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"Retail Gasoline Markets as Networks"

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Retail Gasoline Markets as Networks

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Abstract

The structure of a gasoline market can be an important element in the pricing choices of its participants. However, structure is often measured only indirectly by, for example, the number of independent sellers, or by seller density. Here we present a more direct and literal way of exploring market structure by representing it as a network. We use the structure of the network to delineate submarkets and present some measures from mathematical sociology which can be used to summarise aspects of network structure for use in further analysis. Although our case study here is in retail gasoline markets, the approach has broader application wherever spatial competition is important.

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Retail Gasoline Markets as Networks

1. Introduction

In markets like retail gasoline, an individual outlet might compete most with its nearest neighbours, but movements in prices can ripple across the whole market through the links those neighbours have with outlets further away and so on. This leads us to consider such a market as a network, and to use this network to delineate submarkets and describe the structure of competition. In this paper, we show how a simple model of bilateral interconnection can be used to create a network, summarising market structure, and how that network can be cut into submarkets which we then test for price similarity. Finally, we describe some measures, common in mathematical sociology, which can be used to summarise network structure from the perspective of each of its members, and thus be used in further analysis. We illustrate our approach using the retail gasoline market of Perth, Western Australia, for which excellent data are available.

Section Two of the paper outlines the approach in general. Section Three provides an overview of the case study market of Perth, Western Australia. Section Four outlines the process by which bilateral ties are formed to create the market network. Section Five indicates how this network is cut into distinct sub-networks, and shows how these are tested to ascertain whether the resultant summaries of prices are realistic or not. Section Six concludes with some final thoughts on the broader applicability of this model.

2. Outlining the Approach

The approach we follow can be described as follows:

- **Develop a behavioural rule for local interaction:** This specifies who is connected to whom. We present one such rule in our case study, but the latter steps do not depend upon this rule, potentially giving our approach widespread application.
- **Draw the network:** The network is simply a collection of all of the bilateral ties found by following the rule in the first step. It can be represented graphically or, more usefully, as an adjacency matrix (see below).
- **Cut the network:** Here we use the network structure to determine appropriate ways to cut the network into submarkets. This contrasts with the arbitrary approaches often used in economics, such as defining local markets by reference to town, suburb or zip-code, or by using a defined radius around the firm in question.
- **Test the cuts:** Finally, we present a series of tests by which we establish whether the division of submarkets is reasonable. The test is not a necessary step, but it is useful to perform prior to using summary statistics describing the

submarkets in any further analysis, to prevent erroneous results from arising due to poor submarket definition.

Before outlining our approach in more detail, we provide some information on the case study; the Perth retail gasoline market.

3. *The Perth Case Study*

The data used here 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 that price via its website and on TV, radio and other media. The price 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 had on the price level (see Davidson, 2008, for an account of this controversy), it provides for the researcher a uniquely comprehensive dataset which comprises a census of all prices in Perth.

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 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 the 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 on station characteristics in the *FuelWatch* database.[1]

Table One provides information on branding, ownership structures, presence of convenience stores and location of competitors.

[1] The authors would like to thank the *FuelWatch* regulator for making this dataset available.

Branding			Ownership	
	Total	*With Convenience Store*		
BP	52	16	Branded Independent	23
Caltex	57	29	Company Controlled	99
Woolworths	4		Distributor Controlled	2
Gull	27		Independent	2
Independent	2		Larger Independent	37
Liberty	5		Price Supported	42
Mobil	13	11	Supermarket	4
Peak	13			
Shell	35	8		
Wesco	1			

Competitors Within 5km		Distance to Nearest Competitor	
Number of competitors	*Frequency*	*Distance (km)*	*Frequency*
up to 2	10	up to 0.4	38
3 or 4	16	0.41 to 0.8	38
5 or 6	31	0.81 to 1.2	41
7 or 8	35	1.21 to 1.6	35
9 or 10	43	1.61 to 2	39
11 or 12	37	2.01 to 2.4	8
13 or 14	13	2.41 to 2.8	5
15 or 16	17	2.81 to 3.2	2
> 16	7	> 3.2	3

Table One: Perth Market Summary

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 Two, according to *FuelWatch*, which defines outlets owned directly by the Majors and

[2] Coles and Woolworths are the two major grocery retailers in Australia.

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 One 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 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 the 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, distances to the nearest rival tends to be low (on average just over one km) and the number of competitors within five kilometres is nine.[3]

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

[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.

