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A cointegration analysis of gasoline demand in the United States

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Abstract

Time-series estimation of gasoline demand elasticities often does not take into account the possibility of non-stationarity in the underlying data, which may render the parameter estimates spurious. Studies have shown that the time trending variables used to explain gasoline demand could be difference stationary and therefore may require cointegration analysis to assess the relationship among the trending variables. In this work we use the cointegration technique to derive long run and short run demand elasticities of non-commercial gasoline consumption using time-series data for the USA from 1949 to 2004. We also attempt to incorporate the presence of a structural break in the data generation process of the time trending variables. Our results show that the consumption of gasoline and lifetime income have a long term stable relationship after the second oil shock of 1978. Prior to the first oil shock of 1973, no such long run relationship could be established through cointegration.

Keywords: gasoline demand, elasticities, cointegration

Introduction and motivation

The demand for personal transport fuel has been increasing in the world for the past half a century and currently remains one of the principal sources of aggregate oil demand. The management of gasoline demand is a crucial policy issue in many economies, especially in developed countries, due to concerns about energy security, the environment and global climate change, and the effect of high prices on different societal groups. There are many estimates of gasoline demand that have been derived for different empirical contexts, using different determinants of demand interacting in various ways. The analytical techniques used to derive elasticity estimates also vary widely.¹ Apart from a few disaggregate cross sectional and panel data models, most gasoline demand models employ time-series data. A specific issue with the use of time-series data that has received a great deal of attention over the past two decades concerns the stationarity properties of the data. If two time dependent variables follow a common trend that causes them to move in the same direction, it is possible to find a good correlation between them despite not having any ‘true’ association. This potential feature of time-series data can give rise to spurious regression (Granger and Newbold 1974) and the parameter estimates obtained through these regressions are then unreliable.²

A time-series is non-stationary when its mean and/or variance is changing over time. Two types of non-stationary series are possible: trend stationary and difference stationary. Trend stationary series have a deterministic time trend around which the series is stationary. The time detrended data is therefore stationary. On the other hand, if the data series are to be differenced

¹ Dahl and Sterner (1991), Sterner and Dahl (1992), Dahl (1995), Goodwin et al. (2004), de Jong and Gunn (2001), and Graham and Glaister (2002, 2004) – provided a survey of existing literature on fuel demand elasticities.

² One such spurious regression constructed by Hendry (1980) could explain that cumulative rainfall is a better indicator of price inflation than money stock in the UK!

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3 to obtain a stationary series, then this is known as a difference stationary series. If differencing
4 the level data once results in a stationary series, then the original non-stationary series is
5 integrated to the order 1, or described as an I(1) series. Similarly, if the non-stationary series is
6 differenced twice to produce stationarity, then the series is I(2). Although the regression of
7 difference stationary series in levels may be spurious, a regression on the differenced series, if
8 stationary, is valid.
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20 A simple level regression of an I(1) series with another I(1) series will also normally be a
21 spurious regression, however in some cases, there may exist a linear combination of different
22 I(1) series which are stationary. This means that there is a long term relationship between those
23 variables, which tends to bind them together. If such a combination does exist, then the
24 variables are known to be cointegrated and their long run relationship in levels is a valid one
25 (Granger and Weiss 1983). Granger and Engle (1987) prove that the cointegrated series have
26 an Error Correction Mechanism (ECM) representation, which allows inference on the short run
27 behaviour. An excellent description of the cointegration method appears in Hendry and
28 Juselius (2000).
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43 Since many of the related macroeconomic data series used in gasoline demand modelling tend
44 to be difference stationary, the use of conventional econometric methods may be inappropriate.
45 Therefore, it is necessary to address the non-stationarity of the underlying data series and
46 assess any cointegration among them. Recent studies do report a cointegrating long-run
47 relationship between gasoline consumption and other macroeconomic variables. Bentzen
48 (1994) first estimated the cointegrating relationship between gasoline demand, vehicle stock
49 and price for Denmark, where vehicle stock was used as a proxy for income. Eltoni and Al-
50 Mutairi (1995), Ramanathan (1999), Ramanathan and Subramanian (2003), and Cheung and
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3 Thomson (2004) followed a similar methodology for Kuwait, India, Oman and China,
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5 respectively. Samimi (1995) estimated a cointegration regression for Australian road transport
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7 energy consumption. All these studies found a cointegrating relationship between gasoline
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9 and/or energy demand, income and the respective price of gasoline or energy. Alves and
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11 Bueno (2003) reported a cointegrated relationship between gasoline demand, income and price
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13 of gasoline as well as ethanol fuel.³ On the other hand, Nadaud (2004) concluded that gasoline
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15 demand, income, price and urban sprawl cointegrate in France. The long and short run
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17 elasticities from these studies are presented in Table 1. Bentzen (1994) commented that the
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19 elasticities in Denmark are smaller than found in the gasoline demand literature and attributed
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21 the divergence to different model specification and estimation techniques. Samimi (1995)
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23 found that energy demand for Australian road transport is very inelastic with respect to price,
24
25 even in the long run. His short run price elasticity was statistically not different from zero.
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27 Cheung and Thomson (2004) reported that the long run income elasticity in China is smaller
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29 than the corresponding short run elasticity, which differs from the general consensus.
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31 However, no explanation was offered as to why their estimate was different.
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41 Most cointegration econometric models mentioned above follow the Engle and Granger (1987)
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43 two step method to estimate the long run and short run elasticities. This method involves
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45 estimating a static model by OLS to determine the long run relationship between the variables,
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47 and then using the long run parameters to build an ECM to derive short run parameters. While
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49 this is the most popular method in practical applications of cointegration, it has one significant
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51 drawback: inference on the long-run parameters from the OLS estimation may not be
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53 appropriate because of the possible presence of residual autocorrelation after estimation
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55 (Hendry 1986, Phillips and Loretan 1991). Yet all the above studies report the OLS estimation
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³ Ethanol is used as a motor fuel in Brazil.

