Structural Analysis of energy market failure: Empirical evidence from US

A thesis submitted for the degree of Doctor of Philosophy

by

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October 2013

To my family

Preface

This PhD thesis is completed in November 2013 during my studies at Department of Economics and Finance, Brunel University. The support of the department of Economics and finance at Brunel University is gratefully acknowledged.

I would like to thank my thesis mentor Dr John Hunter for his support and assistance during my PhD research.

I would like to thank Ray Barrell, Iain Clacher, Matthew Greenwood Nimmo, Guy Liu, Kevin Reilly, Cheryl Roberts, Yongcheol Shin, Mauro Costantini and contributors at the Micro-econometrics and Public Policy Conference at the National University of Ireland, Galway for their comments. Many thanks also to contributors at the XVI Applied Economics Meeting at the Granada University, Spain for their comments.

I would like to thank my husband, Hossein Kalatian, and all my family and my friends for their love, encouragement and boundless support during my research.

Declaration

The work described in this thesis has not been previously submitted for any degree in this university or any other university and otherwise the authors work.

Statement of Copyright

Recent and upcoming publications

S.A.Tabaghdehi and J. Hunter, "Cointegration, Exogeneity and Isolating Long-run Price behaviour", paper presented at XVI Applied Economics Meeting at The University of Granada, June 2013

S.A.Tabaghdehi and J. Hunter, "Cointegration and US Regional Gasoline Prices: Testing market efficiency from the stationarity of price proportions", paper presented at the Micro-econometrics and Public Policy Conference at the National University of Ireland, Galway, June2012

S.A.Tabaghdehi and J. Hunter, (2013) ,"Extracting Long-run Information from Energy Prices- The role of Exogeneity", working paper at Brunel university, 2013.

S.A.Tabaghdehi and J. Hunter, (2013), "Cointegration and US Regional Gasoline Prices: Testing market efficiency from the stationarity of price proportions", working paper at Brunel university, 2013.

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Abstract

This thesis is concerned with the econometric modelling of gasoline prices in US. The intention is to characterize the market process in this crucial and significant industry. Overall we have been seeking to identify a mechanism to signal and measure market failure and consequently improve market performance.

Firstly we examine the time series properties of gasoline prices using the criteria for perfect arbitrage to test market efficiency from the stationarity of price proportions. This is done by considering market efficiency across in different regions of the US, by applying a range of different stationary tests. In this analysis we collected a comprehensive data set of gasoline prices for all regions of the US mainland for the longest period available. Forni (2004), outlined reasons why the analysis of price proportions may be advantageous; especially when the sample is limited. Stationarity corresponds to a broad market, it is found here that the US gasoline market is on average broad. Except for the Gulf Coast and Lower Atlantic, which may be seen as economically and/or geographically separated, market structure in the rest of the US would not appear to be a problem

Next we investigate possible long-run price leadership in the US gasoline market and the inter-relatedness of price behaviour relevant to a competitive market. Following Hunter & Burke (2007) and Kurita (2008) market definition is tested. This is done on an extended regional data set to Kurita and following the analysis in Hunter and Burke on a set of company data for the US.

We analysed long-run price leadership through the cointegrated vector auto-regression (VAR) to identify key characteristics of long-run structure in the gasoline market. The analysis of the system of regional prices confirms problems with the Gulf Coast and Lower Atlantic, but also based on the finding that the cointegrating rank is less than N-1 using both types of data (regional price data and company price data) and the findings on weak exogenity it is suggested that competition across the whole of the US is further limited.

We applied further tests to company data on prices and quantity data to investigate further the need to regulate for potential anomalies and to capture more directly consumer harm. The variance screening method applied to recent weekly data indicates that there is too little variation in gasoline prices and this would seem to support the cointegration study. Furthermore we applied a dynamic disequilibrium analysis to attempt to identify long-run demand and supply in the gasoline market. Finding significant variables using the Phillips-Hansen fully modified estimation of the switching regression is necessary to distinguish two long-run equations (S&D).
Moreover a comparison is made with a Markov Switching Model (MSM) of prices and this suggests a similar pattern of regime to the quantity information analysed in by our disequilibrium model.

Keywords: Gasoline, Stationarity, Cointegration, ARCH, Price differential, Market efficiency, Arbitrage, Collusion, Law of one price, Error Correction Model, Long-run relationship, Weak exogeneity, Price dispersion, Supply, Demand, Variance screening, Disequilibrium regime switching model.

JEL Classification: C13, C22, C32,C34, D4, D5, D18, D40, R11.

Introduction

It is well known that oil price shocks are a major concern to the health of the global economy. Unstable oil prices have a significant negative impact on consumer confidence and business decision making. As a result economic recovery may be longer and more complicated. Controlling the global oil price may not be possible, but a main concern of this research relates to energy market efficiency and as to whether prices responds to each other in the long-run across the regions of one country.

The gasoline price instability in the short-run and the long-run is an interesting challenge for econometrics modelling. This thesis investigates gasoline market behaviour with the primary focus being on prices to indicate the potential for consumer harm and evaluate the potential for the abuse of market power.

The core process in the production of gasoline from the oil field to the gas station pump is observed in terms of four main steps: oil exploration, refining, distributing the refined oils to the different companies and regions, selling the product. The price of the gasoline at the pump includes a considerable amount of tax which is one of the vital revenue streams for the government.

The gasoline market has generally been considered competitive, because the product is homogeneous, there are strict rules as to what can be added to fuel, consumers are less influenced by branding, there are many suppliers and consumers, and a significant amount of price related information is commonly available. Nevertheless pump prices at the gas station do differ in terms of location, local tax levels and services provided by the outlet.

If that information on price can be provided effectively to customers, then consumers can monitor retail gasoline resources. To this end government intervention and regulation might be required to control price discrepancy and improve market structure.

In Chapter one the gasoline prices from different geographic areas of a country are analysed to see whether they belong to the same market and as a result the relative prices ought to be stationary. In an efficient market there is no transaction cost and all available information is free and accessible to all market contributors at the same time (Fama, 1970). This implies a price shock in one region would be reflected in all other prices. It is believed that if the gasoline market is sufficiently active in the US, then as a result of arbitrage, long-run gasoline prices by region should follow each other**.**

To test the proposition of stationarity a range of tests are applied: the Augmented Dickey Fuller test (ADF), Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test and DF-Generalized Least Squares (GLS). This is pertinent as such tests have been applied in antitrust cases in Italy and the Netherlands to determine whether prices are responsive and help determine whether there might be market imperfection or in association with more heuristic information, possible collusion.

In Chapter two we consider cointegration analysis to detect key features of long-run structure in the gasoline market. After examining the stationarity and cointegration of the weekly gasoline prices in eight different regions of the US we research long-run price leadership and parallel pricing in the framework of the cointegrated vector auto-regression (VAR). This extends the data applied by Kurita (2008) to 901 weekly gasoline prices to cover eight regions of the US and further more for seven major oil companies in the US. The discovery of a single common trend has been observed for a smaller number of regions, but when the system is estimated across the US it is found that the finding of a single common trend cannot be sustained. In addition to this failure the reject tests of exogeneity suggest that the extent to which regional and company gasoline prices in the long-run respond to each other is limited.

In Chapter three, we report the result of the variance screening estimation to provide further evidence to suggest anti-competitive behaviour in the US gasoline market; this can also be used to compliments the cointegration study. To analyse quantities it is essential to gather monthly data. To this end, a demand and supply study of energy market is important to identify appropriate factors to determine economic policy. To this end a regime switching model illuminates the effect of the energy demand and supply on market conditions and the regulatory environment. We specify an exogenous disequilibrium model to analyse the demand and supply functions in gasoline market. The regimes are benchmarked against a theoretical markov switching model of prices and it is found that the regimes selection appears to correspond across the two methods.

CHAPTER 1

Cointegration and US Regional Gasoline Prices: Testing market efficiency from the stationarity of price proportions

1 Cointegration and US Regional Gasoline Prices: Testing market efficiency from the stationarity of price proportions

1.1 Introduction

"Much of 'classical' econometrics theory has been predicated on the assumption that the observed data come from a stationary process, meaning a process whose means and variances are constant over time. A glance at graphs of most economic time series, or at the historical track record of economic forecasting, suffices to reveal the invalidity of that assumption: economics evolve, grow, and change over time in both real and nominal terms, sometimes dramatically - and economic forecasts are often badly wrong, although that should occur relatively infrequently in a stationary process." Hendry and Juselius (2000)

Gasoline is the primary product that derives from the cracking process as applied to the refining of crude oil. Refineries obtain crude oil and break down its hydrocarbons into different products as refined product; including gasoline, diesel fuel, heating oil, jet fuel, liquefied petroleum gases, and residual fuel oil. The quality of the gasoline depends on the type of crude oil to which the cracking process is applied. Depending on the legal definition of the grade of petroleum, the refinery team as producer may blend a proportion of ethanol with the refined gasoline. The performance of the gasoline must meet industry standards and environmental regulations that depend on local legislation and whether it is produced for home consumption or export.

Since oil price shocks are currently a particular concern for the health of the global economy, unstable oil prices effect are likely to harm consumer confidence and business decision making. It has been suggested that oil prices have shifted from the control of OPEC to the global market for oil and this may not be easy to control. However, it may be possible to determine whether the market is efficient and as a result arbitrage operates to smooth out price discrepancies in the long-run in the US gasoline market?

According to the US Energy Information Administration(EIA) report (2007), US refineries produced over 90% of the gasoline used in the US, but less than 40% of the used crude oil produced in the US with approximately 45% of gasoline produced in the US coming from refineries in Gulf Coast (including Texas and Louisiana).

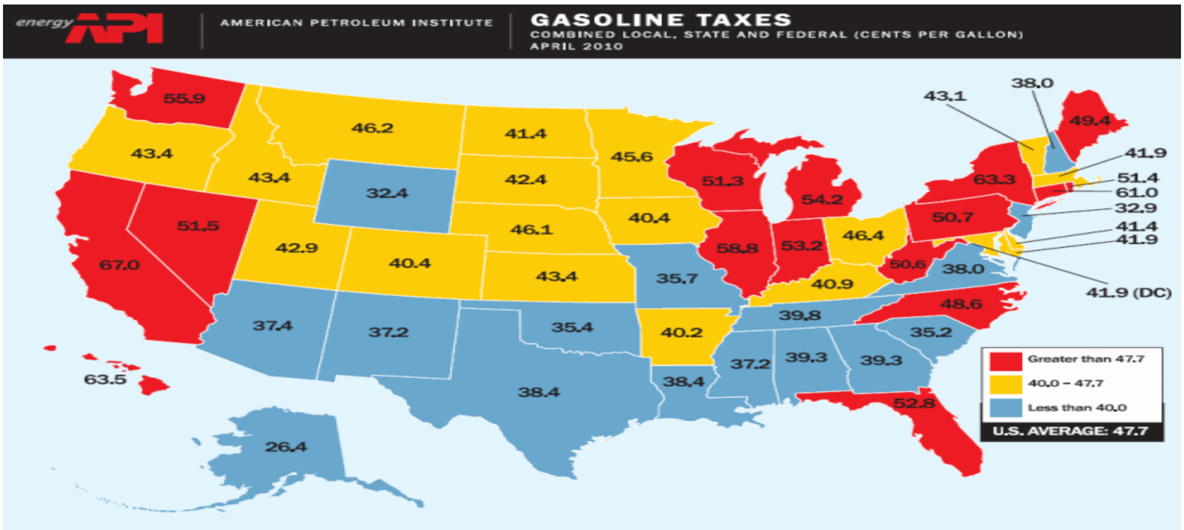
There are many factors that could cause gasoline prices variations in different region of a country like US, such as:

- Taxes
- The cost of crude oil
- Refining costs and profits
- Distribution and marketing costs and profits
- Distance from supplier
- Supply disturbances
- Retail competition
- environmental programs

So where fuel is produced and how it is distributed has significantly affect the price of gasoline to the consumers. The focus of attention here is to evaluate energy price co-movement in the US and to identify considering the price variation, whether the market for petroleum products is efficient in the long-run and as to why the relative price is different in different region of one country.

Figure 1-1 shows the distribution of gasoline taxes across the United States; combined local, state and federal. Red areas indicate high tax levels (greater than 47.70 cents per gallon) on gasoline, yellow areas medium tax levels (between 40 and 47.70 cents per gallon) and blue areas signify low tax (less than 40 cents per gallon). The US average tax level for gasoline is 47.70 cents per gallon. Unless there is a trend in tax differentials then these discrepancies ought not to affect the long-run and short-run affects that are stable would be captured by the intercept.

Figure 1-1- Gasoline Taxes across the US[1]



To consider whether the market is efficient in the long-run tests of stationarity of price proportions are applied to determine whether the market for gasoline is competitive across different regions of the US. This research is primarily empirical

[1]The above diagram was obtained fromwww-static.shell.com.

and econometric with the innovation relating to the methods applied to detect what was termed “a broad market” by Forni (2004) in the context of Milk Prices across different provinces of Italy. The study of Forni was applied to the prices of a homogenous product over time to determine the dimension of either the product or the geographic market. “A broad market” is an active market with minor fluctuation which suggests efficiency. There are also examples of how this type of analysis has been used in practice as may be seen from the review article for the UK Office of Fair Trade by LecG (1999) and the paper by London Economics (2002) that applies the approach of Forni to mobile termination prices. Price data have also been analysed in a similar way using panel methods, Ortero et al (2010) determine competitive behaviour using energy prices for the UK.

An alternative way of analysing the market for gasoline is as a commodity, instead of viewing that as an issue of competition, we might consider the observation of arbitrage as a sign of informational rather than product market efficiency. When a market is efficient in an informational sense, then price signals that impact the market will give rise to price movements that will lead to the removal of mispricing. In a commodity market, prices adjust to eliminate mispricing and this implies that there is arbitrage across prices at least in the long-run or that we find long-run arbitrage pricing.

Why should gasoline prices be dissimilar in different geographic areas in the US? Does this mean the energy market is not efficient and how can it be made more efficient? If the gasoline market is efficient, prices in different regions of a country should follow each other in the long-run which means any price shock in one region of the US should be reflect in all the other region’s prices. No suggestion is being made that arbitrage applies in the short-run, though it ought to be noticed that the application of the unit-root tests regularly applied to determine whether real exchange rates are stationary impose long and short-run efficiency by the structure of the model used to undertake the test (Burke and Hunter, Chapter 3). One conclusion of the observation of inefficiency would be that there is collusion and this was made by London Economics (2002) in their study of the Dutch telecoms market.

As a result it would be of use to identify anti-trust behaviour and possible collusion via an analysis of competitor prices in the US gasoline market and as a result spot the likely effect on the economy. In this paper we are testing the arbitrage hypothesis. Following Forni (2004) the estimation imposing short-run efficiency and parallel pricing in short-run and long-run.

A better understanding of the nature of the time series properties of the gasoline price data may also be useful in helping to explain the short-term behaviour of the data and improve the forecasting of spot prices in short-term and long-term. Improved forecast performance and market efficiency may help to improve both performances in the energy sector and economy wide growth.

1.1.1 Gasoline Market Structure and Price Analysis

Gasoline price perform volatilize such as any other commodity prices and since 1869 US and world oil prices adjusted dramatically. Knowing the highly volatile character of the energy market, the key question at this point is whether the gasoline price can be considered as one of the volatile commodity prices with the practical reasonable value within different region of the energy markets. Considering the energy market as a competitive market, suppose that every healthy economy need to support competition by eliminating certain anti-competitive behaviour such as prices fixing or neglecting market power. As a result any agreement that considerably restricts competition is considered as anti-competitive agreement.

In this study relating to price analysis and competitive market behaviour, we hope to identify why oil prices in different regions of a country do not react to each other and how market inefficiency and unfair competition impact consumers.

To some extent any lack of symmetry in price responses illustrates why competition in the oil market is not fully effective, consequently consumers in some regions are not obtaining the full benefit of competition. Using unit-root tests it is possible to determine when relative prices are stationary that this indicates that a market is competitive in the long-run and the extent to which there is a broad market. This research attempts to identify aspects of market failure from competition issues to consumer detriment and the impact of government regulation.

1.1.2 Market Definition and Anti-trust Legislation

A legislative procedure needs to be:

i. Credible – satisfy precepts of fairness be consistent with natural justice and the presumption of innocence.
ii. Operational – fit with a legal definition so there is some consensus as to meaning of the results related to the methods applied.
iii. Effective – The burden of proof has to be set at an appropriate level (data)

In an efficient market we need to be able to define the market in terms of product and geographical location. The regulation of the market should not be too strict as an action may always appear anti-competitive and need to avoid being too loose such that no company is ever caught and consequently it is not effective.

Regulatory bodies across the world provide precise legal definitions of anti-trust activity:

- Horizontal Merger Guidelines written by the US department of Justice and Federal Trade Commission (1992)
- UK Monopolies and Mergers Commission, defines mergers viewed as being against the public interest
- The UK Competition Commission, rules on non-competitive pricing; this will now include the OFT.

In practice in most of the markets the Legal guidelines do not always yield appropriate measures or benchmarks and each case is considered on its merit with qualitative and common sense definitions often being applied. In this study following Forni (2004) we are studying the market structure by testing whether arbitrage occurs in the long-run suggesting that there is adequate competition in the US gasoline market in the long-run.

In section 1.2 we review the literature. Section 1.3 considers the data for the empirical analysis. Section 1.4 we reviewed the relation between methodology and literature. In section 1.5 we reviewed the stationarity. In part 1.6 and 1.7studied the lag selection and the correlogram related to the ADF and KPSS tests. Section 1.8 tests unit-root. Section 1.9 analysed the stationarity tests under the alternative and the null of stationarity. Section 1.10 tests and analysed panel unit-root. In section 1.11 we reflect on the impact of ARCH on the tests applied. Finally, in Section 1.12 we conclude.

1.2 Review of Essential Literature

Considering the data seen in Figure 2, gasoline prices are not exactly the same across regions of the US, but in a hyper-efficient market[2] where there is perfect arbitrage, then gasoline prices should on average appear equal across states. Gasoline is a relatively homogenous product and in this paper we evaluate such prices without considering technological differences across primary gasoline outlets across the states. Or rather these differences will be considered in the long-run to be small. If they are not small, then the results may still be indicative of market failure.

The proposition that underlines the idea that the market is efficient is that all prices fully reflect all information across the system. One might consider the possibility of anomalies in the short-run, but in the long-run minor differences ought to be smoothed out. Hence one would anticipate prices should respond to the underlying stochastic behaviour that underlines prices that operate in the market and this behaviour is summarized by the stochastic trend.

Some of the early literature on the nature of collusive behaviour suggested this would be indicated by strong correlations between prices (Maunder, 1972). Such price correspondence was seen as a signal of pricing decisions being made in concert and

[2] In a hyper-efficient market all information even private information being seized which this called strong-form efficiency.

this would be suggestive of collusion especially with imperfect competition. To this end, an Antitrust Agency's target is to avoid creating a new firm with the potential to exert market power and increase the over-all price level in the market. However, the market efficiency proposition implies that commodity prices ought to fully reflect all information and this proposition is not necessarily tested via an analysis of price proportions alone. Some of the earliest research on competition suggested that perfect correlations in prices, are a signal of collusive behaviour, and market imperfection, while the target of most of the competition agencies is to recognize an active monopoly or detect collusion between competitors.

The emphasis has changed more recently as the similarity of price movements can also be considered as a signal of an effectively functioning market. The market efficiency proposition implies that commodity prices ought to fully reflect all information, while the associated concept of arbitrage suggests that prices of the same product are likely to move together. To this end Stigler and Sherwin (1985) suggested that products be grouped in a single market when prices move together and that gives support to price co-movement being linked to efficiency when a market is categorized by homogenous products. Buccirossi (2006) has made the observation that price setting being independent is not necessarily consistent with behaviour that can be objectively described as being collusive. Buccirossi finds that in a short-run sense price responses may be different from unity and in certain types of model the behaviour may be competitive.

Empirically, regression analysis, Granger causality, and Exogeneity methods have been proposed to analyse the time series properties of price series to indicate anti-competitive behaviour for example Horowitz (1981), Slade (1986), and Uri, Howell, and Rifkin (1985). A review of quantitative methods applied to the analysis of competition cases was prepared by LecG (1999) for the United Kingdom Office of Fair Trading (OFT). The LecG report points out that causality and correlation may need to be used in concert to distinguish between competitive and non-competitive behaviour. Further, the need to consider the notion of non-stationarity is emphasised in relation to a modern analysis and as a result distinguish between the long and the short-run.

An argument based on price responses in a short-run sense has proven difficult and this leads to an emphasis on arbitrage in a long-run sense. It would seem easier to frame a legal argument in the context of long-run behaviour as short-run pricing anomalies may be seen less as the result of aggressive price leadership (Markham, 1951) and more likely to be as a result of arbitrage or at worse be indicative of barometric pricing (Koutsyiannis, 1975).

The main types of price leadership are identified as: barometric price leadership, aggressive price leadership, and dominant price leadership. For barometric price leadership one firm will announce a price change and hopes that the other firms will accept the price changes. The barometric price leader is not required to be the largest firm and will not necessarily appear to dominate other firms. For aggressive price leadership pricing policies are constructed by a dominant firm and other firms are required to follow the leader. In the case of dominant price leadership one firm dominates the industry on the basis of its size, economic power or its aggressive behaviour or a combination of the above. Consequently the other firms will adopt the price set by the leader (Jain and Khanna, 2011).

Forni (2004) argues that if two product or geographic areas belong in the same market for the purposes of antitrust legislation, their relative log price ratio must be stationary and unit-root tests such as the Augmented Dickey-Fuller (ADF) test and KPSS test can be useful in describing the related nature of markets. If one considers the non-stationarity of the log of the price ratio, then this is indicative of the distinct nature of a geographic market. Testing whether price proportions are stationary can be seen as a technically efficient way of determining whether prices cointegrate where the proportionality of prices is imposed by the structure of the unit-root test.

Forni (2004) in particular has emphasised this approach for analysing anti-trust cases. He considers it to have significant advantages to methods that on one hand consider the elasticity of the residual demand function and on the other cointegration. The test implies that each price within a well-defined product market captures a component of the unit-root that arises from the stochastic trend driving underlying behaviour. Hence, price proportions in an efficient market ought to be stationary.

This analysis links strongly with the literature on testing for a unit-root in the real exchange rates (Beirne, Hunter and Simpson, 2007). In the exchange rate literature there are reasons why these responses may not be exact and this is not always seen as a sign of market imperfection. However, Forni defined the notion of what he termed a broad market definition to characterise market efficiency in relation to a highly homogenous product, Milk related to price behaviour across Italy where the only natural physical break relates to the Straits of Massena lying between Calabria/Puglia and Sicily. With the exception of regulation that forces milk sales to be limited to four days from production and suggests some constraint on sales between the far north and south of the country little else ought to limit arbitrage.

Hunter and Burke (2008) consider the idea of long-run equilibrium price targeting (LEPT) to describe the price setting behaviour of firms. They analysed competitive market behaviour using the properties of cointegration and this requires a single stochastic trend (a cointegrating rank of *n-1*) in an efficient market specifying that in the long-run prices are impelled by the shocks. The finding of a single common trend is consistent with long-run equilibrium price targeting (LEPT). If prices in a market are driven by arbitrage, then subject to the existence of an appropriate number of long-run relations, then arbitrage is consistent with firms LEPT. In the context of firm specific prices as arose in the analysis of the Dutch market for mobile termination charges by London Economics (2002), then it is possible to further distinguish between parallel pricing and aggressive price leadership. The latter arising when a price in the market is seen as being weakly exogenous to the parameters of interest (Johansen (1992)). Hunter and Burke (2007), and Kurita (2008) determined that parallel pricing occurs when there is a single price to which the other n-1 prices are responsive.

If one of a sequence of prices is weakly exogenous, then this implies that one of the price series is not explained by a stationary cointegrating relation or this series is for all intents and purposes explained by a stochastic trend. In terms of the market data analysed here, weak exogeneity implies that the price process in the other regions may be driven by the weakly exogenous price. However, this price cannot be tied down to one of the other companies via the ownership of refining capacity as compared with oil production.

In the gasoline market it is suggested that the existence of refiners in a region can create differences in price levels. Hence, a further concern of this research is not the existence of such differences but the stability of price relations over time. It is suggested that the price of gasoline in a different geographic areas of the same market, should not be different from each other in long run otherwise there is an arbitrage opportunity. Our supporting argument is the statistical concept of stationarity as applied to price proportions. Given the nature of the data, our primary concern here is to consider market efficiency and to only indirectly consider competitiveness were the former proposition to fail.

As was stated above testing a unit-root for price proportions is equivalent to testing for cointegration between log prices and when these series are stationary then the result is consistent with long-run arbitrage. Hence, the approach devised by Forni (2004) is an efficient method to both test cointegration and fix the long-run restriction related to parallel pricing. This may be especially pertinent when as is the case for Forni the time series sample is small. Here this approach is followed, but unlike Forni we limit ourselves to a subset of price proportions. First the upper triangle of unit-root tests for equations for which the lag order has been securely selected will not differ from the reverse calculation associated with the lower triangle. The calculations below show this for a fixed lag order AR(1) (as will be observed in some of the experiments below), then across the matrix of comparisons the ADF test should be the same.

Assume that the ij^{th} ADF price combination is:

$$\Delta y_{ijt} = \delta_{oij} + \beta_{ij} y_{jit-1} + \varepsilon_{ijt}$$

Then the reverse equation is:

$$\Delta p_{jt} - \Delta p_{it} = -\delta_{oij} - \beta_{ij}(p_i - p_j)_{t-1} - \varepsilon_{ijt}$$
$$\Delta y_{jit} = -\delta_{oij} + \beta_{ij}(p_j - p_i)_{t-1} - \varepsilon_{ijt}$$

Using the calculation below it can be shown that the coefficients are the same, where $X'_{ji}X_{ji}$ is the moment matrix of the data that contains the intercept and the lagged price differential and so the OLS estimator for the reverse regression $(X'_{ji}X_{ji})^{-1}X'_{ji}y_{ji}$ is presented as:

$$\begin{bmatrix} \hat{\delta}_{oji} \\ \hat{\beta}_{ji} \end{bmatrix} = \frac{1}{\det(X'_{ji}X_{ji})} \begin{bmatrix} \sum_{t=l}^{T}(p_i - p_j)_{t-1}^2 & -\sum_{t=l}^{T}(p_j - p_i)_{t-1} \\ -\sum_{t=1}^{T}(p_j - p_i)_{t-1} & T-l \end{bmatrix} \begin{bmatrix} \sum_{t=l}^{T}\Delta(p_j - p_l)_t \\ \sum_{t=l}^{T}(p_i - p_j)_{t-1}\Delta(p_i - p_j)_t \end{bmatrix}$$

Following some algebraic manipulation:

$$\begin{bmatrix} \hat{\delta}_{oji} \\ \hat{\beta}_{ji} \end{bmatrix} = \frac{1}{\det(X'_{ij}X_{ij})} \begin{bmatrix} \sum_{t=l}^{T}(p_i - p_j)_{t-1}^2 \sum_{t=l}^{T}\Delta(p_j - p_i)_t - \sum_{t=l}^{T}(p_j - p_i)_{t-1} \sum_{t=l}^{T}(p_i - p_j)_{t-1}\Delta(p_i - p_j)_t \\ -\sum_{t=1}^{T}(p_j - p_i)_{t-1} \sum_{t=l}^{T}\Delta(p_j - p_i)_t + (T-l)\sum_{t=l}^{T}(p_i - p_j)_{t-1}\Delta(p_i - p_j)_t \end{bmatrix}$$
$$= \frac{1}{\det(X'_{ij}X_{ij})} \begin{bmatrix} -\sum_{t=l}^{T}(p_i - p_j)_{t-1}^2 \sum_{t=l}^{T}\Delta(p_i - p_j)_t + \sum_{t=l}^{T}(p_i - p_j)_{t-1} \sum_{t=l}^{T}(p_i - p_j)_{t-1}\Delta(p_i - p_j)_t \\ -\sum_{t=1}^{T}(p_i - p_j)_{t-1} \sum_{t=l}^{T}\Delta(p_i - p_j)_t + (T-l)\sum_{t=l}^{T}(p_i - p_j)_{t-1}\Delta(p_i - p_j)_t \end{bmatrix}$$
$$= \begin{bmatrix} -\hat{\delta}_{oij} \\ \hat{\beta}_{ij} \end{bmatrix}$$

The intercept is the opposite in the reverse regression while the slope coefficients that relate to the ADF test are the same. The equation also has the same residual sum of squares, degrees of freedom and variance covariance matrix:

$$Var\begin{bmatrix} \hat{\delta}_{oji} \\ \hat{\beta}_{ji} \end{bmatrix} = s^2(X'_{ji}X_{ji})^{-1}$$
$$= \frac{e'_{ji}e_{ji}}{T-l} \times \begin{bmatrix} \sum_{t=l}^{T}(p_i - p_j)_{t-1}^2 / \det(X'_{ji}X_{ji}) & -\sum_{t=l}^{T}(p_j - p_i)_{t-1} / \det(X'_{ji}X_{ji}) \\ -\sum_{t=1}^{T}(p_j - p_i)_{t-1} / \det(X'_{ji}X_{ji}) & T-l / \det(X'_{ji}X_{ji}) \end{bmatrix}.$$

Where $e_{ji} = (I - X_{ji}(X'_{ji}X_{ji})^{-1}X'_{ji})y_{ji}$ and $e_{ji} = -e_{ij}$. Therefore the residuals will be the reverse for the reverse regression and so the sum of their squares will be the same as will be the regression standard error scaled by the term $\sum_{t=l}^{T}(p_i - p_j)_{t-1}^2 / \det(X'_{ji}X_{ji})$ and as occurs in the calculation of the regression parameter this is the same whatever the dependent variable the relation is normalised on, the p_i or p_j. This implies that the DF test statistic is the same.

Second, the unit-root tests impose a restriction that arbitrage is imposed on the short and the long-run as the variable tested is a price proportion (ADF or KPSS). The same restriction occurs with the ADF test applied to the residual of a cointegrating regression and is linked to the Generalized Least Squares (GLS) estimation of serial correlation (Burke and Hunter, 2005).

So a sequence of dynamic models can be estimated and direct comparison with the unit-root tests in price proportions limited to the number of coherent price models that might be computed. Smith and Hunter (1985) show that a cross-arbitrage condition occurs in the case of exchange rates and a similar problem arises when real exchange rates are tested for stationarity using cross rates (Hunter and Simpson, 2004). The cross-arbitrage condition reflects an opportunity for a risk-free profit resulting from a pricing inconsistency amongst three different currencies. The first implication is that there is a limit to the number of dynamic price models related to a fixed number of single equation error correction models from which stationarity might be tested. The second being the risk that without such a constraint that stationarity may either be rejected or not rejected by chance permutation of the price pairs.

Subject to the above limitation, as a main focus of this research the approach of Forni (2004) is followed to suggest that gasoline prices be proportional across the US and that this would confirm a broad market or a single market definition in US gasoline market, and thus determine a link to long-run arbitrage and an efficient market.

However according to Hosken and Taylor (2004) the unit-root test results could deceive the market analyst under two conditions. Firstly, where both series suffering from a single shock or secondly were the original price series both stationary. The former suggests that the analyst be aware of the impact of large shocks an indication of which is non-normality. The latter should be prohibited by showing that the univariate series are all non-stationary.

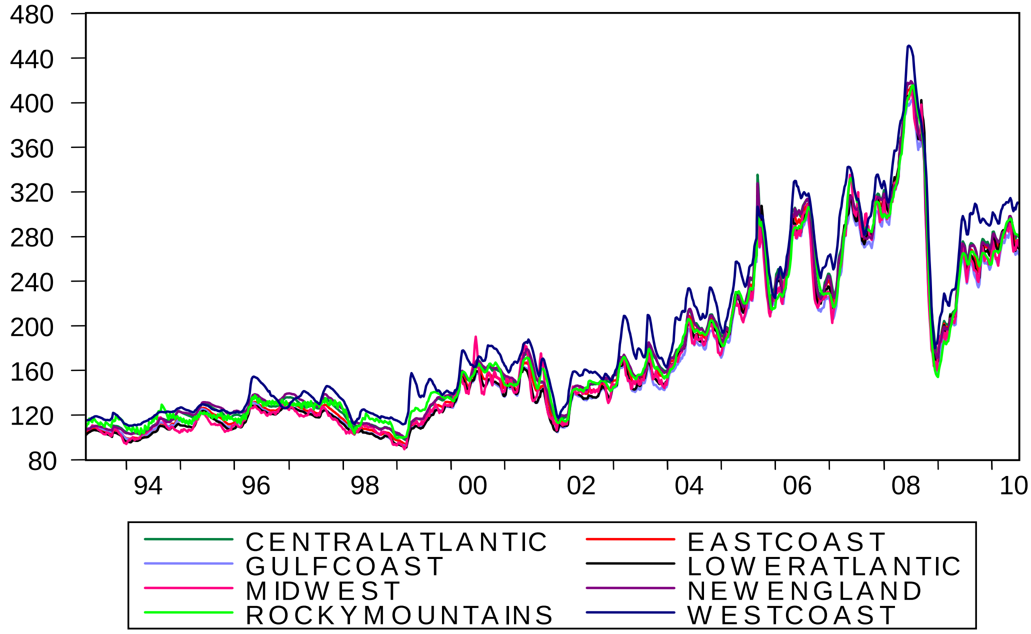
In addition to testing stationarity for single series it is also analysed in a panel context this follows from the notion that the long-run characteristic of the series, the stochastic trend is common to all series in the analysis. It would seem to make sense to compare the univariate analysis with a panel study. It can also be observed that the univariate price series are likely to be volatile and that this may also be considered in testing for stationarity. Following the discussion in Boswijk (2001) and Rahbek et al (2002) that the analysis ought to obtain the asymptotic limit with the sample selected here. The same may not be the case were some extreme distributions to be selected to explain the data such as the Cauchy or a stable Paretian distribution.

1.3 Data and Methodology

In this chapter the stationarity properties of the US gasoline market is analysed using weekly oil price proportions across eight regions of US which should cover most of the US: West Coast, Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England, Rocky Mountains. The sample starts in the first week of May 1993 to the first week of May 2010. The number of observations is 900. The data have been obtained from energy information administration website (www.eia.doe.gov).

In a similar way to the analysis of milk by Forni (2004), gasoline is considered to be a homogeneous product which means that prices collected are for a similar quality and taken for similar types of location for the sale of the product. Hence, the expectation is of similar price levels and relative stability over time. Figure 2 below indicates the behaviour of logs of weekly spot prices for gasoline in West Coast, Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England and Rocky Mountains (all the prices are measured in US$). The figure shows behaviour dominated by the stochastic trend that can be observed with the exception of the large shock following the financial markets crash towards the end of 2008, as a random walk that seems to exhibit little sign of mean-reversion in the series.

Figure 1-2- Plot of weekly spot prices for gasoline in different regions of US



The development and growth of the economy can arise from governmental changes, technological changes and other types of shock that will give rise to the stochastic trend and the unit-root. To analyse the problem it is best to transform the data to stationarity, by differencing and by the observation of cointegration that gives rise to stationary linear combinations of non-stationary series. With that finding the cointegrated series are only influenced by temporary shocks even when the original series are impacted by the full history of shocks to the market.

The methods adopted in this research are ADF tests, also GLS-corrected by Elliot, Rothenberg, and Stock (1996) and for GARCH/ARCH by Beirne et al (2007). The panel methods of Hadri (2000), and Im, Pesaran and Shin (2003) are used to support the univariate analysis.

1.4 Relation between Methodology and Literature

The method is applied to detect a broad market and as a result overcome any potential difficulties that arise from the data. To measure market definition in the US gasoline market stationarity tests are applied to see whether a long-run dependence exists between prices of different market segments. Here univariate tests are used to examine whether a combination of log price differentials are stationary and the acceptance of the stationary behaviour of the series confirms consistency with the appropriate market definition.

The long-run is analysed, as it provides a more convincing frame of reference over which to observe anomalies. The existence of inefficiencies in the long-run concludes that these relate to market failure rather than mistakes. However the market is efficient when there is arbitrage and prices move to clear markets. This implies that firm prices should move in line or that one firm's price responds to another. If one considers the time series model associated with the ADF test as a reduced form equation of relative price behaviour, then the residuals combine the demand and supply shocks associated with regional and national price movements once the dynamic structure of market adjustments is captured by the dynamics in the AR model that underlines the ADF test. The stationarity of the relative price process that is being tested implies that the history of these shocks can be encapsulated in the error correction term that is associated with the log price differential. Hence the underlying econometric hypothesis relates to what has been termed parallel pricing. Often antitrust authorities assume that parallel pricing indicates collusion (see Buccirossi, 2006).

If the stationarity hypothesis is not rejected for a number of sub-markets across a country, then the market might be viewed as being a broad market (Forni, 2004).

A considerable range of methods exist to analyse competitiveness. One approach to monitor the market detects market price irregularities. The early literature considered the observation that prices are correlated as a sign of possible collusive behaviour. One such approach considers the elasticity of the residual demand curve (see Forni, 2004), but such analysis is not very reactive and also depends on being able to estimate components of demand and the supply curve. Supply is often related to the average or marginal cost curve as is discussed in Hunter et al (2001) or linked to a mark-up on price. Unfortunately, the cost information is available for firms with published accounts from which it is possible to measure cost.

One might also formulate a dynamic demand and supply system where information is also available on quantities; this can be used to compute price elasticity or some notion of consumer surplus. This idea will be looked at in the final empirical Chapter. However, when there is uncertainty over quality or price, then a more appropriate measure of loss is termed "Consumer Detriment". Unfortunately, many of these types of measure associated with an analysis of competitiveness depend on some computation of average cost or the mark-up (Hunter et al, 2001). Further, the demand studies refocus on the short-run where some studies consider stationarity to test arbitrage or price behaviour and then seem to forget this when price is used with a demand curve (see the discussion in Hunter and Ioannidis, 2001). Furthermore, Buccirossi (2006) found in micro based theoretical models that some changes in assumptions could show the finding or not finding of parallel pricing could be related to competitive behaviour. The paper is not looking at the long-run or at econometric time series.

This leads to the proposition that the observation of arbitrage gives rise to a broad market and the finding that log prices cointegrate or price proportions are stationary is consistent with this proposition. The method may also be corrected for the existence of ARCH. It is also intended to apply alternate methods to Forni that are robust to misspecification to confirm our findings. That is panel methods such as the test due to Hadri (2000). The Hadri test is seen as not being sensitive to non-normality and can be corrected for heteroscedasticity, it is also optimal when N is small, $T>50$ and with a variance ratio exceeding, 0.1.

