

When Do Consumers Search?

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Abstract

From the beginning of the literature on the economics of information, theory has predicted that consumers will weigh their cost of additional search against the benefits they expect from that search. The benefits, in turn, depend on the dispersion of prices established by sellers. But given that search is occasioned by imperfect information, it is difficult to model the factors that cause consumers to incur the costs of obtaining additional draws from the distribution of prices. In this paper, we provide empirical evidence that relates search behavior to price movements. In particular, we investigate the relationship between the behavior of gasoline prices and consumer search as measured by traffic statistics for web sites that report gasoline pricing information for individual stations. We show empirically that when consumers observe rising prices, they increase the amount of search that they undertake. Their response, however, is asymmetric—falling prices stimulate far less search, even though cost shocks that increase gasoline price dispersion will yield greater returns to search whether prices are rising or falling.

Our results help to explain the asymmetric response of retail prices to cost shocks observed in gasoline markets. Rising wholesale gasoline prices are reflected almost immediately at the pump, but falling wholesale prices translate to lower retail prices at a much slower rate. When rising prices are associated with more search, the distribution of prices will contract as prices rise and expand when they decline. Using station-level gasoline price data, we demonstrate that this relationship is observed. We conclude that consumers base search decisions on the limited amount of pricing data they obtain in the course of their normal purchase behavior. As prices rise, they are induced to increase search. The additional search narrows the distribution of prices, thereby reducing the returns to search. In contrast, when prices fall, price dispersion rises. Thus consumer search decisions are systematically biased toward searching in the face of rising prices, even though search is relatively less beneficial during such periods. Consumers thus tend to search when their search behavior renders additional search less rewarding.

Keywords: Search, retail gasoline, price asymmetry

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Introduction

When do consumers search, and why? When consumers decide to increase their search activity, the amount of information in the marketplace increases. Firms are thereby induced to alter their price-setting decisions. Yet we know little about the factors that trigger additional information acquisition. Search is undertaken in the presence of consumers' imperfect and costly information. The amount of information they choose to acquire is determined by their weighing of the expected benefits from obtaining a lower price against their marginal cost of search. But the expected benefits must be evaluated in terms of the distribution of prices that consumers believe exists. It is implausible to posit that they *know* the mean, variance, and higher moments of the price distribution they face even while they lack knowledge of the prices that comprise the distribution.

Without knowledge of when consumers choose to search, we must infer their search behavior from the prices and price movements that trigger search. This is an uncomfortable position to be in—consumers could easily make systematic errors in timing their search given the price dispersion that their search activity induces. Firms, as specialists in the markets in question, are likely to possess better information and to react to any predictable consumer search patterns in systematic ways. Accordingly, inferences about search behavior derived from the resulting price patterns must necessarily be inferior to direct measurement of consumer search.

In this paper, we provide direct evidence on the role of price movements in triggering consumer search behavior in an important market, that for gasoline at retail. Retail prices for gasoline exhibit a pronounced pattern of asymmetric adjustment to changes in underlying wholesale prices. Reflecting the pricing pattern that has been uncovered for a number of consumer prices (Peltzman, 2000), retail gasoline prices rise rapidly in response to underlying wholesale price increases, but

wholesale price decreases tend to make their way to retail at much slower rates. We show here that price increases are much more likely to generate additional search than are decreases. The asymmetric search behavior, in turn, is capable of inducing the asymmetric price adjustments observed in retail gasoline markets.

Our direct measure of search comes from “hits” recorded for web sites that aggregate consumer price information. We digitized data collected by Alexa, a company that records the Internet peregrinations of consumers who install a toolbar onto the systems. By using a measure of Internet traffic for GasBuddy.com, a gasoline price aggregator that provides consumers with the opportunity to obtain gasoline prices at individual gasoline stations in their area, we are able to measure search intensity directly. The GasBuddy.com site also provides us with price information, permitting us to relate search intensity to average price.

We evaluate the search information we obtain by relating it to a measure of gasoline price dispersion on a market by market basis, again based upon prices obtained from the family of local gasoline price sites under the GasBuddy.com banner. As expected, increased search intensity leads to lower price dispersion. When consumers are well informed, individual gasoline stations cannot stray far from marketplace norms. Falling prices stimulate less search, and so stations are more able to hold back from passing those price declines along at retail. Price dispersion rises as the falling prices are passed along slowly and incompletely.

Our results suggest an explanation for the commonly observed phenomenon of “rockets and feathers” pricing in gasoline markets (Bacon, 1991). Increases in wholesale gasoline prices are passed rapidly through to retail prices while the response to declines in prices is delayed. We believe that the asymmetric behavior of search intensity in response to price changes that we measure plays an important causal role in generating asymmetric price response. Our results suggest that some

recent attempts to theorize about the source of asymmetric price responses need to be modified to reflect the actual amount of search undertaken in the retail gasoline market in response to price changes.

In section 1, we provide a brief summary of the existing evidence on asymmetric pricing response in gasoline retailing. We then sketch reasons to expect search behavior to exhibit asymmetry in response to price changes and discuss how such search is likely to affect the pricing choices of gasoline retailers. Section 2 describes our data collection procedures. Section 3 provides estimates of the relationship between movements in average price and search intensity. Section 4 documents the effect of search intensity on price dispersion. Finally, section 5 offers a brief summary together with suggestions for future research.

