Table 12: Bounds test results for jet fuel demand models

Sample period	F-statistic	10% critical bounds	
		Lower bound ($\mathbf{I(0)}$)	Upper bound ($\mathbf{I(1)}$)
1998Q1-2009Q3	35,03***	3,17 (asymptotic)	4,14 (asymptotic)
		3,33 (finite-sample)	4,31 (finite-sample)
2001Q2-2009Q3	42,26***	4,04 (asymptotic)	4,78 (asymptotic)
		4,29 (finite-sample)	5,08 (finite-sample)

*** Reject null hypothesis at 1% significance level

The regressions results for the specific models are reported in Table 13, while Table 14 shows that the specific models pass all of the diagnostic tests.

Table 13: Specific models for jet fuel demand (dependent variable ΔJ_t)

1998Q1-2009Q3		2001Q2-2009Q3	
Regressor	**Coefficient (standard error)**	**Regressor**	**Coefficient (standard error)**
$\boldsymbol{\Delta J_{t-1}}$	0,11 (0,03)	ΔJ_{t-1}	0,36 (0,12)
		$\Delta P_{J,t-3}$	-0,13 (0,03)
		$\Delta Y_{GDP,t-2}$	1,91 (0,49)
		$\Delta Y_{GDP,t-4}$	2,27 (0,81)
$\boldsymbol{J_{t-1}}$	-0,68 (0,08)	J_{t-1}	-1,11 (0,12)
$\boldsymbol{P_{J,t-1}}$	-0,08 (0,01)		
$\boldsymbol{Y_{GDP,t-1}}$	0,68 (0,08)	$Y_{GDP,t-1}$	0,78 (0,09)
$\boldsymbol{R^2}$	0,67		0,95

Table 14: Misspecification tests for jet fuel demand specific models

	1998Q1-2009Q3	2001Q2-2009Q3
Test name	**Test statistic (probability)**	**Test statistic (probability)**
AR (1-4) test	2,44 (0,07)	0,22 (0,92)
ARCH (1-4) test	0,36 (0,84)	0,75 (0,56)
Normality test	1,82 (0,40)	0,66 (0,72)
Heteroscedasticity test	0,94 (0,51)	0,95 (0,53)
Ramsey RESET	0,69 (0,50)	0,14 (0,87)

The first set of results in Table 13 relate to the period 1998Q1-2009Q3. Similar to the specifications for the gasoline and diesel models, the GUM for this period includes only income and price (in addition to the seasonal and deterministic terms). As argued above, jet fuel demand is derived not only from domestic but also from international tourism demand. Therefore, we fit a second GUM that also includes international departures of foreigners (i.e. tourists leaving), which produces the second set of results. As the latter variable is only available from 2001, the sample period is shorter. This difference in sample period is important when interpreting Table 13.

For the longer sample period, the specific model suggests that jet fuel demand has a fairly low long-run price elasticity of around -0.1 and an income elasticity of about 0.9, as shown in Table 15. For the shorter sample period, only the long-run income elasticity is significant, with an estimate mean value of about 0.7.

Table 15: Long-run elasticities of jet fuel demand

Sample period	Price elasticity (standard error)	Income elasticity (standard error)
1998Q1-2009Q3	-0,11 (0,01)	0,99 (0,03)
2001Q3-2009Q3		0,70 (0,02)

The jet fuel demand function therefore suggests that economic growth, rather than oil prices, is determinative for jet fuel sales in South Africa. Of course, it is possible that the use of crude oil prices, rather than retail price of jet fuel (not available), may bias the price elasticity estimates downward (see Dargay and Gately (2010: 6269)). In addition, the specific models indicate high speed-of-adjustment parameters (-0,68 and -1,11, see Table 13), which suggests that any long-run disequilibrium is corrected within less than two quarters. The long-run equilibrium adjustment process therefore plays a significant role in quarter-to-quarter consumption changes in South African jet fuel demand.