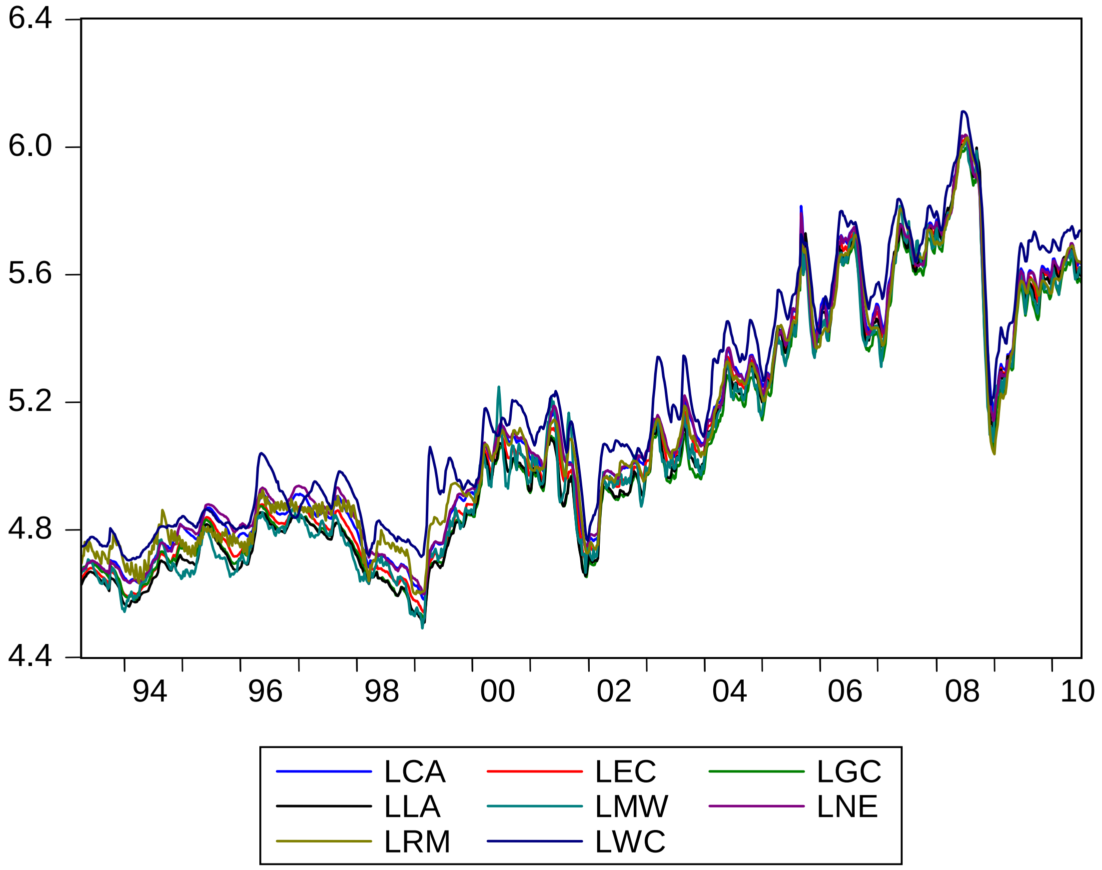
1.5 Stationarity

From the econometrician's point of view it is not a main target as to which fitted model to choose but it is important to find a model that shows a relationship which continues long enough to be useful (David F. Hendry and Katarina Juselius, 2000). Therefore forecasting based on non-stationary data using the OLS estimator is not reliable for long-term analysis and it can relate to spurious results.

Figure1-3 shows the time series of the weekly gasoline price in eight oil regions in the US from the first week of May 1993 to first week of May 2010 on a log scale, and that suggests the series for all intents and purposes follow a random walk. Therefore it might be possible the non-stationarity of data can be removed via the finding of cointegration. If as seems possible from the figure of the series gasoline price appear to follow a similar pattern of behaviour which suggests that they all follow some form of common trend in the gasoline market. The log of weekly spot prices for gasoline in West Coast, Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England, Rocky Mountains are represented by P_{WC}, P_{CA}, P_{EC}, P_{GC}, P_{LA}, P_{MW}, P_{NE}, and P_{RM}, and they are computed in their natural log form. As gasoline is seen as a homogeneous product then gasoline driven between different geographical regions follows the same prices. A main concern of our study is whether these price differentials (the log of one price subtracted from another) are stationary and the relations stable over time.

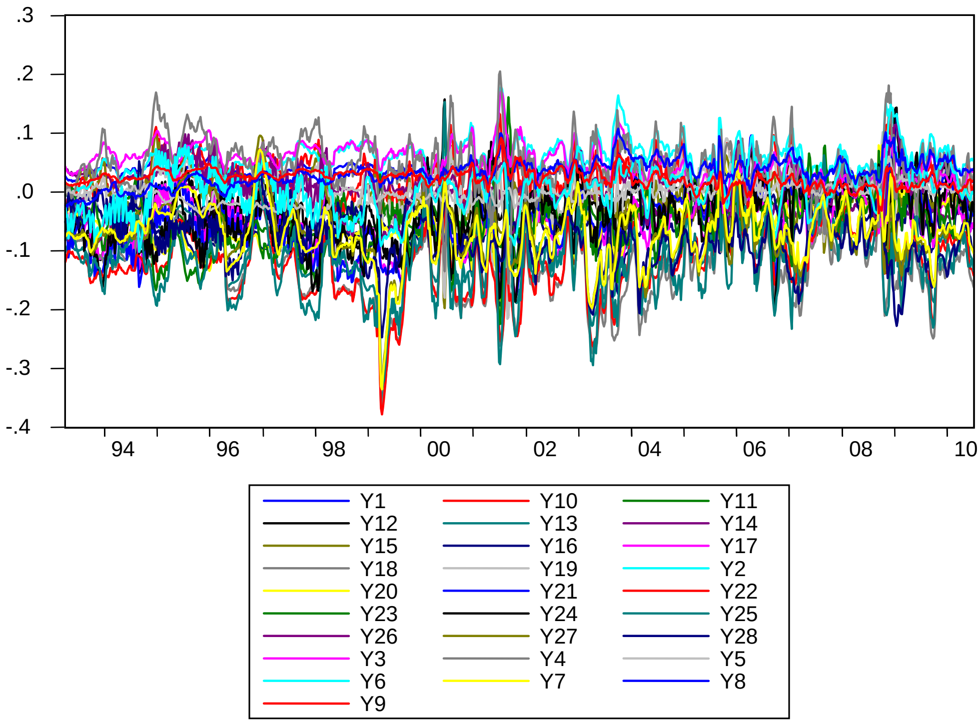
One problem with some of the earlier analysis is that it purely dealt with contemporaneous correlations and that ignores lagged relations. If weekly data are considered and the log price related to P_1 follows a random walk, then ΔP_{1t} is serially uncorrelated, but the log price P_2 with the lag order of *w* weeks from P_1 can be correlated. If $\Delta P_{2t} = \Delta P_{1t-k}$ this leads to a relation between prices but not the contemporaneous correlation between ΔP_{2t} and ΔP_{1t}. So if it is necessary to consider the analysis for a longer lag of w weeks, then it is better to focus on price series in the long-run.

Figure 1-3- Plot of log price in CA, EC, GC, LA and MW, NE, RM, and WC



Correlation and Granger causality analysis are based on prices that are co-stationary, which means the correlation changes over time and so the sample correlation is not good enough to yield a population analysis. As a result we apply the stationarity analysis and if the observed data are I(1) then we apply a cointegration analysis. Figure 1-4 show 28 possible equations for differentials in log prices in different regions of the US: West Coast (WC), Central Atlantic (CA), East Coast (EC), Gulf Coast (GC), Lower Atlantic (LA), Midwest (MW), New England (NE), and Rocky Mountains (RM).

Figure 1-4- Plot of log price differential in CA, EC, GC, LA, MW, NE, RM, WC



Note: above Figure representing the log differential in prices of gasoline in CA, EC, GC, LA, MW, NE, RM, WC; $\mathbf{Y_1}$= log (P_{CA})- log (P_{EC}), $\mathbf{Y_2}$= log(P_{CA})- log (P_{GC}), $\mathbf{Y_3}$= log (P_{CA})- log (P_{LA}), Y_4=log (P_{CA})- log (P_{MW}), Y_5= log (P_{CA})- log (P_{NE}), Y_6= log(P_{CA})- log (P_{RM}), Y_7= log (P_{CA})- log (P_{WC}), Y_8= log (P_{EC})- log (P_{GC}), Y_9= log (P_{EC})- log (P_{LA}), Y_{10}= log (P_{EC})- log (P_{MW}), Y_{11}= log(P_{EC})- log (P_{NE}), Y_{12}= log (P_{EC})- log (P_{RM}) , Y_{13}= log(P_{EC})- log(P_{WC}), Y_{14}= log(P_{GC})- log (P_{LA}), Y_{15}= log (P_{GC}) log-log(P_{MW}), Y_{16}= log(P_{GC})- log (P_{NE}), Y_{17}= log (P_{GC})- log (P_{RM}) , Y_{18}= log (P_{GC})- log(P_{WC}), Y_{19}= log (P_{LA})- log (P_{MW}), Y_{20}= log(P_{LA})- log (P_{NE}), Y_{21}= log (P_{LA})- log (P_{RM}), Y_{22}= log (P_{LA})- log (P_{WC}), Y_{23}= log (P_{MW})- log (P_{NE}), Y_{24}= log (P_{MW})- log (P_{RM}), Y_{25}= log (P_{MW})- log (P_{WC}), Y_{26}= log (P_{NE})- log (P_{RM}), Y_{27}= log (P_{NE})- log (P_{WC}), Y_{28}= log (P_{RM})- log (P_{WC}) ; Where P_{CA}, P_{EC}, P_{GC}, P_{LA}, P_{MW}, P_{NE}, P_{RM}, P_{WC} is price of gasoline in Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England, Rocky Mountains and West Coast.

1.6 Lag Selection and the Correlogram related to the ADF test

Forni (2004) estimated the ADF test with 4 and 8 lags and the KPSS test uses truncation lags for kernels of 8 and 16 periods for all the price series. Whereas in this study the autocorrelation function (ACF) is investigated to determine the lag order of each series to best define the order of the ADF tests and the lag truncation for the non-parametric methods. The first differences of the price differential in the different regions of the US are analysed using up to 60 lags.[3] If the empirical analysis includes too many lags that will cause the estimates to be inefficient and consequently increase the standard errors, and if the underlying distribution is not normal that would give rise to larger than usual critical values. However estimation with too few lags would result in inconsistent coefficient estimates in the proposed model.

Given the nature of the data, they are not likely to be simple IID processes. In the case of the same q lag order[4] for all of price proportions: q_1, q_2, $q_{3,\ \ldots,}q_n$. If q_1,= q_2= q_3 =…=q_n this implies the same order of the autoregressive process relates to each test model and a common process relates to all the series. Otherwise, it would be possible to consider an average of all lag orders (q^{-}); this indicates that on average the analysis is correct and this suggests similar outcome to the **t-bar** test of Im et al (2003). Otherwise, one can consider q^* as a selected lag where $q^*=\text{Max}(q_i)$ for $i=1,2,3,\ \ldots,\ n$. A key concern here is for the t statistic to be well defined and the efficiency of the estimator of the coefficient involved. The way in which this may happen and for which lag selection is also important when these series are pooled together; a process often seen as improving the power of these tests.

The data is also non-normal and this implies any test statistic computed has a broader distribution with the exception of degenerate distributions, for example the Cauchy or Student's *t* distribution with one degree of freedom as the variance does not exist and this is not amenable to conventional inference. Therefore one may consider the *t* statistic with for example with a tail probability of 2.5% being related to a point on

[3] As the data are weekly and there are 52 weeks in a year it is important to consider lags between 52 and 60.
[4] *q* is a particular lag order for all of the n price differentials.

the distribution of 1.96 more likely having with these distortions a value of 3.5. The suggestion being that conventional inference applied at the 5% level may give rise to the inclusion of more lags than required.

One process to capture this might be to set a critical value beyond what is

Conventionally considered such as 1% with the intention of taking account of the possibility that inference is broader than that conceived by a strict application of the conventional approach. Another way of motivating this is that as our sample increases then the sample estimates may converge to their population values and in the limit this may become degenerate. Hence, with very large samples the distribution collapses to a point and for a fixed critical value it becomes impossible to not reject the null.

One interpretation is that this is a trimming or truncation procedure. However, the problem with selecting broader than usual inference is that it may have the reverse effect. It could trim short ordered lags without affecting the inclusion of the extreme lags. To this end a flexible strategy is applied and this relates to the Bonferroni principle. In this context we apply the $\frac{\alpha}{i}$% critical value to a sequence of Box-Pierce test statistics. So the critical value may be selected to reduce the joint rejection region for a sequence of tests. In this context we apply this approach to a sequence of Box-Pierce test statistics (Davidson and MacKinnon, 2004). Hence, the first lag is to be tested at the conventional 5% level and shorter lags will be more likely to be included than when simply testing all lags at the 1% level. The second lag is tested at the 2.5% level after 5 lags the procedure is the same as the test at the 1% level, but subsequently tests will be applied at an increasingly stricter level. Hence, by the 10th lag the test is applied at the 0.5% level. The procedure keeps the short order lags, but is increasingly likely to eliminate the longer lags and is thus less likely to be sensitive to the impact of non-normality or autoregressive conditional heteroscedasticity (ARCH).

The Q-statistic[5] is evaluated and then the sequence of tests applied to a ΔQ statistic. The appropriate p-values are computed for ΔQ using the tail distribution estimator in Ox Metrics (Doornik and Hendry, 2009). It follows that when Q follows a χ^2 distribution with i degrees of freedom, then:

$$\Delta Q_i = Q_i - Q_{i-1} \sim \chi_1^2$$

By applying the above strategy the lag orders are selected for all the price differentials with an overall rejection region of 5%. In the first case $y_1(i)$ with (i) the lag order so then $i=14$ and subsequently: $y_2(11)$, $y_3(9)$, $y_4(25)$, $y_5(6)$, $y_6(20)$, $y_7(9)$, $y_8(11)$, $y_9(11)$, $y_{10}(25)$, $y_{11}(6)$, $y_{12}(20)$, $y_{13}(9)$, $y_{14}(23)$, $y_{15}(16)$, $y_{16}(11)$, $y_{17}(1)$, $y_{18}(24)$, $y_{19}(16)$, $y_{20}(9)$, $y_{21}(20)$, $y_{22}(16)$, $y_{23}(25)$, $y_{24}(16)$, $y_{25}(20)$, $y_{26}(13)$, $y_{27}(10)$ and y_{28} (25).

We have applied unit root tests with two criteria for the lag length: individually selected lag lengths on $y_1, y_2,\ldots, y_{25}$ and with an overall maximum lag length of $q=25$.

1.7 Lag Selection for KPSS Test

Stationarity is referred to as mean reversion and how reversion to mean is observed in response to the data depends on the number of observations. However in this study when considering 900 observations graphically they may appear to return to mean

[5] The Q-statistics used for multiple significance testing across a number of means.

more frequently than would appear usual for a non-stationary series. Observing drift and a stochastic trend in the series suggests that the non-stationary null may seem likely and the reverse is appropriate when the data is differenced and differenced data frequently returns to mean. However, the performance of a parametric test such as the ADF test is sensitive to the model within which it is framed[6]. The ADF critical values are not sensitive to the lag order of the time series model in which they are embedded just the sample so the simplification of the model by excluding intermediate lags does not impact the asymptotic critical value, but may improve the efficiency of the estimation and alter the subsequent results.

If the ADF and KPSS tests are compared, then the ADF is usually defined on a first differenced variable whose dynamic will be shorter than is the case for the non-transformed data especially when it is defined by a random walk. However in addition to the null of the KPSS being stationarity, the numerator of the test statistic includes squared cumulated residuals. The statistic is consistent when scaled by an appropriate measure of the long-run variance and this relates to a residual that in the simplest form of the test simply corrects for the mean[7]. However, these residuals may be quite persistent as they are not differenced. Hence, the lag in the ADF test cannot be an indication of the lag truncation in the KPSS test and the test is likely to be incorrect when the lag truncation is too short[8]. This may be further complicated when the series exhibits near integrated volatility as may occur with financial data.

[6]The ADF test may be sensitive to initial values and Professor Robert Taylor has suggested recursive demeaning of the data is more appropriate than a simple mean correction. Non-normality may also be important and to this end there is evidence on the wild bootstrap while Beirne, Hunter and Simpson (2007) suggest that White standard errors may be robust to simple non-iid errors.

[7] The long-run variance need to have enough lags to include lags truncation that may reflect on autoregressive (AR) process or Moving Average (MA) process that in the limit is I(1).

[8] The shorter lag truncation in the KPSS test will result in inappropriate long-run variance estimation and consequently an inconsistent test.

When a comparison is made between the nature of the dependent variable used in the tests of stationarity, the ADF test analyses the problem in terms of differences, even though the model may be reframed in levels and the difference eliminates a primary reason for the persistence in the data. While the semi-parametric method captures none of the autoregression and uses the autocorrelation function as an alternative way to characterise the autoregression to the AR structure that underlies the model used by the ADF test. Implying that when the test operates on the levels data that even for moderately autoregressive series a longer than anticipated lag structure may be required to capture the autoregressive behaviour that the ACF is attempting to characterise. Yule (1925) showed that the random walk exhibits linear declining autocorrelation structure, such persistence in the empirical ACF is a sign of strong autoregression. The usual significance of individual terms relates to the standard errors and this may be associated with volatile and non-normal data. Ordinarily the test statistic is normally distributed, and one would consider around two or in large samples 1.96 times the standard error for significance. However, referring to the data in this study we might apply the effective limit of the standard normal (3 × S.E.), or in the stationary world almost any statistic as significant at the 3.5 times standard error (3.5 × S.E.)[9]. Hence the correct lag truncation ought to be derived from the last significant terms in the ACF.

Often when semi-parametric corrections are applied as is the case with the Newey-West robust standard errors then the lag truncation is set at T/3. However, applying such a rule coherently with an evolving sample would not be consistent

[9] This follows from the oral econometric tradition at the LSE.

as the truncation on the KPSS test cannot grow at a rate T. However, T/3 could be applied to a fixed sample and when the sample is extended, then the truncation lag must evolve more slowly (T/3, T/4 …). It is also useful to consider the most appropriate approximation method. In this study for a large and fixed T=901, T/3 is an upper limit therefore we select lag truncation (p) less than T/3 and to see how the test statistic behaves we applied KPSS (*p*) where *p*= 25, 50, 75, 100, 125, 150, 175, 200, 225, 250, 275 up to T/3.

1.8 Test of Unit-root and Stationarity

The stationarity testing procedure employed in this research relates to a cointegration study as the analysis is applied to log price differentials across the US gasoline market. Three different methods for confirming the price behaviour in the US gasoline market have been applied below: Augmented Dickey Fuller (ADF) test, Dickey-Fuller GLS (ERS) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Prior to undertaking this analysis it is shown from Table 0 in Appendix A that the underlying prices are all non-stationary (I(1)) so it is possible from the definition of cointegration that a linear combination of I(1) series may in combination be stationary (I(0)). Next these tests are applied to log price differentials. Cointegration and causality are considered in more detail in the next chapter.

1.8.1 Augmented Dickey Fuller (ADF) test

Stationarity analysis of log price differentials in the US Gasoline market by Augmented Dickey Fuller (ADF) test (Dickey and Fuller (1979), uses a parametric time series regression to eliminate the serial correlation. If one considers first a single variable and then this involves estimating a time series model:

$$y_t = \rho_0 + \sum_{k=1}^{l} \rho_k y_{t-k} + \varepsilon_t \,. \qquad (1\text{-}1)$$

If the variable y (assumed to be in logarithmic form) is stationary, then:

$$\sum_{k=1}^{l} \rho_k < 1.$$

This test is a joint test that relies on the efficient estimation of all the parameters ρ. To improve the power and performance of this test we transform (1-1) into an equation in differences and levels form:

$$\Delta y_t = \rho_0 + \gamma + \sum_{k=1}^{l-1} \lambda_k \Delta y_{t-k} + \varepsilon_t. \qquad (1\text{-}2)$$

If we test whether y is a stationary variable we are testing the proposition that:

$$\gamma = \sum_{k=1}^{l} \rho_k - 1 < 0.$$

The latter test is straightforward to undertake as it turns out to be a t-test on the parameter γ in (1-2). We make the conventional regression assumptions that the model is well formulated:

$$E(\varepsilon_t) = 0.$$

An auxiliary assumption to this is that the errors are uncorrelated or there is no serial correlation:

$$E(\varepsilon_t\ \varepsilon_{t-s}) = 0 \text{ for } i=1\ldots j.$$

Hence, correct specification of the models (1-1) and (1-2) is important for the correct formulation of the Dickey Fuller or Augmented Dickey Fuller Test, under the null of non-stationarity:

$$H_0: \gamma=0.$$

Notice that under the null the model is a time series model purely in terms of differences:

$$\Delta y_t = \rho_0 + \sum_{k=1}^{l-1} \lambda_k \Delta y_{t-k} + \varepsilon_t \qquad (1\text{-}3)$$

The related null implies that the first difference of the series is stationary but the level of the series is non-stationary and contains a unit root. Notice that under the null when γ=0, this is an AR(l-1) model in terms of the differences, where the lag length of this AR model is the order of the Augmented Dickey Fuller test (ADF(l-1)). Notice, for the purposes of detecting the lag order of the ADF test we only need to "statistically identify" the time series model associated with the equation (3) or the model in differences. To determine the lag order of the difference model (l-1) the correlogram of the data in differences is investigated (that is the ACF and also the PACF (partial ACF). An ACF pattern that is smooth and declining or cyclical is likely to mean that the series are autoregressive Burke and Hunter (2005). To determine the lag order of an autoregressive process then we look at the most significant lag coefficient in the PACF, that involves looking at the significance of the last lag in an i^{th} order AR model for a sequence $i=1,\ldots l\text{-}1$.

The alternative hypothesis is:

$$H_0\text{: } \gamma<0$$

Under the alternative when γ is significant this implies y_t is stationary. As long as the coefficient is appropriately negative, then the series is stationary and the process that explains the series is an AR(p) process. If the data are stationary, then equation (1-1) is well formulated.

Starting from the proposition that the log price data is non-stationary then it is possible that the log price differential is stationary. Therefore, when we apply an ADF test to y and this is a differential in log prices, then the dependent variable associated with this test is in differences as the model estimated is:

$$\Delta(p_{it}-p_{jt})=\rho_0+\gamma(p_{it-1}-p_{jt-1})+\sum_{k=1}^{l-1}\lambda_k\Delta(p_{it-k}-p_{jt-k})+\varepsilon_t\,. \qquad (1\text{-}4)$$

Notice this model is correctly formulated whether we reject the null or the alternative of the test. Hence, when we test whether the price differential is stationary (y), we determine the lag order of equation (1-2) by analysing the correlogram of the difference in price differential (Δy) to determine the lag order of the ADF test l-1.

By applying the ADF test on the named series we investigate, it is found that all the series apart from Y_8 are stationary.

1.8.2 Dickey-Fuller GLS (DFGLS) test

According to Elliot, Rothenberg, and Stock (1996) the ADF regression including a constant, or a constant and a linear time trend can be adjusted by extracting the effect of these variables via a preliminary regression. This gives rise to the adjusted model:

$$\Delta y_t^d=\alpha y_{t-1}^d+\sum_{k=1}^{l-1}\beta_k\Delta y_{t-k}^d+\varepsilon_t\,. \qquad (1\text{-}5)$$

Comparing this equation with (1-4) then y_t has been replaced by the GLS mean corrected and/or de-trended variable y_t^d. In the DFGLS test we test the series under the null hypothesis of the unit root of the data and this result is presented in the table below. It suggested that the test is more efficient as it eliminates the nuisance parameters associated with the mean and intercept and also takes account of initial values that might impact the test (Beirne et al, 2007).

1.8.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

In this research the observed data are regional data and the concern would be to estimate the problem under the null of efficiency for the gasoline market in US. The KPSS test is for analysing the stochastic properties of series and testing stationarity of the hypothesis by evaluating the problem under null of stationarity against the alternative of non-stationarity. So the price differential y_t is stationary under the null and as the test is derived under the null then it is suggested that this will make it more likely than under the ADF test to not reject the proposition that the series are stationary. This will depend on the sample selected and the nature of the data.

KPSS Lagrange Multiplier statistic is based on the residuals from the following regression between y_t and an independent variable x_t:

$$y_t = \theta x_t + e_t.$$

The KPSS, LM statistic is computed using the following relation below:

$$LM_i = \frac{1/T^2 \sum_{t=1}^{T} S_{it}^2}{\sigma_i^{*2}}$$

σ_i^{*2} is the variance estimated from each individual sample and each partial sum of the residuals is $S_{it} = \sum_{j=1}^{t} e_{ij}$. To account for serial dependence a correction is applied to each cross section variance:

$$\sigma_i^{*2}(x) = \gamma_o + 2\sum_{s=1}^{T-1} \kappa(x)\gamma_s.$$

Where, γ_0 is the constant variance, $x=s/l+1$ is the bandwidth, l is the lag truncation and $\gamma_s = \frac{1}{T}\sum_{t=s+1}^{T} e_{it} e_{it-s}$. Here the Bartlett, Parzen and Quadratic Spectral functions are applied with different bandwidths.

1.9 Analysis of the tests under the alternative and the null of stationarity

It can be seen from Table 1-1 and1-2, the null hypothesis of the unit-root in ADF and DF-GLS tests on most log differential prices has been rejected, and that confirms the existence of stationary combinations at the 5% significance level. This is in contrast to the results of Forni (2004) that were much more mixed. Here the suggestion is that it indicates that the US regions define a broad geographic market so shocks affecting the price differential in the gasoline market have an effect across almost all of the regions. These results suggest that the market is relatively efficient as out of 28 tests it can be observed from Table 1-1 that only in one case the Gulf Coast and the Lower Atlantic can stationarity be rejected at the 5% level.

However, the rejection of stationarity occurs under the null of stationarity and the consistency of the KPSS test relies on the correction evaluation of the long-run variance, which is sensitive to the truncation lag[10]. Here when the KPSS test is significant, then the null of stationarity cannot be accepted. Further consideration of the KPSS test results leads to the observation that the null cannot be rejected at the 5% level in the case of Central Atlantic and Mid-West, Central Atlantic and West Coast, East Coast and Mid-West, Gulf Coast and West Coast, Mid-West and West Coast, New England and the Rockies, and New England and West Coast.

Concern over lag truncation was previously emphasised so to avoid the possibility that these test results are inconsistent the test is investigated with a range of lags.[11] As we mentioned in section 1.7 the lag in the ADF test cannot be an indication of the lag truncation in the KPSS test. Hence, the results for the KPSS test with longer lag truncations[12] are presented in Table 3 and the results identify that all price combinations with 275 lags (<T/3) fail to reject the null of stationarity at the 5% level.

[10] KPSS test applied on same lag order as ADF and DF-GLS tests.
[11] See section 1.7.
[12]KPSS (p) tests with lag truncations of 25, 50, 75, 100, 125, 150, 175, 200, 225, 250, 275, 300, 325 (T/3)

From the table 1-2, the finding of stationary for the ADF test is supported in all cases by not rejecting the null of the KPSS test except even up to the larger lag truncation (275) with $\mathbf{Y_{14}}$ that is the price proportion between the Gulf Coast and Lower Atlantic.

Compared with Forni (2004) the almost over whelming finding of stationarity for the ADF test is supported in the all of cases by not rejecting the null of the KPSS test with larger lag truncation.

Table 1-1- Summary of ADF tests, DF-GLS tests& KPSS tests on the log differential of gasoline prices. (With intercept and no trend)

	P_{LCA}	P_{LEC}	P_{LGC}	P_{LLA}	P_{LMW}	P_{LNE}	P_{LRM}	P_{LWC}
P_{LCA}		-3.724537**	-6.171970**	-4.989478**	-4.928462**	-3.829677**	-4.541653**	-5.441773**
		(-3.706698**)	(-1.990969*)	(-4.707481**)	(-2.335932*)	(-3.747953**)	(-3.167151**)	(-5.411565**)
		[3.452390**]	[0.91515**]	[4.902073**]	[0.446911]	[5.438980**]	[1.165679**]	[0.267441]
P_{LEC}			-4.080439**	-4.648051**	-4.721538**	-3.700019**	-4.011872**	-4.808598**
			(-1.077737)	(-3.939956**)	(-2.055378*)	(-3.640446**)	(-3.121466**)	(-4.800208**)
			[4.317563**]	[2.451975**]	[0.182702]	[7.843325**]	[2.022444**]	[0.749265*]
P_{LGC}				-2.222776	-3.360986*	-5.177154**	-6.013833**	-3.784865**
				(-0.303123)	(-2.815583**)	(-1.868563)	(-5.089623**)	(-2.275466*)
				[3.431025**]	[1.681035**]	[0.861199**]	[4.908352**]	[0.378705]
P_{LLA}					-3.870944**	-3.838434**	-3.917549**	-4.068736**
					(-2.352104*)	(-3.636543**)	(-3.512071**)	(-4.051737**)
					[0.962882**]	[4.868950**]	[2.318920**]	[0.921917**]
P_{LMW}						-3.805266**	-4.430335**	-4.741388**
						(-2.132938*)	(-4.251056**)	(-3.287946**)
						[1.493587**]	[2.443409**]	[0.253900]
P_{LNE}							-5.436560**	-5.108161**
							(-3.795707**)	(-5.030299**)
							[0.365536]	[0.542706]
P_{LRM}								-5.814599**
								(-4.529151**)
								[1.036716**]
P_{LWC}								

Note: Values without the bracket presents ADF/OLS t-statistic, values in ( ) shows DF-GLS/OLS t-statistic, and values in [ ] indicates KPSSLM-statistic. ADF Test Critical value at 1% is -3.437483, at 5% is -2.864578. DF-GLS test Critical value at 1% is -2.567566, at 5% is -1.941180. KPSS test Critical value at 1% is 0.739, at 5% is 0.463. ** Significant at the 99% confidence level, and* Significant at the 95% confidence level. The **bold number** denotes that the series are stationary.

Table 1-2- Summary of ADF tests, DF-GLS tests and KPSS tests on the log differential of gasoline prices

Log price differentials	ADF	DF-GLS	KPSS (25)	KPSS (50)	KPSS (75)	KPSS (100)	KPSS (125)	KPSS (150)	KPSS (175)	KPSS (200)	KPSS (225)	KPSS (250)	KPSS (275)	KPSS (300)	KPSS (325)
Y_1	**-3.72****	**-3.71****	2.35	1.41	1.00	0.81	0.67	0.59	0.52	0.47	**0.44**	**0.41**	**0.39**	**0.37**	**0.36**
Y_2	**-6.17**	**-1.99***	0.63	0.47	**0.37**	**0.34**	**0.30**	**0.28**	**0.25**	**0.23**	**0.224**	**0.219**	**0.217**	**0.216**	**0.215**
Y_3	**-4.99****	**-4.71****	1.98	1.21	0.86	0.70	0.59	0.51	**0.46**	**0.42**	**0.39**	**0.37**	**0.35**	**0.34**	**0.33**
Y_4	**-4.93****	**-2.33***	**0.45**	**0.38**	**0.31**	**0.30**	**0.28**	**0.27**	**0.259**	**0.258**	**0.261**	**0.27**	**0.28**	**0.30**	**0.31**
Y_5	**3.83****	**-3.75****	1.76	1.03	0.74	0.60	0.51	**0.46**	**0.41**	**0.38**	**0.36**	**0.34**	**0.33**	**0.32**	**0.31**
Y_6	**-4.54****	**-3.17****	1.05	0.75	0.59	0.54	0.51	0.49	0.47	**0.45**	**0.44**	**0.43**	**0.41**	**0.40**	**0.38**
Y_7	**-5.44****	**-5.41****	**0.16**	**0.13**	**0.124**	**0.116**	**0.11**	**0.108**	**0.105**	**0.107**	**0.11**	**0.117**	**0.123**	**0.127**	**0.13**
Y_8	**-4.08****	-1.08	2.33	0.137	0.99	0.80	0.68	0.60	0.54	0.50	**0.46**	**0.44**	**0.42**	**0.40**	**0.38**
Y_9	**-4.65****	**-3.94****	1.49	0.92	0.67	0.55	0.47	**0.41**	**0.37**	**0.34**	**0.32**	**0.31**	**0.30**	**0.29**	**0.288**
Y_{10}	**-4.72****	**-2.05***	**0.18**	**0.15**	**0.12**	**0.11**	**0.107**	**0.104**	**0.102**	**0.105**	**0.110**	**0.12**	**0.13**	**0.14**	**0.16**
Y_{11}	**-3.70****	**-3.64****	2.50	1.38	0.96	0.75	0.62	0.54	0.48	**0.44**	**0.40**	**0.38**	**0.36**	**0.35**	**0.33**
Y_{12}	**-4.01****	**-3.12****	1.77	1.14	0.85	0.72	0.63	0.57	0.52	0.49	**0.46**	**0.43**	**0.41**	**0.39**	**0.38**
Y_{13}	**-4.81****	**-4.80****	**0.41**	**0.31**	**0.27**	**0.24**	**0.22**	**0.21**	**0.20**	**0.19**	**0.187**	**0.187**	**0.187**	**0.187**	**0.187**
Y_{14}	-2.22	-0.30	3.19	1.74	1.21	0.95	0.79	0.69	0.61	0.56	0.51	0.48	**0.45**	**0.43**	**0.41**
Y_{15}	**-3.36***	**-2.82****	1.23	0.77	0.58	0.47	**0.40**	**0.35**	**0.32**	**0.30**	**0.29**	**0.28**	**0.27**	**0.27**	**0.27**
Y_{16}	**-5.18****	-1.87	0.53	**0.34**	**0.26**	**0.23**	**0.20**	**0.18**	**0.17**	**0.16**	**0.16**	**0.16**	**0.15**	**0.16**	**0.16**
Y_{17}	**-6.01****	**-5.09****	0.68	0.50	**0.38**	**0.34**	**0.34**	**0.28**	**0.26**	**0.25**	**0.24**	**0.24**	**0.23**	**0.23**	**0.23**
Y_{18}	**-3.78****	**-2.27***	**0.37**	**0.26**	**0.22**	**0.20**	**0.18**	**0.16**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**
Y_{19}	**-3.87****	**-2.35***	0.73	0.50	**0.37**	**0.32**	**0.28**	**0.25**	**0.24**	**0.23**	**0.22**	**0.22**	**0.22**	**0.22**	**0.22**
Y_{20}	**-3.84****	**-3.64****	2.26	1.27	0.90	0.71	0.59	0.51	**0.46**	**0.42**	**0.39**	**0.37**	**0.35**	**0.34**	**0.33**
Y_{21}	**-3.92****	**-3.51****	2.00	1.25	0.91	0.75	0.64	0.57	0.51	0.47	**0.44**	**0.41**	**0.39**	**0.37**	**0.36**
Y_{22}	**-4.07****	**-4.05****	0.70	**0.43**	**0.40**	**0.35**	**0.31**	**0.28**	**0.25**	**0.24**	**0.23**	**0.22**	**0.22**	**0.22**	**0.22**
Y_{23}	**-3.80****	**-2.13***	1.17	0.81	0.61	0.52	**0.46**	**0.41**	**0.38**	**0.36**	**0.35**	**0.35**	**0.34**	**0.34**	**0.33**
Y_{24}	**-4.43****	**-4.25****	1.95	1.38	1.00	0.82	0.70	0.62	0.56	0.52	0.49	**0.46**	**0.43**	**0.41**	**0.39**
Y_{25}	**-4.74****	**-3.29****	**0.25**	**0.23**	**0.23**	**0.21**	**0.20**	**0.20**	**0.20**	**0.20**	**0.21**	**0.21**	**0.21**	**0.21**	**0.21**
Y_{26}	**-5.44****	**-3.80****	**0.28**	**0.21**	**0.17**	**0.17**	**0.18**	**0.19**	**0.22**	**0.25**	**0.30**	**0.35**	**0.39**	**0.41**	**0.41**
Y_{27}	**-5.11****	**-5.03****	**0.34**	**0.27**	**0.24**	**0.22**	**0.21**	**0.21**	**0.21**	**0.22**	**0.23**	**0.43**	**0.25**	**0.25**	**0.25**
Y_{28}	**-5.81****	**-4.53****	0.97	0.83	0.69	0.63	0.57	0.54	0.49	0.47	**0.44**	**0.24**	**0.41**	**0.40**	**0.39**

Note: Y_1= log (P_{CA})- log (P_{EC}), Y_2= log(P_{CA})- log (P_{GC}), Y_3= log (P_{CA})- log (P_{LA}), Y_4=log (P_{CA})- log (P_{MW}), Y_5= log (P_{CA})- log (P_{NE}), Y_6= log(P_{CA})- log (P_{RM}), Y_7= log (P_{CA})- log (P_{WC}), Y_8= log (P_{EC})- log (P_{GC}), Y_9= log (P_{EC})- log (P_{LA}), Y_{10}= log (P_{EC})- log (P_{MW}), Y_{11}= log(P_{EC})- log (P_{NE}), Y_{12}= log (P_{EC})- log (P_{RM}) , Y_{13}= log(P_{EC})- log(P_{WC}), Y_{14}= log(P_{GC})- log (P_{LA}), Y_{15}= log (P_{GC}) log- log(P_{MW}), Y_{16}= log(P_{GC})- log (P_{NE}), Y_{17}= log (P_{GC})- log (P_{RM}) , Y_{18}= log (P_{GC})- log(P_{WC}), Y_{19}= log (P_{LA})- log (P_{MW}), Y_{20}= log(P_{LA})- log (P_{NE}), Y_{21}= log (P_{LA})- log (P_{RM}), Y_{22}= log (P_{LA})- log (P_{WC}), Y_{23}= log (P_{MW})- log (P_{NE}), Y_{24}= log (P_{MW})- log (P_{RM}), Y_{25}= log (P_{MW})- log (P_{WC}), Y_{26}= log (P_{NE})- log (P_{RM}), Y_{27}= log (P_{NE})- log (P_{WC}), Y_{28}= log (P_{RM})- log (P_{WC}) ; Where P_{CA}, P_{EC}, P_{GC}, P_{LA}, P_{MW}, P_{NE}, P_{RM}, P_{WC} is price of gasoline in Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England, Rocky Mountains and West Coast.

ADF test critical value at 1% level is -3.437483 and at 5% level is-2.864578. DF-GLS test critical values at 1% level is -2.567566, at 5% level is -1.941180. The KPSS test critical value at 1% level is 0.739, at 5% is 0.463. ****** Significant at the 99% confidence level, and ***** at the 95% confidence level. The **bold number** denotes that the series are stationary.

Forni (2004) could not find the same consistency of results, but with many fewer observations observed at a lower frequency. So unlike Forni (2004) these results appear roughly consistent with the finding of a broad market. Though, the KPSS test is often considered more appropriate for this type of analysis as the null of stationarity assumes that the firm is assumed to be efficient and this corresponds with natural justice when companies are analysed. However the KPSS test performs poorly when the series are highly autocorrelated. Caner and Killian (2001) suggested that the KPSS test is not powerful especially in the light of possible moving average behaviour when compared with the ADF and DF-GLS tests.

The stationarity and unit-root test give broadly confirmatory findings except only in one case, the Gulf Coast and the Lower Atlantic which cannot reject the unit-root hypothesis at the 5% level using ADF and DF-GLS tests contrary with KPSS results with 275 lags at 5% level.

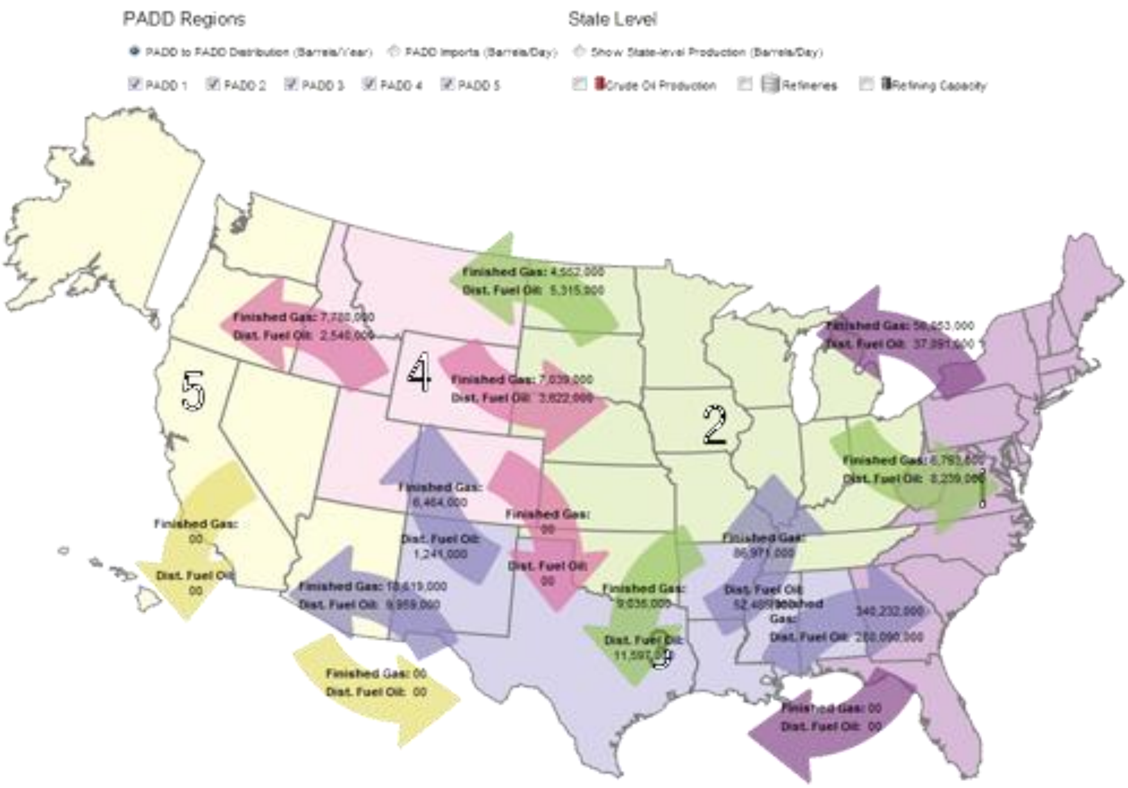
Hence A further extension to the Forni method might be to consider the panel tests due to Im et al (2003) and Hadri (2000). One reason for this might be to investigate the validity of the KPSS test and to this end the small sample corrected panel test due to Hadri (2000) is applied. It has been suggested that the panel case may yield improvements, because there may be benefits to pooling the data in the case where the series are strongly related and panel methods have also been applied by Giulietti et al (2010) to electricity prices for the UK.