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3 results as long run parameters. Banerjee *et al.* (1986) have also shown via Monte Carlo studies
4 that the OLS estimation of long run parameters may have substantial small sample bias. With
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6 that the OLS estimation of long run parameters may have substantial small sample bias. With
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8 this background, we opt to use a dynamic OLS formulation to assess whether cointegration
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10 between gasoline consumption, income and gasoline price is present in US data, and to
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12 estimate corresponding elasticity parameters.
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17 The Model and Methodology

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20 Following the previously mentioned studies, we choose the constant elasticity functional form
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22 for gasoline demand for our econometric analysis:
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$$26 \quad g_t = \beta^y y_t^{\beta_y} p_t^{\beta_p} + \zeta_t \quad (1)$$

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29 Where g_t is gasoline consumption per capita, p_t the real price of gasoline and y_t real income per
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31 capita, all at time t . Taking the logarithm of both sides gives the familiar log-linear form:
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$$35 \quad G_t = \beta_0 + \beta_Y Y_t + \beta_P P_t + \zeta_t \quad (2)$$

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38 Where, G_t , Y_t and P_t refers to respective logarithms $\ln(g_t)$, $\ln(y_t)$ and $\ln(p_t)$, ζ_t is the residual.
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42 We assume that G , Y and P are generally all non-stationary and I(1) series, hence the parameter
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44 estimates will not be spurious only if the variables have at least one stable long run relationship
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46 and their combination is stationary for that specific set of parameters. If cointegration exists at
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48 that combination, ζ_t becomes stationary too. Thus a test to examine if the three variables
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50 indeed cointegrate is to test whether ζ_t is stationary. If the residual ζ_t in Eq. (2) is stationary,
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then the long-run relationship can be determined from the parameters of Eq. (2). Once the long run relationship is established, the short run elasticities are determined from the ECM.

The economic behavioural theory behind the ECM is that there exists a long run desired relationship between the three variables in discussion. At equilibrium the residual ζ_t is zero. However, the consumption at any time 't' generally is not at equilibrium ($\zeta_t \neq 0$), and economic agents respond to the disequilibrium of the previous time period by adjusting their consumption toward the equilibrium target in the next period. At the same time, consumers also respond to changes in exogenous stimuli, and for gasoline consumption, carry through the 'inertia' of previous consumption. Thus the adjustment in consumption, formed as the ECM, is:

$$\Delta G_t = \alpha_0 + \sum_{i=0}^m \alpha_{Yt} \Delta Y_{t-i} + \sum_{i=0}^n \alpha_{Pt} \Delta P_{t-i} + \sum_{i=0}^s \alpha_{Gt} \Delta G_{t-i-1} + \alpha_{res} \zeta_{t-1} + \varepsilon_t \quad (3)$$

where the lags m , n and s are chosen such that ε_t is white noise, and ζ_{t-1} is the disequilibrium from the previous time period. As long as Y , P and G are I(1), and they cointegrate, all the variables in this equation are stationary and therefore inference on the parameter estimates would be valid. Since the economic behavioural theory suggests that the agent responds to the disequilibrium from the desired long run consumption, the estimated parameter α_{res} should be statistically significant if a valid long run relationship exists. Engle-Granger's two step procedure thus involves solving the static Eq. (2) by OLS to obtain the long run cointegrating parameters and the residual ζ_t ; the lag of ζ_t is then used as an explanatory variable in Eq. (3). Estimation of Eq. (3) by OLS provides an estimate of the short run parameters.