The results above are interesting in a number of respects. First, notice that the price variable is statistically significant only in the first sample period that includes the late 1990s and, even in this case, the estimated price elasticity is small. This result is consistent with previous estimates in the international literature (as summarized in the literature review) of statistically insignificant or significant but small price elasticity in recent years. Second, the specific model for the longer sample period does not contain any international departures variables. In other words, the addition of international departures to the model does not lead to a different final model compared. Therefore, and thirdly, the difference between the specific models for 1998Q1-2009Q3 and 2001Q2-2009Q3 is not due to the role of the international departures variable, but due to the change in the sample period: if we run the GUM excluding the international departures variable, the results are virtually similar. In other words, the lower income elasticity and absence of price in the long-run relationship, is due to changes in sample period. However, and fourthly, it is incorrect to conclude that the international departures do not matter at all for jet fuel demand: in the above models, we use seasonally-adjusted departure data. If one uses the unadjusted series and includes seasonal dummies, the specific models do not contain any of the seasonal dummies but do retain the departure variables.

Therefore, it seems that the (significant) seasonal fluctuations in international departures play a role.

One may argue that domestic departures (i.e. flights within South Africa) should also be included. As noted above, this is likely to bias the income elasticity estimates. We did attempt to estimate a GUM that includes both international and domestic departures, but this reduces the data further to a sample period 2003Q1-2009Q3. This model is not congruent with the data and fails some of the misspecification tests. Even if one ignores these problems and obtains a specific model, this model is quite similar to the specific models reported in Table 13 – again containing none of the departure variables in any form. The long-run results from the specific model are also *similar* to the results in Table 15.

Although the sample period is quite short, recursive estimation may still shed some light on how important recent data points are in determining the behaviour of the overall model. The recursive results for the longer sample period suggest that the model produces stable parameter estimates for long-run price and income elasticity.

7. Conclusions

Price and income elasticity estimates feature prominent in South African policy proceedings and corporate planning. Yet, significant structural changes in the behaviour of fuel consumption since the late 1990s are not sufficiently reflected in the literature. This paper employs a quarterly dataset and compares estimates for both a shorter and a longer sample period to assess the extent of structural change. The paper also covers diesel fuel and jet fuel, which have received less attention in previous research.

The results from the ARDL models of gasoline, diesel fuel and jet fuel can be summarized as follows. Firstly, the results for the gasoline models are consistent with earlier estimates. To be sure, the models suggest higher *point* estimates for long-run price and income elasticity: price elasticity estimates of -0,59 for the shorter sample period compared to -0,44 for the longer period; income elasticity of 0,82 compared to 0,67. However, once standard error bands are taken into account, there is no statistical evidence of a significant mean difference. The speed-of-adjustment estimate for both the longer and shorter periods is significantly faster than suggested by previous research: -0,2 suggests 5 quarters for long-run equilibrium to be restored, which contrasts with findings of around five years based on annual data (see Akinboade *et al.* (2008)). These results shed led on the impact of price and income volatility on gasoline volumes. While price and income elasticity for a given price or income level seems to be increasing slowly, most of the recent movements in gasoline fuel sales are not driven by greater elasticity. Instead, volatility in the underlying price and income data in recent years better explain movements in gasoline fuel sales.

Secondly, the results suggest important new findings for diesel demand. The models do not suggest a unique long-run relationship between diesel volumes, price and income over the longer sample period. A unique relationship could yet exist, but structural changes could have altered the relationship, creating different relationships for different periods that are challenging to detect. This is confirmed by the significant long-run relationship uncovered over the shorter sample period. The long-run price elasticity suggested by this relationship is -0,21 compared to around -0,1 suggested in previous (and not publicly available) research (refer back to Table 1). Standard-error confidence intervals do not suggest significant differences. In contrast, income elasticity of diesel demand for the more recent period is found statistically significantly higher than the longer period. This is not surprising, given the strong relationship between diesel demand and economic growth in recent years. The paper also presents the first speed-of-adjustment estimates for diesel: the -0,48 estimate suggests that disequilibria are corrected within two quarters, which is much quicker than for petroleum. In fact, the rapid equilibrium-adjustment estimates for gasoline and diesel fuel suggest that long-run equilibrium adjustment is an important factor in the short-run behaviour of gasoline and diesel fuel demand – lending credence to the focus on long-run estimates in this paper.