1.10 Panel Tests of the Non-Stationary Null and Coherent Univariate Test

Until here the process of Forni (2004) was followed and adapted, but this gives rise to twenty eight price combinations. In this section the problem is limited to a panel problem and a similar set of univariate tests. In the context of a system of error correction models then the analysis considers *n* price equations as a VAR or as single series. However, Forni (2004) has suggested that univariate tests are more appropriate for testing the arbitrage proposition. In particular, unit-root tests are effective as they impose the restriction that the intercept is zero and the slope coefficient unity. Neither the VAR nor the Engle-Granger procedure simultaneously tests for cointegration and the restrictions on the coefficients. Hence, testing long-run arbitrage and unit-root, cointegration can be unified.

A further issue that arises in the context of testing unit-root of real exchange rates relates to cross rates and triangular arbitrage (Smith and Hunter, 1985). This follows from selecting alternative base currencies to determine whether the real exchange rate is stationary. In the exchange rate case the sequence of results that arise from the underlying dynamic exchange rate models are dependent on each other when the different models are coherent (Hunter and Smith, 1982). A similar issue arises when testing unit-root of price proportions using equivalent dynamic models or might be viewed as choosing a different region to act as the base for comparison. Hence, $\frac{1}{2}N(N-1)$ price proportions relate back to N underlying price equations. When compared with the exchange rate where all rates are in dollars, the case of dependency here is less obvious.

Figure 1-5- Map of US regional gasoline infrastructure[13]



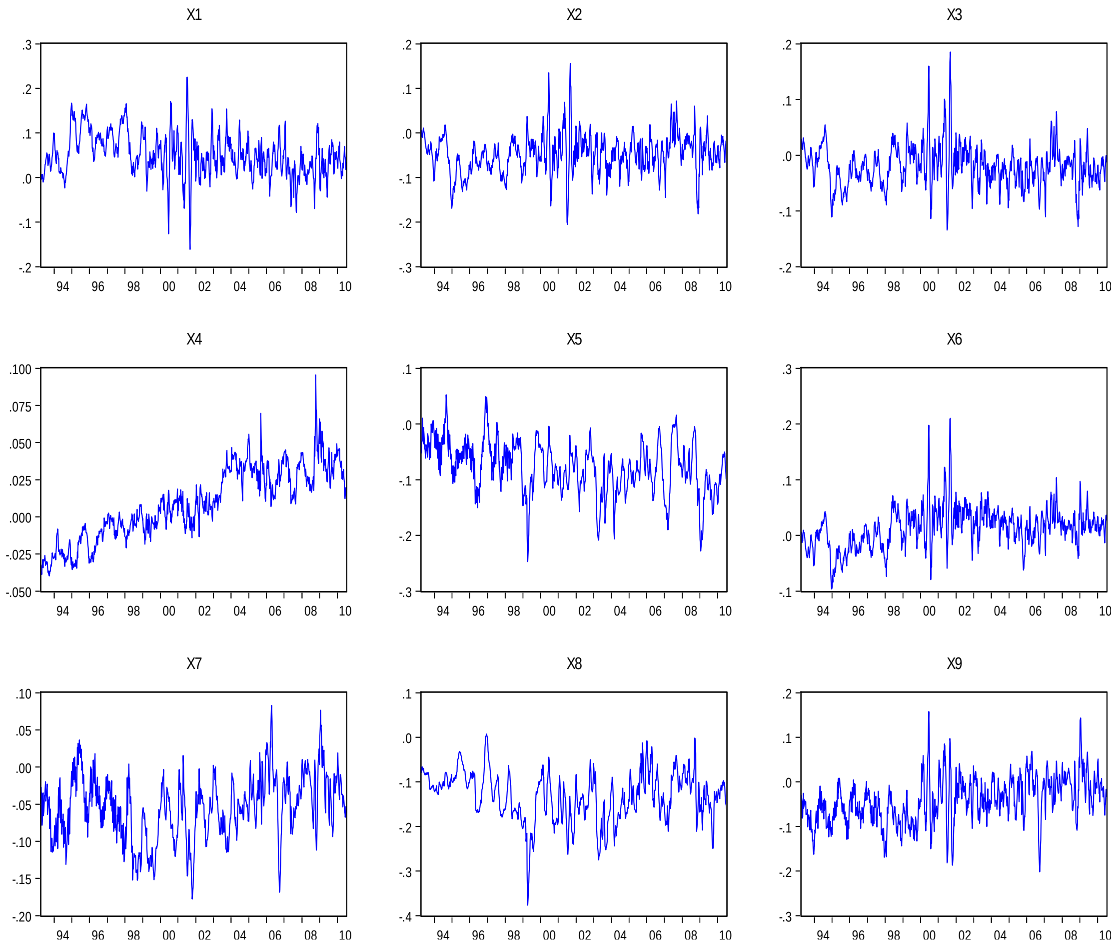
To this end it has been decided to consider a smaller sub-set of prices, and to this end use further information to determine inter-linked chains of price series using the information associated with the map given in Figure 1-5.

The remaining analysis is undertaken paying attention to the US regional gasoline infrastructure and as a result the following pairs of log price differentials are selected: $X_1=\log(P_{\text{New England}} - P_{\text{Mid-West}})$, $X_2=\log(P_{\text{Mid-West}} - P_{\text{Central Atlantic}})$, $X_3=\log(P_{\text{Mid-West}} - P_{\text{Eeast-Coast}})$, $X_4=\log(P_{\text{Lower Atlantic}} - P_{\text{Gulf Coast}})$, $X_5= \log(P_{\text{Rocky Mountain}} - P_{\text{WestCoast}})$, $X_6=\log(P_{\text{Mid-West}} - P_{\text{Gulf Coast}})$, $X_7= \log(P_{\text{Gulf Coast}} - P_{\text{Rocky Mountain}})$, $X_8=\log(P_{\text{Gulf Coast}} - P_{\text{West Coast}})$, $X_9= \log(P_{\text{Mid-West}} - P_{\text{Rocky Mountain}})$.

[13] The above diagram was obtained with permission of the National Association of Convenience Stores, from the 2012 NACS Retail Fuels Report.

Figure 1-6 shows gasoline log price differential in different region of US based on the regional infrastructure. It would appear that for X1, X2, X3, X6 and X9 are mean reverting and seemingly stationary. While X4 and X5 seems to exhibit an upward and a slight downward trend and as a result from visual inspection might appear non-stationary. X7 and X8 do not have any apparent trend, but the behaviour may again from visual inspection appear closer to a random walk without drift and thus are potentially non-stationary. However, this will need to be verified via formal tests under either the non-stationary or stationary null. This is augmented by panel methods that pool the data.

Figure 1-6- Plot of gasoline log price differential in different region of US based on the regional infrastructure



To further evaluate the argument on the above section the ADF, DF-GLS and KPSS test are applied to the log price differentials set out above and the related results revealed in Table 1-3. Using the same process as was presented in the previous section the following lag orders have been selected via inspection of the correlogram. The selected lag orders or the sub set of nine price differential series are as below for $\mathbf{X_i}$ (j) where (j) is the related lag order and:

$X_1(25)$, $X_2(25)$, $X_3(25)$, $X_4(23)$, $X_5(20)$, $X_6(16)$, $X_7(20)$, $X_8(24)$, $X_9(16)$.

Table 1-3- Summary of ADF tests, DF-GLS tests and KPSS tests on the log differential of gasoline prices (With intercept and no trend)

Log price differential	ADF/ OLS t-statistic	DF-GLS/ OLS t-statistic	KPSS LM-statistic	KPSS *(25 lags)*	KPSS *50 lags)*	KPSS *(75 lags)*	KPSS *(100 lags)*	KPSS *(125 lags)*	KPSS *(150 lags)*	KPSS *(175 lags)*	KPSS *(200 lags)*	KPSS *(225 lags)*	KPSS *(250 lags)*	KPSS *(275 lags)*	KPSS *(300 lags)*	KPSS *(325 lags)*	ARCH (1,1) F-statistics (P-value)
$X_1(25)$	__-3.80 *__	__-2.53 *__	1.04**	1.17	0.81	0.61	0.52	**0.46**	**0.41**	**0.38**	**0.36**	**0.35**	**0.34**	**0.34**	**0.34**	**0.33**	16.59** (0.00)
$X_2(25)$	__-4.93 *__	__-2.34 *__	**0.41**	**0.45**	**0.38**	**0.31**	**0.30**	**0.28**	**0.27**	**0.26**	**0.26**	**0.26**	**0.27**	**0.28**	**0.30**	**0.31**	7.49** (0.01)
$X_3(25)$	__-4.72 *__	__-2.05 *__	**0.17**	**0.18**	**0.15**	**0.12**	**0.11**	**0.11**	**0.10**	**0.10**	**0.10**	**0.11**	**0.12**	**0.13**	**0.14**	**0.16**	**3.14 (0.08)**
$X_4(23)$	-2.22	-0.30	2.87	3.19	1.74	1.22	0.95	0.79	0.69	0.61	0.56	0.51	0.48	**0.45**	**0.43**	**0.41**	**0.04 (0.84)**
$X_5(20)$	__-5.81*__	__-4.53*__	0.89	0.97	0.83	0.69	0.63	0.57	0.54	0.49	0.47	**0.44**	**0.43**	**0.41**	**0.40**	**0.39**	**0.03 (0.87)**
$X_6(16)$	__-3.36*__	__-2.82*__	1.23	1.23	0.77	0.58	0.47	**0.40**	**0.35**	**0.32**	**0.30**	**0.29**	**0.28**	**0.28**	**0.27**	**0.27**	**0.54 (0.46)**
$X_7(20)$	__-5.21*__	__-3.99*__	0.63	0.68	0.50	**0.38**	**0.34**	**0.30**	**0.28**	**0.26**	**0.25**	**0.24**	**0.24**	**0.23**	**0.23**	**0.23**	**0.14 (0.71)**
$X_8(24)$	__-3.78**__	__-2.27*__	**0.32**	**0.37**	**0.26**	**0.22**	**0.20**	**0.18**	**0.16**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	15.74** (0.00)
$X_9(16)$	__-4.43*__	__-4.25*__	2.44	1.95	1.38	1.00	0.82	0.70	0.62	0.57	0.52	0.49	**0.46**	**0.43**	**0.41**	**0.39**	**0.34 (0.56)**

Note: ADF test critical value at 1% level is -3.437483 and at 5% level is-2.864578. DF-GLS test critical values at 1% level is -2.567566, at 5% level is -1.941180. The KPSS test critical value at 1% level is 0.739, at 5% is 0.463. __**__ Significant at the 99% confidence level, and__*__ at the 95% confidence level. The **bold** concludes that the series are stationary.

According to the result in the table above The ADF and DF-GLS results suggest that all price differentials are stationary except X_4thisimplies the combination of P_{LA} and P_{GC} is non-stationary by both types of tests. However when the KPSS test is applied with varies lag truncation considering the null of stationarity, in all cases using 275 lags the null hypothesis is not rejected which indicates all series are stationary. Hence again, after considering smaller sub-set of prices by taking account of regional gasoline communication, in the case X_4 the results from ADF and DF-GLS tests differing from KPSS results.

As was mentioned above the KPSS test is believed to lack power (Caner and Killian, 2001). It has been suggested that the panel case may be considered, as in the case of strongly related series there may be benefits to pooling the data. The size of a typical autocorrelation coefficient related to coefficient in the ADF test statistic suggests that the data are strongly autoregressive and this might not be consistent with the test result[14].For further clarification we applied Panel unit-root and stationary tests.

It is of interest to note that were the Bartlet correction applied to a single KPSS test, then the conclusions of the KPSS/Hadri test would be little altered. This should not be surprising as the correction is a small sample correction that should not be important when the sample across time is large. Bearing this in mind, the simulation results in Hadri (2000) suggest that power should not be an issue with a sample of $T=900$ observations, though the power is reduced when N is small and also in response to the scale of the variance ratio. It would seem likely from the scale of the test results that the innate size of the variance ratio is not an issue here.

[14]All series are stationary except X_4

First the Hadri panel stationarity test is applied to different pairs of log price differentials and the related analysis considered in more detail next.

1.10.1 Hadri Panel Unit Root Test

It is suggested that the inconsistency between the ADF and DF- GLS tests as compared with the KPSS test in the case of the Lower Atlantic and Gulf Coast might be as a result of the poor performance of the latter test. A further extension to the Forni method is to consider the panel tests of Im et al (2003) and Hadri (2000). Beirne et al (2007) give empirical support to the suggestion of Hadri that his test has good size properties when the time series exceeds 50 observations and their findings would concur that the test would not seem to be impacted by non-normality. The Hadri test is a correction of the KPSS LM test that also operates under the null of stationarity.

Refocusing on the US regional gasoline infrastructure map on page 25, the Hadri test is applied to the following pairs:

- Series X_1 and series X_2
- Series X_9 and series X_7
- Series X_9 and series X_6
- Series X_4 and series X_8
- Series X_5 and series X_8

The null of stationary assumes that the data moves around a deterministic level:

$$y_{it} = r_{it} + \varepsilon_{it} \quad . \qquad (1\text{-}6)$$

Where $t=1\ldots T$ time, $i=1\ldots N$ cross section units and (1-6) implies the series is decomposed into random walk and stationary disturbance term:

$$r_{it} = r_{it-1} + u_{it}$$

r_{i0} is unknown, the u_{it} are iid across both countries and time and $\sigma_u^2 \geq 0$. The test takes the form:

$$H_0: \lambda=0 \qquad \textit{against} \qquad H_1: \lambda>0.$$

$\lambda = \sigma_u^2 / \sigma_\varepsilon^2$ and under the null $\sigma_u^2 = 0$.

Each panel equation has the form:

$$y_i = X_i B_i + e_i$$

Where, $y'_i = [y_{i1} \ldots y_{iT}]$, $e'_i = [e_{i1} \ldots e_{iT}]$ and X_i is a $Tx1$ unit vector or in the trend case includes both the unit vector and a trend. The LM test statistic under the null is:

$$LM = \frac{1}{N} \sum_{i=1}^{N} \frac{1/T^2 \sum_{t=1}^{T} S_{it}^2}{\sigma_i^{*2}}$$

σ_i^{*2} is the variance estimated from each individual sample and each partial sum of the residuals is $S_{it} = \sum_{j=1}^{t} e_{ij}$. To account for serial dependence a correction is applied to each cross section variance. Therefore:

$$\sigma_i^{*2}(x) = \gamma_o + 2\sum_{s=1}^{T-1} \kappa(x) \gamma_s. \qquad (1\text{-}7)$$

Where, $\gamma_0 = \sigma_i^{*2}$, $x=s/l+1$ is the bandwidth, l is the lag truncation and

$$\gamma_s = \frac{1}{T} \sum_{t=s+1}^{T} e_{it} e_{it-s}.$$

Following Beirne et al the Truncated kernel is:

$$\kappa_T(x) = \begin{cases} 1 \text{ for } x < 1 \\ 0 \text{ otherwise} \end{cases}.$$

The one preferred by Hadri (2000) is the Quadratic-spectral (QS):

$$\kappa_{QS}(x) = \frac{25}{12\pi^2 x^2}\left\{\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5)\right\} \quad .$$

The LM statistic is not distributed chi-squared under H_0, but Hadri (2000) shows that the following finite sample correction follows a standard normal distribution in the limit:

$$Z_u = \frac{\sqrt{N}\ (LM_u - \xi_u)}{\zeta_u}$$

Hadri shows that ξ_u=1/6, ζ_u^2 = 1/45 and for T>50, the empirical size of the test is approximately 0.054 and with λ in the range of $[0.1,\infty]$ the test has maximum power. Tests based on the Bartlett, Parzen and Quadratic-Spectral kernels in Table 5 below. A number of strategies can be followed to select the optimal bandwidth: optimizing on the maximum lag order for each pair. Hunter and Simpson (2001) set a bandwidth equal to the 3 to 4 times the maximum lag order of the ADF tests applied in their study, but that is based on quarterly data. Further based on the direction in Eviews it is suggested that it may be possible to use a bandwidth equal to the total number of observation.

However, the Hadri panel stationarity test is applied first to different pairs of log price differentials and then to the 9 region pairs as a full panel. The Hadri test, whether it is for single or multiple regions, operates under the null of stationarity.[15] Results for the Hadri test based on the Bartlett, Parzen and Quadratic-Spectral kernels[16] are presented in Table 1-4 and 1-5.

[15]Focusing on the US regional gasoline infrastructure map on page 25, the Hadri test is applied to the following pairs: series X_1 and series X_2, series X_9 and series X_7, series X_9 and series X_6, series X_4 and series X_8, series X_5 and series X_8.

[16]The Bartlett Kernel (BT) and Parzen (P) are:

Table 1-4- Hadri panel stationary test based on different bandwidth and kernel with individual intercept

	Kernel	*t-statistics with max lag bandwidth I*	*P-value*	*t-statistics with max lag bandwidth II*	*P-value*	*t-statistics with long bandwidth III*	*P-value*
X_1(25)and X_2(25)	**Bartlett**	7.01801	0.0000	3.39543	0.0003	3.16228	0.0008
	Parzen	7.97431	0.0000	4.28954	0.0000	1.67134	0.0473
	Quadratic spectral	6.15763	0.0000	2.77395	0.0028	4.54125	0.0000
X_9(16)and X_7(20)	**Bartlett**	12.3978	0.0000	6.36771	0.0000	3.16228	0.0008
	Parzen	14.3860	0.0000	7.83900	0.0000	**1.62509**	**0.0521**
	Quadratic spectral	10.4138	0.0000	5.17141	0.0000	4.34528	0.0000
X_9(16)and X_6(16)	**Bartlett**	19.0721	0.0000	9.56826	0.0000	3.16228	0.0008
	Parzen	21.7708	0.0000	11.3763	0.0000	1.68960	0.0456
	Quadratic spectral	16.2368	0.0000	7.84960	0.0000	4.19906	0.0000
X_4(23)and X_8(24)	**Bartlett**	7.99594	0.0000	3.51012	0.0002	3.16228	0.0008
	Parzen	9.86467	0.0000	4.18272	0.0000	**1.59771**	**0.0551**
	Quadratic spectral	6.55805	0.0000	2.78203	0.0027	5.00252	0.0000
X_5(20)and X_8(24)	**Bartlett**	4.18928	0.0000	2.09300	0.0182	3.16228	0.0008
	Parzen	4.93103	0.0000	2.41350	0.0079	**1.63134**	**0.0514**
	Quadratic spectral	3.39104	0.0003	1.66684	0.0478	5.66465	0.0000
X_3(25)and X_6(16)	**Bartlett**	6.14625	0.0000	2.53044	0.0057	3.16228	0.0008
	Parzen	7.44649	0.0000	3.28497	0.0005	1.74157	0.0408
	Quadratic spectral	5.22775	0.0000	1.94076	0.0261	5.35815	0.0000
X_1(25), X_2(25),X_3(25), X_4(23), X_5(20),X_6(16), X_7(20), X_8(24), X_9(16)	**Bartlett**	17.4965	0.0000	8.36028	0.0000	6.70820	0.0000
	Parzen	20.3252	0.0000	10.3208	0.0000	3.53917	0.0002
	Quadratic spectral	14.8680	0.0000	6.78183	0.0000	9.75988	0.0000

Note: The **bold** number denotes that the series are stationary at 5% level.

$$\kappa_{BT}(x) = \begin{cases} 1-|x| \text{ for } |x| \le 1 \\ 0 \text{ otherwise} \end{cases}$$

$$\kappa_{P}(x) = \begin{cases} 1-6x^2(1-|x|) & \text{for } 0.0 \le |x| \le 0.5 \\ 2(1-|x|)^3 & \text{for } 0.5 < |x| \le 1.0 \\ 0 & \text{otherwise} \end{cases}$$

.

The test is compared with a one sided critical value at the 5% level of 1.64. However, in Hadri panel stationary test with individual intercept only with the Parzen kernel for the longest bandwidth we identified that in three cases (X_9- X_7, X_4- X_8 and X_5- X_8) the null of stationarity cannot be rejected. But the result of the Hadri test with individual intercept and linear trend indicates that in one case of X_1- X_2 the null of stationarity cannot be rejected.

Considering US gasoline prices, cross-section independence is considered a critical assumption for the Hadri test so this method might not hold. According to Giulietti et al (2009) in the case of the potential cross-section dependency even with large T and N the Hadri test may suffer severe size distortion, something they investigated using an AR-based bootstrap. However, for price differentials this may be less of a problem when this behaviour is common to the price pairs.

The size of a typical autocorrelation coefficient related to the ADF test statistic suggests the data are strongly autoregressive. The strength of this correlation explains why their behaviour might be seen to be distinct from the constant model underlying the KPSS test as compared with the distance from the unit-root case that arises when considering the ADF test. So the poor performance of the Hadri and KPSS tests may be symptomatic of strong or persistent autoregression and this may not be inconsistent with the suggestion by Caner and Killian (2001) that the poor performance of the KPSS test is particularly problematic in the light of the error process being moving average (MA). One interpretation of the analysis of the lags might be that the long autoregression really relates to MA or ARMA behaviour. For further clarification of the Hadri stationary test result we applied Im, Pesaran and Shin panel unit-root test.

Table 1-5- panel unit root test based on different bandwidth and kernel with individual intercept and linear trend

	Kernel	t-statistic with max lag bandwidth I	P-value	t-statistics with max lag bandwidth II	P-value	t-statistics with long bandwidth III	P-value
$X_1(25)$and $X_2(25)$	**Bartlett**	**0.78477**	**0.2163**	**0.02422**	**0.4903**	14.6660	0.0000
	Parzen	**0.95802**	**0.1690**	**0.21143**	**0.4163**	23.6606	0.0000
	Quadratic spectral	**0.54635**	**0.2924**	**-0.13551**	**0.5539**	299.029	0.0000
$X_9(16)$and $X_7(20)$	**Bartlett**	4.64032	0.0000	3.06494	0.0011	14.6660	0.0000
	Parzen	5.15320	0.0000	3.53599	0.0002	8.46811	0.0000
	Quadratic spectral	3.72147	0.0001	2.48390	0.0065	80.1765	0.0000
$X_9(16)$and $X_6(16)$	**Bartlett**	6.45363	0.0000	4.63206	0.0000	14.6660	0.0000
	Parzen	6.76241	0.0000	4.66014	0.0000	8.20367	0.0000
	Quadratic spectral	5.32907	0.0000	3.87805	0.0001	77.3872	0.0000
$X_4(23)$and $X_8(24)$	**Bartlett**	8.64370	0.0000	4.33535	0.0000	14.6660	0.0000
	Parzen	10.4473	0.0000	4.81604	0.0000	7.19414	0.0000
	Quadratic spectral	7.05987	0.0000	3.54303	0.0002	67.5618	0.0000
$X_5(20)$and $X_8(24)$	**Bartlett**	6.50334	0.0000	3.85241	0.0001	14.6660	0.0000
	Parzen	7.44900	0.0000	4.17385	0.0000	7.34701	0.0000
	Quadratic spectral	5.32888	0.0000	3.26759	0.0005	68.9055	0.0000
$X_3(25)$and $X_6(16)$	**Bartlett**	7.28830	0.0000	3.36174	0.0004	14.6660	0.0000
	Parzen	8.63251	0.0000	4.19913	0.0000	8.69289	0.0000
	Quadratic spectral	6.25753	0.0000	2.56110	0.0040	83.2638	0.0000
$X_1(25)$,$X_2(25)$,$X_3(25)$, $X_4(23)$,$X_5(20)$,$X_6(16)$, $X_7(20)$, $X_8(24)$,$X_9(16)$	**Bartlett**	10.5440	0.0000	5.86412	0.0000	31.1112	0.0000
	Parzen	11.8129	0.0000	6.85383	0.0000	17.7233	0.0000
	Quadratic spectral	8.85473	0.0000	4.86735	0.0000	166.431	0.0000

Note: The **bold** concludes that the series are stationary at 5% level.

1.10.2 Im, Pesaran, and Shin (IPS) Panel Unit root test

For comparison with the panel unit root test under the null of stationarity the test due to Im et al (2003) is applied. The IPS panel unit root test estimates a mean adjusted ADF test statistic that may also be adjusted for fixed and random effects. Individual

ADF tests are computed for the cross section mean adjusted data and the t-tests computed accordingly. The t-bar test statistic is the average of the individual corrected ADF t-statistics and compared with the critical values derived in the tables in Im et al (2003).The result of the IPS test are presented in Table 1-6 below.

Table 1-6- - Im, Pesaran and Shin Unit Root Test with individual intercept

Log differential price	*IPS/ OLS t-statistic*	*P-Value*
X_1(25)and X_2(25)	-4.55156	0.0000
X_9(16)and X_7(20)	-5.62423	0.0000
X_9(16)and X_6(16)	-3.81476	0.0001
X_4(23)and X_8(24)	-2.34972	0.0094
X_5(20)and X_8(24)	-4.58201	0.0000
X_3(25)and X_6(16)	-4.01161	0.0000
X_1(25), X_2(25),X_3(25), X_4(23), X_5(20),X_6(16), X_7(20), X_8(24), X_9(16)	-8.04934	0.0000

Note: The selected lag number for each pair is equal to the maximum lag order within the series.

In all of the IPS panel cases with the null of non-stationarity it is found that the null hypothesis can be rejected and that on average the series are stationary indicating that all 8 regions are belong to the same geographic market. Hence, the same discrepancy arises between the panel and univariate tests with different null hypothesis.

1.11 ARCH Effect Analysis

1.11.1 GLS-ADF- Test using the ARCH Estimator

The energy market is affected by news and an information arrival process that causes shocks and volatility in associated markets. Here, we use the ARCH (Autoregressive Conditional Heteroskedasticity) process to model possible volatility in the series (Engle, 1982). However by handling the heteroskedasticity in the error we can obtain more efficient estimates and this should improve the performance of the test subject to more usual rates of convergence for usual sample sizes[17] (Boswijk, 2001).

A relatively large dataset permits some experimentation with the methodology, but the observation that the Hadri test rejected may also be indicative of ARCH behaviour. If the variance of the price differential is increasing beyond expectation across the observed sample then this increase in the variance may appear to resemble non-stationarity in the context of what is a variance ratio test. This may especially be the case when the volatility is large or close to the non-stationary boundary of the parameter space related to the appropriate definition of the long-run variance.

Alternatively, the test due to Hadri (2000) is a finite sample correction of the KPSS test applied to panel data and the power of this test has been found to be sensitive to Autoregressive Heteroscedasticity suggesting the need to correct stationarity tests for volatility (Eviews, 2009).

According to Beirne, Hunter, and Simpson (2007) the volatility correction makes some difference to the performance of the ADF test and this suggests that in moderately large samples the ADF test is sensitive to dynamics in the conditional variance (ARCH). The ADF test provides a correction for serial correlation via the introduction of lags of the dependent variable in the mean equation, but again in moderately sized samples it may be responsive to non-normality. Here, we correct the

[17] Rahbek et al (2002) find in the context of multivariate models when the spectral radius of the multivariate ARCH model exceeds .85 then a sample in excess of 600 observations is required for convergence of the test statistic to their asymptotic values.

model for ARCH in the case of potential volatility. Boswijk (2001) suggests that by modelling the volatility the power of unit root test might be significantly improved.

In our study we can observe how the DF test has been affected by ARCH behaviour. This means that we use the method to better detect whether the long-run arbitrage exists. Using, a GLS variance correction to the Dickey Fuller model implies that we will transform the standard error to control for a variance moving during the time due to volatility or sequences of shocks. The weighted Dickey-Fuller tests are based on variance estimates corrected for the observed volatility.

The ADF model is tested by the usual LM test for ARCH (Engle, 1982) and the associated estimates of the variance equation can be used as a measure of the conditional variance. If there is ARCH, then the squared residuals computed from (2) are explained by the following variance equation:

$$e_t^2 = \alpha + \delta_1 e_{t-1}^2 + \delta_2 e_{t-2}^2 + \ldots + \delta_k e_{t-k}^2 + \epsilon_t$$

The test for ARCH considers the following hypotheses:

H_0: $\delta_k = 0$ for k=1,2,..l *against* $H_A : \delta_k \neq 0$ for k=1,2,..l

The test is based on the R^2 from the above regression;

$$\chi^2_{ARCH}(l) = TR^2 \sim \chi_l^2$$

The result for the ADF model presented before is given in the table below. Accordingly, the χ_l^2 value from the table indicates that there is no ARCH effect in X_1(log($P_{New\ England}$ - $P_{Mid\text{-}West}$)), but there is ARCH effect for X_2, X_3, X_4 , X_5, X_6, X_7, X_8, X_9.

Table 1-7- ADF-ARCH Test

Log differential price	ADF –ARCH χ^2
$X_1(25)$	23.11
$X_2(16)$	**73.645***
$X_3(3)$	**28.633***
$X_4(4)$	**38.989***
$X_5(4)$	**28.565***
$X_6(3)$	**21.668***
$X_7(4)$	**60.775***
$X_8(4)$	**38.989**
$X_9(16)$	**29.497***

Note: X_1=log($P_{New\ England}$ - $P_{Mid\text{-}West}$), X_2=log($P_{Mid\text{-}West}$ - $P_{Central\ Atlantic}$), X_3=log($P_{Mid\text{-}West}$ - $P_{Eeast\text{-}Coast}$), X_4=log($P_{Lower\ Atlantic}$ - $P_{Gulf\ Coast}$), X_5= log($P_{Rocky\ Mountain}$ - $P_{WestCoast}$), X_6=log($P_{Mid\text{-}West}$ - $P_{Gulf\ Coast}$), X_7= log($P_{Gulf\ Coast}$ - $P_{Rocky\ Mountain}$), X_8=log($P_{Gulf\ Coast}$ - $P_{West\ Coast}$), X_9= log($P_{Mid\text{-}West}$ - $P_{Rocky\ Mountain}$). The **bold** denotes that there is ARCH effect.

An advantage of the OLS method is that these values will always be positive, while the full maximum likelihood method may fail to converge as parameters stray into regions of the parameter space inconsistent with the requirement of a variance estimator.

The GLS estimates are now corrected for ARCH in the residuals, but based on an OLS estimation procedure that is corrected to yield homoscedastic errors. Capturing the volatility in the ADF model implies that the tests will vary relative to the OLS ones and the results in Table 1-8 confirm that a number of the associated series are non-stationary.

Table 1-8- ADF-ARCH Correction Test

Log differential price	ADF –ARCH test statistic
$X_2(16)$	0.473192
$X_3(3)$	-3.906158
$X_4(4)$	-6.853863
$X_5(4)$	2.219102
$X_6(3)$	-5.709768
$X_7(4)$	1.730302
$X_8(4)$	1.820151
$X_9(16)$	-3.647897

Note: ADF-GLS test Critical value at 5% is -2.89.

According to the above table the ARCH effect being corrected in X_2, X_5, X_7, and X_8,thisimplies that for the transformed data gives rise to test results that the series are non-stationary and this is now inconsistent with the Hadri test. So following correction our findings have been impacted by the nature of volatility and the conclusion of a broad market now seems to be less clear than would be suggested by the ADF tests alone.

1.12 Conclusion 1

Forni (2004) suggests that a broad market might be determined by a confirmatory analysis that follows from univariate stationarity tests on the null and alternative of non-stationarity producing a common conclusion. In one case it is found that the market is narrow between the Gulf Coast and the Lower Atlantic based on the ADF and KPSS tests without trend. However, all other cases based on the ADF test, suggests all regions price differentials are stationary. Here as compared with Forni, the reverse relations are accepted by definition and in the case of the ADF test it can be shown that this follows directly from the algebra of least squares.[18]

If now the Forni approach of combining ADF and KPSS tests, results at the 1% level is followed, then it can be concluded that the West Coast defines the broadest market in association with the Central Atlantic, Gulf Coast, Mid-West and New England; from the symmetry of the problem the reverse result also applies. Using this symmetry, the Mid West defines a broad market with the Central Atlantic, East Coast and West Coast. Similarly, the Central Atlantic defines an extended market

[18] In the case of the Dickey Fuller test related to equation (2) it is straightforward to show that the estimate of ψ that arises from the price proportion related to region 1 relative to region 2 is the same as that which arises from the reverse regression and the intercept (π_0) simply has the reverse sign. In the case of the ADF test the same applies when the lag order (q) is the same.

with the Mid West and the West Coast, and New England with the Rockies and West Coast. Finally, for the East Coast and Mid-West, the Gulf Coast and West Coast, and the Rockies and New England prices react to each other.

Beirne et al (2007) concluded in their analysis of real exchange rates that when the majority of univariate unit root tests and a panel stationarity tests reject the null of unit-root, then the conclusion to be drawn is that on average the series are stationary. Here, when the ADF tests are considered alone, eight out of the nine univariate tests reject the null of non-stationarity and so does the IPS test for the panel of nine price proportions. The conclusion related to Beirne et al (2007) would be that on average there is a broad market. The story that derives from the tests that follow from the non-stationary null is that prices are responding to each other in the long-run as the test can distinguish between the type of highly persistent behaviour related to a random walk and behaviour that is still related to quite strong autoregressive behaviour. Roots in each region that exceeds 0.85 can be seen as different from unity based on appropriately specified time series models that underline the ADF test.

It is an irony that the panel tests under the null of stationarity that are orientated towards the notion that the market is broad are the tests that seem least disposed to accept that conclusion. The Hadri tests with $N>1$ give little support to the proposition that the market is broad. Only in three cases with the largest bandwidth and the Parzen kernel testing at the 5% level it is possible not to reject the stationary null.

The underlying data are characterized by ARCH style volatility, strong serial correlation and non-normality. It is possible that the Hadri test may be unable to distinguish between strong autoregressive behaviour and a unit root. Hlouskova and Wagner (2006) provide some evidence that the Hadri tests may over-reject the null hypothesis when there is significant serial correlation, but this result is related to a small sample. Hadri (2000) suggests that his test is robust to non-normality. Though, the Hadri test is not corrected for ARCH and strong ARCH has been shown to affect the rate of asymptotic convergence of the Johansen trace test even with samples up to a 1000 observations with powerful volatility (Rahbek et al, 2002).

The diverse conclusion of stationarity associated with the panel and univariate tests suggests that there is not opportunity for long-run arbitrage correction. We do not feel it reasonable to conclude that the market is a broad. While some less well connected parts of the US do seem to respond less well to price variation from other regions. It is surprising the extent to which the statistics suggest that the Gulf Coast and Lower Atlantic appears to respond less well to almost all of the other regions and this would appear to require further investigation. These results would indicate a geographic market for US gasoline where there is some inefficiency especially where the lines of communication are poor and with that some room for degree of local market power and collusion related to gasoline prices occurs. Moreover, concentration of ownership of gas stations or refining capacity would be advised in the regions where stationarity is called into question.

Hence, since presence of a single common trend (cointegrating rank equal to 1) endorses competitive pricing and a broad market definition, we determine and analyse cointegrating rank and weak exogeneity in next chapter to clarify further our finding in chapter 1.

CHAPTER 2

Extracting Long-run Information from Energy Prices- The role of Exogeneity

2 Extracting Long-run Information from Energy Prices- The role of Exogeneity

2.1 Introduction

Gasoline is one of the products with the highest price variation in the world and the current dramatic changes in gasoline prices significantly affect the consumer and business behaviour in the market. The gasoline price is significantly influenced by innovation, technological progress, and political instability in the global economy.

The main concern of this research is long-run price differentiation in the gasoline market. In the short-run there is likely to be some price differentiation related to regional factors, but it seems less easy for this to arise in the long-run. Observing the process that gives rise to equilibrium in a market can confirm the appropriateness of the structure and the completeness of a market. Price disequilibria in the long-run between neighbouring regions would affect regional activity and consumers might react radically towards high price differentials by moving job and/or house to reduce travel costs, by the purchase of more fuel efficient vehicles etc., but the persistent price differential suggest discrimination and identifies the possibility of some market power and informational inefficiency.

In the preceding chapter we studied the log price differential and adapted the method of Forni (2004) to analyse price behaviour. In anticipation that in practice more limited samples would be available the panel approach was also considered. The approach of Forni is driven by the ready availability of price data and the suggestion by Forni that the time series method based on findings related to the stationarity of price proportions is econometrically efficient as parallel pricing can be tested in the long-run in one step. We employed the KPSS and Hadri unit root tests to test market definition and determined that the finding of non-stationarity across the US gasoline market would designate separate geographic markets for gasoline and suggests a narrower market definition as a result of market power or possible local collusion related to gasoline prices in different regions of the US.

The ECM approach is well motivated when the price proportions define an appropriate summary of the long-run (James Lothian, 2012). This occurs when the prices have significant common features that are extracted from the underlying series by analysing the price proportions.

- The first feature is a common stochastic trend that relates to cointegration.
- The second might be a common volatility pattern, were this to be a feature of the univariate series not observed in the price proportions.

The simulations reported in Rahbek et al (2002) suggest that the Johansen methodology is not greatly affected by the dynamic structure in variance associated with ARCH and GARCH. However this is only correct for moderately large samples when the stochastic process associated with the variance is not very persistent.

Forni (2004) suggests univariate unit-root tests of log price differentials can be used to determine a broad or a narrow market. However the regulation literature suggests that other information may be required to support an analysis based on unit-root tests alone to determine whether pricing is fair. In the previous chapter an amended version of the unit-root test process developed by Forni was applied to regional data by considering whether arbitrage can be observed as occurring at the regional level. The main concern of the chapter was whether prices follow each other in the long-run and to detect any anomalies and to determine whether structural breaks can also be viewed as a common feature.

In the preceding chapter the importance of stationarity for empirical modelling was considered and the nature of the null hypothesis used for testing stationarity. In the current study we apply in a more direct way the notion of cointegration introduced by Granger (1983) to investigate whether linear combinations of interrelated price data are stationary. Here, Johnsen (1988 & 1996) testing procedure for cointegration is used within the context of a vector autoregressive (VAR) model. This makes possible a test of the cointegrating rank to determine simultaneously the number of long-run relations that explain the market. Subject to the finding that there are N-1 such relations, it may then be possible to examine the existence of long-run price leadership. The former condition (N-1) is consistent with a single stochastic trend and this is consistent with weak exogeneity for one price in the US gasoline market. The main hypothesis is to study the long-run behaviour or the long-run efficiency of the US gasoline market. Linking parallel pricing and causal structure.

In this chapter We discover the weak exogeneity of variables for investigating the implication of cointegration for policy analysis and we discuss further the developments in the literature previously summarized in Hendry and Juselius (2001), Hunter and Burke (2012), Hunter and Tabaghdehi (2013) among others. That information on price can be provided efficiently to customers and that consumers are then able to monitor retail gasoline prices to enhance market efficiency and reduce detriment caused by imperfect information over prices (Hunter et al, 2001). The market efficiency hypothesis was first developed by Fama (1970) specifies that at any time *t* prices should fully reflect all available information on the market. To this end government intervention and regulation may be required to control price discrepancy and improve market structure or limit further concentration in the industry either at the national or the regional level.

In section 2.2 we reviewed of essential literature. Section 2.3 considers the data for the empirical analysis. Section 2.4 we reviewed the price analysis and cointegration. In section 2.5 we seek to find sufficient long-run relations that are then consistent with arbitrage correction and long-run equilibrium price targeting (LEPT) in gasoline market (Burke and Hunter, 2012). In part 2.6 we test for weak exogeneity, long-run exclusion, and strict exogeneity to investigate the nature of parallel pricing in the gasoline market. Finally, in Section 2.7 we conclude.

