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By Harry Bloch & Nick Wills-Johnson

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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The Shape and Frequency of Edgeworth Price Cycles in an Australian Retail Gasoline Market

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

Gasoline prices in many markets follow a saw-toothed pattern known as an Edgeworth Cycle. Lewis (2009) introduces a novel way of measuring the shape of the cycle, the median change in price, and regresses this against a number of explanatory variables in US markets. Here, we undertake a similar regression analysis, but using data from Perth, Australia, and with a novel measure of market structure as a regressor. We also explore a novel measure, based on spectral analysis, of the use of cycles in a mixed strategy, and the factors which drive this use.

* corresponding author

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Introduction

Variability of prices is a direct concern to consumers, with clear evidence that consumers are antagonised by price variation even when there is no increase in average price (see Courty & Pagliero, 2008). Further, there is widespread suspicion that price variability indicates market power, for price variation without cost variation would be inconsistent with marginal-cost pricing. There have been numerous studies that have identified a saw-tooth pattern of pricing, the Edgeworth Cycle, in many retail gasoline markets in Canada, the US and Australia (see, for example Verlinda, 2008, Atkinson, 2009, Noel, 2009 or Wang, 2009). These studies have largely focussed on the explaining the existence of the Edgeworth cycle and the implications for the average price.

Here we focus on other aspects of the Edgeworth cycle in retail gasoline prices. In particular, we follow Lewis (2009) and use the median price change as a measure of the extent to which prices are saw-toothed and investigate variables that might drive this shape. We incorporate a unique way of measuring market structure that emphasises network connections between spatially distributed retail stations. Our measure of market structure addresses the complex issues of competition across spatial locations that have featured in discussions of the competition impact of mergers among retail gasoline stations (see, for example, Eckert and West, 2006). We also explore a second aspect of cyclicality; the use of different cycles in the mixed strategies of gasoline stations, which we measure using spectral analysis.

Section Two of this paper explores the Edgeworth Cycle literature, whilst Section Three explores the dataset, with a particular focus on the development of the market structure measures and price spectra. Section Four introduces the results of our model based upon Lewis's (2009) measure of median price change. Section Five introduces the results of the mixed strategy model. Section Six concludes.

Edgeworth Cycles

Edgeworth Cycles were first posited as an equilibrium in a dynamic game by Edgeworth (1925) and formalised by Maskin & Tirole (1988), who gave them their name. Their distinct pattern is shown in Figure One.

Figure One about here

Maskin & Tirole (1988) show that Edgeworth Cycles are one equilibrium of an alternate move game between symmetric duopolists producing an homogenous good with sufficiently high discount rates and who use Markov-perfect strategies in choosing their price from a finite grid. 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, and each plays a war of attrition as it waits for the other to raise first. Since the first mover will be out of the market for two periods (the period where it raises and the period when its rival raises to a price slightly below its own), the incentive is to raise the price as high as possible, to capture maximum benefits across the 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.

Most of the empirical evidence for Edgeworth Cycles has come from studies of retail petroleum markets, and much of it has come from Canada. Eckert (2003) was the first to study Edgeworth Cycles in Canada, focussing on examining the empirical evidence associated with his differential firm size model, by exploring the extent to which small firms are associated with cities where cycles persist. Eckert further extends the literature in collaborative work with West (Eckert & West, 2004a, b, 2005) and Atkinson (Atkinson, Eckert & West, 2009), with a particular focus on market differences between Vancouver and Ottawa and, in the latter case, the characteristics of the market in Guelph, Ontario, which is also studied by Atkinson (2009).

Noel (2007a, b) also examines Edgeworth Cycles in Canada, through the lens of a Markov-switching model. He explores differences between cities, periods of time (days of the week and months), station characteristics (particularly whether an outlet is controlled by a refiner-marketer or an independent chain), the market penetration of independents and cycle position. The modelling framework he uses allows him to not only explore what drives prices during an upswing or a downswing, but what causes retailers to switch from one part of the cycle to another.

Wang (2009) studies Edgeworth Cycles in Perth, using data for a time-frame roughly consistent with our own. However, his focus is different; examining the patterns of relenting to ascertain how the different brands use mixed strategies to determine when they will raise price in the outlets across the city.

Lewis (2009) takes a different approach, measuring the degree to which cycles are saw-toothed with his median change in price measure and then investigating drivers for saw-toothedness via OLS regression. Doyle, Muehlegger & Samphantharak (2008) also use this approach. The median price change measure works because, absent of a trend in prices, a mismatch in the number and size of price increases and decreases will, if the latter dominates, result in a small median change in price. The greater the mismatch, the smaller is the median change in price, and the more saw-toothed the cycle. Lewis (2009) explores the relationship between his median change in price measure and a set of explanatory variables including the market share of independent firms, station density, population, income, number of cars per household and land area.

