Consumer Search in Retail Gasoline Markets*

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Abstract

This paper develops novel direct tests for search 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. Our simple yet powerful tests provide strong evidence of both cross-sectional and intertemporal price search behavior.

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Keywords: search, price dispersion, retail gasoline

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1 Introduction

Searching for deals across products at a point in time, or for a given product over time, is a problem virtually all consumers solve in retail markets. 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, price dispersion and sources of market power. Yet despite its pervasiveness and importance, there are few studies that empirically identify search behavior. This is because search intensity and/or search costs are difficult measure. Given this constraint, researchers often take indirect approaches to identification. Indeed, earlier papers have claimed that variability in retail prices across products with similar characteristics are best explained by the existence of unobserved search costs and hence search behavior.[1]

In this short paper, 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 intensity at the market level: the number of daily website visits from a comprehensive gasoline price reporting website.[2] Second, the data contain the universe of station-level prices, which allows us to perfectly measure market-level price dispersion. We can therefore precisely and directly identify the empirical relationship between search intensity and price dispersion to investigate cross-sectional search behavior. Third, retail prices in our data exhibit regular price jumps that consumers can potentially anticipate, permitting savings through well-timed purchases. These price dynamics allow us to test for intertemporal search behavior in advance of price jumps.

We find a statistically and economically significant increase in search intensity when prices are more disperse, and just before price increases. That is, we evidence of cross-sectional and

[1] 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 temporal price dispersion is smaller among more geographically proximate gasoline stations (e.g., where consumers face smaller search costs in comparing prices).

[2] We thus 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).

intertemporal price search.[3] We believe that mechanisms likely to exist in gasoline markets more broadly, and that our findings as having implications for research on industry models for 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 are also relevant for competition authorities who use price transparency policies to subsidize search costs, promote competition and increase consumer welfare in gasoline markets.

The paper mainly contributes to the cited empirical literature on search in retail markets.[4] Within this literature, our paper is most closely related to Chandra and Tappata (2011). These authors use rich station-level gasoline price data to provide simple, compelling indirect tests of search behavior based on supply-side predictions from search models. In particular, they show temporal price dispersion is smaller among stations that are closer to each other. This is consistent with equilibrium pricing behavior in a world where consumers face lower search costs in comparing prices among nearby stations.[5] This paper, in contrast, provides direct tests of search behavior based on demand-side predictions from search models. In this way our simple, transparent tests of search behavior complement and reinforce the indirect test results from Chandra and Tappata (2011). The key innovation inherent to our direct tests is we are the first in the empirical search literature to match a market-level search measure to perfect measures of market-level price dispersion.

We also contribute to an empirical literature on retail gasoline demand. We most closely relate to Lewis and Marvel (2011) and Byrne, Leslie, and Ware (2014). The prior paper uses an

[3] We discuss potential supply-side simultaneity issues in relating search behavior to daily changes in retail price levels and dispersion. We argue that the variation in price levels and dispersion we use for identification is likely exogenous in our setting as the market exhibits regular retail price cycles. Moreover, we acknowledge that the relationship between search and price dispersion is potentially non-monotonic (Brown and Goolsbee, 2002; Chandra and Tappata, 2011), and interpret our estimates as revealing that the economic primitives in the market are such that we are in the region of the parameter space where the gains from searching is increasing in price dispersion. Like earlier empirical research on search behavior (e.g., Sorensen, 2000), we highlight a positive relationship between search intensity and price dispersion.

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

[5] In addition, Chandra and Tappata (2011) provide evidence that price dispersion rises with the number of firms in a market and proxies for search costs, and falls with marginal costs. These patterns can also be rationalized by an oligopoly model of pricing behavior in which consumers face search frictions.

aggregate search measure – the number of U.S.-based website visits to a gasoline price reporting website called GasBuddy. Therefore, they can only identify how aggregate search changes with aggregate price level changes and cannot match their search measure to a corresponding measure of price dispersion. The latter paper studies market-level data, however uses price reporting counts for the select group of consumers who actively upload prices to GasBuddy's websites as a search proxy. Further, their paper relies on reported prices and not a random sample to measure price dispersion. Our paper thus improves on these studies by using a valid search measure (as in Lewis and Marvel 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 market structure is similar to many cities worldwide with three major, vertically-integrated retailers (BP, Caltex, Shell) dominating 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. The policy requires stations to post these prices at 6am the next day and keep them 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] The Fuelwatch 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] Therefore, from 6am to 2:30pm consumers can use the website to find low prices today (e.g., cross-sectional search). From 2:30pm today to 6am tomorrow, consumers can use the website to find low prices today *and* to

[6] A secondary contribution is we provide rare evidence of high-frequency consumer behavior in gasoline markets. This complements studies 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.

avoid paying high prices tomorrow (e.g., intertemporal search).

