WHEN DO CONSUMERS SEARCH?*

Matthew S. Lewis[†]
Howard P. Marvel[‡]

This paper provides empirical evidence relating search to price movements. We measure consumer search directly from traffic statistics for web sites that report gasoline prices. We show empirically that consumers search more as prices rise than they do when prices fall. Asymmetric search patterns have consequences for price behavior. Our findings indicate that retail margins are squeezed by increased search. In addition, we show that there is more price dispersion when prices are falling than when prices are either stable or rising. Our results provide a search-based explanation for the 'rockets and feathers' phenomenon of asymmetric price adjustment.

Keywords: Search, retail gasoline, price asymmetry
JEL D8, L8, C8

*We thank Robert de Jong, Saul Lach, Huanxing Yang, Lixin Ye, and three referees for this journal for their comments and suggestions. David Knapp provided outstanding research assistance. All conclusions and/or errors are solely the responsibility of the authors.
[†]Authors' Affiliations: Department of Economics, The Ohio State University, 1945 North High Street, Columbus, OH 43210–1172.
email: mlewis@econ.ohio-state.edu.
[‡]Department of Economics and Moritz College of Law, The Ohio State University, 1945 North High Street, Columbus, OH 43210–1172.
email: marvel.2@osu.edu.

I. 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. Without knowledge of when consumers choose to search, researchers must either infer their search behavior from the prices and price movements that trigger search, or, alternatively, must infer search from measures of the cost of search. As an example, Brown & Goolsbee [2002] argue that 'it is important to investigate the extent to which consumers search, how they search and why they search—or don't search.' They do not, however, measure search directly, but instead infer search from measures of Internet usage generally. Here, we instead provide a direct measure of search intensity that we can then relate to observed price movements and dispersion.

We examine empirically the manner in which price movements trigger consumer search 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 demonstrate that there is an underlying asymmetry in consumer search behavior that can yield asymmetric price adjustment: price increases are much more likely to generate additional search than are decreases.

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 their Internet browsers. 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.

Our primary interest is in how recent price movements impact search behavior. We estimate this relationship by regressing our measure of search on current and past price movements in a form that allows for asymmetric response of search intensity to price changes. But search, in turn, has consequences for competition among retailers and hence for the prices they set, so that current prices and search are determined simultaneously. In the regression analysis, we instrument for recent gasoline prices in individual markets by employing the New York harbor spot market wholesale price for gasoline.

The amount of search that consumers undertake affects the amount of information they possess, which in turn affects the pricing decisions of retailers. In particular, when consumers are well informed, competition among retailers is heightened, resulting in lower retail margins. We investigate the relationship between search and margins, and find evidence that increases in our search measure lead to smaller margins, as predicted. Our direct link between search and asymmetric retail margins provides evidence that asymmetric search is the source of the often observed 'rockets and feathers' retail price asymmetry documented both in the gasoline market (Borenstein et al. [1997]; Bacon [1991]) and elsewhere.

A related question concerns the relationship between search and price dispersion.[1] Our data do not permit us to relate consumer search directly to dispersion.[2] However, since we have shown that more search occurs when prices are rising, and since dispersion is expected to respond to search, we relate dispersion to the direction of price movement. Using prices obtained from the family of local gasoline price sites under the GasBuddy.com banner, we construct measures of average price levels and price dispersion for 103 cities. The data reveal that price dispersion is much greater when prices are falling than when they are rising. 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. Thus our findings on dispersion and margins reflect and also support the asymmetric search behavior that we observe in response to price movements.

The paper is organized as follows. In Section II, we 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 III describes our data collection procedures. Section IV provides estimates of the relationship between movements in average price and search intensity. Section V provides evidence that the additional search that occurs when prices are rising is associated with lower retail gasoline margins. Section VI documents the effect of search intensity on price dispersion, using price movements as a proxy for search. Finally, Section VII offers a brief summary together with suggestions for future research.

[1] For a survey of work on search and price dispersion that focuses on the role of the Internet, see Baye et al. [2006].

[2] It is necessary to analyze price dispersion at the city level, but unfortunately, city-level search data are not available.

II. ASYMMETRIC SEARCH

When consumers face price dispersion, they must decide whether to accept a particular price or to continue to search for a better one. As Stigler's (1961) seminal article on search behavior highlights, 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 distribution 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 station's price 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 in consequence of the signal extraction problem that consumers face. 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. Alternatively, the supplier's price may have moved up idiosyncratically. 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.

In contrast, when a consumer encounters a price that has fallen, 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 induces 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.

This basic intuition is not well captured by traditional search models because these models assume that consumers know the distribution of prices that they face. In traditional models, wholesale cost changes result simply in a shift up in the distribution of prices being charged and, accordingly, do not impact consumers' search intensity.[3] In contrast, our approach is to

[3] In models where the underlying demand for gasoline is downward sloping or is capped at some reserve price, an increase in cost can have a small impact on the distribution of prices charged in equilibrium, which will alter the

acknowledge and to investigate empirically the possibility that wholesale cost changes and the retail price changes they generate can have a much more fundamental impact on search behavior. The intuition is in some ways similar to that modeled by Bénabou & Gertner [1993]. That paper presents a consumer search model in which firms' marginal costs include a common shock (experienced by all firms) and a firm-specific shock. This framework creates a signal extraction problem for consumers which leads the expected payoff of search to be asymmetric based on whether the initial price observed is 'high' or 'low.' If the consumer observes a relatively high price, that price could have been a consequence of a higher cost shock common to all firms, resulting in an across-the-board high prices. Alternatively, the observed high price may have been the result of a high cost draw specific to the firm whose price the consumer observes. This latter possibility of an idiosyncratic high cost will induce the consumer to search. Conversely, when a consumer observes a low price, it may be a consequence of a low common cost shock received by all firms. As with a common positive cost shock, the incentive to search is unaltered. The possibility that the lower price is due to an idiosyncratic cost shock introduces asymmetry into consumers' responses to price change—a lower price due to an idiosyncratic shock will not generate additional search. But without knowledge of the source of the price change a consumer faces, that consumer will respond asymmetrically to price movements, searching less when he/she observes a lower price because that lower price could simply be lucky, and searching more when a higher price is observed, as a consequence of the possibility that the consumer's luck was bad. Though the Bénabou & Gertner [1993] model is static, we posit that a very similar asymmetry in search occurs when a consumer observes a price change from a previous period at one station and must decide whether to search knowing that the price change may or may not reflect a price change common to all stations.

Our analysis is concerned in the first instance with the effect of price movements in triggering search, but clearly to the extent that consumers respond asymmetrically to price movements, their actions will have consequences in constraining the price-setting behavior of the retailers from which they purchase. Recent papers by Cabral & Fishman [2008], Tappata [2009], and Yang & Ye [2008] all attempt to model formally mechanisms through which consumer search behavior can generate an asymmetric response of prices to changes in cost. Though the models differ in structure, their predictions of asymmetric price response all rely on consumers searching more when prices and costs are increasing and less when prices and costs are falling. In all

equilibrium level of consumer search. We view these effects to be of second order.

of the models, this pattern of search fluctuation is achieved by relaxing the assumption that consumers know the equilibrium price distribution. Using a somewhat different approach, Lewis [2010] shows that consumers with adaptive expectations of prices will also search more when prices are increasing than decreasing, resulting in asymmetric price adjustment. Regardless of the particular mechanism, search based explanations of asymmetric adjustment all imply that price increases (decreases) should be associated with greater (lesser) consumer search intensity.

