THE UNIVERSITY OF
MELBOURNE

Department of Economics

Working Paper Series

Search and Stockpiling in Retail Gasoline Markets

David P. Byrne, Nicolas de Roos

May 2014

Research Paper Number 1181

ISSN: 0819 2642
ISBN: 978 0 7340 4531 7

Search and Stockpiling in Retail Gasoline Markets*

David P. Byrne
University of Melbourne
byrned@unimelb.edu.au

Nicolas de Roos
University of Sydney
nicolas.deroos@sydney.edu.au

May 21, 2014

Abstract

This note presents some simple, direct tests for search and dynamic demand behavior in retail gasoline markets. We exploit a unique market-level dataset that allows us to directly measure search intensity with daily web traffic data from a gasoline price reporting website, and perfectly measure daily changes in price levels and dispersion. We find stark evidence of both search and stockpiling behavior.

JEL Codes: D8, L8
Keywords: search, dynamic demand, retail gasoline

*Corresponding author: David P. Byrne, Department of Economics, University of Melbourne, The FBE Building Level 4, 111 Barry Street, Carlton, 3010, Victoria, Australia. We are grateful to the Fuelwatch team at the Western Australian Government for their cooperation in this project, and the Melbourne School of Government for funding. Seminar participants at The University of Melbourne have provided various helpful comments. Daniel Tiong provided excellent research assistance. The views in this article solely represent those of the authors. All errors and omissions are our own.

1 Introduction

Searching for deals across an array of products at a point in time, or for a given product over time, is a problem virtually all consumers solve in retail markets. Anticipating future sales is a particularly important part of intertemporal search in markets for storable goods, where stockpiling is possible. Identifying whether such cross-sectional or intertemporal search behavior exists, and what form it takes, is important as it helps explain violations of the Law of One Price, intertemporal price dispersion, and sources of market power.

While consumer search is pervasive, empirically identifying cross-sectional or intertemporal search in the data is a non-trivial task. This is largely because search intensity and/or search costs are difficult to directly measure. Given this constraint, many researchers have taken indirect approaches to identification. On the cross-section, researchers have claimed that the observed variability in retail prices across products or firms at a point in time are best explained by the existence of unobserved search costs, and hence search behavior.[1] When individual-level (scanner) data on prices and quantities for a storable good are available, researchers have similarly inferred from the temporary rise in quantity sold after a sale that stockpiling and hence intertemporal search exists.[2]

In this note, we exploit a unique retail gasoline dataset that permits simple, direct tests of both cross-sectional and intertemporal search behavior. Three key features of the data permit such an analysis. First, we have a direct measure of daily search at the market level: the number of daily hits from a comprehensive gasoline price reporting website.[3] Second, the data

[1]For example, Sorensen (2000) finds pharmaceuticals that require more frequent purchases (and hence more search activity) have less disperse prices. Brown and Goolsbee (2002) show life-insurance markets become more competitive after the internet was introduced (which presumably lowered search costs in comparing prices). Chandra and Tappata (2011) find price dispersion among more geographically disparate gasoline stations (which consumers presumably face higher search costs in determining the lowest-priced station) exhibit larger price dispersion. Another indirect test comes from Lewis (2011) who infers from “rockets and feathers pricing” (Peltzman 2000) that search is more responsive to past price increases than decreases.

[2]See Hendel and Nevo (2006b) for a reduced-form analysis that makes this inference, and Erdem, Imai, and Keane (2003) and Hendel and Nevo (2006a) for structural analyses. Seiler (2013) is a particularly relevant study since he explicitly introduces cross-sectional search costs into a dynamic demand model.

[3]We therefore follow a recent strategy of measuring search behavior and testing search models with web usage data. See, for example, De Los Santos, Hortacsu, and Wildenbeest (2012).

contain the universe of station-level prices, which allows us to perfectly measure market-level price dispersion. We can therefore directly test for a positive relationship between search intensity and price dispersion, and hence cross-sectional search behavior. Third, the retail prices in our data exhibit regular price jumps that consumers can potentially anticipate, permitting savings through careful stockpiling. These price dynamics allow us to test whether search rises in advance of price jumps.[4]

Our tests reveal both forms of search are statistically and economically significant and the mechanisms we identify are likely to exist in gasoline markets more broadly. The results therefore have implications for academic research on industry models for retail gasoline. To date, prominent models in the literature presume myopic consumers. We find a notable presence of sophisticated consumers who appear to engage in both cross-sectional *and* intertemporal search behavior. These results also relevant for competition authorities who use price transparency policies to subsidize search costs, promote competition, and increase consumer welfare in gasoline markets.

