Centre for Research in Applied Economics (CRAE)

Working Paper Series
200810
August

"Price Cycles in Perth Petrol Markets: A spectral analysis"

By 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
ISSN 1834-9536

Curtin
University of Technology

Price Cycles in Perth Petrol Markets: A spectral analysis

Nick Wills-Johnson
School of Economics and Finance
Curtin University of Technology
Perth, Western Australia
Email: n.wills-johnson@curtin.edu.au

Abstract

Numerous commentators have noted the tendency of retail petroleum prices to cycle. This paper undertakes a formal analysis of petroleum price cycles, using spectral analysis to uncover which cycles are most important, and regression analysis to ascertain what drives that importance.

INTRODUCTION

This paper explores a phenomenon which has been widely observed in the past by both policymakers (ACCC, 2007, WASCPPP, 2000) and academic researchers (Wang, 2006, 2007b); the prices of retail petroleum in Perth tend to cycle. The paper extends extant analysis in two important ways. Firstly, it formally studies the price cycles using spectral analysis. Secondly, it endeavours to uncover some of what the ACCC (2007) calls the enigmatic nature of price cycles, by regressing the importance of certain key cycles against a range of explanatory factors.

Section Two of this paper provides a brief overview of the Perth retail petroleum market. Section Three summarises the technique of spectral analysis and the results of the spectral analysis of Perth's retail petroleum outlets' prices. Section Four introduces the econometric model which seeks to explain certain key elements of the petroleum price cycle and presents the results of this analysis. Section Five concludes.

THE PERTH RETAIL PETROLEUM MARKET

Perth, the capital city of Western Australia, is served by roughly 350 petrol stations. It is located thousands of kilometres from any city of comparable size, and a hundred from the nearest major town. Its retail petroleum market is thus isolated from any other. BP, Caltex-Ampol, Mobil and Shell, the four "majors" (vertically integrated firms with upstream refining operations) operational in Australia, also operate in Perth, with Caltex-Ampol having the largest market share and BP the only refining operations. As is common elsewhere in Australia, and indeed globally, the majors own and operate only a small number of outlets directly, utilising either franchising arrangements or independent stores which carry the major's brand under a licensing arrangement for the remainder. The former often receive price-support during the low points of the price cycle, whilst the latter do not. This obviously influences their competitiveness.

A number of independent brands also serve the city; Gull, Peak, Liberty and Wesco. Of these Gull has both the largest presence and the only import terminal. During the study period, there is also one joint venture between a supermarket and a major; that between Woolworths and Caltex-Ampol. Each of the majors has a wholesaling terminal (BP has two), as does Gull. However, their location is not an important factor in retail competition, as Comonar & Riddle (2003) suggests they are in California, because almost all of them are located in the same place.

Perhaps the most striking feature of the Perth retail petroleum market is the prices of petrol stations; they cycle, as shown in Figure One.[1]

[1]Other brands behave similarly, but are omitted from Figure One to aid clarity.

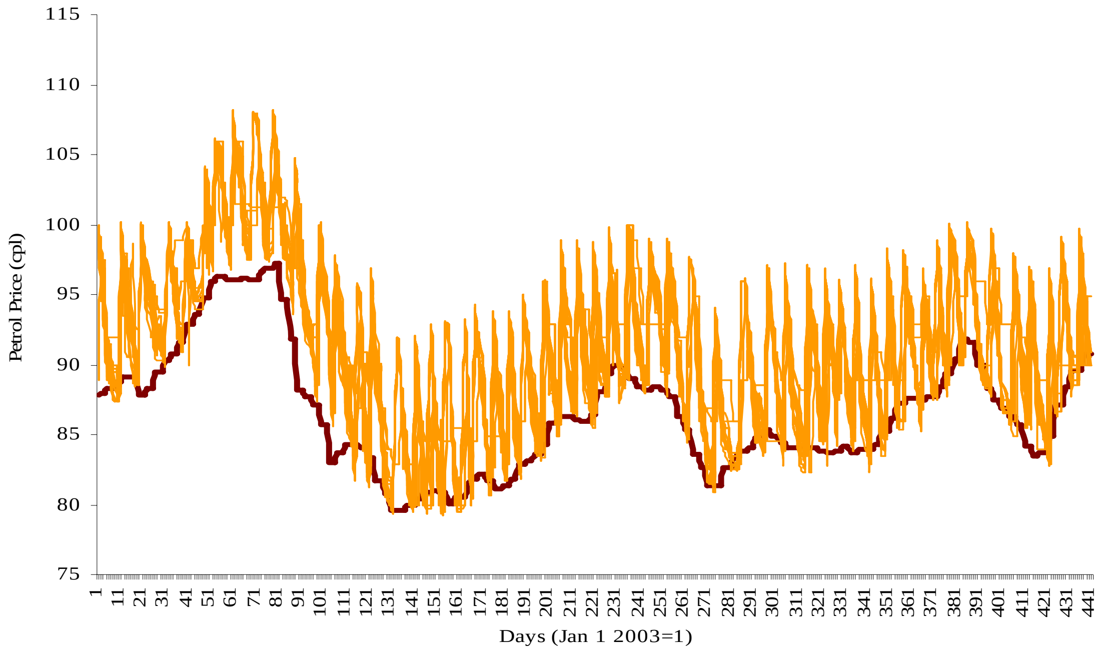

Figure 1: An Example of Perth's Price Cycles – Shell

During the period of study, the cycle lasts roughly a week, increasing over the first day or two, and then decreasing slowly through the remainder of the week. This pattern is known as an Edgeworth Cycle (Maskin & Tirole, 1988). Both academic (Wang, 2006, 2007a, 2007b) and government (ACCC, 2007) authors have noted such cycles before, and the ACCC study shows they are not restricted to Perth. Indeed, they are not a uniquely Australian phenomenon; Noel (2007a, 2007b) and Eckert & West (2003) study them in a Canadian context, and Allvine & Peterson (1974) and Castanias & Johnson (1993) note their presence in some US markets. They are not, however, ubiquitous; they are much rarer in Australia's regional centres than in its capital cities. Noel (2007) notes that some Canadian cities have cycling retail petroleum prices and some do not. The variation induced by cycling prices causes community concern, and calls for political action; WASCPPP (2000) provides a rather heated example of both.

Like all retail petroleum markets in Australia, Perth has been subject to substantial regulation, beyond the environmental, health and safety and planning controls which one might expect as standard practice. During the study period, the most pervasive Federal Government controls were the *Sites Act*, and the *Franchisees' Act*. Each of these Acts had its origin in the 1976 Royal Commission on the Marketing and Pricing of Petroleum Products, and each was passed in 1980. The former is designed to limit the number of outlets each of the majors can own and restricted the majors to a total of five percent of each market, roughly half their share prior to the passage of the Act. Originally the Royal Commission recommended complete divorcement, but the majors argued successfully that they needed some retail presence for training and market research purposes. From 1984, the proportion of the five percent which each major could own was based on its market share over the previous three years. The latter is designed to protect the interest of retail petroleum outlet franchisees, and places a number of restrictions on the terms and conditions of franchise contracts written between each major and its franchisees. Both the *Sites Act* and the *Franchisees Act* were repealed in 2007 and replaced with an industry code, the *OilCode*.

The Perth market is also subject to the State Fuelwatch scheme. Under the aegis of the *Petroleum Pricing Regulations 2000*, retail petroleum outlets are required to report their proposed prices for the next day's trading to a government regulator (Fuelwatch) before 2pm. The prices change at 6am the next day, and the retailer is not permitted to change them again for 24 hours. The lowest prices are publicised in television and print media, and on the Fuelwatch website (www.fuelwatch.com.au/). Recently, following a report by the ACCC (2007), the Federal Government has advocated the adoption of a nation-wide Fuelwatch scheme, but at the time of writing, this has yet to come to pass.

The Study Period

Fuelwatch has generated a census of price data from its inception in 2001 as it legally requires all retailers of all types of fuel (unleaded petrol, premium unleaded petrol, diesel and liquefied petroleum gas) to report their prices everyday.[2] However, this study concerns itself with only a portion of this data; from January 1st 2003 to March 14th 2004, only unleaded fuel and only roughly two-thirds of the sites which retail fuel in Perth. The start date is chosen because, prior to this date, terminal gate prices are not available and hence gross margins (retail prices minus the TGP) cannot be calculated. The end date is chosen because, on the following day, Coles and Shell operationalised their joint venture, turning 40 Shell Select and Shell outlets into Coles Express outlets. This greatly increased the number of supermarket-affiliated outlets which operate "shopper-docket" schemes; spending a certain amount in the supermarket in question allows one a discount of a few cents per litre (see ACCC, 2004, for a detailed account). This may have changed consumer and supplier behaviour. To avoid these effects influencing model results, the study period focussed on the period prior to the advent of Coles Express. Unleaded fuel was the main focus of the study because diesel and LPG are subject to different market pressures due to their use by the transport and taxi industries (respectively), and premium unleaded fuel is excluded because it is a much smaller niche market.

During the study period, roughly 350 outlets operated within the Perth metropolitan area; 357 at the outset, and 341 by the end. Perth is a relatively low-density city, and is ringed by smaller urban centres on its fringes. Retail petroleum outlets in these smaller centres form small local groupings, but are sufficiently distant from any other outlet within the Metropolitan area that it seems unlikely that they are being influenced by price movements within it. For this reason, 76 outlets on the fringes of the city have been excluded from the study. Of the remainder, not all were open for the entire period; 28 closed and 18 opened between January 2003 and march 2004. These 46 sites have incomplete datasets. Most new sites which opened (in fact, all but four of the 18) were not green-field sites, but new owners (usually independents) opening on an existing site (usually sold by a major). Typically, there were many months between one site closing and its replacement opening. A small number of Caltex-Woolworths outlets, operating from shopping centre car-parks, were not open on Sundays when the shopping centre was closed and hence also had missing data. These stations with missing data were excluded from the sample.[3] Finally, 21 outlets had fewer than ten price increases of more than five percent in a single day; the indicator used for the upward phase of a price cycle. By contrast, most outlets had roughly 50 such events. The 21 outlets were thus excluded from the sample. For most, either fuel sales were a secondary part of their business,[4] or they were relatively small, independently owned businesses, distant from competition and serving only a local niche market. We are thus left with 209 outlets which form the basis of this analysis. Figure Two shows the proportion of different brands in the market.

