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This article considers cointegration analysis to detect key features of long-run structure in the gasoline market. The main purpose of this study is to investigate possible long-run price leadership in the US gasoline market and the characteristics relevant to a competitive market using the vector autoregressive model. After examining the stat

Gasoline is one of the products with the highest price variation in the world and the

In this article 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.

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 market and the nature of integration of the price series. However energy storability makes it suitable for price arbitrage and hedging. When considering the price of gasoline in the different region 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, poor regulation in the gasoline market would distort competition.

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In this section we consider the 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.[3] Considering regional gasoline infrastructure across the US we test cointegration on eight different regions and nine price differentials. The data in (log) levels and (log) differences are graphed in the plots in figure 1 and the frequency distributions of the data are graphed in figure 2. From figure 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 whereas the frequency distribution of the differences suggest the series are closer to normality.

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

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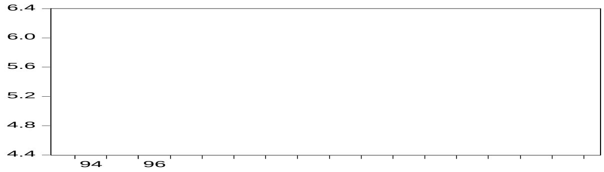
6.4
6.0
5.6
5.2
4.8
4.4
94
96

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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).

Following Hosken and Taylor (2004), and Kurita (2008) we analysed the cointegration and exogeneity properties of regional gasoline pri 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 (}

(LOP), although the observed may differ from 1 by an arbitrary constant(*c*) where $|\beta - 1| \leq c$. In the case of perfect integration *c* is close to zero.

According to Engle and Granger (1987) the linear combination of two non-stationary series of p_{at} and p_{bt} can be transformed to stationarity:

$$\eta_t = p_{at} - \beta p_{bt} \qquad (2)$$

and $\eta_t = \mu_0 + u_t \sim I(0)$. The latter 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 relationship between p_{at} and p_{bt} otherwise this relates to a nonsense regression. Consequently for the price of any homogeneous good in an identical market a cointegrating relation is necessary as arbitrage would clear 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 LOP in a VAR and the potential for price leadership.[4] 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 all regions. This trading mechanism will be inclined to equalize the prices in the long term by raising prices in the low-price regions and lowering prices in the high-price regions.

In empirical modelling multivariate time series analysis is applied to estimate long-run equilibrium relations. The ECM provides one method to investigate the nature of adjustment across prices to determine long-run equilibrium, see Patterson (2000).

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We investigate long-run equilibrium in the US gasoline market using the error correction model that is also termed arbitrage correction by Burke and Hunter (2012). The hypothesis underlying this argument relates to the possibility that the sequence of regional gasoline prices that deviate from equilibrium give rise to an arbitrage opportunity that is correcting in the long-run when there are *N-1* arbitrage correction terms across *N* markets (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 relationship 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. However the ECM might not accurately identify the suitable long run relationship in the presence of structural change as this may result in finding inconsistent cointegrating relations that are poor in terms of prediction (Clements and Hendry, 1995).

To further investigate the short-run dynamics of the relationship in gasoline prices of different regions in the US we employ a vector error correction model (VECM) specification. For example, Bachmeier and Griffin (2006) found that the prices of crude oil in different geographical regions of the world are cointegrated. De Vanya and Walls (1999) using the ECM, 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 regression residual:

$$\hat{\eta}_t = e_t = p_{at} - m_o - bp_{bt} \qquad (3)$$

We may test whether these series are stationary by applying the Dickey-Fuller test to these residuals:

$$\Delta\hat{\eta}_t = \gamma\ \hat{\eta}_{t-1} + v$$

removed from the system or the speed at which arbitrage occurs[5]. 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: $\gamma < 0$.[6] The acceptance of H_A 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.

The results for the augmented Dickey Fuller (ADF) test and ECM estimations are compared in Table 1.[7] Acceptance of the alternative hypothesis underlining the ADF tests imply 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

[5] ***r %*** of the disequilibrium at time ***tʅ1*** is removed in period ***t***.
[6] **γ** >0 implies that variables are moving in the wrong direction to correct for disequilibrium.
[7] All estimations are undertaken using Oxmetrics Professional (Doornik and Hendry, 2009).

move in proportion to each other in the long-run, but any rejection of the alternative

In further investigating the system we follow Boswijk (1992), Hunter and Simpson (1996), and Bauwens and Hunter (2000) and apply restrictions on **α**, **β** (dimensioned N r), and **α** as well as **β** to study the exogeneity structure of the data and identify potentially WE variables.

Following Forni (2004) the test of stationarity jointly tests $\mu_0=0, \beta=1$ and $\gamma<0$, finding stationarity implies both cointegration and a relation with $\mu_0=0, \beta=1$. The VAR under the assumption of normality of the errors and based on the notion that there is drift in the individual price series implies an unrestricted intercept to determine the number of long-run relations or cointegrating rank (*r*). It can be shown (Hunter and Burke, 2007) that when all the series are I(1), then there are *r=N-1* cointegration relations in the competitive case and a single common trend.