As in other retail markets, gasoline consumers will choose to search for additional prices only as long as their expected reduction in price exceeds the cost of an additional search. Even with the low costs of information acquisition,[4] consumers will not optimally force retailers to set identical prices, and thus price dispersion is characteristic in gasoline, as it is in most consumer products markets.[5] Ongoing search pays because service stations change positions within price distributions. Both Lewis [2008] and Hosken et al. [2008] 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.' It is important to note, however, that both the incentive for the consumer to acquire more information and the competitive pressures faced by firms depend on consumers' current level of knowledge about the price distribution, which is not necessarily the same as consumers' current search intensity. We suggest that consumers' knowledge of prices from the recent past will be more informative about the current price distribution during periods when the overall price level is relatively stable. In many ways this is akin to the situation in Bénabou and Gertner's (1993) static model when the variance of the shock common to all firms is very low and what remains is only firm specific cost heterogeneity. The overall uncertainty about the current price distribution is lower and, therefore, consumers search less yet are still relatively well informed.

In summary, fluctuations in retail prices can be expected to impact fundamentally consumers' knowledge of the price distribution they face, both by affecting consumers' search intensity and by altering the informativeness of past price information.[6] Of course, the equilibrium impacts of price

[4]The low costs are a consequence of a relatively homogeneous product with prices advertised on highly visible signage at outlets that the consumer encounters in the ordinary course of travel.

[5]See Lach [2002] for empirical evidence on the persistence of price dispersion for homogeneous consumer products. Indeed, price dispersion is characteristic of prices even within Internet markets, where search costs are thought to be very low. Brynjolfsson & Smith [2000] show that Internet prices are lower for equivalent branded goods compared to prices charged at brick-and-mortar retailers. They also provide evidence that while price dispersion may be attenuated in on-line prices, it is not eliminated.

[6]To be specific, price movements affect consumers' expected benefit of search by influencing consumers' expectations about the current price distribution. This change in the benefit of search could manifest itself as a change in the number of consumers choosing to search or a change in the amount of search each consumer chooses to undertake.

volatility stimulated by an underlying cost shock are more complex than this discussion suggests due to the endogeneity of retail prices and search behavior. As search activity increases when firms start passing the cost increase through to prices, firms are more strongly constrained in their attempts to raise prices the full amount of the cost increase. Asymmetric search will thus result in shrinking margins in response to underlying cost increases, and, conversely, increasing margins as costs fall, a prediction discussed and tested in Section V below. As consumers become better informed, the resulting increase in retailer competition will also reduce the benefits of search, the source of our endogeneity concern. But as long as consumers possess less than perfect information about the price distribution and price changes have a direct impact on consumers' level of price information, then the first order impact of an underlying cost change will be determined by how consumers respond to the price changes that the underlying cost changes induce.[7]

III. DATA

This section describes the data sources from which we have collected data on gasoline search behavior and 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. We therefore expect traffic on the GasBuddy.com sites to reflect actual search activity in the marketplace. That is, increased GasBuddy traffic can be expected when consumers believe that adding to their price information is most useful.

We would have preferred to obtain data directly on the number of visits to local GasBuddy websites for individual cities, but were unable to do so. The city sites did not generate traffic sufficient to rank them in the set of websites covered by our traffic rankings. We were able to obtain price data from these local sites for individual cities. 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.

For our purposes this makes little difference as both will lead to a higher level of price information for consumers and generally greater competitive pressure for the firms.

[7] The alternative would be that cost changes only (or primarily) impact consumer search indirectly through firm behavior. Here search behavior would only be affected if the cost shock led firms to charge a different price distribution, thereby altering consumer incentives to search. However, a cost shock that led firms to charge less disperse prices would likely result in less consumer search (as the benefit of search falls). This prediction is opposite to that which we suggest above and is inconsistent with the empirical evidence we present.

III (i). *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 who have downloaded and installed the toolbar, as the behavior of Alexa toolbar users is recorded in a central database under Alexa's control.[8] 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.[9]

Alexa claims that its web traffic information is based upon 'the Web usage of millions of Alexa Toolbar users,'[10] 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). The Gasbuddy.com site is a national portal to local gas prices, and therefore traffic measured for the site represents nationwide search activity. At the time we collected our data, Alexa expressed reach as the number of 'hits' per one million Internet users.[11]

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.[12] Alexa does, however, make available graphical depictions of their data for various windows. We captured a snapshot of the Alexa daily reach data for GasBuddy.com as a bitmap file. We then digitized the Alexa graphs in order to extract daily traffic data.

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

[8] The toolbar is described at http://www.alexa.com/site/download.

[9] *Id.*

[10] See http://www.alexa.com/site/help/traffic_learn_more.

[11] Alexa has changed its reporting so that reach is now expressed as the percentage of all Internet users who visit a given site.

[12] See also 'Historical data for ranks and pages,' http://developer.amazonwebservices.com/connect/thread.jspa?messageID-38979.

few hits. The data threshold is that the site must rank within the top 100,000 sites among Alexa toolbar users.[13] Many of the competing gasoline price aggregation sites fail to meet that threshold on a consistent basis.[14] 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.

III (ii). *Gasoline Prices*

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 Columbus-GasPrices.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.

We obtained a daily listing for each of these local sites of the fifteen highest and lowest prices reported that day by volunteer spotters in the corresponding locality. The spotters are asked to report the pump prices for regular unleaded gasoline. We visited each local site at 7 P.M. to obtain prices recorded during the previous twelve hours. Accordingly, no price could be more than 1/2 day old. When more than one price is reported for a station, the GasBuddy listing reports only the most recent value, and thus the prices in our sample will be on average more recent than that would be expected from the distribution of samples throughout the day. When prices are moving in a particular market, the high and low prices in the marketplace could be separated in time by nearly the length of the window. Thus if prices are rising, the list of low prices may include stations early in the day, while the high prices are current, and the reverse can hold when prices in that market are falling. But given the narrow window and the inclusion of only the most recent price observed, any resulting bias is likely to be small.

There are other potential problems with the GasBuddy data. For example, Lach & Moraga-Gonzalez [2009] point out that by relying on consumer reporting, GasBuddy could oversample low prices, as these will be the ones that GasBuddy's searchers actually pay. However, this problem

[13] The 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.

[14] The 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.

is mitigated by the fact that most GasBuddy spotters appear to report prices far more frequently than they can reasonably be expected to have purchased.[15] This concern and others are also allayed by a comparison (Atkinson [2008]) between GasBuddy data for a particular market and a panel of gasoline prices collected by direct observation for that same market (Guelph, Ontario). Atkinson concludes that GasBuddy data 'can be reliable for answering questions that require daily, company-operated, major brand station prices... ' Atkinson's results indicate that the only group of stations whose prices are underreported by Gasbuddy.com spotters are those 'mom-and-pop' independent stations that have strongly differentiated themselves by offering gasoline primarily to customers who visit them for automotive repair services.[16]

While the GasBuddy site only posts current prices, 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 regular grade unleaded gasoline prices 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, gasoline outlets that serve primarily as automotive service providers may 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.