---

[2] The author acknowledges the kind assistance of the Department of Consumer and Employment Protection in providing the data used in this study.

[3] The result is that Caltex-Woolworths outlets are under-represented in the sample; 20 were open for part of the period, 11 were open for the whole period, but only four are in the sample. Results in the econometric analysis should be interpreted with this in mind.

[4] Legally, all retailers of petrol, diesel or LPG must provide data, and this includes a number of mechanic shops, a marina, a taxi firm and a number of outlets which primarily serve trucks.

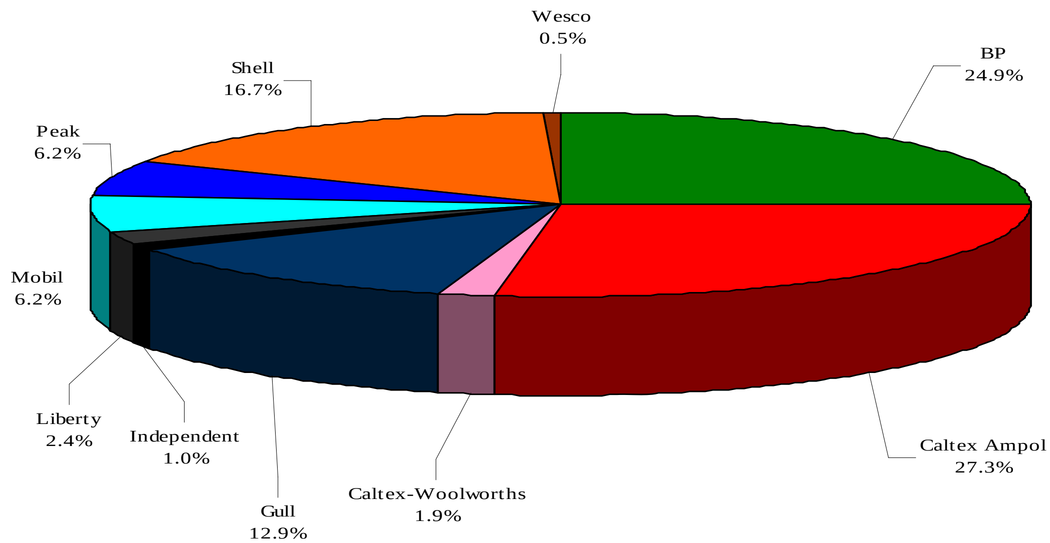

Figure 2: Retail Petroleum Outlets by Brand

Caltex-Ampol has the largest share, followed by BP and Shell. Mobil, despite being a major, only has a relatively small presence in Perth, only half that of the largest of the independent chain, Gull. Whilst there are many stores which are independently-owned, only two of these carry no branding. Branding is not the same as ownership; a retail petroleum outlet carrying a particular brand might be owned by the brand owner, a franchisee or an independent operator who has merely paid a licensing fee for the use of the brand. It is therefore also important to examine ownership. Figure Three provides results for the whole market, and Figure Four for the 157 major-branded stations.

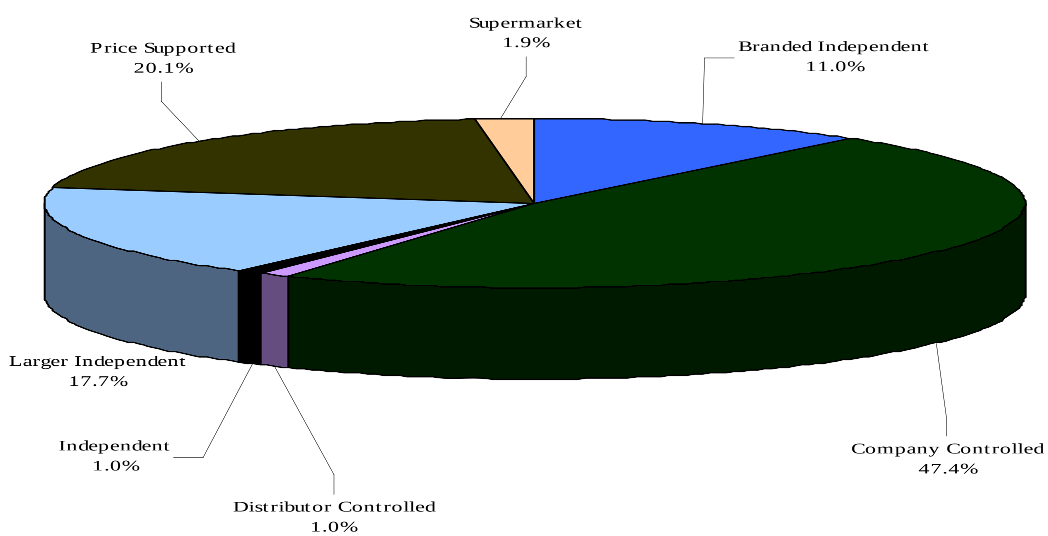

Figure 3: Ownership Patterns

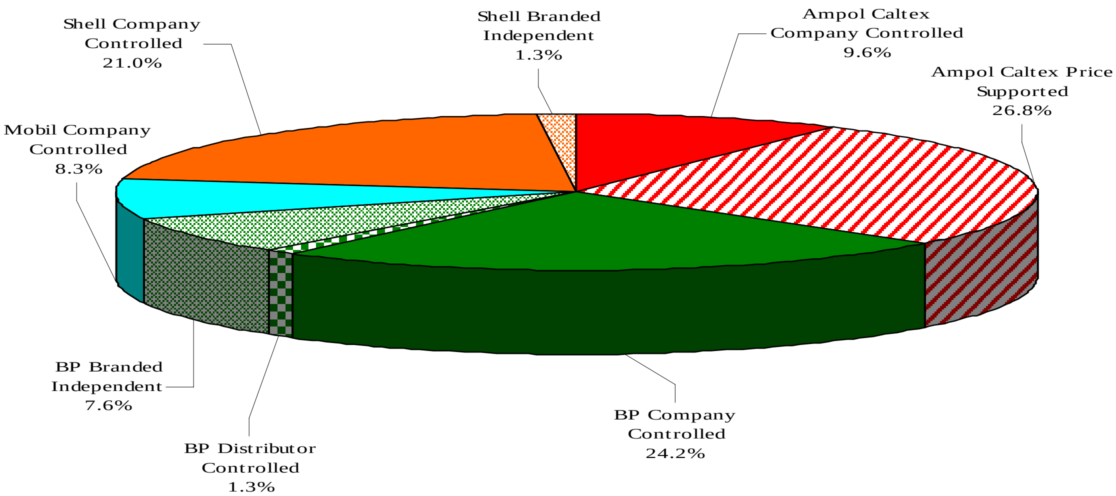

Figure 4: Ownership Patterns Amongst Major-Branded Outlets

Not all of those carrying the brand of a larger independent chain (Gull, Peak or Wesco) in Figure Two are labelled "larger independent" in Figure Three. Some Peak and Gull outlets are not owned by Gull or Peak, but are independently-owned, and just carry their respective brands. The independent chains are thus engaging in the same kind of risk management that the majors use for their own branded independents.

In Figures Three and Four, the "company controlled" designation refers to outlets owned and operated by the independent chains, and, where branded with a major's brand, to both outlets owned by the majors themselves, and outlets owned by multi-site franchisees. This is an artefact of the Fuelwatch reporting system. BP and Shell operate multi-site franchises. Thus, there are no BP or Shell outlets listed as "price supported", even though some of the franchisees may have been. By contrast, Caltex-Ampol has only single-site franchises, all of which are price supported. To understand how many outlets in listed as company controlled are owned by BP and Shell, it is necessary to turn to data from the Federal Department of Resources, Industry and Tourism, which administered the *Sites Act* whilst it was in operation. These data are presented in Figure Five.

Unfortunately, the Department of Resources Industry and Tourism data do not indicate which outlets were owned by the majors. Thus, whilst we know that roughly five of the 50 BP sites in WA and eight of the 58 Shell sites listed as company controlled were actually owned by BP and Shell (respectively), we do not know which ones. This has obvious ramifications when interpreting the econometric results below.

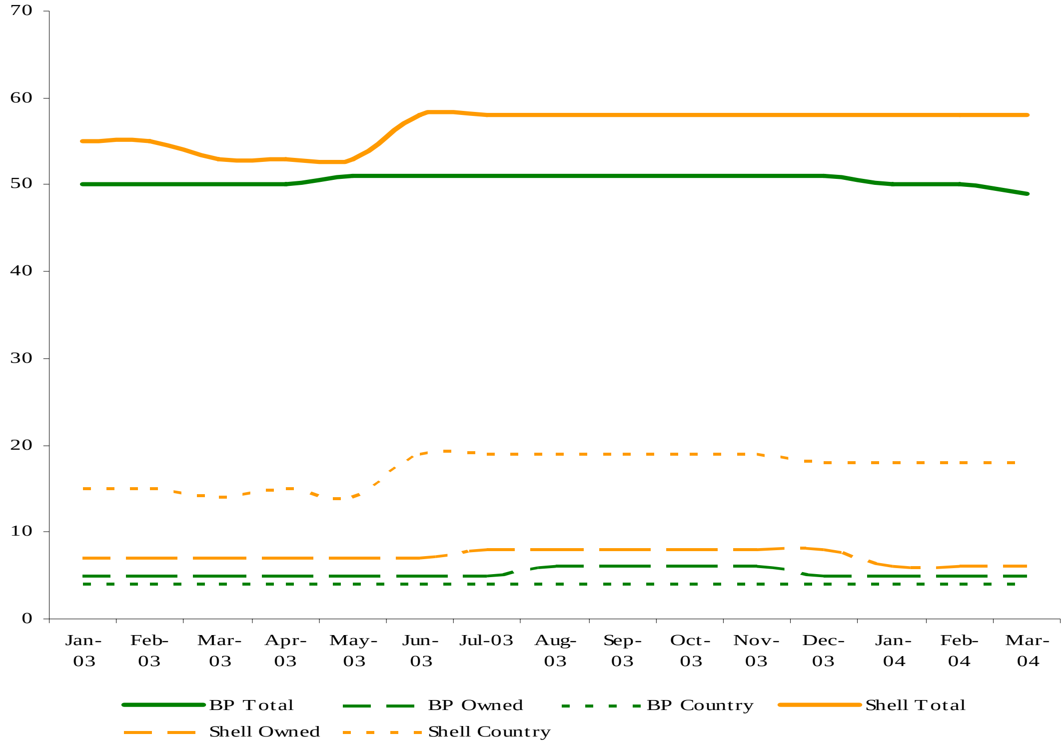

Figure 5: BP and Shell Outlets – Owned and Franchised

One final aspect worth exploring is the prevalence of convenience stores. Each of the majors has one convenience store brand, and Caltex has two. These are: Shell Select, BP Connect, Caltex Starshop, Caltex Starmart and Mobil Quix. Whilst Mobil, Shell and BP own all of their convenience stores, Caltex convenience stores are as likely to be operated by franchisees as they are to be operated by Caltex itself. Convenience stores are important because most of the profit comes from the sale of non-fuel items such as hot snacks, drinks, newspapers and cigarettes; fuel is a loss-leader. Figure Six provides an overview of the number of convenience stores operated by each of the majors.