In collaboration with the state government we constructed a measure of daily search intensity in the market, the number of unique daily visits to the Fuelwatch website. These data were provided to us from November 1, 2012 - December 18, 2013. The website typically receives between 10,000-20,000 visits per day.[9] These counts include multiple visits from the same user and users from all cities and towns in the state. Given that 94% of state residents live in Perth, daily variations in website traffic almost entirely corresponds 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 1 plots time series for website visits and price levels (panel A) and website visits and price dispersion (panel B). A number of interesting patterns emerge. Panel A highlights a stable weekly price cycle, where retail prices infrequently jump, followed by a period of price undercutting.[10] 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.[11]

The figure also highlights the evolution of search incentives. The day before a price jump, the price level is at a trough, providing strong incentives for consumers to engage in intertemporal search. If, however, consumers fail to anticipate a price jump, they still have strong search incentives on price jump days. On these days, price dispersion across stations spikes as sta-

[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]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).

[11]See Lewis (2012) and Byrne, Leslie, and Ware (2014) for further discussion and empirics regarding 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. See Eckert (2013) for a review of this large body of research.

tions imperfectly coordinate on a new price level. This implies consumers can engage in cross-sectional search and find low-priced stations who failed to raise their prices.

Table 1 presents descriptive statistics that reaffirm this evolution in search behavior in response to daily changes in price levels and dispersion over the cycle.[12] 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.[13] 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 visits, 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; 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 visits 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 $\Delta p_t = p_t - p_{t-1}$ is the change in average prices between dates t and $t-1$.[14] 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

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

[13] Historical price data from Fuelwatch reveal that price jumps had occurred solely on Thursdays since November 2010. Thursdays had been established as the main price jump day for two years at the start of the sample period and was thus a well-established fact among consumers.

[14] 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.

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 fluctuations in price levels and dispersion using OLS estimates of equation (1). There are two potential issues with this strategy. First, the coefficient estimates will suffer from simultaneity bias if firms' pricing behavior is a function of consumer search.[15] Features of our setting mitigate these concerns, however. First, recall that every price jump in the sample occurs on a Thursday. Hence, cycle timing and related variation in price levels and dispersion around price jumps is plausibly exogenous to website visits.[16] Moreover, there is minor variation in the change in the average price over the cycle; most of the variation is associated with price jump days. The size of the jump is likely determined more by readily observable variation in costs than more opaque variation in search.[17]

The second issue is that even if OLS estimates of equation (1) identify a causal relationship, theory predicts a non-monotone relationship between search and price dispersion. This implies both a positive and negative values of α_2 are consistent with theory. Comparative statics from Chandra and Tappata (2011) suggest that a negative search-price dispersion relationship can emerge if sufficiently many consumers in a market are informed about the price distri-

[15] 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.

[16] 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."

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

bution.[18] The fact that Perth likely contains far lower search costs and many more informed consumers than typical gasoline markets increases our chances of finding a negative relationship. However, we believe this chance is slim as Fuelwatch receives 10,000-20,000 visits per day from a market of 1.7 million people. Ignorance over prices is still high overall, implying we are likely in a region of the parameter space where the gains to searching are increasing with price dispersion, and where a positive search-price dispersion relationship exists.

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 1 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, in columns (4) and (5) we 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 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 wholesale cost shocks

[18] See Figure 1 of their paper. See also Brown and Goolsbee (2002) for discussion and evidence of a non-monotonic relationship between search and price dispersion in the life insurance industry.

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 1: 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.[19]

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.[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 an intertemporal search process in which a growing body of consumers fill up their cars' gasoline tanks as we approach the trough.[22]

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

[19]We have also run auxiliary regressions to examine longer-term relationships between search, price levels, and price dispersion (which are completely absorbed in the week fixed effects in equation (1)). While we do not find systematic trends in these variables on price jump days or non-price jump days in the sample, we do find for the April - August 2012 subsample (e.g., fall and winter in Australia) statistically significant positive (negative) weekly trends in website visits (price dispersion) on non-price jump days during this period of low seasonal gasoline demand and price levels (though price levels are not statistically significantly lower than other parts of the year). These seasonal patterns are directly in-line with the finding from Lewis and Marvel (2011) that over longer time horizons search intensity falls and price dispersion rises when there are long-run downward trends in price levels.