Thirdly, the study presents the first price and income elasticity estimates for jet fuel demand in South Africa. Long-run price elasticity is estimated at -0,1 and income elasticity at 1,0 for the period 1998Q4-2009Q3. The speed of adjustment is quite rapid and is estimated to be less than two quarters.

In addition, the seasonal effects from the models suggest that seasonal effects have become more accentuated in recent years, especially for diesel fuel demand: volumes in the first quarter tend to be about 10%-12% lower than the peak in the fourth quarter. Jet fuel volumes are also higher on average in the second-half of the year.

In general, the demand models shed new light on emerging fuel demand patterns in South Africa. There are slow increases to be seen in price and income elasticity of gasoline demand, while the models suggest much higher income elasticity for diesel demand. Furthermore, adjustment to long-run disequilibria occurs much quicker than previous research suggests. The study also estimates jet fuel price and income elasticity for the first time, showing that income elasticity is much higher than price elasticity.

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Appendix A: Graphical relationships between price and volume

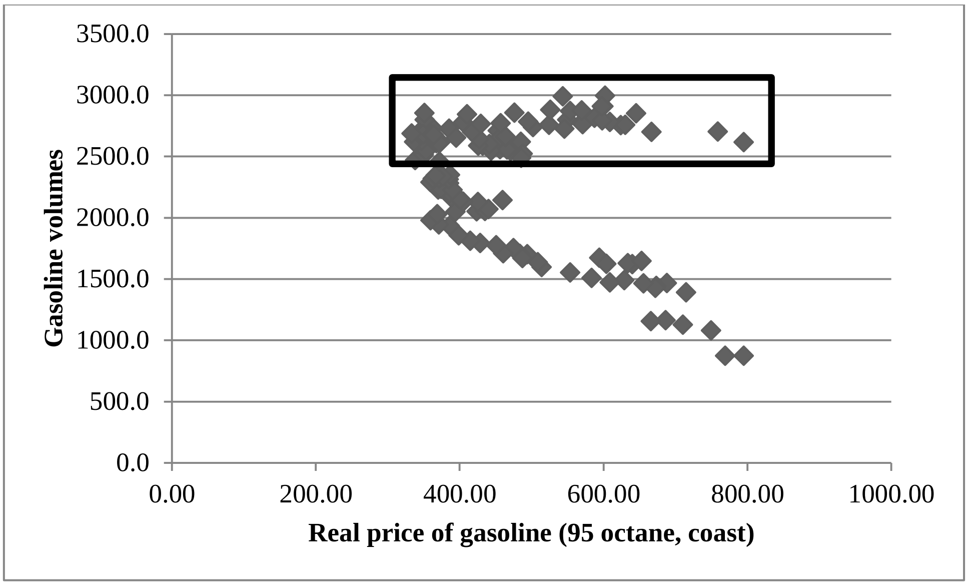

Figure A.1: Scatter plot of gasoline sales and the real gasoline price (95 octane, coast) (1998-2010 data indicated by black box)