1 Rockets and Feathers

Retail gasoline markets exhibit substantially asymmetric price responses to changes in a market's terminal (wholesale) gasoline price. Rising wholesale prices are translated rapidly into higher prices at retail. But the rocket-like upward price trajectory is not matched when wholesale prices fall—retail prices float downward more like feathers (Bacon, 1991). Borenstein et al. (1997) document the substantial asymmetric response of retail gasoline prices to crude oil prices—a broader measure of asymmetry than we are interested in here. The evidence they supply supports the widely held belief that retail gasoline prices react far more rapidly to crude oil price increases than to price decreases. They decompose the asymmetric response by distribution tier, finding substantial asymmetry in the adjustment of retail prices to terminal prices (terminal prices are local wholesale prices for gasoline). In particular, they find that about 60 percent of a terminal price increase is passed

through to retail in the two weeks following the increase, compared to about 20 percent of a terminal price decrease. The asymmetry is far less pronounced by week 4 following the terminal price change. Numerous other studies (See e.g., Lewis (2005), Galeotti et al. (2003), and Deltas (2004))¹ have found similar asymmetries for retail gasoline price responses to changes in wholesale prices.²

Asymmetric price response helps to cushion the bad news for retailers inherent in wholesale gasoline price increases. Lewis (2005) shows that rising wholesale prices are associated with shrinking margins as the even rapid retail price increases do not keep pace with the underlying wholesale price increase. In contrast, the delay in price adjustment means that wholesale price declines work to the benefit of dealers—their margins rise as retail prices again fail to keep pace with wholesale prices. But since the adjustments speed is slower when prices move down, volatility combined with asymmetry yields short term gains for retailers.

While there is broad agreement as to the existence of asymmetric retail gasoline price response to changes in wholesale gasoline prices, there is little understanding of the source of this asymmetry. Borenstein et al. (1997) offer two hypotheses as possible explanations for the asymmetric price response of retail to wholesale gasoline prices. The first of these hypotheses is that “prices are sticky downwards because when input prices fall the old output price offers a natural focal point for oligopolistic sellers.” This oligopolistic coordination hypothesis is elaborated as follows: “retailers would refrain from cutting prices in response to a negative shock and would instead rely on prevailing prices as a focal point for oligopolistic coordination.” (Borenstein et al., 1997, p. 326) Imperfectly

¹A number of such studies are listed and summarized briefly by Geweke (2004).

²Bachmeier and Griffin (2003) do not find the asymmetric relationship claimed by Borenstein et al. (1997), but their study is restricted to the adjustment of *wholesale* gasoline prices to changes in the price of crude oil. Hosken et al. (2006) claims that Galeotti et al. (2003) finds the reverse result from that of Borenstein et al. (1997), but our reading indicates agreement (p. 189): “[We] find that rockets and feathers appear to dominate the price adjustment mechanism of gasoline markets in many European Countries.”

informed retailers are expected to cling to current prices until convinced by sales declines that their competitors have responded to the underlying terminal price. It is not clear, however, how the price cutting that triggers responses begins. The underlying asymmetry is induced by margin pressures caused by wholesale price increases that are not present when the wholesale price falls. But since the hypothesis requires consumer information to be imperfect, and since retailers have much more at stake in price decisions than do individual customers, one can expect that retailers will choose to be far better informed than their customers, which suggests focusing on the consumer's search problem.

More importantly, since the role of a focal point is to provide a focus for price setting, evidence that retail price dispersion grows more rapidly when price decline than when they rise should reject the oligopolistic coordination hypothesis. We provide such evidence below.

A second hypothesis is that “volatile [wholesale] prices may create a signal extraction problem for consumers that lowers the expected payoff from search and makes retail outlets less competitive.” Borenstein et al. (1997) attribute a formalization of this hypothesis to Bénabou and Gertner (1993). More recently, Cabral and Fishman (2006), Tappata (2006), and Yang and Ye (2007) have further developed this theory, with each providing predictions about search behavior. Unfortunately, the predictions are rather definitively contradicted by the evidence on search behavior that we provide.

Our approach is in the tradition of Stigler's 1961 seminal partial equilibrium approach to search behavior. Stigler focuses on a consumer's decision to accept a price or, alternatively, to continue to search. The decision rule is straightforward—the consumer continues to search as long as his/her marginal cost of search is less than the expected benefit (expected price reduction weighted by purchase volume), given the consumer's understanding of the dispersion of prices. A consumer

who purchases at a particular station thus has determined that the expected benefit of additional price shopping is not worth the cost of further sampling.

This condition means that a consumer who has chosen to purchase at a particular station is likely to continue to purchase at that station if the price it charges does not change, and if the consumer receives no outside information that the distribution of prices has changed. One obvious source of fresh information is that the price of gasoline has changed since the consumer's previous purchase. But the information provided by a price change has an asymmetric impact on the search decision. An increase in price can signal that the entire price distribution has risen and that the consumer's previous supplier has simply moved its price along with the distribution. If the shape of the price distribution has changed as the distribution has moved, the consumer may or may not wish to undertake more search, but it is clear that a relative increase in a supplier's price increases the desirability of additional search.³

When the consumer's price falls, the source of the decline can be either a movement in the entire distribution, yielding effects generally symmetric to the effect of an increase in the location of the price distribution, or the consumer's price may have declined relative to the location of the distribution. But this latter effect is to induce the consumer to refrain from search. A price that has moved farther into the lower tail of the relevant distribution is one that will be harder to beat through additional search.