The Alexa traffic numbers indicate that the GasBuddy websites are the most popular Internet source for prices at individual stations. We were, however, concerned about two issues inherent in the manner that prices can be retrieved from the GasBuddy databases. GasBuddy.com is the primary portal to gasoline prices, but experienced users can also go directly to prices for individual

[15]We checked the member profiles for the Gasbuddy.com spotters who posted the highest and lowest prices on ColumbusGasPrices.com reported on March 12, 2010. Of the thirty postings, only eight were recorded by a spotter who was represented only once among the posters. Of these eight, all but one had also posted at least three consecutive days.

[16]Independent stations that provide self-service pumps and (mostly) offer convenience stores are well represented in the Gasbuddy.com data. The underrepresented gasoline outlets offer only full-service gasoline sales, operate service bays, and do not have convenience stores.

cities using the affiliated city-specific sites like Columbusgasprices.com This could confound our results if users visited GasBuddy.com on an initial visit as prices rose but continued to search by visiting the appropriate city-specific site on return visits. To check for this possibility, we recorded Internet traffic at an alternative site, http://GasPriceWatch.com. This site, while less heavily trafficked than GasBuddy.com, has only a single domain—traffic by all visitors, whether new or repeat, is thus recorded by the Alexa traffic statistics. Accordingly, we have provided alternative estimates using the GasPriceWatch.com data in place of Gasbuddy.com data.

We were also concerned that some GasBuddy.com visitors might have been interested only in obtaining general information on gasoline prices, rather than having been driven to the site to search for prices prevailing at individual stations. Visiting a site to learn about overall gasoline price movements is informative for consumers and may trigger additional price search. However, to look directly at search behavior on the Internet, we wanted to control for the effect of traffic that was driven to sites by publicity of gasoline price movements but which did not necessarily induce search for particular station prices. To do so, we gathered traffic information for a very popular gasoline price information site, the AAA Daily Fuel Gauge Report, http://www.fuelgaugereport.com. This site provides extensive price reporting, including daily retail gasoline price averages by grade, for a large number of urban areas. By employing traffic received by the AAA site as a control, we allow for increases in interest in gasoline prices generally. A visit to this site will not yield information on the prices at individual stations, though easy observation of the general level of prices could trigger (or inhibit) further search.

IV. SEARCH AND PRICES

We begin by illustrating the relationship between prices and search. Figure 1 charts the GasBuddy gasoline price data together with the Alexa reach data for GasBuddy.com traffic. It is apparent that prices and reach are systematically related.[17] Moreover, it appears that reach is at its highest level when prices are increasing, a relationship examined in detail in the empirical work below. Two episodes stand out in Figure 1. The high prices in September 2005 occurred in the days following two devastating hurricanes, Katrina and Rita, that disrupted important production and refining areas offshore and in Louisiana and Texas. This was not, however, simply a weather-related event, as prices before Katrina had already exceeded $2.50 per gallon as a result of rising crude oil prices and refining capacity issues. The price spike of 2006 was also a consequence of increasing crude

[17]The correlation coefficient between price and ln(reach) is 0.724.

prices and major refinery capacity problems.

Place Figure 1 approximately here

Table I provides summary statistics for the data used in our empirical analysis. The first grouping of data provides statistics that summarize the price and search data used in our search and margin regressions. Our city-by-city data collection of prices and price dispersion are for a later time period, and are summarized in the second portion of the table.

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 GasBuddy.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

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

Place Table I approximately here

Search behavior can be influenced by both current and lagged price changes. We regress the natural log of our *Reach* variable on the daily price change for each of the previous 50 days interacted with ξ_t to allow separate coefficients to be estimated for positive and negative changes.[18] Rather than estimate the large number of price change coefficients separately, we divide the 50 days into three periods and restrict the coefficients to be the same within each period. The periods are defined as the most recent five days, the interval between twenty and five days previous, and the thirty days prior to that interval. The resulting specification appears in Equation 1. By cumulating price movements over an interval separately for price increases and decreases, we are assuming that the coefficient of a daily price movement in one direction remains constant over the corresponding interval.[19] As a result, the effect of a price movement is allowed to be asymmetric

[18] Our regressions employ ln(*Reach*), rather than simply *Reach*, as the dependent variable. The data for the *Reach* variable are highly skewed, in marked contrast to the rough symmetry observed after transformation. The logged variable yields a much higher goodness of fit in our linear regressions. In addition, using ln*Reach* gives rise to easier-to-interpret coefficients, given its (approximate) percentage interpretation.

Nevertheless, regressions using reach in levels as the dependent variable yield the same basic patterns of signs and magnitudes for the various price change coefficients.

[19] A joint F-test of the restrictions of the coefficients within periods cannot be rejected (p-value = 0.472). In addition, specification tests reject the significance of additional lags beyond the previous 50 days.

based on the movement's direction.

$$
\begin{aligned}
\ln(Reach)_t &= \alpha_0 + \alpha_1 \sum_{k=0}^{4} \Delta p_{t-k}\xi_{t-k} + \alpha_2 \sum_{k=0}^{4} \Delta p_{t-k}(1-\xi_{t-k}) \\
&\quad + \alpha_3 \sum_{k=5}^{19} \Delta p_{t-k}\xi_{t-k} + \alpha_4 \sum_{k=5}^{19} \Delta p_{t-k}(1-\xi_{t-k}) \\
&\quad + \alpha_5 \sum_{k=20}^{49} \Delta p_{t-k}\xi_{t-k} + \alpha_6 \sum_{k=20}^{49} \Delta p_{t-k}(1-\xi_{t-k}) \\
&\quad + \alpha_7 \text{date} + \alpha_8 \text{date}^2 + \text{day-of-week indicator variables} + \epsilon_t \qquad (1)
\end{aligned}
$$

Equation 1 models search activity as a function of the cumulative positive and negative price movements described above, as well as a quadratic time trend and a set of day-of-week indicator variables. The time trend—represented by a date variable ranging from 50 to 726—helps control for the fact that both prices and search are increasing slightly during the time period. Our main specification includes a quadratic time trend, though alternative specifications including up to a quartic time trend generate very similar coefficient estimates. Day-of-week indicator variables control for any systematic differences in the intensity of search throughout the week.

Not surprisingly, given our use of daily observations, the residuals from Equation 1 are highly serially correlated. As a result we estimate Equation 1 using a Prais-Winsten feasible GLS procedure to correct for serial correlation assuming a first-order autoregressive process.[20] To acknowledge the possibility that some serial correlation may still remain in the residuals of the Prais-Winsten estimation, we report Newey-West robust standard errors that allow for autocorrelation of up to three lags.