Dataset

To explore the factors which influence the pattern of pricing at each retail petroleum outlet, we make use of data from Perth, Western Australia. Gasoline stations in Western Australia are governed by a unique regulatory regime known as *FuelWatch*. Each must report its next-day price to the regulator by 2pm. The regulator then publicises that price 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 the strategic games that firms play (see Wang, 2009), or the influence it may or may not have on the price level (see Davidson, 2009, for an account of this controversy), it provides for the researcher with a census of all prices in Perth. 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 analyses in Sections Four and Five.

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 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.[1]

Table One provides information on branding, ownership structures, co-location with convenience stores and distance to competitors.

Table One about here

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.[2] Today, the two comprise almost half of overall fuel sales in Australia (ACCC, 2007).

Company controlled outlets comprise roughly half of those in Table One. However, *FuelWatch* defines outlets owned directly by the Majors and outlets owned by their multi-site franchisees as being company controlled. In WA as a whole, Shell owns eight sites, BP owns five and Mobil none. Thus, most of the outlets listed as company controlled in Table 2 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 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 their 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, distance to the nearest rival tends to be low (on average just over one km) and the average number of competitors within five kilometres is nine.[3]

Table Two summarises the demand data for the ABS statistical areas in Perth, showing city-wide averages and the upper and lower bounds of 95 percent confidence intervals around these averages.

Table Two about here

Market Structure

An important aspect of this paper is the way in which we measure market structure. Rather than use an indirect measure, such as seller density or, as in the Edgeworth cycle literature reviewed in Section 2 above, the penetration of independents, we develop a simple theoretical model of bilateral competitive interaction and use this to determine who competes with whom. We collect these bilateral links to form a network, which summarises the structure of competition in the marketplaces as a whole and use simple graph-cutting tools to delineate local sub-markets. We then use a number of 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 models outlined in Sections 4 and 5. We describe the process of network formation and division briefly below, and in more detail in Bloch & Wills-Johnson (2010a).

The simple theoretical model is based upon that of Hoover (1937) and MacBride (1983), who study how spatial differentiation can give rise to local market power. Our point of departure is to assume 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 a set of consumers whose travel plans take them past one retail gasoline outlet but who must deviate to frequent another (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 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. It is also relatively simple to show that the minima of such price cycles will be related in a consistent fashion where firms compete. 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, 2010b).

This gives rise to a simple criterion 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.[4] We then undertake a simple statistical test of the difference between the means for each pair of outlets within five kilometres of one another.[5] 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, Brookfield, 1973): Cliff, Haggett & Ord, 1979, Boots: 1985, O'hUallachain, 1985: Thill, 1998: Tinkler, 1972 and 1975;, Hay, 1975; 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 (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 in the overall network. The approach is somewhat judgemental, but subsequent testing of the submarkets suggests they are reasonably robust (see Bloch & Wills-Johnson, 2010a), and indeed gives groups where prices are more similar than in intra-brand groupings.

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 Two, overleaf, 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.[6] The different shaded dots represent different brands.

Figure Two about here

There are a wide variety of measures that are used to summarise network structure in the mathematical sociology literature.[7] We use one measure of centrality and three measures that 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 elements of the leading eigenvector of the adjacency matrix.[8]

The importance of structural holes, or the parts of the network where there are few connections between densely intra-connected sub-groups, was first suggested by Burt (1992) who developed a series of measures associated with them. His notion is that those nodes at either end of links between sub-groups will be able to leverage considerable informational advantage due to their location.

To capture structural holes, Burt (1992) uses a number of measures. 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. 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. 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.

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. We calculate the centrality, efficiency and constrain scores for each outlet, both globally and in each local sub-market, using the *Ucinet* software developed by Borgatti, Everett & Freeman (2002). The distribution of scores for each of the network characteristics is presented in Table Three. Note that we have normalised the centrality scores such that they range from zero to one, like the constraint and efficiency scores.

Table Three about here

Prices

In Sections Four and Five, we explore two models; with median change in price and spectral power as the dependent variables, respectively. Here we explore the data underlying these two dependent variables in more detail, beginning with spectral power.

Spectral power summarises the amount of variation in prices which can be attributed to cycles of a particular length. The higher the spectral power for a particular cycle, the more that cycle is used in the pricing strategies of the relevant gasoline station.

To calculate spectral power, we follow the approach outlined in Granger & Hatanaka (1964) and construct a spectrogram for prices and margins,[9] dividing the spectra into 42 different frequency bands.[10] Spectral analysis becomes complicated with non-stationary data, so prior to constructing the spectrograms, we conduct a Phillips-Perron unit root test on the data in their natural order (from t_0 to t_{441}), and in their reversed order (t_{441} to t_0) to demonstrate robustness. There is little evidence of non-stationarity.

Figure Three shows the resulting spectrogram for margins. The results for price are similar, but those for margins are clearer as marginal costs (which contribute to variation) have been removed. In Figure Three, the solid light grey lines indicate shell outlet, the medium grey line indicate BP, the dark grey lines Caltex, the black lines Mobil and the dotted light-grey lines the independent and supermarket brands. The thick black line shows the average power for each frequency band.