	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 Two: Demand-Side Characteristics

One of the most important characteristics of prices in Perth's retail petroleum market is that they cycle in an Edgeworth (1925) fashion. Wang (2009) provides considerable detail in regards to such cycles in Perth, and Maskin & Tirole (1988) provide the theoretical underpinnings of this dynamic equilibrium. To explore price cycles in more detail, we perform an auto-spectral analysis on the prices of each outlet,[4] following the approach outlined in Granger & Hatanaka (1964) and construct a spectrogram for prices and margins, dividing the spectra into 42 different frequency bands.[5] The auto-spectral analysis underpins the cross-coherency analysis discussed below.

The resulting spectrogram for margins is shown in Figure One. The results for price are similar, but those for margins are clearer as marginal costs (which contribute little to variation) have been removed. The red lines indicate Caltex or Ampol-branded stations, green indicates BP, orange indicates Shell, light blue indicates Mobil, and dark blue indicates all of the non-Major branded and independent outlets. The thick black line shows the average power for each frequency band.

[4] Spectral analysis requires the data to be stationary and we find that they are.
[5] 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.

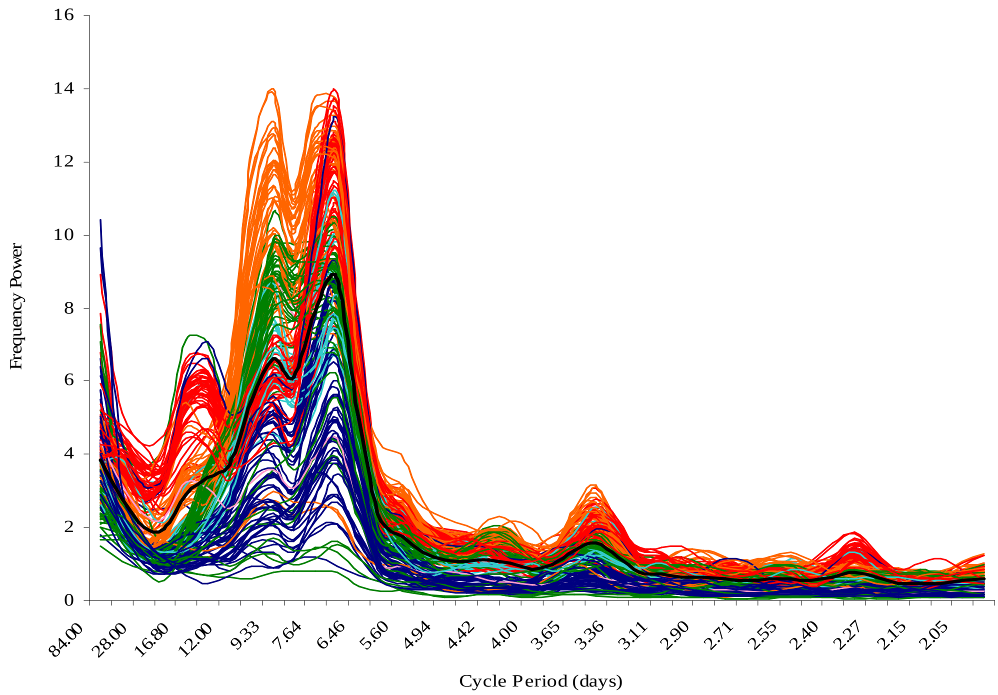

Figure One: Spectra for Price Margins

The most obvious aspect of Figure One is the dual peak at seven and ten days.[6] 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 which 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.

4. *Forming the Network – The Behavioural Rule*

In order to develop a network-based picture of the structure of competition in the retail petroleum market in Perth, one must first devise a way in which one can connect two retail petroleum outlets; to show that they are in fact competing. These bilateral ties, when collected together, give an overall picture of the

[6] 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.

structure of competition in the marketplace as a whole. Our connectivity rule is based upon earlier work by Hoover (1937) and McBride (1983).

Consider the situation of two firms, A and B, located on a section of road, and selling an homogenous product to homogenous consumers whose travel plans take them past one of the retailers but who would have to deviate from their chosen path to frequent the premises of the other retailer. They would only choose to do so if the retailer in question had prices lower than the retailer they have passed (and can thus patronise at zero cost) by a margin greater than the travel costs associated with deviation. Each retailer maximises profit by trading off the extra per-unit profits which can be made by charging higher prices to those consumers for whom deviating to the competing retailer is costly against the extra gross profits which can be made by selling to more customers if a retailer undercuts its rival.