While we wish to focus on the manner in which price movements influence consumers to engage in search, it is also apparent that prices will respond to the stock of consumer information, a stock that is augmented by search. While today's search will not affect past prices, the response of current prices to current search should not be ignored. Hence we have used recent changes in the wholesale price of gasoline to construct instruments for the most recent changes in retail price.[21] The terms from Equation 1 representing price changes over the most recent 5 days, $\sum_{k=0}^{4} \Delta p_{t-k}\eta_{t-k}$

[20] In most specifications the correlation coefficient on the error term is between .8 and .9. A Durbin-Watson test rejects the hypothesis of no serial correlation at the 1% significance level. However, both a Dickey-Fuller test and a Phillips-Perron test reject the hypothesis of a unit root in the *Reach* variable at the 1% significance level.

[21] The wholesale price we use is the daily New York harbor spot price for conventional regular grade gasoline as reported by the U.S. Department of Energy, Energy Information Administration, http://tonto.eia.doe.gov/dnav/pet/hist/rrunyhd.htm.

and $\sum_{k=0}^{4} \Delta p_{t-k}(1-\eta_{t-k})$, are instrumented for using daily wholesale price changes from the most recent 30 days. Since the retail price change variables are split to allow separate coefficients for positive and negative changes, the wholesale price change instruments are also split to allow separate coefficients for positive and negative wholesale price changes in the first stage regression.[22]

For comparison, Table II includes non-IV GLS estimates in Column 1. Columns 2–4 are all IV estimates that treat the most recent price movements as endogenously determined. Column 2 provides estimates based simply on the GasBuddy.com data. These estimates are directly comparable to the un-instrumented estimates on Column 1. Column 3 adds the log of the Alexa Reach of the AAA Daily Fuel Gauge Report as an explanatory variable. The estimates in Column 4 are identical to those in Column 2, except that the Alexa reach data for GasBuddy.com are replaced with data for an alternative gasoline price comparison web site, GasPriceWatch.com.

The instruments are strongly significant in the first stage regressions for each of the IV specifications in Table II. The partial R^2 of each of the first-stage regressions for $\sum_{k=0}^{4} \Delta p_{t-k}\eta_{t-k}$ exceeds 0.67. For the first-stage regressions for $\sum_{k=0}^{4} \Delta p_{t-k}(1-\eta_{t-k})$, each of the partial R^2 values exceeds 0.37.

Place Table II approximately here

We begin our interpretation of the IV results by considering those that employ GasBuddy.com data. Inspection of the results in Table II, Column 2, shows that price movements trigger search, but that the response is highly asymmetric. The responses are generally 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. Indeed, the only time that the coefficients of negative price changes are even marginally statistically significant is for the 20–49 day price declines in Column 3, where the coefficient is positive. If price declines were to yield increased search, the coefficients should be negative. Thus only the day 5–19 price declines show any tendency for price declines to trigger search, and in each case the estimated effect differs insignificantly from zero.

To test for asymmetry, we compute t-statistics for the difference in the values of the coefficients paired for each lag interval. Once again restricting attention to the results in Column 2, we obtain t-values of 2.64, 4.75, and 2.55 for, respectively, the price movement intervals $[0, 4]$, $[5, 19]$, and $[20, 49]$. Thus the asymmetry is strongly statistically significant—when prices are rising, search

[22]This procedure results in 60 instrumental variables: $\Delta w_{t-k}\eta_{t-k}$ and $\Delta w_{t-k}(1-\eta_{t-k})$ for k from 0 to 29, where here η_{t-k} is one if $\Delta w_{t-k} > 0$ and zero otherwise.

rises. Falling prices may or may not trigger additional consumer search, but the effect is never close to as large as the impact of rising prices.[23]

To summarize, the results reported in Table II indicate that price increases serve to induce additional search. Price decreases do not. [24]

Given the log-linear functional form of Equation 1, the coefficient estimates can identify the percentage change in search that is associated with an x cents per gallon change in the price of gasoline. However, the coefficient value itself is a good approximation of this percentage effect only when the implied percentage effect is small. Therefore, we interpret the results using an exact calculation for percentage effects.[25]

The coefficient estimate of 2.20 for a positive change in price within the last 5 days from Table II, Column 2, indicates that a 10 cent increase in price over the last 5 days is associated with a 24% increase in search, while the coefficient estimate of 2.33, while insignificant, implies that a 10 cent/gallon decrease in price within the last 5 days corresponds to an reduction of 20.5% in search. These are large effects, reflecting the very substantial volatility observed in our search measure, as is illustrated in Figure 1. The asymmetry present is similar to that for the interval from day 19 to day 5, where the effect of a positive price is a 36.8% increase in search, while a negative price change leads to a small and insignificant increase in search. These estimates identify substantial differences in search intensity between periods of rising and falling prices. But such large effects are plausible given the extent to which search activity changes over time, as illustrated in Figure 1.

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 1 are included to reflect the salience of gasoline

[23] Indeed, the only significant coefficients are for instances when declining prices are associated with reduced search.

[24] Even though the coefficients are asymmetric, they are consistent with a roughly stable amount of search over time. One might be concerned that a price increase of a given percentage will increase search, but unless the increase is reversed by a later offsetting fall in prices, the search series will be permanently higher. To see why this is not the case, imagine that the price of gasoline is constant, but subject to a one period permanent increase in price at, say, date j, after which the price is stable at the new higher price. Our estimates indicate that search rises in the short term as the price increase is observed by some consumers. As the price increase continues to be observed over the 5-19 day interval, the effect of that one increase in price on search is larger. With the passage of time, the effect is attenuated, and ultimately, by date $j + 51$ it vanishes and the amount of search returns to that observed before the price increase. There is no need for an offsetting price decline to return search to its prior level.

[25] For a log-linear regression ($ln(Y) = X\beta + \epsilon$) the correct calculation of the estimated percentage effect on Y from a 1 unit change in X is: $\%Change = 100(e^{\beta} - 1)$. This correction implies that the true percentage effect will be larger than β when $\beta > 0$ and will be smaller in absolute value than β when $\beta < 0$. The exact calculation used here is: $100(e^{\cdot 10\beta} - 1)$ since we are considering a 10 cent change and prices are measured in dollars per gallon.

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, we believe that the inclusion of the AAA Daily Fuel Gauge Report traffic over-corrects for general market information, since information on average prices is both useful directly and can trigger additional search. The results reported in Column 3 indicate that search asymmetry is present and significant even after controlling for traffic for a website that provides non-station-specific gasoline pricing information.

