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"Gasoline Price Cycle Drivers: An Australian Case Study"

By Nick Wills-Johnson & Harry Bloch

Centre for Research in Applied Economics,
School of Economics and Finance
Curtin Business School
Curtin University of Technology
GPO Box U1987, Perth WA 6845 AUSTRALIA
Email: michelle.twigger@cbs.curtin.edu.au
Web: http://www.cbs.curtin.edu.au/crae

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Curtin
University of Technology

Gasoline Price Cycle Drivers

Gasoline Price Cycle Drivers: An Australian Case Study

Nick WILLS-JOHNSON*
Centre for Research in Applied Economics
Curtin University of Technology
GPO Box U1987
Perth, Western Australia 6845
email: n.wills-johnson@aciltasman.com.au
tel: +61894499616
fax: +61893223955

Harry Bloch
Centre for Research in Applied Economics
Curtin University of Technology
GPO Box U1987
Perth, Western Australia 6845
email: Harry.Bloch@cbs.curtin.edu.au
tel: +61892662035
fax: +61892663026

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Abstract

In many retail gasoline markets, prices follow a saw-toothed cycle first posited by Edgeworth (1925) and formalised by Maskin & Tirole (1988). A growing literature explores driving factors behind such cycles, most particularly in Canada and the US. This paper explores price cycles in a retail gasoline market in Australia with a unique regulatory environment that provides a census of data. We make use of a threshold regression model, and pay particular attention to local market effects and market structure. Both are novel in the study of retail petroleum prices.

*corresponding author

Gasoline Price Cycle Drivers: An Australian Case Study

1. Introduction

Retail gasoline prices in many jurisdictions follow a saw-toothed pattern, shown in Figure Two and called an Edgeworth Cycle. Figure One shows prices at Shell-branded outlets in Perth, Western Australia over the course of three months during 2003. Other time periods and other brands show a similar pattern. The thin grey lines show the price path of each outlet, whilst the thick grey line shows the daily wholesale price.

Figure One about here

Note that prices all seem to rise together, and often to roughly the same level. Clearly, Shell head-office in Perth plays a major role in determining when and by how much each Shell-branded outlet increases its price.

Wang (2009) studies such co-ordination during the upwards phase of the price cycle. However, note that the downward phase of the cycle exhibits a wide band of price paths indicating that each outlet acts far more independently of head office during this phase of the cycle. Here, we explore what drives prices in both phases of the cycle, utilising Hansen's (1999) threshold regression model to differentiate between downward and upward phases and we employ a novel measure of market structure.

Section Two of this paper briefly reviews the empirical price cycle literature, while Section Three provides an explanation of threshold regression models. Section Four provides an overview of the approach we take to obtain a structural measure of local market competition. Section Five provides a brief overview of the Perth data used. Section Six introduces the model and its results. Section Seven concludes.

2. Edgeworth Cycles and Threshold Regression Models

Price Cycles were first posited as an equilibrium of a dynamic game by Edgeworth (1925) and formalised by Maskin & Tirole (1988), who named the cycles after Edgeworth . Their distinctive pattern is shown in Figure Two.

Figure Two about here

Maskin & Tirole (1988) show that Edgeworth Cycles are one equilibrium of a repeated, alternate move game when symmetric duopolists produce an homogenous good and who use Markov-perfect strategies to choose prices from a finite grid, provided that the discount rate is sufficiently high.. The cycles arise because, for prices above the minimum, a small reduction in price is sufficient to capture the whole market from a rival until it moves again. At the minimum, it is in the interests of both parties for prices to move up again, but not for either party to be the first-mover. They thus play a war of attrition. However, once one firm moves, since the optimal response by its rival will be a slight undercut, the initiator of the price rise has an incentive to increase price by as much as possible in order to maximise its benefits over the price cycle.

The model has been extended by Eckert (2003), who allows firms to be of different sizes, by Lau (2001), who shows that the necessary strategic commitment can arise in simultaneous move games as well, and by Noel (2008), who relaxes a host of assumptions such as identical marginal costs, elasticities of demand and product characteristics, as well as extending the model to the three-firm case.

There is considerable empirical evidence that prices in retail gasoline markets often follow an Edgeworth cycle, notably in Canada (Eckert 2003, Eckert & West 2004a,b, 2005a, Atkinson, Eckert & West 2009, Atkinson 2009 and Noel 2007a,b), but also in the US (Lewis 2009 and Doyle, Muehlegger & Samphantharak 2008) and Australia (Wang 2009 and ACCC 2007).

Lewis (2009) and Doyle, Muehlegger & Samphantharak (2008) follow Lewis's approach of measuring the extent to which a cycle is saw-toothed in nature by using the median change in price, which is then regressed against a number of explanatory variables such as the market share of independent firms, station density, population, income, number of cars per household and land area. In Bloch & Wills-Johnson (2010a), we follow a similar approach using the Perth case study that is also used in this paper. Wang (2009) focuses on the increasing phase of price cycles, and explores what the pattern of first movement amongst the brands in Perth reveals about the mixed strategies followed by each brand in the relevant price-wars. In Bloch & Wills-Johnson (ibid) we also explore the use of mixed strategies, through the use of spectral analysis.

The remaining authors consider the entire price path and endeavour to uncover what drives prices during both phases of the cycle. In order to do so, one must consider how to incorporate potential differences in behaviour in the increasing and decreasing phases of a price cycle. Atkinson, Eckert & West (2009), Atkinson (2009) and Eckert (2002) address this issue by treating the upward and downward phases in separate regressions, whilst Eckert & West (2004b) do so by allowing the coefficients to vary over the four phases of the cycle they identify in their work. Noel (2007a,b, 2008, 2009) uses a Markov-Switching regression, which is more computationally intensive. Here, we are able to utilise Hansen's (1996, 1999, 2000) threshold regression model as we have a census of data, not a sample, and can thus observe turning points.

3. Threshold Regression Models

Threshold regression assumes that the model behaves differently when a certain critical variable is above or below a threshold value. The approach's novelty lies in allowing the data to determine where the threshold should lie, rather than imposing the threshold externally.

The threshold regression approach has many applications, with Hansen's three seminal papers (1996, 1999, 2000) widely cited. It has found perhaps its widest application in macro-economics, particularly in problems concerning economic growth (see, for example, Papageorgio, 2002, Savides & Stengos, 2000, Deidda & Fattouh, 2002, and indeed Hansen himself, 1996, 2000). A number of authors have also used it in micro-economic analysis (see for example Huang & Yang, 2006, who study cigarette demand and Boetel, Hoffmann & Liu, 2007, who study the demand for hogs). There have also been a number of studies that have examined the rockets and feathers hypothesis in retail petroleum markets using threshold autoregression models (see Chan, 1993), such as Godby et al, 2000 and Chen et al 2005. However, to the knowledge of the authors, this study represents the first time the model has been used to separate the stages of an Edgeworth Cycle in retail petroleum markets, although Eckert's (2002) approach is similar.

4. Modelling Market Structure

An important aspect of this paper is the way in which we model market structure. Rather than use an indirect measure such as seller density or, as in the Edgeworth cycle literature above, the penetration of independents, we develop a simple theoretical model of bilateral interaction and use this to test who competes with whom. We collect these bilateral links to form a network that summarises the structure of competition in the marketplace as a whole and use simple graph-cutting tools to delineate local sub-markets. We then use measures of network structure from the mathematical sociology literature to summarise the position of each retail gasoline outlet in the overall structure of the global market and local sub-markets. These measures are used as regressors in the model outlined in Section Six. We describe the process of network formation and division briefly below, and in more detail in Bloch and Wills-Johnson (2010b).