We regard this fundamental asymmetry as a first-order effect of changing prices. Consumers will sensibly search more if they believe their price may have risen relative to the distribution of prices generally, and to search less if their price has fallen. The signal extraction theories typi-

³In contrast to Yang and Ye (2007), our consumers may search, but they do not obtain perfect information by doing so.

cally attempt to characterize circumstances in which consumers can infer whether the underlying source of a price movement was a common cost increase, or alternatively, whether an observed price change was idiosyncratic. Thus Cabral and Fishman (2006, p. 1) suggest that firms are reluctant to decrease prices to avoid, in their terms, “rocking the boat,” and thereby stimulating search. But consumers in their view will not search in the face of small price increases. They argue for the same sort of asymmetry that we posit in the face of large price changes, but their mechanism is somewhat different:

If prices decline by a lot, it is unlikely that further search will reveal even lower prices. Hence, large cost reductions may lead to commensurately large price reductions. By contrast, if search costs are not too high, a large price increase might well trigger consumer search because there is the likelihood that competitors’ prices have risen by substantially less.

But these expectations will be incorrect to the extent that substantial search narrows the price distribution and thereby cuts the returns to search.

In any event, while theory may suggest how search might respond to price changes, our goal here is to provide empirical evidence as to how it does respond. It is clear that it will not pay gasoline consumers to perfect their price information. Hosken et al. (2006) provide empirical evidence that “gasoline stations do not appear to follow simple static pricing rules.” Both Lewis (2007) and Hosken et al. (2006) document the latter’s claim that “gasoline stations do not appear to charge constant margins, nor do they appear to simply maintain a relative position in the pricing distribution from period to period.” Consumer search costs may be low, but they are clearly not low enough to force price dispersion down to the point where search is no longer necessary. Retailers face the

same churning environment and react to their costs, the observed demand at their locations, and the price movements of rivals in seeking to select profit-maximizing prices. Retailers will pass along cost increases rapidly because the high search environment that results punishes deviations from the market norm. An individual firm is more nearly a price taker in a high search environment. But when costs fall, the penalty to a retailer who does not pass those cost decreases along is attenuated by the limited information that consumers choose to obtain. Since price decreases need not be matched as readily as price increases, price dispersion will rise as prices fall, but will be attenuated as prices rise. We now turn to the data to establish these relationships.

2 Data

This section describes the data sources from which we have collected data on gasoline search behavior and on gasoline prices. All of the data derive ultimately from the websites of GasBuddy.com. These advertiser-supported sites exist to help consumers seek out lower gasoline prices by aggregating price information reported by volunteer spotters. Traffic on the GasBuddy.com sites is thus likely to reflect actual search activity in the marketplace. We would have preferred to obtain data directly on the number of visits to GasBuddy websites, but were unable to do so. Those sites are the source for price data used in this analysis, but the traffic statistics we employ are obtained from a secondary source, Alexa.com. We first describe our procedure for obtaining traffic statistics and then describe the characteristics of our price data.

2.1 Search Data: Alexa.com

Our goal is to use the number of visits to a web site that provided price information to consumers as a measure of the amount of search being undertaken at a particular point in time. Our measure of search is provided by the traffic rankings available from www.alexa.com. Alexa Internet, Inc., (a subsidiary of amazon.com) offers a toolbar (an add-on for the Internet Explorer browser for users running Microsoft Windows.) that consumers can install to obtain information on the sites they visit. The information is an aggregate of the INTERNET surfing behavior of all of the users that have downloaded and installed the toolbar, as the behavior of Alexa toolbar users is recorded in a central database under Alexa's control.⁴ That is, the Alexa "Toolbar community" provides information to Alexa, information that is aggregated and reported back to users:

Simply by using the toolbar each member contributes valuable information about the web, how it is used, what is important and what is not. This information is returned to the community as Related Links, Traffic Rankings and more.⁵

Alexa claims that its web traffic information is based upon "the Web usage of millions of Alexa Toolbar users,"⁶ but we cannot independently verify the number or composition of toolbar users.

We have chosen to use the Alexa daily "reach" values for a gasoline price search site, GasBuddy.com (described below), as our measure of search activity. Reach is defined by Alexa as follows:

Reach measures the number of users. Reach is typically expressed as the percentage of all Internet users who visit a given site. So, for example, if a site like yahoo.com has a

⁴The toolbar is described at <http://www.alexa.com/site/download>.

⁵*Id.*

⁶See http://www.alexa.com/site/help/traffic_learn_more.

reach of 28%, this means that if you took random samples of one million Internet users, you would on average find that 280,000 of them visit yahoo.com. Alexa expresses reach as number of users per million.⁷

Inquiries to Alexa indicate that Alexa does not currently have a product that permits us to obtain daily reach data directly from the company's database.⁸ Alexa does, however, make available graphical depictions of their data for various windows. We captured a snapshot the Alexa daily reach data for GasBuddy.com as a bitmap file. All data smoothing options were disabled in our calls to the Alexa database. We chose the longest period for which data appeared to be recoverable, which appeared to be two years.

Extraneous items such as labels and color information were removed from the image files as an intermediate step. We then converted the resulting graphical representation to the constituent data points using the Engauge digitizer, available from <http://digitizer.sourceforge.net>. Engauge is a free software program designed for the purpose of converting image files to numbers. Our data cover a period just short of 2 full years from September 2004 to September 2006. We divided the time axis of the 2 year plot into the largest number of increments permitted by our software. We then obtained numeric values for the height of the reach data plot for each increment. We assigned these values to the nearest date then averaged the values for each date, using the average as our reach statistic for that date. Queries to the Alexa database for the plots of the same reach series for shorter time intervals provided more finely grained images that permitted more accurate digitizing. We digitized these as well and compared the results for the overlapping intervals available in order to check the robustness of the two year series. The numbers obtained

⁷*Id.* Alexa has changed its reporting somewhat. Our data are expressed in terms of users per thousand, not million.