The trade-off can be summarised in the form of a profit function thus:

$$\pi_i = \begin{cases} q_i(p_i - c_i)d - q_i(p_i - c_i)\left(\dfrac{p_i - p_j}{d\tan\alpha}\right) & if \quad p_i > p_j \\ q_i(p_i - c_i)d & if \quad p_i = p_j \\ q_i(p_i - c_i)d + q_j(p_i - c_i)\left(\dfrac{p_j - p_i}{d\tan\alpha}\right) & if \quad p_i < p_j \end{cases} \qquad (1)$$

Where:
p_i = price charged by firm *i*.
q_i = proportion of overall customers that pass firm *i*.
c_i = marginal cost of firm *i*.
d = distance between firm *i* and firm *j*.
$\tan\alpha$ = the per-unit cost of travel (cost/distance).

It is relatively simple to show (see Bloch & Wills-Johnson, 2010a) that the equilibrium of this dynamic game will be:

$$p = \frac{1}{3q_A q_B}\left(\left(2q_A{}^2 + q_B{}^2\right)d^2\tan\alpha + \left(2c_A + c_B\right)q_A q_B\right) \qquad (2)$$

for Firm A, and

$$p = \frac{1}{3q_A q_B}\left(\left(q_A{}^2 + 2q_B{}^2\right)d^2\tan\alpha + \left(c_A + 2c_B\right)q_A q_B\right) \qquad (3)$$

for Firm B.

In Perth, the terminal gate prices, which proxy marginal costs, are almost exactly the same across the five wholesalers (BP, Shell, Caltex, Mobil and Gull) for almost every day in the sample period.[7] If one also assumes $q_A=q_B$, the Equilibrium is not Equation Three, but rather (for both firms):

$$p = \tfrac{1}{2} d^2 \tan\alpha \tag{4}$$

It is worth noting that this equilibrium is not stable, but rather that each firm has an incentive to raise its price, triggering an Edgeworth Cycle (see Bloch & Wills-Johnson, ibid).

Equation Four 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.[8] We then undertake a simple statistical test of the difference between the means for each pair of outlets within five kilometres of one another.[9] 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 which summarises the patterns of connection in the overall market.

The results are summarised in Figure Two (overleaf). The blue area represents the Swan River, which divides the city North from South, and the 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.[10] The different coloured dots represent different brands. Brands tend to be spread throughout the Perth market, rather than focussing on any particular area.

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[7] The correlation coefficients between each pair of wholesalers across the period exceed 99 percent in each case. The ACCC (2008, 2009) finds similar close matches between the tgp average wholesale price in each city it studies, using actual wholesale price data which are not in the public domain.

[8] 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.

[9] 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.

[10] 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.