The simple theoretical model is based upon that of Hoover (1937) and McBride (1983), who study how spatial differentiation can give rise to local market power.[1] Our point of departure is an assumption that consumers come to the retailer rather than having goods delivered to them, and this requires the retailer to set a single price for all consumers without knowing from whence each has come.

We examine a duopoly where each firm sells one unit of an homogenous good to identical consumers whose travel plans take them past one retail gasoline outlet but who must deviate to frequent the other (meaning purchase from the former is costless but that from the latter is not). Each firm has two choices; set a higher price than its rival and collect rents from those customers

[1] Eckert & West (2005b) also study a spatial model of retail petroleum competition in Canada, investigating how tacit collusion contributes to the rationalisation of station numbers.

for whom deviation to its rival is costly or set a price lower than its rival and endeavour to steal market share.

The advantages of each choice change depending upon overall price levels, and it is relatively simple to show the situations whereby this will give rise to an Edgeworth Cycle (see Bloch & Wills-Johnson, 2010c). It is also relatively simple to show that the minima of such price cycles will be related for in a consistent fashion where firms compete (ibid). Moreover, if marginal costs and the proportion passing each outlet first are equal, one can easily show that the minimum of each price cycle for each outlet in the duopoly will be the same (see Bloch & Wills-Johnson, 2010c, for an illustration of these results).

This gives rise to a simple test of connection. We first form the series of price cycle minima for each gasoline station by taking the lowest price in the three days prior to each price increase of greater than five percent.[2] We then undertake a simple statistical test of the difference between the means for each pair of outlets within five kilometres of one another.[3] Where there is no statistically significant difference between the means, we deem the two outlets to be connected. By collecting these connected pairs, we are able to construct a network that summarises the patterns of connection in the overall market.

We then divide this network in to a series of submarkets, using an approach pioneered by Gould (1967), and subsequently widely used in geography (see, for example, Cliff, Haggett & Ord,

[2] Looking four days prior and using different price increases makes little difference to results; the increasing phase of each price cycle is quite clear in the data.

[3] The ACCC adopted this local market definition in a recent merger decision (see http://www.accc.gov.au/content/index.phtml/itemId/904296), and a similar distance measure has been used to define local markets in the US literature (see Hastings, 2004 or USSPSICGA, 2002). We use it as a provisional measure of local markets, to avoid having to test every possible bilateral pair in a collection of 208 gasoline stations.

1979, Boots, 1985, O'hUallachain, 1985 and Straffin, 1980). The network is first converted into an adjacency matrix; a symmetric, zero-one matrix where a zero in the ij^{th} position indicates that nodes i and j are not connected, and a one indicates that they are. We then take the eigenvectors of this adjacency matrix. The first eigenvector (that is, the eigenvector associated with the largest eigenvalue) has all positive entries. In order to be orthogonal to the first, the remaining eigenvectors must contain positive and negative elements. Gould (1967) suggests that clusters of positive and negative eigenvector elements indicate sub-groups within the network. The approach is somewhat judgemental, but subsequent testing of the submarkets (see Bloch & Wills-Johnson, 2010b) suggests they are reasonably robust, and indeed give a better characterisation of groups of like-priced outlets than branding does.

The results of following Gould's (1967) approach using the second to sixth eigenvectors (after which the signal to noise ratio makes it impossible to uncover further structure) divides the market into eight distinct sub-markets. Figure Three shows the overall market with the eight sub-markets superimposed. The dark-grey area represents the Swan River, which divides the city North from South, and the light-grey line represents the main north-south freeway, which divides East from West. Placement of each station is approximate, but roughly correlates to the physical shape of the Perth market.[4] The different shaded dots represent different brands.

Figure Three about here

[4] The software used to construct the networks and calculate their structural characteristics (Borgatti, Everett, & Freeman, 2002) has only limited capabilities in terms of spatial mapping.

There are a wide variety of measures which can be used to summarise network structure in the mathematical sociology literature.[5] We use one measure of centrality, and three measures which reflect Burt's (1992) notion of a structural hole in a network. Centrality is measured using the approach of Bonacich (1972, 1987), who bases his measure on the leading eigenvector of the adjacency matrix.[6]

The importance of structural holes, or the parts of the network where there are few connections between densely intra-connected sub-groups, is suggested by Burt (1992). Burt uses a number of measures to capture structural holes. The effective size of the network for a given node is the sum of the non-redundant portions of its relationships with all other nodes in the network, and ranges from one to *N*, the total number of nodes in the network.[7] Further, the efficiency of the network for a given node is its effective size divided by *N*. A more efficient network is one where structural holes are better situated from the perspective of the node for which efficiency is being calculated. Finally, constraint is the absence of structural holes, meaning that, even if a node severs its direct connection with another node, indirect connections mean that it is still restricted by that node. Burt (1992) defines constraint as the sum of the proportion of network time spent on connections with a given node and across all other nodes which that node and the node for which constraint is being calculated are connected to. We make use of Burt's (1992) measures of efficiency and constraint, and also limited use of his measure of redundancy.

[5] See Borgatti & Everett (2005) for a mathematical treatment of different centrality measures, Granovetter (2005) or Burt (2000) for a summary of the debate in the literature about the importance of density vs structural holes, and Burt (2000, 2002, 2005) for a summary of the literature on structural holes.
[6] Gould (1967) uses an identical measure, but not the term centrality. Bonacich (1972) appears to developed his measure independently of Gould.
[7] What Burt (1992) terms the redundant portion of one node's relationship with another node is the extent to which their relationship is through other nodes connected to both of them. The more indirect connections the two nodes have, the more redundant are these connections, as there are many paths down which information can flow.

5. Perth Market and Data Used

The data used in the threshold regression models come from Perth, Western Australia, which is governed by a unique regulatory regime known as *FuelWatch*. Every gasoline retailer must report its next-day price to the regulator by 2pm. The regulator then publicises those prices, which comes into effect at 6am the next day and must remain in effect for 24 hours. Quite apart from the effect this regulatory regime has on strategy (see Wang, 2009), or the influence it may or may not have on the price level (see Davidson, 2008, for an account of this controversy), it provides the researcher with a census of price data. This makes Perth an excellent case study.

Considerable data on the Perth market and on retail petroleum in Australia in general, can be found in the various recent reports by the ACCC (2007, 2008, 2009). Here, we focus on the data which are used in the analysis in Section Six. The data are summarised in Table One.

Table One about here

The data cover the period from January 1st 2003 to March 14th 2004. The start-date is chosen as data on wholesale or terminal gate prices (the proxy for the marginal cost of retailers) are unavailable before this date, and the end-date is chosen because the following day marked the conversion of some 40 Shell outlets into Coles Express outlets through a joint venture between Coles supermarkets and Shell. The data do not cover all outlets in Perth, omitting some on the outskirts of the city, those for which the data series are incomplete (usually because they are new, or were closed for long periods during the sample period owing to a change in ownership) and those for which the retailing of fuel is not a core business (such as taxi depots and marinas).

Data on demand come from the ABS *Census* (ABS, 2006) whilst the remaining data come from *FuelWatch*, or are based on data in the *FuelWatch* database.[8]

Table Two provides information on branding, ownership structures, presence of convenience stores and location of competitors. Caltex has the largest market share, followed by BP and Shell. Mobil, the fourth of the Majors (vertically integrated, multi-national firms active in refining, wholesale and retail in Australia), has a much smaller market share. Independent chains (Gull, Liberty and Peak) make up roughly a quarter of the sample, making them collectively more important than either Shell or Mobil and slightly smaller than BP. Supermarkets are more prevalent today than in the dataset, which precedes the entry of Coles, and is from a time when only small numbers of Woolworths outlets existed.[9] Today, the two comprise almost half of overall Fuel sales in Australia (ACCC, 2007).