⁸See also "Historical data for ranks and pages," <http://developer.amazonwebservices.com/connect/thread.jspa?messageID-38979>.

from the overlapping series were sufficiently close as to suggest that our two-year numbers were a reasonable approximation of the underlying Alexa data.

The patterns evident in the data were also checked by comparison to digitized data for two other sources of localized gas price information, GasPriceWatch.com, <http://www.gaspricewatch.com/new/> and the American Automobile Associations Daily Fuel Gauge Report, <http://www.fuelgaugereport.com/>. Each of these sites recorded similar pattern of usage. Neither of these sites, nor any of GasBuddy.com's remaining competitors obtain enough traffic to rank consistently among the set of most popular sites that Alexa monitors on a daily basis, but the similarity of their patterns of use suggest that the general outlines of Web usage of the GasBuddy.com data are representative of the patterns of search for gasoline prices on the Internet.

Alexa reach data are compiled once daily, so that the reported reach data for a particular date actually apply to the previous day. Data are not returned for days on which a website receives too few hits. The data threshold is that the site must rank within the top 100,000 sites among Alexa toolbar users.⁹ Many of the competing gasoline price aggregation sites fail to meet that threshold on a consistent basis.¹⁰ The GasBuddy.com site almost always meets the threshold requirement throughout the data period we analyze, but more recently has fallen from the ranks of the top 100,000 sites. None of GasBuddy.com's competitor sites consistently scores as high.

The Alexa data are tied to the locations of toolbar users. These tend to be technically sophisticated computer users skewed toward the west coast. Some indication of the location of Alexa toolbar users is can be obtained by reviewing the rankings of local GasBuddy.com sites. Rankings

⁹The collection of sites for which information is available is a superset of the top 100,000 sites on any particular day, as tabulations appear to be made for sites that hit that threshold only for a short time.

¹⁰The data threshold and the absence of data for sites that fall below the threshold are documented on the Amazon Web Services Developer Connection web site. See <http://developer.amazonwebservices.com/connect/thread.jspa?messageID=49479>.

obtained for February 22, 2007 are listed in table 1.

2.2 Gasoline Prices: GasBuddy.com

The GasBuddy Organization, Inc., (see http://www.gasbuddy.com/gb_aboutus.aspx) operates a collection of local websites that aggregate and display user-supplied price information for gasoline markets. The GasBuddy.com website is a portal to the local sites with names such as ColumbusGasPrices.com for Columbus, Ohio, and NewYorkGasPrices.com for New York City. The site also contains a number of state-level sites such as OhioGasPrices.com and NewYorkStateGasPrices.com that provide data obtained from stations located throughout the state but outside of the boundaries of the metropolitan areas with their own sites.

Each of these local sites provides a listing of the fifteen highest and lowest prices reported by volunteer spotters in the corresponding locality during the most recent 48 hours. The spotters are asked to report the pump prices for regular unleaded gasoline. In consequence of the 48 hour pricing window, when prices are moving in a particular market, the high and low prices in the marketplace may be separated in time by nearly the length of the window. Thus if prices are rising, the list of low prices will typically include stations from the previous day, while the high prices are current, and the reverse is true when prices in that market are falling.

While the prices in the GasBuddy database are retained for only 72 hours, we have collected daily national average prices for more than two years. In addition, we have collected a series of daily measures of price dispersion for the period September 15, 2006 to January 15, 2007. Each local site reports the highest 15 and the lowest 15 prices regular grade unleaded gasoline for that locality for each day. We use this information on the extrema of the price distribution to construct

a measure of the daily dispersion of prices in each market. One option we could have chosen is simply to compute the price range using the difference between the highest and lowest prices for each locality and each day. We were concerned, however, about data anomalies, which could be introduced due to spotter error in recording or entering prices, and by the possibility that the extreme prices in the sample could be obtained from stations whose prices are not linked closely to the gasoline market. For example, some communities have gasoline outlets that serve primarily as automotive service providers, but who provide high-priced gasoline as a convenience to their customers. Fortunately, since we have data on the 15 highest and lowest prices for each day, we are able to check the robustness of our analysis by using alternative specifications of our price range measure that exclude some of the most extreme prices recorded.

3 Search and Prices

Table 2 provides summary statistics for the data used in our empirical analysis. Given the data on prices and search behavior, we are in position to estimate the degree to which price movements trigger search, and the extent to which the triggering mechanism is asymmetric in response to price movements up or down. Define the one day price differences for the national average Gas-Buddy.com regular unleaded price series, $\{p_t\}$ as $\Delta p_t \equiv p_t - p_{t-1}$ and define a sign operator for price differences as

$$\xi_t \equiv \begin{cases} 1 & \text{if } \Delta p_t > 0, \text{ and} \\ 0 & \text{otherwise.} \end{cases}$$

We compute the cumulative price increases and decreases for three periods. These consist of price changes during the previous five days, during the interval between twenty and five days previous,

and for the movement in the thirty days prior to that. We then regress the natural log of our *Reach* variable on the corresponding lagged price movements as in equation 2. Notice that for each lag interval, equation includes separate terms for the cumulative positive and negative price movements over the interval. We are thus assuming that the effect of a signed daily price movement is the same throughout the lag interval in question.¹¹ This specification allows for the possibility that more volatile lag intervals result in more consumer search.