Although the regression of various I(1) variables is valid when their combination is I(0), as in Eq. (2), an OLS estimation of I(1) variables may result in substantial residual autocorrelation. Thus the t-statistics on the long run coefficients do not have the usual t-distribution, even asymptotically (Patterson 2000). This makes the inference on the long run parameters from OLS estimation of Eq. (2) inappropriate. In addition, as previously mentioned, Banerjee *et. al.* (1986) showed that the OLS estimator can be substantially biased in small samples and suggest using a dynamic model to get long run parameters. Such a dynamic formulation is an autoregressive distributed lag model:

$$G_t = \lambda_0 + \sum_{i=0}^m \lambda_{Yt} Y_{t-i} + \sum_{i=0}^n \lambda_{Pt} P_{t-i} + \sum_{i=0}^s \lambda_{Gt} G_{t-i-1} + \varepsilon_t \quad (4)$$

If the dynamics are correctly specified, the residual ε_t is serially uncorrelated in Eq.(4) and the parameter estimates have valid t-statistics. Another approach that combines the two stages of the Engle-Granger process into one is the single equation error correction model. Substituting the value of ξ_{t-1} from Eq. (2) in Eq. (3) and considering a simplified case of $i=0$,

$$\Delta G_t = \alpha_1 + \sum_{i=0}^m \alpha_{Yt} \Delta Y_{t-i} + \sum_{i=0}^n \alpha_{Pt} \Delta P_{t-i} + \sum_{i=0}^s \alpha_{Gt} \Delta G_{t-i-1} + \alpha_{res} (G_{t-1} - \beta_Y Y_{t-1} - \beta_P P_{t-1}) + \varepsilon_t \quad (5)$$

where $\alpha_1 = \alpha_0 - \alpha_{res}\beta_0$. Eq. (5), however, is not linear in parameters (because of the multiplication of α_{res} with β 's) and has to be estimated by the non linear least squares (NLLS) method. If G , Y and P are cointegrated, then $(G_{t-1} - \beta_Y Y_{t-1} - \beta_P P_{t-1})$ is stationary and the residual ε_t is a white noise process, as long as the dynamics are correctly specified. The nonlinear estimation of Eq.(5) is a one step process and gives the long run (β) and short run (α) elasticities directly. As ε_t is white noise, the usual inference procedure based on t-statistics is

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3 valid for the estimated parameters. All three models are estimated here to test the sensitivity of
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5 the parameter estimates with respect to model specification.
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10 Prior to estimating the model, however, each of the variables is tested for its difference
11 stationarity properties. Difference stationarity of a time-series is detected through the presence
12 of unit roots in the data generation process of the variable.⁴ Among the ‘unit-root’ tests, the
13 ADF (Dickey and Fuller 1979) and PP (Phillips and Perron 1988) tests are the most popular.
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15 Previous studies in the gasoline demand literature utilising cointegration methods and cited
16 above have opted for the ADF test. However, the ADF and PP tests both tend to under reject
17 the presence of unit roots and have been superseded by alternative tests (Maddala and Kim
18 1998); one such test is a modified version of the ADF test known as the DF-GLS test, where
19 the data are first GLS detrended as per Elliott *et al.* (1996). We use this test to detect the
20 presence of a unit root in the data generation process of each of the variables.
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36 Still, all unit root tests have a significant drawback in that they tend to accept the presence of a
37 unit root, when the data is actually trend stationary, but with a break in the trend (Perron 1989).
38 Since our data consists of the time period from 1949 to 2004, there is at least one major
39 incident, the 1973 oil shock, that could cause a break in the underlying data generation process
40 for the variables. Also we expect another break due to the second round of oil price hikes in
41 1978. As the time-series between 1974 and 1978 is very small we cannot statistically test for
42 any difference for these years. We assume this brief period as a transitory phase when the data
43 generation process may have changed, and choose to divide the sample into two, pre-1974 and
44 post-1978 and test for the presence of unit roots in different variables for both samples.
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⁴ For example, a simple unit root test on G with a single lag involves testing for $\rho = 1$ in the equation $G_t = \gamma + \rho G_{t-1} + (\delta t) + \varepsilon_t$

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3 In addition to a break in the stationarity properties and thus the data generation process of any
4 of the variables, there could also be a structural change between the cointegrating relationship
5 among the variables, i.e. the parameters corresponding to the cointegration relationship may
6 have changed between 1974 and 1978. The stability of the cointegration parameters across
7 these two periods can be tested using Chow (1960) or Quandt (1960) type tests, which have
8 been extended to I(1) processes by Hansen (1992). We also assess the possibility of a
9 cointegrating relationship for the whole sample.
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20 21 Data

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27 National Income and Product Account (NIPA, Bureau of Economic Analysis 2005) data on
28 personal expenditure is used. The NIPA database contains records for per capita disposable
29 personal income and total gasoline expenditure in the USA from 1929 to the present. Usability
30 of the long time-series data is however limited by the availability of the gasoline price data,
31 which is available only from 1949 from the US Energy Information Administration (2005).
32
33 Total gasoline expenditure is converted to per capita consumption by dividing the consumption
34 expenditure by mid-year total population, also available in the NIPA database. Gasoline
35 consumption expenditure is then converted to gallons of gasoline consumed per capita by
36 dividing it by nominal gasoline price for the respective years. All income and price data for the
37 analysis are then normalized to 2003 US dollars using the consumer price index (CPI).
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53 The time-series data for logarithms of per capita income, gasoline consumption and gasoline
54 price are depicted in Fig. 1, and the disruption to gasoline consumption and gasoline price in
55 1974 and 1978-79 are clearly visible. The slope of gasoline consumption also differs between
56 the pre-1974 and post-1978 periods. In the income series, although there is no sudden drop or
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3 jump around 1973 and 1978, the slope does differ between the pre-1974 and post-1978
4 periods. The data generation process, therefore, could have changed during the 1974-1978
5 period. It is also possible that there would be a structural change in the cointegrating
6 relationship (provided there is one) between these three variables.
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12 13 14 15 Results 16