The note's main contribution is to the aforementioned empirical literature on search in retail markets. Our innovation lies in the simplicity and transparency of our tests compared to previous studies; indeed, we cannot find a previous direct test that matches a market-level search measure to perfect measures of market-level price dispersion. The importance of such a matching cannot be understated given that the positive demand-side relationship between search intensity and price dispersion underpins the entire consumer search theory literature.[5]

We also contribute to the empirical literature on retail gasoline demand. We are most closely related Lewis and Marvel (2011) and Byrne, Leslie, and Ware (2014). The prior paper uses a similar search measure to ours – the number of website hits for a U.S.-based gasoline price reporting website called GasBuddy – to test for asymmetric search responses to positive and negative retail price changes. Their search measure is, however, at the national (U.S.) level, so they can

[4]We discuss potential supply-side simultaneity issues below in relating search behavior to daily changes in retail price levels and dispersion, and argue is it likely of second-order importance in our empirical setting.

[5]See Baye, Morgan, and Scholten (2006) for an extensive overview of this literature.

only identify how aggregate search changes with aggregate price level changes, and they cannot directly match their search measure to a corresponding measure of price dispersion. The latter paper studies more disaggregate market-level data like us, however uses price reporting counts for the select group of rare consumer-types who actively upload prices to GasBuddy's websites as a proxy for consumer shopping behavior. Further, this paper relies on reported prices and not a random sample (or the universe) of prices to measure price dispersion, which represents another source of bias. Our paper thus improves on these previous studies by using a valid search measure (as in Lewis 2011) at the market-level (as in Byrne, Leslie, and Ware 2014), and with unbiased measures of market-level price dispersion.[6]

2 Context and Data

The context for our study is the retail gasoline market from Perth in the state of Western Australia, a city of approximately 1.7 million people. The retail gasoline market structure is similar to many cities worldwide: three major, vertically-integrated retailers (BP, Caltex, Shell) dominate the market. The remaining stations are largely run by independent retailers.

An important feature of the market is a unique state-wide price transparency policy called Fuelwatch. Before 2pm each day, retailers must submit, via CSV file web uploads, their station-level prices to the state government. These prices then become effective at 6am the next day and must be kept fixed for 24 hours. Using these data, the government posts online information on today's stations-level prices, as well as tomorrow's prices at 2:30pm.[7] Figure 1 depicts how the website (www.fuelwatch.wa.gov.au/) presents this information as a rank-ordering of prices for a user-specified geographic region in the market.[8]

In collaboration with the state government, we were provided daily data on the number of hits the website received during the November 1, 2012 - December 18, 2013 period. The

[6]A secondary contribution within this literature is we provide rare evidence of high-frequency consumer behavior in these markets. This complements recent work by Levin, Lewis, and Wolak (2012) and Byrne, Leslie, and Ware (2014)

[7]These data undergo an integrity check between the 2pm submission deadline and 2:30pm.

[8]In addition, the website can tell you where the cheapest station is in the market, or provide travel planners to determine where the lowest-price station is given your route. Historical and recent price series are also available.

site receives between 10,000-20,000 hits on a given day.[9] These counts include multiple hits from the same user, and users from all cities and towns in the state.[10] Given that 94% of state residents live in Perth, daily variations in web traffic will almost entirely correspond to daily price fluctuations in Perth and not rural markets. We matched to these data the universe of daily station-level price observations which are publicly available from the Fuelwatch website. Using these data, we compute the daily mean and standard deviation of prices in the market.

Figure 2 plots time series for search and price levels (panel A) and search and price dispersion (panel B). A number of interesting patterns emerge. Panel A highlights a stable weekly gasoline price cycle, where retail prices infrequently jump, followed by a period of price undercutting.[11] Panel B shows market-wide price dispersion also drastically rises during price jumps. This occurs because some firms successfully coordinate on the new price level following a price jump, while others stay at the bottom the cycle and subsequently raise their price after the new market-wide price level has been established.[12]

Together, Figures 1 and 2 illustrate how search incentives operate in practice. The day before the price jump, the price level is at a trough, providing a strong incentive for forward looking consumers to search.[13] If a household fails to anticipate a price jump, it still has strong search incentives on price jump days. Figure 1 provides an example. The market has jumped 'Today' to a new price level around 159.9 cents per liter (cpl), however the first two United-run stations in the list with prices of 146.7 and 147.7 cpl have failed to jump. We further see that

[9]As a rough calibration exercise on the extent of web use, there are approximately 1.1 million working age adults in Perth. If we assume consumers search for gas prices only when their tank is empty and they fill up once per week, then the Perth gas market has approximately 157,000 consumers each day.