Table Two about here

Company controlled outlets comprise roughly half of those in Table Two, according to *FuelWatch*, which defines outlets owned directly by the Majors and outlets owned by their multi-site franchisees as being company controlled. In Western Australia, Shell owns eight sites, BP owns five and Mobil none. Thus, most of the outlets listed as company controlled in Table Two are owned by one of the multi-site franchisees of these brands. Caltex has no multi-site franchises due to the terms of its 1995 merger with Ampol (see Walker & Woodward, 1996, for

[8] The authors would like to thank the *FuelWatch* regulator for making this dataset available.
[9] Coles and Woolworths are the two major grocery retailers in Australia.

details). Instead, it uses single site franchises and a price-support scheme described in detail in Wang (2009).

Convenience stores attached to retail petroleum outlets are often an important source of profits for the brands which own them. Caltex has two convenience store brands, whilst Shell, Mobil and BP have one apiece. Most Mobil outlets have a convenience store attached, as do around two-thirds of Caltex outlets. The shares for BP and Shell are each less than one-third. None of the independent brands has a convenience store brand, though some (Gull in particular) sell convenience store items in many of its outlets.

Although Perth is a relatively low-density city, retail petroleum outlets tend to be located along highways or at the major shopping centres which exist in some suburbs. This is in part due to zoning laws and in part due to a desire to be located at nodes of demand. For this reason, the distance to the nearest rival tends to be low (on average just over one km) and the number of competitors within five kilometres is nine.[10]

Table Three summarises the demand data, showing city-wide averages and the upper and lower bounds of 95 percent confidence intervals around these averages.

Table Three about here

[10] Distances between each pair of outlets were calculated manually using en electronic version of the Perth street directory. All distances were calculated based on the shortest distance by road.

Table Four summarises the frequency of scores for global and local centrality, constraint and efficiency, which were calculated using the *Ucinet* software developed by Borgatti, Everett & Freeman (2002). Note that we have normalised the centrality scores such that they range from zero to one, like the constraint and efficiency scores.

Table Four about here

Although prices and margins form the dependent variables in the regressions in Section Six, we also endeavour to capture some of the past history of these variables by including lags in the regressions, and through the "occurrence" families shown in Table One (*OCO1* to *OCO9* and *OCS1* to *OCS9*). These track the number of times a given gasoline station has exhibited a particular characteristic (highest price, median price etc) in the period up to *t-1*. For the whole time period, examining the frequency of such occurrences shows that most have very low frequencies. This suggests that there are no consistent price leaders or followers, but rather that each outlet plays mixed strategies; a finding highlighted by Wang (2009) at the brand level and also by the spectral analysis in Bloch & Wills-Johnson (2010a) for each outlet.

6. Model Construction and Results

We now explore in more detail the threshold regression models and the results of the regressions undertaking using these models. The two models used are:

$$\begin{aligned}
&RPRICE_{it} = \alpha + \tau_{it} MC + \omega_{it} RPRICE_{i,t-1} + \xi_{it} RPRICE_{i,t-7} + \beta_i BR_i + \\
&\chi_i TP_i + \delta_i SV_i + \phi_i CS_i + \varphi_{ij} DCHAR_{ij} + \gamma_{ik} NCHAR_{ik} + \\
&\eta_i SUBM_i + \lambda_{im} EGOR_{im} + \pi_i DWD_i + \kappa_i MD_i + \theta_{in} OCO_{in,t-1} + \rho_{io} OCS_{io,t-1}
\end{aligned} \quad (1)$$

and

$$
\begin{aligned}
M_{it} &= \alpha + \omega_{it} M_{i,t-1} + \xi_{it} M_{i,t-7} + \beta_i BR_i + \\
&\chi_i TP_i + \delta_i SV_i + \phi_i CS_i + \varphi_{ij} DCHAR_{ij} + \gamma_{ik} NCHAR_{ik} + \\
&\eta_i SUBM_i + \lambda_{im} EGOR_{im} + \pi_i DWD_i + \kappa_i MD_i + \theta_{in} OCO_{in,t-1} + \rho_{io} OCS_{io,t-1}
\end{aligned} \tag{2}
$$

Each of the variables is defined in Table One, with the exception of M, which is the gross retail margin (the daily retail price minus the daily terminal gate price from the same-branded wholesaler), *DWD*, which is the day of the week dummy and *MD*, which is the monthly dummy.

A threshold regression model can be expressed thus:

$$
\begin{aligned}
y_t &= \theta_1' x_t + e_{1t} \quad if \quad q_t \le \gamma \\
y_t &= \theta_2' x_t + e_{2t} \quad if \quad q_t > \gamma
\end{aligned} \tag{3}
$$

where here $\theta_i^{`}$ refers to the entire right hand side of Equations One and Two above. The threshold variable q can be any variable the modeller chooses, including the change in the left-hand side variable, which we use here. One can reduce the two equations shown in Equation Three into a single equation by allowing $I_t(\gamma)$ to be an indicator variable that takes a value of one when the second argument above is true and zero otherwise, and by setting $\theta_3 = \theta_2 - \theta_1$, to obtain:

$$
y_t = \theta_1' x_t + \theta_3' x_t I_t(\gamma) + e_t \quad with \quad e_t \approx iid\left(0, \sigma_i^2\right) \tag{4}
$$

In order to find the correct threshold, Hansen (1999) suggests performing a grid-search over a number of potential thresholds and choosing the threshold that gives the regression containing it the smallest sum of squared errors. We use an uneven grid with 33 intervals between zero and ten cents per litre, where the interval is 0.2 cpl (cents per litre) for price changes between zero and five cpl (where the threshold is most likely to lie) and 0.5 cpl thereafter, and find that the minimum sum of squared errors occurs at a change in price of 3.6 cpl. The same threshold is optimal for both models (price and margins) and indeed for most variants of each model with different independent variables omitted.

We assess the robustness of these results using tests suggested by Hansen (1999). We first test first for the existence of a threshold following his bootstrap approach and find test statistics of 543801.4 for prices and 447339.1 for margins, with *p*-values of 0.0000 for both. This suggests that a threshold exists. We then test whether the threshold of 3.6 cpl is the most appropriate threshold by estimating a confidence interval around our result (see Hansen, 1999) and find that the confidence interval is very tight, suggesting 3.6 cpl is the most appropriate threshold. Finally, because independent outlets often stagger their price increases over a couple of days whilst majors (BP, Shell, Mobil and Caltex) tend to jump in just one day, we explore whether the threshold is inadvertently capturing brand or ownership differences. We find that all brands and ownership types have roughly the same proportion of price changes above the threshold, which means it is unlikely that the threshold is inadvertently capturing brand or ownership differences in behaviour.

We now turn to the empirical estimation of Equations One and Two in the threshold regression form of Equation Four. We examine the consequences of removing various of the independent variables in the model, but the likelihood ratio test results associated with this process suggest that the most general model is also the one which performs best from a statistical perspective. Since the model is estimate in the form of Equation Four, it contains θ_3 rather than θ_2. The coefficients and variances for θ_2 are recovered manually. The results for the prices and margins regressions are presented in Tables Five and Six, where the prefix "T" indicates the upward phase of the cycle.

Tables Five and Six about here

Both models provide a good fit to the data and neither exhibits evidence of serial correlation. Breusch-Pagan tests statistics indicate heteroscedasticity, which we address by using robust standard errors.[11] Since each regression is large (although many variables are dummies), there is potential scope for multicollinearity or misspecification in the regression models. We address this by testing many different formulations of the models, with different independent variables excluded. The results, particularly those pertaining to network characteristics,[12] are generally robust to these changes.