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20 Variables were initially checked for their stationarity properties using the DF-GLS test. This
21 test, however, is sensitive to the choice of lag length. There are different methods to choose the
22 optimum lag length, such as the Schwarz Information Criteria, the Ng-Perron sequential t (Ng
23 and Perron 1995), and the Modified Akaike Information Criteria (Ng and Perron 2001). Often
24 the three tests report contradictory lag lengths for the same variable. We therefore employed
25 all three tests but chose the lag length supported by the majority of them. All three variables
26 have been found to be non-stationary at level, for the entire sample, as well as the two sub-
27 samples (Table 2), as indicated by the test statistics being less than the critical value.⁵
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41 The test statistics for the DF-GLS tests on the first differences, exceed the critical value for the
42 full sample and the post-1978 sample. These are stationary at first differences, whereas the
43 variables from the pre-1974 sub-sample are still non stationary (Table 2). Thus the variables,
44 when considered in the full sample and in the post-1978 sub-sample are I(1), but this cannot be
45 said about the pre-1974 sub-sample. This is an indication that there could have been a break in
46 the data generation process during the 1974 and 1978 oil price escalation.
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⁵ Income appears to have a large lag-structure post-1978. This is behaviourally quite interesting as it may imply less income mobility between wage groups post-1978 as opposed to pre-1974.

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3 The inconclusive results of the unit root test for the pre-1974 sub-sample does not allow us to
4 test for cointegration in this sample. Static estimation results involving the variables using the
5 Engle-Granger two step process for the full sample and the post-1978 sample are presented in
6 Table 3. For the post-1978 sub-sample the residuals from the OLS estimation of Eq. (7) are
7 stationary confirming a cointegrating relationship between the three variables. For the full
8 sample case, the residuals still show a unit root (the absolute value of the test statistic 0.824 is
9 smaller than the critical value of 2.245), thus no cointegration among these variables can be
10 found. This is not surprising as the full sample contains the pre-1974 sub-sample and
11 cointegration among the variables for this subset could not be assessed because of inconclusive
12 unit root test results. The results suggest that it is not possible to estimate a long term stable
13 relation between gasoline consumption, income and price prior to 1974.
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32 The error correction model (Table 4) gives the short run response to price and income change
33 for the post-1978 sub-sample. The residuals of the ECM fulfill the conditions of a normally
34 distributed, white noise process (the test statistic does not reject the null of normality, and the
35 Q-test statistic for white noise does not reject the null of a white noise process). The long run
36 income elasticity (0.565) is higher than the short run elasticity of 0.473.⁶ The price response in
37 the long run (-0.102) is also larger but not very different from the short run response (-0.065).
38 The coefficient of the error correction term is 0.778, meaning around 78% of the
39 disequilibrium in the previous period is adjusted in the current time period. This adjustment
40 parameter is statistically significant, another verification that a cointegrating relationship exists
41 between the variables.
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⁶ Long run elasticities are calculated from $\beta = \lambda / (1 - \lambda_G)$

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3 OLS estimation results of the dynamic model are presented in Table 5. We selected the
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5 dynamic model on the basis of the highest adjusted R^2 and passing of the misspecification tests
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7 such as residual autocorrelation, normality, ARCH and white noise tests. The resulting model
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9 contains three lags of gasoline consumption, but no lags of income or price. The parameter
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11 estimates of Y and P in this model give the short run elasticities directly (0.457 and -0.091 for
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13 income and price respectively). Corresponding long run estimates are calculated to be 0.593
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15 and -0.118 respectively (Table 7). A DF-GLS test on the residuals involving only long run
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17 parameters finds that a cointegrating relationship exists between the three variables. It is
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19 important to note that if a unit root had been found in the residuals with the long run
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21 parameters, then the dynamic model estimates would be spurious parameters. In the dynamic
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23 model, cointegration is thus tested after the model is estimated.
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32 The non-linear single step estimation (Table 6) gives a similar long run relationship with
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34 income and price as the dynamic model. This is expected as both the models have lags of the
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36 variables incorporated, the principal difference being the different choice of the length of lags.
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38 The significant coefficient of $G_{t-1} - \beta_Y Y_{t-1} - \beta_P P_{t-1}$ indicates that there is a cointegrating
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40 relationship. The DF-GLS test of residuals involving the long run parameters again rejects the
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42 presence of a unit root, confirming cointegration.
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Of all three models, the dynamic model reports the smallest standard errors for the parameter estimates, and also the highest adjusted R^2 . A comparison of the elasticity estimates (Table 7) show that the long run response for the dynamic model is slightly higher than that from the static Engle-Granger models, but statistically are not very different. Since the residuals of the static cointegration regression do not show any autocorrelation through the Breusch-Godfrey LM test, the long run parameters from the static model have a valid inference for this dataset.