2.2 Review of Essential Literature

2.2.1 Price Dispersion and the Law of One Price

"Market is the whole of any region in which buyers and sellers are in such free intercourse with one another that the prices of the same goods tend to equality easily and quickly" (Alfred Marshall, 1920). In 1987 Scheffman and Spiller construe the market definition as "economic market is the area and set of products within which prices are linked to one another by supply-side or demand-side arbitrage and in which those prices can be treated independently of prices of goods not in the market." According to the "market" definition, in any homogeneous products industry such as gasoline, price will tend to equality. Maunder (1972) provides an early example where price correlations are interrogated to detect irregularities in pricing by companies.

The "law of one price" implies that in any market the price of identical goods must tend to be the same for an efficient market regardless of where they are traded. The law of one price can be reformulated in the case of transport and transaction cost. When prices at different locations differ as a result of transport and transaction cost, the arbitrage opportunity will still act to close the price gap after a short period of time. The error correction model (ECM) would appear to be an appropriate mechanism for analyzing the law of one price in the long-run (Johansen, 1995).

The "law of one price" is a paradigm that in practice at any point of time is unlikely to be valid even for homogeneous goods which are often sold at different prices by competitors.[19]Asplund and Friberg (2001) have evidence that the law of one price does not hold for identical goods even when they are sold in the same location.[20] Further, the cost heterogeneity and tax heterogeneity could lead to minor price differences.

However discrepancies in service or location can't explain completely the observed price distinction. Goldberg and Verboven (2005) indicate that there is a convergence towards the absolute and the relative version of the Law of One Price, and suggest that institutional changes can diminish the main source of segmentation in international markets.

[19] It is suggested that from the perspective of a shopper in one location the cost related to small variations in price will not cause them to shift the location of their purchase. However, supermarkets to enhance competition now advertise the extent to which some standardised price bundle differs from other major outlets. While some stores provide vouchers to make up any price disparity on the day of purchase, but these often are redeemed later on.
[20] Though care has to be taken as to the nature of the term location, Harrods and Sainsburys may be located close to each other, but the same product may be on sale at different prices.

Price dispersion arises from imperfect consumer information which is positively related to inflation (Van Hoomissen, 1988). In practice regular change in the gasoline price and highly frequent usage of gasoline makes the price-shop more difficult for consumers for whom the problem may be resolved by more comprehensive price information. Gasoline is also a derived demand and a product that is essential especial to local points in time and place. There may be no choice to be made.

As Chandra and Tappata (2008) pointed out consumer search is a significant and important factor affecting price dispersion in the gasoline market. They identified that production costs and price dispersion are negatively correlated where the number of firms is positively related to the price dispersion.

Carlson and McAfee (1983) introduced a search-theoretic model to reach the equilibrium price dispersion, where consumers identify suppliers' pricing strategies and consequential price distribution with the exclusion of the location of specific prices. They recognize an equilibrium price distribution depends on consumers' visiting costs heterogeneity and firm production costs heterogeneity assuming a limited number of sellers.

The other type of search-theoretic model of the equilibrium price dispersion states that consumers identify sellers' pricing strategies and the resulting price distribution, with the assumption of heterogeneity in consumers' visiting costs related to informed and uninformed consumers [21](Varian, 1980, Stahl, 1989 and Guimãraes, 1996).

[21]Informed consumers are those who compensate very low costs toward the search for the additional sellers thus they purchase from the lowest-priced seller, but uninformed consumers are those with high search cost which visiting the additional suppliers is accordingly expensive for them.

Stiglitz (1987) specifies a similar result when the market is large and consumers' search is price inelastic in a market with large number of firms[22]. Marvel (1976), using city-level data found that increases in the frequency of consumer search leads to a decline in price and price dispersion.

Png and Reitman (1994) studied station-level gasoline price as a homogeneous product and identified that gasoline stations distinguish themselves based on the offered service time and they classified that as service time competition[23]. Therefore, consumers on stations with higher prices face shorter queues and stations which offer lower price face longer queues. Therefore retail demand is responsive to service time. Barron, Taylor and Umbeck (2004) find using station-level data the number of competitors is negatively correlated to the average price levels and price dispersion, this indicates that large numbers of stations within a particular geographic area are related to lower average price and a lower level of price dispersion.

While, Adams (1997) finds that the price dispersion of gasoline in stations is lower than for grocery items sold in the convenience stores. Giulietti and Waterson (1997) compare the price of several products across Italian supermarkets and they find that lower consumer switching costs are related with lower levels of dispersion. However Schmidt (2001) suggests that there is a negative correlation between the number of competitors and average price in the rail freight markets meaning that an increase in the number of competitors decreases average prices respectively.

[22] In the market with many number of the firm a change in price construct a smaller proportion of consumers to modify their search respectively.

[23] Service time is the time which consumers' are willing to wait in order to buy the gasoline from the gasoline station.

In any competitive market the price differential must be equal to the cost differential of the firms as based on the assumption of free-entry with zero fixed cost the price is settled at marginal cost levels. In the multi-firm market price discrimination can be derived from consumer's readiness to spend relative to the quality of the related product (Shepard, 1991).

Slade (1992) identified a price war in US and Canada in the 1990s due to fuel tourism.

2.2.2 Competition and Geographical Price Discrimination

Considering the gasoline market as a competitive market, then the applied price for gasoline must be identical in the different regions of any country. Slade (1992) specified that the high steady-state equilibrium price in the Vancouver gasoline market when compared with Bertrand-Nash prices was an indication of implicit collusion, but she excluded the impact of the location in the analysis. Pinks, Slade and Brett (2002) estimate a competitive pricing model, which takes into consideration the location of the firm but for the differentiated product identify that competition in the US wholesale gasoline market is limited to a small area.

Slade (1992) identified that gasoline as a homogeneous product has a different price (station-level price) in the different regions of Canada, because of differences in the type of ownership, services offered and the location. Slade developed an econometric model of station pricing strategy and estimated a competitive pricing model by identifying the petrol suppliers whose competing daily prices in each period are based on the previous period price, consequently the current selected price has an impact on the supply level at each station.

Hotelling(1929), Salop(1979), and Gabszewicz and Thisse(1979) distinguish between local competition where firms are competing only with their neighbours directly with global competition where all products compete with all others without symmetric competition. However there has been a decline in the number of refineries in the last decade, which can have a considerable effect on the oil price increase and consequently generate price discrimination.

Stigler (1969) describes the geographical market as "the area within which the price of a commodity tends to uniformity, allowance being made for transportation costs". Considering any non-homogenous goods the quality differences can be considered as well as the transportation cost (Stigler and Sherwin, 1985).

LECG (1999) reported on much of the prior empirical work based on price series and found that a distinction had to be drawn in relation to the earlier literature on correlation and the more recent analysis considering non-stationarity in the estimation of and causal relations in a dynamic model. Vanya and Walls (1999) and La Cour and Møllgaard (2002) identified that cointegration analysis can be a practical mechanism for measuring competition in markets.

As was considered in the previous chapter, Forni (2004) viewed the unit-root test of the log price differential as a more effective way to analyse price relations and determine a broad (stationary) as compared with a narrow (non-stationary) market. A broad market identifies that the market is competitive[24]. To this end Giulietti et al (2010), and Hunter and Tabaghdehi (2013) have also applied univariate and panel

[24] A broad market is a terminology identified in Forni (2004) for a competitive market and the otherwise is narrow market as indicative of non-competitive market.

stationarity as compared with non-stationarity tests to study gasoline market competitiveness. We have applied a range of time series methods to test whether log price differentials were stationary as a monitoring procedure to examine the potential for an anti-trust case in the gasoline market, and investigate the structure of the gasoline market without any need to normalize on a specific price in the long-run or condition the problem relative to a price seen as exogenous. The Forni (2004) approach may be seen as relevant to the limited context of the data set used to analyse milk prices, but there were limitations with the nature of the analysis.

In this Chapter we address the issue of exogeneity and the interrelatedness of prices when we consider the VAR in error correction form.

An unanticipated gain from analysing price properties may be effective in testing for "market definition" when the persistence of the volatility is reduced by this transformation of the data. If volatility is quite persistent (the largest eigen value – spectral radius of the ARCH[25] polynomial exceeds .85) then the Johansen test may only converge to the asymptotic distribution for sample sizes in the range 600-1000 [26]depending on the specific Data Generation Process (DGP) selected (See the simulations in Rahbek et al (2002)).

The approach in this studyis appropriate for more extensive data sets of the variety we have here. It is hoped that it will be possible to verify the competitive behaviour in the market from the long-run decomposition of prices. Consequently we use the conditional ECM and VAR approach for testing cointegration, to develop the long-

[25]The notion of Autoregressive Conditional Heteroscedasticity (ARCH) relates to Engle (1982) and was first applied to price data for the UK.

[26]The interested reader is directed to the simulation results obtained by Rahbek et al (2002).

run relationships and consider the potential for arbitrage correction in the gasoline market.

2.2.3 Cointegration, Arbitrage and the Efficient Markets Hypothesis (EMH)

Since the last decade world oil consumption has been growing considerably which is one of the important factors driving the oil price boost and generates significant gains for the oil companies. However the key investigation of this study is why the gasoline price segregates in the different regions of one country at a specific time and this is contrary to market efficiency and may breach antitrust laws[27]. Price differentiation in different regions of a country identifies that prices are not fully reflecting all available information at any point in time.

In the gasoline market economists are concerned over market efficiency. Consequently any information spreads rapidly throughout all participants (Fama, 1970). Since all participants have identical information there is an **invisible agreement** which causes unremitting price differentiation without facing an arbitrage opportunity.

According to Fama (1979) there are three types of market efficiency as below:

I. Weak form efficiency
II. Semi-strong form efficiency
III. Strong form efficiency

[27] The Antitrust law it is a competition law that supports market competition by regulating anti-competitive performance of firms.

The difference between these three forms of market efficiency is based on the nature of the available information. In weak form efficiency the available information is historical prices and future prices can be predicted from historical prices signifying no chance of profit creation. Semi-strong form of efficiency reflects all public information in price movements, and finally strong form efficiency indicates that all types of information is reflected in the price movements which signifies no opportunity of profit making from that information (Fama, 1970).

Any specific patterns of pricing behaviour in the market that can give rise to profitable opportunities from arbitrage cannot survive for long and over time they will dissipate as others seek them out (Fama, 1998). However, in the US gasoline market the specific pattern of regional price differentiation may be constantly affecting market efficiency. Hence we employ the cointegration methodology of Johansen (1995) to test empirically the definition of the efficient market and the nature of the integration and cointegration of the price series.

However energy storability makes it suitable for price arbitrage and hedging. When considering the price of gasoline in the different regions of the US it is possible to observe opportunities for location arbitrage. Consequently to tackle arbitrage opportunities in a market-oriented industry to address market power there needs to be some form of regulation (Küpper and Willems, 2010). However, it is often argued that poor regulation in the gasoline market would distort competition.

2.2.4 Location Arbitrage

Energy storability makes it suitable for price arbitrage and hedging. When considering the dissimilar price of gasoline in different regions of the US it is possible to observe opportunities for location arbitrage.

An arbitrage opportunity in the gasoline market will increase energy transfer from the high-price regions to the low-price regions where the market size changes in both regions respectively. Therefore arbitrage opportunities should direct the market price towards a stable equilibrium price. In the short-run, arbitrage decreases the production efficiency in high-price regions since the production level increases, but in long-run it moderates the regional price discrepancy and all this informs the positive welfare effect of arbitrage in the economy as a result of “allocative efficiency”. However, increases in the production level for the high-price region, indicates a decrease in “productive efficiency”. Therefore there could be a negative impact from the arbitrage opportunity to welfare assuming the regions produce or refine their own fuel. By comparison in the electricity market there are three factors affecting the welfare effect of arbitrage: allocative, output and productive efficiency (Kupper and Willems, 2007).

In the 80s the retail gasoline price segregation in North America caused major demand shifts and consequently “fuel tourism” between the USA and Canada resulting in significant price war and market disruption (Slade 1992).

Dreher and Krieger (2008) investigated the weaker notion of consumer price arbitrage as compared to producer price arbitrage related to commodities such as diesel, gasoline and fuel oils analysed here in EU countries. Serletis and Herberst (1999) specified cointegration relations between natural gas and fuel oil and an effective arbitrage mechanism between markets. To tackle arbitrage opportunities in a market-oriented industry to address market power there needs to be some form of regulation (Willems and Küpper, 2010). However imperfect regulation in the gasoline market would distort perfect competition (Arrow, 1962 showed that imperfect information gives rise to a limit in the market place and this leads to downward sloping demand curves). The classical model is not applicable in the gasoline market as there are different production costs across disparate regions in the gasoline market.

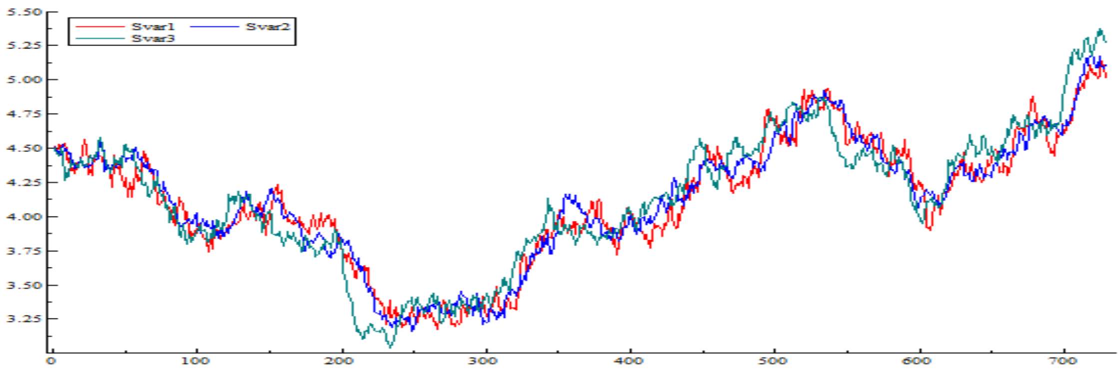
Graphical price dissimilarities are the most damaging factor for society when it gives rise to the greatest profit for the monopolist (Layson, 1988).

Giulietti, Price and Waterson, (2005) identified that in order to increase welfare through the competitive process there is a need to reduce switching cost by subsidising information for consumers to reduce search costs.

2.3 Time-series Properties of the Data

The following series were simulated by Burke and Hunter (2012) for comparison with the data analysed by Kurita (2008). It is tempting to find that there is a structural break, but these three series follow a common stochastic trend and cointegrate. The period used for calibration of these series did not include 2008 so the large movements arise purely as a result of the logarithmic random walk.

Figure 2-0- weekly gasoline prices across eight different regions in the US



Now consider the actual time series properties of a data set consisting of weekly gasoline prices across eight different regions in the US (West Coast (WC), Central Atlantic (CA), East Coast (EC), Gulf Coast (GC), Lower Atlantic (LA), Midwest (MW), New England (NE), Rocky Mountains (RM)) from May 1993 to May 2010.[28]

Considering regional gasoline infrastructure across the US we test cointegration on eight different regions. The data in (log) levels and (log) differences are graphed in Figure 2-1 and the frequency distributions of the data are graphed in Figure 2-2. From figure 2-1, the price level drifts upwards, whereas the price differences appear to move randomly around a fixed mean. While, the frequency distributions of the price level in figure 2 suggests non-stationarity and the frequency distribution of the differences suggest the series are closer to normality.

It is also of note that the data are volatile and that there are some large movements. It might be considered that the largest shocks relate to the financial markets crisis in 2008, but that is not the case. As can be observed from the time series plots and the

[28]The data have been obtained from the energy information administration website (www.eia.doe.gov).

findings in Kurita (2008) log gasoline prices are clearly difference stationary. Hunter and Tabaghdehi (2013) have applied a broad range of stationarity test on the log levels and log differentials of the data analysed here and they are also unable to reject the notion that these series are difference stationary (I(1)). As the largest movements relate to the earlier sample excluding the recent crisis, then it is anticipated the strongly persistent autoregressive behaviour during 2008 is indicative of the powerful movements that can be observed with series following stochastic trends. Burke and Hunter (2012) show that similar data can be readily calibrated and simulated as random walks. It should be noted that in the latter case the simulated data do not have any structural break, but vary in the same way as the actual data for the shorter sample used by Kurita.

Figure 2-1- Gasoline price at eight US locations in (log) levels and (log) differences

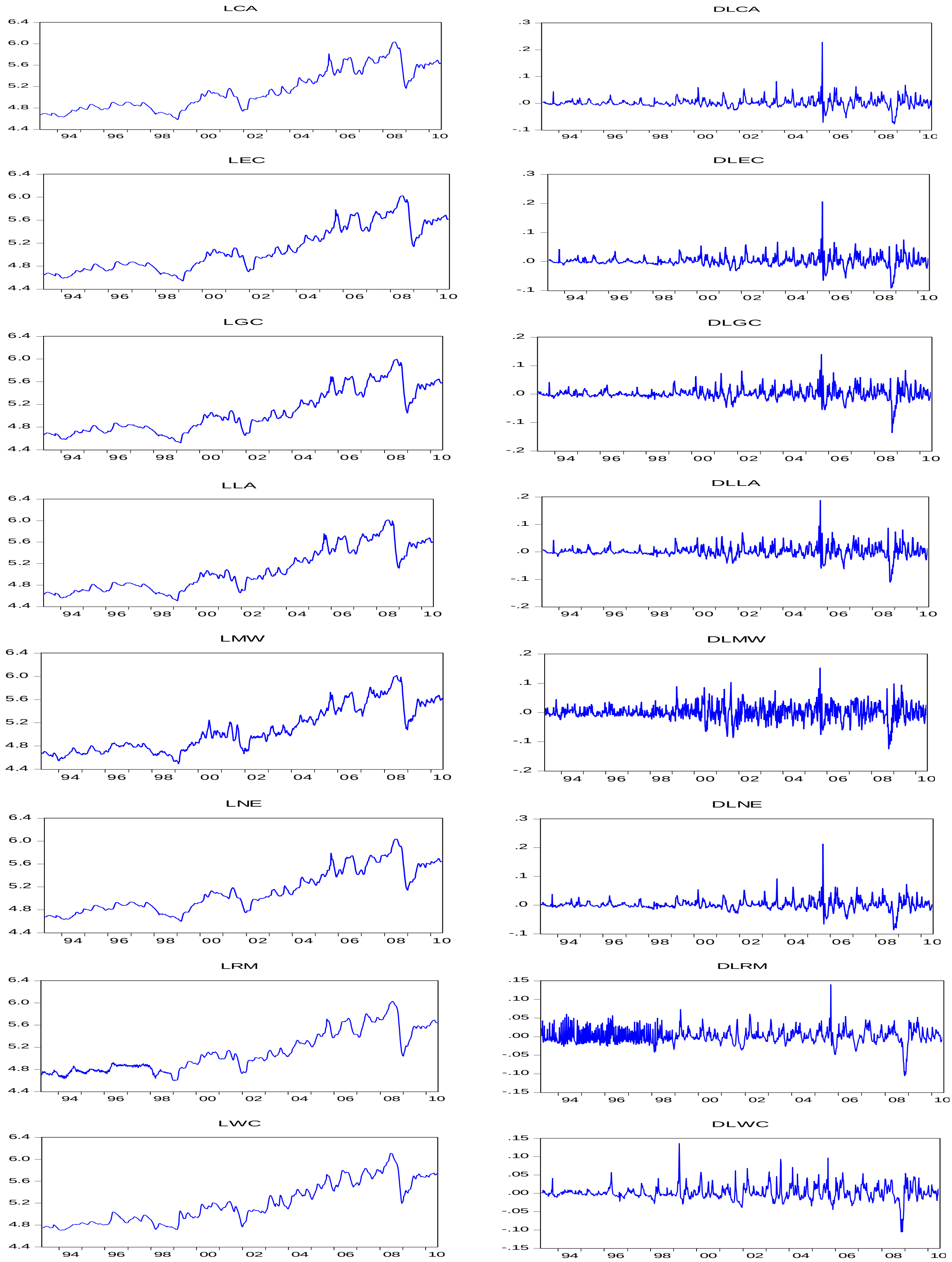
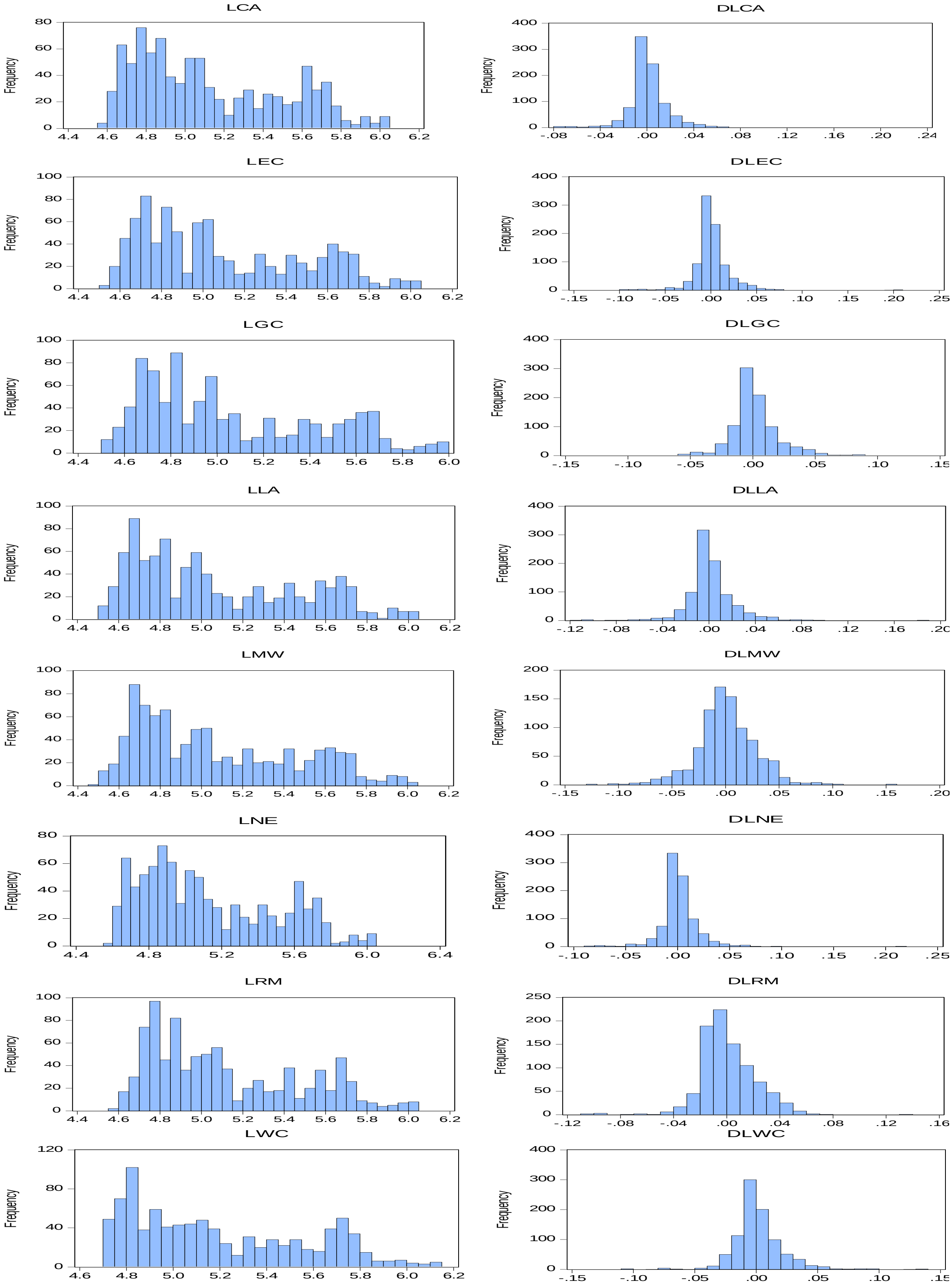


Figure 2-2- Frequency distribution of Gasoline price at eight US locations in (log) levels and (log) differences



2.4 Price Analysis, Cointegration and Arbitrage Correction in Gasoline Market

Time series might be non-stationary as a result of technological progress, economic evolution, crises, changes in the consumers' preference and behaviour, policy or regime changes, and organizational or institutional improvement. However, regressions based on stochastic non-stationary series simply as a result of cumulating the events or shocks of the past may give rise to 'nonsense regression', and this can cause significant problems in forecasting and inference (Hendry and Juselius, 2000).

The notion of cointegration is very important in the context of non-stationary variables. Cointegration implies that there is a linear combination of integrated variables which are stationary (Engle and Granger, 1987). In contrast to the previous chapter where stationarity is investigated in terms of price proportions, the coefficient does not have to be unity. Unit coefficients relate to an older literature on error correction models (Davidson et al, 1978). When a linear combination of two or more non-stationary variables is stationary and the coefficients differ from unity, then cointegration relates to what has come to be called equilibrium correction and this defines a long-run relation. If a long-run relation exists, then economic variables may drift away from equilibrium in the short-run but economic forces will eventually drive the variables back to the equilibrium relation.

Cointegration indicates the existence of a long-run correlation among variables when compared with the possibility that these relations are spurious (Granger and Newbold, 1974) implying that the regression obtained from non-stationary data many not be truly related. If the residuals of a regression between two variables have a pattern this signifies that proposed regression is miss-specified, but if the residuals are stationary, identifying that two series are cointegrated, then there is a long-run equilibrium relation between the two variables. [29]

Following Hosken and Taylor (2004), and Kurita (2008) we analysed the cointegration and exogeneity properties of regional gasoline prices in the US using regional data across the US mainland, this excludes Alaska that has a significant physical border, Canada.

De Vany and Walls (1999), Hendry and Juselius (2001), and Forni (2004) suggest that finding cointegration between two prices is indicative of an efficient market. Forni (2004) analyses all possible price combinations to determine whether the market is efficient basing the conclusion on a typology of the findings on stationarity tests under both the null of stationarity and non-stationarity. However this is a single equation approach that is not able to bind the findings to a test of all market segments.

[29]It has been known for some time that on-stationary data become stationary by linear transformation and differencing, $\Delta x_t = x_t - x_{t-1}$, is one such transformation when Δx_t is stationary. In the bivariate case when x_t and y_t are both non-stationary, there might be a linear combination of x_t and y_t which is stationary such as;

$\eta_t = y_t - \mu_0 - \beta x_t$ (4.1)

Engle and Granger (1987) showed that this relation could be found from estimation using linear least squares regression (cointegrating regressions):

$$y_t = \mu_0 + \beta x_t + u_t \quad (4.2)$$

and η_t does not equal $\mu_0 + u_t$ for that only occurs when $y_t = 0$ and $x_t = 0$. Granger (1986) identified (4.1) as a long-run equilibrium relation. Consequently cointegration is a restriction on a dynamic model (Hendry and Juselius, 2000). The cointegrating vector is usually normalized on one of the variables such as in the cointegrating combination of $y_t - \beta x_t$ it has been normalized on y_t where the $[1 - \beta]$ is relative cointegrating vector. Hence:

$[1 - \beta]\begin{bmatrix} yt \\ xt \end{bmatrix} = \eta_t \sim I(0).$

If there are more than two variables there can be more than one cointegrating vector.

Following Hunter and Burke (2007) it is suggested that arbitrage implies that there are *(N-1)* cointegrating relations derived from *N* price series and this is consistent with a broad market. While a narrow market implies fewer than *(N-1)* cointegrating relations. However, the finding of *(N-1)* long-run relations does not negate the possibility that the market is segmented in the sense that some prices do not respond to the other prices in the market. This may arise when the form of long-run causality related to cointegrating exogeneity (Hunter (1990)) is observed or detect that one or more prices is weakly exogenous (WE) for all the cointegrating vectors (Johansen, 1992).

Forni (2004) suggests that when comparison is made between the prices of two regions then competitive behaviour is consistent with parallel pricing when in testing price proportions it is found that they are stationary. However, such an approach has merit when the data is limited by the extent of the time series. Hunter and Burke (2007) suggest that univariate time series analysis does not provide a formal mechanism by which it may be confirmed that there are *N-1* such relations. They show that this may be better tested in a multivariate context and that it is possible to distinguish between a case where arbitrage holds and all the series follow a common stochastic trend and the case where there is aggressive price leadership or a single variable is WE for the matrix of cointegrating vectors (β).

In a bivariate case using gas prices conditioned on a WE oil price, Hendry and Juselius (2001) find that competition implies a common trend driving prices across markets and this idea is generalized by Hunter and Burke (2007) to a multi-price framework. We pay particular attention to the role of the common trend and exogeneity in explaining the competitive structure. Here there is a large time series sample and this is useful as the series are volatile.

In this study to determine potential long-run equilibrium relations in US gasoline prices in different regions, first for comparison with the stationarity testing methods applied by Forni (2004) we utilise the single equation cointegration analysis based on a bivariate model:

$$p_{at} = \mu_0 + bp_{bt} + u_t, \qquad (2\text{-}1)$$

where p_{at} and p_{bt} are prices of gasoline in two different regions of the US, and u_t is a random disturbance term. Here μ_0 represents the log of the proportionality coefficient

Now $\mu_0 = 0$ when the prices in different regions are identical, and $\mu_0 \neq 0$ if there is a fixed transportation and other characteristics related to different regions. However with a perfectly integrated market the price reflects all available information and traders ought not to benefit consistently from arbitrage opportunities. Equation [2-1] is a cointegrating regression where b explains the nature of the relation between the regional prices. The hypothesis related to parallel pricing implies that $b=1$ is the key hypothesis to be tested as when $b=1$, regional prices respond in proportion to each other and this conforms with the law of one price. Though the observed value may differ from 1 by an arbitrary constant(c) where $|b-1| \leq c$. In the case of perfect integration c is close to zero.

In contrast with the tests of stationarity of price proportions, the linear combination of two non-stationary series p_{at} and p_{bt} can be transformed to stationarity (Engle and Granger (1987)) when:

$\eta_t = p_{at} - bp_{bt} \sim I(0)$. (2-2)

This embodies the notion of cointegration that two (or more) I(1) series, here p_{at} and p_{bt}, give rise to a relation that is stationary. Therefore when η_t represents a residual from a regression, then when this combination is stationary there is a long-run relation between p_{at} and p_{bt} otherwise the relation is nonsense. Consequently for the price of any homogeneous good in an identical market a cointegrating relation is required as arbitrage should remove mispricing in the long-run.

One difficulty with the Engle and Granger (1987) test is the nonstandard nature of the statistical inference and that it does not provide a direct test of the law of one price (Forni, 2004). However, the methodology developed by Johansen (1995) can be applied to test the law of one price in a VAR and the potential for price leadership. When the gasoline prices of different regions in the US are identical, then the associated market will be in equilibrium, otherwise there would arbitrage opportunities across regions.

Here, the ECM provides one method to investigate the nature of adjustment across prices to determine long-run equilibrium, see Patterson (2000). We investigate long-run equilibrium in the US gasoline market using the error correction model. This case in particular is termed arbitrage correction by Burke and Hunter (2012). The hypothesis underlying this argument relates to the possibility that a sequence of regional gasoline prices that deviate from equilibrium give rise to an arbitrage opportunity that is correcting in the long-run. If there are *N-1* arbitrage correction terms across *N* markets, then this also relates to LEPT (Burke and Hunter, 2011).

According to Kremers, Ericsson, and Dolado (1992) the ECM is a good model to detect long-run behaviour. The single equation ECM is a starting point for modelling, which binds the cointegration relations in the long-run and as a result of super consistency (Ericson and MacKinnon, 2002) the approach is robust to specific lag lengths and model dynamics.

To further investigate the short-run dynamics of the relations in gasoline prices of different regions in the US we employ a vector error correction model (VECM). For example, Bachmeier and Griffin (2006) found that the prices of crude oil in different geographical regions of the world are cointegrated. While De Vany and Walls (1999) using a VECM, identified cointegration between eleven regions of the US in relation to electricity prices.

The first step of the Engle and Granger (1987) method identifies equilibrium relations from a cointegrating regression that gives rise to an error correction term estimated from the OLS residual:

$$\hat{\eta}_t = e_t = p_{at} - \hat{\mu}_o - \hat{b} p_{bt}. \quad (2\text{-}3)$$

We may test whether these series are stationary by applying the Dickey-Fuller test to these residuals and this relates to the following dynamic model:

$$\Delta\hat{\eta}_t = \gamma\, \hat{\eta}_{t-1} + v_t \qquad (2\text{-}4)$$

$$\Delta\hat{\eta}_t = \gamma_0\, \Delta p_{bt} + \gamma\, \hat{\eta}_{t-1} + \epsilon_t \qquad (2\text{-}5)$$

where:

$\epsilon_t = \gamma_0\, \Delta p_{bt} + v_t$ then $b = b_0$ and $\gamma_0 = b - b_0$

It is also possible to have cointegration as a result of $\gamma < 0$, but this may not be consistent with efficiency as $\mu_o \neq 0$ and $b \neq 1$. In the long-run when the prices are set to their long-run average values $p_{at} = \check{p}_{at}$, $p_{bt} = \check{p}_{bt}$, then:

$$\check{p}_{at} = \mu_0 + b\check{p}_{bt}$$

where the μ_0 and b are long-run parameters. For efficiency in the market, to avoid persistent long-run profit being exploited from arbitrage possibilities we require $\mu_0=0$, $\beta=1$. Therefore:

$$p_{at} = p_{bt} + \eta_t \text{ or } \eta_t = p_{at} - p_{bt}\,;\ \hat{\eta}_t = \eta_t$$

It follows that the ECM gives rise to a long-run relation restricted to the same form as the Dickey-Fuller model used to test stationarity (Dickey and Fuller, 1979). It is shown in Kremers et al (1992) that the Dickey Fuller (DF) test that is applied by Forni (2004) is a special case of a pure ECM (see Davidson et al, 1978). Therefore:

$$\Delta\, (p_{at} - p_{bt}) = \gamma\, (p_{at-1} - p_{bt-1}) + v_t. \qquad (2\text{-}6)$$

Equation (2-6) is a restricted version of the model applied at the second step of the Engle-Granger approach where the lagged equilibrium error is defined by Hendry (1995) in this more general case as an equilibrium correction term. Here we follow the pure ECM approach where $(p_{at-1} - p_{bt-1}) = \eta_t \sim I(0)$ indicates that the

ECM defines the equilibrium error or when $\eta_t \sim I(1)$ this is not an equilibrium error. The γ in equation (2-6) is a short-run parameter and specifies how quickly the disequilibrium will be removed from the system or the speed at which arbitrage occurs.[30] Therefore the larger the absolute value of γ the more quickly any disequilibrium or mispricing will be removed. The null hypothesis H_0: $\gamma = 0$ tests the significance of the error correction coefficient, when compared with the one sided alternative of H_A: $\gamma < 0$.[31] The rejection of H_0 is evidence supporting cointegration and market efficiency.

The error correction representation exists if p_{at} and p_{bt} are cointegrated. Furthermore, with *N* price variables, adapting the results in Smith and Hunter (1985) to the non-stationary case, there are *1/2N(N-1)* non-trivial combinations of error or cross arbitrage correction terms between all the prices. Such relations are termed coherent by Smith and Hunter (1985) when the slope coefficients are the same and for pure arbitrage that is unity. The zero intercept restriction is not critical to the argument though it gives rise to the same error correction applying in the long-run for all these combinations. It follows from Smith and Hunter (1985) in relation to the cross arbitrage for exchange rates that in the coherent case when *N-1* stationary relations are found, then by simple algebraic manipulation and the stationarity of the primary relations the remaining *½(N-1)(N-2)* should also be stationary. Non-coherence implies that different stationary or some non-stationary combinations may arise and as a result some of the long-run relations may include all the prices.

[30] ***γ %*** of the disequilibrium at time ***t-1*** is removed in period ***t***.
[31] ***γ*** >0 implies that variables are moving in the wrong direction to correct for disequilibrium.

The results for the augmented Dickey Fuller (ADF) test on differentials and ECM estimations are presented in Table 1.[32] Acceptance of the alternative hypothesis underlining the ADF tests implies that the price proportions related to eight combinations are stationary based on a one sided test at the 5% level. Significant results indicate that the series move in proportion to each other in the long-run, but any rejection of the alternative may arise as a result of the bivariate analysis of the problem.

Table 2-1- Summary of ADF test, ECM test of regional price proportion. (With intercept and no trend)

Log price differential (q)[33]	ADF (q)/ OLS t-statistic	ECM (q)/ OLS t-statistic
$P_{NE\text{-}MW}$ (25)	-3.81**	-14.48 **| P_{MW}
$P_{MW\text{-}CA}$ (25)	-4.93 **	-8.70 **| P_{CA}
$P_{MW\text{-}EC}$ (25)	-4.72 **	-10.15 **| P_{EC}
$P_{LA\text{-}GC}$ (23)	-2.22	-5.63 **| P_{GC}
$P_{RM\text{-}WC}$ (16)	-5.81 **	-6.62**| P_{WC}
$P_{MW\text{-}GC}$ (20)	-3.36*	-8.46 **| P_{GC}
$P_{GC\text{-}RM}$ (16)	-5.21**	-1.22 | P_{RM}
$P_{GC\text{-}WC}$ (20)	-3.78**	-2.65 | P_{WC}
$P_{MW\text{-}RM}$ (24)	-4.43**	-3.76 **| P_{RM}

Note: Critical value at 1% is -3.44, at 5% is -2.87 computed in Oxmetrics Professional (Doornik and Hendry, 2009). * Significant at the 95% confidence level and ** significant at the 99% confidence level

In the case of the ECM, testing for cointegration follows from an analysis of each single equation in turn via individual significance of the error correction term. In all but one case the error correction terms are significant, this one exception may arise due to a lack of cointegration, weak exogeneity,[34] or that the cointegrating relation cannot be identified from a single error correction term in

[32] All estimations are undertaken using Oxmetrics Professional (Doornik and Hendry, 2009).
[33] q is the lag order of each series which had been selected by using same process as the previous study via inspection of the correlogram.
[34] I a single equation context one may observe more WE variables than can arise when the rank restriction is applied across the system.

a single equation dynamic model. In the case of the ADF test this may arise, because this model imposes efficiency on both the short-run and the long-run relations. This is given support by the observation that this coefficient is significant in the error correction model for the GC and LA.

Based on Dickey Fuller inference (Patterson, 2000) the coefficient on the error correction term is not significant in two cases that relate to the RM and the WC relative to the GC. However, according to Kremers, Ericsson and Dolado (1992), the error correction test is asymptotically normal, but converges at a slower rate than is usual with conventional inference (Ericsson and MacKinnon, 2002). Assuming such convergence and normal inference the only insignificant case would relate to the WC. The latter may arise for three reasons, the most obvious when comparison is made with the ADF tests, would be that the model is over-parameterised or the test inefficient as a result of the number of lag terms included in the model. This relation may arise as a result of inefficiency or the RM model may not contain an error correction term as this price is WE for the long-run relation. In the latter case it forces, but is not forced by the rest of the US market. The rejection of cointegration may also be a function of the bivariate nature of these models.

In further investigating the system we follow Boswijk (1992), Hunter and Simpson (1996), and Bauwens and Hunter (2000) and apply restrictions on $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ (dimensioned $N \times r$), and $\boldsymbol{\alpha}$ as well as $\boldsymbol{\beta}$ to study the exogeneity structure of the data and identify potentially WE variables.

The following equation is the VECM parameterisation of the VAR:

$$\mathbf{\Gamma}\,(\mathbf{L})\;\Delta\;\mathbf{p_t} = \mathbf{\Pi p_{t-1}} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_\mathbf{t} \qquad (2\text{-}7)$$

Where $\mathbf{\Gamma(L)}$ =($\mathbf{I}$ - $\mathbf{\Gamma_1}$ L - ... -$\mathbf{\Gamma_{k-1}}$ L^{k-1}), $\mathbf{\Gamma_i}$ are $N \times N$ matrices and $\mathbf{I}$ an N dimensioned identity matrix. The hypothesis that relates to the cointegrating rank is:

$H_1(r)$: $\mathbf{\Pi} = \alpha\beta'$.

Using the Johansen trace test we identify the number of cointegrating vectors (r) and the number of common trends. The results on the Johansen trace test for eight regional gasoline prices in the US are presented in Table 2-2. We find that it is possible to accept the null hypothesis that there are $r=5$ cointegrating vectors for a test applied at the 5% level, the alternative is rejected as the test is not significant so $r>5$ cannot be accepted. This also implies that there are N-$r=3$ stochastic trends. This does not correspond with the results that arise when cointegration is tested based on the single equation methods. If $r<N-1$ there are more stochastic trends than might be anticipated by a single competitive market implying that LEPT cannot hold and the market is partitioned.