$$\begin{aligned}
\ln(\text{Reach})_t = & \alpha_0 + \alpha_1 \text{date} + \alpha_2 \sum_{k=0}^4 \Delta p_{t-k} \xi_{t-k} + \alpha_3 \sum_{k=0}^4 \Delta p_{t-k} (1 - \xi_{t-k}) \\
& + \alpha_4 \sum_{k=5}^{19} \Delta p_{t-k} \xi_{t-k} + \alpha_5 \sum_{k=5}^{19} \Delta p_{t-k} (1 - \xi_{t-k}) \\
& + \alpha_6 \sum_{k=20}^{49} \Delta p_{t-k} \xi_{t-k} + \alpha_7 \sum_{k=20}^{49} \Delta p_{t-k} (1 - \xi_{t-k}) + \epsilon_t
\end{aligned} \tag{2}$$

Table 3 reports the results of our estimation. The table includes Newey-West standard errors to account for possible serial correlation.¹² The estimate of equation 2 reported here measures the

¹¹We have estimated an alternative specification in which each lag interval is represented by the cumulative price movement over that interval. Define the difference operator $\Delta^{(m,n)}$ as applied to the GasBuddy price series p_t as follows:

$$\Delta^{(m,n)} p_t \equiv p_{t-m} - p_{t-n},$$

where we adopt the convention that $\Delta^{(n)} \equiv \Delta^{(0,n)}$. The alternative specification is given by

$$\begin{aligned}
\ln(\text{Reach})_t = & \alpha_0 + \alpha_1 \text{date} + \alpha_2 \Delta^{(5)} p_t \xi_t^{(5)} + \alpha_3 \Delta^{(5)} p_t (1 - \xi_t^{(5)}) \\
& + \alpha_4 \Delta^{(5,20)} p_t \xi_t^{(5,20)} + \alpha_5 \Delta^{(5,20)} p_t (1 - \xi_t^{(5,20)}) \\
& + \alpha_6 \Delta^{(20,50)} p_t \xi_t^{(20,50)} + \alpha_7 \Delta^{(20,50)} p_t (1 - \xi_t^{(20,50)}) + \epsilon_t
\end{aligned} \tag{1}$$

where

$$\xi_t^{(m,n)} = \begin{cases} 1 & \text{if } \Delta^{(m,n)} p_t > 0, \text{ and} \\ 0 & \text{otherwise.} \end{cases}$$

Since the results obtained with this alternative are consistent with those we report, we do not present them here.

¹²A Durbin-Watson test rejects the hypothesis of no serial correlation at the 1% significance level. However, both a

impact on search activity on a trend and on cumulative price movements up or down in earlier intervals. The date variable is simply t , $t \in 50, 726$.

Inspection of the results in table 3 shows that price movements trigger search, but that the response is highly asymmetric. The responses are large and significant, but those for positive price changes are significantly larger in both statistical and economic terms in pairwise comparisons for each lag interval. The last column of the table provides t -statistics for the difference in the values of the coefficients paired for each lag interval. These results indicate that price changes increase search, whether the change is positive or negative, but for a given (in absolute value) change in the average price of gasoline in a previous interval, the increase in search is larger for positive cumulative price changes in that interval than for equivalent cumulative price decreases.¹³ Given the log-linear functional form of equation 2, the estimates imply that a 10 cent/gallon increase in price occurring within the last 5 days is associated with an 58% increase in search, while a 10 cent/gallon decrease in price within the last 5 days would correspond to an insignificant increase of 5.2% in search. The asymmetry present is similar to that for the interval from day 20 to day 5, where the effect of a positive price is again nearly triple that of a price decline. Even earlier price movements (days 50 to 20) have a smaller impact, with increases yielding significantly more search than price declines.

We use movements in the retail price as our proposed triggers for search because those retail prices are what a consumer encounters when passing a gasoline price sign or checking a gasoline pump. The longer lag terms included in equation 2 are included to reflect the salience of gasoline

Dickey-Fuller test and a Phillips-Perron test reject the hypothesis of a unit root in the *Reach* variable at the 1% significance level.

¹³The same pattern holds for the specification in equation 1 that uses the aggregate of all price movements over the lag interval as an explanatory variable, differentiating between positive and negative movements over the entire interval.

pump prices to the consumer. For example, a change in the retail price today will often generate additional search only when a consumer's gasoline tank is emptied. The results in column 2 indicate that the effects of price increases on search are lingering, and that the asymmetric effect is present consistently. As noted above, for each set of lags, the impact on search is dramatically larger for price increases compared to the effect for price decreases.

The greater information consumers obtain through search is likely to constrain the actions of retailers who experience changes in their wholesale prices. In the event of either an increase or decrease in prices, it is reasonable to suppose that some resellers will choose to pass at least a portion of the wholesale price change to their customers. In the high search environment corresponding to price increases, highly elastic demand at particular stations will force closer price matching compared to that likely to be observed when prices are falling.

How can we observe this matching behavior enforced by consumer search? It should show up in the distribution of retail prices. We expect more search to narrow price dispersion, so that the dispersion of prices should narrow considerably in response to price increases, given the added search they generate, and less sharply for price decreases. We provide evidence of this pattern in our next section.

4 Price Movements and Price Dispersion

Our search results are for Internet traffic statistics for the Gasbuddy.com web site. We could not use data for the individual city sites that are under the GasBuddy umbrella since the sites for individual cities did not consistently attract enough Internet activity to remain in the Alexa collection of most popular websites for which time series data are available. But we were able to use these

individual city sites to collect city-by-city measures of price dispersion. We collected price information from daily visits to the main page of each GasBuddy city site. These pages include the 15 highest and 15 lowest prices reported each day as well as the mean prices over all reported prices for the same day. Hosken et al. (2006) provide empirical work that demonstrates both that gasoline prices distributions have “relatively thick tails” and that “stations charging very low or very high prices are much more likely to maintain their pricing position over time than stations charging prices near the mean.” We are most interested in stations whose position in the distribution shifts, and have accordingly eliminated the most extreme values from our measures of dispersion. We cannot, however, compute a variance simply because we are limited to the extreme values available for individual cities. Instead, we utilize measures of the price range.