The following equation is a VECM that is a re-parameterisation of a VAR:

$$ط\ \text{'E})\ \Delta \quad = \mathbf{\Pi} \ _{-} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}\ .$$

Where =(- L - ... - - L^{k-1}), are *N* *N* matrices and and *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 trend when there is less than *N-1* cointegrating relations. The results on the Johansen trace test for eight regional gasoline prices in the US are presented in Table 2. The results related to this test indicate that there are *r=4* cointegrating vectors for a test applied at the 5% level. This implying that there are *N-r=4* stochastic trends, this is not consistent with the results that arise when cointegration is tested based on the single equation tests of stationarity.[9] When *r<N-1* there are more stochastic trends than might be anticipated by a single competitive

[9] Result can be provided in request.

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) for defining market boundaries. Here, subject to the finding on rank, the focus will be on exogeneity restrictions and long-run exclusion.

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 efficiency being imposed on the short-run relations, thus causing arbitrage to be imposed on the short-run parameters. Hence by estimating the VAR 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 inter-related market prices.

The VECM model (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 the *N* variables give rise to *r* long-run relations where $0<r<N$. It would seem clear from the analysis conducted in this study thus far that the finding of no cointegration ($r=0$) can be rejected. However, a generous or more careful interpretation of all the above analysis might suggest *N-1* stationary relations subject to finding WE variables, but a stris [illegible]est N- N-

accordingly. The sample includes 901 observation and the results relate to weak exogeneity tests, long-run exclusion test and strict exogeneity with *k=20* lags in the estimation. The first block of results in Table 3 relate to a weak exogeneity test conditional on *r=4* and from the p-values it can be determined that the log price of the GC, LA, EC and MW are potentially WE for $\boldsymbol{\beta}$. However, there can be no more than *N-r=4* WE variables. Ordering by the weak exogeneity test suggests the most likely WE variables are the Gulf Coast and Lower Atlantic. This suggests that the gasoline prices of GC and LA determines the other regions prices, consistent with Burke and Hunter (2012).

However as the GC price changes will directly affect the other region's prices, then everything can be conditioned on the GC. Following Juselius (1995) the next section of the table tests long-run exclusion. These results are strongly significant in all regions indicating the appropriateness of the rank condition and the likely robustness of propositions on the cointegrating vectors. We could order the system using the test on long-run exclusion[11] as it is not appropriate to normalise on a variable that may be the long-run excluded (LE) as is explained in Boswijk(1996). Here finding a variable is not LE implies that it may interact with all the other variable in the long-run and that variable must be present in at least one cointegrating vector.

Next in Table 3 following the normalization and weak exogeneity, the system is conditioned on LA log prices as the variable that is most likely to be weakly exogenous. Next, testing for the normalization and weak exogeneity conditioned on the log price of GC. The same values of the χ^2 test apply from the normalization and weak exogeneity test and the weak exogeneity test confirms that the normalisation is innocuous.[12]

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[11]

[Table 3 goes here]

In the final section of Table 3 the system might be reordered based on the imposition of strict exogeneity by testing whether a variable can be LE and WE at the same time. However, the conclusion in Hunter and Simpson (1996) does not seem appropriate as a mechanism to reorder and condition the system as none of the series are strictly exogenous.

The result indicates that long-run arbitrage may be driven by GC and LA and this is consistent with the findings of Burke and Hunter (2012). 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. To further investigate market structure it would be useful to study US company gasoline prices and search for WE price series with that data (Burke and Hunter, 2011). A difficulty associated with analysing company price series, is that they are volatile and these data sets are not as large.[13]

For non-stationary variables, the Johansen methodology of cointegration and exogeneity testing appears an appropriate approach to investigate market performance. Here a range of tests for the integrated nature of the market have been employed to analyse US gasoline prices. The empirical findings indicate that gasoline prices of different regions are cointegrated and this suggests that the market 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 i time series observations. One problem with that approach is that the long-run restrictions are also binding on the short-run. For this reason preference is given to the test based on the ECM. Furthermore, the ECM as part of an N dimensioned system with N error correction terms can be coherently defined (Boswijk, 1992). Further from the findings in Kremers, Ericsson and Dolado (1992) the test based geographical conditions and this may be further reflected in the ownership of regional refinery capacity.

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. 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.

Bachmeier, L.J. and J.M. Griffin, 2006. Testing for market integration crude oil, coal, and natural gas, The Energy Journal 27(2), 55-71.

Bauwens, L., and Hunter J., 2000. Identifying long-run behaviour with non-stationary data.

Hunter, J. and Tabaghdehi, A.S.H., 2013. Cointegration and US Regional Gasoline Prices:

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

Log price differential (q)[14]	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 Professionl Oxmetrics Professional (Doornik and Hendry, 2009). ***** Significant at the 95% confidence level and ** significant at the 99% confidence level

Table2: Johansen trace test for cointegratione

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.

[14] 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.