The set of variables measuring network structure provide reasonably consistent results across the two models, with centrality at both the global and local levels being negative (albeit only at the ten percent level for global centrality) during the downward phase of the price cycle and local centrality being positive during the upswing. Efficiency and constraint are positive at the local level, and constraint is negative at the global level, during the downswing, whilst neither is significant (except for constraint in the margins regression) during the upswing. *EGOR* coefficients are generally positive and statistically significant during both the downswing and the upswing. The interpretation of the network results are discussed in detail below

[11] All of the results in Tables Five and Six are for the robust standard errors versions of each regression model, excepting of course the Breusch-Pagan test statistic results.
[12] With the exception of *NCHAR1*, which is only significant in some model forms.

The *SUBM* results, when viewed geographically, suggest that sub-markets located next to each other do not necessarily price in a consistent fashion but rather follow prices of sub-markets which are further away.

Marginal costs, lagged prices and lagged margins are all roughly in line with expectations. All suggest that higher levels of marginal cost today, or prices or margins at the relevant lags imply higher levels today for prices or margins, with the exception of one-day lagged margins during the upswing. Note also that the coefficients on one-day lagged prices and margins are roughly 0.8 during the downswing, which highlights the small declines during that phase, and that both have much stronger effects than either marginal cost or seven-day lags. The same is true, vis-à-vis one-week lags during the upswing, but not marginal costs, which become much more important during the upswing, suggesting that the impetus to hike price increases as one nears marginal cost. Noel (2007a,b) has similar findings.

The results on the various station characteristics are reflective of the omitted dummy variables. They suggest that Woolworth (*BR4*), the no-brand independents (*BR6*), Peak (*BR9*) and Wesco (*BR11*) all have higher prices than Shell during the downswing but that Gull (*BR5*) has lower prices and the other major brands (Caltex, BP and Mobil) have prices with no consistent pattern relative to Shell. The coefficients on branding are also much smaller during the downswing, which suggests that brand discipline is much less important during this phase.[13] Note especially

[13] Sensitivity analysis whereby different branding and ownership characteristics were removed shows broadly similar results to those presented here.

the low coefficient on Gull. If it is a "maverick" leading prices downwards, it is not a particularly strong one.

For ownership types, the more independent types (*TP1*, *TP2* and *TP3*) tend to have higher prices than company controlled outlets during the downswing, but lower prices during the upswing. This potentially indicates that the majors (Shell, Caltex, BP and Mobil) are using the outlets that they have more control over (either through ownership or via franchising) to lead prices upwards. However, price supported outlets, all of which are owned by Caltex, show lower prices, potentially highlighting their use by Caltex in price wars to lead prices down and capture market share.

Demand coefficients are generally small, which suggests that demand effects are not particularly important. One clear exception to this is the number of vehicles per household, which has a small positive coefficient during the downward phase of the cycle, but a very large coefficient during the upward phase. Absent of model issues, this may be because markets with many cars represent the most profitable markets.

Being on a main road, near a competitor or having many competitors nearby all lead to lower prices during the downward phase of the price cycle, which reflects their pro-competition effects. However, the number of competitors within five kilometres has a positive, significant coefficient during the upward phase, indicating that outlets packed more densely together raise price together, potentially a network-density effect.

The day of the week dummies indicate that prices tend to be higher earlier in the week. There is less evidence of seasonal factors, although the evidence from the downward phase of the price cycle tends to suggest that prices are lower in winter than in summer.

Finally, the occurrence family results tend to suggest, at least during the downswing, that there is a degree of mean-reverting behaviour occurring. The same is not true during the upswing, but this may be because each successive upswing is roughly a week apart, by which time price levels during the last upswing may well be ancient history.

We now explore in more detail the possible reasons for the findings outlined above, focussing most particularly on the network characteristic variables, which are the main focus of this analysis, and which provide some of the more counter-intuitive results.

The negative *NCHAR2* coefficient during the downswing may be suggestive of outlets sitting at the junction points between sub-markets (the least constrained) acting to attenuate price signals travelling between sub-markets. This is partially confirmed by the fact that the submarkets neighbouring each other have opposite coefficients, which may indicate that the border outlets act to reduce information flow between submarkets.

Centrality does seem to be associated with leading prices downwards; both global (*NCHAR4*) and local (*NCHAR8*) centrality have negative coefficients. However, the most central stations at the local level also have the highest prices during an upswing, suggesting perhaps that they lead prices upwards in both the downswing and the upswing. This is s not too surprising, as such outlets would have the greatest ability to disseminate price information, owing to their location. However, the size of the coefficient is very small; indicating that the effect is not substantial. It suggests the Majors can co-ordinate price increases through simply dictating them to all outlets bearing their brand, as argued by Wang (2009).

The positive *NCHAR5* and *NCHAR6* coefficients at first appear counter-intuitive. A positive local efficiency coefficient suggests similar conclusions to the negative global constraint conclusion; that those in a good position (one for which the local market is efficient for the given retailer) can exploit the informational advantage that results and leverage some market power. However, the positive local constraint coefficient does not fit this story. Further examination shows that the outlets with the higher local constraint scores tend to be on the periphery of each local market (and indeed on the periphery of the Perth market as a whole), and we suggest that what is actually occurring is that these outlets, with access to customers unavailable to those not on the periphery, exploit their higher degree of local market power by charging these customers higher prices rather than fighting for the customers they must share with more centrally located outlets. Eckert & West (2005b) find that stations on the periphery of Canadian cities are less likely to close, which may be indicative of a similar effect to the one we find.

The EGOR results provide some confirmation for the efficiency results above. The outlets with the highest efficiency scores, sitting one or two steps away from the centre of each local network, are likely to have a large number of contacts in common with the centre, and hence high redundancy scores. These are the outlets that price higher than the centre, ameliorating the price decreases which originate there.

7. Conclusions

Gasoline prices in Perth, as in almost all capital cities in Australia and many cities in North America, follow an Edgeworth Cycle. Factors driving Edgeworth Cycles have been explored in other markets, and Wang (2009) studies the strategic interaction between brands in Perth that gives rise to the patterns of price increases. However, our study is the first to examine the factors driving prices across the whole Edgeworth Cycle in the context of the Perth market.

The paper introduces two innovations. First, Hansen's (1999) threshold regression technique is used for the first time to explore Edgeworth Cycles. It is particularly suited to the Perth market because, with a census of data, one can observe turning points in the cycle directly. Second, we introduce new measures of market structure. Rather than incorporating this indirectly through the use of proxies, such as seller density or the number of independents in the market, the paper introduces a method based on a simple model of bilateral interaction that gives rise to a network picture of competition in the marketplace as a whole. The network is cut into sub-markets based upon its structure (rather than some arbitrary delineation such as suburbs or post codes), and summarised relatively easily using summary statistics common in mathematical sociology. These summary statistics are then incorporated into regression analyses as independent variables to highlight how structure influences pricing.

We find that market structure does indeed influence pricing, most particularly during the downswing and most particularly at the sub-market level. This confirms Wang's (2009) suspicion that local competition is most strongly at work during this phase of the cycle. We find that outlets facing the least constraint in the network as a whole, generally those which sit between sub-markets, have higher prices during the downswing, potentially indicating they act to reduce the flow of information between submarkets. We find that outlets for whom the relevant sub-market is efficient (in Burt's 1992 sense) act in a similar manner. We also find that the locally constrained outlets have higher prices during the downswing, but suspect that this is due to their peripheral location, and thus their ability to capture demand outside the sub-market (where they face less competition).

Once market structure is taken into account, we find that independents often have higher prices than the majors and that Caltex's price-supported outlets tend to have the lowest prices. Thus, price leadership by a particular brand, particularly during the downswing may be at least partially a function of market position. Similarly, we find that outlet density has a positive coefficient, which suggests that density is not a good proxy for the competitiveness of market structure.