We encountered several problems in using the GasBuddy.com city-level price data. First, reporting of the highest 15 and lowest 15 prices spotters on a given day is dependent on the willingness of GasBuddy.com’s volunteer spotters to record and report prices. For some days, the spotters do not record the 30 prices necessary to provide this level of detail. This means that any range-based measure of dispersion will be sensitive to the number of prices sampled. Second, the extreme value prices, with their tendency to maintain their position relative to the distribution over time, may not be representative of shifts in the shape of the distribution away from its tails.

Our strategy for dealing with these problems is to compute separate coefficient estimates for two different measures of dispersion and three different samples. Our measures of dispersion are the true range (maximum price - minimum price) and a range computed as the difference of the median for the reported highest prices and that for the reported lowest prices. We term this dispersion measure the “median range.” The samples include one restricted to ranges for cities that had 30 prices reported for every day in our sample. This dropped the number of U.S. cities from the

103 recorded by GasBuddy.com to 49, and reduced our sample size to 4666. For this sample, the median range measure is always the eighth-highest recorded price minus the eighth-lowest price. The second sample consists of all city/day pairs for which 30 prices were available. This raised the number of observations considerably, to 9718. All cities in the sample except one (Waterbury, CT) generated at least 30 prices on at least one day. The median range is the same as for our first, most restricted sample. Our final sample of 12211 observations consists of all city/day pairs for which prices are available. Here the observation corresponding to the median varies according to available sample size.

One additional pattern became apparent when we compared recorded ranges across days of the week. We collected data daily for 103 cities for a four month period from September 15, 2006 to January 15, 2007. Our recorded ranges were substantially smaller on weekends than on weekdays. We believe that this narrowing of dispersion is a consequence of fewer reports of prices entered by GasBuddy volunteers on weekends. Further investigation of the Gasbuddy.com data shows that the average number of prices reported for a typical city drops significantly on weekend days. Nevertheless, we cannot rule out the possibility that actual price distributions narrow on weekends.

Notice, however, that the sample size effect works against our hypothesized relationship. If GasBuddy price reporting tracks GasBuddy search as measures by Alexa, the effect is to reduce recorded dispersion during periods of low search. This means that recorded dispersion should be biased downward compared to actual dispersion due to restricted sample sizes during periods of falling prices as opposed to periods when price is rising. We seek to identify whether price dispersion actually rises as prices fall. The potential bias works in opposition to such a finding.

Recognizing the lagged effects of price changes on search, we anticipate that these lags will be reflected in dispersion as well, as higher search intensity associated with rising prices should force

dispersion down in comparison to what otherwise would have been observed. But moving prices should also add volatility to pricing, thereby increasing dispersion. Hence, as for search, we seek to compare the effects of falling and rising prices—each presumably the source of volatility—on dispersion so that the comparison can inform us about the differential effects of search. Similar to the search analysis, we estimate the influence of recent price changes on price dispersion in city c at time t with the following specification:

$$\begin{aligned}
\ln(\text{Range})_{ct} = & \beta_1 \sum_{k=0}^4 \Delta p_{t-k} \xi_{t-k} + \beta_2 \sum_{k=0}^4 \Delta p_{t-k} (1 - \xi_{t-k}) + \beta_3 \sum_{k=5}^{19} \Delta p_{t-k} \xi_{t-k} \\
& + \beta_4 \sum_{k=5}^{19} \Delta p_{t-k} (1 - \xi_{t-k}) + \beta_5 \sum_{k=20}^{49} \Delta p_{t-k} \xi_{t-k} + \beta_6 \sum_{k=20}^{49} \Delta p_{t-k} (1 - \xi_{t-k}) \\
& + \sum_1^6 \text{day of week}_t + \sum_1^C \text{city}_c + \epsilon_{ct}
\end{aligned} \tag{3}$$

where

$$\xi_{ct}^{(m,n)} = \begin{cases} 1 & \text{if } \Delta p_{ct} > 0, \text{ and} \\ 0 & \text{otherwise,} \end{cases}$$

and C denotes the number of cities (between 49 and 103 according to the sample employed). Notice that the average price that is the basis for our explanatory variables here is the price for each city separately, and not, as in our search results, the national average price.

Table 4 provides the results of the estimation of equation 3. The table includes results for four of the six possible combinations of dispersion measures and samples. While the significant differences in sample size lead to differences in the estimated outcomes, the results across all of our diverse samples and specifications are consistent in the lessons they provide. Hence we will focus on just

one set of results, those in the last column of the table that utilize our full sample and the standard measure of the price range. City fixed effects are included in the estimates, but are not presented in the table. The results show that the short term effects of price movements are different. An increase in price leads to an insignificant increase in dispersion, while a price decline results in a very large increase in dispersion. It is reasonable to suppose in each case that the price movement is the result of an underlying change in wholesale cost, but the effect of such cost changes will likely not occur simultaneously across stations. It is not surprising, therefore, that we observe a small increase in dispersion associated with a recent price increase—the effects of search are partially offset by the roiling of the market accompanying an underlying cost change. In addition, any increase in search reflected in more price reporting may also increase recorded dispersion.