Figure Three about here

The most obvious aspect of Figure Three is the dual peak at seven and ten days.[11] This is most pronounced for BP and Shell. It is not the case that some outlets follow cycles of seven days and some follow cycles of ten days; most in fact exhibit peaks at both frequency bands. It is this dual peak that is suggestive of the use of mixed strategies.

The dual peak should not be surprising. Indeed, it is more logical than a single peak. If a retail petroleum outlet consistently followed a seven day cycle, this would become immediately obvious to all of its rivals, each of whom could then underbid it on the eighth day and capture market share.

Calculation of Lewis's (2009) median change in price measure is much simpler, and the results are presented in Figure Four as a histogram. Note that most stations have a value close to minus one; indicative of the saw-toothed Edgeworth cycle pattern.

Figure Four about here

Median Price Change Model

We now turn to the first of our models; that exploring factors influencing the median change in price. The basic form of the model is as follows:

$$MPC_i = \beta_i BR_i + \chi_i TP_i + \delta_i SV_i + \phi_i CS_i + \varphi_{ij} DCHAR_{ij} + \gamma_{ik} NCHAR_{ik} + \eta_i SUBM_i + \lambda_{im} EGOR_{im} \tag{1}$$

The variables in Equation One are defined in Table Four below.

Table Four about here

We test a number of different forms of the model defined in Equation One, omitting different independent variables. The results for the model which, based upon likelihood ratio tests, best fits the data are presented in Table Five.

Table Five about here

The F-test and R-squared results suggest, respectively, that the model is valid and fits the data reasonably well. The Breusch-Pagan test statistic suggests homoscedasticity.

There appears to be little influence on median change in price from any of the network structure variables; only global eigenvector centrality, is significant and only then at the ten percent level. It suggests that more central outlets are the ones with higher median price changes and hence cycles which are less saw-toothed in nature, but the coefficient is very small.

The independent brands and Woolworths, along with the branded independents and larger independent types tend to have higher median price changes, and hence cycles with a less saw-toothed nature, than the omitted dummies. This may be reflective of these outlets increasing their prices more cautiously; often taking two days when the Majors take one.

Very few of the variables in Table Five above are statistically significant. It is thus helpful to consider what happens if variables are added.[12] Adding the demand characteristic variables makes little difference to overall results, and indeed, most of the demand characteristics have insignificant coefficients. Subsequently adding the EGOR variables changes little outside the network characteristic variables, but it does make some important changes to the network characteristic variables. Global centrality loses its significance, but global constraint becomes negative and significant at the five percent level, whilst local efficiency and local constraint become positive and significant at the ten percent level.

The negative global constraint coefficient suggests that more constrained outlets are likely to have cycles with sharper upswings, which may be suggestive of outlets sitting at the junction points between sub-markets (the least constrained in the dataset) acting to attenuate price signals travelling between sub-markets.

The positive local constraint and local efficiency 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 (here a position 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 market power by charging these customers higher prices rather than fighting for the customers they must share with non-peripheral outlets.

Spectral Power Models

The spectral power models are intended to capture the extent to which outlets use more or less of a cycle of a given length in their pricing strategies, and the factors that might drive such a decision. The models have the form below, where again the variables are as defined in Table Four, except *SPM7* and *SPM10*, which refer to the spectral power of the seven and ten day cycles in margins, respectively:

$$SPM7_i = \beta_i BR_i + \chi_i TP_i + \delta_i SV_i + \phi_i CS_i + \varphi_{ij} DCHAR_{ij} + \gamma_{ik} NCHAR_{ik} + \eta_i SUBM_i + \lambda_{im} EGOR_{im} \quad \text{(XX)}$$

and

$$SPM10_i = \beta_i BR_i + \chi_i TP_i + \delta_i SV_i + \phi_i CS_i + \varphi_{ij} DCHAR_{ij} + \gamma_{ik} NCHAR_{ik} + \eta_i SUBM_i + \lambda_{im} EGOR_{im} \quad \text{(XX)}$$

As with the median change in price model above, we examine more restrictive forms of the models by dropping independent variables and conducting likelihood ratio tests to ascertain whether this provides more robust results. The seven-day cycle regression results favour a slightly more restrictive model (omitting the *DCHAR* variables) than the ten-day cycle regression, but we use the more general model in both cases to allow a comparison of like with like. The results of these analyses are shown in Table Six.

Table Six about here

Both models provide a reasonably good fit to the data. Whilst heteroscedasticity may be an issue, the characteristics of the dependent variable force the use of robust standard errors in any case.[13] Hence, Breusch-Pagan test statistic results are not presented here.

We examine a number of different model types by omitting different dummies and explanatory variables, but find that the results are consistent with those shown in Table Six, with the exception noted below. Thus the models do not appear to be mis-specified.

The results above are reasonably consistent with those in the median price change regressions. The globally more constrained outlets are more likely to exhibit price cycles of both durations, but are most likely to be using more seven-day cycles in their mix of strategies. Thus, those outlets with cycles with sharper upswings are also likely to exhibit shorter cycles. Similar conclusions as drawn above for median changes in price might also be drawn for local efficiency and constraint in Table Six. Local efficiency and constraint results are negative, with both having a higher absolute value for seven-day cycles. This suggests that those with some market power (due either to superior location in the market or to peripheral location with access to consumers others cannot access) use cycles less in their mixed strategies, and seven-day cycles least.