The way we account for market structure here may have broader application than retail gasoline markets. In particular, it might be useful to both academic researchers and antitrust practitioners seeking to delineate market boundaries as part of tests associated with defining market power. This is perhaps the most useful result from this paper

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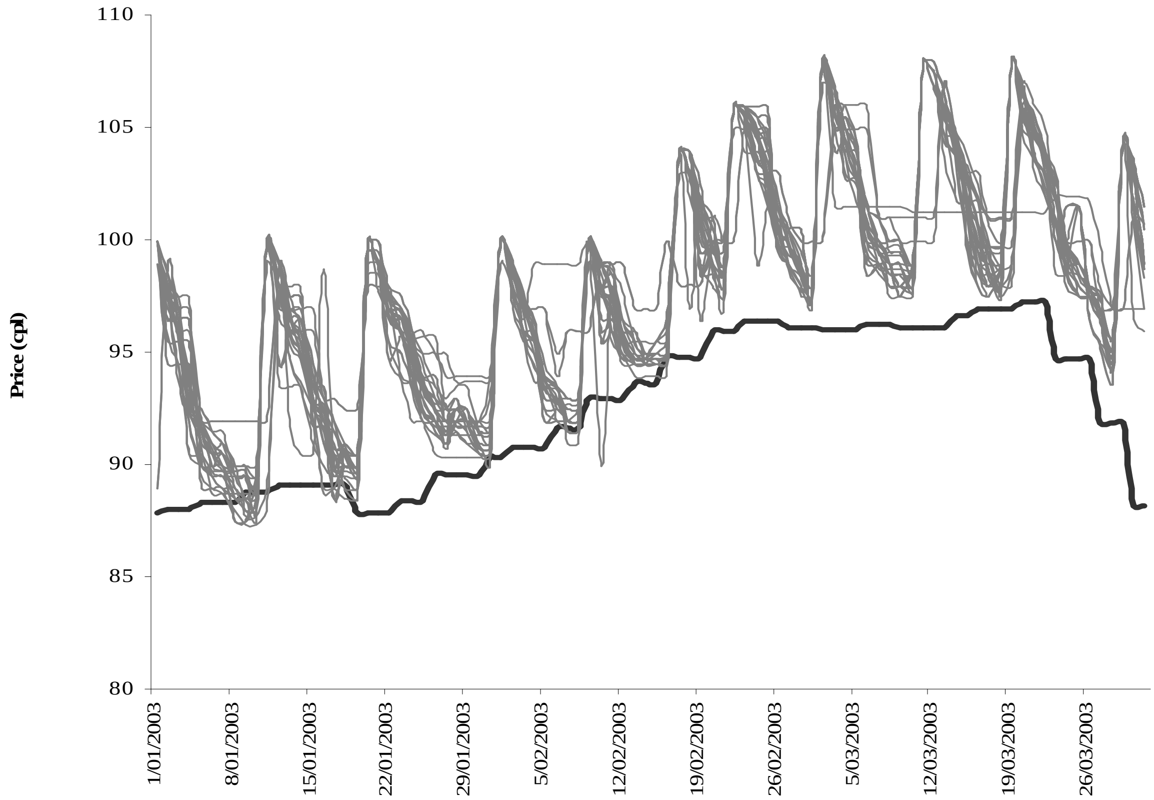