Table 2-2- Johansen trace test for cointegration

H_0 : rank ≤	Trace test	P-value
rank =0	226.673	[0.0000] **
rank =1	159.485	[0.0001] **
rank =2	115.337	[0.0012] **
rank =3	76.017	[0.0147] *
rank =4	48.471	[0.0437] *
rank =5	28.207	[0.0754]
rank =6	11.631	[0.1755]
rank =7	1.1499	[0.2836]

Note: * significant at the 5% level and ** significant at the 1% level.

Further analysis is required to interrogate the nature of the inter-relations that may impact price behaviour. Each long-run relation will be forced by up to three trends so there may be up to three different prices driving the system in the long-run. There may also be the type of separation in the market place related to cointegrating exogeneity and quasi-diagonality (Hunter, 1992) or weak exogeneity (Johansen, 1992). In the first instance gas prices in different parts of the US may respond to a different stochastic trend or in some parts of the US there may be relations linked to all the trends and in others to a subset of trends. Up to three variables may also be WE implying that they are not affected by the long-run price behaviour in the other segments of the market.[35] Such segmentation may be consistent with price differentiation and these anomalies are indicative of collusive agreements or when long-run causality can be detected there is potential for leadership by some of the major gasoline suppliers'.

Exogeneity and Causality Analysis- Test of Weak Erogeneity and Parallel Pricing

Granger (1969) devised a means to test for causality in the context of stationary series, while the concept of cointegrating exogeneity was developed by Hunter (1990) to handle causality between non-stationary variables in the long-run. Giannini and Mosconi (1992) tested Granger Causality subject to CE. Testing for causality has been found useful by Horowitz (1981), Ravallion (1986), Slade (1986), and Gordon, Hobbs, and Kerr (1993) in defining market boundaries. Here, subject to the finding on rank, the focus will be on exogeneity restrictions and long-run exclusion.

[35] See Chapter 5 of Burke and Hunter (2005) for further discussion of weak exogeneity related to sub-blocks of the cointegrating vectors.

The most general test for cointegration is the multivariate test based on the vector autoregressive model (Johansen, 1988). Following the VAR analysis we verify the interrelationships between variables and model the ECM in a multivariate context by first identifying *r* cointegrating combinations with a set of *N* variables. As a result of the VECM structure we are able to further investigate:

- long-run exogeneity
- short-run causality
- The nature of causality in the variance and the mean equation

The adjustment parameters in the VAR system clarify the potential causality and weak exogeneity in the market and provide information on price leadership and the extent to which one region may be important in relation to setting price.

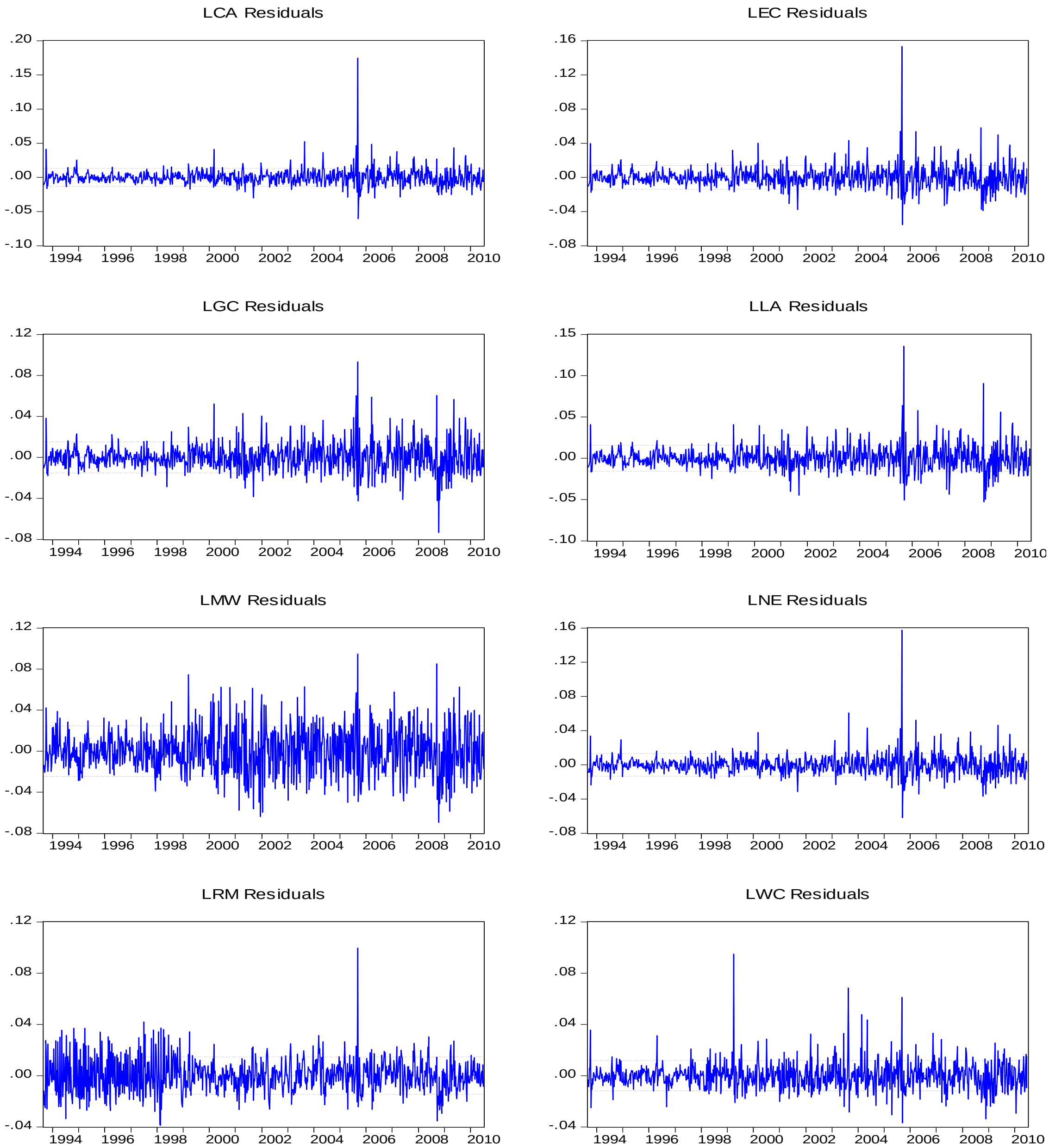
Table 2-3 indicates some descriptive statistics for the log gasoline price, differences, and for the residuals of the VAR model. Noticeably the gasoline price changes (price differences seems to be stationary around a constant mean of approximately zero. Using the Jarque-Bera test normality is tested under the null that the series are normal and this is strongly rejected in most of the price changes series. The significant rejection of the null hypothesis could be explained by the excess kurtosis or skewness.

Table 2-2- Descriptive statistics

1993 – 2010	$\bar{x}$	$S\bar{x}$	Skew	Kurt	Jarq.Bera	Min	Max
P_{CA}	5.123	0.374	0.56	2.10	77.27	4.58	6.04
P_{EC}	5.095	0.384	0.57	2.10	78.50	4.54	6.03
P_{GC}	5.063	0.375	0.64	2.21	84.41	4.52	6.00
P_{LA}	5.072	0.393	0.58	2.10	81.11	4.51	6.02
P_{MW}	5.076	0.383	0.58	2.14	77.32	4.49	6.02
P_{NE}	5.127	0.366	0.56	2.16	74.02	4.60	6.04
P_{RM}	5.117	0.361	0.65	2.24	84.15	4.60	6.03
P_{WC}	5.194	0.370	0.52	2.03	75.51	4.70	6.11
ΔP_{CA}	0.001068	0.018	2.14	33.25	35004.83	-0.08	0.23
ΔP_{EC}	0.001078	0.019	1.17	20.94	12274.99	-0.09	0.21
ΔP_{GC}	0.001008	0.020	0.12	10.43	2070.90	-0.14	0.14
ΔP_{LA}	0.001074	0.021	0.60	13.96	4554.93	-0.11	0.19
ΔP_{MW}	0.001042	0.028	0.01	5.42	219.65	-0.12	0.15
ΔP_{NE}	0.001073	0.018	1.59	25.64	19599.10	-0.09	0.21
ΔP_{RM}	0.001046	0.021	0.11	7.35	712.90	-0.10	0.14
ΔP_{WC}	0.0011	0.020	0.61	9.82	1799.24	-0.11	0.14

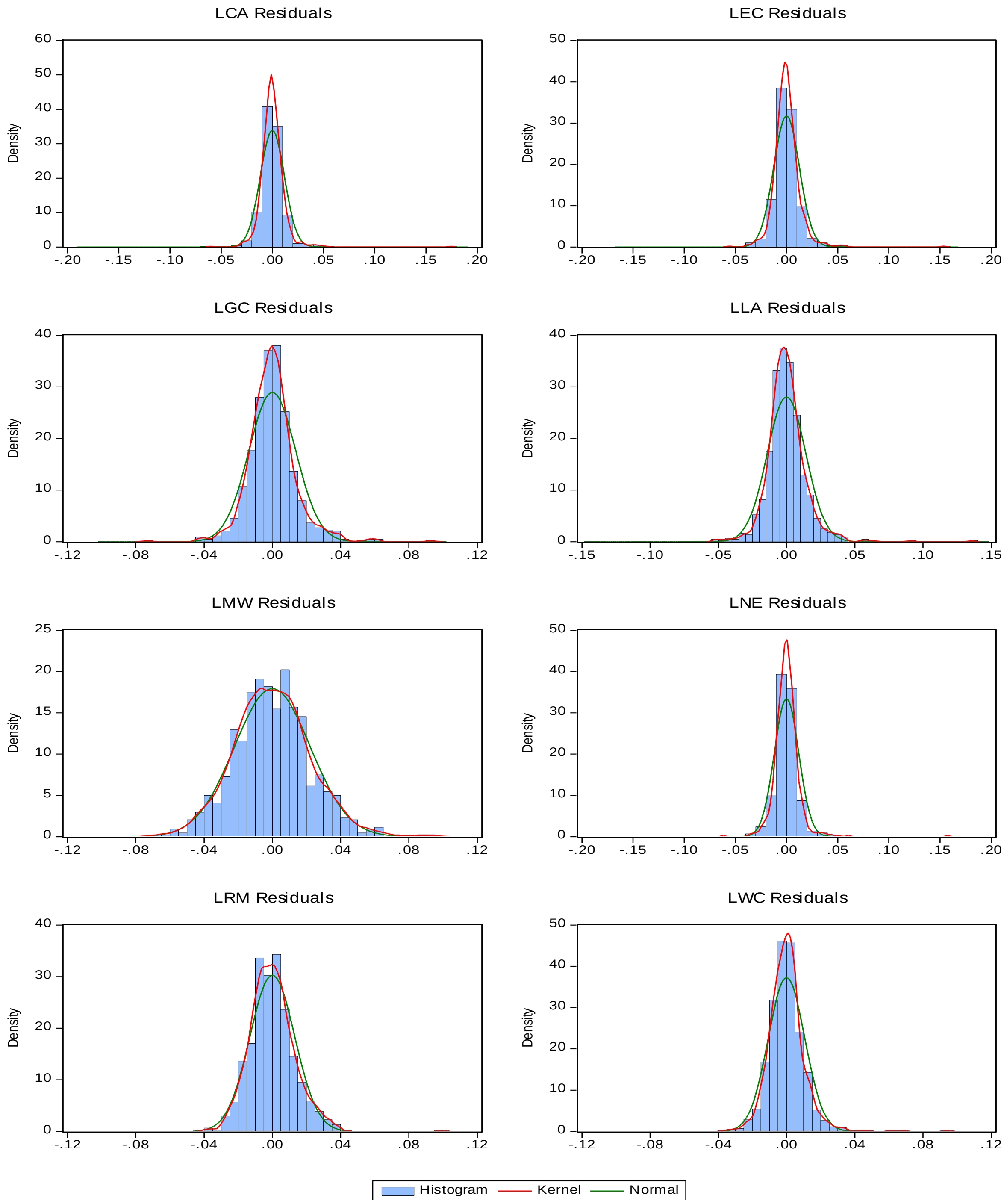
Considering Figure 2-3, there are some outlier observations in the residuals and the largest outlier is at end of 2004 and beginning of 2006 which needs to be effectively explained in the specification of the VAR model. These observed outliers could be caused by extreme demand and supply shocks in regions.

Figure 2-3- Graph of residuals from a VAR (20) of US regional gasoline price and 99% confidence bands



In Figure 2-4, the density of 8 VAR residuals is reported. The kernel density should not deviate excessively from the normal density; whereas residuals need to be homoskedastic with constant variance over time. However having longer tails in a kernel density comparing with normal density indicates the existence of the outliers and confirms the non-normality, finding from Jarque-Bera test in Table **2-3**.

Figure 2-4- Normal Density of 8 VAR residuals of US regional gasoline price



Analysing single equations from the VAR, econometrically and theoretically is less restrictive. At one level the ADF test imposes a common factor restriction that relates to market efficiency being imposed on the short-run relations, thus causing the arbitrage restriction to be imposed on the short-run parameters. Hence by estimating the VAR the short-run restriction does not bind and relating this to the ECM, we can determine whether there is market segmentation and the nature of arbitrage across the system. Following Hendry and Juselius (2001) we consider the conventional VECM, but with eight potentially inter-related market prices.

The VECM model (2-7) applied here is based on a VAR(k) where Δp_t is stationary the error term is stationary and based on the previous analysis there are *r=N-3* long-run relations. However, a generous or more careful interpretation of the results derived from the single equation approach might suggest *N-1* stationary relations subject to finding of a WE variable. A stricter reading of the ADF tests might also suggest *r=N-2*, the error correction models somewhere between *N-2* and *N-3* when compared with the Johansen test where it is *N-3*.

Following De Vany and Walls (1999) we consider cointegration as a system and that may relate to the more general case of LEPT (Burke and Hunter, 2011). Cointegration across the system gives rise to a set of long-run relations that are tested jointly. Furthermore, the finding of weak exogeneity can distinguish between parallel pricing and aggressive price leadership (Hunter and Burke, 2007 and Kurita, 2008).

Irrespective of *r*, when the series are cointegrated there is a restricted long-run parameter matrix:

$\boldsymbol{\Pi} = \boldsymbol{\alpha\beta}'$.

These can be identified in turn by setting $\boldsymbol{\alpha}'=[\mathbf{A}\ \mathbf{I_r}\ ]$ or $\boldsymbol{\beta}'=[\ \mathbf{I_r}\ \mathbf{B}]$ and then we either find the $\boldsymbol{\beta}$ specifying the long-run relations, or we identify all the elements of $\boldsymbol{\alpha}$ that gives rise to adjustment to each cointegrating relation in the short-run. Let the i^{th} column vector of $\boldsymbol{\beta}$ be denoted $\boldsymbol{\beta}_{.\mathbf{i}}$. Subject to a normalisation on the ith element, then $\boldsymbol{\beta}_{.i}=$ $[\beta_{1i} \quad \dots \quad 1 \quad \dots \quad \beta_{Ni}]'$. The existence of cointegration in a VAR system implies that the stochastic trends are combined as *r* stationary linear combinations; there are *N-r* of these trends and this may give rise to no more than *N-r* weakly exogenous variables (Johansen (1995)). In this study there are eight price series and *r=N-3* the corresponding unrestricted model is specified as follows:

$$\begin{bmatrix} \Delta p_{1t} \\ \vdots \\ \Delta p_{8t} \end{bmatrix} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,5} \\ \vdots & \ddots & \vdots \\ \alpha_{8,1} & \cdots & \alpha_{8,5} \end{bmatrix} \begin{bmatrix} 1 & \cdots & \beta_{7,1} & \beta_{8,1} \\ \vdots & \ddots & \vdots & \vdots \\ \beta_{1,5} & \cdots & \beta_{7,5} & \beta_{8,5} \end{bmatrix} \begin{bmatrix} p_{1t-1} \\ \vdots \\ p_{8t-1} \end{bmatrix} + \begin{bmatrix} \gamma_{1,1}(L) & \cdots & \gamma_{1,8}(L) \\ \vdots & \ddots & \vdots \\ \gamma_{8,1}(L) & \cdots & \gamma_{8,8}(L) \end{bmatrix} \begin{bmatrix} \Delta p_{1t-1} \\ \vdots \\ \Delta p_{8t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{8t} \end{bmatrix}.$$

Where $\gamma_{i,j}(L)$ for $i, j = 1,\dots,8$ is a univariate polynomial of lag order *k*. Hence for studying the gasoline market structure and identifying the number of long-run relations, it is necessary to impose further restrictions on the VAR model.

Following, Johansen (1992), Hunter and Simpson (1995), Bauwens and Hunter (2000), and Burke and Hunter (2012) weak exogeneity in the long-run has been identified by imposing a restriction on a each row vector $\boldsymbol{\alpha}_{\mathbf{i}.}=[0, 0, 0, 0, 0]$ from $\boldsymbol{\alpha}$ in turn (for i=1, … ,8) and that excludes the long-run from each equation in the system. While long-run exclusion (Juselius, 1995) can be tested by imposing restrictions in $\boldsymbol{\beta}_{\mathbf{i}.}=[0, 0, 0, 0, 0]$ on each row vector of $\boldsymbol{\beta}$ in turn for i=1, … , 8 and that excludes a variable from all the cointegrating vectors. Weak exogeneity and long-run exclusion impose r restrictions on $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ for the variable excluded. Strict exogeneity combines the weak exogeneity and long run exclusion restrictions for the i^{th} variable and imposes *2r* restrictions for each variable excluded from $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. The restrictions are tested by further likelihood ratio test statistics, which conditional on *r* are distributed $\chi^2(i)$ with *i=r* and *2r* respectively**.**

A further component of the process used to identify is to select the most appropriate normalisation of the data by imposing the restriction below:

$$\beta_{ii}=1, \text{ for } i=1, \ldots, 5$$

$$\beta_{ij}=0 \text{ , for } \begin{cases} i = 1, \ldots, 5 \\ j = 1, \ldots, 5 \\ i \neq j \end{cases}.$$

Bauwens and Hunter (2000) suggest it is important not to normalise on a variable that is weakly exogenous and Boswijk (1996) suggests the same for long-run exclusion. For parallel pricing let the first column of $\boldsymbol{\beta}$ be tested by imposing restrictions of the form $\boldsymbol{\beta}_{.1} = \begin{bmatrix} 1 & 0 & \mathrm{L} & -1 \end{bmatrix}'$ and subsequently for $\boldsymbol{\beta}_{.i}$ the i^{th} term is set to unity and all the other up to N^{th} can be set to zero to confirm a long-run correspondence between the price series.

In Table (2-4), tests of cointegration are derived from the VAR model and the results related to the imposed restrictions on $\boldsymbol{\alpha}$ or $\boldsymbol{\beta}$ or both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are presented accordingly. The sample includes 901 observation and the results relate to tests of weak exogeneity, long-run exclusion and strict exogeneity.

There are $k=21$ lags in the VAR estimations. The first block of results in Table (2-4) relate to a weak exogeneity test conditional on $r=5$ and from the p-values it can be determined that the log price of the GC, the LA and the MW are potentially WE for $\boldsymbol{\beta}$. The joint test that all the $N\text{-}r=3$ variables are WE for $\boldsymbol{\beta}$ giving rise to 15 restriction is clearly rejected at the 5% level as the test, 38.227 has a p-value = [0.0008]. However, the null hypothesis cannot be rejected that the GC and the MW price series are WE for $\boldsymbol{\beta}$ as the test is 14.273 [0.1609], and similarly for the LA and the MW prices as the test is 15.280 [0.1222]. However, this does not hold for the GC and the LA prices. There are good reasons to order the system based on these tests as when the system is normalised this can be seen as a conditioning on the series most likely to be exogenous (Hunter and Simpson (1995)).

Table 2-3- -Test of cointegration, WE, LE, SE and Parallel Pricing of US Gasoline Price (1993-2010)

Hypothesis		Null ($r \leq 5$)	Statistics [p-value]
(WE)| r=5	P_{CA}	$\alpha_{1i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 18.872 [0.0020]**
	P_{EC}	$\alpha_{2i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 11.359 [0.0447]*
	P_{GC}	$\alpha_{3i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 5.1254 [0.4008]
	P_{LA}	$\alpha_{4i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 6.2379 [0.2838]
	P_{MW}	$\alpha_{5i}=0$, for i=1, ..., 5	$\chi^2(5)$ =8.9639 [0.1105]
	P_{NE}	$\alpha_{6i}=0$, for i=1, ..., 5	$\chi^2(5)$ =13.569 [0.0186]*
	P_{RM}	$\alpha_{7i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 32.671 [0.0000]**
	P_{WC}	$\alpha_{8i}=0$, for i=1, ..., 5	$\chi^2(5)$ = 19.753 [0.0014]**
(LE)| r=5	P_{CA}	$\beta_{j1}=0$, for j=1, ..., 5	$\chi^2(5)$ = 21.249 [0.0007]**
	P_{EC}	$\beta_{j2}=0$, for j=1, ..., 5	$\chi^2(5)$ = 12.304 [0.0308]*
	P_{GC}	$\beta_{j3}=0$, for j=1, ..., 5	$\chi^2(5)$ = 17.971 [0.0030]**
	P_{LA}	$\beta_{j4}=0$, for j=1, ..., 5	$\chi^2(5)$ = 10.782 [0.0559]
	P_{MW}	$\beta_{j5}=0$, for j=1, ..., 5	$\chi^2(5)$ = 26.335 [0.0001]**
	P_{NE}	$\beta_{j6}=0$, for j=1, ..., 5	$\chi^2(5)$ = 1.0869 [0.9553]
	P_{RM}	$\beta_{j7}=0$, for j=1, ..., 5	$\chi^2(5)$ = 40.178 [0.0000]**
	P_{WC}	$\beta_{j8}=0$, for j=1, ..., 5	$\chi^2(5)$ = 29.493 [0.0000]**
Normalization (N) + (WE) P_{GC}, P_{MW} | r=5		$\beta_{ii}=1$, for i=1, ..., 5 $\beta_{ij}=0$, for $\begin{cases} i = 1, \dots, 5 \\ j = 1, \dots, 5 \\ i \neq j \end{cases}$ $\alpha_{3i}=0$, for i=1, ..., 5	$\chi^2(10)$ = 14.273 [0.1609]
SE = (LE) + (WE)| r=5	P_{CA}	$\alpha_{1i}=0$, for i=1, ..., 5 $\beta_{j1}=0$, for j=1, ..., 5	$\chi^2(10)$ = 35.633 [0.0001]**
	P_{EC}	$\alpha_{2i}=0$, for i=1, ..., 5 $\beta_{j2}=0$, for j=1, ..., 5	$\chi^2(10)$ = 20.717 [0.0232]*
	P_{GC}	$\alpha_{3i}=0$, for i=1, ..., 5 $\beta_{j3}=0$, for j=1, ..., 5	$\chi^2(10)$ =22.520 [0.0127]*
	P_{LA}	$\alpha_{4i}=0$, for i=1, ..., 5 $\beta_{j4}=0$, for j=1, ..., 5	$\chi^2(10)$ =30.611 [0.0063] **
	P_{MW}	$\alpha_{5i}=0$, for i=1, ..., 5 $\beta_{j5}=0$, for j=1, ..., 5	$\chi^2(10)$ =32.287 [0.0004]**
	P_{NE}	$\alpha_{6i}=0$, for i=1, ..., 5 $\beta_{j6}=0$, for j=1, ..., 5	$\chi^2(10)$ =19.658 [0.0327]*
	P_{RM}	$\alpha_{7i}=0$, for i=1, ..., 5 $\beta_{j7}=0$, for j=1, ..., 5	$\chi^2(10)$ =49.721 [0.0000]**
	P_{WC}	$\alpha_{8i}=0$, for i=1, ..., 5 $\beta_{j8}=0$, for j=1, ..., 5	$\chi^2(10)$ = 46.086 [0.0000]**

Note: Weak Exogeneity (WE), Long-run Exclusion (LE), and Strict Exogeneity (SE). * significant at the 5% level and ** significant at the 1% level.

Prior to further investigation of α, following Juselius (1995) the next section of Table (2-4) presents tests of long-run exclusion. These test results are significant for all regions except the NE ($\chi^2(5)$ = 1.0869 [0.9553]) and GC ($\chi^2(5)$ = 5.1254 [0.4008]). When there are long-run excluded variables, then it would be appropriate to order the system using this test prior to normalisation, because it is not appropriate to normalise on a variable that may be the long-run excluded (LE) and this can be viewed as one of the criteria devised by Boswijk (1996) to identify the long-run. The final section in Table (2-4) relates to strict exogeneity and that combines the weak exogeneity with the long-run exclusion restriction. However, this will not be considered further as none of the price series appear to be strictly exogenous.

Next in Table (2-4) the system is normalised and conditioned in turn on the two price series that satisfy most readily the joint weak exogeneity tests that is for GC and MW. If the GC and MW prices are viewed as weakly exogenous for $\boldsymbol{\beta}$, then the test subject to the normalisation restriction is still 14.273. Based on the SE tests once MW and GC are conditioned it is not possible to impose the restriction on these prices for LE even though GC might be long-run excluded in isolation. This would suggest the ordering by the WE tests so that the long-run equations are conditioned on the GC and MW prices and this representation gives rise to a long-run reduced form.

It makes sense not to normalise on the variables for which the weak exogeneity joint test is accepted that is GC and MW and from the normalisation rule (Boswijk (1996)) each long-run equation can be viewed as explaining variables that are not exogenous. The normalisation imposes *r-1* restrictions that generically identify each cointegrating vector in $\boldsymbol{\beta}$ exactly. However, this does not test identification as the likelihood is unaltered as the restrictions are not binding. In the case of GC it would also not make sense to normalise on this price as the single variable tests would also not have precluded long-run exclusion.

So this would suggest that it makes sense not to normalise on a variable that is LE and this is a criterion used by Boswijk (1996) to empirically identify the long-run parameters. However, there is a further long-run excluded and weakly exogenous variable. The former requires further testing to confirm that it make sense to normalise on that variable, the latter does not give rise to a unique long-run relation as the test of weak exogeneity is rejected for this additional variable. In terms of the indication of anti-competitive behaviour finding a variable that is not LE implies that it may interact with all the other variables in the long-run as that variable must be present in at least one cointegrating vector.

The last variable in the revised system is the GC price and α is restricted to impose weak exogeneity and this price will condition the long-run. Then based on subsequent investigation a further 21 restrictions are imposed on α and thenβ, and this gives rise to the matrices based on restricted coefficients:

$$\alpha = \begin{bmatrix} -0.252 & .222 & 0.0 & -0.03 & 0.025 \\ -0.189 & 0.223 & 0.0 & -0.018 & 0.021 \\ 0.0 & -0.182 & 0.025 & -0.198 & 0.077 \\ -0.109 & 0.0 & 0.0 & -0.045 & 0.028 \\ -0.187 & 0.314 & 0.0 & 0.0 & 0.014 \\ 0.0 & 0.0 & 0.038 & 0.0 & 0.0 \\ 0.0 & 0.0 & -0.014 & 0.0 & -0.053 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix} \text{ and}$$

$$\beta' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & -.371 & -.638 \\ 0 & 1 & 0 & 0 & 0 & 0 & -.429 & -.611 \\ 0 & 0 & 1 & 0 & 0 & -0.933 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & -2.707 & .66 & 1.134 \\ 0 & 0 & 0 & 0 & 1 & 0 & -.39 & -.671 \end{bmatrix} = \begin{bmatrix} \beta_{.1}' \\ . \\ . \\ . \\ \beta_{.5}' \end{bmatrix}.$$

The system is ordered such that $x_{t-1}' = \left[p_{CA} \quad p_{EC} \quad p_{RM} \quad p_{NE} \quad p_{LA} \quad p_{WC} \quad p_{MW} \quad p_{GC} \right]_{t-1}$. These restrictions gives rise to a likelihood ratio test of 20.936 and from the p.value=[.7453] it is not possible to reject them. In addition, the likelihood ratio test statistic related to further 21 over-identifying restrictions is computed as 15.8106 and as the p.value is [0.7802] then these are also not significant.

Following the imposition of the normalization rule the first r columns of $\mathbf{\Pi}$ reflect $\boldsymbol{\alpha}$ and as a result of this it can be observed that on top of the WE restriction there is a block triangular section that is zero and this is consistent with the MW and the WC prices being CE for $\boldsymbol{\beta}_{.1}$ and $\boldsymbol{\beta}_{.2}$ (the first two cointegrating vectors).[36] The former is consistent with the joint test of WE that implies the prices for the MW and the GC might be considered WE for $\boldsymbol{\beta}$. This

[36] More strictly a row from $\boldsymbol{\alpha}$ annihilates a column from $\boldsymbol{\beta}$ or $\pi_{ij}=\boldsymbol{\alpha}_{.i}\,\boldsymbol{\beta}_{j.}=0$ (Hunter and Simpson (1995)) or more generally the necessary condition for cointegrating exogeneity is $\mathbf{\Pi}_{21}=0$, an $N_2 \times N_1$ sub-block of $\mathbf{\Pi}$ (Hunter (1990)).

would imply a system that could be conditioned on both these prices; implying two stochastic trends relating to the GC and the MW price. However, it was decided from inspection of α that as the MW price seemed to depend on $\beta_{.3}$ and $\beta_{.5}$ it was better to consider this as a CE for these two vectors. This seems pertinent as the MW price has a very similar coefficient in $\beta_{.1}$, $\beta_{.2}$ and $\beta_{.5}$. The long-run non-causality related with CE, seems to extend to $\beta_{.4}$. Similarly the block triangularity of Π implicit in the structure of the restricted α and β implies that the WC price is cointegrating exogenous for $\beta_{.1}$ and $\beta_{.2}$. However, in this case this is trivial as the terms related to the WC prices are excluded from these equations, but it can be observed from α that $\beta_{.2}$ is the only vector that appears in the dynamic equation for the WC price and this implies that it is also CE for $\beta_{.4}$.

Considering the cointegrating vectors in turn, it follows from the restriction on $\beta_{.1}$ and $\beta_{.2}$ that the CA and EC price are driven by the same CE and WE variables the GC and the MW prices. These prices for all intents and purposes have similar coefficients and the two prices would appear to define a sub-block variant of LEPT (Burke and Hunter (2011)) that relates to $\beta_{.1}$ $\beta_{.2}$ and $\beta_{.5}$. Here we will focus on the equations explaining the prices for the CA and the EC that are being forced and as a result the GC and MW prices do not reflect the price related to these regions.

The form of $\beta_{.3}$ appears very close to what has been termed parallel pricing. It should be recalled that this only relates to LEPT when there are *N-1* similar vectors. Here this defines a partitioned market so the RM and WC prices are reflected in each other and none of the other prices are forcing this long-run relation so they share a common stochastic trend.

The cointegrating vector $\beta_{.4}$ relates to the NE price and this is driven by the GC, MW and WC prices. This appears to indicate that the NE price reflects information from across the US. This is given further support as the dynamic equation from the VAR is also impacted by the correction related to $\beta_{.1}$ that explains the CA price in the long-run and $\beta_{.5}$ that explains the LA price in the long-run. Based on the normalisation this may be viewed as the own vector, but the form of $\beta_{.4}$ seems less easy to understand given that it is anticipated that we observe parallel pricing and LEPT. However, this vector can be seen as a combination of three parity relations between the NE and WC price, the WC and MW price, and the WC and GC price. These are combinations that would arise from the tests of stationarity, but are rejected as stationary when it comes to the system. Furthermore, the NE prices are not being reflected in prices for the GC, MW and WC.

The long-run equation explained by $\beta_{.5}$ relates the LA to the MW and the GC prices. The GC price is again the driver and is not impacted by the LA price in the long-run. This is consistent with the investigation of the trivariate system results in Burke and Hunter (2012) and Kurita (2008), but over a shorter time frame that excludes the 2008 financial markets crisis as is the observation that the GC price is WE. However, as the MW price is dependent on $\beta_{.1}$ and $\beta_{.5}$, then it is appropriate to say that a linear relation between the LA and MW price is forced by the GC price and so in this case the MW and the LA are interdependent.

Hence, the exogenous variables appear to force the long-run equations, but in the case of the cointegrating exogenous variables the causality does not run the other way and for the weakly exogenous variable this is essentially a random walk. In the latter case the GC price is only impacted by shocks that impact this segment of the market and thus the history of demand and supply shocks that impact the price. Thus contrary to a competitive market, it is partitioned in the long-run.

To this end regional gasoline pricing may not be consistent with a fully functioning gasoline market in the US. There may be geographical or structural reasons for this to occur, but the reactivity of NE prices would suggest that this is not the case. To further investigate market structure it would be useful to study US company gasoline prices and search for WE price series with such data (Burke and Hunter, 2011). A difficulty associated with analysing company price series, is that they are volatile and that a similar historical data set does not seem to exist.[37]

[37] Company data were analysed, but these results are preliminary. The findings suggest $r=N-2$, but with a smaller sample and volatile price data they are viewed as tentative and for reasons of space and consistency with the above discussion they are not reported here as a compelling story still relates to the regional data.

2.5 Cointegration and Exogeneity Analysis of Gasoline Market Using Company Data

Next the gasoline market structure is explored using company data as competitive and collusive behavior can be better inferred from such data. Following Hendry and Juselius (2001), and Hunter and Burke (2012), we consider the cointegrating relationship and the dynamic model using companies data across the US to determine whether there is a market leader. The main concern of this part of our study is to focus on exogeneity by applying the cointegration and WE test to explain the gasoline market structure and price behaviour in the market using company data.

The data is weekly gasoline companies prices in the US. The data are for seven major gasoline producing companies in the US for the period of May 2009 - November 2012 (187 observations). Here seven companies are selected, Citgo, Sunoco, BP, TransMontaigne, Marathone. Gulf Oil, and Hess Corporation. Figure 2-5 shows the log company prices, Citgo (C), Sunoco Logistic Partners (SLP), BP, TransMontaigne (TM), Marathon Petroleum Corporation (MPC). Gulf Oil (GO), and Hess Corporation (HC). Figure 2-6, 2-7 and 2-8 below shows the US log companies' price differentials.