Global centrality is significant at the ten percent level, and is negative, suggesting that more central outlets are less likely to have either kind of cycle and least likely to have ten-day cycles. This is consistent with the median price change results, where such outlets exhibited cycles which are less saw-toothed, and is similarly weak as alterations to the model specification mean this variable loses its significance.

Differences in results for submarkets are not particularly clear, but those for branding are; all brands have less cycle power than the omitted dummy, Shell. Recall from Figure

Three that the Shell outlets had the highest spectral power across these two bands. This same result is reflected in the branding coefficients.

Branded independents and larger independents are both likely to make less use of cycles than the omitted case (company controlled outlets). This is consistent with the results for median price in that these outlets cycle less and have cycles with a less saw-toothed nature. In general, however, these outlets have higher prices, suggesting that their pro-competitive effect is limited in the Perth market once location in the market structure is taken into account.

There are very few demand characteristics that are significant. The only one which is significant across both regressions is the number of competitors within five kilometres (*DCHAR15*), and it is positive. This suggests that seller density leads to more cycles. Thus, if more players lead to more competition, one could infer that cycles are pro-competitive. The fact that the coefficient is the same for both types of cycle suggests that this demand-side factor does not favour one kind of cycle over another.

Conclusions

In this paper, we have explored factors which drive both the Edgeworth shape of retail petroleum prices in the Perth market and the degree to which each outlet utilises cycles of a particular length in its mixed strategies. The former we measure using Lewis's (2009) measure, the median change in price, and the latter we measure via the spectral power of the two most common cycles seen in the data. The latter measure is novel to this paper, although Wang (2009) has also explored the use of mixed strategies in the Perth retail petroleum market in a different context by examining which brand leads prices upwards in each cycle.

We also introduce a novel measure of market structure. Whereas previous papers in the literature have proxied market structure by use of variables, such as density of sellers or numbers of independents, we measure it here more directly by developing a network outlining which outlets compete with which. Then we use methods from the mathematical sociology literature and from geography to develop summary statistics for these networks that can then form inputs into the regression.

We find that market structure does influence both the shape of cycles and their length, and the results suggest that a position wherein outlets can exercise a degree of market power both decrease the saw-toothed nature of cycles and decrease their use of both types of cycles. Demand factors, interestingly, appear to play little role in the shape or the length of cycles. Greater independence from the Majors, either through independent ownership or through being an independent brand, tends to decrease the saw-toothed nature of cycles and the use of cycles, but all brands make less use of cycles than Shell does. This suggests that independents might not have the pro-competitive effect found elsewhere in the Edgeworth Cycle literature, once market location is taken into account.

The results of this study are useful not only for the light they shed on market behaviour, but also for the novel techniques introduced. The use of spectral analysis allows for a more subtle appreciation of the use of cycles than has existed previously, particularly in

Australia. The more direct network measures allow a different interpretation of market structure, which might find use not only in academic studies, but also in competition policy. In particular, our results using the new measures suggest that competition is a more complex phenomenon than often recognised in either academic research or policy formulation.

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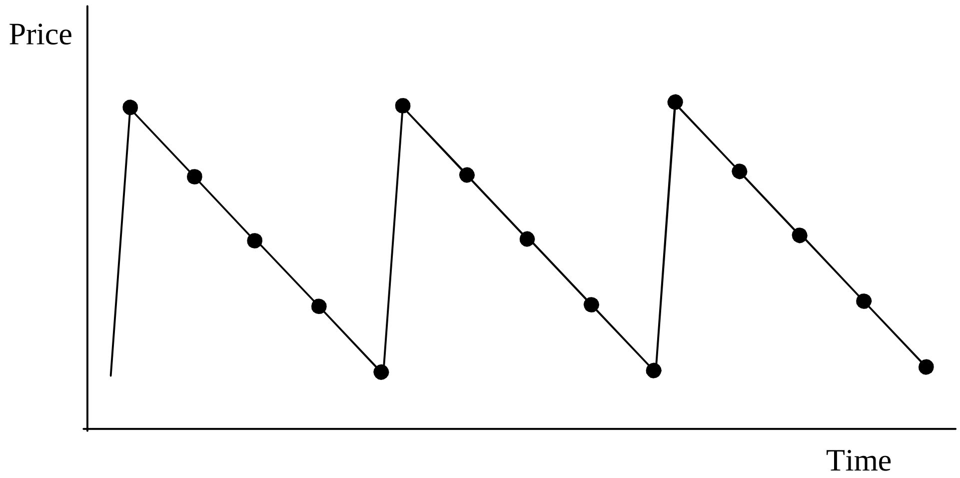