Fig.1 Price cycles at Shell gasoline stations in Perth

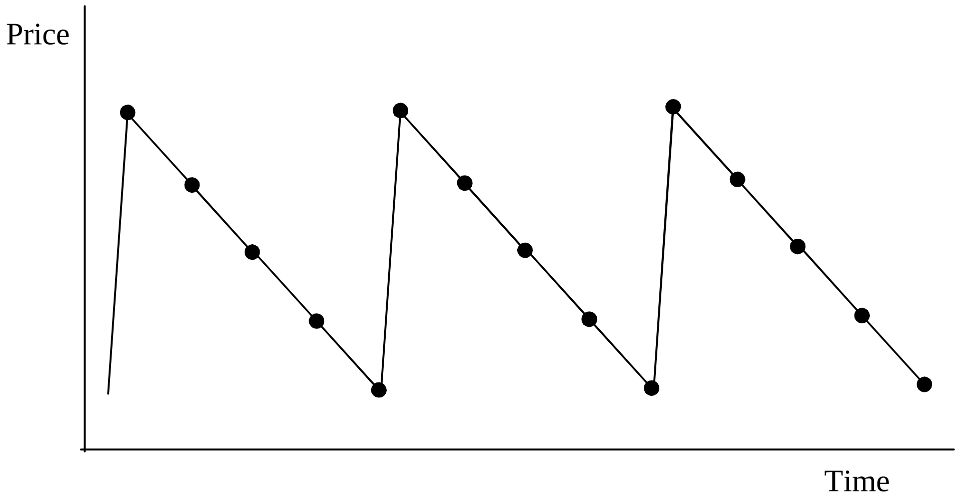

Fig.2 A diagrammatic representation of an Edgeworth cycle

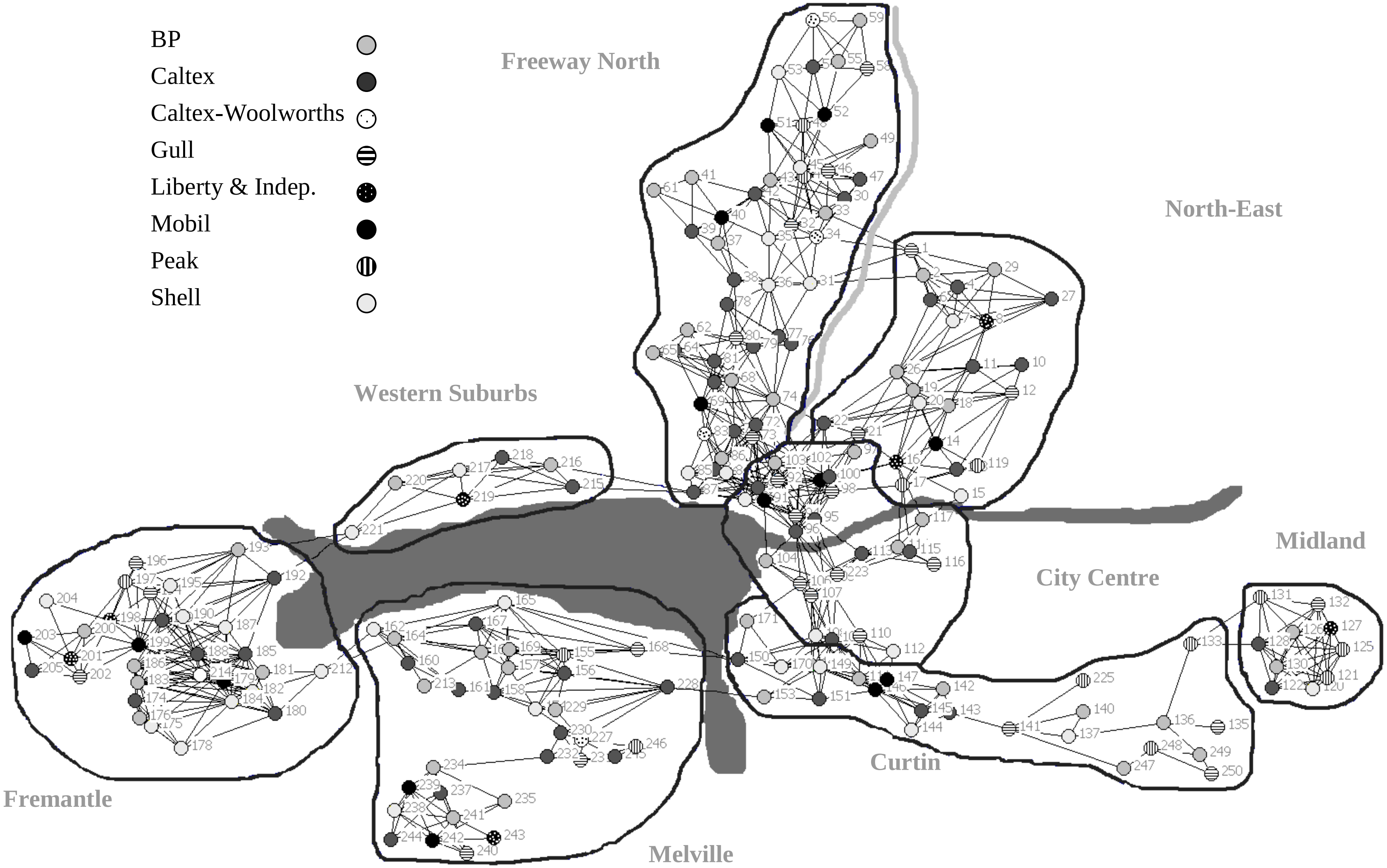

Fig. 3 Sub-markets in market network

Table 1. Description of the data

Group	Variable	Code
Price	Retail Price	RPRICE
	Marginal cost (tgp)	MC
	Median Price Change	MPC
Brand	Ampol	BR1
	BP	BR2
	Caltex	BR3
	Caltex-Woolworths	BR4
	Gull	BR5
	Independent	BR6
	Liberty	BR7
	Mobil	BR8
	Peak	BR9
	Shell	BR10
	Wesco	BR11
Type	Branded Independent	TP1
	Company Controlled	TP2
	Distributor Controlled	TP3
	Independent	TP4
	Larger Independent	TP5
	Price Supported	TP6
	Supermarket	TP7
Convenience Store	BP Connect	CS1
	Caltex Starmart	CS2
	Caltex Starshop	CS3
	Mobil Quix	CS4
	Shell Select	CS5
Demand Side Characteristics	Median family Income	DCHAR1
	Average Household size	DCHAR2
	Number aboriginal	DCHAR3
	Number persons	DCHAR4
	Number born overseas	DCHAR5
	Number of families with dependent children	DCHAR6
	Number of families with Single Mother	DCHAR7
	Number of families	DCHAR8
	Av Number vehicles per hh	DCHAR9
	Dwelling density (houses per sq km)	DCHAR10
	Number of rented dwellings	DCHAR11
	Number of state housing dwellings	DCHAR12
	Number of dwellings	DCHAR13
	Number with post-school qualification	DCHAR14
	Number employed	DCHAR15
	Number using public transport for work travel	DCHAR16
	On a main Rd	DCHAR17
	Number of competitors within 5km	DCHAR18
	Distance to nearest competitor	DCHAR19

Group	Variable	Code
Network characteristics	Global Efficiency	NCHAR1
	Global Constraint	NCHAR2
	Global Centrality	NCHAR4
	Local Efficiency	NCHAR5
	Local Constraint	NCHAR6
	Local Centrality	NCHAR8
Influence of Most Important Alters on Ego	Redundancy of most central	EGOR1
	Redundancy of 2nd most central	EGOR2
	Redundancy of 3rd most central	EGOR3
	Redundancy of 4th most central	EGOR4
	Redundancy of 5th most central	EGOR5
Sub-markets	Fremantle	SUBM1
	Curtin	SUBM2
	Midland	SUBM3
	North East	SUBM4
	Fwy North	SUBM5
	City Central	SUBM6
	Western Suburbs	SUBM7
	Melville	SUBM8
Occurrences where outlet is… out of all outlets in sample	Max	OCO1
	Min	OCO2
	Median	OCO3
	Lower Quartile	OCO4
	Upper Quartile	OCO5
	Below Average	OCO6
	Above Average	OCO7
	Leader	OCO8
	Follower	OCO9
Occurrences where outlet is… out of all outlets in sub-market	Max	OCS1
	Min	OCS2
	Median	OCS3
	Lower Quartile	OCS4
	Upper Quartile	OCS5
	Below Average	OCS6
	Above Average	OCS7
	Leader	OCS8
	Follower	OCS9

Table 2. Perth market players summary

Branding			Ownership		Competitors Within 5km		Distance to Nearest Competitor	
	Total	*With Convenience Store*			*Number of competitors*	*Freq.*	*Distance (km)*	*Freq.*
BP	52	16	Branded Independent	23	up to 2	10	up to 0.4	38
Caltex	57	29	Company Controlled	99	3 or 4	16	0.41 to 0.8	38
Woolworths	4		Distributor Controlled	2	5 or 6	31	0.81 to 1.2	41
Gull	27		Independent	2	7 or 8	35	1.21 to 1.6	35
Independent	2		Larger Independent	37	9 or 10	43	1.61 to 2	39
Liberty	5		Price Supported	42	11 or 12	37	2.01 to 2.4	8
Mobil	13	11	Supermarket	4	13 or 14	13	2.41 to 2.8	5
Peak	13				15 or 16	17	2.81 to 3.2	2
Shell	35	8			> 16	7	> 3.2	3

Table 3. Demand-side characteristics

	Lower Bound	*Average*	*Upper Bound*
Median family Income	1321.5133	1362.7889	1404.0645
Average household size	2.4503018	2.4922705	2.5342392
Number aboriginal	312.46014	362.88406	413.30798
Number persons	19931.575	21479.348	23027.121
Number born overseas	7627.2796	8243.0386	8858.7977
Number of families with dependent children	2360.4874	2569.7826	2779.0778
Number of families with Single Mother	817.59251	896.27536	974.95822
Number of families	5295.9837	5731.7971	6167.6105
Av Number vehicles per household	1.4479305	1.4681488	1.4883671
Dwelling density (houses per sq km)	431.34798	468.12804	504.90811
Number of rented dwellings	1830.5952	1969.9517	2109.3081
Number of state housing dwellings	265.2835	308.80676	352.33003
Number of dwellings	7355.8529	7889.7585	8423.664
number with post-school qualification	6566.6349	7041.1932	7515.7516
Number employed	9735.9579	10502.449	11268.941
Number using public transport for work travel	861.12314	915.24638	969.36962

Source: ABS (2006)

Table 4. Summary of network characteristics

Frequency Bands	*Global Efficiency*	*Global Constraint*	*Global Centrality*	*Local Efficiency*	*Local Constraint*	*Local Centrality*
0.1	0	206	168	0	204	64
0.2	7	0	12	15	0	18
0.3	15	0	2	22	0	16
0.4	52	0	6	54	0	18
0.5	55	0	1	58	0	20
0.6	44	0	3	36	0	18
0.7	23	0	7	13	0	24
0.8	7	0	5	3	0	21
0.9	0	0	1	0	0	4
1	5	2	3	7	4	5