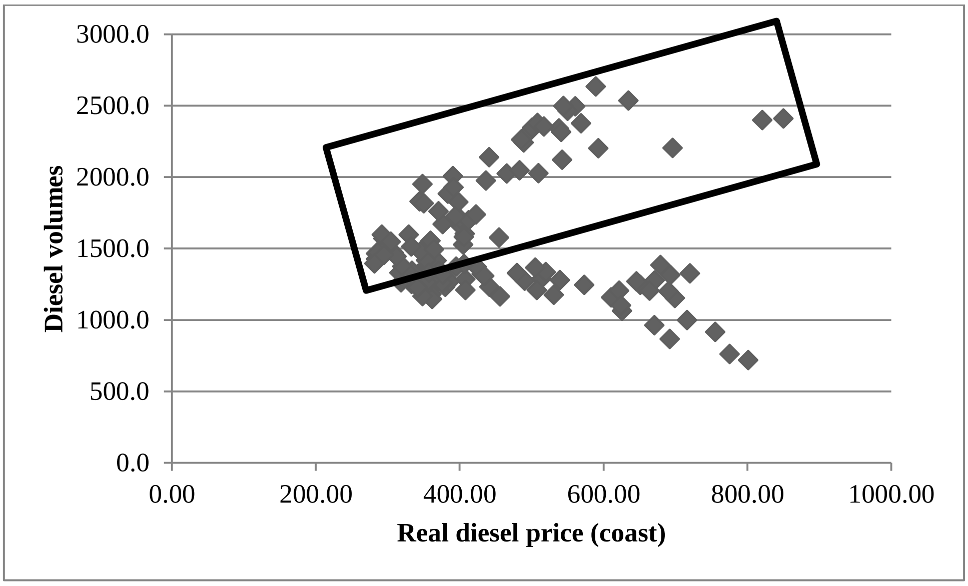

Figure A.2: Scatter plot of diesel sales and the real diesel price (0.05% sulphur, coast) (1998-2010 data indicated by black box)

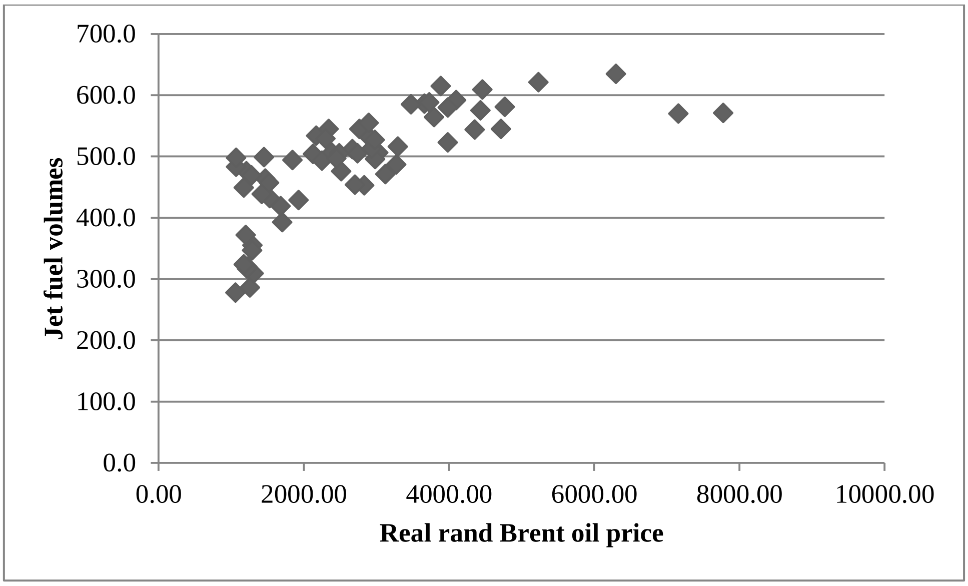

Figure A.3: Scatter plot of jet fuel sales and the real jet fuel price (Brent crude in Rand)

Appendix B: Graphical relationships between income and volume

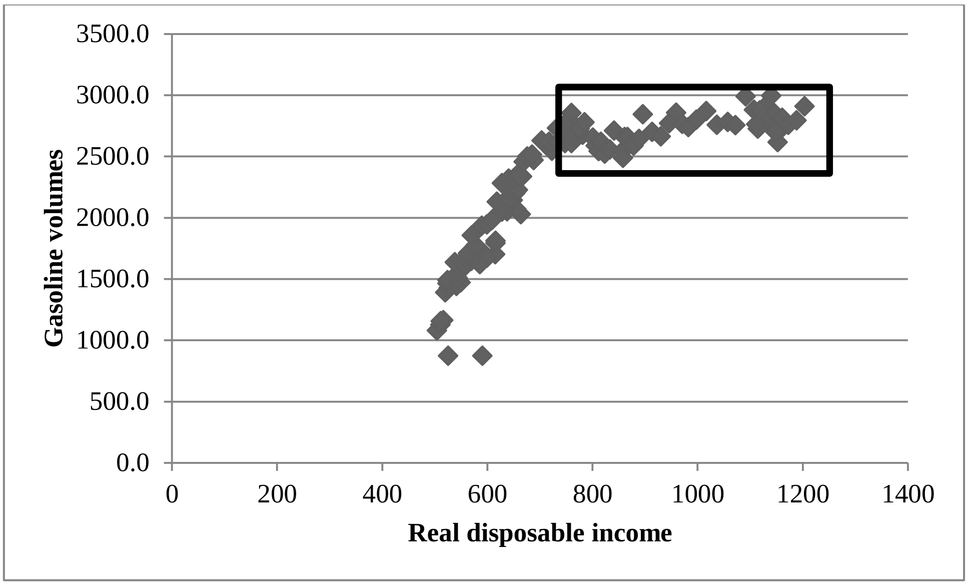

Figure B.1: Scatter plot of gasoline sales and real disposable income (1998-2010 data indicated by black box)