Figure 1. A diagrammatic representation of an Edgeworth cycle

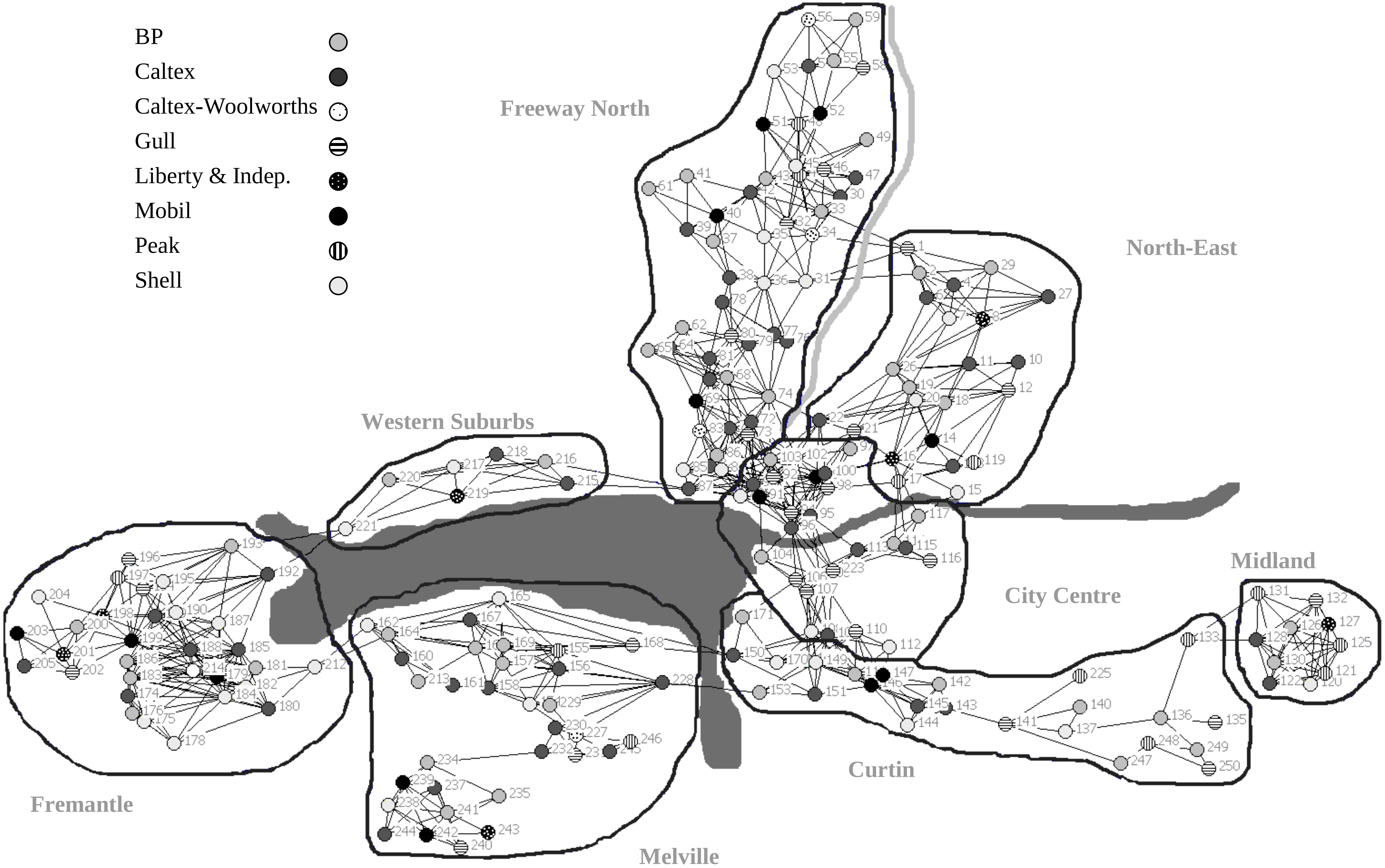

Figure 2. Sub-markets in market network

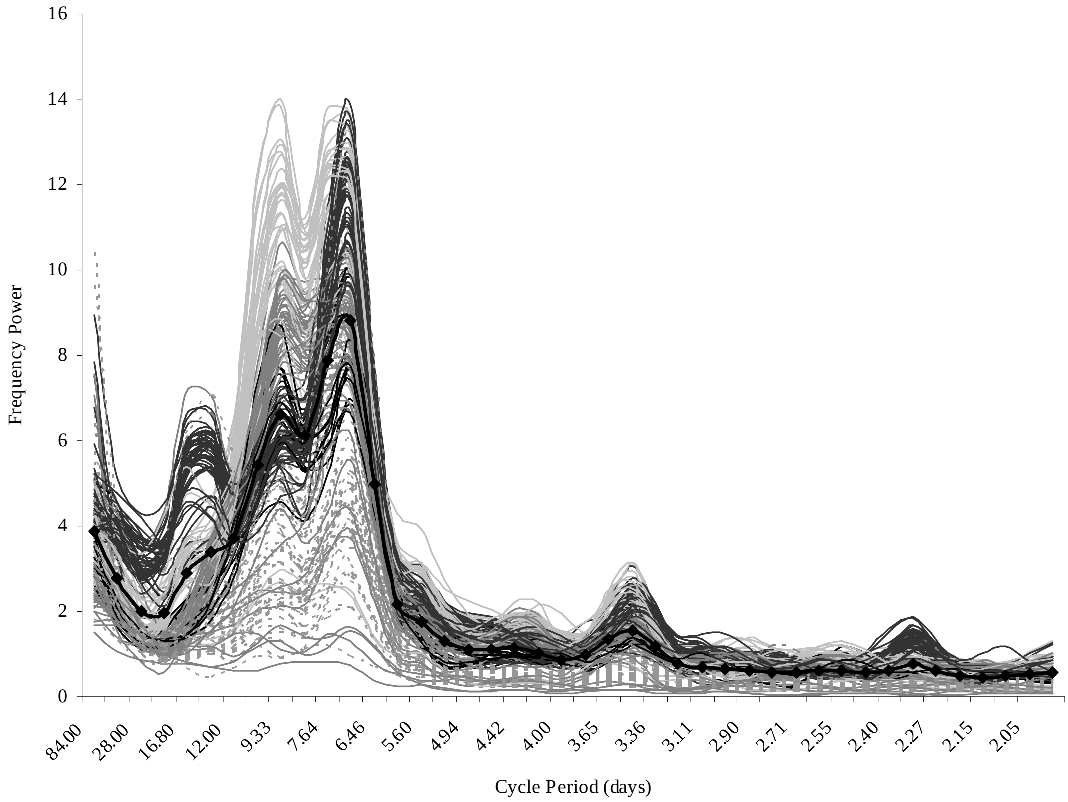

Figure 3. Spectra for price margins

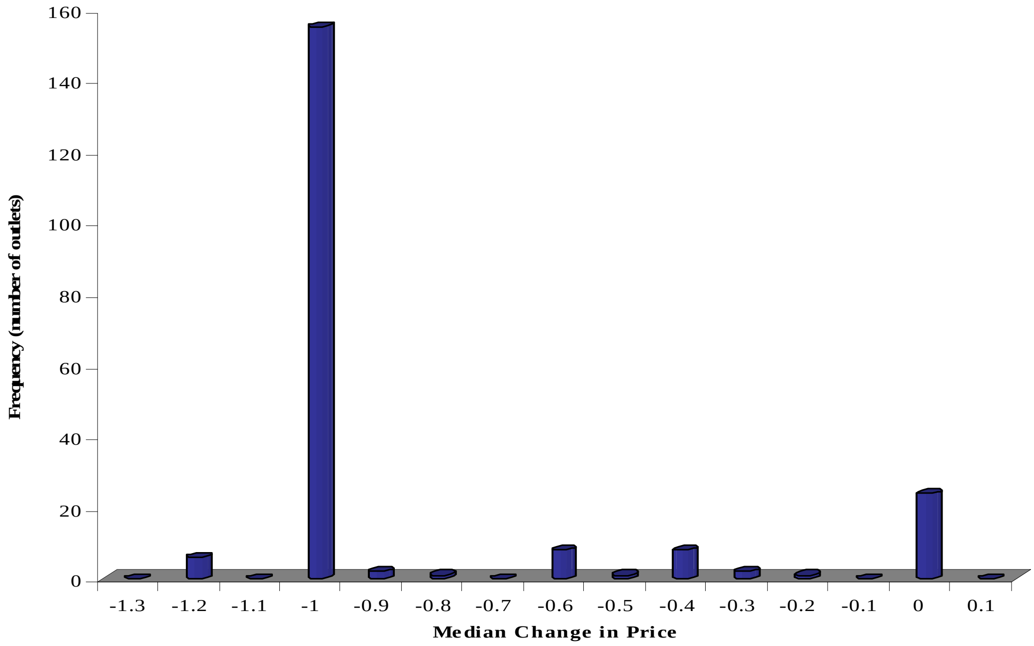

Figure 4. Median change in price

Table 1. Perth market players summary

Branding			*Ownership*		*Competitors Within 5km*		*Distance to Nearest Competitor*	
	Total	*With Convenience Store*			*Number of competitors*	*Frequency*	*Distance (km)*	*Frequency*
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
Wesco	1							

Table 2. 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 3. 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 Four: Abbreviations for Variables