The pattern changes dramatically when we investigate the effects of lagged price changes—those that have had time to affect both searchers and firms responding both the underlying source of the price movement and to changes in search that the movement triggers. Past price increases (those beyond the most recent five days) are associated with large and significant reductions in dispersion. An increase of 10 cents in the average price in a city leads to a 5.5% decline in dispersion for the 5-20 day lag and a 1.4% decline for the 20-50 day lag. Price decreases continue to be linked as in the short run to large *increases* in dispersion, with a 10 cent decrease in price estimated to yield a 11.2% increase in dispersion for the 5-20 day lag and a 1.2% increase for the longest lag. Thus the effects trail away for the longest lags we consider, but price increases continue to be associated with less dispersion and price decreases with more. Each effect is significantly different from zero and the differences are therefore significant as well.

Our dispersion results are thus consistent with our search results. Price dispersion shrinks for as prices increase as the effect of increase search overcomes the tendency of volatility to increase

dispersion. But when prices decline, dispersion rises as the costs of holding back from cutting prices are not nearly so large as those of being away from the market average in an environment populated by unusually well-informed consumers.

5 Summary and Conclusions

Gasoline markets are only the most salient of those that exhibit asymmetric price adjustments. Peltzman (2000, p. 493) remarks that “The odds are better than two to one that the price of a good will react faster to an increase in the price of an important input than to a decrease. This asymmetry is fairly labeled a ‘stylized fact.’ ” But the reasons for this asymmetry are far from clear. Peltzman (p. 467) notes that

Economic theory suggest no pervasive tendency for prices to respond faster to one kind of cost change than to another. In the paradigmatic price theory we teach, input price increases or decreases move marginal costs and then prices up or down symmetrically and reversibly. Usually we embellish these comparative statics results with adjustment cost or search cost stories to motivate lags in response. But there is no general reason for these costs to induce asymmetric lags.

We have here offered direct evidence about what is inside the black box of adjustment costs for an important consumer price, that for retail gasoline. When gasoline prices rise, consumers increase their search. The search response to price declines is far smaller. As a result, the dispersion of consumer prices falls as prices rise as gasoline stations find the penalty for deviation from the market norm has increased. In contrast, when prices fall, dispersion increases—the penalty

for failing to pass along price declines is diminished. Consumers' imperfect information is the underlying source of pricing asymmetry. We believe that at least for gasoline, the pattern of greater search in responses to price increases in comparison to price declines deserves to be accorded the status of a stylized fact, one that can serve as a basis for further theoretical developments. We are in addition hopeful that our approach can extend to other product markets, so that we can identify search asymmetry as a source of the widespread stylized fact of asymmetric price adjustment that Peltzman has established.

References

- Bachmeier, L. J. and J. M. Griffin, 2003, "New Evidence on Asymmetric Gasoline Price Responses," *Review of Economics & Statistics*, 85, 772–776.
- Bacon, R. W., 1991, "Rockets and Feathers: The Asymmetric Speed of Adjustment of UK Retail Gasoline Price to Cost Changes," *Energy Economics*, 13, 211–218.
- Bénabou, R. and R. Gertner, 1993, "Search with Learning from Prices: Does Increased Inflationary Uncertainty Lead to Higher Markups," *The Review of Economic Studies*, 60, 69–93, URL <http://links.jstor.org/sici?sici=0034-6527%28199301%2960%3A1%3C69%3ASWLFDP%3E2.0.CO%3B2-7>.
- Borenstein, S., A. C. Cameron and R. Gilbert, 1997, "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *The Quarterly Journal of Economics*, 112, 305–339, URL <http://links.jstor.org/sici?sici=0033-5533%28199702%29112%3A1%3C305%3ADGPRAT%3E2.0.CO%3B2-U>.
- Cabral, L. and A. Fishman, 2006, "A Theory of Asymmetric Price Adjustment," URL <http://www.econ.yale.edu/seminars/apmicro/am06/cabral-060921.pdf>, <http://www.econ.yale.edu/seminars/apmicro/am06/cabral-060921.pdf>.
- Deltas, G., 2004, "Retail Gasoline Price Dynamics and Local Market Power," Unpublished paper, University of Illinois, Urbana-Champaign, <https://netfiles.uiuc.edu/deltas/www/UnpublishedWorkingPapers/GasolinePriceDynamics.pdf>.

- Galeotti, M., A. Lanza and M. Manera, 2003, "Rockets and Feathers Revisited: An International Comparison on European Gasoline Markets," *Energy Economics*, 25, 175–190.
- Geweke, J., 2004, "Issues in the 'Rockets and Feathers' Gasoline Price Literature," Report to the Federal Trade Commission, University of Iowa.
- Hosken, D. S., R. S. McMillan and C. T. Taylor, 2006, "Retail Gasoline Pricing: What Do We Know?" U.S. Federal Trade Commission, paper presented at the International Industrial Organization Conference, Savannah, GA, April 2007.
- Lewis, M., 2005, "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market," Technical report, The Ohio State University, available at http://www.econ.ohio-state.edu/mlewis/Research/Lewis_Asymmetric_Adjustment.pdf.
- Lewis, M. S., 2007, "Price Dispersion and Competition with Differentiated Sellers," *Journal of Industrial Economics*, forthcoming.
- Peltzman, S., 2000, "Prices Rise Faster than They Fall," *The Journal of Political Economy*, 108, 466–502, URL <http://links.jstor.org/sici?sici=0022-3808%28200006%29108%3A3%3C466%3APRETTTF%3E2.O.CO%3B2-8>.
- Stigler, G. J., 1961, "The Economics of Information," *The Journal of Political Economy*, 69, 213–225, URL <http://links.jstor.org/sici?sici=0022-3808%28196106%2969%3A3%3C213%3ATEOI%3E2.O.CO%3B2-D>.
- Tappata, M., 2006, "Rockets and Feathers: Understanding Asymmetric Pricing," UCLA.