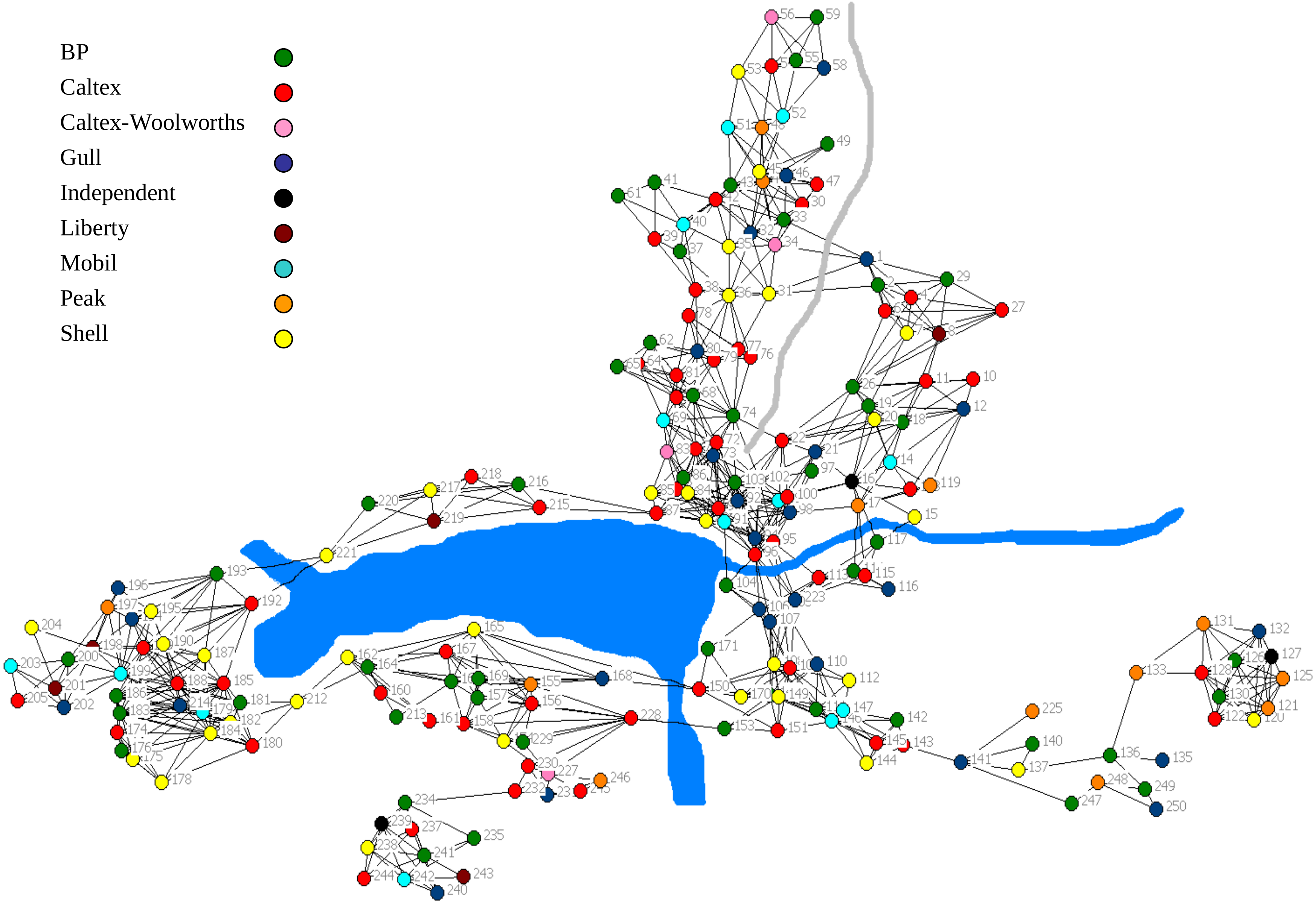

Figure Two: Retail Petroleum Market Network

One can then summarise this network structure by using summary statistics widely used in mathematical sociology, and based upon the adjacency matrix of Figure Two.[11] Commonly used summary statistics include Bonacich's (1972, 1987) measures of centrality and Burt's (1992) measures of redundancy, efficiency and constraint. All are well established in the mathematical sociology literature, and there is a lively debate as to which are best in what types of network situations. Burt (2000) or Granovetter (2005) contain reviews of this debate, whilst Burt (2000, 2002, 2005) contain reviews of empirical applications of his measures and Borgatti & Everett (2005) contains a detailed mathematical treatment of the relationships between the various measures of centrality. We calculate these measures for both the network as a whole and for each of the sub-markets in separate work (Bloch & Wills-Johnson, 2010b, 2010c). Here, we focus on determining the relevant sub-markets; a topic to which we now turn.

5. Cutting and Testing Sub-Markets

We now explore the use of network structure to determine sub-markets. In principle, using network structures to delineate sub-networks is simple; the appropriate sub-network divisions are those such that the number of connections internal to each sub-group are greater than the number of connections between sub-groups (Freeman, 1993). In the context of a retail petroleum market, this would suggest that outlets in a sub-market are paying closer attention to each other than they are to outlets outside their sub-market.

Examining every possible sub-network is time consuming, and approaches to delineating sub-networks usually employ some form of rule to search for appropriate groupings; Girvan & Newman (2003 a,b) divide such approaches into two broad families; agglomerative and divisive. Agglomerative approaches start with the empty network and add links based on some measure of similarity between each pair of nodes. Every round of adding creates a new set of sub-networks, but there is nothing which favours one round over the next. Divisive approaches (which they favour) start with all the links in place, and then remove links based on some rule; theirs is based upon the number of paths which flow through each link, and they advocate removing links with the greatest number of paths first. Again, each round creates a new set of sub-networks, and there is nothing in the approach to favour one round over another.

Gould (1967), takes a much simpler approach and is indeed the starting point for much of the literature on graph-cutting. He uses the eigenvectors of the adjacency matrix. Predating Bonacich (1972),[12] he suggests that the first eigenvector, which contains all positive entries, might measure centrality (though he does not use the term). However, he goes on to suggest that clusters of positive and negative elements in each subsequent eigenvector might indicate subgroups in the network, indexed by the eigenvalue and with the largest (by absolute value) element in each subgroup representing its centre. He illustrates his case with some road networks and gives

[11] Adjacency matrices are 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. They are widely used in mathematical sociology as a basic mathematical representation of a network. There is nothing, mathematically which requires one to use a zero-one matrix. If, for example, the basic behavioural model used for connection utilised cross-price elasticities, these could stand in for the zeroes and ones.