[10]Only data on the daily aggregate number of hits are available. Unfortunately, data is not available for website hits by user or market, nor is web data on which stations were searched for/viewed available.

[11]Previous researchers have empirically documented the price cycle in Perth specifically; see Wang (2009) and de Roos and Katayama (2013). It has existed dating back at least to 2000, with some disruptions due to the introduction of Fuelwatch, the entry of supermarket chains, and Hurricane Katrina. The cycle is stable for our entire sample period. Cycling gasoline markets have also been documented in markets across the U.S. Midwest (Lewis 2011), Canada (Byrne, Leslie and Ware 2014), and in Norway (Foros and Steen 2013).

[12]See Lewis (2012) and Byrne, Leslie, and Ware (2014) for further discussion and empirics regarding analogous price coordination in retail markets from the U.S. and Canada. A number of supply-side explanations for these patterns have been put forth in the literature. We refer the interested reader to Eckert (2013) for a review of this large body of research.

[13]Because price information is available with a lead time of one afternoon, intertemporal search incentives peak either the day before the minimum price or the day of the minimum price.

'Tomorrow' these stations will jump their prices to 155.7 and 156.5 cpl, levels which will be much more in-line with their competitors' prices. All else being equal, these differences in the cross-sectional variation in prices Today and Tomorrow imply consumers have a larger cross-sectional search incentive today. Moreover, the differences in price levels today and tomorrow implies that households also have intertemporal search incentives to purchase fuel from these lower-priced stations today.

Table 1 presents descriptive statistics that reaffirm this evolution in search behavior in response to daily changes in price levels and dispersion. Following Lewis (2011) and various other studies, we use a threshold-based classification rule, and define a price jump day as any day where there is more than a 1 cpl increase in average retail prices.[14] We find *all* price jumps in the sample occur Thursdays, and involve a daily price change of 9.44 cpl on average, which is approximately 6.5% of the sample average for the daily average retail price. As alluded to in the figures, we also see price dispersion is considerably higher with a standard deviation of 5.71 cpl on average on price jump days. Average search intensity the day before price jumps nearly doubles at 18,000 website hits, compared to days just following a price jump.

Another notable result from Table 1 is that non-negligible standard deviations are associated with the means for search intensity, price jumps, and price dispersion by cycle day. This is important for our econometric analysis below, as we will exploit this within-cycle day variation to identify empirical relationships between search, price levels, and price dispersion.

3 Econometric analysis

We formally test for consumer search behavior with the following empirical model:

$$\ln(\text{Search}_t) = \alpha_0 + \sum_{\tau=-3}^{3} \alpha_{1\tau} d_\tau + \alpha_2 \sigma_{p_t} + \sum_{k=t+1}^{t-1} \alpha_{3k} \Delta p_t + \mathbf{X}_t \beta + \epsilon_t \tag{1}$$

where Search_t is the number of website hits on date t, d_τ is a dummy variable that equals one τ days before/after a price jump, σ_{p_t} is the standard deviation of market prices on date t, and

[14] We have confirmed this definition of the price jump day by examination of the station-specific price data.

$\Delta p_t = p_t - p_{t-1}$ is the change in average prices between dates t and $t-1$.[15] The vector of controls $\mathbf{X}_t$ includes daily weather-related variables (maximum daily temperature and a dummy for whether there is rain), holidays and holiday weekend dummies, and week of the year fixed effects to control for secular trends in search intensity. To account for autocorrelation in the idiosyncratic search shock ϵ_t we report Newey-West standard errors with seven lags.

Cross-sectional search incentives depend on the current range of prices. If consumers search locally, then the local range of prices is relevant. We consider the market-level standard deviation to be a proxy for the extent of contemporaneous local search benefits. Intertemporal search incentives depend instead on intertemporal measures of price dispersion. Effectively, the cycle day dummy variables act as a proxy for intertemporal search benefits in equation (1).