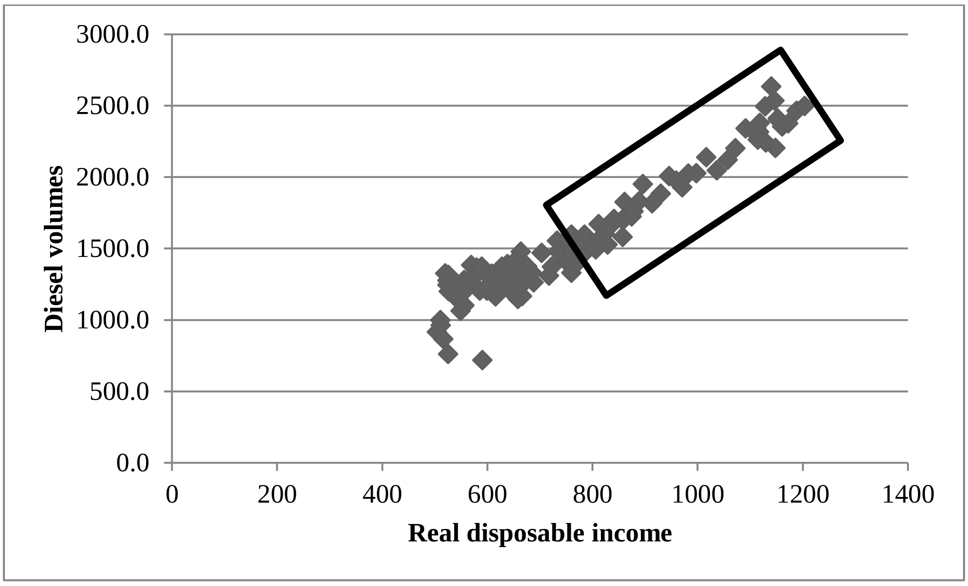

Figure B.2: Scatter plot of diesel sales and real disposable income (1998-2010 data indicated by black box)