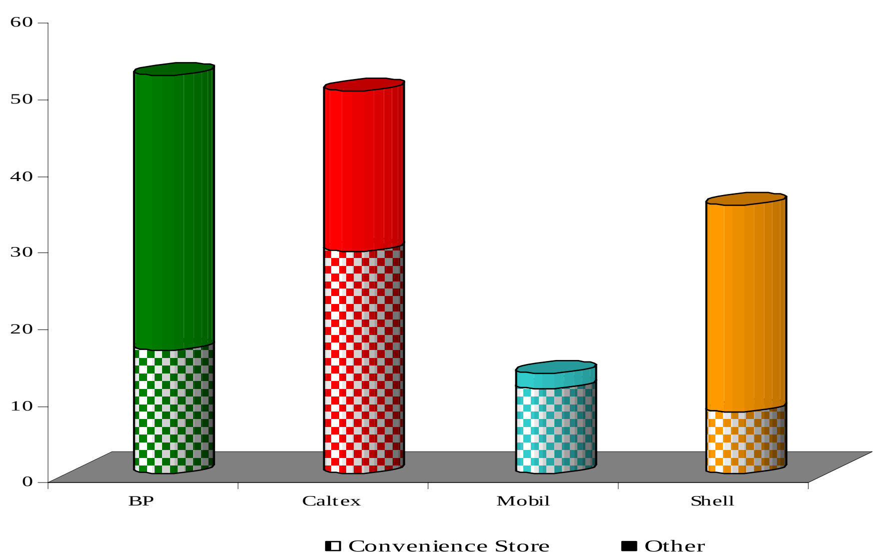

Figure 6: Convenience Stores and Other Outlets Operated by the Majors

SPECTRAL ANALYSIS

Spectral analysis involves examining the relevant data in the frequency domain rather than in the time domain. If a certain lag is important in a model constructed in the time domain, then the cycle with period equal too that lag will have high power in the frequency domain analysis. It is thus not a case of which method is "right", but rather of which more clearly highlights underlying patterns in a dataset.

Spectral analysis is widely used in the physical sciences, but less so in economics. However, it has found application in areas where variables cycle such as business cycle analysis (Jagric, 2002, Englund, Persson & Svenson, 1992, Baxter, 1991 and Diebold & Ruderbusch, 1990), commodity cycles (Rausser & Cargill, 1975, Weiss, 1975 and Slade, 1982) and housing cycles (Clembout & Nefti, 1981, Wilson & Okunev, 1998). It has also proven particularly useful in examining relationships between variables that cycle (Grace & Hotchkiss, 1995, Pakko, 1994, Orlov, 2006 and Rua & Nunes, 2005). Finally, it has found important application in financial time series analysis (Brooks & Hinich, 2006, Kim & In, 2003), although it is being replaced by wavelet analysis in this regard, as it is better able to handle transient shocks.

There are a number of reasons why spectral analysis might not be widespread in economics. Firstly, economic time series are often non-stationary. Of those that are stationary, many follow processes with simple lag structures, and indeed it is possible to speak of a "typical spectral shape" for many economic variables (Granger, 1966, Levy & Dezbakhsh, 2003). There may be few advantages in examining such variables in the frequency domain. Also, spectral analysis does not lend itself easily to prediction, often a major focus for economic analysis of time series. Here, however, I have a stationary time series (see below) with a complex lag structure, for which I am seeking explanation, rather than prediction. Thus, the use of spectral analysis seems appropriate.

It is not the intention to provide here a detailed exposition of spectral analysis; Granger & Hatanaka (1964), Hamilton (1994) and Chatfield (2006) provide three detailed treatments. Rather, I provide a brief overview of the procedures followed here. Spectral analysis is intimately linked with the autocovariance function and reveals a great deal about variance. In fact, it allows one to decompose variance into components of different frequency, and see how much smoother the series would be without each one.

The explanatory power each cycle has over variance can be shown via the periodogram, which contains all of the information in the autocovariannce function (all of the lags). However, periodograms are rarely used because, whilst they are unbiased, they are inconsistent; longer lags in the autocovariance function are based on very little information. Thus kernel estimators are used to derive a spectrogram, which is consistent, but which contains some bias (see Granger & Hatanaka, 1964). Many kernel estimators are possible (see Chatfield, 2006), but here I use the Tukey-Hanning estimator, which assigns a decreasing weight to each cycle, up to a certain period, and a zero weight to all those with longer periods. The three steps followed are as follows:

- First, the autocovariance function is specified, out to a certain lag length (or down to a certain frequency in the frequency domain), using the following formula:

  $$C_k = \frac{1}{n-k}\left\{\sum_{t=1}^{n-k} x_t x_{t+k} - \frac{1}{n-k}\sum_{t=1+k}^{n} x_t \sum_{t=1}^{n-k} x_t\right\}$$

  where n is the total sample size (441 here), and $k=0,1,2,\ldots M$ represents the lags of the variable in question, x.
- Next, the Tukey-Hanning weights are constructed thus:

  $$\lambda_k = \frac{1}{2}\left\{1 + \cos\left(\frac{\pi k}{m}\right)\right\}$$

- Finally, the spectrogram is estimated for the band centred around each (angular) frequency w_j:

$$\hat{f}(w_j) = \frac{1}{2\pi}\left\{\lambda_0 C_0 + 2\sum_{k=1}^{M} \lambda_k C_k \cos w_j k\right\}$$

Whilst the angular frequency is mathematically easiest to use, it is difficult to interpret. Thus, for all the spectrograms presented in this paper, the horizontal axis shows the frequency band in terms of its period ($2m/j$) rather than its angular frequency ($\pi j/m$). The derivation of the spectrogram as outlined above is relatively simple, but three issues are important to consider; the number of observations, the size of the truncation point M and the frequency of observations.

The number of observations will obviously influence the length of cycle which can be captured. Granger & Hatanaka (1964) suggest that five or six repetitions of a cycle are required before there is sufficient information to capture the cycle's characteristics. The very lowest frequency band captures not only the lowest frequencies which the data can reveal, but also all of the variation for which cycles are too long to be captured by the data. It can thus often be very large, particularly in economic data, where longer cycles are common. Petrol price cycles are roughly one week long. With 441 daily observations, there should be sufficient information to capture this cycle effectively.

The choice of the truncation point M influences the width of the frequency bands for which power is estimated. The wider are the bands, or the more smoothing is applied to the periodogram to derive the spectrogram, the greater is the likelihood that important information will remain buried. A larger M results in narrower bands, but also replicates the problems of consistency which plague the periodogram. Unfortunately, there is no clear, objective standard to judge which level of M is correct. However, Chatfield (2006) suggests the use of, $M=2\sqrt{N}$ is common in the literature. With 441 observations, this gives $M=42$. I examined different values of M for a small number of retail petroleum outlets and found no more cycles when a higher value of M was used, and lesser clarity in distinguishing between cycles of around a week in length when a smaller M was used. For this reason, $M=42$ is used in the analysis below.

In most cases, the frequency of observation is important for spectral analysis, due to the problem of aliasing. If the variable of interest changes with greater frequency than the frequency of observation, then it is not clear whether the power one observes at a particular frequency is really due to cycles of that frequency, or to some linear combination of frequencies with shorter period than the gap between observations. Here, however, this is less of an issue; the highest frequency captured is two days and by law, petrol stations can change their prices only once per day. Since one needs more than one change in a variable for a cycle to occur, there is no chance of aliasing. This will obviously not be the case in jurisdictions where intra-day variation in prices is possible.

Spectra of Perth's Retail Petroleum Outlets

This section presents the results of the spectral analysis for each of the 209 stations in the sample, for 441 days from January 1st 2003 to March 14th 2004. As noted previously, the spectral representation theorem applies only to covariance-stationary data. Thus, the first step of the spectral analysis is a test of the stationarity of the retail petroleum price data.[5] I tested this using a Philips-Peron unit root test (which has higher power in samples characterised by serial correlation or heteroscedasticity) on the price series for each station in the sample. Unit root tests have relatively low power. To increase the robustness of results, therefore, I undertook two unit root tests; one on the data ordered from t_0 to t_{441}, and one on the data ordered from t_{441} to t_0. The results of this analysis are shown in Figure Seven, which summarises those from tests undertaken on data ordered t_0 to t_{441}. The results of the reverse-order tests are very similar. The solid lines in Figure Seven represent critical values, and the diamonds (each set matching the colour of one line) show the test scores for each outlet in each of the six different specifications of the test which SHAZAM (2004) reports.

[5] I have not tested retail petroleum margins, also used in this paper. However, if prices are stationary, it seems unlikely that margins are non stationary, since they are just the prices minus the terminal gate price.