We attempt to identify search responses to daily price fluctuations using OLS estimates of equation (1). There is reason to worry, however, such parameter estimates will potentially suffer from simultaneity bias if firms' pricing behavior is a function of consumer search.[16] This would generate correlation between price dispersion, price changes, and the error term in the equation.[17]

Features of our setting mitigate our concern with simultaneity bias. First, there is no variation in the timing of the price cycle in our sample; recall that every price jump in the sample occurs on a Thursday. Hence, cycle timing is plausibly exogenous to search behavior.[18] Second, there is only relatively minor variation in the change in the average price over the cycle. Most of the variation is associated with the day of the price jump. The size of the price jump is likely determined more by readily observable variation in costs than more opaque variation in

[15]Because every price jump occur on a Thursday, and cycle length is very stable at one week, the d_τ will also account of day-of-the-week effects in search behavior.

[16]For instance, suppose firms can charge higher prices if search behavior (and price sensitivity) is lower.

[17]Commonly used instrumental variable strategies for overcoming this simultaneity problem are likely to be invalid in our setting. If, as the raw data shows, individuals are forward-looking and stations condition on this behavior in setting prices, then lagged retail price levels and dispersion and lagged search will be correlated with current search behavior, therefore making them invalid instruments.

[18]Studies by Pesendorfer (2002) and Erdem, Imai, and Keane (2003) of dynamic demand responses to retail sales similarly argue that the timing of weekly sales is likely to be exogenous to idiosyncratic daily demand shocks. Like these papers, we study daily demand responses to frequent discrete price changes, however we study price increases and not cuts. That is, the price jumps we study are effectively "anti-sales."

consumer search.[19]

Our main concern is with the relationship between price dispersion and search. Figure 2 exhibits a trend in price dispersion over our sample. We suspect this may result in conservative estimates of the effect of price dispersion on search. Intuitively, supply-side forces are likely to generate a negative correlation between search and dispersion. That is, greater search may be associated with more aggressive price competition and hence less dispersion.

Results

Table 2 presents our empirical results. Columns (1)-(3) provide some benchmark regression coefficients that provide context for the main findings in columns (4) and (5). The column (1) estimates summarize the percentage change in search behavior by day of the cycle. Columns (2) and (3) show that contemporaneous and leading price changes explain much of the variation in search behavior over the cycle, and that the addition of price dispersion to the model provides little extra explanatory power. The unintuitive negative and significant coefficient on the price dispersion term in column (3) reflects the patterns from Figure 2 and Table 1 that search is relatively higher (lower) one day before (during) price jump days when price dispersion is lower (higher). This suggests that the co-movement in price levels and dispersion around price jumps makes it difficult to separately identify the effect price dispersion and intertemporal price changes have on cross-sectional and intertemporal search behavior.

To deal with this co-movement issue, in columns (4) and (5) we also include the day-of-the-cycle dummies from column (1). Doing so partials out the cyclical variation in price levels and dispersion, allowing us to identify how search responds to variation in prices and price dispersion within cycle day. Recall the discussion from Table 1 that we indeed have ample within-cycle day variation to do this. Identification of the impact of price changes and price dispersion on search effectively comes from exogenous variation in prices levels and dispersion due to idiosyncratic shocks to the coordination process that drives price jumps and undercutting. Daily

[19] For example, Noel (2007b) suggests that in the Toronto gasoline market price jumps were calibrated to achieve a target retail margin.

wholesale cost shocks, for example, might generate such residual variation in prices and search within cycle day.

Columns (4) and (5) reveal statistically and economically significant relationships between search and both price dispersion and price changes. Comparing the column (1) and (4) estimates, we see that adding price dispersion to the model has a particularly large impact on the price jump day coefficient. This is consistent with our discussion of Figure 2: there are heightened cross-sectional search incentives on price jump days when firms fail to perfectly coordinate on price jumps, and price dispersion is particularly pronounced.

The column (5) estimates show the search – price dispersion relationship is robust to the inclusion of price changes in the model. They further show that search rises with larger leading and contemporaneous price changes. The leading price changes effect is evidence of intertemporal search behavior and stockpiling.[20] The contemporaneous effects are consistent with predictions from Lewis (2011) that consumers have reference prices, and that (all else equal) increases in price levels signal there are deals to be found in the market, which results in an increase in search activity.[21] The coefficients on the cycle day dummies also exhibit a trend increase in search as we approach the cycle minimum, consistent with a stockpiling process in which a growing body of consumers need to fill up as we approach the trough.