[12] Bonacich apparently discovered hi measure independently of Gould, and there is limited crossover between the geographers, who follow Gould, and the sociologists, who follow Bonacich.

plausible results. His approach has been followed by other geographers, most particularly by his students, who use it widely in Africa (see Brookfield, 1973). Cliff, Haggett & Ord (1979) use it to examine airline networks, whilst Boots (1985) shows how the approach gives consistent divisions for cellular networks. O'hUallachain (1985) uses a variant of Gould's methodology to reduce the dimensionality of input-output tables, and Thill (1998) uses it to group precincts into electorates. Tinkler (1972, 1975) and Hay (1975) debate an extension by Tinkler (1972) that considers flows of information whilst Straffin (1980) explores the mathematical underpinnings of Gould's (1967) work through the use of the Perron-Freobenius theorem.

The approach requires judgement to determine which groupings of positive and negative entries represent appropriate sub-groups within the network, and it usually requires one to have a visual representation of the network as well to check results for reasonableness. Moreover, beyond the first few eigenvectors, the signal-to-noise ratio is too high to extract much useful information. However, it is a useful approach, and the amount of judgement required is arguably no more than that required to determine which round of a divisive or agglomerative approach is best. We find that the second to sixth eigenvectors of the adjacency matrix of Figure Two provide a reasonable division into eight sub-markets. The results are shown overleaf.[13]

[13] With 208 elements, the actual eigenvectors are too large to show here, but they are available from the authors upon request.