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3 The short run price response is slightly higher for the dynamic model, but still statistically not
4 different from the static model.
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10 Conclusion

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15 In this paper we have assessed the cointegration between gasoline consumption, gasoline price
16 and income in US data using an annual time-series from 1949 to 2004. The results indicate that
17 no stable and meaningful long run relationship exists between these three variables for the
18 whole period. Dividing the sample into two subsets, pre-1974 and post-1978, similar tests
19 indicate that cointegration exists between the three variables for the post-1978 sub-sample, but
20 not for the pre-1974 sub-sample in which unit root tests could not detect the order of
21 integration for two of the variables and therefore the long run association between the variables
22 could not be estimated. This suggests there may have been a structural break in the data
23 between 1974 and 1978, coinciding with the oil supply and price shocks, as well as during
24 introduction of fuel economy standards in the US.
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41 Due to the inference and bias issues associated with the popular Engle-Granger method of
42 estimation, we employed single stage non linear least squares and dynamic models to test the
43 sensitivity of the estimates for the post-1978 sub-sample. The models do not report a
44 statistically significant divergence in parameter estimates, although some elasticities vary
45 slightly. Among all three specifications, the dynamic model reports the lowest standard error
46 for the parameter estimates. Even if the time-series models do not take into account the
47 cointegrating relationships explicitly, the dynamic models give robust estimates of long and
48 short run elasticities, provided there is underlying cointegration between the variables. Since
49 gasoline consumption, income and price tend to cointegrate, at least during the post oil-shock
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3 period, previous studies employing dynamic models with these variables would tend to give
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5 valid elasticity estimates despite not testing for the cointegrating relationship explicitly.
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10 Our results using the cointegration model for the post-1978 period give a lower elasticity of
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12 both short-run and long-run demand than most other studies. This is typical of most
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14 cointegration studies. Examples can be found in studies in Australia (Samimi 1995), Denmark
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16 (Bentzen 1994), and France (Nadaud 2004). The consensus gasoline price elasticity is typically
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18 assumed to range from -0.25 in the short-run to -0.64 in the long-run (Goodwin *et al* 2004).
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20 The much lower elasticity estimates from this and most other cointegration studies provides a
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22 lower bound of estimates and suggest a need for further investigation of these effects. The
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24 level of aggregation used here of annual data, could mask many of the individual level effects
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26 found in other studies that estimate larger elasticities. However, this study provides an
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28 interesting perspective on the nationwide impacts of gasoline price changes.
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38 References

39
40
41 Alves, D.C.O., and Bueno, R.D.L.S., 2003, Short-run, long-run and cross elasticities of gasoline
42
43 demand in Brazil, *Energy Economics*, Vol. 25, pp. 191-199.
44
45

46 Banerjee, A., Dolado, J.J., Hendry, D.F., and Smith, G.W., 1986, Exploring equilibrium relationships in
47
48 econometrics through static models: some Monte Carlo evidence, *Oxford Bulletin of Economics and*
49
50 *Statistics*, Vol. 48, No. 3, pp. 253-277.
51

52 Bentzen, J. 1994, An empirical analysis of gasoline demand in Denmark using cointegration
53
54 techniques, *Energy Economics*, Vol. 16, No. 2, pp. 139-143.
55
56

57 Bureau of Economic Analysis, 2005 [online], National income and product database,
58
59 <http://www.bea.gov/bea/dn/nipaweb/index.asp>
60

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3 Cheung, K-Y, and Thomson, E., 2004, The demand for gasoline in China: a cointegration analysis,
4 Journal of Applied Statistics, Vol. 31, No. 5, pp. 533-544.
5
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8 Chow, G.C., 1960, Test of equality between sets of coefficients in two linear regressions,
9 Econometrica, Vol. 28, pp. 591-605.
10

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13 Dahl, C., 1995. Demand for transport fuels: A survey of demand elasticities and their components, the
14 Journal of Energy Literature I 2, 1995.
15
16

17
18 Dahl, C., and Sterner, T., 1991, Analysing gasoline demand elasticities: A survey, Energy Economics
19 Vol. 13, pp. 203-210.
20

21
22
23 de Jong, G., and Gunn, H., 2001, Recent evidence on car cost and time elasticities of travel demand in
24 Europe, Journal of Transport Economics and Policy, Vol. 35, No. 2, pp. 137-160.
25
26

27
28 Dicky, D.A., and Fuller, W.A., 1979, Distribution of estimators for autoregressive time-series with a
29 unit root, Journal of the American Statistical Association, Vol. 74, pp. 427-431.
30
31