To get a sense of the magnitude of these estimates, a one standard deviation increase in the price jump of 2 cpl leads to an anticipatory 2% increase in search behavior the day before the price jump, and a 3.2% increase on the price jump day. Similarly, a one standard deviation increase in price dispersion on a price jump day of 0.81 cpl leads to a similar 2.4% increase in search intensity. That is, the effects of price dispersion and intertemporal price changes on cross sectional and stockpiling effects yield similar contributions to within price jump day increases in search intensity.[22] By comparison, the weekly cycle in search intensity exhibits

[20] Local media coverage may also play a role. Price rises are highlighted on evening news broadcasts of Channel Seven, one of the local commercial television stations. In addition, a subset of consumers who have signed up to an email notification service will be alerted to upcoming "price hikes".

[21] Within only one year of data for one market, we cannot estimate search models by day of the cycle, given the need to include week fixed effects in our specifications to control for secular trends in search levels.

[22] All of the results in this section, both in terms of signs and magnitudes, are robust to the following robustness

swings an order of magnitude greater.

Figure 3 provides further evidence on the relative importance of cross-sectional and intertemporal search. The government provided us with auxiliary data on the aggregate number of monthly website hits by hour of the day for each for the 14 months in our sample. With these data, we depict the median, 25$^{\text{th}}$, and 75$^{\text{th}}$ percentiles of the distribution of the share of website hits by hour of the day across the months in the figure. Recalling how the policy works, between 2:30pm and 6am in a given day, consumers can search on the website and receive information on the distribution of prices today and tomorrow, so both cross sectional and intertemporal search incentives potentially play a role. Between 6am and 2:30pm there is only information on today's prices, implying cross sectional search incentives will dominate.

The large rise in search intensity between 2pm and 3pm, which is exactly when tomorrow's prices are posted online, highlights the importance of dynamic incentives for search behavior.[23] Between 2pm and 6pm each day, nearly 40% of a typical day's search occurs. Cross-sectional search incentives are also quantitatively relevant. Between 6am and 9am each day, during the morning commute when only information on current prices is available, approximately 14% of a day's search occurs.

checks on the specification of equation (1): using Search_t in levels as the dependent variable, using the interquartile range as the price dispersion measure, and the inclusion of various other regressors (lagged retail price changes up to seven lags, the size of the previous price jump before date t, lags of the dependent variable up to seven lags).

[23]There are alternative explanations for the peak in search in the afternoon. First, afternoon search is more efficient: information for two days is available at once, lowering search costs per data point. Second, consumers may face different time pressures in the morning and afternoon. For example, consumers may be in a rush to get to work in the morning, and find searching for petrol prices an attractive alternative to work activities in the afternoon. We are unable to control for these possibilities.

References

BAYE, M. R., J. MORGAN, AND P. SCHOLTEN (2006): "Information, Search, and Price Dispersion," In Hendershott, Terry (Eds.), *Handbook on Economics and Information*.

BROWN, J. R., AND A. GOOLSBEE (2002): "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," *Journal of Political Economy*, 110, 481–507.

BYRNE, D. P., G. W. LESLIE, AND R. WARE (2014): "How do Consumers Respond to Gasoline Price Cycles?," *The Energy Journal*, forthcoming.

CHANDRA, A., AND M. TAPPATA (2011): "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets," *Rand Journal of Economics*, 42(4), 681–704.

DE LOS SANTOS, B., A. HORTACSU, AND M. R. WILDENBEEST (2012): "Testing Models of Consumer Search Using Data on Web Browsing and Purchasing Behavior," *American Economic Review*, 102(6), 2955–2980.

DE ROOS, N., AND H. KATAYAMA (2013): "Gasoline price cycles under discrete time pricing," *Economic Record*, 89(3), 175–193.

ECKERT, A. (2013): "Empirical Studies of Gasoline Retailing: A Guide to the Literature," *Journal of Economic Surveys*, 27(1), 140–166.

ERDEM, T., S. IMAI, AND M. P. KEANE (2003): "Brand and Quantity Choice Dynamics Under Price Uncertainty," *Quantitative Marketing and Economics*, 1(1), 5–64.

FOROS, O., AND F. STEEN (2013): "Vertical Control and Price Cycles in Gasoline Retailing," *Scandinavian Journal of Economics*, 115(3), 640–661.

HENDEL, I., AND A. NEVO (2006a): "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74(6), 1637–1673.

——— (2006b): "Sales and Consumer Inventory Behavior," *Rand Journal of Economics*, 37(3), 543–561.

LEVIN, L., M. S. LEWIS, AND F. A. WOLAK (2012): "High Frequency Evidence on the Demand for Gasoline," mimeo, Ohio State University.