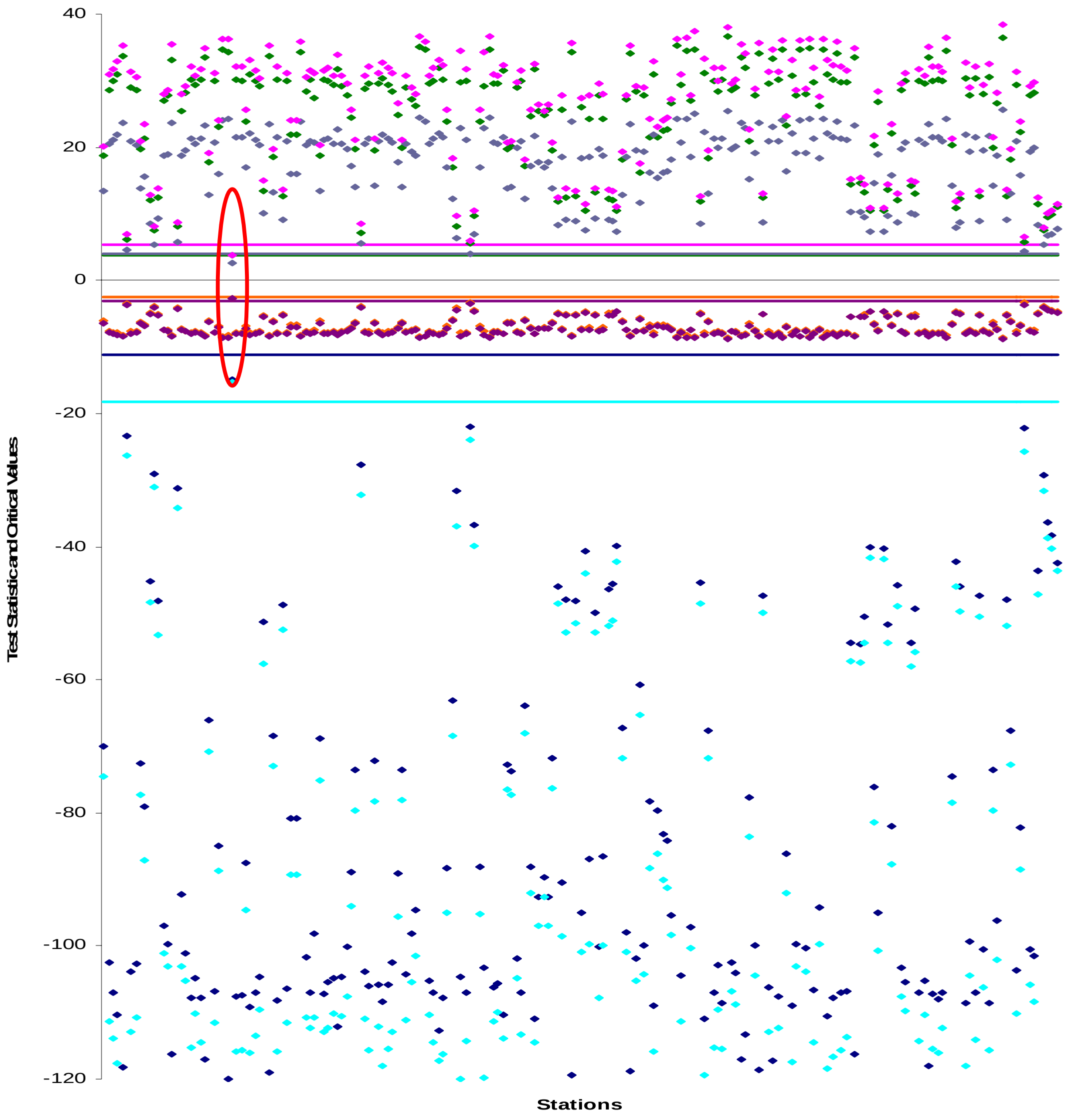

Figure 7: Unit Root Test Results

Aside from one outlet (circled in red) for which the null hypothesis was rejected in some versions of the test, all outlets rejected the null in all formulations of the test and in both orderings of the data. It thus seems unlikely that the data are non-stationary, and therefore reasonable to use spectral analysis.

Spectra for price levels and gross margins were estimated for all 209 stations. The results are shown in Figures Eight and Nine. In each, 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.

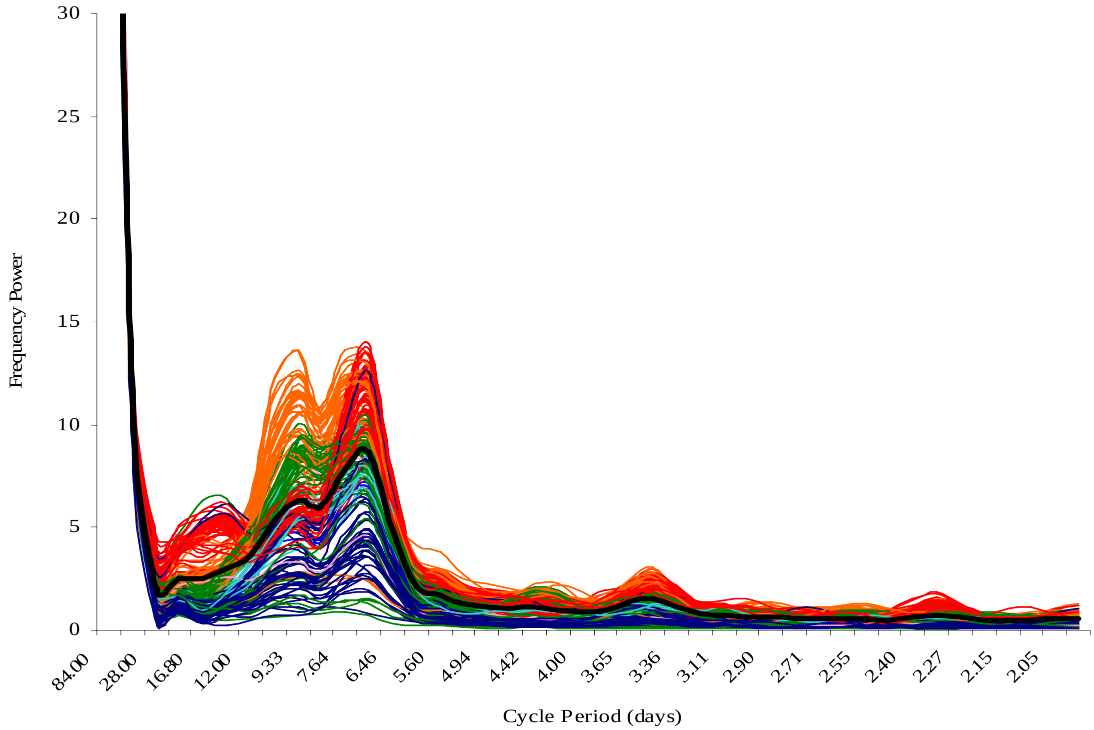

Figure 8: Spectra for Price Levels

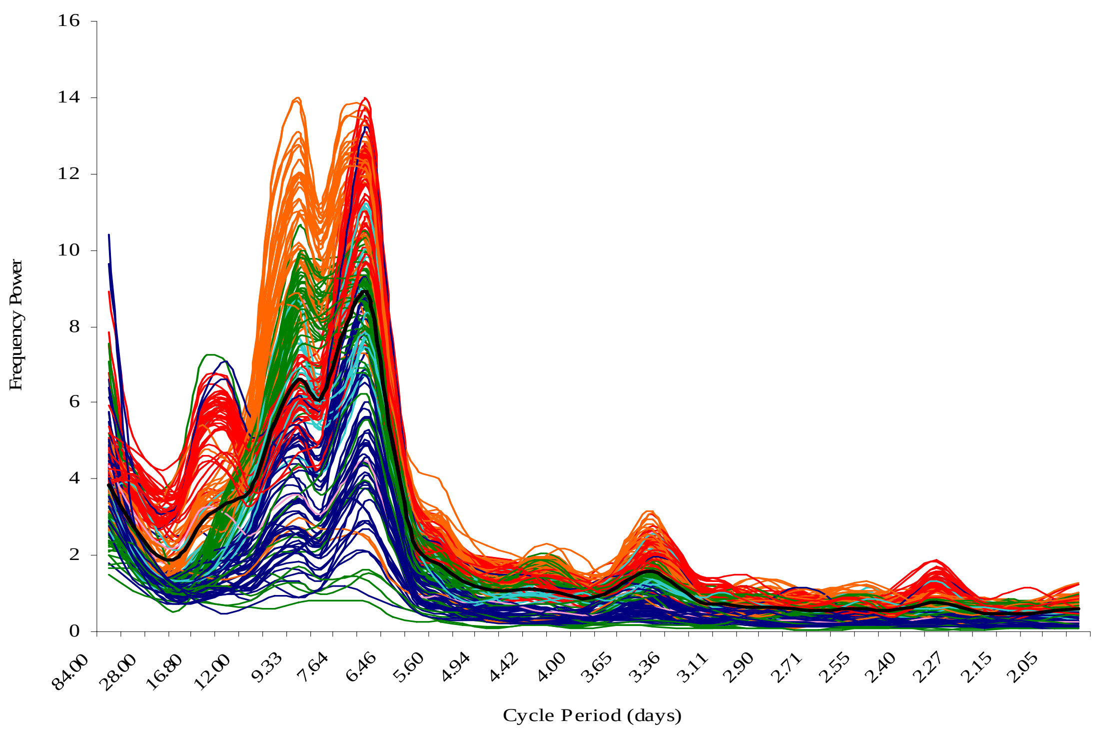

Figure 9: Spectra for Price Margins

The first and most obvious aspect of Figures Eight and Nine is the dual peak; whilst most of the Caltex-Ampol stations have peaks at seven days, BP and Shell stations show peaks at seven and ten days. Moreover, it is not the case that some of the BP or Shell outlets follow cycles of seven days and some follow cycles of ten. In fact, most BP and Shell outlets exhibit both seven and ten day cycles. In terms of strategy, they appear to randomise between the two cycle lengths.