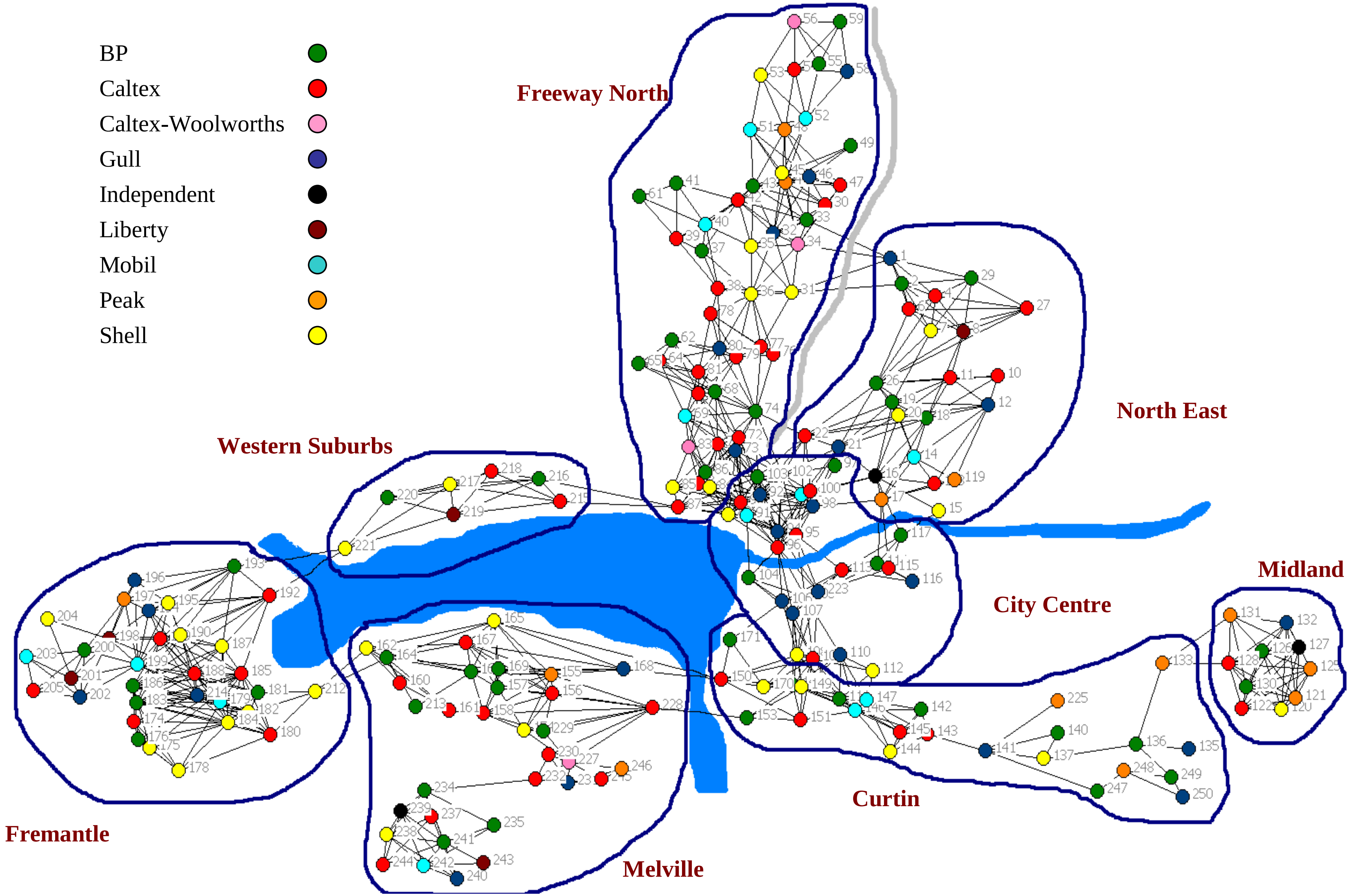

Figure Three: Sub-markets in Market Network

5.1 Testing the Sub-networks

Since our submarket delineation process is judgemental, it behoves us to test the submarkets. Girvan & Newman (2003 a,b) introduce a network-based measure they call modularity, which compares how many connections there are in each sub-group with the number which might be expected in a random network with the same number of sub-groups and connections. The measure ranges from zero to one, with a random network division scoring one-half. Our network division scores over two-thirds, which indicates that it is reasonable. Moreover, had we followed Girvan & Newman's (2003a,b) divisive approach, we would have created roughly the same sub-groups as in Figure Three. This should not, perhaps, be surprising, and likely signifies the mathematical links between eigenvectors and the agglomerative and divisive approaches of Girvan & Newman (2003 a,b). To be more robust, we need to step outside of the network framework.

Since this is an economic network, the most obvious way to step out of the network framework is to look at supply and demand. Demand is simplest to explore, and we use the ABS (2006) data which is summarised at a city-wide level in Table Two, matching the post-codes of each outlet with post-code level data from the Census and then grouping the demand data by sub-market.[14] The results provide some differentiation; the Western Suburbs market is, for example, distinctly richer, older and better educated than the rest, and the North-East market has relatively low socio-economic characteristics. However, the differences are not definitive. If an ANOVA test across all demand characteristics and all submarkets indicated all were different, one could safely conclude the submarkets were different. Here, the result is not so clear cut, and it is unclear how much difference across characteristics is enough to deem that the submarkets are indeed different from a demand perspective.

We thus turn to the supply-side, and price. If the outlets in a particular sub-market really are paying most attention to their submarket peers, then one would expect similar prices. We test this pricing similarity by comparing how similar prices are within each submarket to how similar they are amongst like-branded outlets and, as a control, four random groups whose members are neither in the same submarket nor carry the same brand. We could have tested amongst many different submarket groupings, aiming for optimality. However, this would not really involve stepping outside the network, so instead, we use a counterfactual which has been widely used in the literature to collect outlets; branding. Wang (2009), for example, shows how price increases are very closely related across outlets with the same brand in Perth

The obvious tool to test similarity is an ANOVA test. However, the volatility of the prices for all outlets is such that such a test provides no clear results at all; on average, almost all of the groupings (the eight sub-markets, the nine brands and the four random groups) pass the ANOVA tests and might hence be seen as equally valid. Indeed, it is very hard to distinguish any differences between outlets using ANOVA, and thus we turn from comparing averages and variances to looking at the price paths in more detail.

To do this, we utilise an approach based on that suggested by Brillinger (1975) and used by Bartels (1977) to explore regional unemployment in Holland. The approach relies upon examining the eigenvalues of the cross-coherency matrix for each group in

[14] This thus assumes that all demand is local, but we have no data on where actual demand comes from on a station-by-station basis and thus this is perhaps the best that one can do.

(brands, submarkets and random). The coherency between any two outlets shows the degree of linear relationship between the magnitudes of their power spectra at the relevant frequency band of the spectrogram; the degree to which each element in the pair has the same amount of its total variance explained by cycles of a particular length.[15]

As Brillinger (1975) points out, the eigenvectors of the cross-spectral matrix (using the cross-coherency matrix normalises the results) gives the closest result of any mapping from the smaller space described by the frequency data to the larger space described by the original data. It is thus the best way to reduce the dimensionality of a problem involving a comparison of a large number of pairs of outlets to one where comparisons are between groups of outlets. The spectral density matrix of this mapping mechanism has the eigenvalues of the cross-coherency matrix down the main diagonal and zeroes on the off-diagonal elements.[16] Thus, the key to the analysis is to examine the relevant eigenvalues; the closer these are to zero, the better is the mapping and thus the more cohesive is the relevant subgroup.