[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]An alternative behavioral interpretation of this latter finding is consumers search more at the bottom of the cycle because of a price-level effect (e.g., they become enraged in anticipation of another gouging price jump). See Rotemberg (2011) for discussion of this phenomena and a behavioral theory of fair pricing where consumers experience anger and become more sensitive to prices when they increase.

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 daily price changes on cross-sectional and intertemporal search effects yield similar contributions to within price jump day increases in search intensity.[23] By comparison, the weekly cycle in search intensity exhibits swings an order of magnitude greater.

Figure 2 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 visits by hour of the day for each for the 14 months in our sample. With these data, we depict the median, 25^{th} and 75^{th} percentiles of the distribution of the share of website visits 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.[24] 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.

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

[24] 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.

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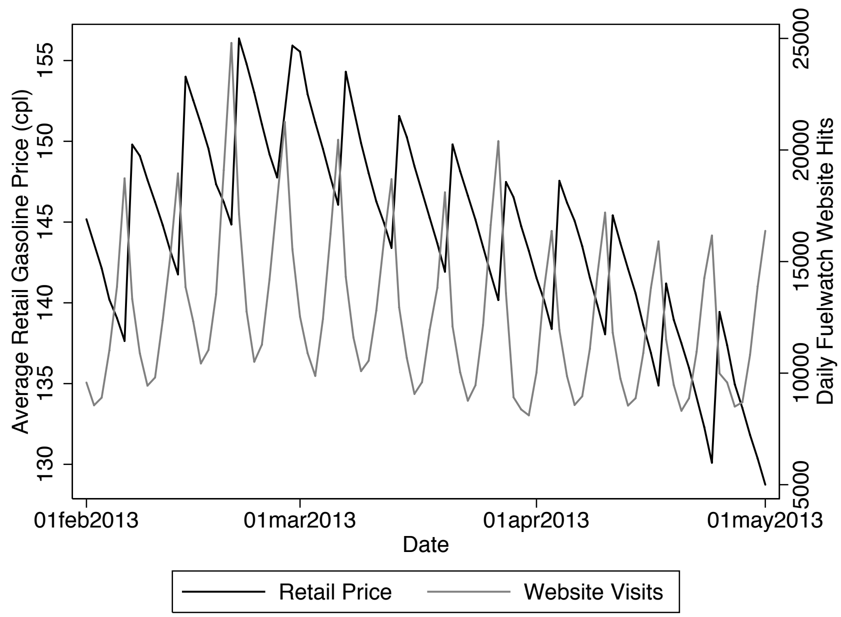
Figures and Tables