The dual peak should not be surprising. Indeed, it is more intuitively logical than a single peak. If a retail petroleum outlet only followed one seven day cycle, this would become immediately obvious to all of its rivals, and indeed if a set of retail petroleum outlets all strictly followed seven day cycles, then they would very quickly be able to co-ordinate around this strategic equilibrium. Such co-ordination is, however, sub-optimal; if firms can co-ordinate, they should do so around the peak of each cycle, where profits are higher. Since cycles represent a failure of co-ordination, then they should logically not be so consistent that they can be easily guessed each time the outlets interact.

Two other sets of peaks exist. The first of these is in the lowest frequency band. It is much more pronounced in the prices spectrogram than in it is for margins. This suggests evidence of underlying long cycles in petroleum demand, which may be related to seasonal demand differences or a rising crude oil price. The low frequency peak in the margins spectrogram is much smaller than it is for prices, which is not surprising, as margins are less closely related to crude oil and wholesale price levels.

Peaks also occur at 21, 14 and 3.5 days. These are the harmonics of the seven-day price cycle. Since few cycles are perfectly sinusoidal, harmonics such as this are common in spectral analysis. All that they indicate is that the seven-day cycle is both important and not perfectly sinusoidal; they are not important cycles in their own right.

Importance of Seven and Ten Day Cycles

Figures Eight and Nine indicate that cycles of seven and roughly ten days are important. Moreover, they are not demonstrably tied to upstream factors such as changes in wholesale prices This raises two important questions:

- How important are these cycles?
- What drives them?

The first of these questions is addressed below, whilst the latter is addressed in the modelling in the following section.

The area under the spectrogram over a band of frequencies indicates the contribution of those frequencies to overall variance. Thus, the area under the seven and ten day cycles in each spectrogram will indicate the importance of these cycles. Put differently, it will indicate how much smoother price cycles would be likely to be without these two cycles.

Since 42 is not divisible by 10, I combine the two bands either side of this frequency, that centred around 9.33 and that centred around 10.55 days. Each has roughly equal power. Since these two cycles are combined, using the seven day cycle alone would give results that understate that cycle's importance relative to the nine and ten day cycle. Thus, I use two approaches. The first makes use of the concept of spectral leakage (see Granger & Hatanaka, 1964, pp132-4); some of the power of a particular bandwidth is due to its neighbours, as no spectral window is perfect at its edges, and is the sum of seven and 7.64 day cycles. The second makes use of harmonics, and is the sum of 21, 14, seven and 3.5 day cycle powers. In each case, the share of the seven-day cycle in the total is between a half and two thirds for most outlets. Figure Ten shows four histograms highlighting the distribution of cycle power. The seven day cycles refer to the sum of seven and 7.64 day cycles; the harmonic sums give similar results.

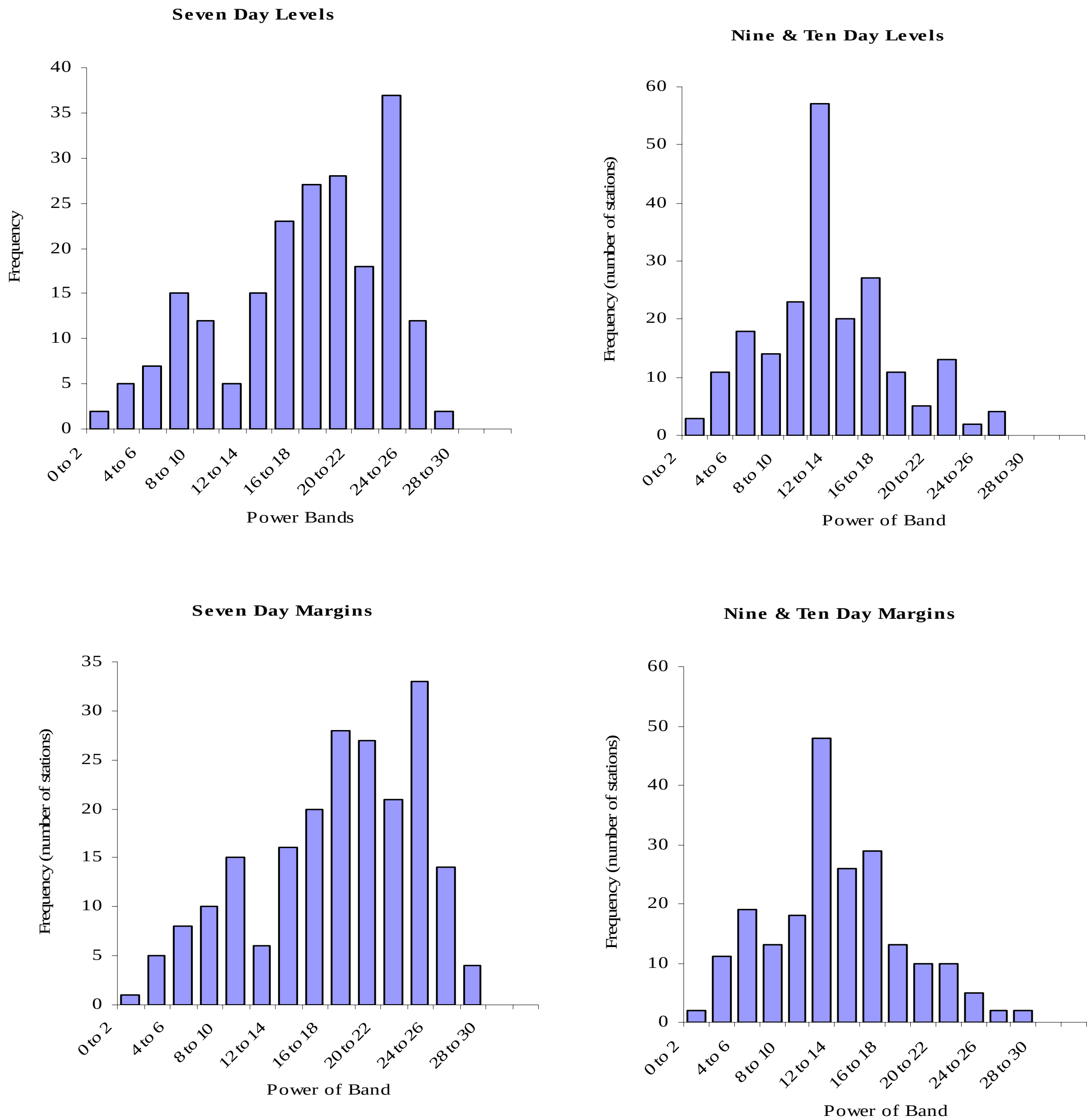

Figure 10: Power of Seven and Ten Day Cycles

On average, the seven day cycle contributes roughly ten percent of the variation in prices and 18-19 percent of the variation in margins. The figures for the nine and ten day cycle are roughly three-quarters of these figures, for both price levels and margins. This is useful for policymakers, for it indicates that removing these two cycles would reduce variability by only roughly a third and, as the econometric analysis below suggests, may increase prices at the same time.

Given an understanding of the contribution these cycles make to overall price variability, it remains to examine what drives this contribution. This is the task of the next section.

MODEL OF CYCLE DRIVERS

In order to explore what drives the seven and ten day cycles, I regress the power of each frequency for each outlet against a range of explanatory variables in a cross-sectional regression consisting of all retail outlets in the sample. Table One explains each of the variables, grouped into three categories.

Table One: Regression Model Explanatory Variables

Station Characteristics		
Variable Type	*Variable Name(s)*	*Variable Description*
Brand	*AM, BP, CAL, CW, GL, IND, LIB, MOB, PK, SH, WC*	10 dummy variables, one for each brand; Ampol, BP, Caltex. Caltex-Woolworths, Gull, independent, Liberty. Mobil, Peak, Shell and Wesco)
Location	*NM, SM, EM*	3 dummy variables, denoting North of the Swan River, South of the Swan River and on the Eastern fringe of the city
Type	*BI, CC, DC, I, LI, PS, SUP*	7 dummy variables indicating whether a station is a (major) branded independent, company controlled, distributor controlled, independent, a larger independent (Gull or Peak), price supported or a joint venture with a supermarket (just Woolworths).
Service	*CS, FS, NS*	3 dummy variables indicating the availability of conditional service, full service or no mechanical servicing.
Convenience Store	*BPC, CSM, CSS, MQ, SS*	5 dummy variables indicating whether the outlet has one of the majors' convenience stores; BP Connect, Caltex Starmart, Caltex Starshop, Mobil Quix or Shell Select.
Main Road	*MRD*	Dummy variable indicating whether an outlet is on a main road or a side street.
Number of Competitors	*COMP*	Number of competitors located within 5km of an outlet, with the distance measured along the shortest road route.
Distance to Competitor	*DISTC*	Distance to the nearest competitor via the shortest road route from each outlet.

Price Characteristics	
Variable Name	*Variable Description*
PID	Number of days when prices increase.
PRD	Number of days when prices decrease
AVMIN	Average gross margin at minimum retail price
MAXMIN	Average difference between the maximum and minimum of a price cycle
APRU	Average daily price reduction during the declining phase of the price cycle

Demand Characteristics	
Variable Name	*Variable Description*
MFY	Median family Income
AHHS	Average Household size
NA	Number aboriginal residents in the area
NP	Total number of persons in the area
NOS	Number born overseas in the area
NDC	Number of families with dependent children in the area
NSM	Number of families headed by a single mother in the area
NF	Total number of families in the area
NV	Average number vehicles per household
DD	Dwelling density (houses per square km)
NRD	Number of rented dwellings in the area
NSHCD	Number of state housing dwellings in the area
ND	Total number of dwellings in the area
ED	Number of inhabitants with post-school qualification
EMP	Number of inhabitants employed
PUBT	Number of inhabitants using public transport to travel to work

The data in the price characteristics group were simply drawn from the set of prices for each retail outlet. The data for station characteristics were mostly drawn from the Fuelwatch dataset from which the price data were drawn. The data for the number of nearby competitors and the distance to the nearest competitor was not drawn from the Fuelwatch dataset, but was calculated by hand for each station using an electronic version of the Perth street directory which contained simple distance-measuring software. Distances are not Euclidean, but are rather "as the car drives"; the shortest distance alonge the road network between each station. The five kilometre cut-off point is somewhat arbitrary, but it has some basis in the literature, which suggests retail petroleum stations influence each other's behaviour over roughly this distance (see Hastings, 2004, USSPSICGA, 2002 or FTC, 2001).