Figure 2-5- The log of gasoline price for Citgo (C), Sunoco Logistic Partners (SLP), BP, TransMontaigne (TM), Marathon Petroleum Corporation (MPC). Gulf Oil (GO), and Hess Corporation (HC)

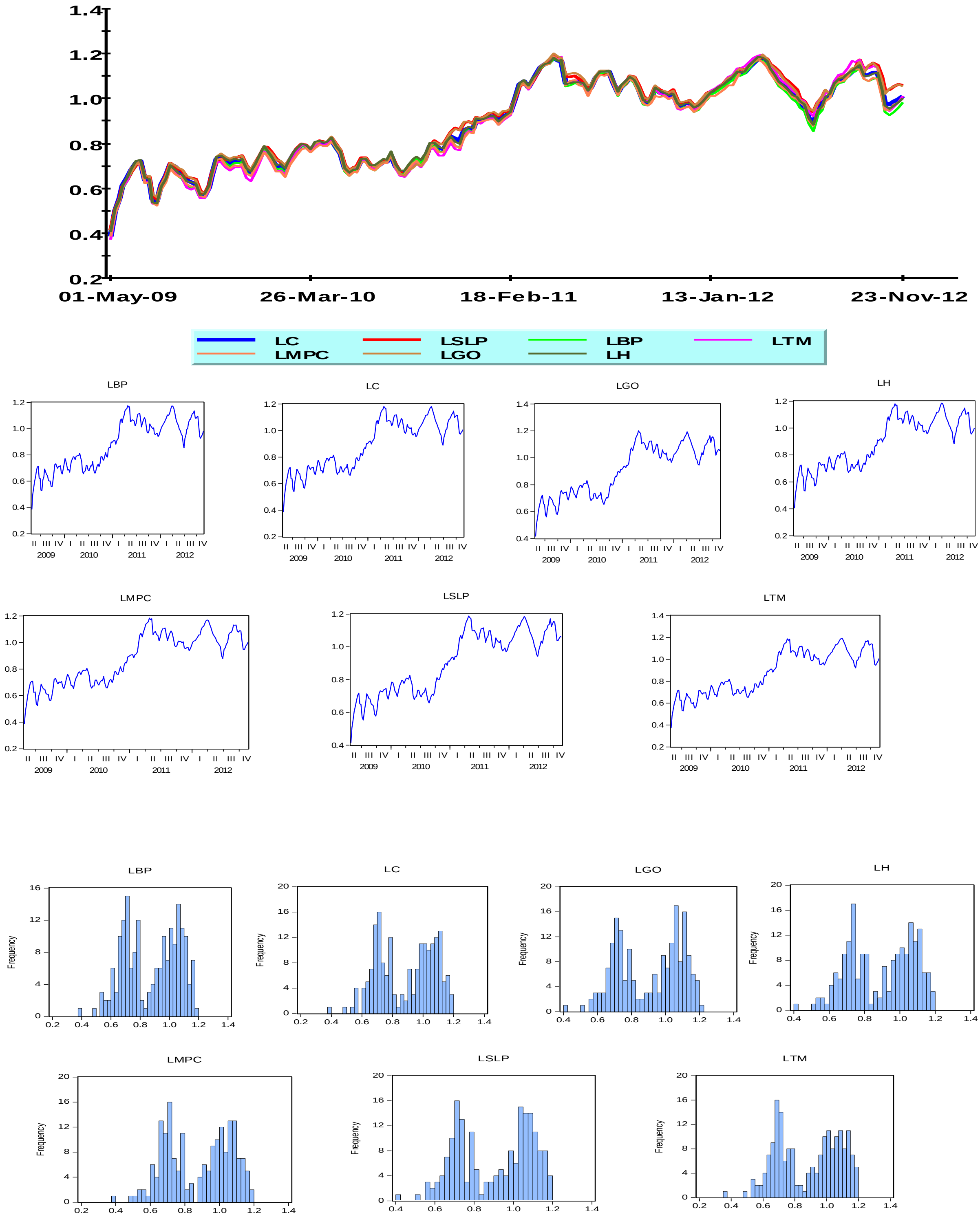
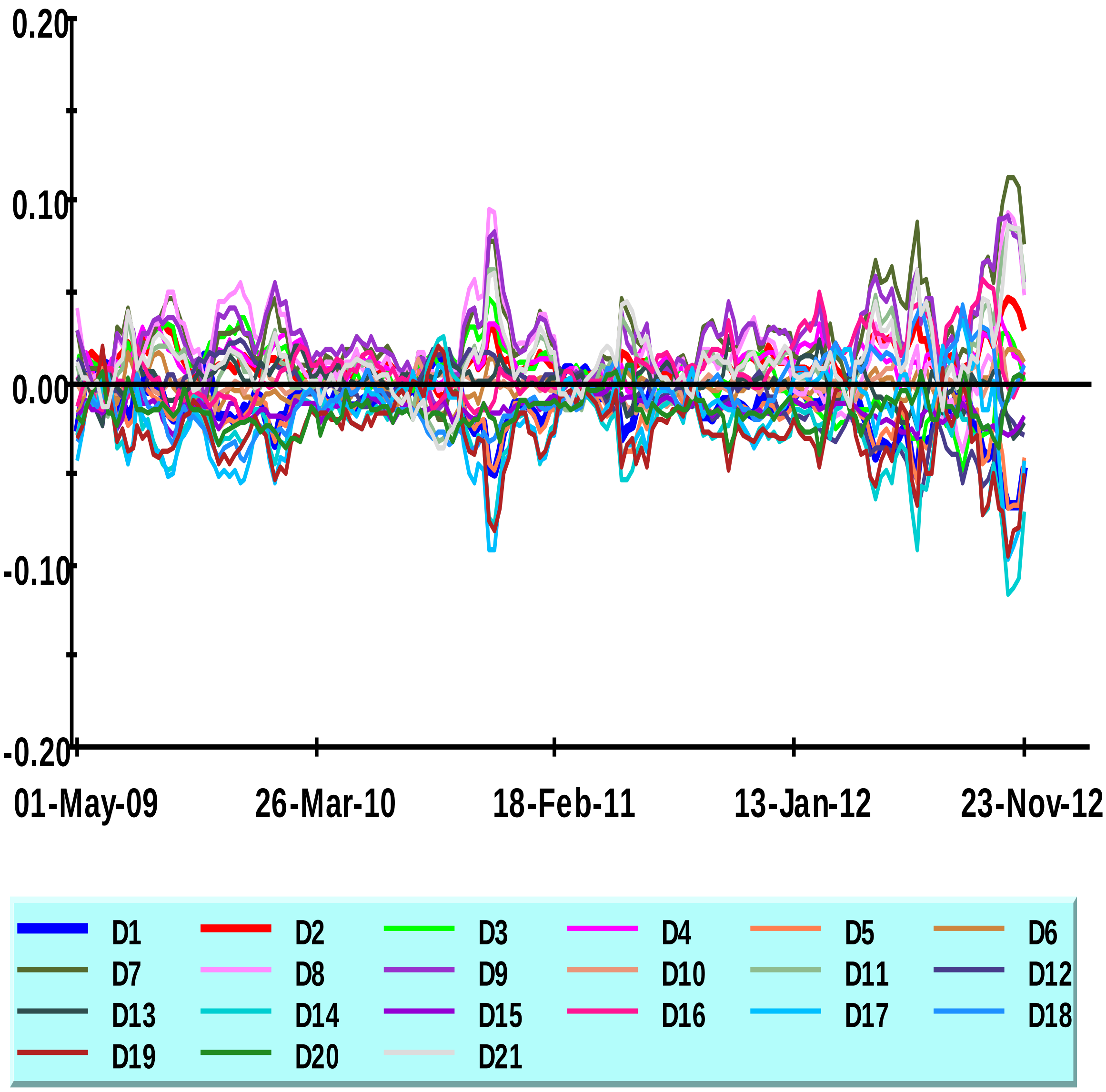


Figure 2-6- The log of gasoline price differential[38] within seven different companies



[38] D_1=C and SLP, D_2=C and BP, D_3=C and TM, D_4=C and MPC, D_5=C and GO, D_6=C and H, D_7=SLP and BP, D_8=SLP and TM, D_9=SLP and MPC, D_{10}=SLP and GO, D_{11}=SLP and H, D_{12}=BP and TM, D_{13}=BP and MPC, D_{14}=BP and GO, D_{15}=BP and H, D_{16}=TM and MPC, D_{17}=TM and GO, D_{18}=TM and H, D_{19}=MPC and GO, D_{20}=MPC and H, D_{21}=GO and H

Figure 2-7- The log of gasoline price differential within seven different companies

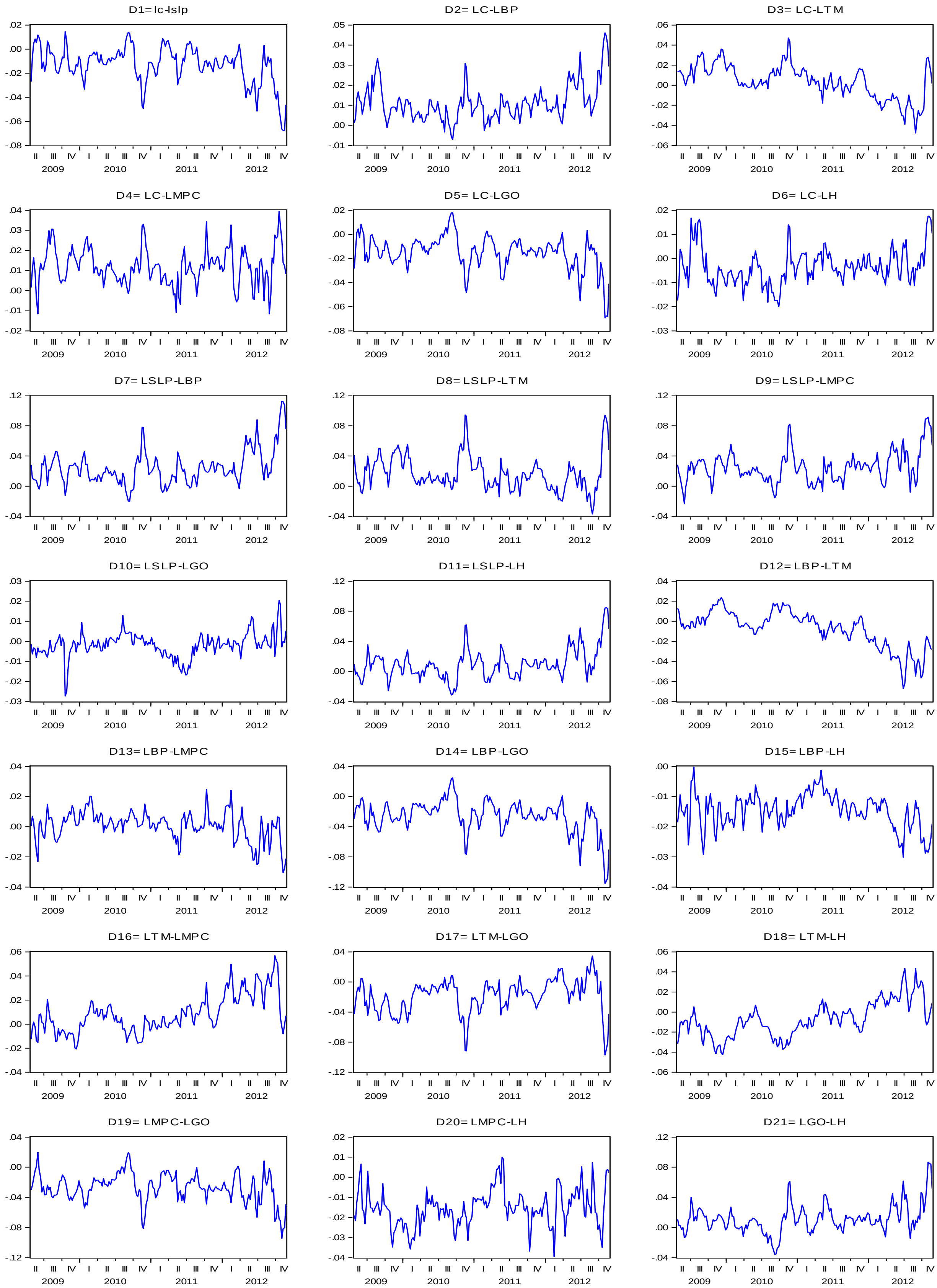
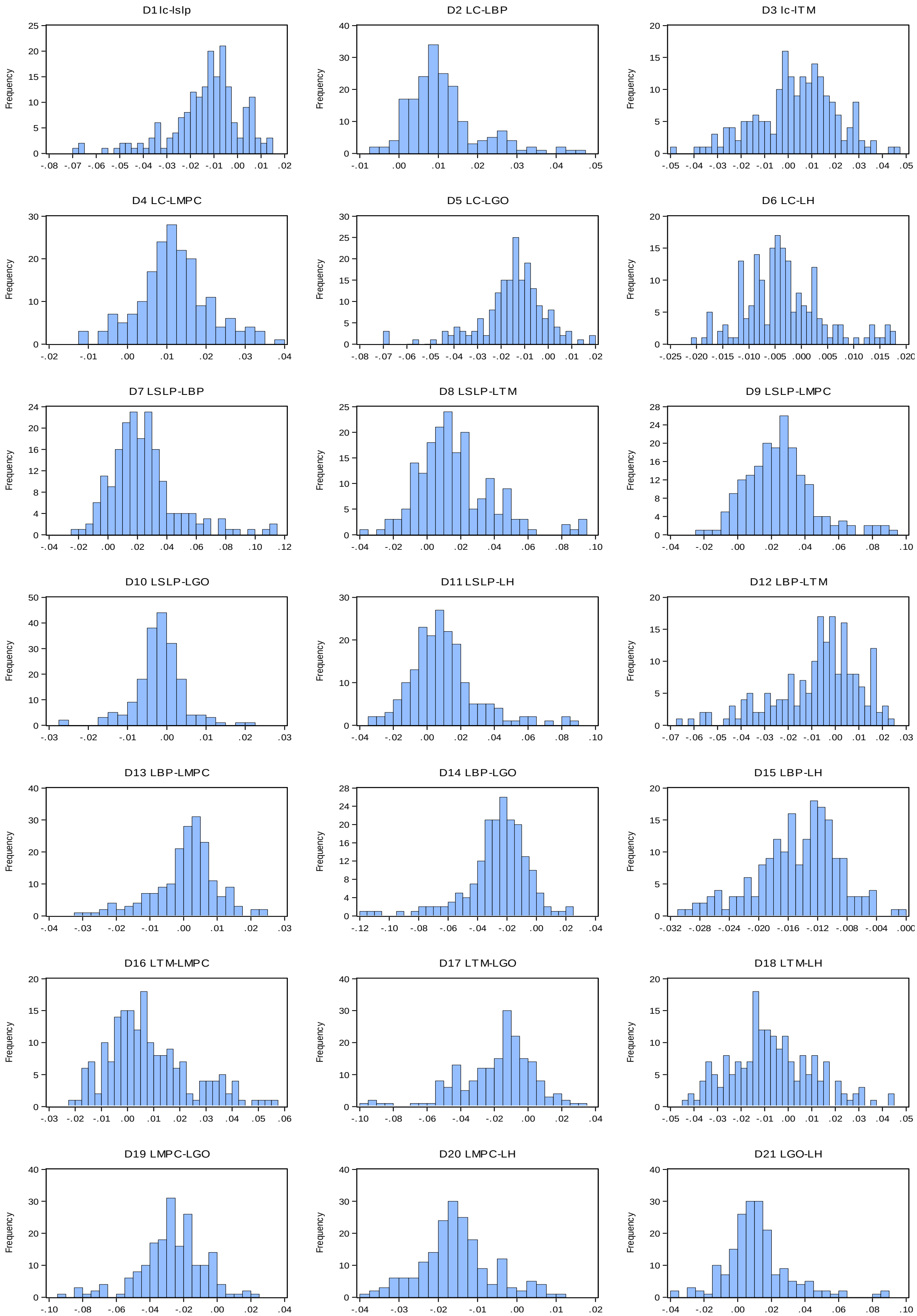


Figure 2-8- Frequency distribution of the gasoline log price differential within seven different companies



The test of unit-root on company data is obtained from a single equation using a sample of T=187 weekly observations and the results of the ADF tests and ECMs with q lags are presented in the table below.

The ADF test results show out of 21 company price proportions, that 19 of those are significantly different from the one sided critical value which implies those 19 price proportions are stationary at 5%. Stationarity of the company price proportions indicates that in the long-run the series move in proportion to each other and as a result it might be imputed that they follow the same stochastic trend; the stationarity suggests that arbitrage is correcting in the long-run. Furthermore we applied the ECM to determine whether prices move in proportion in both the long-run and short-run. This can be used to test whether in the long and short-run the market is efficient. The result of tests of such restrictions are presented in Table 2-5 indicating that many of q lagged log price differentials ($\Delta \log P_{(q)}$) are significant are significant and this implies that mostly market is efficient in the short-run and for further study we applied the system analysis. However in the case of 4 price proportions,[39] there is a discrepancy between the results for the ADF tests and ECM tests. Next, using weekly company[40] data we defined the cointegration rank and present the results in Table 2-6. The Johansen trace test results indicate that there are 4 (N-3) cointegrating relations when the test is applied at the 5% level.

[39] $P_{C\text{ and }BP}$, $P_{C\text{ and }TM}$, $P_{BP\text{ and }TM}$, $P_{TM\text{ and }MPC}$

[40] Citgo (C), Sunoco Logistic Partners (SLP), BP, Transmontaigne (TM), Marathon Petroleum Corporation (MPC). Gulf Oil (GO), and Hess Corporation (HC)

Table 2-4- Summary of ADF tests, ECM test of company price proportion (with intercept and no trend)

Log price differential	ADF (q)/ OLS t-statistic	ECM (q)/ OLS t-statistic
$P_{\text{C and SLP}}$	-3.68** (2)	-5.14 ** |P_{SLP}
$P_{\text{C and BP}}$	-3.43* (2)	5.63 ** | P_{BP}
$P_{\text{C and TM}}$	-2.90* (2)	-3.93 ** | P_{TM}
$P_{\text{C and MPC}}$	-4.83** (2)	-6.22 ** | P_{MPC}
$P_{\text{C and GO}}$	-4.24** (2)	-5.03 ** | P_{GO}
$P_{\text{C and H}}$	-3.79** (2)	-5.72 ** | P_{H}
$P_{\text{SLP and BP}}$	-3.51** (2)	-5.19 ** | P_{BP}
$P_{\text{SLP and TM}}$	-3.86** (2)	-5.30 ** | P_{TM}
$P_{\text{SLP and MPC}}$	-3.91** (2)	-5.56 ** | P_{MPC}
$P_{\text{SLP and GO}}$	-4.34** (2)	-6.29 ** | P_{GO}
$P_{\text{SLP and H}}$	-3.66** (2)	-5.23 ** | P_{H}
$P_{\text{BP and TM}}$	**-2.08 (2)**	**-2.24 | P_{TM}**
$P_{\text{BP and MPC}}$	-4.29** (2)	-5.00 ** | P_{MPC}
$P_{\text{BP and GO}}$	-3.88** (2)	-4.35 ** | P_{GO}
$P_{\text{BP and H}}$	-4.22** (2)	-5.31 ** | P_{H}
$P_{\text{TM and MPC}}$	-2.98* (2)	-3.72 ** | P_{MPC}
$P_{\text{TM and GO}}$	-3.88** (2)	-4.06 ** | P_{GO}
$P_{\text{TM and H}}$	**-2.47 (2)**	**-2.79 | P_{H}**
$P_{\text{MPC and GO}}$	-4.34** (2)	-4.77 ** | P_{GO}
$P_{\text{MPC and H}}$	-4.74** (2)	-5.23 ** | P_{H}
$P_{\text{GO and H}}$	-4.00** (2)	-4.75 ** | P_{H}

Note:ADF Critical value at 1% is -3.44, at 5% is -2.87 computed in Oxmetrics Professional (Doornik and Hendry, 2009). ***** Significant at the 95% confidence level and ** significant at the 99% confidence level. The **bold number** denotes that the series are non-stationary.

Table 2-5- Unrestricted Cointegration Rank Test – Trace of US Gasoline company Price 2009-2012

H_0 : rank ≤	Trace test	P-value
rank ≤0	218.63	[0.000] **
rank ≤1	1140.46	[0.000] **
rank ≤2	81.25	[0.004] **
rank ≤3	49.60	[0.032] *
rank ≤4	22.73	[0.268]
rank ≤5	8.28	[0.443]
rank ≤6	0.005	[0.943]

Note: * significant at the 5% level and ** significant at the 1% level. Computed in Oxmetrics Professional (Doornik and Hendry, 2009).

In Table (2-7), tests of cointegration are derived from the VAR model and the results related to the imposed restrictions on **α** or **β** or both **α** and **β** are presented accordingly. The sample includes 127 observation and the results relate to tests of weak exogeneity, long-run exclusion and strict exogeneity. There are *k=15* lags in the VAR estimations. The first block of results in Table (2-7) relate to a weak exogeneity test conditional on *r=4* and from the p-values it can be determined that none of the log company prices are WE for **β**. In the second part of Table 2-7 the significant p-values shows that none of the prices could be long-run excluded. In terms of the indication of competitive behaviour finding all the variables that are neither WE nor LE implies that the company prices may interact with each other in the long-run.

Table 2-6- Test of WE, LE and SE of US Gasoline company Price 2009-2012

Hypothesis		Null r=5	Statistics [p-value]
(WE)| r=4	P_{BP}	α_{1i}= 0, for i=1, …, 4	$\chi^2(4)$ = 16.875 [0.0020]**
	P_{CITG}	α_{2i}= 0, for i=1, …, 4	$\chi^2(4)$ = 17.799 [0.0014]**
	P_{GO}	α_{3i}= 0, for i=1, …, 4	$\chi^2(4)$ = 28.131[0.0000]**
	P_H	α_{4i}= 0, for i=1, …, 4	$\chi^2(4)$ =16.383 [0.0025]**
	P_{MPC}	α_{5i}= 0, for i=1, …, 4	$\chi^2(4)$ =20.384 [0.0004]**
	P_{SLP}	α_{6i}= 0, for i=1, …, 4	$\chi^2(4)$ =19.637 [0.0006]**
	P_{TM}	α_{7i}= 0, for i=1, …, 4	$\chi^2(4)$ =18.309 [0.0011]**
(LE)| r=4	P_{BP}	β_{1i}= 0, for i=1, …, 4	$\chi^2(4)$ = 37.688 [0.0000]**
	P_{CITG}	β_{2i}= 0, for i=1, …, 4	$\chi^2(4)$ = 23.828 [0.0001]**
	P_{GO}	β_{3i}= 0, for i=1, …, 4	$\chi^2(4)$ =44.171 [0.0001]**
	P_H	β_{4i}= 0, for i=1, …, 4	$\chi^2(4)$ =43.502 [0.0000]**
	P_{MPC}	β_{5i}= 0, for i=1, …, 4	$\chi^2(4)$ = 27.064 [0.0000]**
	P_{SLP}	β_{6i}= 0, for i=1, …, 4	$\chi^2(4)$ =27.031 [0.0000]**
	P_{TM}	β_{7i}= 0, for i=1, …, 4	$\chi^2(4)$ = 41.501 [0.0000]**
SE = (LE) + (WE)| r=4	P_{BP}	α_{1i}= 0, for i=1, …, 4 β_{j1}= 0, for j=1, …, 4	$\chi^2(8)$ = 54.157[0.0000] **
	P_{CITG}	α_{2i}= 0, for i=1, …, 4 β_{j2}= 0, for j=1, …, 4	$\chi^2(8)$ = 38.288 [0.0000] **
	P_{GO}	α_{3i}= 0, for i=1, …, 4 β_{j3}= 0, for j=1, …, 4	$\chi^2(8)$ =57.479 [0.0000] **
	P_H	α_{4i}= 0, for i=1, …, 4 β_{j4}= 0, for j=1, …, 4	$\chi^2(8)$ =60.631 [0.0000] **
	P_{MPC}	α_{5i}= 0, for i=1, …, 4 β_{j5}= 0, for j=1, …, 4	$\chi^2(8)$ =44.638 [0.0000] **
	P_{SLP}	α_{6i}= 0, for i=1, …, 4 β_{j6}= 0, for j=1, …, 4	$\chi^2(8)$ =46.130 [0.0000] *
	P_{TM}	α_{7i}= 0, for i=1, …, 4 β_{j7}= 0, for j=1, …, 4	$\chi^2(8)$ =44.689 [0.0000] *

Note: Weak Exogeneity (WE), Long-run Exclusion(LE), and Strict Exogeniety (SE). * significant at the 5% level and ** significant at the 1% level.

The final section in Table (2-7) relates to strict exogeneity the combination of the weak exogeneity with the long-run exclusion restriction. However, this will not be considered further as none of the price series appear to be strictly exogenous.

2.6 Conclusion 2

For non-stationary variables, the Johansen methodology of cointegration and exogeneity testing appears an appropriate approach to investigate market performance. The empirical findings indicate that gasoline prices for different regions are cointegrated and this suggests that market segments may not be distinct. Forni (2004) found with a very modest regional data set for Italian milk prices that stationarity tests such as that of Dickey and Fuller (1979) can provide an effective way of defining the dimensions of a market, especially when there is a limit to the number of time series observations.

One problem with that approach is that the long-run restrictions are also binding on the short-run, this provides one reason why the test based on the ECM may be preferred. Furthermore, the ECM as part of an N dimensioned system with N error correction terms can be coherently defined (Boswijk, 1992). While Kremers, Ericsson and Dolado (1992) have shown that tests based on the error correction term in a dynamic model should be more powerful than the ADF test.

However, the single equation methods do not bind the reduced rank restriction across the whole set of prices. This suggests that when there is a large data set available that the VECM is to be preferred. In particular in the presence of relatively strong ARCH behaviour the simulations presented in Rahbek et al (2002) imply that testing may only be reliable with data sets in the range 600-1000 observations. Here even though there is some evidence of ARCH we feel confident in an analysis based on a sample of 901 observations with a clear finding that the cointegrating rank (r) is less than N-1. This is also not inconsistent with a strict analysis of the single equation results.

The single equation findings based on the ECM combined with the results on long-run exclusion call into question the existence of long-run arbitrage pricing across the eight US regions investigated here. Hunter and Burke (2007), and Kurita (2008) suggest that even where there are N-1 cointegrating relations that the results may be inconsistent with an efficient market when one of the prices is weakly exogenous. In that case a single variable drives the stochastic trend and as a result the long-run can be appropriately conditioned on that price.

The preferred model reveals that possibly three regional prices can be considered weakly exogenous. The preferred model is derived here conditioned on the GC and this price does not react to other prices when it is WE for $\boldsymbol{\beta}$. If the long-run structure is further investigated it is suggested that the MW and the WC prices are CE for $\boldsymbol{\beta}_{.1}$, $\boldsymbol{\beta}_{.2}$ and $\boldsymbol{\beta}_{.4}$ this implies that these prices are not responding to the other prices in the long-run.

The observed market behaviour in the long-run could be due to the geographical conditions or may be a reflection of the ownership of regional refinery capacity and their location across the US. Considering the empirical results we are suggesting a change in the regulation of the gasoline market to enhance competition. This could relate to tax breaks to extend the refinery and distribution capacity of smaller firms.

Similar conclusions to Forni (2004) arise as the failure to find a “Broad Market” in the long-run suggests that the anti-trust authorities resist further concentration in the industry via merger or acquisition. The availability and accessibility of market information to the consumer could also affect price responsiveness in this market. Similar conclusions may also be pertinent to countries such as the UK where concentration in refinery ownership has been criticised especially following the consumer and corporate driver strike actions in 2000/2001.

Considering company data could be a better indicator of competitive and collusive behaviour in relation to gasoline prices of seven major oil companies in the US. It is found on the system that there are no more than 4 long-run relation and this is not consistent with parallel pricing. However, it was determined that none of the company prices could be WE or LE meaning that they do seem to react with each other.

CHAPTER 3

Pricing asymmetry and switching in the market for gasoline in the US

3 Pricing asymmetry and switching in the market for gasoline in the US

3.1 Introduction

Gasoline demand, supply and price volatility:

Since 2003 the gasoline price increased sharply and gasoline turned into a profitable and tradable commodity, this in part probably relates to extreme shocks that have affected demand and supply for both oil importing and exporting countries. In a similar way to any other identical product gasoline production and price formation are driven by supply and demand.

In 2004, according to the IMF the demand for oil increased significantly in 2003-2004. This was influenced by the continued fast growth of the Indian and Chinese economies whose populations now exceed a billion people. India spent $15 billion, equivalent to 3% of its GDP on oil imports in 2003 which was 16% greater than its oil-import in 2001.

However, political instability in the Middle-East and Oil producing countries, and consequent international events caused further interruptions in the global demand and supply of oil. The problem of energy scarcity and a potential gasoline crisis lead for the need to better regulate and monitor the energy sector. In the market under equilibrium conditions supply should equal demand and this implies that in the long-run the market price is equivalent to the equilibrium price confirming the efficient allocation of the resources. In the energy market the relationship between energy supply and demand has important implications for economist and policy makers as it is a scarce resource with the high global demand. In an efficient market, arbitrage between the spot and the forward market should lead prices to move together in the long-run, but US gasoline market price differentials confirm the "law of one price" cannot be fully operational across all regions of the US.

It is possible that such price discrepancies may depend upon regional demand and supply conditions. To this end the key question is whether overall gasoline prices tend to converge or market inefficiencies prevent the "law of one price" to hold across the US.

Gasoline retail price volatility caused consumers to become more concerned with the gasoline companies' price setting behaviour and the harm or detriment that this may cause to the consumer. Hunter, Ioannidis, Iossa, and Skerratt (2001) determined how to measure detriment subject to uncertainty either over quality or price. With a homogenous product that is controlled as is the case for gasoline in developed economies quality should not be at issue so it is the extent to which harm may be as a result of imperfect information over prices that is an issue.

In the previous chapters price setting of firms was seen as a mechanism by which inefficiency might be detected and monitored. However, to measure detriment requires information on cost and market structure. Hunter, Ioannidis, Iossa, and Skerratt (2001) show that such analyses given similar quality requires measures of cost that permit an analysis of the mark-up. Such data is extracted from annula company accounts and this limits our capacity to develop a significant time series.

Furthermore, the number of firms on which such information is available on a reliable basis is limited.

The general conclusion from the univariate analysis of regional price proportions in Chapter One indicates that long-run prices are responsive to each other. The only evidence that might be contrary relates to the data corrected for volatility.

The further analysis of regional data related to cointegration and exogeneity in Chapter Two emphasises the limitations of the univariate analysis as when the VAR system is considered then finding of parallel pricing cannot be confirmed as only 5 long-run relations from 8 can be found so there are insufficient long-run relations for this proposition to be sustained. If there are fewer than N-1 such relations, then this is not consistent with LEPT (Burke and Hunter, 2011)[41]. The finding of up to four WE variables indicates that certain regions are not responding appropriately to the prices in the other regions and this indicates that competition may be an issue.

Similar findings based on company price series are closer to meeting the requirement for LEPT as there are 4 from 7 long-run relations[42], but with the smaller sample and price processes that appear volatile further analysis is required controlling for ARCH in variance to confirm the rank condition finding of $r=4$. This is for further study and both data sets confirm the nature of the reduced rank problem.

[41] For more detail of LEPT see page 30.
[42] LEPT explained in page 30.

Here competitiveness is analysed in terms of short-run and long-run asymmetry of price responses. This means that the market may have more than one regime. This may reflect agent behaviour or the importance of the demand and supply side of the market place. The methods used in this chapter will involve different regimes.

The first method that has been reviewed in the literature on competition and regulation and applied here is the variance screening method. Following this methodology the differences in price reaction can be detected through the variance and this leads to asymmetry in price reaction where significant asymmetry will indicate different regimes.

Further, imperfect price adjustment due to imperfect competition could cause short-run or long-run disequilibria. To further investigate this proposition price and quantity data are obtained to study the market. The market data on quantity is only available at the aggregate level and on monthly basis. The approach is intended to observe regime shift and identify demand and supply phenomena in the long-run and also potentially in the short-run[43].

Therefore in this chapter we study the gasoline market to investigate the response of gasoline demand to changes in relative prices detecting potential gasoline market disequilibrium via the behaviour of relative changes in prices calculated from $\Delta lp_{\text{Retail Price}} - \Delta lp_{\text{Consumer Price Index}}$. The disequilibrium approach does not mean that prices do not adjust, but that the long-run quantity response is faster than that of price. The main contribution is to investigate the structure of the energy market and identify

[43] This approach is to decide whether price shift is due to shift in demand or supply.

long-run demand and supply at the aggregate level. A significant concern of this study is to investigate whether prices are sufficiently flexible to clear markets in terms of supply and demand. The method leads to a dynamic model that incorporates a single non-linear error correction term via a switching long-run regression model.

Since Fair and Jaffee (1972) there is significant literature studying the econometric problem of demand and supply estimation under disequilibrium. Most of the studies followed the maximum likelihood methodology to handle endogenous switching to estimate disequilibrium in the market. Maximum likelihood is required to compute endogenous switching as the method of Fair and Jaffee was considered inconsistent when the price is endogenous. Here, the problem does not arise as a result of super consistency (Davidson and MacKinnon, 2004).

The other method applied here is the exogenous switching regression method following Fair and Jaffee (1972) to analyse market disequilibrium. The method attempts to identify different demand and supply regimes by observation of a switch via relative price changes, this will then be compared with the other regime switching methods. The approach undertaken here is different from the majority of procedures used to identify demand and supply in a dynamic long-run context. For further comparison regimes are determined using a Markov switching model made operational on the key switch variable relative price in the endogenous switching case.

To summarize, in this chapter we use three different methodologies to study the gasoline market: the variance screening method, the disequilibrium regime switching model and the Markov switching model. In Section 3.2 we introduce asymmetric price analysis. In Section 3.3 we review market competition using the variance screening analysis. Section 3.4 we carry out the estimation of disequilibrium regime switching models in the gasoline market. In section 3.5 the Markov regime switching model is applied. Finally, in Section 3.5 we conclude.

3.2 Asymmetric price analysis

In gasoline pricing, the transaction price of selling oil from the oil field to refiners is called the producer price. The wholesale price is the value charged by refiners or jobbers to the retail gasoline station. Finally the price that the consumer pays to the gasoline stations is recognized as the retail price. The price disparity at different levels is a measure of the margin. Here there are three different margins: wholesale price margin, producer price margin, and producer-retail price margin.

In the gasoline market it is noticeable that price increases incorporate the cost increase and this follows a symmetric pattern whereas the price changes due to the cost decrease are more likely to be asymmetric. Gasoline cost and price asymmetry can have a considerable effect on consumer’s perceptions, because of the high level of gasoline consumption compared to other regular commodity purchases. These asymmetries could indicate uncompetitive behaviour and potential collusion in the gasoline market. However this analysis is highly sensitive to the quality and quantity of data, the estimator, and the model used in the estimation.

There are three types of price asymmetries mentioned below:

- Price asymmetry based on time: where wholesale price increases pass through more rapidly to the retail level than price decrease.
- Price asymmetry based on the order of pass through from wholesale to the consumer prices. For example a $1.00 increase in the wholesale price may lead to $0.90 increase in the retail price while $1.00 decrease in the wholesale price may only produce a $0.50 decrease in the retail price.
- Price asymmetry based on the time and order of the price change. The retail price response may differ in relation to the wholesale price.

Price asymmetry has been studied by many researchers based on a number of aspects such as the location and the time of the experiment, the type of the experimental variables (wholesale level, retail level, etc.), the applied econometric methodology used for empirical investigation, and the effect of the price asymmetry on economic activity and the potential for consumer detriment. In this part of the research we applied different econometric methodologies to identify the regime then we compared these methods to analyse their effectiveness in practice.

Karrenbrock (1991) applied tests of timing and order symmetry to different grades of gasoline from 1983-1990 using the OLS estimator. He analysed the price asymmetry in the gasoline market focusing on the wholesale–retail margin to observe the influence of retailer behaviour on price asymmetry as well as the wholesalers' behaviour. Karrenbrock found in terms of timing and extent that retail gasoline price changes respond fully and symmetrically to wholesale price changes, which is contrary to consumers' belief. This result was not found for leaded regular gasoline prices when timing symmetry was investigated. In contrast, Borenstein et al. (1997)

found some evidence that price responses were asymmetric in the US gasoline market.

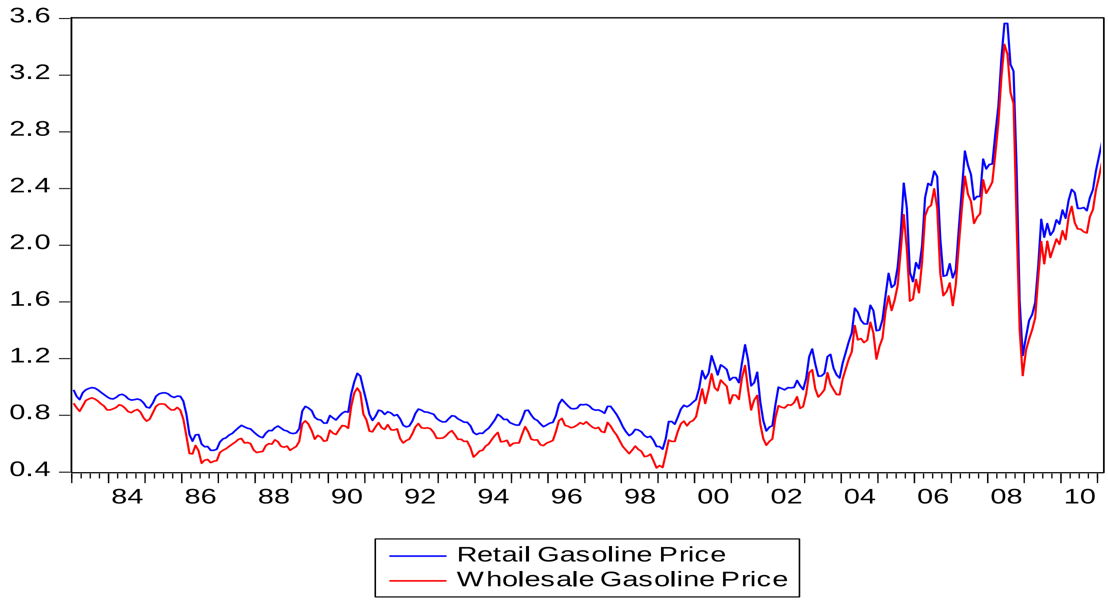
Bettendorf et al. (2003) concluded that price behaviour depends on the day of the week on which data on prices were collected and consequently the results may be different. In support of the studies of asymmetric price response for commodity prices, Frey and Manera (2007) reviewed the causes and estimation of symmetric price transmission in the food, agriculture and gasoline industries and they found that asymmetry is possible to arise in most of the markets and econometrics models. Deltas (2008) specified that retail gasoline prices are significantly responsive to wholesale price rises as compared with wholesale price falls. Borenstein et al. (1997) indicated an asymmetric relation between the US retail price and spot price adjustment, and they indicated that collusion in the retail gasoline market could be the cause of the asymmetric responsiveness of retail prices. This indicates that economists are concern to evaluate the asymmetry in gasoline pricing and clarify the main cause of this asymmetry. Likewise Borenstein and Shepard (2002) used a VAR model and specified a price asymmetry model for wholesale gasoline and crude oil prices and they found that competitive firms adjust prices faster than do firms with market power.

Fafaliou and Polemis (2011) studied market power in the oil industry and indicated that the oil market is not coherent globally and the degree of competition is different between countries or within one country, and this generates price volatility and gasoline price asymmetry. Galeotti, *et al*. (2003) computed cointegrating relations and estimated an asymmetric error correction model to examine price asymmetries between crude oil prices and retail gasoline prices. Likewise, Clerides (2010) applied the error correction methodology on local and international oil price in EU countries, but couldn't provide enough evidence of asymmetric price adjustment in most of the EU countries and it was observed for some countries that oil prices fall faster than they increase. Furthermore Angelopoulou and Gibson (2010) found no significant price asymmetry in the Greek diesel market. However, they considered that the market structure was uncompetitive due to the impact of tax changes and market power in the regional diesel market. More specifically, Polemis (2012) applied an error correction model to the Greek gasoline market and identified that in long-run and short-run the retail gasoline price responded asymmetrically to cost increases and decreases. While Fotis and Polemis (2013) using the Generalized Method of Moments (GMM) and ECM methodology, determined that retail and wholesale gasoline prices in eleven euro zone countries responded asymmetrically to cost increases and decreases.

Figure 3-1 shows the average monthly retail and wholesale gasoline prices from January 1983 to February 2011,[44] (337 observations). The graph indicates continuous fluctuations in gasoline retail- and wholesale prices and shows significant volatility since January 2000. Furthermore, retail price changes suggest similar parallel movement with wholesale price deviations and suggest a contemporaneous correlation between retail- and wholesale price. To consider the asymmetry, in the next section the variance screening methodology is used with US wholesale and retail gasoline prices to examine the degree of competition in the market.

[44]The data have been obtained from energy information administration website (www.eia.doe.gov), Bureau of Labour Statistics website (www.bls.gov), and from the Brunel University subscription to Bloomberg.

Figure 3-1- Average Monthly Retail and Wholesale Gasoline Prices, 1983 - 2011



3.3 Analysis of Market Competition Using Variance Screening

In the preceding chapter using the VECM, we identified the potential collusive behaviour and localized non-competitiveness related to the Lower Atlantic (LA) and Gulf Coast (GC). Here we investigate the potential for antitrust behaviour using the variance screening methodology applied to prices. Abrantes-Mets et al. (2005) estimated the coefficient of variation (CV) for retail gasoline prices in Louisville and found that firms with the lower price volatility and high prices may be in a cartel and indicated a market conspiracy might generate an effective price above their measure of the competitive equilibrium level. It is very difficult to determine the form of the conspiracy as they can take different forms and the conspirators do not flag up who they are and what they are doing.

It is useful to consider the structure of the market prior to any analysis. There are three types of interaction between branded gasoline sellers and suppliers:

- Company-owned-and –operated stations: branded gasoline stations which are owned and operated by the major oil companies.
- Lessee-dealer-stations: branded gasoline stations which are owned by a major oil company but are leased to an individual.
- Jobber-supplied-stations: branded gasoline stations which are owned by individuals who contract with major oil companies to sell their brand of gasoline.

Here the variance screening methodology has been applied to the retail gasoline industry to investigate the potential for collusion in the market. It has been suggested that pricing differences across gasoline stations are more significantly affected by closeness to major routes and the brand characteristics rather than the price of the neighbouring stations and as a result stations with low normalized standard deviation of price are potentially in collusive regimes.

Following Abrantes-Mets et al. (2005) here we consider weekly gasoline prices across different oil companies in the US from May 2009 to November 2012.[45] The data have been obtained from Bloomberg. The sample includes seven major gasoline producing companies in different regions of the US: Citgo (C), Sunoco Logistic Partners (SLP), BP, Transmontaigne (TM), Marathon Petroleum Corporation (MPC). Gulf Oil (GO), and Hess Corporation (HC). We use gasoline prices as they are widely available and the gasoline market is regularly suspected of anti-competitive

[45] The short period of 3 years has been selected as it is believed that local cartels may be short-term and likely to disappear in the long-term.

behaviour. The Federal Trade Commission screens daily gasoline prices to identify anomalous pricing (Froeb et al, 2005).

We compute the mean ($\bar{P}$), standard deviation (SD), and coefficient of variation (CV) of each gasoline station and present this information in Table 3-1 and as figures below in Figure 3-2, 3-3 and 3-4.

To identify outliers consider the scatter plot of the standard deviation against the mean for gasoline stations prices. Outliers are identified as those stations with high means and low standard deviations these are indicated as red dots in the Figure 3-2. This figure indicates that Citgo in South Portland (Maine), Gulf in South Portland (Maine), Gulf in Williamsport (Pennsylvania) and Sunoco in Rochester (New York) are the outliers. From 3-2 we can sense that there is considerable variation in the standard deviations. Furthermore we construct a bar chart for the data and based on the entries in the bars identify stations with high mean and low standard deviations or low coefficient of variation: Citgo in Maine, Gulf Oil in Maine and Pennsylvania, and Sunoco in New York have high mean whereas the BP in South Carolina and Citgo in North Carolina have a low standard deviation while Sunoco in New York, Citgo in North Carolina and BP in South Carolina have low coefficients of variation.