32
33 Elliott, G., Rothenberg, T., and Stock, J.H., 1996, Efficient tests for an autoregressive unit root,
34 Econometrica, Vol. 64, pp. 813-836.
35
36

37
38 Eltony, M.N., and Al-Mutairi, N.H., 1995, Demand for gasoline in Kuwait: An empirical analysis using
39 cointegration techniques, Energy Economics, Vol. 17, No. 3, pp. 249-253.
40
41

42
43 Energy Information Administration, 2005 [online], Retail motor gasoline and on-highway diesel
44 fuel prices, 1949-2004, <http://www.eia.doe.gov/emeu/aer/petro.html>
45
46

47
48 Engle, R.F., and Granger, C.W.J., 1987, Co-integration and error correction: Representation,
49 estimation, and testing, Econometrica, Vol. 55, No. 2, pp. 251-276.
50
51

52
53 Goodwin, P., Dargay, J., and Hanly, M., 2004. Elasticities of road traffic and fuel consumption with
54 respect to price and income: A review, Transport Reviews, Vol. 24, No. 3, 275-292.
55
56

57
58 Graham, D.J., and Glaister, S., 2002. The demand for automobile fuel: A survey of elasticities, Journal
59 of Transport Economics and Policy, Vol. 36, Part 1, pp. 1-26.
60

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4
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48
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50
51
52
53
54
55
56
57
58
59
60

Graham, D.J., and Glaister, S., 2004. Road traffic demand elasticity estimates: A review, *Transport Reviews*, Vol. 24, No. 3, pp. 261-274.

Granger, C.W.J., and Newbold, P., 1974. Spurious Regressions in Econometrics, *Journal of Econometrics*, Vol. 2, pp. 11-20.

Granger, C.W.J., and Weiss, A.A., 1983, Time series analysis of error correction models, in Karlin, S, Amemiya, T., and Goodman, L.A. (Eds.), *Studies in Econometric Time-Series and Multivariate Statistics*, New York (Academic press, UCSD Discussion paper 82-28)

Hansen, B.E., 1992, Test for parameter instability in regressions with I(1) processes, *Journal of Business & Economic Statistics*, Vol. 10, No. 3, pp. 321-335.

Hendry, D.F., 1980, *Econometrics: Alchemy or science?* *Economica*, Vol. 47, pp. 387-406.

Hendry, D.F., 1986, Economic modelling with cointegrated variables: an overview, *Oxford Bulletin of Economics and Statistics*, Vol. 48, No. 3, pp. 201-212.

Hendry, D.F., and Juselius, K., 2000, Explaining cointegration analysis: Part I, *The Energy Journal*, Vol. 21, No. 1, pp. 1-42.

Maddala, G.S., and Kim, I.-M., 1998, *Unit roots, Cointegration and Structural Change*, Cambridge University Press, Cambridge.

Nadaud, F., 2004, The demand for car gasoline in France: a long run econometric perspective, 6th IAEE European Energy Conference, 2-3 September, Zurich, Switzerland.

Ng, S., and Perron, P., 1995, Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag, *Journal of the American Statistical Association*, Vol 90, pp. 268-281.

Ng, S., and Perron, P., 2001, Lag length selection and the construction of unit root tests with good size and power, *Econometrica*, Vol. 69, No. 6, pp. 1519-1554.

Perron, P., 1989, The great crash, the oil price shock, and the unit root hypothesis, *Econometrica*, Vol 57, No. 6, pp. 1361-1401.

1
2
3 Phillips P.C.B., and Loretan, M., 1991, Estimating long-run economic equilibria, *Review of Economic*
4 *Studies*, Vol. 58, pp. 407-436.
5
6

7
8 Phillips, P.C.B., and Perron, P., 1988. Testing for a unit root in time series regression. *Biometrika*, Vol.
9 75, pp. 335–346.
10
11

12
13 Patterson, K., 2000, *An Introduction to Applied Econometrics: A Time series Approach*, Palgrave, New
14 York.
15
16

17
18 Quandt, R., 1960, Tests of hypothesis that a linear regression system obeys two separate regimes,
19 *Journal of the American Statistical Association*, Vol. 55, pp. 324-330.
20
21

22
23 Ramanathan, R., 1999, Short- and long-run elasticities of gasoline demand in India: An empirical
24 analysis using cointegration techniques, *Energy Economics*, Vol. 21, pp. 321-330.
25
26

27
28 Ramanathan, R., and Subramanian, G., 2003, An empirical analysis of gasoline demand in the Sultanate
29 of Oman using Cointegration Techniques, *Pacific and Asian Journal of Energy*, Vol.13, No. 2, pp. 33-
30 41.
31
32

33
34 Samimi, R., 1995, Road transport energy demand in Australia: A cointegration approach, *Energy*
35 *Economics*, Vol. 17, No. 4, pp. 329-339.
36
37