LEWIS, M. S. (2011): "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market," *Journal of Economics and Management Strategy*, 20(2), 409–449.

——— (2012): "Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles," *International Journal of Industrial Organization*, 30(4), 342–351.

LEWIS, M. S., AND H. P. MARVEL (2011): "When Do Consumers Search?," *Journal of Industrial Economics*, 59(3), 457–483.

NOEL, M. D. (2007b): "Edgeworth Price Cycles: Evidence from the Toronto Retail Gasoline Market," *Journal of Industrial Economics*, 55(1), 69–92.

PELTZMAN, S. (2000): "Prices Rise Faster than They Fall," *Journal of Political Economy*, 108, 466–502.

PESENDORFER, M. (2002): "Retail Sales: A Study of Pricing Behavior in Supermarkets," *The Journal of Business*, 75(1), 33–66.

SEILER, S. (2013): "The Impact of Search Costs on Consumer Behavior: A Dynamic Approach," *Quantitative Marketing and Economics*, 11(2), 155–203.

SORENSEN, A. (2000): "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs," *Journal of Political Economy*, 108(4), 833–850.

WANG, Z. (2009): "(Mixed) Strategies in Oligopoly Pricing: Evidence from Gasoline Price Cycles before and under a Timing Regulation," *Journal of Political Economy*, 117(6), 987–1030.

Figures and Tables

Figure 1: Fuelwatch Online Price Reports
(January 19, 2014)

Home | About FuelWatch | My FuelWatch | Price Search | FuelWatch News | Fuel Information | For Industry

FuelWatch Quick Search - Results

Product: ULP
Metro Region: Any Metro
Suburbs: PERTH (including surrounding suburbs)
Brands: Any Brand
Country Region: None
Date: Today and tomorrow

Refine Search | New Search

Best prices available from 6:00am for today and tomorrow

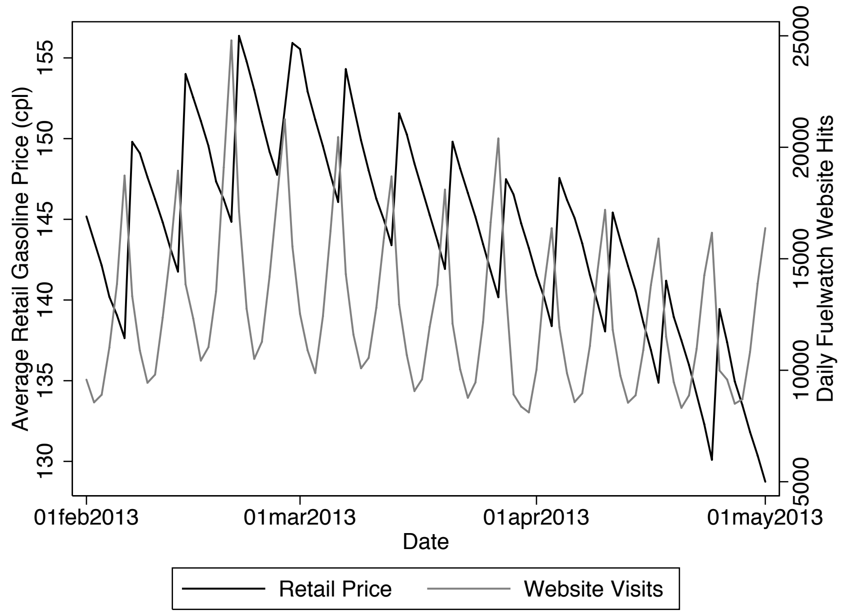
Today	Tomorrow	Product	Brand	Name **Mouse over Name for details**	Address	Suburb/Town	Map
146.7	155.7	ULP	United	United Mt Lawley	791 Beaufort Street	MT LAWLEY	
147.7	156.5	ULP	United	United Northbridge	31 Fitzgerald Street	NORTHBRIDGE	
153.4	153.4	ULP	Gull	Gull East Perth	Cnr Pier St & Brisbane Sts	EAST PERTH	
158.9	156.9	ULP	Gull	Gull First Avenue Mt Lawley	81 Guildford Rd	MT LAWLEY	
159.9	157.9	ULP	BP	BP Connect East Perth	Cnr East Parade & Brown Street	EAST PERTH	
159.9	157.9	ULP	Caltex	Caltex StarMart East Perth	157 Lord St	EAST PERTH	
159.9	157.9	ULP	Caltex Woolworths	Caltex Woolworths Highgate	Cnr Beaufort St & Bulwer St	HIGHGATE	
159.9	155.9	ULP	Caltex	Caltex StarShop Mt Lawley	810 Beaufort Street	MT LAWLEY	
159.9	158.9	ULP	Coles Express	Coles Express Highgate	1-5 Guildford Rd	MT LAWLEY	
159.9	158.9	ULP	Coles Express	Coles Express Perth	480 William St	PERTH	
159.9	157.9	ULP	Caltex	Caltex Wellington Street	141 Wellington Street	PERTH	
159.9	158.9	ULP	Coles Express	Coles Express West Perth	Cnr Wellington & Thomas Sts	WEST PERTH	