The analysis of the cross-coherency matrix eigenvalues involves these steps:

- Firstly, we undertake an auto-spectral analysis (see Figure One) and ascertain the cycles with the most power and hence the most important lags for each of the 208 stations.
- Secondly, we regress these lags (which differ for each outlet, but usually contain the seventh and tenth lags) against price for each outlet, and collect the residual vector. Coherency analysis is undertaken using this residual vector to avoid auto-correlation from introducing bias to results (Chatfield, 2006).
- Thirdly, having found the coherency between each pair in each of the nine brand groups, eight sub-market groups and four random groups, we arrange these into symmetric matrices. Each of the 21 groups has 42 such matrices; one for each frequency band analysed.
- Fourthly, we reduce the amount of data to be analysed. There are 42 frequency bands for each of the 21 groups, but the first 12 comprise more than 80 percent of the variance in the average outlet, so we consider only these 12. Moreover, each coherency matrix has as many eigenvalues, as there are outlets in that group. We take only sufficient of the eigenvalues to explain 90 percent of the variation in each of the coherency matrices.
- Finally, we take a weighted average for each of the eigenvalues (weights being the proportion of the 90 percent of variance each comprises) to give us a single score for each group at each frequency band.

The results of this rather involved procedure are shown in Figure Four. There is clearly a wide dispersion of scores, with the branding groups exhibiting much more diversity than the sub-markets. There are also not many differences between the various groupings for longer-term cycles but, over the shorter cycles of roughly a week, there is much greater variation. Importantly, the branding groupings appear to be above the sub-

[15] The auto-spectra are examined under pricing above, where we create spectrograms with 42 frequency bands. Chatfield (2006), Brillinger (1975) or Granger & Hatanaka (1964) provide further details on coherency, phase and gain, the three elements of cross-spectral analysis, and the formulae used to calculate coherency in this analysis are taken from Granger & Hatanaka (1964, Chapters Five and Six).

[16] Under certain assumptions that seem reasonable to assume hold here, see Brillinger, 1975, pp. 344-5.

market groupings in most cases at these frequencies, suggesting, albeit weakly, that sub-markets describe these cycles better than brands.