The results in Column 4 of Table II permit comparison of the results reported in Column 2 for the GasBuddy.com traffic measures with those for a similar site, GasPriceWatch.com. The results obtained are very similar, suggesting that concerns about repeat visits to the GasBuddy data through city-specific domains do not constitute a significant problem.[26]

Acknowledging the fact that the time periods over which we have accumulated price changes in Equation 1 are rather arbitrary, we also check the robustness of our findings by specifying Equation 1 using alternative time windows. For example, we have estimated an alternative model accumulating price changes within three periods corresponding to the most recent seven days, the interval between twenty-one and seven days previous, and the fourteen days prior to that interval. The patterns of the statistically significant coefficients in the original specification change very little under the alternative specification.[27]

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 wholesale 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

[26] The similar results also suggest that the GasBuddy results are not distorted by the presence of an active gasoline price discussion forum on the GasBuddy site. The GasPriceWatch site offers both 'live chat' and a discussion board, but the number of posts is small relative to the total claimed traffic. As of November 27, 2007, a total of 2106 messages had been posted in the entire history of the discussion board, in comparison to a claim of 361,532 'prices input this week' and 160,989 'member spotters.' The *de minimis* traffic on the GasPriceWatch forum cannot have had much of an impact on our GasPriceWatch regression results, and their similarity to those for GasBuddy suggests that the latter are also not influenced substantially by discussion traffic.

We would also expect that traffic on the GasBuddy forum would be correlated with general interest in gasoline pricing such as that driving traffic to the AAA Daily Fuel Gauge Report. As noted above, including that site's traffic as an explanatory variable did not substantively modify our results.

[27] The average coefficient estimate within a time period necessarily changes as one lengthens or shortens a window, but comparisons regarding relative magnitudes of the coefficients on positive and negative price movements are largely unaffected.

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. In the next section, we consider the effect of search on retail competition, as measured by the retailer margins that such competition induces.

While consumers likely face more price uncertainty during periods when overall price levels are changing, our results show that they only compensate by searching and become more informed when prices are increasing. This asymmetry implies that consumers will be relatively uninformed when prices are falling. Hence, as prices fall, less elastic demand will allow stations to charge higher prices and may lead to greater price dispersion. We investigate these predictions in the next two sections.

V. SEARCH AND MARGINS

In this section, we investigate the relationship between measured search and retail gasoline margins. The literature has established that retail margins shrink as prices rise and increase as prices fall. (Borenstein et al. [1997]; Lewis [2010]). When wholesale prices rise, retail prices rise rapidly as well, but not sufficiently to 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. Our finding that search responds asymmetrically to price movements provides the link between price movements and margins, thus explaining 'rockets and feathers' behavior of retail gasoline prices.

When consumers are better informed about prices firms are constrained by competitive pressures to charge lower margins.[28] Brown & Goolsbee [2002] provide evidence for this proposition using Internet utilization as a proxy for search. Since we have a direct measure of search, we can investigate directly whether increase search is associated with lower margins.

We measure our dependent variable, retail gasoline margins, as the GasBuddy daily national average price for regular gasoline minus the cost of gasoline as measured by the daily New York harbor spot price for conventional regular grade gasoline as reported by the U.S. Department

[28]Our explanation for this relationship differs from the simple application of search theory in the presence of a fixed price distribution. For a given distribution of prices, an increase in search intensity will cause consumers to obtain prices from lower in the price distribution, thereby reducing average margin. In contrast, we emphasize that consumers typically must infer when to search based on limited price information. Thus search intensity is altered in response to a changing price distribution. Therefore the effect of changes in search intensity flows from underlying price movements, and the asymmetry of this relationship drives asymmetry in the response of margins to underlying shocks.

of Energy, Energy Information Administration.[29] The EIA spot price series represents the price of generic gasoline on the east coast and is calculated from a daily survey of major traders. We attempt to explain margins, rather than prices, because we wish to limit our attention to the effects of consumer search for retail price information on competition among gasoline retailers. Although the proxy employed by Brown & Goolsbee [2002] does not measure search directly, it does have the advantage of being plausibly exogenous. Given that we have argued above that search activity will respond to price movements in the gasoline market, our search measure obviously presents problems of simultaneity. We note, however, that the simultaneity works against finding a relationship between margins and search. Consumer search theory predicts that margins will contract when consumers are unusually well informed. However, to the extent that search compresses price dispersion, it may reduce the desire to search further, attenuating the negative effect of search on margins.[30] As a result, we conclude that estimating a negative relationship between margins and search is consistent with search increasing competitive pressure and reducing margins, even though the coefficient may be biased downward due to possible endogeneity.

There may be some unobserved market factors that influence the levels of both margins and search in the long run. To better isolate the direct relationship between margins and search and control for other factors we estimate the relationship in first differences as follows:

$$\Delta Margin_t = \underset{(0.0067)}{-0.0143^{**}}\Delta \ln(Reach_t) + \underset{(0.0021)}{0.0006} + \epsilon_t \tag{2}$$

where *Reach* reflects search activity as measured by the log of the Alexa "reach" for Gasbuddy.com. Standard errors are presented in parenthesis. [31]

It is apparent from our results that when search activity rises, margins fall. The estimated coefficient indicates that a one standard deviation increase in ln(*Reach*) is associated with a 1.4 cent/gallon decrease in margins. The coefficient is both statistically significant at the 5% level and economically meaningful.[32] The results provide some further evidence that increases in search constrain the ability of firms to select relative high prices in order to pick off uninformed consumers

[29] http://tonto.eia.doe.gov/dnav/pet/hist/rrunyhd.htm.

[30] Section VI contains results that show that price dispersion falls when prices rise. But since rising prices are associated with increased search, the feedback effect of reduced dispersion must be smaller than the impetus to search that rising prices provide.

[31] We have not applied a serial correlation correction, given that the margins in our specification have been differenced. In addition, the Durbin-Watson statistic for the regression, 1.78, suggests little reason for concern. Finally, when lagged changes in $ln(reach_t)$ are added to the specification, their coefficients do not approach significance and have no noticeable impact on the estimated coefficient of the contemporaneous $\Delta ln(reach)$.

[32] The standard deviation of ln(reach) is 0.97.

who are unaware that the price they are offered is relatively unattractive.

As we have noted, search represents a flow of information that adjusts the stock of information that consumers possess. Therefore, search does not perfectly represent consumers' information levels. If consumers' uncertainty of prices tends to be lower when prices are more stable, then they will be relatively well informed even if they search less. Acknowledging this, we also examine the relationship between margins and search excluding periods with relatively stable prices. Estimating Equation 2 using only days in which the average price level changes (positively or negatively) by at least 0.5 cents per gallon,[33] we obtain

$$\Delta Margin_t = \underset{(0.011)}{-0.029^{**}}\Delta \ln(Reach_t) + \underset{(0.0034)}{0.0021} + \epsilon_t$$

These results indicate that on days when we think it will be particularly difficult for consumers to be well informed without searching, margins are ever more strongly related to search activity.

The negative relationship between search and margins is both of direct interest, showing empirically that informed customers stoke competition, and relevant to the question of why margins adjust asymmetrically to price changes. Since search rises with rising prices, higher prices mean lower margins. But falling prices do not have a similar effect on search, and hence margins can increase.