Items per page 20

12 Prices found

Figure 2: Search, Price Levels, and Price Dispersion

Panel A: Search and Price Levels



Panel B: Search and Price Dispersion

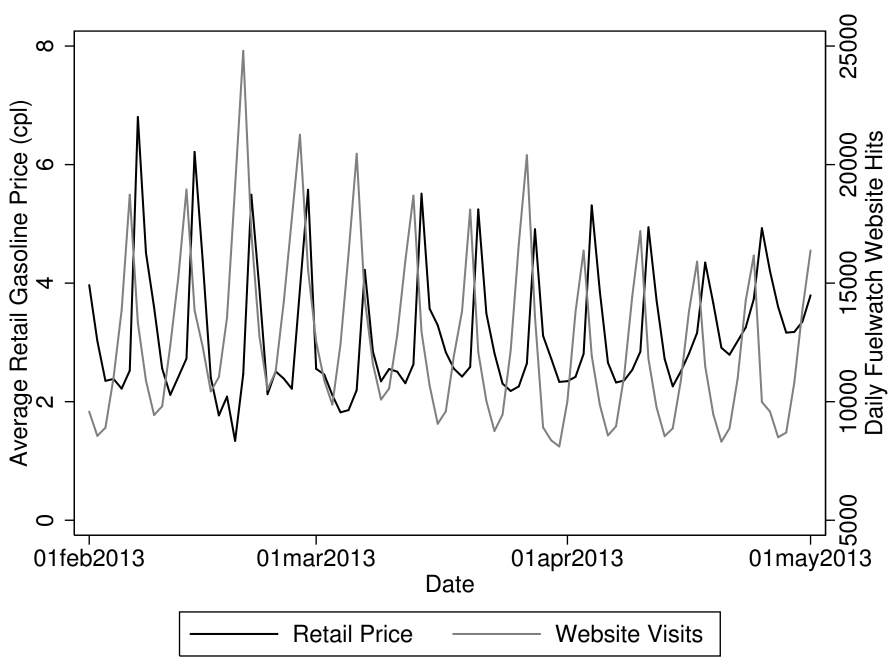


Figure 3: Search Intensity by Hour of the Day

(January 19, 2014)