Demand-side data were drawn from the 2006 Australian Census Community Profiles (ABS, 2006). The choice of demand characteristics was drawn from the literature on demand elasticity for retail petroleum (see, for example, Nicol, 2003, Epsey, 1996, Kayser, 2000, Ridler & Greening, 1999 or Archibald & Gilligan, 1980). Community profile data at the post-code level were matched with the post-code of each retail petroleum outlet. Australia undertakes a census once every five years, and the 2006 census data were used over the 2001 data because the former were slightly easier to extract from the ABS website. There may be some bias in this approach, if the values of demand-side variables have changed in a relative sense between suburbs since 2003. However, any bias which results is likely to be smaller than that which results by assuming demand is associated with geographically localised areas, particularly for outlets which are located on major roads, and attract passing traffic from other areas.[6]

Model Results

Tables Two and Three below present the results of econometric modelling undertaken using the data summarised above in Table One. The models were estimated using standard ordinary least squares procedures, but with White's (1980) heteroscedasticity-consistent estimator to account for potential heteroscedasticity amongst the retail petroleum outlets.[7] As shown in Table One above, there are six families of dummy variables from which to choose, and four of them (Brand, Location, Type and Service) fully specify the data. Thus, one of these dummies must be dropped, or else the model will suffer from the dummy variable trap, and OLS estimation will no longer be possible due to perfect multi-collinearity. Due to the large number of dummies, the constant term was also dropped from the regression.

The approach followed was to try and obtain final models which were as close to each other as was practicable, in terms of the variables which are included. Also, as a general rule, I excluded dummies where the number of ones in the dummy vector was relatively high. This was a rather ad-hoc procedure which was designed to avoid the dummy variable trap. This was a concern because, with four such families of dummies, if the dummy removed in one family had only one or two ones in it, then it was much more likely that the remaining dummies across the four families, could be combined to form an orthogonal basis to the regression space. The likelihood was increased if two such 'rare-dummies' were removed.

Partly for 'rare-dummy' reasons, the dummy variable for "independents" within the "type" family above was always removed, in conjunction with other type dummy. Models which retained the independent dummy in this family but removed another all performed poorly. Also, since there is only one joint venture between a supermarket chain and a major (the Caltex-Woolworths joint venture), the brand dummy CW is identical to the type dummy "SUP". Thus, CW was removed from the analysis. Changing the location dummy or the service dummy made no difference to results. Since it did not matter which of these was removed, each model is presented with SM and CS removed. Changing the brand dummy which was removed and the type dummy which was removed did influence results. This is because branding and type are fairly closely tied together (see Figures Three and Four and associated discussion). I thus experimented with different removal combinations until obtaining the most robust results.

[6] This assumption was necessary, given the lack of any other information on where an individual retail petroleum outlet's customers come from. Commuter traffic is an important source of out-of-area demand in many cities (See, for example, Marvel, 1976). In Perth, this is likely to be less important, given that the CBD is the dominant work location, and travel into the CBD is largely along freeways, which contain no retail petroleum outlets. Some bias, however, remains.

[7] The LM test statistics from the Breusch-Pagan tests for heteroscedasticity ranged from 5.6 to 21.6. The critical value is 3.84 (at the five percent level of significance) and hence all models exhibit heteroscedasticity.

In terms of demand and price characteristics, the discussion above suggests a number of variables which might be important, but many of those shown in Table One transpired not to be statistically significant. This lack of statistical significance was quite robust across model specifications. To ascertain which of the price and demand-side variables might safely be removed, I first undertook an F-test for each of those which was not significant in the fully-specified model, to ascertain whether the explanatory power of a model which included these variables (individually) was greater than one which did not. In no case did the F-test results suggest this was the case. I then took out each of these non-significant variables in turn, and examined whether their removal altered the significance of any of the remaining price and demand variables. Where a variable did nothing, it was discarded. Where its removal did alter the significance of another demand or price variable (all of these made either PUBT or EMP significant, none had any other effect), I kept them in, and went through the same procedure again; with models that had eliminated all the variables which had no effect, I went through and removed each of the non-significant variables in turn, to ascertain whether such removal changed the significance of any other variable. I also examined whether the removal of all non-significant variables except each one in turn changed the significance of any other demand or price variable. The results of all of this testing were fairly consistent; the only variable which became statistically significant was PUBT, and when PUBT was the removed variable, EMP became statistically significant. I therefore kept these two variables. Thus, the models in Tables Two and Three, in terms of the price and demand variables (as specified in Table One above) contain all of those variables which were statistically significant in the original, unrestricted models, plus EMP and PUBT. It is worth nothing that these changes in price and demand variables did not alter the significance of coefficients elsewhere in each model.

One final point of note before the results are presented. There were very few differences between the seven-day cycle results which were obtained by combining seven, and 7.64 day cycle frequencies, and those which were obtained using the harmonics of the seven-day cycle. To save space, just the results of the former are presented below.

Tables Two and Three present the results of the price level models and margins models respectively. There are four models in each case; two for the seven-day cycle (one omitting BP and one Caltex) and two for the nine and ten-day cycles. Since the data are not time series data, I do not test for serial correlation. In each case, the R^2 and adjusted R^2 show that the models indicate good fit. The model specification tests (the F-tests) show the models are unlikely to be mis-specified, and the tests on the normality of the residuals show that the t and F statistics are reliable, and that the model has the correct functional form.

Table Two: Price Levels Model Results

	Price Levels, 7 Day Cycle				Price Levels, 9&10 Day Cycle			
	CAL, SM, PS & CS Out		BP, SM, CC & CS Out		CAL, SM, PS & CS Out		BP, SM, CC & CS Out	
Variable Name	Estimated Coefficient	t-Ratio	Estimated Coefficient	t-Ratio	Estimated Coefficient	t-Ratio	Estimated Coefficient	t-Ratio
AM	0.1709	0.2953	1.6921	3.5730	0.5026	0.9776	-4.1991	-7.1640
BP	-1.7571	-3.1500			4.6832	10.2900		
CAL			1.3594	2.4790			-4.8958	-11.3600
GL	0.1187	0.1330	1.8607	2.4020	3.9178	4.1660	-0.8522	-1.1060
IND	0.0854	0.0843	1.8606	1.8650	1.5998	2.1770	-2.7890	-3.8860
LIB	-0.2346	-0.2349	1.4222	1.6720	4.4279	6.6810	-0.2418	-0.4449
MOB	-1.9754	-2.1320	-0.5093	-0.6651	2.2925	2.4700	-2.2304	-2.8710
PK	-0.2701	-0.2651	1.6972	1.9760	3.4638	3.5520	-1.5884	-2.0190
SH	0.1604	0.2345	1.8245	3.7610	7.9181	13.4100	2.8689	6.8920
WC	2.4746	2.0570	4.2705	3.7380	4.1394	3.8600	-0.7215	-0.8394
EM	0.3079	0.9744	0.2542	0.7956	0.0775	0.2383	0.0696	0.2304
NM	-0.0870	-0.3861	-0.0773	-0.3331	0.2482	1.2270	0.2551	1.3460
CC	-0.2761	-0.6157			-0.1486	-0.4422		
LI	-0.2104	-0.2331	-0.1805	-0.2191	-2.1272	-2.1260	-1.6929	-1.9510
DC	-1.3751	-1.3810	-1.3605	-1.5180	-0.3588	-0.6898	-0.2764	-0.6803
BI	-0.2115	-0.3088	-0.2073	-0.4066	-3.8675	-4.7150	-3.4522	-4.8700
PS			0.2199	0.4859			0.0567	0.1761
SUP	-2.3360	-3.5820	-0.4956	-0.8295	3.0908	3.3080	-1.5245	-1.7810
FS	0.0316	0.0696	0.0176	0.0384	-0.5888	-1.1750	-0.5037	-1.0500
NS	0.0196	0.0823	-0.0361	-0.1490	-0.1324	-0.5830	-0.1002	-0.4844
BPC	-0.2312	-0.7592	-0.4351	-1.3970	-0.5441	-1.6040	-0.6410	-1.9970
CSM	0.7170	1.5510	0.9194	1.9410	0.1235	0.3859	0.2439	0.8518
CSS	0.4825	0.9262	0.6757	1.2780	0.1599	0.4222	0.3821	1.1330
MQ	0.4970	0.6111	0.4948	0.6144	-0.4311	-0.4622	-0.4076	-0.4681
SS	0.2923	0.4167	0.2573	0.3659	0.7653	0.8443	0.7804	0.9503
MRD	-0.0247	-0.0864	-0.0592	-0.2050	-0.1506	-0.6360	-0.0224	-0.1028
COMP	-0.0621	-2.1800	-0.0669	-2.2910	0.0213	0.7153	0.0349	1.2590
DISTC	-0.0095	-0.0693	-0.0218	-0.1564	0.0921	0.8232	0.0738	0.6996
NMIN	0.1261	5.8610	0.1253	5.6640	0.0821	4.4220	0.0822	4.7800
PID	-0.0530	-2.6570	-0.0626	-3.1060	-0.0010	-0.0585	0.0149	0.8945
AVMIN	-0.8821	-4.6140	-0.9641	-4.7890	-0.3795	-1.9290	-0.2159	-1.1870
MAXMIN	2.8601	15.7400	2.8284	15.0400	1.5585	8.5980	1.7017	10.1500
NV	-4.7414	-4.1150	-5.2474	-4.4420	-4.4141	-3.7970	-2.9334	-2.7270
DD	0.0017	2.8890	0.0017	2.8940	-0.0008	-1.4140	-0.0009	-1.6700
NSHCD	-0.0018	-3.8620	-0.0019	-3.8430	-0.0013	-3.3560	-0.0009	-2.6860
ED	0.0002	2.1060	0.0002	2.1310	0.0002	2.2500	0.0002	2.0110
EMP	0.0002	2.1560	0.0002	2.2030	0.0000	-0.0728	0.0000	-0.6464
PUBT	-0.0028	-4.7760	-0.0030	-4.8470	-0.0009	-1.9300	-0.0005	-1.0410
Model Robustness and Diagnostic Test Results								
R^2	0.9546		0.9527		0.9436		0.9510	
Adjusted R^2	0.9454		0.9432		0.9322		0.9411	
Normality of Residuals	62.9414 (22 df)		66.4859 (22 df)		85.1756 (22 df)		66.7175 (22 df)	
Model specification	876.146		841.249		526.130		607.039	