VI. PRICE MOVEMENTS AND PRICE DISPERSION

Increased retailer competition will result not only in narrowed retail margins, but also in more constricted price dispersion. Retailers who face well-informed consumers will find that their own-price demand elasticities are high in absolute value. A high-price retailer (where 'high' is relative to the current distribution of offer prices) will see more customer defections when its customers are better informed about alternative prices available to them. We expect consumers to be relatively well informed when prices are stable or when they are increasing. Price increases trigger greater search activity, and when prices have been stable, consumer information stocks do not deteriorate rapidly, so consumers are comparatively well informed, with little incentive to search further. When retail prices are changing in response to underlying cost shocks, that movement entails more rapid depreciation of consumer information stocks. But because the search response to changing prices

[33] The cutoff of 0.5 cents per gallon is chosen because it is the median of the distribution of absolute price changes in our sample. Our findings using alternative cutoff values suggest that the estimated coefficient increases in magnitude as the sample becomes more restricted to include only days with larger absolute price changes.

is asymmetric, consumers will be better informed when prices rise than when they fall. In this section, we present empirical results for gasoline similar to those reported by Sorensen [2000] for prescription drugs: information and dispersion are inversely related.[34] We find greater price dispersion when prices are falling and less price dispersion when prices are stable or rising.

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 sufficient Internet activity to remain in the Alexa collection of most popular websites—those 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 of all prices reported for the same day.[35]

We are unable to estimate directly the relationship between search and dispersion because our search data are only measured nationally, and because the time periods of our search data and the price distribution data available to us do not overlap. We instead estimate how price changes impact citywide price dispersion, allowing us to relate these patterns directly to our earlier results on search.[36]

One difficulty in using the GasBuddy city-level price data is that the reporting of the highest 15 and lowest 15 prices on a given day is dependent on the willingness of GasBuddy'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 most extreme prices may be outliers

[34] Sorensen [2000, p. 835] suggests that the relationship between search and dispersion is straightforward: 'That increases in search intensity will lead to lower prices and less dispersion is a common and intuitive finding in the theoretical literature on price dispersion.' There are, however, both theoretical (Stahl [1989]) and empirical studies (Brown & Goolsbee [2002]) that either predict or report a non-monotonic relationship. In particular, in the Stahl model, price dispersion will increase as some search is introduced into a no-search situation. With some informed customers, retailers can choose either to compete for these customers with low prices or to retain high prices in hopes of selling to the uninformed. But faced with customers who have at least some information on alternative offer prices, more information reduces dispersion. Given the low cost of obtaining gasoline price information from the large price signs that stations typically post, it is likely that consumer information about gasoline price is sufficient to place gasoline markets into the range in which price dispersion and information are inversely related.

[35] While the mean is based on all prices reported to Gasbuddy.com, we do not observe all such prices. We thus cannot compute a variance for the price distribution.

[36] We would clearly prefer to employ dispersion in markets of smaller size, given the localized nature of competition in gasoline retailing (See Lewis [2008] and Hosken et al. [2008]). Our data limit us to investigating citywide price dispersion.

and therefore may not accurately represent overall shifts in the shape of the distribution.

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 to 49, and reduced our sample size to 4783. 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 9978. 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 12611 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.

We illustrate the relationship between prices and the median range in Figure 2, which graphs city average prices and median range for two cities in our sample, Dallas and Denver. While the price range measure is volatile, the graph clearly reflects a systematic relationship between dispersion and price fluctuations. Observed prices exhibit a wider range when prices are falling, narrowing when prices are or have recently been stable or increasing.

Place Figure 2 approximately here

Though we possess range information for only four months,[37] Figure 2 exhibits cross-sectional variation in the patterns of price fluctuations and price ranges. In particular, prices in Dallas increased modestly at the end of 2006 but then fell early in 2007. In contrast, prices were stable in Denver over the same period. Correspondingly, we see a sharp increase in price range in Dallas in January as price fell, but not in Denver. The empirical analysis quantifies these relationships in more detail.

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. As a result,

[37]GasBuddy changed its price reporting from numeric to graphical, ending our window.

we expect dispersion to be low when prices are fairly stable and when consumers are searching in response to increasing prices. Hence we compare dispersion during these times to dispersion when prices are falling to isolate the impact of search. Similar to the search analysis, we estimate the influence of recent price changes on price dispersion in city c on date t with the following specification:[38]

$$\begin{aligned}
\ln(Range)_{ct} \quad = \quad & \beta_1 \sum_{k=0}^{4} \Delta p_{c,t-k}\xi_{c,t-k} + +\beta_2 \sum_{k=0}^{4} \Delta p_{c,t-k}(1-\xi_{c,t-k}) + \beta_3 \sum_{k=5}^{19} \Delta p_{c,t-k}\xi_{c,t-k} \\
& +\beta_4 \sum_{k=5}^{19} \Delta p_{c,t-k}(1-\xi_{c,t-k}) + \beta_5 \sum_{k=20}^{49} \Delta p_{c,t-k}\xi_{c,t-k} + \beta_6 \sum_{k=20}^{49} \Delta p_{c,t-k}(1-\xi_{c,t-k}) \\
& +\gamma_d + \mu_c + \epsilon_{ct} \qquad (3)
\end{aligned}$$

where

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

γ_d is the coefficient of a day-of-the-week indicator variable corresponding to t, μ_c is a city fixed effect. 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 III 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. City fixed effects are included in the estimates, but are not presented in the table. The results show that dispersion is significantly higher during periods when prices are declining. A ten-cent/gallon price decrease within the last 5 days is associated with between 11.7% and 21.4% more dispersion depending on the specification.[39] Past price reductions are also associated with significantly higher dispersion, with a 10 cent decrease in price estimated to yield an increase in dispersion of between 9.7% and 10.6% for the 5-19 day lag and an increase of between 1.2% and 1.4% for the longest lag.[40] In

[38] For a very small number of observations, the range is zero. We assigned a value of one cent to the range for these observations for purposes of taking logs.

[39] These percentage change estimates result from corresponding coefficient estimates ranging from -12.5 to -24.1.

[40] Corresponding coefficient estimates used for this calculation range from -1.02 to -1.12 for the 5-19 day period

contrast, there is less price dispersion during periods of stable or increasing prices. Coefficients for price increases are all much smaller in magnitude and are either insignificant or negative, indicating that dispersion may be slightly lower when prices are rising than when they are stable. An increase of 10 cents in the average price in a city leads to a decline in dispersion of between 1.3% and 5.4% for the 5-19 day lag and a decline of up to 1.4% for the 20-49 day lag.[41]

Place Table III approximately here

Our results suggests that price dispersion is largest during periods when prices are falling and consumers' search intensity is, according to our earlier results, relatively low. These patterns parallel our findings on margins and are consistent with the idea that (in equilibrium) firms charge prices that exhibit less dispersion when they know consumers will be better informed about the price distribution. The only other empirical study that we know of that reports similar results is Lewis [2010]. He reports patterns similar to our findings here: price dispersion is greater during high-margin periods when prices are falling.[42]

VII. SUMMARY AND CONCLUSIONS

We began this paper by asking 'When do consumers search, and why?' Our search data tell us that search increases substantially when prices are rising, but that the response to falling prices is insignificant. This consumer behavior is sensible—when consumers do not know the distribution of prices that they face, an increase in price encountered at a station could be due to an idiosyncratic rise in price, rendering search more worthwhile, but a lower price due to station-specific factors is hardly an incentive for additional search.