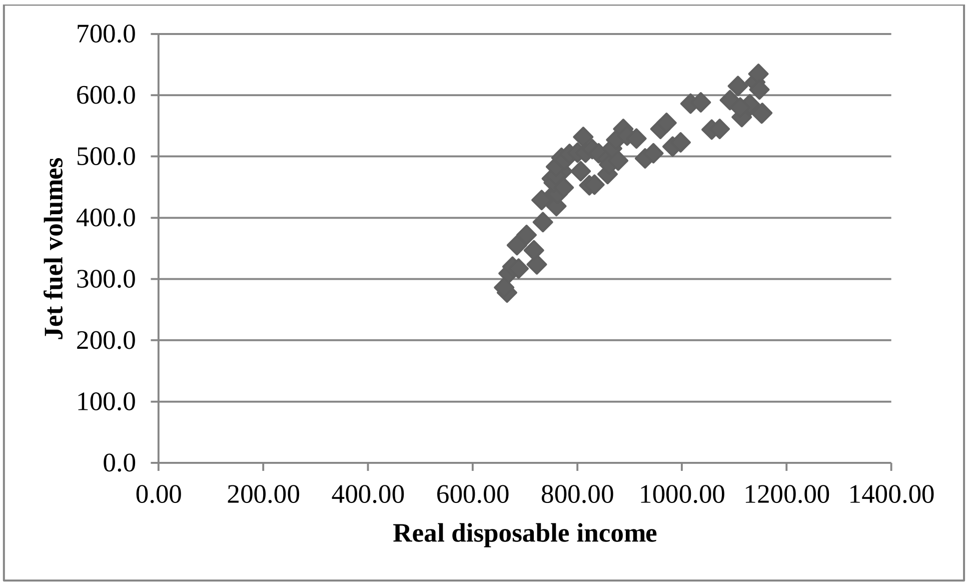

Figure B.3: Scatter plot of jet fuel sales and real disposable income

Appendix C: Recursive Chow tests for parameter non-constancy

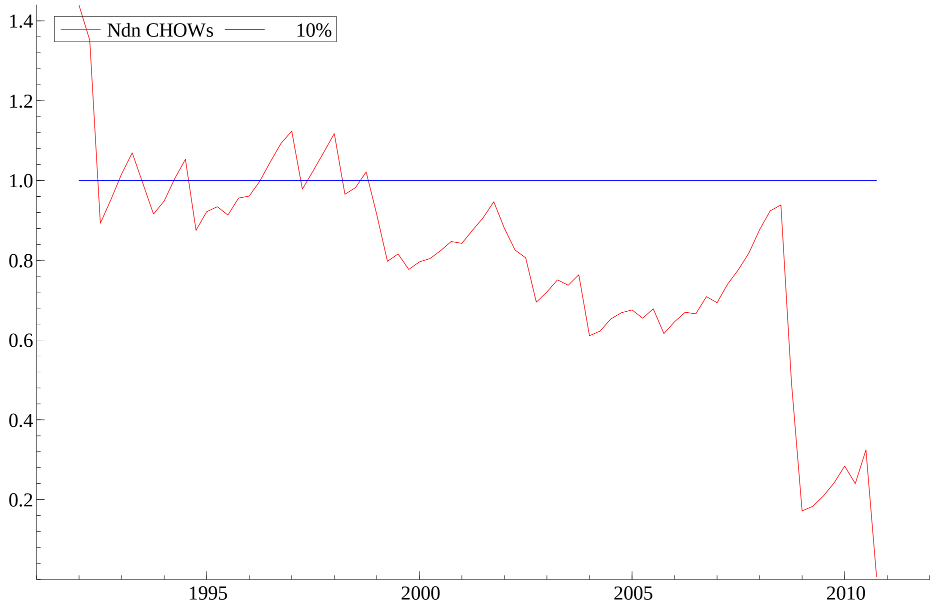

Figure C.1: Recursive Chow tests for parameter non-constancy in gasoline model

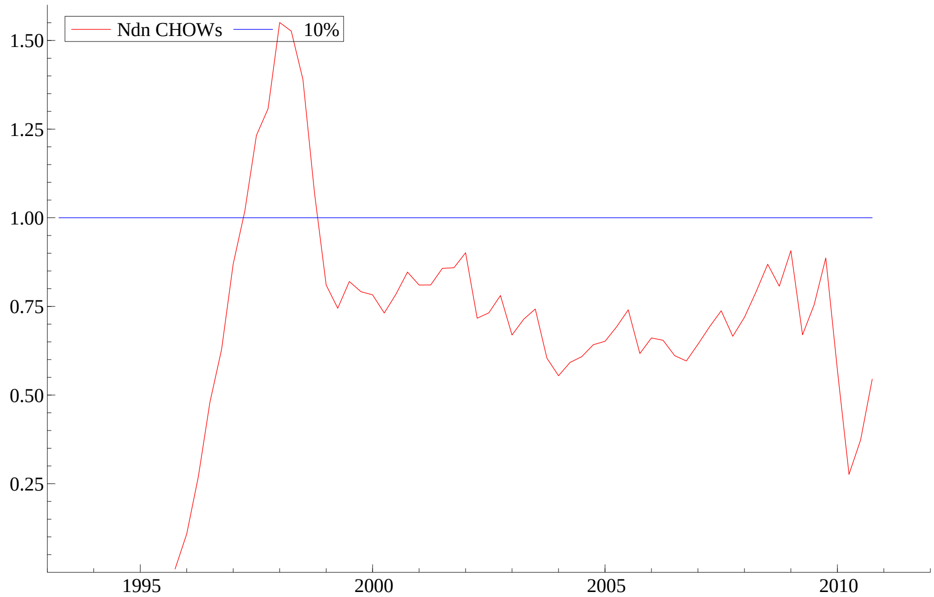

Figure C.2: Recursive Chow tests for parameter non-constancy in diesel model