Group	*Variable*	*Code*	*Group*	*Variable*	*Code*
Price	Retail Price	RPRICE	Demand Side Characteristics	Median family Income	DCHAR1
	Marginal cost (tgp)	MC		Average Household size	DCHAR2
	Median Price Change	MPC		Number aboriginal	DCHAR3
Brand	Ampol	BR1		Number persons	DCHAR4
	BP	BR2		Number born overseas	DCHAR5
	Caltex	BR3		Number of families with dependent children	DCHAR6
	Caltex-Woolworths	BR4		Number of families with Single Mother	DCHAR7
	Gull	BR5		Number of families	DCHAR8
	Independent	BR6		Av Number vehicles per hh	DCHAR9
	Liberty	BR7		Dwelling density (houses per sq km)	DCHAR10
	Mobil	BR8		Number of rented dwellings	DCHAR11
	Peak	BR9		Number of state housing dwellings	DCHAR12
	Shell	BR10		Number of dwellings	DCHAR13
	Wesco	BR11		Number with post-school qualification	DCHAR14
Type	Branded Independent	TP1		Number employed	DCHAR15
	Company Controlled	TP2		Number using public transport for work travel	DCHAR16
	Distributor Controlled	TP3		On a main Rd	DCHAR17
	Independent	TP4		Number of competitors within 5km	DCHAR18
	Larger Independent	TP5		Distance to nearest competitor	DCHAR19
	Price Supported	TP6	Network characteristics	Global Efficiency	NCHAR1
	Supermarket	TP7		Global Constraint	NCHAR2
Convenience Store	BP Connect	CS1		Global Centrality	NCHAR4
	Caltex Starmart	CS2		Local Efficiency	NCHAR5
	Caltex Starshop	CS3		Local Constraint	NCHAR6
	Mobil Quix	CS4		Local Centrality	NCHAR8
	Shell Select	CS5	Influence of Most Important Alters on Ego	Redundancy of most central	EGOR1
Sub-markets	Fremantle	SUBM1		Redundancy of 2nd most central	EGOR2
	Curtin	SUBM2		Redundancy of 3rd most central	EGOR3
	Midland	SUBM3		Redundancy of 4th most central	EGOR4
	North East	SUBM4		Redundancy of 5th most central	EGOR5
	Fwy North	SUBM5			
	City Central	SUBM6			
	Western Suburbs	SUBM7			
	Melville	SUBM8			

Table Five: Median Price Change Model Results

Variable	*Coefficient*	*T-Statistic*	*Variable*	*Coefficient*	*T-Statistic*
Constant	-1.04732	-8.25631	BR1	0.05899	0.70147
NCHAR1	-0.11031	-0.58854	BR2	0.03700	0.72697
NCHAR2	-0.33715	-1.51988	BR3	0.05093	0.67496
NCHAR4	0.00426	1.86880	BR4	0.27993	2.74504
NCHAR5	0.26703	1.59974	BR5	-0.03128	-0.24265
NCHAR6	0.33809	1.53300	BR6	0.82450	5.79575
NCHAR8	-0.00083	-0.54209	BR7	-0.01143	-0.10191
SUBM1	0.05362	1.04624	BR8	0.00815	0.05836
SUBM2	-0.09129	-1.41096	BR9	0.27001	2.14117
SUBM3	-0.01592	-0.19248	BR11	0.70771	3.05880
SUBM4	-0.06958	-1.27080	CS1	-0.00554	-0.08641
SUBM5	-0.10595	-2.02266	CS2	-0.04707	-0.67879
SUBM6	-0.11317	-1.83955	CS3	-0.00305	-0.04675
SUBM7	-0.12746	-1.18920	CS4	0.02073	0.14003
			TP1	0.81040	11.73039
			TP3	-0.04194	-0.29146
			TP4	0.00000	0.00000
			TP5	0.29887	2.31416
			TP6	-0.02020	-0.32377
			TP7	0.00000	0.00000
Centred R^2				0.7490	
R-Bar^2				0.7047	
Regression F Statistic				16.9386	
Log Likelihood				69.7611	
Breusch Pagan Test Statistic				55.0298	