The asymmetric response of search activity to price movements that we have documented can help to explain asymmetric response of retail prices to cost shocks. This price adjustment asymmetry is endemic in gasoline markets, but appears throughout the economy. Peltzman [2000, p. 493] remarks '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

and -0.12 to -0.14 for the 20-49 day period.

[41] These percentage effects were calculated from the corresponding coefficient estimates between -0.13 and -0.55 for the 5-19 day lag, and coefficient estimates between -0.01 and -0.14 for the 20-49 day lag.

[42] The results in Lewis [2010] are for residual dispersion once controls are applied for station heterogeneity. The markets he uses are local, in addition to citywide estimates. His similar results provide a worthwhile check that suggests our results are robust.

a “stylized fact.” ’ But the reasons for this asymmetry are far from clear. Peltzman (p. 467) notes that

> Economic theory suggests 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.

Our results suggest that any analysis of asymmetric pricing should take into account the asymmetric response of consumer search to cost and price movements.

Increased consumer search means that retailers face more elastic demand for their gasoline, and compete more vigorously with one another. Thus price increases yield higher search, which, in turn, is associated with lower retail margins. When wholesale gasoline prices fall, retailers face less competitive pressure to pass along those prices to consumers, and margins rise.

Price dispersion responds in similar fashion. As the price of gasoline rises, the dispersion of consumer prices falls 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.

Our paper provides a direct measure of search for an important product, gasoline, and links that search to characteristics of offer prices. The Internet now offers prices for a wide variety of firms and products. We expect analysis of traffic statistics for price aggregators analogous to GasBuddy.com to be a rich source of search data, and look forward to better understanding of the constraints firms face and the resulting prices they set in response to the search that can be measures from such data.

REFERENCES

Atkinson, B., 2008, 'On Retail Gasoline Pricing Websites: Potential Sample Selection Biases and Their Implications for Empirical Research,' *Review of Industrial Organization*, 33, pp. 161–175.

Bacon, R. W., 1991, 'Rockets and Feathers: The Asymmetric Speed of Adjustment of UK Retail Gasoline Price to Cost Changes,' *Energy Economics*, 13, pp. 211–218.

Baye, M. R.; Morgan, J. and Scholten, P., 2006, 'Information, Search, and Price Dispersion,' in Hendershott, T., ed., *Handbook of Economics and Information Systems* (Elsevier, New York) chapter 6, pp. 323–376.

Bénabou, R. and Gertner, R., 1993, 'Search with Learning from Prices: Does Increased Inflationary Uncertainty Lead to Higher Markups,' *The Review of Economic Studies*, 60, pp. 69–93.

Borenstein, S.; Cameron, A. C. and Gilbert, R., 1997, 'Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?,' *The Quarterly Journal of Economics*, 112, pp. 305–339.

Brown, J. R. and Goolsbee, A., 2002, 'Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry,' *The Journal of Political Economy*, 110, pp. 481–507.

Brynjolfsson, E. and Smith, M. D., 2000, 'Frictionless Commerce? A Comparison of Internet and Conventional Retailers,' *Management Science*, 46, pp. 563–585.

Cabral, L. and Fishman, A., 2008, 'Business as Usual: A Consumer Search Theory of Sticky Prices and Asymmetric Price Adjustment,' http://pages.stern.nyu.edu/~lcabral/workingpapers/CabralFishmanAug08.pdf.

Hosken, D. S.; McMillan, R. S. and Taylor, C. T., 2008, 'Retail Gasoline Pricing: What Do We Know?,' *International Journal of Industrial Organization*, 26, pp. 1425–1436.

Lach, S., 2002, 'Existence and Persistence of Price Dispersion: An Empirical Analysis,' *The Review of Economics and Statistics*, 84, pp. 433–444.

Lach, S. and Moraga-Gonzalez, J. L., 2009, 'Asymmetric Price Effects of Competition,' Tinbergen Institute Discussion Paper 09–049/2.

Lewis, M. S., 2008, 'Price Dispersion and Competition with Differentiated Sellers,' *Journal of Industrial Economics*, 56, pp. 654–678.

Lewis, M. S., 2010, 'Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market,' *Journal of Economics & Management Strategy,* forthcoming.

Peltzman, S., 2000, 'Prices Rise Faster than They Fall,' *The Journal of Political Economy*, 108, pp. 466–502.

Sorensen, A. T., 2000, 'Equilibrium Price Dispersion in Retail Markets,' *Journal of Political Economy*, 108, pp. 833–850.

Stahl, D. O., II, 1989, 'Oligopolistic Pricing with Sequential Consumer Search,' *American Economic Review*, 79, pp. 700–712.

Stigler, G. J., 1961, 'The Economics of Information,' *The Journal of Political Economy*, 69, pp. 213–225.

Tappata, M., 2009, 'Rockets and Feathers: Understanding Asymmetric Pricing,' *RAND Journal of Economics*, 40, pp. 673–687.

Yang, H. and Ye, L., 2008, 'Search with Learning: Understanding Asymmetric Price Adjustments,' *RAND Journal of Economics*, 39, pp. 547–564.

Table I
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(*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

Notes to Table I: 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 II
Gasoline Price Movements as a Determinant of Price Search

Dependant Variable: ln(*Reach*)

Variable	Coefficients (Newey-West Standard Errors)			
	OLS	Instrumental Variables		
	(1)	(2)	(3)	(4)
α_0	2.09***	2.13***	2.17***	1.15*
(intercept)	(0.28)	(0.28)	(0.20)	(0.62)
α_1	3.13***	2.20**	1.72*	2.11***
price change, +, most recent 5 days)	(0.71)	(1.06)	(1.02)	(0.40)
α_2	-1.19	2.33	2.70	2.06
(price change, -, most recent 5 days)	(1.19)	(2.56)	(2.51)	(1.45)
α_3	3.11***	3.13***	2.85***	1.69***
(price change, +, days 5-19)	(0.71)	(0.71)	(0.56)	(0.43)
α_4	-1.10	-1.02	-1.06	-0.50
(price change, -, days 5-19)	(0.84)	(0.85)	(0.71)	(0.66)
α_5	1.11**	1.20**	0.93**	0.48
(price change, +, days 20-49)	(0.49)	(0.50)	(0.36)	(0.33)
α_6	1.01**	0.80	0.86**	0.96
(price change, -, days 20-49)	(0.51)	(0.54)	(0.37)	(0.64)
α_7			0.26***	
(ln(*Reach*) for fuelgaugeport.com)			(0.05)	
Website for ln(*Reach*)	GasBuddy	GasBuddy	GasBuddy	GasPriceWatch
Number of Observations	667	667	667	667

Notes to Table II: Search is measured by ln(*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. Coefficients for date variables and day-of-week indicators are not reported. Estimates computed with the Prais-Winsten method. The standard errors presented reflect a Newey-West correction.