Table Three: Price Margins Models Results

	Price Margins, 7 Day Cycle				Price Margins, 9&10 Day Cycle			
	CAL, SM, PS & CS Out		BP, SM, SUP & CS Out		CAL, SM, PS & CS Out		BP, SM, SUP & CS Out	
Variable	Estimated	t-Ratio	Estimated	t-Ratio	Estimated	t-Ratio	Estimated	t-Ratio
AM	0.3307	0.6251	1.5861	3.6390	0.3842	0.7043	-4.4095	-7.3970
BP	-1.3305	-2.3790			4.8805	10.4400		
CAL			1.1144	2.0320			-4.9672	-11.0700
GL	0.7674	0.8602	2.0906	2.7920	4.0694	4.5600	-0.8799	-1.2250
IND	0.5479	0.5231	1.7110	1.3960	1.4782	2.0730	-2.4604	-2.1570
LIB	0.4938	0.4853	1.7541	2.0280	4.7254	6.7740	-0.1344	-0.2275
MOB	-2.4407	-2.8480	-1.1224	-1.6630	3.4679	3.5800	-1.0786	-1.2870
PK	0.4685	0.4580	2.0357	2.4180	3.6749	3.8930	-1.4561	-1.8970
SH	0.7477	1.0930	2.0534	4.2030	8.0499	13.4000	2.9053	6.9680
WC	3.2744	2.7070	4.7082	4.1950	4.5497	4.4470	-0.4161	-0.5083
EM	0.3368	1.0560	0.3535	1.0950	0.0823	0.2509	0.1293	0.4285
NM	-0.1192	-0.5168	-0.1654	-0.7069	0.2853	1.4170	0.2427	1.2600
CC	-0.3374	-0.7663	-0.5444	-0.7439	-0.0977	-0.2807	0.5000	0.5603
LI	-0.3391	-0.3821	-0.4496	-0.4589	-2.6134	-2.7280	-1.5109	-1.2970
DC	-1.5559	-1.4390	-1.8408	-1.4880	-0.4701	-0.9223	0.1901	0.1990
BI	-0.3267	-0.4842	-0.5545	-0.6830	-4.1145	-4.9700	-3.1146	-2.8290
PS			-0.2599	-0.3042			0.5132	0.5416
SUP	-2.2679	-3.5290			3.1862	3.4190		
FS	0.0513	0.1146	0.0257	0.0585	-0.5366	-1.1640	-0.4777	-1.0970
NS	-0.0188	-0.0780	-0.0873	-0.3615	-0.0885	-0.3885	-0.0826	-0.3965
BPC	-0.2125	-0.6840	-0.2240	-0.6997	-0.5482	-1.5900	-0.4934	-1.5200
CSM	0.7446	1.5870	0.9294	1.9460	0.0627	0.1936	0.1842	0.6264
CSS	0.4798	0.9052	0.6797	1.2810	0.1691	0.4496	0.3967	1.1660
MQ	0.6006	0.8285	0.6344	0.8982	-0.3377	-0.3463	-0.2861	-0.3071
SS	0.1831	0.2564	0.1721	0.2392	0.7075	0.7938	0.7356	0.8935
MRD	-0.0856	-0.3061	-0.1294	-0.4572	-0.0869	-0.3812	0.0069	0.0331
COMP	-0.0650	-2.2350	-0.0704	-2.3960	0.0213	0.7195	0.0314	1.1160
DISTC	-0.0044	-0.0311	-0.0087	-0.0612	0.0849	0.7621	0.0743	0.7030
NMIN	0.1296	5.9470	0.1292	5.7990	0.0800	4.3790	0.0803	4.6560
PID	-0.0531	-2.6090	-0.0616	-3.0040	-0.0024	-0.1366	0.0104	0.5858
AVMIN	-0.8908	-4.6590	-0.9015	-4.5130	-0.3973	-2.0490	-0.2098	-1.1680
MAXMIN	2.9039	15.9200	2.9432	15.3500	1.5880	8.7280	1.7668	10.1200
NV	-5.0307	-4.2920	-5.5566	-4.5870	-4.3129	-3.7120	-3.1707	-2.7640
DD	0.0017	2.8140	0.0018	2.9780	-0.0007	-1.3050	-0.0007	-1.3650
NSHCD	-0.0018	-3.8760	-0.0019	-3.8220	-0.0013	-3.3460	-0.0010	-2.7250
ED	0.0003	2.2680	0.0003	2.2650	0.0002	2.3760	0.0002	2.1200
EMP	0.0001	2.0250	0.0002	2.0920	0.0000	-0.1002	0.0000	-0.5374
PUBT	-0.0029	-4.9330	-0.0031	-5.0060	-0.0010	-2.1020	-0.0006	-1.3490
Model Robustness and Diagnostic Test Results								
R^2	0.9518		0.9533		0.9470		0.9543	
Adjusted R^2	0.9420		0.9438		0.9363		0.9450	
Normality of Residuals	52.2747 (22 df)		60.3923 (22 df)		69.4807 (22 df)		84.5310 (22 df)	
Model specification	842.190		869.572		560.890		650.741	

The results of the price levels and margins models are very similar, indicating that both are yielding roughly the same information about the underlying data. Examining the variables by family, and taking branding first, the most obvious characteristic is the different between BP and Caltex. BP outlets have a significant positive coefficient for nine and ten-day cycles, and a significant, negative coefficient for seven-day cycles. This suggests that, relative to Caltex being a BP reduces the amplitude of a seven day cycle and increases the amplitude of a nine and ten-day cycle. For Caltex, the opposite is true. By contrast, Shell is positive in both models, indicating that it has larger seven-day cycles than Caltex, and larger nine and ten-day cycles than BP. This suggests that, whilst all three brands might randomise between cycles, Caltex outlets favour seven day cycles, BP outlets favour nine and ten-day cycles and Shell outlets use both roughly equally. None of the other brands give consistent results of the same clarity. However, it seems that Gull outlets tend to follow the longer cycle with greater prevalence, whilst Wesco outlets tend to randomise, like Shell.

Location, service and the presence of a convenience store tell us almost nothing about the likelihood of either type of cycle that we do not already know from other characteristics. The former two are unsurprising; location effects may in fact be being picked up by some of the demand-side variables, whilst the fact that full or partial service outlets are generally independent or branded independent outlets means the relevant type characteristics might be picking up the relevant effects. The convenience store variables are interesting, however. If convenience stores use fuel as a loss-leader, then one might expect that these outlets cycle less, using consistently low prices to attract customers. However, this is not the case; such outlets appear little different in their cycles from their parent brands.

The results for type are somewhat intertwined with those for brand, as the discussion following Figure Three suggests. The clearest results come from the SUP variable which, since Caltex-Woolworths is the only supermarket joint venture during the same period, suggests that these outlets favour a longer cycle over a shorter cycle as BP does. This is interesting, given that one part of the joint venture, Caltex, predominantly uses seven-day cycles. The other variable of interest here is branded independents; although the coefficient is not statistically significant for seven-day cycles, it is negative for both types of cycle, which indicates that branded independents tend not to follow cycles. This is reinforced by the negative AVMIN results, which suggest that those outlets with higher gross margins (usually branded independents not benefiting from price supports) have less of a tendency to cycle. This result is important for policymakers, for it suggests that, perhaps, larger cycles are the trade-off the market makes for having lower margins, and hence prices, during parts of the cycle.

Main road location does not appear to be important, which is unsurprising, as most of the outlets are on main roads. The results for the number of competitors within a five-kilometre drive and the distance to the nearest competitor results are more interesting, because the former has statistically significant results (at least for seven-day cycles) but the latter does not. Given that Perth is not a particularly densely populated city, these results should perhaps not be surprising; it does not take long to travel 5km on Perth's roads.

The fact that the variable for the number of competitors is negative and significant for seven-day cycles but not for nine and ten day cycles is, perhaps, indicative of the effects of competition. More outlets in close proximity should be associated with more competition, and it is thus unsurprising that this would reduce the amplitude of cycles. What is surprising is that it reduces the amplitude of the shorter seven-day cycles, but does not appear to have the same effect on the longer nine and ten-day cycles. Perhaps, therefore, an increase in competition leads to longer cycles, as the competitive rivals are more wary of raising price to signal the end of the cycle. This casts the ACCC's (2007) finding that the more recent Perth market exhibits longer cycles in a different light, suggesting that it has become more competitive during a time when the supermarkets have increased their market share, not less competitive. To explore this issue more fully, one would also need to examine price levels (and extend the analysis to the present day), which is beyond the scope of this analysis, but perhaps indicative of useful future work.

The results for the number of minima and the MAXMIN variable are unsurprising; both are positive and significant, suggesting, rather obviously, that more minima are associated with more cycles and that those with a large difference between their maximum and minimum prices over the few days when a price change occurs are more likely to cycle. The negative coefficient on the number of price increase days is perhaps reflective of the fact that many independents brands (like Gull) often increase prices over two days, rather than one. However, the lack of significance makes it difficult to interpret much from these results.