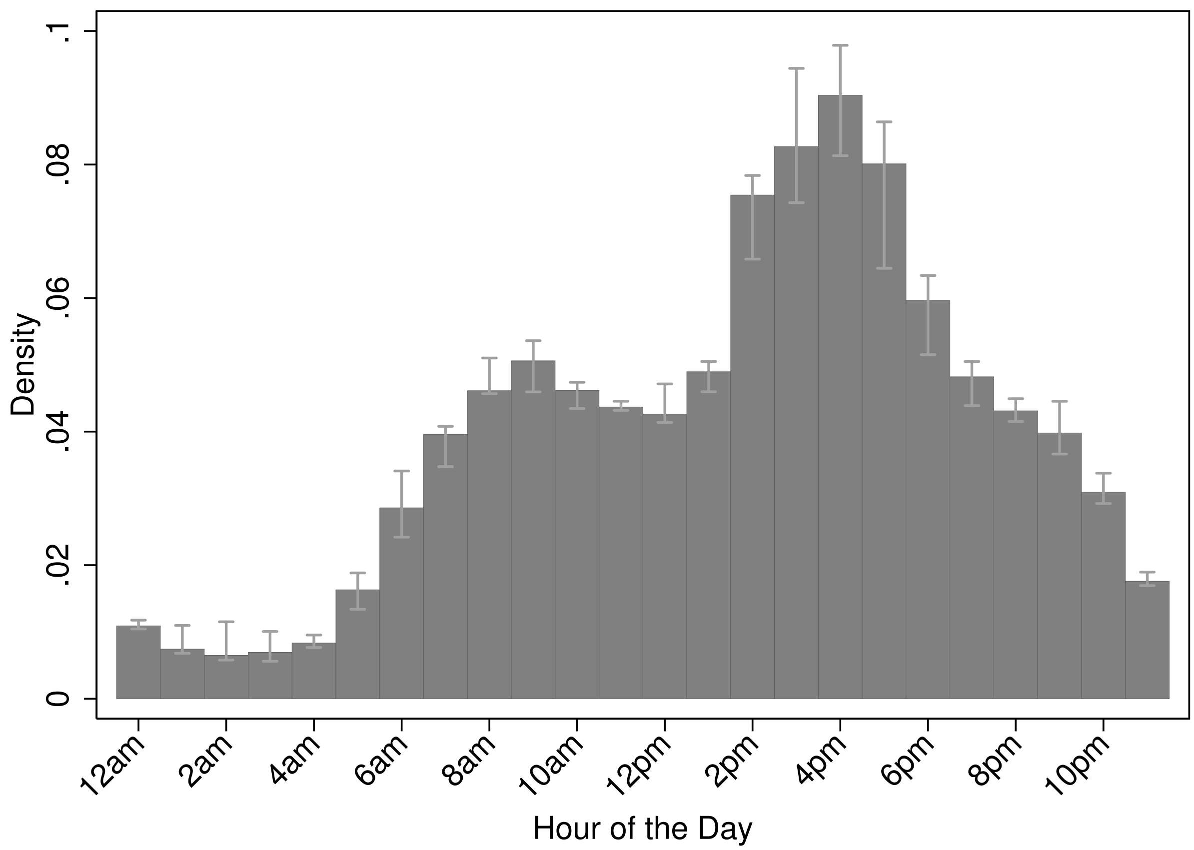


Table 1: Descriptive Statistics

	Day of the Cycle	Fuelwatch Website Hits		Price Changes		Price Dispersion	
(Mon)	3 days before price jump	11718.80	(1053.70)	-1.76	(0.21)	2.56	(0.43)
(Tue)	2 days before price jump	14778.25	(1864.02)	-1.62	(0.24)	2.61	(0.45)
(Wed)	1 day before price jump	17991.29	(2907.60)	-1.64	(0.20)	2.96	(0.40)
(Thu)	Price jump day	12965.93	(1687.83)	9.44	(2.03)	5.71	(0.81)
(Fri)	1 day after price jump	10417.66	(1796.57)	-1.18	(0.66)	3.93	(0.89)
(Sat)	2 days after price jump	9062.16	(968.03)	-1.76	(0.49)	3.17	(0.77)
(Sun)	3 days after price jump	9462.62	(852.76)	-1.58	(0.28)	2.76	(0.57)

Notes: $N = 381$. Sample averages and standard deviations (in parentheses) by day of the cycle reported. Price jump days classified as those where the daily change in the average price across stations is positive.

Table 2: Search, Price Changes, and Price Dispersion

	(1)	(2)	(3)	(4)	(5)
2 days before price jump	0.213***			0.211***	0.209***
	(0.019)			(0.019)	(0.019)
1 day before price jump	0.416***			0.400***	0.287***
	(0.016)			(0.016)	(0.059)
Price jump day	0.096***			-0.037	-0.188**
	(0.010)			(0.034)	(0.082)
1 day after price jump	-0.091***			-0.154***	-0.211***
	(0.013)			(0.015)	(0.051)
2 days after price jump	-0.249***			-0.276***	-0.273***
	(0.015)			(0.015)	(0.016)
3 days after price jump	-0.216***			-0.224***	-0.222***
	(0.007)			(0.008)	(0.008)
Price Dispersion			-0.082***	0.043***	0.030***
			(0.017)	(0.011)	(0.010)
Δp_{t+1}		0.042***	0.043***		0.010**
		(0.002)	(0.002)		(0.005)
Δp_t		0.013***	0.033***		0.016**
		(0.001)	(0.004)		(0.007)
Δp_{t-1}		-0.003***	0.004**		0.006
		(0.001)	(0.002)		(0.004)
Observations	381	381	381	381	381
R-Squared	0.916	0.608	0.628	0.921	0.924

Notes: The dependent variable, ln(Search$_t$), is the natural logarithm of the number of Fuelwatch website hits on date t. Newey-West standard errors with seven lags are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels. Price jump days classified as those where the daily change in the average price across stations is positive. All specifications control for week-of-the-year, national holidays, and weather-related variables such as maximum and minimum temperature and total rainfall.