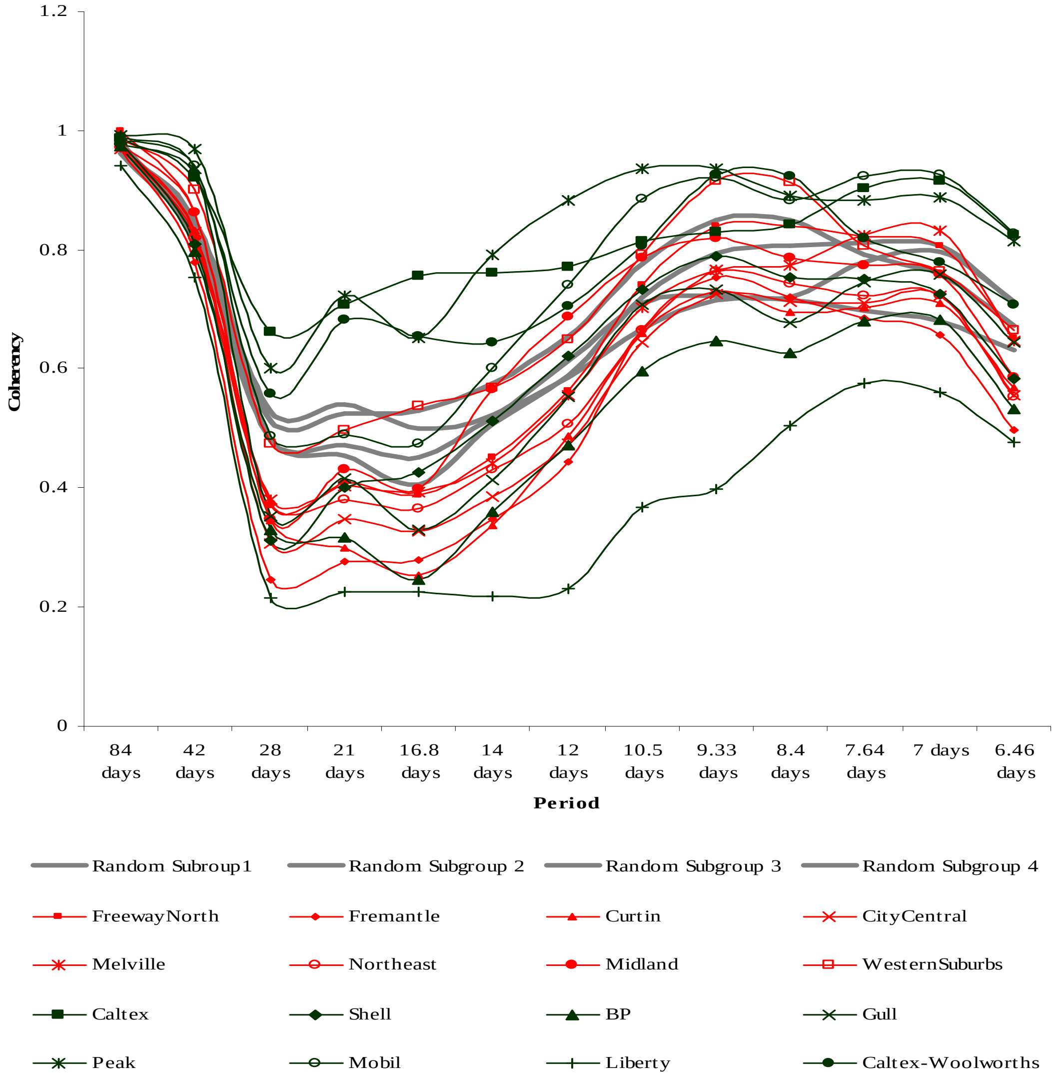

Figure Four: Brillinger Analysis Results

As a straight average across all frequency bands, the four randomised groups scored 0.684, whilst the sub-market groupings scored 0.636 and the branding groupings scored 0.687. If this is weighted by the power of the relative frequency band in explaining total variance for the average outlet across the whole sample, then the averages are 0.717, 0.685 and 0.724 respectively. There are differing numbers of outlets in each of the branding and submarket groupings, and if the (unweighted) average frequency scores for each grouping are themselves weighted by the number of elements in that grouping, then the weighted average scores for sub-markets and branding groups are 0.628 and 0.690 respectively.

It is difficult to assess the statistical significance of the differences between each of the average values above, or between each of the coherency curves shown in Figure Four, unless one makes some rather heroic assumptions concerning the distribution of each after being subjected to the various procedures outlined above. However, it does not seem completely unreasonable to suggest that, based upon the procedure above, the sub-market grouping of outlets does perform better, albeit marginally so, in explaining the degree to which prices are similar within a group than does the branding grouping which, in general, does no better than a random collection of stations. That is not to say, however, that all brands are equal; BP and (more particularly) Liberty, have pricing which is as similar as or more so than the best of the sub-market groupings. Nor is it to say that each sub-market is equal; the Western Suburbs and (to a lesser extent) the Freeway North sub-markets do not have particularly similar pricing compared to the other sub-markets.

6. Conclusions

Understanding the structure of competition within a marketplace can often be difficult. At an anecdotal level, there may be considerable understanding of who competes with whom, but translating this into something formal which can be used in further analysis is more difficult. Here, we present a methodology for doing so which relies upon constructing a network to summarise the structure of competition in the network based on bilateral interactions at the local level. We show how this network can be cut, and outline some useful summary statistics which can be used in analysis. In further work (Bloch & Wills-Johnson, 2010c), we utilise the summary statistics in a regression analysis to explore how market structure influences pricing.

The methodology outlined herein contains four very broad steps:

- Define a behavioural rule for bilateral interaction.
- Draw the network of bilateral ties and developing summary statistics.
- Cut the network to allow network structure to define sub-markets.
- Test the submarkets for similarity before further use.

The last step is not strictly necessary, but it is a useful way of ensuring that the analyst is on the right track. Here, it also shows that local competition is important in determining retail gasoline prices; potentially more so than branding. This suggests, in turn, that a focus on brands as the sole driver might be misplaced. The same test could also be used to compare different formulations for local markets, potentially (although it would be very time-consuming) finding the optimal one. The second, third and fourth steps are not dependent upon the nature of the behavioural rule described in the first step. For illustrative purposes, we have described the behavioural rule we have used for interaction between two retail petroleum outlets. However, provided any replacement rule allows the analyst to deem two nodes (here, retail petroleum outlets) as being in competition with each other, and thus gives grounds for linking them in Step Two, the behavioural rule can be replaced.

The approach outlined here is very flexible and might find application anywhere where spatial competition or product differentiation means that a network is a useful way of looking at the structure of competition. Apart from academic studies, this means it might be a useful adjunct to procedures used to determine markets in antitrust analysis and economic regulation. It is thus an approach with broader academic and potential policy relevance as well.

7. References

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