Figure 3-2- Means and standard deviations

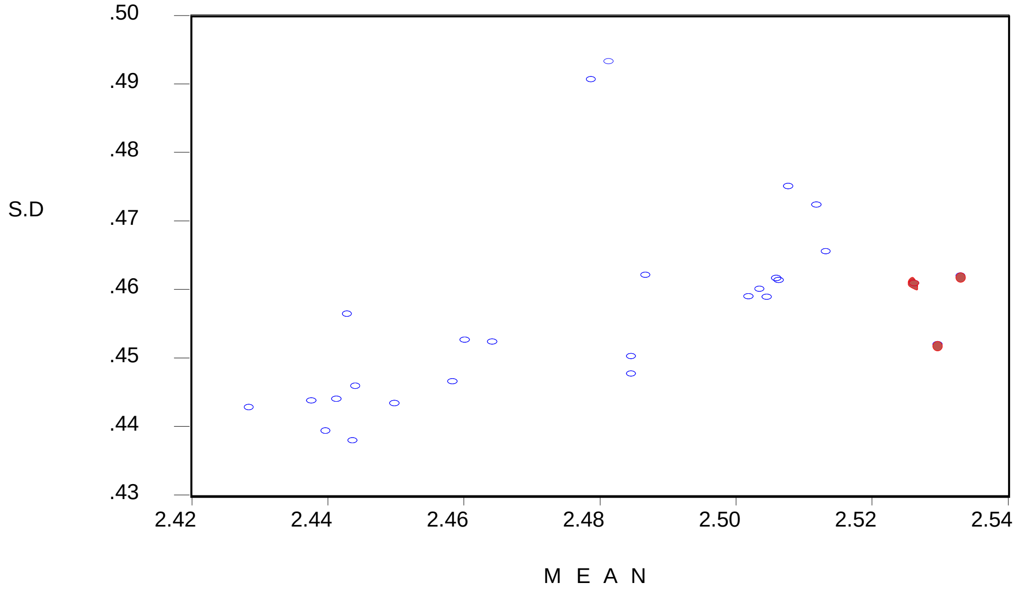
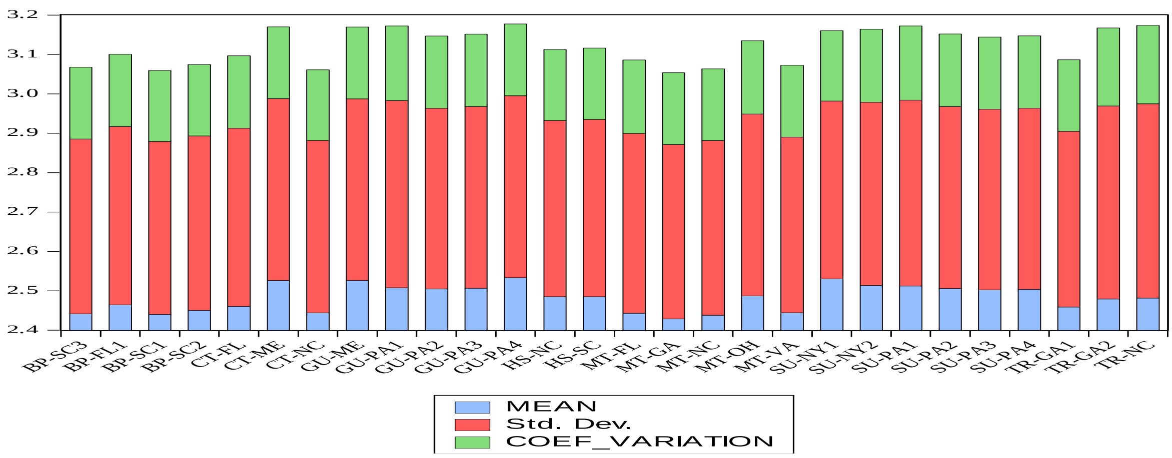


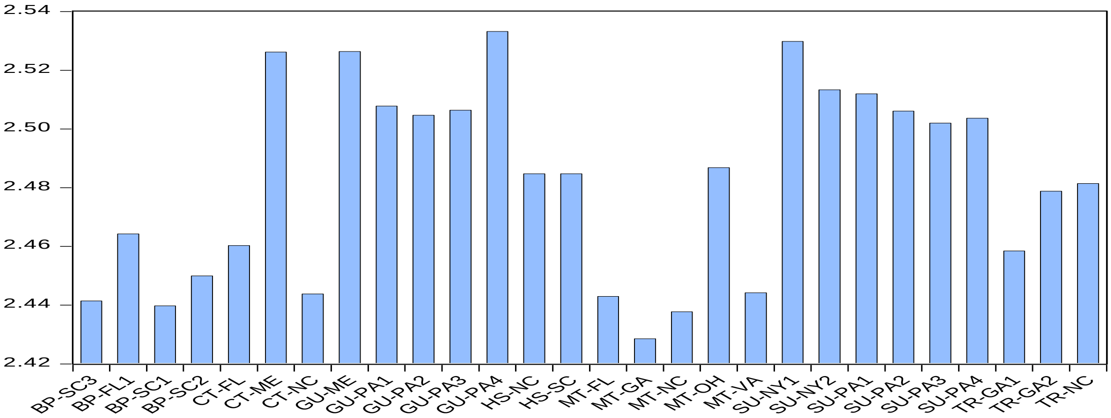
Figure 3-3- Mean, standard deviation and coefficient variation of seven major gasoline companies in different regions of the US



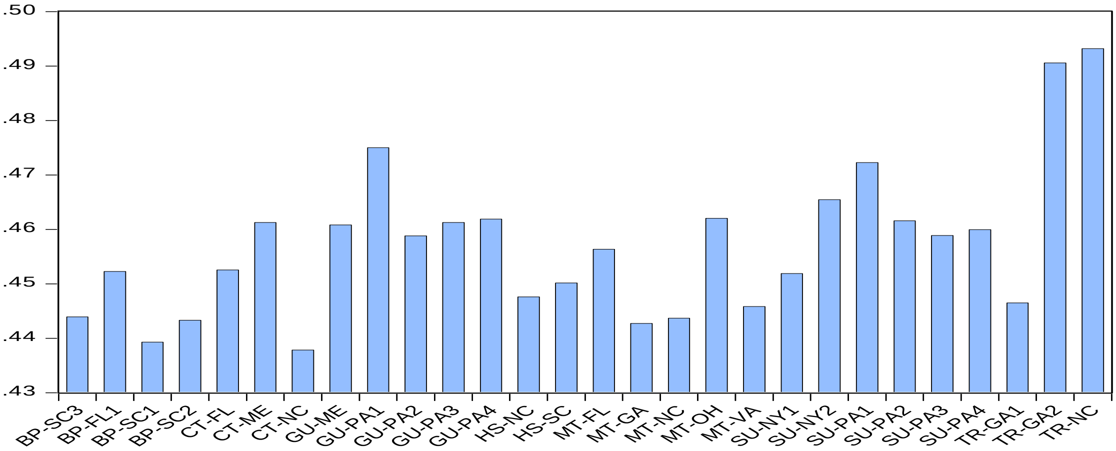
Note:BP-FL is BP in Tampa (Florida), **BP-SC1** is BP in North Augusta (South Carolina), **BP-SC2** is BP in North Augusta (South Carolina), **BP-SC3** is BP in Spartanburg (South Carolina), **CT-FL** is Citgo in Tampa (Florida), **CT-ME** is Citgo in South Portland (Maine) , **CT-NC** is Citgo in Selma (North Carolina) , **GU-ME** is Gulf Oil in South Portland (Maine), **GU-PA1** is Gulf Oil in Mechanicsburg (Pennsylvania), **GU-PA2** is Gulf Oil in Scranton(Pennsylvania), **GU-PA3** is Gulf Oil in Whitehall (Pennsylvania), **GU-PA4** is Gulf Oil in Williamsport (Pennsylvania), **HS-NC** is Hess in Wilmington (North Carolina), **HS-SC** is Hess in North Charleston (South Carolina), **MT-FL** is Marathon Petroleum Corporation in Tampa (Florida), **MT-GA** is Marathon Petroleum Corporation in Columbus (Georgina), **MT-NC** is Marathon Petroleum Corporation in Charlotte (North Carolina), **MT-OH** is Marathon Petroleum Corporation in Steubenville (Ohio), **MT-VA** is Marathon Petroleum Corporation in Roanoke (Virginia), **SU-NY1** is Sunoco in Rochester (New York), **SU-NY2** is Sunoco in Tonawanda (New York) , **SU-PA1** is Sunoco in Altoona (Pennsylvania), **SU-PA2** is Sunoco in Fullerton (Pennsylvania), **SU-PA3** is Sunoco in Kingston (Pennsylvania) , **SU-PA4** is Sunoco in Northumberland ((Pennsylvania), **TR-GA1** is TransMontaigne in Athens (Georgina), **TR-GA2** is TransMontaigne in Rome (Georgina), **TR-NC** is TransMontaigne Charlotte (North Carolina).

Figure 3-4- Mean, standard deviation and coefficient variation of seven major gasoline companies in US

Mean



Standard Deviation



Coefficient Variation

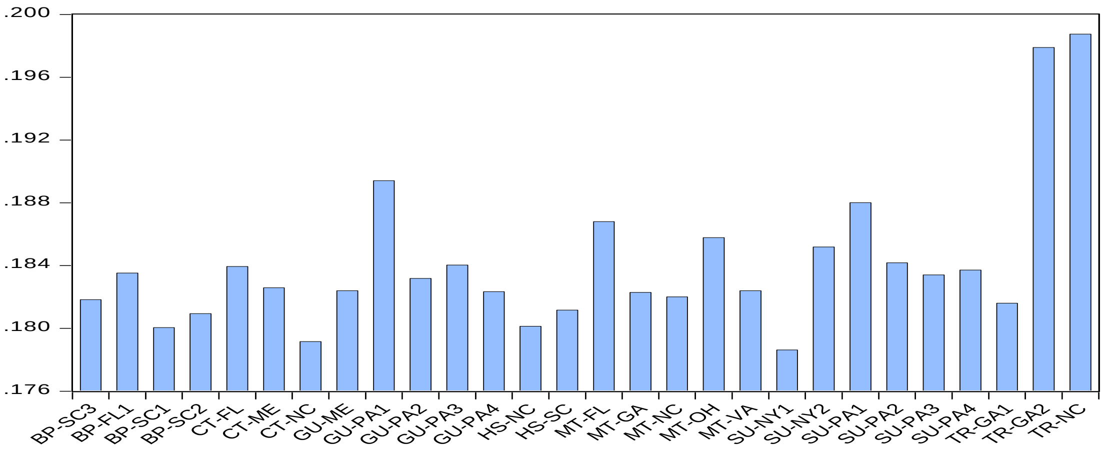


Table 3-1- Mean, standard deviations and Coefficient Variation of the US Gasoline company

	Coefficient Variation	STD-DEV	Mean
BP-SC3	0.181831177	0.443925	2.441413
BP-FL1	0.183533065	0.452282	2.464308
BP-SC1	0.180047217	0.439281	2.43981
BP-SC2	0.18093806	0.443293	2.449971
CT-FL	0.183944524	0.45256	2.460307
CT-ME	0.182592001	0.461263	2.526195
CT-NC	0.179166505	0.437848	2.443805
GU-ME	0.182405441	0.460824	2.526372
GU-PA1	0.189412696	0.475012	2.507815
GU-PA2	0.183184937	0.458818	2.504671
GU-PA3	0.184036856	0.461272	2.506411
GU-PA4	0.182340163	0.461901	2.533183
HS-NC	0.180138629	0.4476	2.484753
HS-SC	0.181171955	0.450171	2.484772
MT-FL	0.186807375	0.456365	2.442971
MT-GA	0.182295572	0.442713	2.428545
MT-NC	0.182005016	0.443682	2.437746
MT-OH	0.185786586	0.462023	2.486848
MT-VA	0.182400335	0.445826	2.444217
SU-NY1	0.178622505	0.451881	2.52981
SU-NY2	0.185189002	0.465447	2.513362
SU-PA1	0.188012347	0.472281	2.511968
SU-PA2	0.184182458	0.461578	2.506091
SU-PA3	0.183405415	0.458882	2.502009
SU-PA4	0.183716101	0.459961	2.503651
TR-GA1	0.181609849	0.446484	2.458479
TR-GA2	0.197899908	0.490563	2.478844
TR-NC	0.198751599	0.493185	2.481414

Note:BP-FL is BP in Tampa (Florida), **BP-SC1** is BP in North Augusta (South Carolina), **BP-SC2** is BP in North Augusta (South Carolina), **BP-SC3** is BP in Spartanburg (South Carolina), **CT-FL** is Citgo in Tampa (Florida), **CT-ME** is Citgo in South Portland (Maine) , **CT-NC** is Citgo in Selma (North Carolina) , **GU-ME** is Gulf Oil in South Portland (Maine), **GU-PA1** is Gulf Oil in Mechanicsburg (Pennsylvania), **GU-PA2** is Gulf Oil in Scranton(Pennsylvania), **GU-PA3** is Gulf Oil in Whitehall (Pennsylvania), **GU-PA4** is Gulf Oil in Williamsport (Pennsylvania), **HS-NC** is Hess in Wilmington (North Carolina), **HS-SC** is Hess in North Charleston (South Carolina), **MT-FL** is Marathon Petroleum Corporation in Tampa (Florida), **MT-GA** is Marathon Petroleum Corporation in Columbus (Georgina), **MT-NC** is Marathon Petroleum Corporation in Charlotte (North Carolina), **MT-OH** is Marathon Petroleum Corporation in Steubenville (Ohio), **MT-VA** is Marathon Petroleum Corporation in Roanoke (Virginia), **SU-NY1** is Sunoco in Rochester (New York), **SU-NY2** is Sunoco in Tonawanda (New York) , **SU-PA1** is Sunoco in Altoona (Pennsylvania), **SU-PA2** is Sunoco in Fullerton (Pennsylvania), **SU-PA3** is Sunoco in Kingston (Pennsylvania) , **SU-PA4** is Sunoco in Northumberland ((Pennsylvania), **TR-GA1** is TransMontaigne in Athens (Georgina), **TR-GA2** is TransMontaigne in Rome (Georgina), **TR-NC** is TransMontaigne Charlotte (North Carolina).

In view of the gasoline retail market behaviour, the highest value of coefficient of variation is 1.11 times higher than the lowest value of the coefficient variation and as such changes are insignificant this suggests anti-competitive behaviour in the US gasoline market. Furthermore in the next section via the regime switching model we detect the potential disequilibrium in the long-run.

3.4 Disequilibrium Regime Switching Model

Global demand for gasoline is affected by technological change, global population growth, motor vehicle ownership and heating oil consumption. Since the last decade we can clearly observe that gasoline prices are highly volatile and this makes price modelling and forecasting, and risk management very challenging. Global warming and greenhouse gas emissions interact with the demand for gasoline. However political instability in the oil producing countries caused a remarkable disruption in energy supply, market equilibrium and prices since the 1990s. Gasoline demand modelling, following Ramsey et al (1975), Dhal (1977), and Yang and Hu (1984) considers supply and demand to emphasize supply along with demand in the gasoline market, and also the level of supply-side intervention and policy in the gasoline market.

For a product such as gasoline there is little quality uncertainty as the quality of the product is regulated for reasons of safety and the manufacturer needs to meet a standard for the product to avoid litigation from the public, corporate employees and the motor vehicle manufacturers who might engage in a class action where such failure to impact their reputation and affect sales.

Price uncertainty is an important issue and it might reflect the potential for disequilibrium (Arrow, 1962) in the energy market. Hence using different regime switching models we identify potential market disequilibrium caused by imperfect competition or price leadership. Subsequently we investigated this disequilibrium as characterized by excess demand or excess supply. Yang and Hu (1984) used this approach to formulate an endogenous switching model to examine a gasoline market. However, the analysis paid no attention to non-stationarity.

In the following section we analysed disequilibrium switching model using the regular gasoline sales level(Q), regular retail gasoline real price (RP), WTI crude oil price (P_W), consumer price index(CPI), producer price index(PPI), gasoline unleaded regular cost of insurance and freight(Cost), total energy consumption(EXP), city-gate gas real price(P_{GAS}), disposable income(Y), automobile sales (Auto), price of the residual fuel oil(P_{Res}), price of the distillate fuel oil(P_{dst}), and refineries net input of crude oil(RI) from 1992:1 to 2012:9 in the US.[46] The data in log levels and their differences are graphed in Figure 3-5 and 3-7, and the frequency distributions of both datasets are plotted in Figure 3-6 and 3-8.

From the 3-5 and 3-7, the price level has drift whereas the differenced series appear to move randomly around the fixed mean. Furthermore figure 3-5 suggests LEXPN, LRI, LCPI, LAUT, and LQ are seasonal. Considering Figure 3-6 and 3-8, the frequency distributions of all the log data (Fig. 3-6) suggests the series do not revert

[46]The data set have been obtained from energy information administration website (www.eia.gov), and Bureau of Labour Statistics website (www.bls.gov).

to mean and overall might suggest two regimes, while the frequency distribution of data in their log differences (Fig. 3-8) seems to be closer to normality.

Figure 3-5- Plot of LExpn, LRP, LRPGas, LPRes, LPdst, LPW, LY, LRI, LPPI, LCPI, LCost, LAUT and LQ in the US

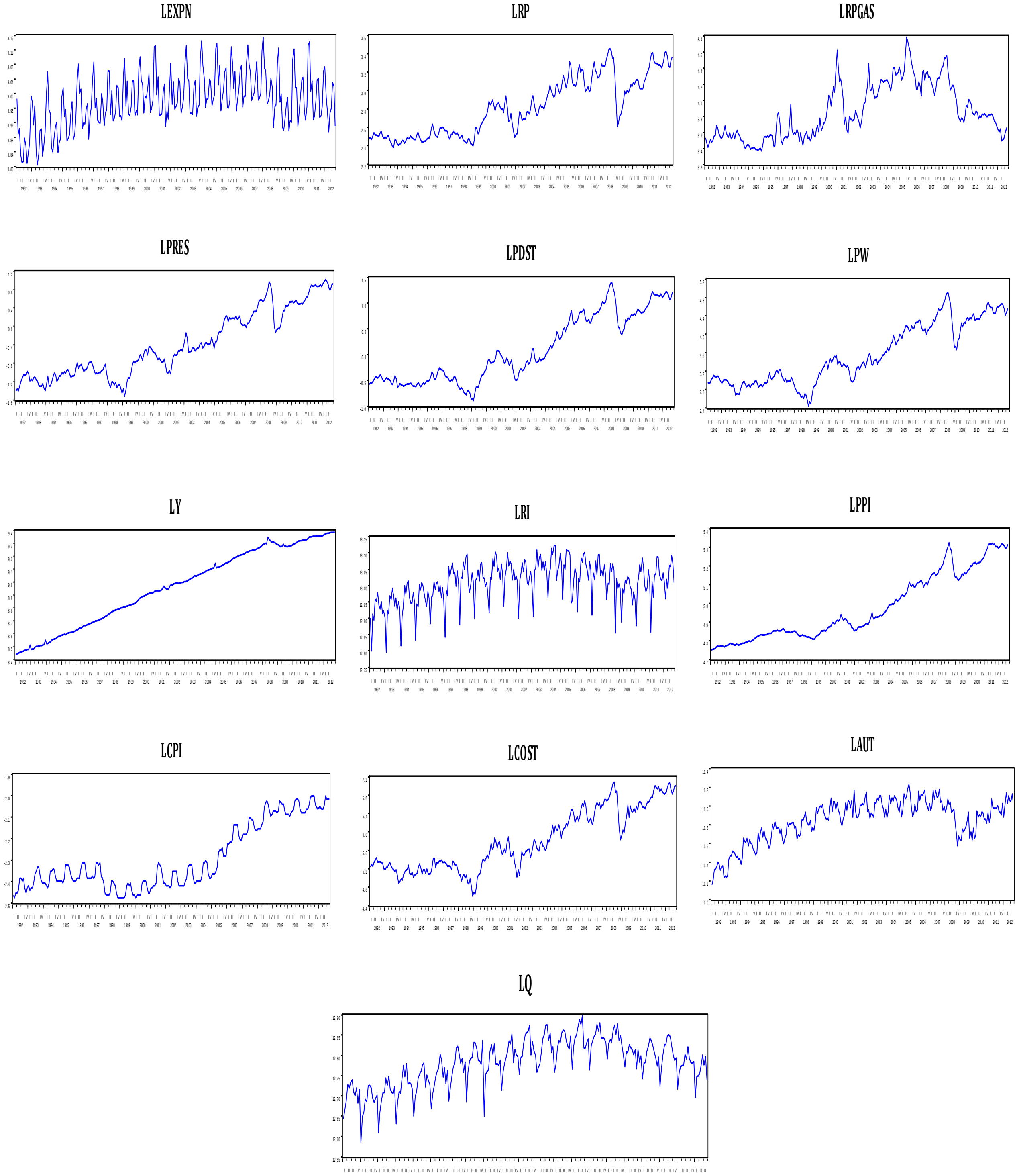


Figure 3-6- Frequency distributionsof LExpn, LRP, LRPGas, LPRes, LPdst, LPW, LY, LRI, LPPI, LCPI, LCost, LAUT and LQ in the US

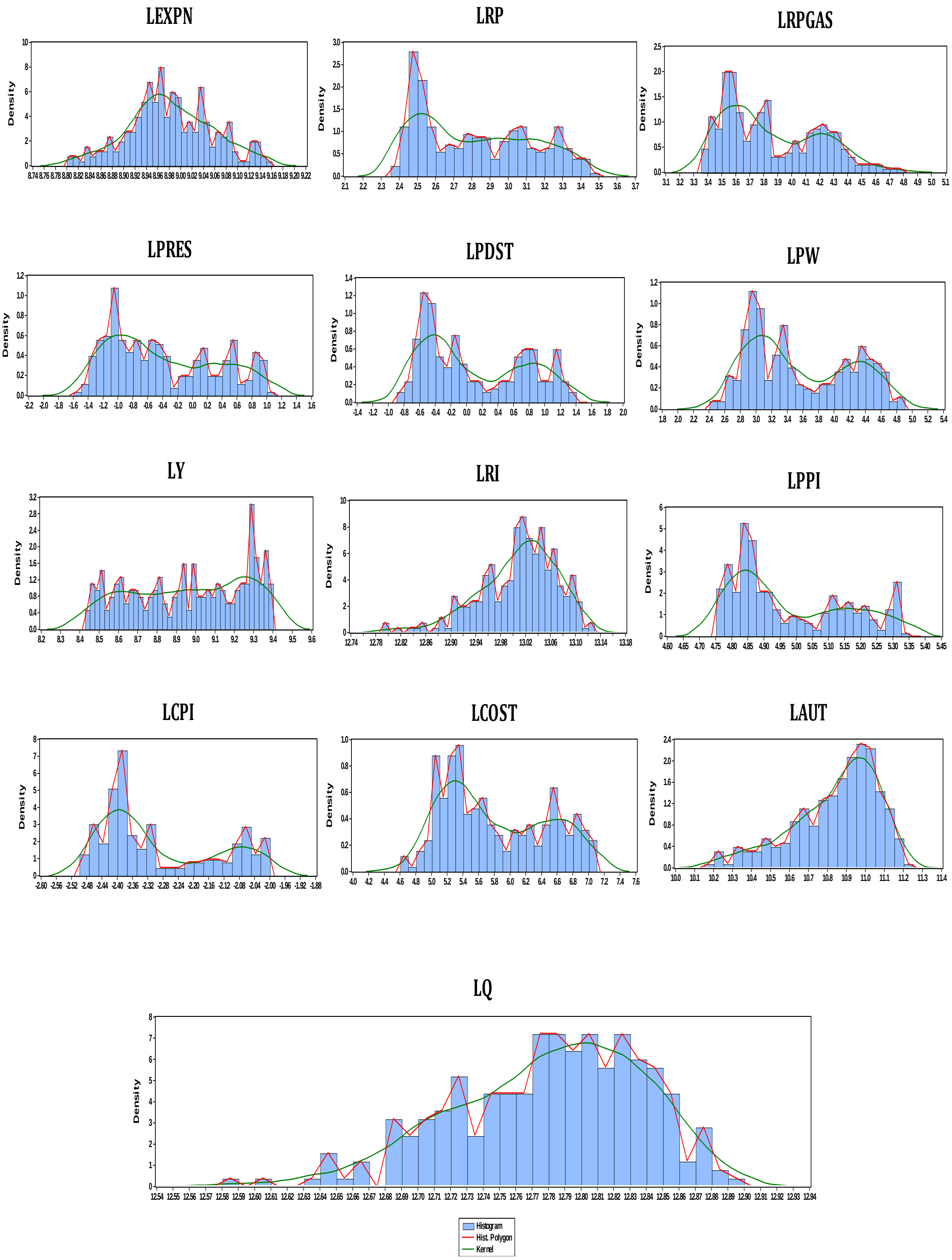


Figure 3-7- Plot of DLEXP, DLRP, DLRPGAS, DLPRES, DLPDST, DLPW, DLY, DLRI, DLPPI, DLCPI, DLCOST, DLAUT and DLQ in the US

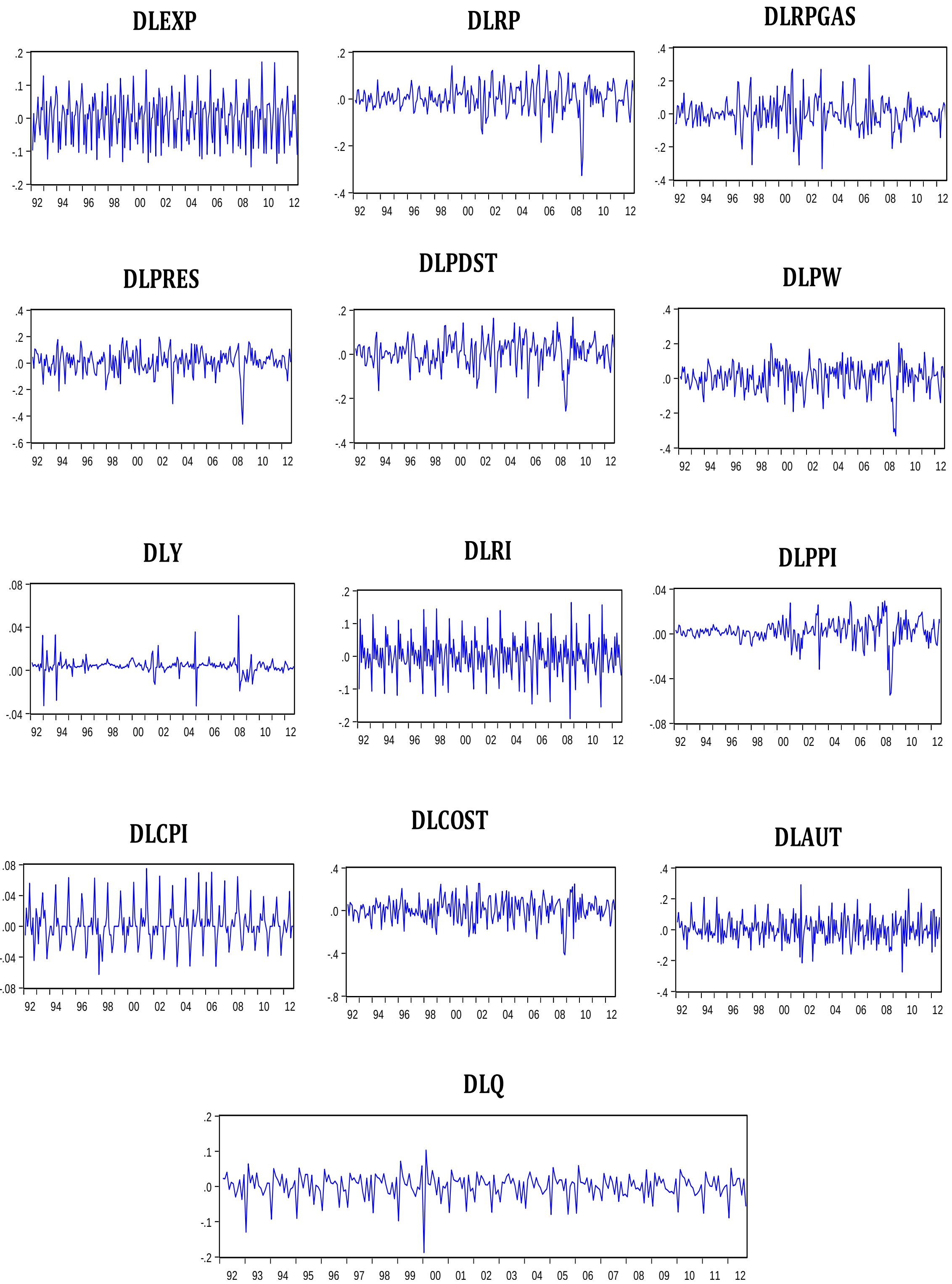
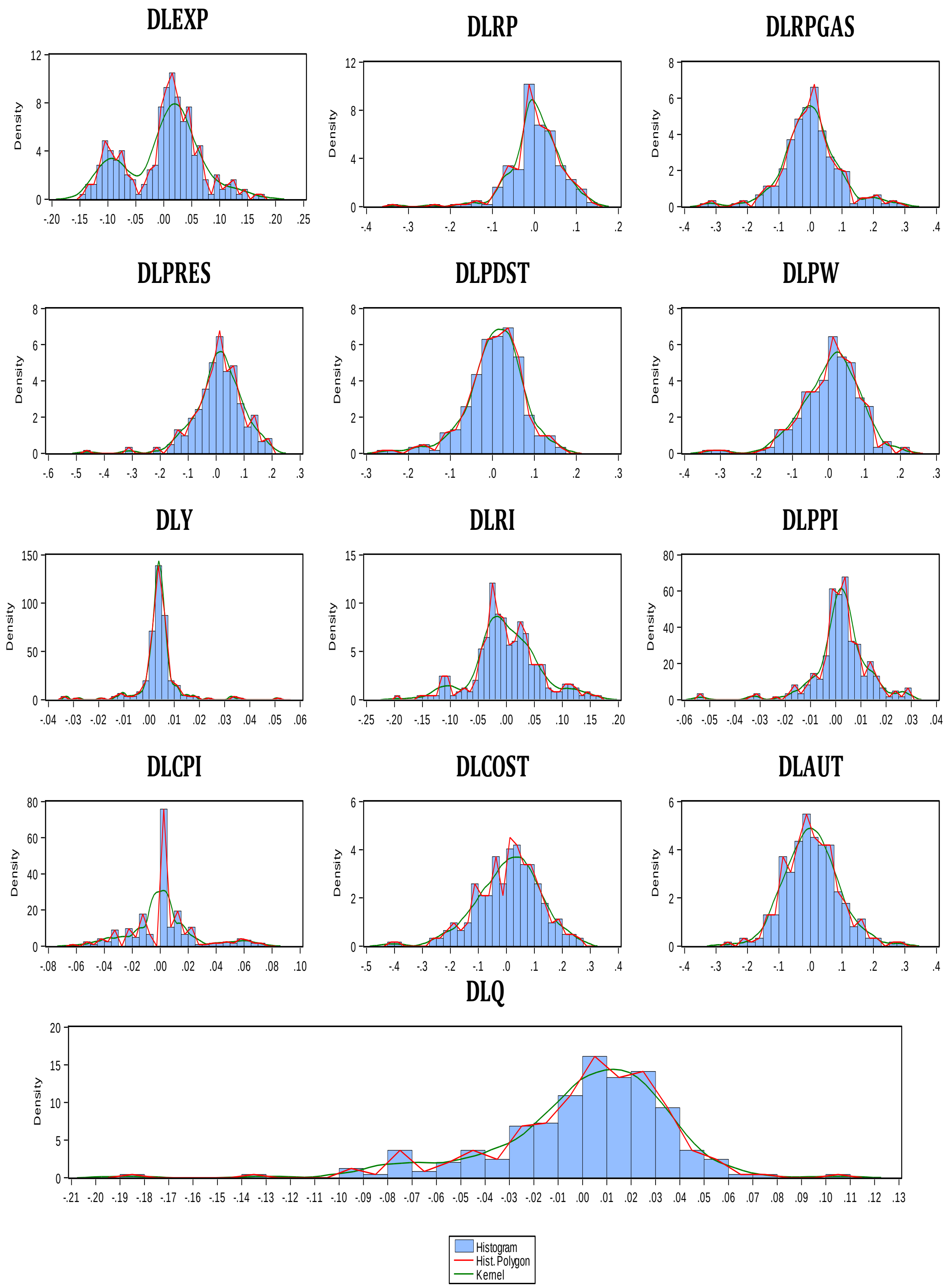


Figure 3-8- Frequency distributions of DLEXP, DLRP, DLRPGAS, DLPRES, DLPDST, DLPW, DLY, DLRI, DLPPI, DLCPI, DLCOST, DLAUT and DLQ in the US



Classical economic theory suggests that market forces move supply and demand towards the equilibrium as a result of prices moving. A market is in equilibrium when the sum of agent demands and the aggregate level of supply by corporations intersect. It is often suggested that firms in the short to medium term fix a price as a mark-up but in the long-run they supply what the market demands.

In the gasoline market the equilibrium price is set at the intersection point of market aggregated demand and supply. In the preceding chapters we examined gasoline price behaviour across different regions in the long-run and the short-run, specifying that the market structures and price dynamics may differ across regions. In this section we formulate two different switching models and examine their behaviour and the nature of the different regimes.

Fair and Jaffee (1972) used the maximum likelihood method to examine the econometric problems related to estimating demand and supply in disequilibrium markets.[47] The main assumption of their model was the presence of excess demand or supply in the market. Hence market disequilibrium is observed when quantity demanded and supplied are not equal to each other. The notion that the economy or a market is not in full equilibrium was investigated by Hicks (1936), the notion of adjustment along a demand curve was based on the idea that prices might be taken as

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[47] Fair and Jaffee (1972) indicated supply and demand equations as following:

$D_t = \alpha P_t + \beta X'_{dt} + \varepsilon_{dt}$ (*1)

$S_t = \alpha' P_t + \beta' X'_{st} + \varepsilon_{st}$ (*2)

Where D_t is unobserved quantity demanded and S_t is unobserved quantity supplied during the period t, P_t is the exogenous price of the gasoline, X'_{dt}, X'_{st} are other factors or vectors of exogenous variables that impact D_t and S_t, β and β' are vectors of parameters, and ε_{dt} and ε_{st} are the residuals that are assumed independently distributed. Fair-Jaffee (1972) model solved equation (*1) and (*2) simultaneously and identified that the market equilibrium is where:

$Q_t = D_t = S_t$ (*3)

Where Q_t is the observed traded quantity of the good at time t. Equation (*3) identifies that in an equilibrium the quantity transacted is equal to quantity demanded and supplied in the market.

fixed within a neighbourhood and that movements in price do not lead to income effects. Then consumers make their decisions subject to these prices to give rise to a temporary equilibrium. Arrow (1962) suggests that uncertainty over prices gives rise to Demand curves that slope downwards and as a result there is a limit to the market even when there is no explicit barrier to entry into the market place. The disequilibrium model follows from the dual decision hypothesis of Clower (1968) and this implies that demands are made effective when money is available to purchase goods. It is the latter process that places a limit on the market and leads prices to respond more slowly than quantities. The min condition below follows from the notion that the consumer and producer cannot be forced to consume or produce more than they might wish at any price. There are some exceptions in relation to the consumption of public goods, but when products are supplied in a market where forced trading is not possible, the following equation applies:

$$Q_t = \min(D_t, S_t) \qquad \begin{cases} Q_t = S_t & \text{if } D_t > S_t \text{ and there is excess demand} \\ Q_t = D_t & \text{if } D_t < S_t \text{ and there is excess supply} \end{cases} \qquad (3\text{-}1)$$

Equation (3-1) follows from the disequilibrium hypothesis which implies that only one regime can be observed at the time.[48] When $D_t > S_t$ then quantity transacted in the market is equal to quantity supplied and in the opposite situation when there is excess supply in economy ($D_t < S_t$) then quantity transacted in the market is equal to quantity demanded.

Maddala and Nelson (1974) examined the maximum likelihood estimation method of Fair and Jaffee under four different conditions. They specified that the challenges with the model are related to the model specification and the data rather than the

[48]Muellbauer (1983) suggested at the aggregate level the switch would be smoothed that gave rise to continuous switching.

methods applied. However Rosen and Quandt (1978) argued that if there is monopoly power in the demand side or supply side then the Q_t may lie somewhere between D_t and S_t.

More specifically, Robinson (1994) summarise the literature and adapts the method to provide an autoregressive correction that attempted to transfer the disequilibrium method to the dynamic context. Andrews and Nickell (1985) in analysing unemployment at the economy level derived a dynamic switching model where the disequilibrium is smoothed via aggregation over markets using the cumulative normal distribution as the aggregation device. This is an extension of the model of Muellbauer (1983), which simplified the problem by selecting a uniform distribution.

Although this method is well motivated in the context of the cointegration and non-stationarity, the switching method was overtaken by the notion that disequilibrium at the aggregate level was overtaken by rational expectations as applied to prices and not quantities. In econometrics the notion of disequilibrium became embedded in the error correction model and cointegration, this is considered in Maddala (1983).

Here a static switching structure is devised and the switching is handled in the long-run by the switching regression.[49] In this section we identify demand and simply via the min condition using an exogenous switching model to measure long-run market failure. We analyse demand and supply equations and in a similar way to Engle and Granger (1987) the errors are stacked to form the error correction term. The error

[49] Endogeneity is no longer an issue as long as the data are all I(1) as a result of super-consistency (see Burke and Hunter (2005)).

correction model can also include a dynamic switch where the correction to the demand and supply disequilibrium is not symmetric. As a result of this excess demands in the long-run may correct in a different way to excess supply.

Yang and Hu (1984) formulated a gasoline market model testing disequilibrium that may have been caused by either imperfect price adjustment by both potential buyers and sellers or institutional price restrictions. In Yang and Hu (1984) they take no account of non-stationarity or the potential that the estimations may need to handle an autoregressive unit root. In their estimation using the errors are serially correlated and the test statistics are non-standard.

Here we analysed a similar model, but applied the Phillips-Hansen fully modified regression to estimate the parameter of the long-run relation. Phillips and Hansen (1990) developed a semi parametric method of estimation to take account of moving average or autoregressive errors. The Phillips-Hansen method estimates the parameters of a single cointegration relation by fully modified regression. Consider the OLS regression below:

$$y_t = \alpha_0 + \alpha_1 x_t + \varepsilon_t. \tag{3-2}$$

Where y_t is an I(1) variable, x_t is a k×1 vector of I(1) regressors and the first-difference of x_t is stationary:

$$\Delta x_t = \mu + \upsilon_t.$$

The distribution of the OLS estimator in equation (3-2) with non-stationary series is non-standard the parameters are super consistent when there is cointegration, but the t-tests are not well defined. The Phillips and Hansen fully-modified OLS estimator computes an estimate of the long-run variance that corrects the regression to takes account of the serial correlation associated with the potential unit root in the error. With the exception of the conventional least squares regression result that applies with truly exogenous variables such as indicators, dummies and time, according to Kitamura and Phillips (1995) the estimations and inference are valid as long as the dependent variable and any potentially endogenous regressors are I(1).

Hence using same variables as Yang and Hu (1984) and Phillips-Hansen modified method we identified following switching disequilibrium equation:

$$\mathbf{Q_t} = \gamma_0 + \gamma_1 \mathbf{D_d} + \gamma_2 \boldsymbol{d^d P_t} + \gamma_3 \boldsymbol{d^d Y_t} + \gamma_4 \boldsymbol{d^d Aut_t} + \boldsymbol{\omega_{dt}} + \gamma_5 d^s \boldsymbol{P_t} + \gamma_6 \boldsymbol{d^s P_{res\,t}} + \gamma_7 \boldsymbol{d^s P_{dst\,t}} + \gamma_8 \boldsymbol{d^s P_{w\,t}} + \gamma_9 \boldsymbol{d^s RI_t} + \boldsymbol{\omega_{st}}. \qquad (3\text{-}3)$$

In equation 3-3 D_t and S_t are aggregated gasoline demand and aggregated gasoline supply, P_t is the regular retail gasoline real price, Y_t is disposal income, and Aut_t is automobile sales, and $\boldsymbol{\omega_{dt}}$ include explanatory variables not clarified in the demand function. Similarly in the supply equation the P_w is the WTI crude oil price[50], P_{res} is price of residual fuel oil, and P_{dst} is price of distillate fuel oil to analyse the substitution effect in the production process,[51] RI is refineries net input of crude oil, $\boldsymbol{d^d}$ is dummy demand and $\boldsymbol{d^s}$ is dummy supply, and $\boldsymbol{\omega_{st}}$ comprise unexplained explanatory variables.

To identify the dummy for demand (***d^d)*** and supply ***(d^s)*** we evaluated relative price from the following equations, where if $\Delta lp_{\text{Retail Price}} - \Delta lp_{\text{Consumer Price Index}} > 0$ indicates

[50] Hotelling (1932) determined that profit-maximising price-taking firms based their prices on selection of their input and output levels. Thus the crude oil price plays an important role in the supply function for the gasoline market.
[51] No.2 distillate fuel oil is used in high-speed diesel engines, such as those in railroad locomotives, trucks, and automobiles.

that the relative price is increasing and D>S which classifies $\boldsymbol{d^s}$, otherwise ($\Delta lp_{\text{Retail Price}} - \Delta lp_{\text{Consumer Price Index}} < 0$) there is a decrease in the relative price identifying that D<S and that indicates $\boldsymbol{d^d}$. Descriptive statistics of the above key variables are presented in Appendix B. All the above are in logarithms and regime dependent. The results for the above disequilibrium switching estimations are presented as demand and supply equations in Table 3-2. In the demand-side equation all estimated parameters are statistically significant with their expected sign. A 1% increase in the retail gasoline price will reduce the demand for gasoline by 3.43% and this implies that consumers are sensitive to gasoline price changes in changing their gasoline consumption level. A significant positive income coefficient indicates that an increase in consumer income and automobile sales level may increase gasoline demand in the market. This result indicates that a 1% increase in the consumer income will increase the gasoline demand by 2.87% and it shows consumers are responsive to their income changes in changing gasoline demand.