Yang, H. and L. Ye, 2007, "Search with Learning: Understanding Asymmetric Price Adjustments,"

Department of Economics, The Ohio State University.

Table 1: Rankings of GasBuddy.com local price sites

Alexa.com traffic rank for February 22, 2007
 (a period of low gas prices
 compared to those prevailing in the previous year)

Location	Alexa Traffic Rank
GasBuddy.com	70,456
San Jose	680,565
San Francisco	905,384
Los Angeles	622,956
San Diego	1,552,704
Chicago	2,178,953
Seattle	546,295
Detroit	890,277
Boston	2,180,036
Denver	644,598
Columbus, Ohio	1,103,777
Dallas	1,661,050
Atlanta	910,937
...	
gaspricewatch.com	164,500
fuelgaugereport.com	693,807

Table 2: Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Reach regression (726 days)					
Reach	726	82.76	146.07	3.21	1819.74
$\ln(\text{Reach})$	726	3.88	0.95	1.17	7.50
Price	726	2.37	0.38	1.75	3.07
Range regressions (123 days, 103 cities)					
Price (U.S. average)	123	2.28	0.07	2.15	2.51
Price (City average)	12621	2.28	0.18	1.90	3.09
Median range	12621	0.13	0.08	0	0.60
$p^{\max} - p^{\min}$	12621	0.30	0.19	0	5.17
$\ln(\text{median range})$	12515	-2.21	0.67	-5.30	-0.51
$\ln(p^{\max} - p^{\min})$	12613	-1.38	0.58	-4.60	1.64

Notes to table 2: Prices are measured in dollars per gallon. U.S. average prices are included with the range regressions data for comparison purposes. The regression estimates employ city-specific average prices as explanatory variables for the corresponding city price dispersion measure.

Table 3: Gasoline Price Movements as a Determinant of Price Search

Variable	Coefficient (Newey-West std. error)	t -statistic for difference in coefficients	
α_0 (intercept)	2.56*** (0.118)		
α_1 (date)	0.0016*** (0.0002)		
α_2 (price change +, most recent 4 days)	5.77*** (0.885)	$\alpha_2 \neq -\alpha_3$	2.49
α_3 (price change, -, most recent 4 days)	-0.52 (2.064)		
α_4 (price change, +, days 5-20)	4.48*** (0.814)	$\alpha_4 \neq -\alpha_5$	3.55
α_5 (price change, -, days 5-20)	-1.75** (0.838)		
α_6 (price change, +, days 20-50)	1.59*** (0.335)	$\alpha_6 \neq -\alpha_7$	4.80
α_7 (price change, -, days 20-50)	0.21 (0.297)		
Number of Observations	676		

Notes to table 3: Search is measured by $\ln(\textit{Reach})$, that is, the natural log of the Alexa.com measure of the “reach” (an Internet traffic measure) of GasBuddy.com for the date in question. Prices are national average prices recorded by for the corresponding data on GasBuddy.com. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Gasoline Price Dispersion as a Function of Price Movements

Sample: Dependent Variable:	Specification			
	49 cities median range	City/date pairs with 30 prices $p^{\max} - p^{\min}$	median range	full sample $p^{\max} - p^{\min}$
Variable	Coefficients (Newey-West standard errors in parenthesis)			
β_1 (price change +, most recent 4 days)	0.30 (0.173)	0.11 (0.119)	0.25* (0.147)	0.10 (0.129)
β_2 (price change, -, most recent 4 days)	-2.41*** (0.222)	-1.81*** (0.153)	-2.31*** (0.178)	-1.25*** (0.183)
β_3 (price change, +, days 5-20)	-0.13 (0.101)	-0.27*** (0.089)	-0.13 (0.097)	-0.55*** (0.100)
β_4 (price change, -, days 5-20)	-1.02*** (0.094)	-1.09*** (0.068)	-1.04*** (0.072)	-1.12*** (0.080)
β_5 (price change, +, days 20-50)	-0.01 (0.057)	-0.08* (0.047)	-0.08 (0.053)	-0.14*** (0.052)
β_6 (price change, -, days 20-50)	-0.14*** (0.037)	-0.13*** (0.030)	-0.13*** (0.032)	-0.12*** (0.032)
Day of Week Indicator Variables				
Monday	0.14*** (0.011)	0.09*** (0.011)	0.16*** (0.011)	0.11*** (0.011)
Tuesday	0.17*** (0.011)	0.08*** (0.011)	0.19*** (0.011)	0.11*** (0.011)
Wednesday	0.16*** (0.012)	0.08*** (0.012)	0.18*** (0.012)	0.12*** (0.012)
Thursday	0.15*** (0.012)	0.08*** (0.012)	0.18*** (0.012)	0.11*** (0.012)
Friday	0.13*** (0.011)	0.09*** (0.011)	0.16*** (0.011)	0.12*** (0.011)
Saturday	-0.00 (0.010)	0.01 (0.012)	0.00 (0.011)	0.01 (0.012)
Number of Observations	4783	9978	9960	12613

Notes to table 4: Price dispersion is measured by the natural log of the price range for a city on a particular date. Pricing data are available for 103 U.S. cities that are covered by GasBuddy.com web sites. To eliminate the effect of non-competitive stations (particularly at the high end of the price distribution) we measured the range as the fifth highest recorded price minus the fifth lowest price, again for a given city as recorded on a given day. Our dataset consisted of observations for the 103 available U.S. cities daily for the period September 15, 2006–January 15, 2007. The estimates included city fixed effects which are omitted from the values reported above. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.