Figure 1: Website Visits, Price Levels and Price Dispersion

Panel A: Website Visits and Price Levels



Panel B: Website Visits and Price Dispersion

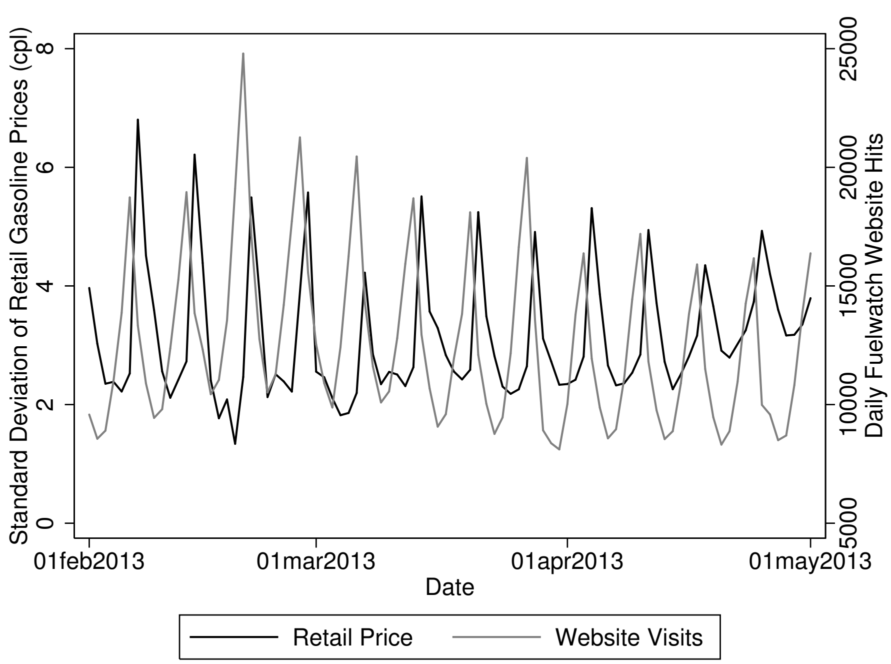


Figure 2: Distribution of Website Visits Across Hours of the Day

(Median, 25th and 75th Percentiles Across Months Reported)

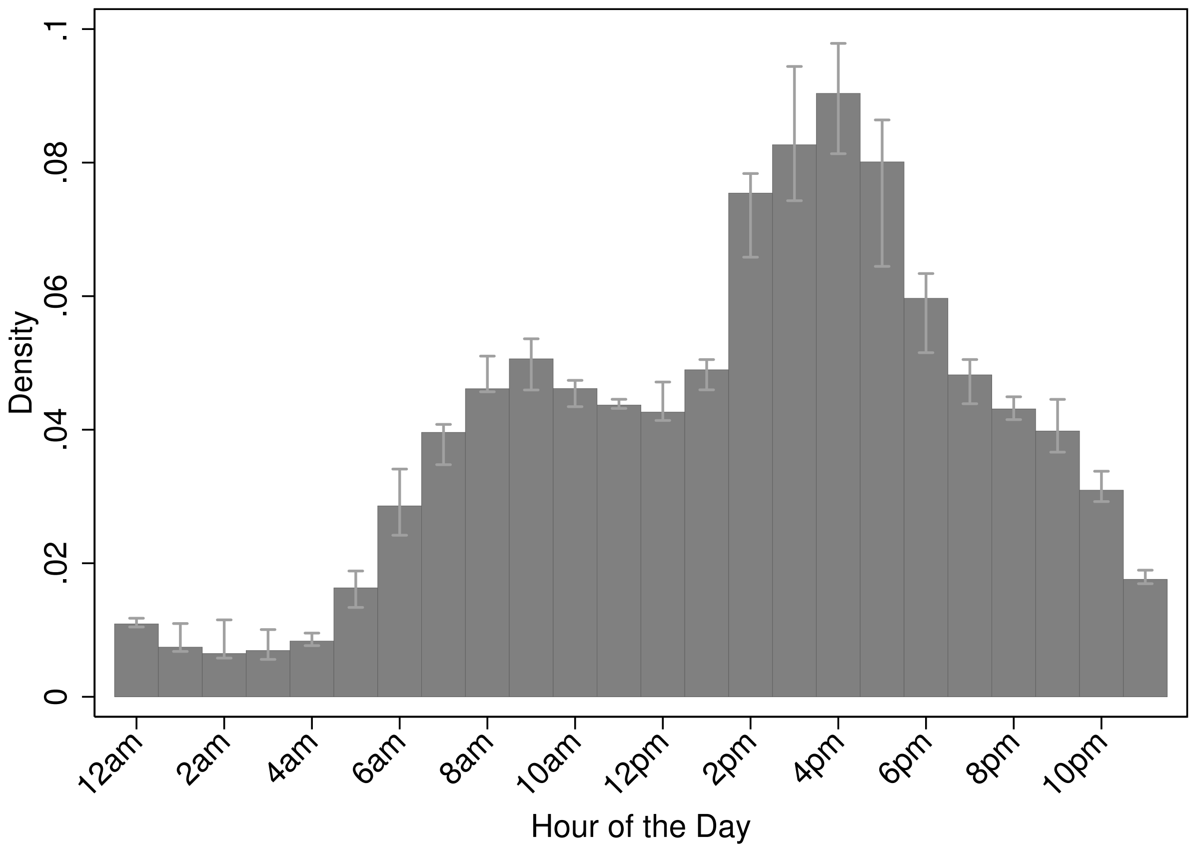


Table 1: Descriptive Statistics

	Day of the Cycle	Fuelwatch Website Visits		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: Website Visits, 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 visits 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.