38
39 Sterner, T., and Dahl, C.A., 1992. Modelling transport fuel demand, in: Sterner, T. (Ed.), *International*
40 *Energy Economics*, London, pp. 65-79.
41
42
43
44
45
46
47
48
49
50
51
52
53
54
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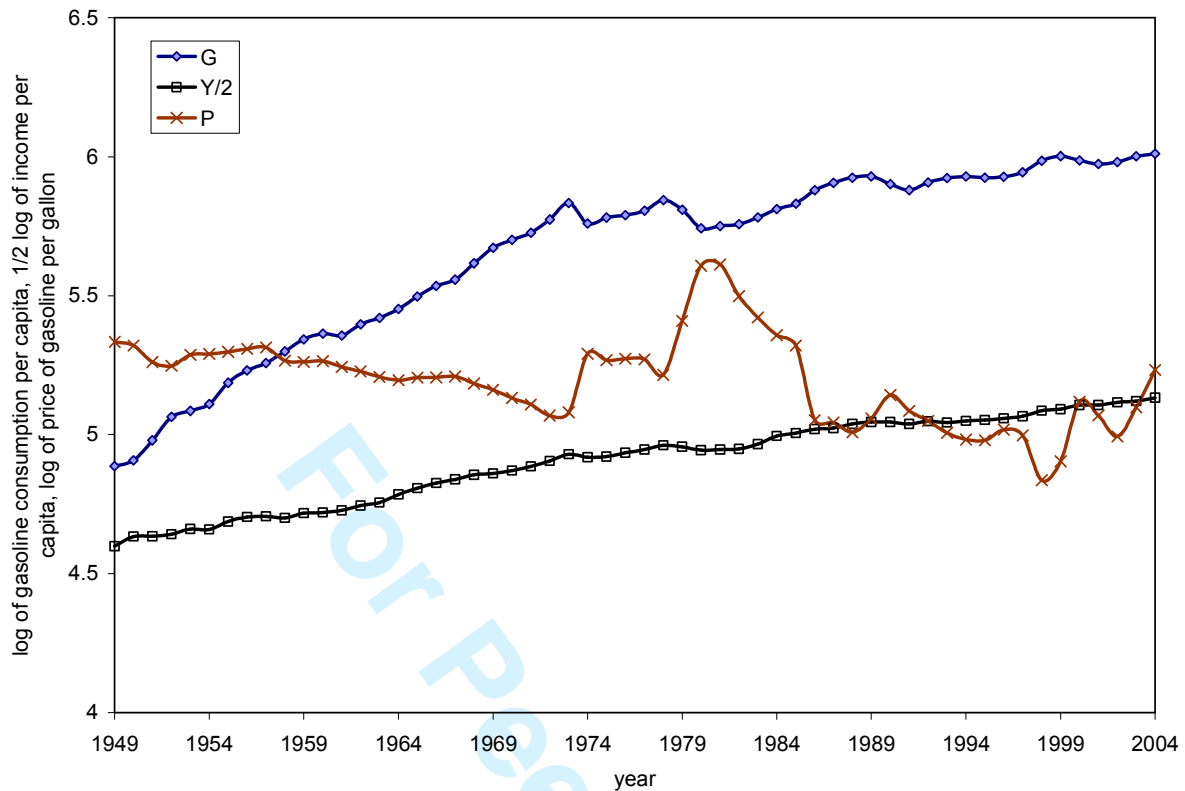


Figure 1. Gasoline consumption, gasoline price (real) and income per capita (real) from 1949-2004

Table 1. Estimates from cointegrating regression for gasoline demand

Country	Reference	Income elasticity		Price elasticity	
		Short run	Long run	Short run	Long run
Denmark	Bentzen 1994	0.89 ^a	1.04 ^a	-0.32	-0.41
Australia ^b	Samimi 1995	0.25	0.52	-0.20 ^c	-0.12
Kuwait	Eltoni and Al-Mutairi 1995	0.47	0.92	-0.37	-0.46
India	Ramanathan 1999	1.18	2.68	-0.21	-0.32
Brazil	Alves and Bueno 2003	0.12	0.12	-0.09	-0.47
Oman	Ramanathan and Subramanian 2003	0.35	0.96	-0.05	-0.52
France	Nadaud 2004	0.27	0.28	-0.06	-0.09
China	Cheung and Thomson 2004	1.64	0.97	-0.19	-0.56

^a income proxied by vehicle per capita

^b road transport energy demand

^c statistically insignificant

Table 2. DF-GLS test for the presence of unit root in level and differenced variables (H_0 : unit root exists, series non-stationary)

Sample	Full sample			Post-1978 sub-sample			Pre-1974 sub-sample			
	Variable	No of lags	DF-GLS test	5% DF-GLS critical value	No of lags	DF-GLS test	5% DF-GLS critical value	No of lags	DF-GLS test	5% DF-GLS critical value
G	1	-0.633	-3.195	1	-3.438	-3.498	2	-1.550	-3.349	
Y	1	-1.130	-3.195	7	-0.830	-3.014	1	-1.309	-3.509	
P	1	-2.498	-3.195	1	-1.202	-3.498	1	-2.020	-3.509	
ΔG	1	-4.751	-3.202	1	-5.140	-3.509	1	-2.858	-3.517	
ΔY	1	-3.844	-3.202	6	-4.344	-3.114	8	-1.875	-3.702	
ΔP	1	-5.195	-3.202	1	-6.156	-3.509	1	-2.802	-3.517	
$\Delta^2 G$							1	-4.517	-3.521	
$\Delta^2 Y$							2	-1.550	-3.332	
$\Delta^2 P$							2	-1.970	-3.332	
N		56			26			25		
Remarks		All 3 variables I(1)			All 3 variables I(1)			G is I(2), others inconclusive		