Table Six: Seven and Ten Day Spectral Power – Regression Model Five Results

Seven - Day Price Cycles						***Ten - Day Price Cycles***					
Variable	*Coeff.*	*t-stat*	*Variable*	*Coeff.*	*t-stat*	*Variable*	*Coeff.*	*t-stat*	*Variable*	*Coeff.*	*t-stat*
Constant	15.6935	3.2248	TP1	-7.4207	-4.7725	Constant	10.1932	2.9666	TP1	-7.90027	-7.46104
NCHAR1	1.3964	0.5901	TP3	-1.1206	-0.7492	NCHAR1	1.2213	0.8730	TP3	-0.39152	-0.42224
NCHAR2	8.2825	2.2181	TP4	0.0000	0.0000	NCHAR2	6.6673	2.5691	TP4	0.00000	0.00000
NCHAR4	-0.0820	-1.8182	TP5	-4.6258	-2.3006	NCHAR4	-0.0538	-1.8031	TP5	-4.70191	-3.35201
NCHAR5	-5.0727	-2.1955	TP6	0.3555	0.4451	NCHAR5	-4.0269	-2.7092	TP6	-0.13542	-0.31789
NCHAR6	-8.6476	-2.7830	TP7	0.0000	0.0000	NCHAR6	-5.4102	-2.5799	TP7	0.00000	0.00000
NCHAR8	-0.0124	-0.4499	DCHAR1	0.0031	1.1274	NCHAR8	-0.0081	-0.4388	DCHAR1	0.00378	2.21696
SUBM1	-0.4146	-0.3849	DCHAR2	4.2475	1.3189	SUBM1	-0.0045	-0.0065	DCHAR2	0.10420	0.04551
SUBM2	1.3942	1.0280	DCHAR3	0.0045	1.0977	SUBM2	2.0552	2.2799	DCHAR3	0.00174	0.70982
SUBM3	-4.4610	-2.1161	DCHAR4	-0.0009	-0.9218	SUBM3	-2.8790	-2.0824	DCHAR4	-0.00056	-0.75507
SUBM4	0.0343	0.0312	DCHAR5	0.0002	0.4606	SUBM4	0.7634	1.2679	DCHAR5	0.00003	0.07540
SUBM5	0.7627	0.7170	DCHAR6	0.0029	1.3251	SUBM5	1.2644	1.7900	DCHAR6	0.00252	1.56020
SUBM6	-0.1087	-0.0832	DCHAR7	0.0004	0.2129	SUBM6	0.4372	0.5178	DCHAR7	-0.00071	-0.49998
SUBM7	4.5183	1.6181	DCHAR8	-0.0023	-0.9720	SUBM7	2.2679	1.5028	DCHAR8	-0.00057	-0.35805
BR1	-1.8069	-1.7737	DCHAR9	-6.4642	-0.9333	BR1	-9.0679	-10.2682	DCHAR9	1.34370	0.26985
BR2	-5.1517	-7.0662	DCHAR10	0.0011	0.8162	BR2	-5.1842	-10.2087	DCHAR10	-0.00140	-1.51763
BR3	-2.4791	-2.5083	DCHAR11	0.0019	1.1635	BR3	-9.1768	-15.7920	DCHAR11	0.00070	0.65442
BR4	-8.4755	-5.1112	DCHAR12	-0.0026	-1.5559	BR4	-8.1238	-6.2792	DCHAR12	0.00018	0.16694
BR5	-5.1594	-2.3128	DCHAR13	0.0004	0.2048	BR5	-7.2429	-4.7907	DCHAR13	0.00071	0.49815
BR6	-12.8443	-12.1843	DCHAR14	-0.0002	-0.2949	BR6	-13.7604	-11.8007	DCHAR14	-0.00084	-2.00682
BR7	-5.4631	-1.8442	DCHAR15	0.0020	2.3063	BR7	-6.9554	-4.7183	DCHAR15	0.00069	1.06348
BR8	-7.3549	-4.4694	DCHAR16	-0.0053	-1.9396	BR8	-7.4531	-12.6108	DCHAR16	0.00005	0.02877
BR9	-8.3313	-4.1622	DCHAR17	0.7583	0.8401	BR9	-8.4403	-5.9852	DCHAR17	0.71491	1.30862
BR11	-13.3722	-6.4875	DCHAR18	0.3620	2.5098	BR11	-12.9712	-8.8309	DCHAR18	0.36107	3.44100
CS1	-0.1282	-0.1784	DCHAR19	0.0205	0.0800	CS1	-0.1893	-0.3865	DCHAR19	0.08961	0.50854
CS2	1.5066	2.0913				CS2	0.3687	0.8726			
CS3	0.6025	0.7780				CS3	0.4473	1.0915			
CS4	-0.7673	-0.4642				CS4	-0.5706	-0.8174			
Centred R^2				0.818533		Centred R^2				0.894139	
R-Bar^2				0.760741		R-Bar^2				0.860426	
Log Likelihood				-491.45311		Log Likelihood				-405.94114	

[1] The authors would like to thank the *FuelWatch* regulator for making this dataset available.
[2] Coles and Woolworths are the two major grocery retailers in Australia.
[3] 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.
[4] Looking four days prior and using different price increases made little difference to results; the increasing phase of each price cycle is quite clear in the data.

[5] 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 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.

[6] 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.

[7] 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 (summarised by centrality for a given node) versus structural holes, and Burt (2000, 2002, 2005) for a summary of the literature on structural holes.

[8] Gould (1967) uses an identical measure, but not the term centrality. Bonacich (1972) appears to develop his measure independent of Gould, and there appears to be only limited crossover between the literature in the fields of geography and sociology.

[9] In most cases, particularly in the physical sciences where spectral analysis is widely used, this approach has been superseded by the use of fast Fourier transformation or, more recently, by maximum entropy approaches (see Press, Teukolsky, Vetterling and Flannery, 2007 for a textbook treatment). These approaches give more precise results, but require specialist software, whilst the approach of Granger and Hatanaka (1964) can be relatively easily implemented using a spreadsheet. Moreover, experimentation with more sophisticated techniques for some retail petroleum outlets produced spectrograms very similar to those in Figure 3.

[10] Chatfield (2006) suggests the use of, $M=2\sqrt{N}$ is common in the literature, where M is the number of frequency bands and N the number of observations. Here, N=441, thus M=42.

[11] Peaks at 21, 14 and 3.5 days are echoes of the seven-day cycle, a common occurrence in spectrograms. The longest period encapsulates all cycles longer than 84 days, and is thus picking up longer-term cycles such as changes in crude prices and seasonal variation.

[12] We also explore the consequences of omitting different dummy variables, but the results (available from the authors upon request) are not significantly different from those presented here.

[13] The processing of the data required to obtain the spectral power results seen in Figure Three mean that it is unlikely that normality of the error terms remains a valid assumption.