Table 5. Regression model results – price as dependent variable

Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat
Constant	-1.5896	-8.6924	TP1	0.6905	30.5696	DWD1	0.2159	14.6318	TCNST	-1.5896	-8.6924	TTP1	-1.3282	-10.6592	TDWD1	0.50285	7.56612
NCHAR1	-0.0869	-1.5632	TP3	0.1866	4.6754	DWD2	0.2115	15.1043	TNCHAR1	-0.3316	-1.2431	TTP3	-0.0069	-0.0357	TDWD2	0.12260	1.79225
NCHAR2	-0.8164	-11.5144	TP4	0.0000	0.0000	DWD3	0.0728	5.6051	TNCHAR2	0.5094	1.4256	TTP4	0.0000	0.0000	TDWD3	0.05595	0.83083
NCHAR4	-0.0019	-1.8069	TP5	0.1876	4.5444	DWD5	-0.2291	-16.8392	TNCHAR4	-0.0008	-0.1529	TTP5	-1.0453	-5.1015	TDWD5	-1.08490	-11.76190
NCHAR5	0.2498	4.8519	TP6	-0.1111	-6.6494	DWD6	-0.1081	-8.4268	TNCHAR5	0.3497	1.4250	TTP6	-0.0951	-1.2003	TDWD6	-0.60024	-4.37781
NCHAR6	0.6470	9.4409	TP7	0.0000	0.0000	DWD7	0.3497	27.5065	TNCHAR6	1.0753	3.1595	TTP7	0.0000	0.0000	TDWD7	1.44851	21.79995
NCHAR8	-0.0033	-4.7218	CS1	0.0131	0.7378	MD1	0.3153	15.4528	TNCHAR8	0.0088	2.5420	TCS1	0.0849	0.8934	TMD1	-1.53188	-16.91409
SUBM1	0.0225	1.0228	CS2	-0.0329	-1.7293	MD2	0.1762	8.4743	TSUBM1	0.2965	2.6703	TCS2	-0.1042	-1.1648	TMD2	-1.34988	-12.27875
SUBM2	-0.0579	-2.5406	CS3	-0.1246	-6.7247	MD3	0.1847	8.0598	TSUBM2	-0.2523	-2.1778	TCS3	0.0594	0.6977	TMD3	-1.49619	-13.38230
SUBM3	-0.0198	-0.4368	CS4	-0.0664	-1.7718	MD5	0.0006	0.0256	TSUBM3	-1.1561	-5.1706	TCS4	0.1793	0.8505	TMD5	-0.72168	-6.52607
SUBM4	0.0479	2.5567	DCHAR1	-0.0003	-6.3876	MD6	-0.0654	-2.6789	TSUBM4	-0.0077	-0.0823	TDCHAR1	0.0008	3.2025	TMD6	-0.53068	-4.42738
SUBM5	0.0823	3.6480	DCHAR2	-0.5543	-7.9318	MD7	0.1782	7.9007	TSUBM5	0.1922	1.6042	TDCHAR2	0.2730	0.7830	TMD7	-0.15699	-1.47928
SUBM6	-0.0135	-0.5540	DCHAR3	-0.0007	-9.8812	MD8	0.1431	6.3027	TSUBM6	-0.0407	-0.3240	TDCHAR3	0.0005	1.4106	TMD8	-1.38848	-10.51760
SUBM7	-0.2772	-5.8900	DCHAR4	0.0002	10.4960	MD9	0.0587	2.7256	TSUBM7	-0.0381	-0.1729	TDCHAR4	0.0000	-0.4947	TMD9	-0.92455	-8.02988
EGOR1	0.1837	9.8298	DCHAR5	-0.0001	-13.7428	MD10	0.4212	19.2140	TEGOR1	0.0801	0.8733	TDCHAR5	0.0001	2.9023	TMD10	-0.36558	-3.26920
EGOR2	0.2137	11.4990	DCHAR6	-0.0002	-4.7878	MD11	0.1215	5.7419	TEGOR2	0.0294	0.3303	TDCHAR6	-0.0006	-2.3239	TMD11	-0.79761	-7.36826
EGOR3	-0.0678	-3.9575	DCHAR7	-0.0001	-3.3662	MD12	0.0819	3.8469	TEGOR3	0.1032	1.2051	TDCHAR7	-0.0011	-4.6351	TMD12	-1.22443	-11.56668
EGOR4	0.0224	1.2282	DCHAR8	0.0005	9.8781	OCO1{1}	0.1927	4.9564	TEGOR4	0.0559	0.6079	TDCHAR8	-0.0006	-2.5593	TOCO1{1}	0.04683	0.70782
EGOR5	0.1228	6.3345	DCHAR9	0.7829	5.4204	OCO2{1}	0.1011	4.8485	TEGOR5	0.1116	1.1611	TDCHAR9	4.8555	6.8145	TOCO2{1}	-0.05780	-0.32147
MC	0.1334	59.2855	DCHAR10	0.0000	-0.6723	OCO3{1}	-0.0154	-1.5580	TMC	0.5881	21.5121	TDCHAR10	-0.0007	-4.1591	TOCO3{1}	0.26736	6.63683
RPRICE{1}	0.8352	532.5761	DCHAR11	0.0003	9.7727	OCO4{1}	0.0598	4.6188	TLRP1	0.3184	10.7253	TDCHAR11	0.0004	2.1507	TOCO4{1}	-0.31623	-4.15985
RPRICE{7}	0.0470	48.2224	DCHAR12	0.0002	4.5647	OCO5{1}	-0.3555	-20.7774	TLRP7	0.1097	19.7641	TDCHAR12	0.0009	4.9198	TOCO5{1}	0.22151	4.30429
BR1	-0.0263	-1.0911	DCHAR13	-0.0005	-12.2808	OCO6{1}	0.0331	2.7531	TBR1	-0.0340	-0.3002	TDCHAR13	0.0003	1.5718	TOCO6{1}	-0.96992	-6.78831
BR2	-0.0231	-1.4855	DCHAR14	0.0000	-1.3373	OCO8{1}	-0.9869	-7.5862	TBR2	-0.8532	-10.7388	TDCHAR14	-0.0005	-6.4897	TOCO8{1}	1.42211	9.68568
BR3	-0.0389	-1.8131	DCHAR15	-0.0002	-11.0519	OCS1{1}	0.0109	0.4700	TBR3	-0.1009	-1.0127	TDCHAR15	0.0005	5.6386	TOCS1{1}	-0.02258	-0.43030
BR4	0.2568	7.8449	DCHAR16	0.0005	9.6149	OCS2{1}	0.1069	6.2534	TBR4	-2.2397	-14.2300	TDCHAR16	0.0000	0.1657	TOCS2{1}	0.01660	0.17286
BR5	-0.1201	-2.8185	DCHAR17	-0.0792	-6.0090	OCS3{1}	-0.0162	-1.7042	TBR5	-1.4772	-7.0084	TDCHAR17	0.0804	1.1438	TOCS3{1}	0.37541	9.96171
BR6	0.7234	18.2268	DCHAR18	-0.0241	-9.6336	OCS4{1}	0.1218	8.7587	TBR6	-2.8131	-15.8592	TDCHAR18	0.0868	6.7438	TOCS4{1}	0.04608	0.64946
BR7	0.0272	0.7347	DCHAR19	0.0344	6.0271	OCS5{1}	-0.1835	-10.7607	TBR7	-0.8025	-4.0479	TDCHAR19	0.0414	1.4190	TOCS5{1}	0.03113	0.71320
BR8	0.0010	0.0282				OCS6{1}	0.1579	13.9256	TBR8	-1.7508	-8.7614				TOCS6{1}	0.02427	0.19261
BR9	0.0566	1.3940				OCS8{1}	0.1543	1.3644	TBR9	-2.4414	-12.2409				TOCS8{1}	0.46609	3.56045
BR11	0.8611	12.0047							TBR11	-2.3256	-6.7568						

Centred R^2	0.9625
R-Bar^2	0.9625
Log Likelihood	-137584.8
Breusch-Pagan Test Statistic	11791.06
Durbin-Watson Test Statistic	1.9077