Table 3. Engle-Granger static estimation of long run behaviour

Dependent variable	Full sample		Post-1978 sub-sample	
		G		G
Explanatory variables	Coefficient	t-statistic	Coefficient	t-statistic
Y	0.999	27.95	0.565	15.34
P	0.022	0.30	-0.102	-5.27
Constant	-4.259	-6.89	0.724	1.60
<u>Test diagnostics</u>				
Adjusted R ²	0.948		0.973	
Breusch-Godfrey LM test of residual autocorrelation	44.882	(p=0.000)	2.345	(p=0.126)
DF-GLS test for residual unit root	-0.824 ^a		-4.551 ^b	
N	56		25	

^a 5% critical DF-GLS value -2.245

^b 5% critical DF-GLS value -3.498

Table 4. ECM based on Engle-Granger static long run estimates for the post-1978 sub-sample

Dependent variable	ΔG_t		
Explanatory variables	Coefficient	Standard error	t-statistic
ΔY_t	0.473	0.109	4.35
ΔP_t	-0.065	0.018	-3.68
ΔG_{t-1}	0.441	0.093	4.74
ΔG_{t-2}	-0.040	0.077	-0.51
ξ_{t-1}	-0.778	0.162	-4.79
Constant	-0.004	0.002	-1.54
<u>Test diagnostics</u>			
Adjusted R ²	0.843		
Breusch-Godfrey LM test of residual autocorrelation	1.435	(p=0.231)	
Shapiro Wilk W test for residual normality	1.207	(p=0.114)	
Engle's LM test for ARCH	2.420	(p=0.120)	
Portmanteau Q test for white noise	11.019	(p=0.274)	
N	25		

Table 5. OLS estimation of dynamic model for post-1978 sub-sample

Dependent variable	G_t		
Explanatory variables	Coefficient	Standard error	t-statistic
Y_t	0.457	0.053	8.61
P_t	-0.091	0.012	-7.34
G_{t-1}	0.720	0.112	6.45
G_{t-2}	-0.566	0.123	-4.62
G_{t-3}	0.076	0.066	1.15
Constant	0.406	0.231	1.76
<u>Test diagnostics</u>			
Adjusted R ²	0.991		
Breusch-Godfrey LM test of residual autocorrelation	0.118	(p=0.731)	
Shapiro Wilk W test for residual normality	0.084	(p=0.466)	
Engle's LM test for ARCH	1.025	(p=0.311)	
Portmanteau Q test for white noise	10.712	(p=0.296)	
DF-GLS test for unit root for $G - \beta_Y Y - \beta_P P$	-3.761 ^a		
N	25		

^a 5% critical DF-GLS value -3.498

Table 6. Single step NLLS estimation of the ECM for post-1978 sub-sample

Dependent variable	ΔG_t		
Explanatory variables	Coefficient	Standard error	t-statistic
ΔY_t	0.520	0.102	5.07
ΔP_t	-0.085	0.018	-4.70
ΔG_{t-1}	0.556	0.109	5.12
ΔY_{t-1}	-0.177	0.121	-1.46
ΔG_{t-2}	-0.066	0.081	-0.81
$G_{t-1} - \beta_Y Y_{t-1} - \beta_P P_{t-1}$	-0.782	0.151	-5.19
Y	0.592	0.035	16.89
P	-0.116	0.020	-5.77
<u>Test diagnostics</u>			
Adjusted R ²	0.880		
Shapiro Wilk W test for residual normality	-0.699	(p=0.758)	
Portmanteau Q test for white noise	6.444	(p=0.695)	
DF-GLS test for unit root test for $G - \beta_Y Y - \beta_P P$	-3.839 ^a		
N	25		

^a 5% critical DF-GLS value -3.498

Table 7. Comparison of elasticity estimates for post-1978 sub-sample from various models (standard error in brackets)

Parameter estimates	Estimation procedure		
	Engle-Granger	Dynamic OLS	NLLS
Income elasticity, long run	0.565 (0.037)	0.593 (0.025)	0.592 (0.035)
Price elasticity, long run	-0.102 (0.019)	-0.118 (0.015)	0.116 (0.020)
Income elasticity, short run	0.473 (0.109)	0.457 (0.053)	0.520 (0.102)
Price elasticity, short run	-0.065 (0.018)	-0.091 (0.012)	0.085 (0.018)
Speed of adjustment	-0.778 (0.162)	-0.771 (0.075)	-0.782 (0.151)