Table III
Gasoline Price Dispersion as a Function of Price Movements

	Specification			
Sample:	49 cities	City/date pairs with 30 prices		full sample
Dependent Variable:	median range	$p^{\max} - p^{\min}$	median range	$p^{\max} - p^{\min}$
Variable	Coefficients (Newey-West standard errors in parenthesis)			
β_1 (price change +, most recent 5 days)	0.30 (0.173)	0.11 (0.119)	0.25* (0.147)	0.10 (0.129)
β_2 (price change, -, most recent 5 days)	-2.41*** (0.222)	-1.81*** (0.153)	-2.31*** (0.178)	-1.25*** (0.183)
β_3 (price change, +, days 5-19)	-0.13 (0.101)	-0.27*** (0.089)	-0.13 (0.097)	-0.55*** (0.100)
β_4 (price change, -, days 5-19)	-1.02*** (0.094)	-1.09*** (0.068)	-1.04*** (0.072)	-1.12*** (0.080)
β_5 (price change, +, days 20-49)	-0.01 (0.057)	-0.08* (0.047)	-0.08 (0.053)	-0.14*** (0.052)
β_6 (price change, -, days 20-49)	-0.14*** (0.037)	-0.13*** (0.030)	-0.13*** (0.032)	-0.12*** (0.032)
Number of Observations	4783	9978	9960	12621

Notes to Table III: 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 and day-of-week indicator variables which are omitted from the values reported above. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

FIGURE 1
AVERAGE GASOLINE PRICE AND GASBUDDY TRAFFIC, 2004–2006

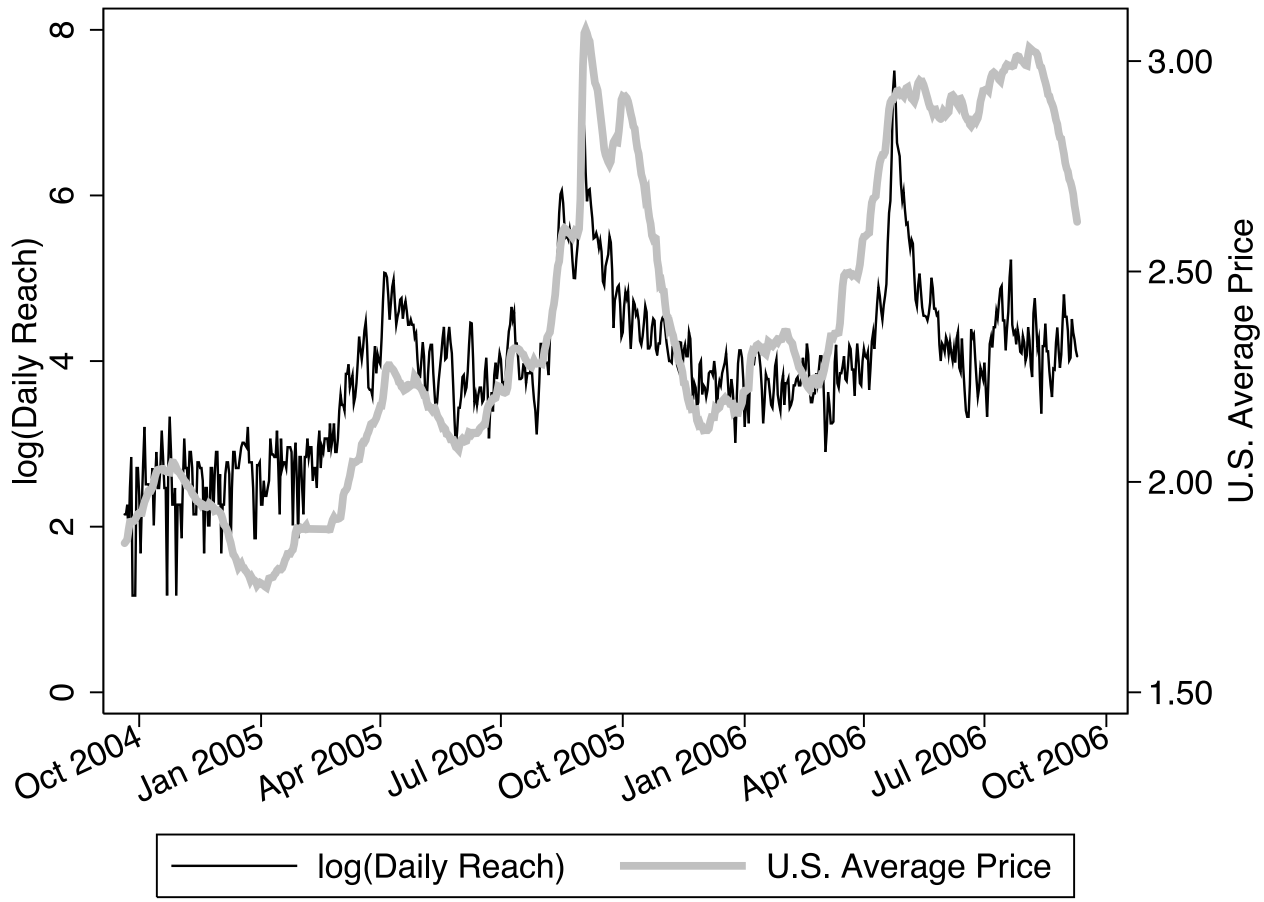
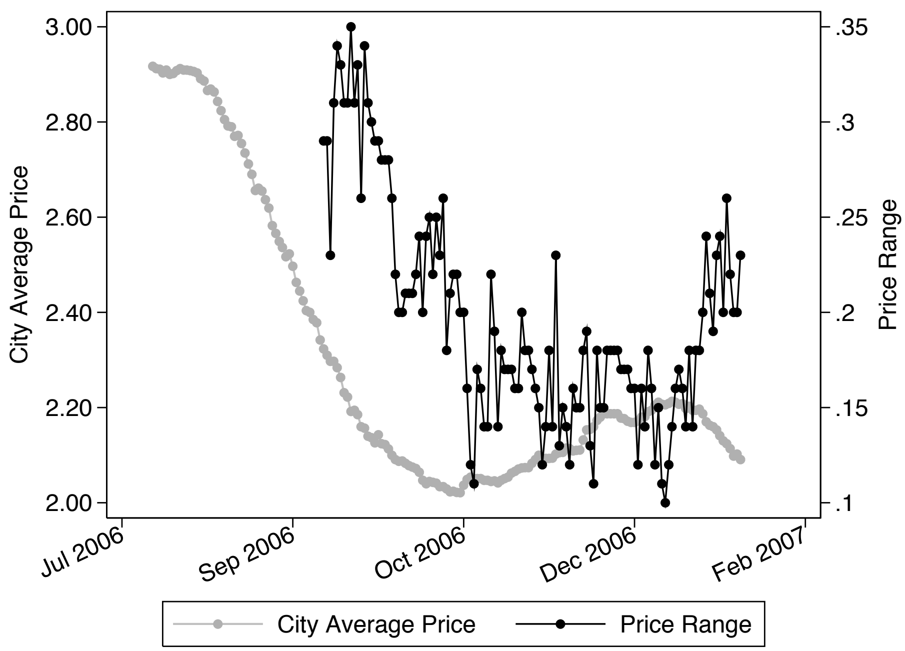


Figure 2
Gasoline Price Levels and Dispersion, Dallas and Denver

Dallas



Denver