Table 6. Regression model results – Margins as Dependent Variable

Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat	Variable	Coeff	t-stat
Constant	0.0085	0.0640	TP1	0.6776	27.7914	DWD1	0.2434	15.0828	TCNST	0.0085	0.0640	TTP1	-1.3210	-10.2836	TDWD1	0.4196	6.0642
NCHAR1	-0.0886	-1.4143	TP3	0.1802	4.3311	DWD2	0.2361	15.1974	TNCHAR1	-0.3300	-1.1707	TTP3	0.0229	0.1146	TDWD2	-0.0074	-0.1044
NCHAR2	-0.8130	-10.1459	TP4	0.0000	0.0000	DWD3	0.0686	4.8006	TNCHAR2	0.4887	1.2851	TTP4	0.0000	0.0000	TDWD3	-0.0549	-0.7642
NCHAR4	-0.0020	-1.6927	TP5	0.1749	3.7748	DWD5	-0.1764	-10.8672	TNCHAR4	-0.0011	-0.2016	TTP5	-1.0593	-4.9011	TDWD5	-1.0357	-10.2295
NCHAR5	0.2477	4.3418	TP6	-0.1089	-5.7688	DWD6	-0.1047	-7.6752	TNCHAR5	0.3615	1.3911	TTP6	-0.1063	-1.2741	TDWD6	-0.7397	-5.2657
NCHAR6	0.6392	8.3278	TP7	0.0000	0.0000	DWD7	0.3648	26.5025	TNCHAR6	1.1422	3.2170	TTP7	0.0000	0.0000	TDWD7	1.2258	17.9602
NCHAR8	-0.0033	-4.2468	CS1	0.0108	0.5688	MD1	0.0603	2.8279	TNCHAR8	0.0088	2.4374	TCS1	0.0802	0.8280	TMD1	-1.7992	-19.7590
SUBM1	0.0232	0.9357	CS2	-0.0335	-1.5555	MD2	-0.0471	-2.2232	TSUBM1	0.3193	2.7826	TCS2	-0.0901	-0.9647	TMD2	-1.5746	-14.5109
SUBM2	-0.0535	-2.1113	CS3	-0.1223	-5.9328	MD3	0.1552	6.8974	TSUBM2	-0.2406	-2.0390	TCS3	0.0493	0.5504	TMD3	-1.5461	-14.6038
SUBM3	-0.0200	-0.3950	CS4	-0.0713	-1.5606	MD5	-0.2085	-8.9425	TSUBM3	-1.1902	-5.0694	TCS4	0.1871	0.8000	TMD5	-1.0874	-9.7647
SUBM4	0.0480	2.2601	DCHAR1	-0.0003	-5.6953	MD6	-0.4026	-16.3066	TSUBM4	0.0209	0.2127	TDCHAR1	0.0008	3.1436	TMD6	-0.8628	-7.0917
SUBM5	0.0921	3.6754	DCHAR2	-0.5509	-7.0899	MD7	-0.2248	-9.4797	TSUBM5	0.2272	1.8326	TDCHAR2	0.2732	0.7499	TMD7	-0.2947	-2.7998
SUBM6	-0.0133	-0.4916	DCHAR3	-0.0007	-8.6924	MD8	-0.1375	-5.5979	TSUBM6	-0.0293	-0.2234	TDCHAR3	0.0004	1.0863	TMD8	-1.3932	-10.4461
SUBM7	-0.2584	-4.9157	DCHAR4	0.0002	9.3957	MD9	0.1222	5.2489	TSUBM7	-0.0228	-0.0994	TDCHAR4	0.0000	-0.3485	TMD9	-1.3965	-11.8416
MARG{1}	0.8294	458.0596	DCHAR5	-0.0001	-12.2437	MD10	0.0674	3.0273	TEGOR1	0.7416	8.3320	TDCHAR5	0.0001	2.5677	TMD10	-0.6104	-5.4525
MARG{7}	0.0513	45.3011	DCHAR6	-0.0002	-4.2406	MD11	-0.1005	-4.5869	TEGOR2	-0.1121	-1.3029	TDCHAR6	-0.0006	-2.3180	TMD11	-1.0292	-9.4245
EGOR1	0.1851	8.9245	DCHAR7	-0.0001	-2.8064	MD12	-0.2810	-12.5758	TEGOR3	0.3538	4.1579	TDCHAR7	-0.0011	-4.7050	TMD12	-1.0087	-9.3923
EGOR2	0.2105	10.1262	DCHAR8	0.0005	8.8546	OCO1{1}	0.1935	4.7632	TEGOR4	0.2571	2.7941	TDCHAR8	-0.0007	-2.5091	TOCO1{1}	-0.0061	-0.0868
EGOR3	-0.0645	-3.3890	DCHAR9	0.7465	4.6424	OCO2{1}	0.1075	4.8548	TEGOR5	-0.0466	-0.4907	TDCHAR9	5.0922	7.1571	TOCO2{1}	-0.0057	-0.0272
EGOR4	0.0231	1.1518	DCHAR10	0.0000	-0.3074	OCO3{1}	-0.0165	-1.4678	TMARG1	-0.5162	-14.9566	TDCHAR10	-0.0007	-4.4776	TOCO3{1}	0.2336	5.1185
EGOR5	0.1200	5.5390	DCHAR11	0.0003	8.5527	OCO4{1}	0.0545	3.7464	TMARG7	0.1342	6.0346	TDCHAR11	0.0004	2.4677	TOCO4{1}	-0.3058	-3.7531
BR1	-0.0110	-0.4035	DCHAR12	0.0002	3.9449	OCO5{1}	-0.3187	-17.6819	TBR1	-0.0933	-0.7810	TDCHAR12	0.0009	5.0690	TOCO5{1}	0.1763	3.2014
BR2	-0.0031	-0.1879	DCHAR13	-0.0005	-10.9815	OCO6{1}	0.0731	5.3681	TBR2	-0.8998	-10.9645	TDCHAR13	0.0003	1.4431	TOCO6{1}	-1.1665	-7.9332
BR3	-0.0197	-0.8178	DCHAR14	0.0000	-1.0389	OCO8{1}	-1.1159	-8.4266	TBR3	-0.1937	-1.8449	TDCHAR14	-0.0005	-6.8259	TOCO8{1}	1.4245	9.3798
BR4	0.2637	7.2450	DCHAR15	-0.0002	-10.0685	OCS1{1}	-0.0219	-0.8965	TBR4	-2.3626	-14.1985	TDCHAR15	0.0005	5.5963	TOCS1{1}	0.0666	1.1557
BR5	-0.0979	-2.0515	DCHAR16	0.0005	8.6293	OCS2{1}	0.1043	5.6354	TBR5	-1.5863	-7.1149	TDCHAR16	0.0001	0.2626	TOCS2{1}	-0.1375	-1.2255
BR6	0.7418	16.0577	DCHAR17	-0.0811	-5.3019	OCS3{1}	-0.0197	-1.8249	TBR6	-2.8996	-15.3320	TDCHAR17	0.0815	1.0994	TOCS3{1}	0.3640	8.5715
BR7	0.0439	1.0668	DCHAR18	-0.0244	-8.7835	OCS4{1}	0.0933	6.0239	TBR7	-0.8666	-4.1571	TDCHAR18	0.0889	6.7680	TOCS4{1}	0.0578	0.7402
BR8	0.0334	0.7697	DCHAR19	0.0342	5.3728	OCS5{1}	-0.2018	-11.1367	TBR8	-1.9152	-8.6154	TDCHAR19	0.0454	1.4984	TOCS5{1}	0.0684	1.4499
BR9	0.0864	1.9004				OCS6{1}	0.1256	9.8648	TBR9	-2.5921	-12.2370				TOCS6{1}	0.2571	1.9075
BR11	0.8774	10.8120				OCS8{1}	0.3024	2.5192	TBR11	-2.4017	-6.5422				TOCS8{1}	0.3566	2.5394
						Centred R^2					0.89668						
						R-Bar^2					0.896479						
						Log Likelihood					-145796.9						
						Breusch-Pagan Test Statistic					10242.99						
						Durbin-Watson Test Statistic					1.936846						