Finally, when turning to demand side results, the strongest results come from the number of vehicles. Indeed these are the largest coefficients in most of the regressions, meaning perhaps that they are picking up additional factors pertaining to the uniqueness of each suburb as a local market. In contrast to the results for the number of competitors, both shorter and longer cycles have smaller amplitudes when there are more cars in surrounding households. However, supporting the findings associated with the numbers of competitors, the negative effects on nine and ten-day cycles are smaller. Public transport also has a negative coefficient (albeit only for shorter cycles), which perhaps suggest that retail outlets compete harder in areas where people are less likely to choose their car for commuting trips. The amount of public housing also has a negative effect, suggesting perhaps that income effects drive greater competition in poorer areas, where petrol is likely to take up a larger share of the family budget. In both cases, however, the effects are very small.

The demand-side variables with positive coefficients are those for dwelling density, education and employment. All the effects are very small, and they are only significant for the seven-day models. It is not clear what these variables are indicating. Perhaps, where customers are more well-informed, retailers vary price more often to negate some of the benefits of being better-informed. Again, however, these results are rather small, and it is difficult to conclude much that is conclusive from them.

CONCLUSIONS

This paper set out to establish a greater understanding of the nature and the drivers of cycles in the Perth retail petroleum market. In terms of their nature, it appears that the relevant cycles of importance are not just a weekly cycle, but actually a cycle of roughly a week, and another of roughly ten days. In fact, it seems that individual outlets will often randomise between these two cycles in an effort to seek comparative advantage over nearby rivals.

In terms of explaining the drivers of cycles, branding is clearly important; Caltex outlets tend to favour shorter cycles, whilst BP, Gull and Caltex-Woolworths tend to favour longer ones. Shell and Wesco apply both roughly equally. Very little else about the stations themselves has additional explanatory power, except that branded independents tend to cycle less. Interestingly, despite their using petrol as a loss-leader, convenience stores do not cycle in a manner which is demonstrably different from their parent company.

Branding is not the only driver of cycles; local market conditions also have an impact. This is most strongly reflected through car ownership, and less so through car use for work. An increase in both of these is associated with longer cycles, perhaps suggesting that as competition increases, cycle length increases, as firms are less willing to lead prices up again into the next cycle. The number of competitors nearby also suggests similar effects. By contrast, where education and employment levels are higher, short cycles have greater amplitude, which might indicate outlets changing prices more rapidly to counteract the effects of better-informed customers. However, these effects are very weak.

The results of this study shed some light on why the ACCC (2007) might have found price cycles enigmatic. Whilst demand-side factors appear to have some role, this is largely location specific, and might be lost if one were to examine the market as a whole. Moreover, whilst it is possible to differentiate differences in behaviour between brands, there is no logical reason why a given brand might adopt a particular randomisation strategy.

BIBLIOGRAPHY

Allvine, P & Patterson, J, 1974, *Highway Robbery: An analysis of the gasoline crisis*, Indiana University Press: Bloomington Indiana.

Archibald, R & Gillingham, R, 1980, "An Analysis of the Short-Run Consumer Demand for gasoline Using Household Survey Data", *Review of Economics and Statistics*, 62(4), 622-28.

Australian Bureau of Statistics (ABS), 2006, *2006 Census of Population and Housing*.

Australian Competition and Consumer Commission (ACCC), 2004, *Assessing Shooper-Docket Petrol Discounts in the Petrol and Grocery Sectors*, February 2004, ACCC: Canberra.

Australian Competition and Consumer Commission (ACCC), 2007, *Petrol Prices and Australian Consumers: Report of the ACCC inquiry into the price of unleaded petrol*, December 2007, ACCC: Canberra

Baxter, M, 1991, "Business Cycles, Stylized Facts, and the Exchange-Rate Regime: Evidence from the United-States", *Journal of International Money and Finance,* 10(1), 71-88.

Brooks, C & Hinich, MJ, 2006, "Detecting Intraday Periodicities with Application to High Frequency Exchange Rates", *Journal of the Royal Statistical Society Series C-Applied Statistics*, 55(2), 241-59.

Castanias, R & Johnson, H, 1993, "Gas Wars: Retail Gasoline Price Fluctuations", *The Review of Economics and Statistics*, 75(1), 171-4.

Chatfield, C, 2006, *The Analysis of Time Series: An introduction (6th ed)*, CRC Press: Boca Raton Florida

Clemhout, S & Neftci, SN, 1981, "Policy Evaluation of Housing Cyclicality - A Spectral-Analysis", *Review of Economics and Statistics*, 63(3), 385-94.

Comanor, WS & Riddle, JM, 2003, "The Costs of Regulation: Branded open supply and uniform pricing of gasoline", *International Journal of the Economics of Business*, 10(2), 135-55.

Diebold, FX & Rudebusch, GD, 1990, "Nonparametric Investigation of Duration Dependence in the American Business-Cycle", *Journal of Political Economy*, 98(3), 596-616.

Eckert, A, 2003, "Retail Price Cycles and the Presence of Small Firms", *International Journal of Industrial Organization,* **21** 151-70.

Englund, P, Persson, T & Svensson, L, 1992, "Swedish Business Cycles - 1861-1988", *Journal of Monetary Economics,* 30(3), 343-71

Epsey, M, 1996, "Explaining the Variation in Elasticity Estimates of Gasoline Demand in the United States: A meta-analysis", *Energy Journal*, 17(3), 49-60.

Grace, MF & Hotchkiss, JL, 1995, "External Impacts on the Property-Liability Insurance Cycle", *The Journal of Risk and Insurance*, 62(4), 738-754.

Granger, C. W. J. (1966), "The Typical Spectral Shape of an Economic Variable", *Econometrica*, 34(1), 150–61.

Granger, CWJ & Hatanaka, M, 1964, *Spectral Analysis of Economic Time Series*, Princeton University Press: Princeton NJ.

Hamilton, 1994, *Time Series Analysis,* Princeton University Press: Princeton, NJ

Hastings J, 2004, "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical evidence from contract changes in Southern California", *American Economic Review*, **94(1)** 317-28.

Jagric, T, 2002, "Measuring business cycles - The case of Slovenia", *Eastern European Economics*, 40(1), 63-87.

Kayser, HA, 2000, "Gasoline Demand and Car Choice: Estimating gasoline demand using household information", *Energy Economics,* 22, 331-48

Kim, S & In, F, 2003, "The relationship between financial variables and real economic activity: Evidence from spectral and wavelet analyses", *Studies In Nonlinear Dynamics And Econometrics*, 7(4), Article 4.

Levy, D & Dezhbakhsh, H, 2003, "On the Typical Spectral Shape of an Economic Variable", *Applied Economics Letters,* 10(7), 417-23.

Marvel, HP, 1976, "The Economics of Information and Retail Gasoline Pricing: An empirical analysis", *Journal of Political Economy*, vol84 no5 pp1033-60.

Maskin E & Tirole J, 1988, "A Theory of Dynamic Oligopoly II: Price competition, kinked demand curves and Edgeworth Cycles", *Econometrica* **56(3)** 571-99.

Michael R. Pakko MR, 1994, "A Spectral Analysis of the Cross-Country Consumption Correlation Puzzle", *Economics Letters*, 84, 341–7.

Nicol, CJ, 2003, "Elasticities of Demand for Gasoline in Canada and the United States", *Energy Economics*, 25, 201-14.

Noel, MD, 2007a, “Edgeworth Price Cycles, Cost-Based Pricing and Sticky Pricing in Retail Gasoline Markets”, *Review of Economics and Statistics*, **89(2)** 324-34
Noel, MD, 2007b, “Edgeworth Price Cycles: Evidence from the Toronto retail gasoline market”, *Journal of Industrial Economics*, **55(1)** 69-92.
Orlov, AG, 2006, “Capital Controls and Stock Market Volatility in Frequency Domain”, *Economics Letters*, 91(2), 222-8.
Puller, SL & Greening, LA, 1999, “Household Adjustment to Gasoline Price Change: An analysis using 9 years of US survey data”, *Energy Economics,* 21, 37-52.
Rausser, GC & Cargill, TF, 1975, “The Existence of Broiler Cycles: An application of spectral analysis”, *American Journal of Agricultural Economics*, 52(1), 109-121.
Rua, A & Nunes, LC, 2005, “Coincident and Leading Indicators For the Euro Area: A frequency band approach”, International Journal of Forecasting, 21(3), 503-23.
SHAZAM 2004, *User’s Reference Manual Version 10*, Northwest Econometrics, Vancouver.
Slade, ME, 1982, “Cycles in Natural-Resource Commodity Prices: An analysis of the frequency-domain”, *Journal of Environmental Economics and Management*, 9(2), 138-48
United States Federal Trade Commission (FTC), 2001, *Factors That Affect Prices of Refined Petroleum Products*, Proceedings of a public workshop, Aug 2nd 2001, mimeo.
United States Senate Permanent Subcommittee on Investigations: Committees of Government Affairs (USSPSICGA), 2001, *Gas Prices: How are they really set?*, mimeo.
WA Senate Committee of the Pricing of Petroleum Products, 2000, *Getting a Fair Deal for Western Australian Motorists*, WA Legislative Assembly, Perth WA.
Wang, Z, 2005a, *Strategy, Timing and Oligopoly Pricing: Evidence from a repeated game in a timing-controlled gasoline market,* Northeastern University, Department of Economics Working Paper, September 2005.
Wang, Z, 2006, *Endogenous Timing in Oligopoly Pricing: Evidence from a repeated game in the field”,* Northeastern University, Department of Economics Working Paper, October 2006.
Wang, Z, 2007a, *Do Firms Play Mixed Strategies? Evidence from relenting patterns in wars of attrition*, Northeastern University, Department of Economics Working Paper, May 2007.
Wang, Z, 2007b, *Station Level Gasoline Demand in a Market with Price Cycles*, Northeastern University, Department of Economics Working Paper, July 2007.
Weiss, JS, 1975, “A Spectral Analysis of World Cocoa Prices”, *American Journal of Agricultural Economics*, 52(1), 122-126.
White H, 1980, “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity”, *Econometrica*, **48** 817-38.
Wilson, P & Okunev, J, 1999, “Spectral Analysis of Real Estate and Financial Assets Markets”, *Journal of Property Investment & Finance*, 17(1), 61-74