The positive sign of γ_5 indicates that the price of gasoline affect a gasoline supply positively that is consistent with economic theory. Its significance with a t value of 3.07 identifies that refiners are sensitive to gasoline price changes in changing output level. However the negative sign of $\boldsymbol{\gamma_6}$ and $\boldsymbol{\gamma_7}$ indicates that residual fuel oil and distillate fuel oil price rises will reduce the supply of gasoline so the refiner produces for these markets where possible and substitute away from gasoline. While insignificant coefficients $\boldsymbol{\gamma_6}$ and $\boldsymbol{\gamma_7}$ identify that changes in gasoline production cannot be attributed to fluctuations in price of residuals and distillate fuel oil. The crude oil price which explains the effect of the input price on gasoline supply has an expected negative sign but statistically insignificant identifying that change in gasoline production cannot be impacted by input price fluctuations. Finally, the refineries net input of crude oil, explains the scale effect in the supply equation, has a negative sign and is statistically insignificant indicating that it appears not to affect gasoline supply.

As we see in table (3-2) the supply equation mostly contains insignificant coefficients and to further investigate this relation we estimate the model below. However, from economics theory gasoline consumption might be highly dependent on other factors such as: consumer price index, total energy expenditure, and the city-gate real gas price as a substitute good that affects consumer's gasoline consumption behaviour. Similarly the firm supply equation may be effected by other factors such as the crude oil price, cost and producer price index. Hence we developed a new approach to estimate the demand and supply model by including different variables. The proposed demand function incorporates the global price level. Again we estimated the following disequilibrium switching equations using Phillips and Hansen modified method:

$$\mathbf{Q_t} = \varphi_0 + \varphi_1 \mathbf{D_d} + \varphi_2\, d^d P_t + \varphi_3\, d^d CPI_t + \varphi_4\, d^d EXP_t + \varphi_5\, d^d P_{Gas} + \varphi_6\, d^d Y_t + \nu_{dt} + \varphi_7\, d^s P_t + \varphi_8\, d^s C_t + \varphi_9\, d^s PPI + \varphi_{10}\, d^s P_{W\,t} + \nu_{st} \qquad (3\text{-}4)$$

where P_t is the price of the gasoline, *CPI* is consumer price index, and *EXP* is total energy expenditure, and P_{Gas} is city-gate gas real price, Y_t is disposal income, and ν_{di} includes explanatory variables not clarified in the demand function. Also in the supply equation P_W is the WTI crude oil price[52], *PPI* is the producer price index, and C_t is unleaded regular gasoline costs (insurance and freight), and ν_{st} comprise

[52] Hotelling (1932) identified that profit-maximising price-taking firms based to their prices they determine their input and output level. Thus crude oil price plays an important role in the supply function of the gasoline market.

unexplained explanatory variables in the supply equation. Descriptive statistics of the above key variables are presented in Appendix C.

The results for the estimation of equation (3-4) are presented in the Table 3-3. For the demand-side equation all estimated parameters are significant with expected sign except φ_3 that could be due to the high usage of the other energy sources in comparison with gasoline. The φ_2 indicates that a 1% increase in the retail gasoline price will reduce the demand for gasoline by 11.19%, this implies that consumers are highly sensitive to gasoline price in changing their gasoline consumption level. The income coefficient (φ_6) suggests that a 1% increase in consumer income will increase the gasoline demand by 6.26% and it shows consumers are responsive to income in changing their gasoline demand level. In the supply-side of the equation only φ_{10} has the expected sign that is also statistically insignificant. This implies that gasoline supply is not be strongly affected by other factors.

Comparing above estimation of 3-3 and 3-4 via the regression that imposes the switch, the variables used in equation 3-4 seem to explain the model more appropriately as most of the variables are statistically significant. The significant coefficient subject to all series being I(1) implies that this is a long-run relation. This suggests that models based on the supply and demand regimes give rise to meaningful long-run equations.

Table 3-2- Static Disequilibrium Switching Estimation 1

	Variable	Parameter	Bartlett Weighs, truncation lag=64
Demand-side Equation		γ_0	14.16** [0.00] (0.89)
	D_d	γ_1	-3.78** [0.00] (0.94)
	P_t	γ_2	-3.43** [0.00] (0.03)
	Y_t	γ_3	2.87** [0.00] (0.04)
	Aut_t	γ_4	10.21** [0.00] (0.03)
Supply-side Equation	P_t	γ_5	3.07** [0.00] (0.05)
	$P_{res\ t}$	γ_6	-1.005 [0.92] (0.03)
	$P_{dst\ t}$	γ_7	-3.26 [0.74] (0.05)
	$P_{w\ t}$	γ_8	-0.02 [0.98] (0.05)
	RI_t	γ_9	-0.34 [0.73] (0.07)

Note: $\mathbf{Q_t = \gamma_0 + \gamma_1 D_d + \gamma_2 d^d P_t + \gamma_3 d^d Y_t + \gamma_4 d^d Aut_t + \omega_{dt} + \gamma_5 d^s P_t + \gamma_6 d^s P_{res\ t} + \gamma_7 d^s P_{dst\ t} + \gamma_8 d^s P_{w\ t} + \gamma_9 d^s RI_t + \omega_{st}}$. All variables are in log scales and all prices are real price data. Values without the brackets presents Fully Modified Phillips-Hansen t-statistic, values in ( ) shows standard errors, and values in [ ] displays p-values. ******is significant at the 1% and*****is significant at the 5%.

Table 3-3- Static Disequilibrium Switching Estimation 2

	Variable	Parameter	Bartlett Weighs, truncation lag=64
Demand-side Equation		φ_0	24.17** [0.00] (0.62)
	D_d	φ_1	-8.91** [0.00] (1.19)
	P_t	φ_2	-11.19** [0.00] (0.06)
	CPI_t	φ_3	9.71** [0.00] (0.09)
	EXP_t	φ_4	7.15** [0.00] (0.13)
	P_{Gas}	φ_5	-3.21** [0.00] (0.06)
	Y_t	φ_6	6.26** [0.00] (0.00)
Supply-side Equation	P_t	φ_7	-0.82 [0.41] (0.09)
	C_t	φ_8	4.31** [0.00] (0.09)
	PPI	φ_9	-5.31** [0.00] (0.15)
	$P_{W\,t}$	φ_{10}	-1.18 [0.24] (0.08)

Note: $Q_t = \varphi_0 + \varphi_1 D_d + \varphi_2 d^d P_t + \varphi_3 d^d CPI_t + \varphi_4 d^d EXP_t + \varphi_5 d^d P_{Gas} + \varphi_6 d^d Y_t + v_{dt} + \varphi_7 d^s P_t + \varphi_8 d^s C_t + \varphi_9 d^s PPI + \varphi_{10} d^s P_{W\,t} + v_{st}$. All variables are in log scales and all prices are real price data. Values without the brackets presents Fully Modified Phillips-Hansen t-statistic, values in ( ) shows standard errors, and values in [ ] displays p-values**is significant at the 1% and*is significant at the 5%.

3.5 Markov Regime Switching Model (MRSM)

In this section we analyse a Markov Regime Switching (MRS) model to capture different regimes in the energy markets. In the previous two chapters we found evidence that markets may not be efficient either across regions or within local markets. There is also evidence in financial markets of asymmetry in price reactions as upward price corrections are more often smaller than downward movements. Further in energy markets there is evidence that market prices react more quickly to increases in wholesale prices while when wholesale prices fall the market price reaction is much slower. The Markov model may also be used as a benchmark to make comparison with other methods.

As mentioned above, there are a number of reasons why behaviour could change over time, which may give rise to different regimes and different dynamic adjustments to disequilibrium. The Markov switching method generates different regimes between which the relation being analysed might adjust. The variable modelled in this way is the real price change and this is used as a result of the asymmetries discussed in the previous paragraph. Further, finding switching in terms of the Markov model may be consistent with finding switching in terms of other types of model. So the Markov method can be compared with the dependent variable being used to define exogenous disequilibrium switching process to define the disequilibrium model in terms of separate regimes related to demand and supply in the long-run.

Here, the intention is to use this as a mechanism to identify supply and demand in the long-run. Each regime is characterized by a different parameterisation. Here the Markov regime switching error-correction model (MRSECM) is used to determine regimes that are latent in the data. We focus on modelling the gasoline market as a single market and to observe both sides of the market. The primary method to estimate disequilibrium models was investigated in a static context by Fair and Jaffee (1972), Fair and Kelejian (1974), and Maddala and Nelson (1974). Maddala (1983) provides a useful summary of this early literature and compares this with the same latent effects captured by error correction models. Here the error correction model is also embedded in a Markov switching equation.

Let us assume that the linear regression model is:

$$y_t = \beta X_{ti} + u_t .$$

Where y_t denotes the dependent variable, X_{ti} denotes the matrix of independent variables. The above regression model is separated into two relations for:

$$\text{Regime (1): } y_i = \beta_1' X_{1i} + u_{1i} \qquad if\ \gamma' Z_i \geq u_i \qquad (3\text{-}5)$$

$$\text{Regime (2): } y_i = \beta_2' X_{2i} + u_{2i} \qquad if\ \gamma' Z_i < u_i \qquad (3\text{-}6)$$

Where Z_i determines the i^{th} observation that is generated for each regime, based on the unknown coefficient vector γ' that defines the switch and u_{1i} and u_{2i}, are assumed normally distributed with mean zero and variance-covariance matrix:

$$\boldsymbol{\sigma} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1u} \\ \sigma_{21} & \sigma_2^2 & \sigma_{2u} \\ \sigma_{1u} & \sigma_{2u} & 1 \end{bmatrix}$$

where σ_1 is the variance of the first regime and σ_2 indicates the variance of the second regime. If $\sigma_1 \neq \sigma_2$ and $\beta_1 \neq \beta_2$, then the regression relation switches between the two regimes.[53]

A problem with the previously discussed models is that they were static in nature implying that the models would usually be poorly specified, especially in relation to serial correlation. A number of corrections were applied to take account of this and these are explained in Robinson (1994). Further, the econometric methods went hand in hand with an economic literature (Barro and Grossman (1978)) that seemed to be

[53] By knowing which observation of the dependent variable of y was generated by which regime a Chow test can examine whether $\sigma_1 = \sigma_2$ and $\beta_1' = \beta_2'$. However if this is unknown and it is not clear which of the dependent variable (y) was generated by, then Goldfeld and Quandt's D-method for switching regression might clarify this problem.

outdated by the development of rational expectations, while the notion of disequilibrium in dynamic equations was embedded in error correction models (Davidson et al (1978)). Furthermore, Muellbauer (1983), and Nickell and Andrew (1983) developed at the macro level continuous switching when markets are aggregated. Maddala (1983) discussed disequilibrium where the latent variable equilibrium term is determined by switching and this is embedded in an error correction term.

The regime switching ECM can be explained as an expanded linear error correction model by allowing the short-run parameters to switch in different regimes. Hence a Markov switching error correction model (MSECM) can be used to describe the short-run variation in gasoline sales. MSECM signifies that when the system is in a stable state then the error correction takes place and in the unstable state there are deviations from the long-run equilibrium that cannot be corrected through the ECM. In terms of the disequilibrium model these would be the same when there is correction to another equilibrium state.

We defined the Markov regime switching error correction model using the logarithms of the following data: gasoline retail price (P_g), gas retail real price (P_{GAS}) to analyse the substitute effect in the demand process, consumer price index (CPI), producer price index (PPI), unleaded regular gasoline costs -insurance and freight (COST), WTI spot price (P_{WTI}), residual fuel oil price (P_{res}) and distillate fuel oil price (P_{dst}) to analyse the substitute effect in the production process.

The MRSEC model that might be a single equation from the VECM, with two regimes, is defined on the first-differenced monthly relative gasoline price:

$(\Delta LP_g - \Delta LCPI)_t =$

$\beta_{r,i}(LP_g - LCPI)_{t-1} + \sum_{i=1}^{p-1} \gamma_{s,i}(\Delta LP_g - \Delta LCPI)_{t-i} + \delta_{s,i}(LCPI - LPPI)_{t-1} +$

$\sum_{i=1}^{p-1} \zeta_{s,i}(\Delta LCPI - \Delta LPPI)_{t-i} + \sum_{i=1}^{p-1} \eta_{s,i}(\Delta LCost)_{t-i}$

$+\sum_{i=1}^{p-1} \theta_{s,i}(\Delta LP_{WTI})_{t-i} + \sum_{i=1}^{p-1} \lambda_{s,i}(\Delta LP_{GAS})_{t-i} + \sum_{i=1}^{p-1} \kappa_{s,i}(\Delta LP_{dst})_{t-i} +$

$\sum_{i=1}^{p-1} \nu_{s,i}(\Delta LP_{res})_{t-i} + \varepsilon_t$ (3-7)

where $\boldsymbol{\gamma_{r,i}}$, $\boldsymbol{\zeta_{r,i}}$, $\boldsymbol{\eta_{r,i}}$,$\boldsymbol{\theta_{r,i}}$, $\boldsymbol{\lambda_{r,i}}$, $\boldsymbol{\kappa_{r,i}}$, and $\boldsymbol{\nu_{r,i}}$are the short-run dynamics of price data which is allowed to change within the regimes, ***s*** identifies the regime at time ***t***, and $\boldsymbol{\varepsilon_t}$ is the vector of error terms. Using the Markov regime switching model we describe the equilibrium correction via a non-linear algorithm that computes and maximises the empirical likelihood here in a two-regime model. With a Markov process at each period (*t*), the probability of the switch from regime ***i*** to ***j*** can be calculated using the equation below:

$$p_{ij} = \Pr(s_{t+1} = j \mid s_t = i)$$

Where the probability of remaining in a given regime ***i*** is signified as $p_{ii,}$ consequently $p_{ij} = 1 - p_{ii}$ signifies the probability of switching from regime ***i*** to the other regime, ***j***. Similarly p_{jj} is the probability of remaining in the regime ***j*** and $p_{ji} = 1 - p_{jj}$ is probability of switching to regime ***i***.

Figure 3-9 provides a graphical illustration of smoothed regime probability of US gasoline relative price. This figure reflects the model that indicates the existence of two regimes and the switch among them. First figure in Fig. 3-9 indicates the real price information that we used to identify the regimes of demand and supply for the switching model.

Correspondingly Table 3-4 shows that parameters used in switching equation 3-7 are affected by the regimes and we identified that regimes are persistent and the probability of staying in regime 0 is 0.502 and the probability of staying in regime 1 is 0.465. By comparing the demand and supply dummies (d^d and d^s used in equation 3-3 and 3-4) with the regimes we identified that regime 0 is demand and regime 1 is supply regime. This implies that regular gasoline costs (insurance and freight), gas retail real price, residual fuel oil price, and distillate fuel oil price significantly affect the relative real gasoline price. While roughly half the observations relate to one as compared with the other regime. It is of interest to note that this would seem to lend support to the notion of switching and that equilibrium may not just be captured by the disequilibrium term related to error correction behaviour.

Assuming stationarity of price proportion based on conventional inference the two correction terms in table 3-4 are significant and this implies negative reaction of gasoline market prices to CPI which it is indicative of demand responds, and positive reaction of gasoline market price to PPI indicative of supply responds.

Figure 3-9- Smoothed regime-probability estimates for two-regime MRS EC model of US gasoline relative prices

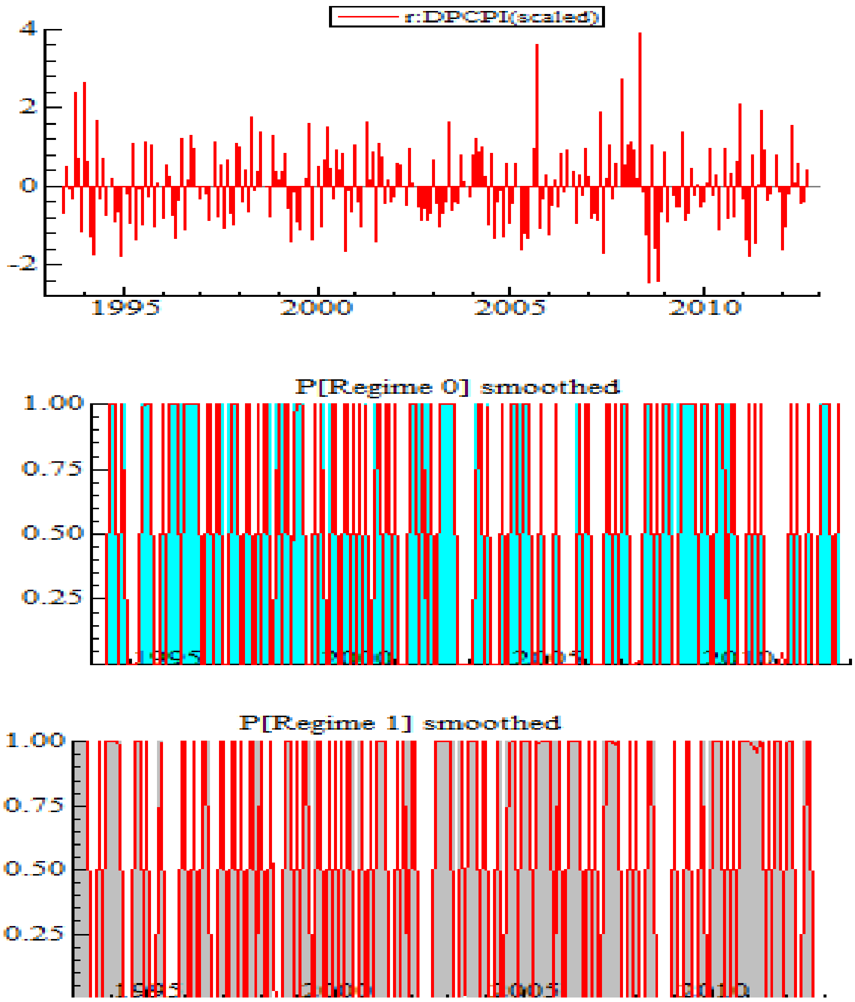

Table 3-4- Dynamic Disequilibrium Switching

Variables in eq. 3-7	coefficient	t-Statistics
DPCPI_2	-0.668**	-16.7
DPCPI_3	-0.425**	-8.86
DPCPI_5	-0.359**	-7.79
DPCPI_6	-0.295**	-5.91
DPCPI_7	-0.338**	-6.67
DPCPI_8	0.150**	2.76
DPCPI_9	-0.570**	-11.0
DPCPI_10	0.226**	4.48
DPCPI_12	-0.184**	-4.38
DPCPI_14	0.092**	3.65
DPCPI_15	-0.171**	-6.64
DPCPI_16	0.338**	14.2
LPCPI_1	-0.011**	-2.00
LCPIPPI_1	0.058**	1.95
DCPIPPI_1	-0.333**	-4.82
DCPIPPI_3	0.186**	2.34
DCPIPPI_5	-0.869**	-10.8
DCPIPPI_6	-0.956**	-12.1
DCPIPPI_7	-0.491**	-5.99
DCPIPPI_8	0.314**	3.95
DCPIPPI_9	-0.228**	-2.64
DCPIPPI_10	0.520**	6.54
DCPIPPI_12	-0.874**	-12.6
DLCOST_1	0.097**	5.46
DLCOST_2	0.157**	7.20
DLCOST_3	0.241**	10.3
DLCOST_4	0.063**	3.19
DLCOST_6	0.164**	7.61
DLCOST_7	0.225**	8.94
DLCOST_8	0.135**	5.55
DLCOST_9	0.155**	6.60
DLCOST_10	0.065**	2.96
DLCOST_11	0.162**	8.54
DLPW_1	0.137**	6.16
DLPW_2	0.074**	2.78
DLPW_3	0.203**	8.55
DLPW_4	-0.199**	-7.22
DLPW_5	0.181**	6.68
DLPW_6	-0.088**	-3.54
DLPW_7	0.075**	2.68
DLPW_8	0.105**	4.02
DLPW_11	-0.157**	-5.95
DLPW_12	-0.080**	-3.64
DLPW_13	-0.060**	-2.43
DLRPGAS_1	0.020	1.51
DLRPGAS_2	0.043**	3.26
DLRPGAS_3	0.064**	4.83
DLRPGAS_6	-0.100**	-7.13
DLRPGAS_8	0.091**	6.37
DLRPGAS_9	-0.070**	-4.93
DLRPGAS_10	-0.049**	-3.35
DLRPGAS_11	-0.072**	-5.50
DLPDST_2	0.070*	1.80
DLPDST_4	0.240**	6.37
DLPDST_5	-0.411**	-9.94
DLPDST_7	-0.188**	-4.78
DLPDST_8	-0.421**	-11.4
DLPDST_9	0.198**	5.92
DLPDST_11	0.086**	2.19
DLPDST_13	-0.050	-1.52
DLPRES_1	0.070**	3.50
DLPRES_3	-0.071**	-3.32
DLPRES_5	0.069**	3.32
DLPRES_6	0.074**	3.87
DLPRES_7	-0.113**	-5.56
Constant(0)	0.417**	2.04
Constant(1)	0.489**	2.39
P_{11}	0.502	
P_{22}	0.465	
Log-likelihood	502.20	

3-6 Conclusion 3

In this chapter a number of methods have been used to identify and analyse regimes in gasoline market. The first method is variance screening that has been used in the regulatory literature to determine whether the market is competitive or open to collusion.

The disequilibrium approach derived initially to estimate demand and supply equation in a static context was not developed to handle non-stationary series. However, when the series are all I(1) it possible to estimate these equations in one go via regression as when a regression is estimated and all the series are I(1) then irrespective of endogeneity the regression estimates satisfy the super consistency result of Stock (1987) as the estimates converge at a rate of 1/T (see Chapter 3 of Burke and Hunter (2005)).

Here it has been shown that the switch model can be estimated by a single regression with the series being scaled by a dummy variable DS and DD. The dummy DS is 1 when the change in the relative price exceeds zero while DD is 1 when the change in the relative price is less than zero. With sufficient data it should be possible to utilise the two step regression method of Engle and Granger (1987) to test whether the regression residuals are stationary. Unfortunately, the switch increases the number of parameters as the demand and supply equations are being computed simultaneously so with more than two hundred observations the critical value for the Dickey Fuller test cannot be computed by the available software. To determine the importance of the parameters in the cointegrating regression they are computed using the fully modified estimation procedure of Phillips and Hansen (1990). The semi-parametric method corrects the estimator for both autoregressive and moving average errors and this implies that it is possible to determine the significance of these parameters via conventional inference as long as the regressors are I(1) except for series that are truly exogenous.

The data are then separated using the relative as compared with absolute price changes. This separation is applied to the static model of Yang and Hu (1984) on a more recent data set. However, the static model only has a long-run interpretation. Based on the estimation results, the demand curve seems well defined, while it is less easy to interpret the second relation as a supply equation. A more recent approach to demand has also been used to define this equation and compared with a new supply equation, but this worked less well than the model of Yang and Hu (1984). Another interpretation of the supply equations is that the long-run supply function is flat implying firms set price as a mark-up of cost.

The final analysis relates to a dynamic model for real gasoline prices in the US from 1993 to 2012. This approach is based on an error correction model where the adjustment coefficients switch between regimes. Disequilibrium is captured by the correction, but this may be unstable or relate to a further equilibrium. Estimation of the Markov Switching ECM indicates that deviations from long-run equilibrium have an effect on gasoline price dynamics and that there are two different regimes.

Conclusion

The search for structure in the energy market has recently become an attractive field of research for economist and policy makers. This thesis explores different methods of analysing the gasoline market structure. The goal of this thesis is to test the market efficiency using various methodologies to identify whether the gasoline market reflects all available information in prices.

In Chapter one, we evaluated the methodology developed by Forni (2004) to define the market definition. Forni (2004) used unit-root tests under the non-stationary and stationary null. Forni (2004) also defined an ordering based on a combination of both forms of the test and categorise market definition based on accepting these tests at the 1%, 5% and 10% levels. This led to the conclusion that policy should be defined to stem further concentration in the Italian market for milk and resist any attempt for the major milk suppliers to merge. Here the US gasoline market is analysed using weekly gasoline price relatives across eight regions of the US (WC, CA, EC, GC, LA, MW, NE, RM)[54]. The ADF and KPSS results indicate that the market definition is narrow between GC and LA and suggests a broad market for all other regions price differentials. While Beirne et al (2007) suggest that their finding that on average the real exchange rate is stationary for a panel of 12 countries based on their corrected univariate ADF tests is valid as at least eight of the twelve series are found stationary and this is given further support by all, but one of the panel results derived under either the non-stationary or the stationary null. A similar conclusion arises here that on average the price differentials are stationary in eight out of nine cases and following Forni(2004) this supports the proposition that there

[54]West Coast, Central Atlantic, East Coast, Gulf Coast, Lower Atlantic, Midwest, New England, Rocky Mountains

is a broad market. In addition, the panel test results for the t-bar test of Im et al (2003) provides further support for this.

The finding that GC and CA prices are not as responsive to the market may indicate that further investigation is required. Though given the number of tests used especially following the multiple testing that Forni (2004) suggested, it would seem unlikely that all the tests are going to lead to one conclusion. It also has to be recalled that in our analysis some adjustments were made to the Forni approach, in particular eliminating the upper triangle of tests as they can be directly imputed from the reverse regressions. The advantage of the Forni (2004) method and the application of panel tests arise when the sample is not large as it simply requires price proportions to be stationary and does not assume the series are of the same order of integration. Furthermore, the stationarity test simultaneously imposes a slope coefficient of unity and an intercept of zero. However, this is bought at the cost of assuming that these restrictions apply in the short and the long-run.

In Chapter Two for comparison the same data is used, but in this case the weekly gasoline prices are applied to an error correction equation. Data is also obtained for seven major gasoline producing companies.[55] Given some of the difficulties presented by the Forni approach in terms of the most appropriate relative prices to be analysed, support is given to the error correction approach mentioned in Kremers, Ericsson and Dolado (1992) when the sample is small. The single equation or panel error-correction dynamic model approach only requires that the error correction defines a

[55]Citgo (C), Sunoco Logistic Partners (SLP), BP, Transmontaigne (TM), Marathon Petroleum Corporation (MPC), Gulf Oil (GO), and Hess Corporation (HC)

stationary variable, as with the ADF test on price proportions, but it does not impose the same restriction on the short-run. The results indicate that the gasoline prices of different regions are cointegrated.

With a large data set though it would seem best to use a VECM as this will relate to *N* price equations, and also does not impose any short-run restriction. The VECM jointly tests the number of cointegrating vectors and allows one to determine whether there are *N*-1 of these relations as is suggested by Hunter and Burke (2008). It is also possible to test cointegrating and weak exogeneity, the former being the key long-run causality condition when $r>2$.

For the system based on the regional we find $r=5<N-1$ cointegrating relations and as a result it is not possible to find sufficient parallel pricing relations. The tests of weak exogeneity imply that the long-run equilibrium relations can be conditioned on the GC and either the MW and LA prices. However, the most appealing model arises with the long-run conditioned on the GC while the MW price is cointegrating exogenous. Then the long-run relations can be further restricted so that three equation satisfy LEPT (Burke and Hunter (2011)). Only one relation is consistent with parallel pricing that is the error correction terms that arise when the stationarity tests are applied, though when the system is complete ($r=N-1$), LEPT and parallel pricing are equivalent. The final relation requires a linear combination of two proportional price or error corrections for the long-run to be stationary in the VAR. Hence, the VAR gives rise to more complicated long-run models than arise with the single equation stationarity tests.

A similar, investigation of seven company prices implies that *r=4* and this is also not consistent with long-run arbitrage. Care must be taken as unlike the results that arise in the case of the regional prices where there are 900 observations, the company sample may be sensitive to the impact of volatility on the Johansen test statistic that may not be innocuous with a sample of 192 observations. This implies that the market may be segmented, but for the company prices no single company price can be used to condition the long-run as non of these series are WE for the cointegrating vectors. This suggests the need for further investigation either correcting the volatility and investigating further the price relations when the cointegrating rank might be seen as being reliable.

Considering the empirical results we are suggesting a change in the regulation of the regional gasoline market in the US to enhance competition. This could relate to tax breaks to extend the refinery and distribution capacity of smaller firms. A similar conclusion to Forni (2004) arises as the failure to find a "Broad Market" in the long-run suggests that the anti-trust authorities resist further concentration in the industry via merger or acquisition. The availability and accessibility of market information to the consumer could also affect price responsiveness in this market. Similar conclusions may also be pertinent to other countries such as the UK.

In Chapter Three we analysed energy demand and supply as an appropriate approach to represent consumers and suppliers in a competitive market. In the gasoline market potential price leadership may arise as a result of quantity adjustment being faster than price adjustment. First, the analysis is based on weekly gasoline prices for companies' based on the variance screening approach. Anti-competitive behaviour is detected in the US gasoline market as a result of low variability in prices and the results presented here suggest that may be the case. To further investigate this issue at the level of the market we applied different regime switching models (RSM)[56] to identify any potential disequilibrium in the long-run.

The observation of disequilibrium in the long-run in energy markets indicates the need to consider the demand and supply to improve energy market efficiency and stability. The first finding for disequilibrium based on an endogenous switching model, implies that even in the long-run gasoline price dynamics may not clear the market. This may arise as a result of non-competitive behaviour by companies. Though the switching approach subject to the min condition allows the demand and supply equation to be detected.

Whereas the Markov regime switching model implies that price correction is not symmetric in the long-run. Hence, the capacity to correct mispricing depends on the nature of the different regimes. That the two regimes are significant gives some support to the disequilibrium method as that is driven by the behaviour of the price series. However, the switching method identifies two separate long-run equations. The demand equation implies that in the demand equation regular gasoline costs, the real retail gas price, the residual fuel oil price, and distillate fuel oil price on retail gasoline prices affect the demand for gasoline in the US. That the own price is elastic and the supply curve does not respond to prices suggests a system that is stable and self correcting in the long-run.

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[56] regular gasoline sales level(Q), regular retail gasoline real price (RP), WTI crude oil price (P_W), consumer price index(CPI), producer price index(PPI), gasoline unleaded regular cost of insurance and freight(Cost), total energy consumption(EXP), city-gate gas real price(P_{GAS}),disposal income(Y), automobile sales (Auto), Price of the residual fuel oil(P_{Res}), price of the distillate fuel oil (P_{dst}), and refineries net input of crude oil(RI).

Considering the results presented in this thesis, then further study into the methods applied in Chapter Two and Three may benefit from more appropriate corrections for ARCH especially in the VAR model and to correct the cointegration test. The disequilibrium regime switching analysis gives rise to too many variables to simulate the EG test. Either more data is required or a non-linear VAR may better handle the problem.

Appendix

Appendix A- Summary of ADF tests, DF-GLS tests & KPSS tests on the log gasoline prices. (With intercept and no trend)

Log gasoline price	ADF/ OLS t-statistic	DF-GLS/ OLS t-statistic	KPSS LM-statistic
LCA(0)	-0.587625	0.935263	76.17527
LCA(1)	-1.531763	-0.233328	38.14503
LCA(2)	-1.514424	-0.414377	25.46772
LEC(0)	-0.594370	0.843922	76.27340
LEC(1)	-1.362423	-0.293232	38.19435
LEC(2)	-1.497411	-0.443477	25.50107
LGC(0)	-0.587120	0.615377	73.95684
LGC(1)	-1.468286	-0.530520	37.03674
LGC(2)	-1.604339	-0.677296	24.73113
LLA(0)	-0.649083	0.658324	75.91653
LLA(1)	-1.402584	-0.387962	38.01797
LLA(2)	-1.518582	-0.514502	25.38538
LMW(0)	-0.918373	0.142988	75.67162
LMW(1)	-1.505961	-0.554558	37.91779
LMW(2)	-1.748858	-0.772669	25.33272
LNE(0)	-0.619944	0.918439	75.15725
LNE(1)	-1.418776	-0.268809	37.63891
LNE(2)	-1.621628	-0.472785	25.13233
LRM(0)	-0.681506	0.631150	74.28679
LRM(1)	-1.227909	-0.170134	37.21110
LRM(2)	-1.647491	-0.594555	24.85048
LWC(0)	-0.575360	0.878637	77.66324
LWC(1)	-1.956408	-0.811769	38.89792
LWC(2)	-1.850433	-0.712189	25.97839

Note: ADF Test Critical value at 1% is -3.4374, at 5% is -2.8645.

DF-GLS test Critical value at 1% is -2.5675, at 5% is -1.9412.

KPSS test Critical value at 1% is 0.7390, at 5% is0.4630.

****** Significant at the 99% confidence level, and***** Significant at the 95% confidence level

Appendix B- Descriptive statistics of equation 8

Variables	Mean	Std. Dev.	Minimum	Maximum
DDP	1.254644	1.424912	0	3.455429
DY	3.963073	4.452339	0	9.380775
DAUT	4.802026	5.391770	0	11.16832
SP	1.563088	1.415824	0	3.412161
SPRES	-0.210711	0.550565	-1.518684	1.019569
SPDIS	0.059302	0.468357	-0.894040	1.272846
SPW	1.991498	1.842046	0	4.759349
SRI	7.235501	6.473106	0	13.12318

Appendix C- Descriptive statistics of equation 9

Variables	Mean	Std. Dev.	Minimum	Maximum
DDP	1.259723	1.425553	0	3.455429
DY	3.979118	4.454189	0	9.380775
DCPI	-1.024980	1.150464	-2.476933	0
DEXP	3.994286	4.466937	0	9.154450
DLRPGAS	0.000497	0.091348	-0.331544	0.295131
SP	1.559348	1.417471	0	3.412161
SCOST	3.227208	2.936155	0	7.046647
SPPI	2.764297	2.485357	0	5.319100
SPW	1.987685	1.844805	0	4.759349

Appendix D- Regime classification based on smoothed probabilities

Regime 0		Regime 1	
1993(6) - 1993(6)	1.000	1993(7) - 1993(8)	0.999
1993(9) - 1993(9)	0.983	1993(10) - 1993(11)	0.999
1993(12) - 1993(12)	1.000	1994(1) - 1994(1)	1.000
1994(2) - 1994(3)	1.000	1994(4) - 1994(4)	0.997
1994(5) - 1994(5)	1.000	1994(6) - 1994(6)	1.000
1994(7) - 1994(7)	1.000	1994(8) - 1994(9)	0.640
1994(10) - 1994(10)	1.000	1994(11) - 1994(12)	1.000
1995(1) - 1995(1)	0.998	1995(2) - 1995(2)	0.998
1995(3) - 1995(4)	0.917	1995(5) - 1995(5)	0.991
1995(6) - 1995(6)	0.952	1995(7) - 1995(7)	1.000
1995(8) - 1995(10)	0.998	1995(11) - 1995(11)	1.000
1995(12) - 1995(12)	1.000	1996(1) - 1996(1)	1.000
1996(2) - 1996(2)	0.972	1996(3) - 1996(3)	1.000
1996(4) - 1996(5)	0.999	1996(6) - 1996(8)	1.000
1996(9) - 1996(10)	0.997	1996(11) - 1996(11)	0.966
1996(12) - 1996(12)	1.000	1997(1) - 1997(1)	0.985
1997(2) - 1997(2)	0.995	1997(3) - 1997(3)	0.994
1997(4) - 1997(5)	0.990	1997(6) - 1997(6)	0.999
1997(7) - 1997(8)	1.000	1997(9) - 1997(10)	1.000
1997(11) - 1997(11)	1.000	1997(12) - 1997(12)	0.988
1998(1) - 1998(3)	0.966	1998(4) - 1998(4)	1.000
1998(5) - 1998(7)	0.991	1998(8) - 1998(8)	1.000
1998(9) - 1998(9)	0.999	1998(10) - 1998(10)	0.998
1998(11) - 1998(11)	0.998	1998(12) - 1998(12)	0.987
1999(1) - 1999(2)	1.000	1999(3) - 1999(3)	1.000
1999(4) - 1999(4)	1.000	1999(5) - 1999(6)	0.996
1999(7) - 1999(7)	0.995	1999(8) - 1999(8)	1.000
1999(9) - 1999(9)	0.956	1999(10) - 1999(10)	0.974
1999(11) - 1999(11)	1.000	1999(12) - 1999(12)	0.997
2000(1) - 2000(1)	1.000	2000(2) - 2000(3)	1.000
2000(4) - 2000(4)	1.000	2000(5) - 2000(5)	0.987
2000(6) - 2000(8)	0.998	2000(9) - 2000(10)	1.000
2000(11) - 2000(11)	0.998	2000(12) - 2000(12)	1.000
2001(1) - 2001(3)	0.998	2001(4) - 2001(4)	0.995
2001(5) - 2001(5)	1.000	2001(6) - 2001(6)	0.840
2001(7) - 2001(7)	0.998	2001(8) - 2001(8)	0.955
2001(9) - 2001(11)	0.999	2001(12) - 2002(1)	0.997
2002(2) - 2002(4)	1.000	2002(5) - 2002(6)	0.903
2002(7) - 2002(8)	1.000	2002(9) - 2002(11)	0.999
2002(12) - 2002(12)	0.996	2003(1) - 2003(3)	0.993
2003(4) - 2003(4)	0.999	2003(5) - 2003(5)	0.990
2003(6) - 2003(6)	0.999	2003(7) - 2003(7)	1.000
2003(8) - 2003(8)	0.999	2003(9) - 2003(10)	0.956
2003(11) - 2003(11)	1.000	2003(12) - 2004(2)	0.999
2004(3) - 2004(3)	0.997	2004(4) - 2004(5)	0.997
2004(6) - 2004(7)	1.000	2004(8) - 2004(9)	0.994
2004(10) - 2004(10)	0.640	2004(11) - 2004(11)	1.000
2004(12) - 2004(12)	1.000	2005(1) - 2005(2)	0.998
2005(3) - 2005(4)	0.998	2005(5) - 2005(6)	0.999
2005(7) - 2005(9)	0.991	2005(10) - 2005(11)	1.000
2005(12) - 2005(12)	1.000	2006(1) - 2006(1)	1.000
2006(2) - 2006(2)	1.000	2006(3) - 2006(3)	0.997
2006(4) - 2006(4)	1.000	2006(5) - 2006(5)	0.997
2006(6) - 2006(6)	1.000	2006(7) - 2006(7)	1.000
2006(8) - 2006(8)	1.000	2006(9) - 2006(9)	0.999
2006(10) - 2006(12)	0.966	2007(1) - 2007(1)	1.000
2007(2) - 2007(2)	0.985	2007(3) - 2007(3)	0.999
2007(4) - 2007(4)	0.994	2007(5) - 2007(7)	0.854
2007(8) - 2007(9)	0.999	2007(10) - 2007(11)	0.999
2007(12) - 2007(12)	1.000	2008(1) - 2008(2)	0.993
2008(3) - 2008(3)	0.988	2008(4) - 2008(4)	1.000
2008(5) - 2008(5)	1.000	2008(6) - 2008(6)	0.959
2008(7) - 2008(9)	1.000	2008(10) - 2008(12)	0.937
2009(1) - 2009(2)	0.998	2009(3) - 2009(3)	0.991
2009(4) - 2009(5)	0.987	2009(6) - 2009(7)	0.999
2009(8) - 2009(8)	1.000	2009(9) - 2009(9)	1.000
2009(10) - 2009(11)	0.996	2009(12) - 2010(1)	1.000
2010(2) - 2010(2)	1.000	2010(3) - 2010(4)	0.998
2010(5) - 2010(5)	0.974	2010(6) - 2010(6)	0.999
2010(7) - 2010(7)	0.997	2010(8) - 2010(10)	0.99
2010(11) - 2010(11)	1.000	2010(12) - 2010(12)	0.546
2011(1) - 2011(1)	0.987	2011(2) - 2011(2)	1.000
2011(3) - 2011(3)	1.000	2011(4) - 2011(6)	0.867
2011(7) - 2011(7)	1.000	2011(8) - 2011(9)	0.993
2011(10) - 2011(10)	0.995	2011(11) - 2011(12)	1.000
2012(1) - 2012(2)	0.840	2012(3) - 2012(3)	0.998
2012(4) - 2012(6)	0.955	2012(7) - 2012(8)	0.983
2012(9) - 2012(9)	0.997		

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