An Empirical Investigation of the Determinants of Asymmetric Pricing

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Abstract

This paper empirically investigates the cause of asymmetric pricing: retail prices responding faster to cost increases than decreases. Using daily price data for over 11,000 retail gasoline stations I find that prices fall slower than they rise as a consequence of firms extracting informational rents from consumers with positive search costs. Premium gasoline prices are shown to fall slower than regular fuel prices but rise at the same pace, and this pricing pattern supports theories based upon competition with consumer search. Further testing also rejects focal price collusion as an important determinant of asymmetric pricing.

1 Introduction

A burgeoning body of economic literature has focused on the retail gasoline industry. The increased attention stems from the market being substantially influenced by factors rigorously studied by microeconomic theorists: search costs, spatial differentiation, tacit collusion, and Edgeworth cycles to name a few. The primary line of investigation in this paper will center around the issue of asymmetric pricing: the tendency for firms to adjust retail prices in greater magnitude in response to cost increases than cost decreases.

Using data from the UK retail gasoline market, Bacon (1991) was the first to document that firms respond more quickly to cost increases than decreases, while also coining the phrase "rockets and feathers" to describe the phenomenon. Supporting the hypothesis that gasoline prices shoot up

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like rockets but fall like feathers are the findings of Borenstein, Cameron, and Gilbert[1] (1997), whose empirical model has served as the foundation for identifying asymmetric price adjustments. Building on the work of BCG, a substantial body of literature has identified rockets and feathers in retail gasoline markets in Canada, the United States, Chile, and a host of European countries. Asymmetric pricing, however, is not confined to the retail gasoline industry; Peltzman (2000) examines 242 diverse product markets and confirms rockets and feathers to be a common pricing phenomenon in more than two thirds of the markets. The study finds, on average, the immediate retail price response to a positive cost shock to be twice the size of the response to a negative cost change, and the difference in magnitude can persist for months following the initial cost shock.

These empirical findings, until recently, were unexplained by economic theory, and even now there exists a lack of consensus as to asymmetric pricing's underlying cause. One of the first explanations to gain traction was that it was a precipitant of a type of focal price collusion;[2] firms coordinate on the previous period's price until demand or wholesale cost conditions impel a change. When costs drop firms hold retail prices constant so as to increase profit margins, but they raise prices in response to a cost increase to maintain a positive margin and/or not be viewed as cheating on the collusive agreement. Thus, retail prices respond faster to cost increases than decreases. While this variant of focal price collusion offers a convenient framework within which to discuss asymmetric price movements, there is no formal analysis showing that it is equilibrium price behavior.

Conversely, a number of recent papers have theoretically derived asymmetric pricing as a consequence of search costs. In particular, Lewis (2005), Tappata (2009), Yang and Ye (2008), and Cabral and Fishman (2008) each find that firms may extract informational rents from consumers unaware of input cost changes and therefore exhibit price asymmetry. Lewis (2005) posits consumers to form adaptive expectations about the current market price distribution, and shows that firms can exploit these irrational beliefs by slowly lowering prices in response to a negative cost change. Tappata (2009) and Yang and Ye (2008) each construct a model where consumers rationally form expectations of current market prices, and find, similar to Lewis (2005), that firms capitalize on buyers' imperfect information by pricing asymmetrically. Lewis (2005) finds empirical support for his search-based theory, however, his paper critically relies upon consumers disregarding all current information in forming their search strategy. To the best of my knowledge, other than Lewis (2005), no other paper has been able to empirically verify or discredit any specific theory of rockets and feathers.

The goal of this paper is to employ an expansive data set to determine the underlying cause of asymmetric pricing. In the process, rockets and feathers is identified as a property of retail gasoline prices across a wide variety of markets. To investigate the sources of asymmetric pricing, I exploit

[1] Hereafter referred to as BCG.

[2] BCG (1997) and Lewis (2005) both discuss this possibility.

one year of daily regular and premium unleaded gasoline price observations for more than 11,000 firms. An overwhelming majority of the rockets and feathers literature employs temporally and/or spatially aggregated data to document the phenomenon. In establishing the existence of asymmetric pricing with data disaggregated to the daily-firm level, I estimate its magnitude with a high degree of precision. I find that five days after an initial wholesale price shock firms incorporate 46% of a positive cost change into their final price, but only 24% of a negative change. The difference in the speed of retail price adjustment to positive and negative cost changes persists for more than eight days, and the slower adjustment to negative shocks costs consumers an additional 1.3¢ per gallon.

While confirming the existence of asymmetric pricing is in accordance with much of the literature, heretofore, there has been almost no empirical sifting of the various theoretical explanations of this pricing behavior. With the aid of a rich data set, I find robust evidence in favor of the consumer search-based theories posited in Yang and Ye (2008) and Tappata (2009), and little support for focal price collusion. The theories based upon competition with consumer search offer a number of testable predictions, three of which are supported by the empirical analysis in this study. First, Yang and Ye (2008) show that products whose consumers are less likely to shop for the lowest price are slower to adjust downwards following a negative cost shock, but increase at the same rate following a cost increase. This implication is confirmed by examining the dynamic properties of firms' markup of premium over regular unleaded fuel. Specifically, the gap increases following a cost decrease but remains constant following a cost increase; premium prices, therefore, fall slower than regular prices, but rise at the same speed. I argue that there is a systematic difference in the search costs of consumers who purchase either premium or regular gasoline, and as such confirm the prediction of Yang and Ye (2008).

By studying the markup of premium over regular, I isolate how specific firms price products purchased by distinctly different consumers. The value added by this approach to a study such as Peltzman (2000) is it measures not only the relative asymmetry of different products, but also how the same firm prices two different goods that are subject to nearly identical cost shocks. Thus, many important determinants of the dynamic price behavior of the two products are controlled for, except the type of consumers buying the goods. The unique pricing patterns of premium and regular gasoline is, therefore, partially attributable to differences between the two products' consumers.

A second implication of Yang and Ye (2008) and Tappata (2009) is that the gains from search inversely relate to the magnitude of price asymmetry. This is confirmed by quantifying the connection between market price dispersion and the degree of price asymmetry; markets with a greater price range or variance (both positively correlated with gains from search) are found to adjust slower to cost increases and and faster to decreases. A third test of search-based theory investigates the pricing pattern of monopolistic firms. The theory predicts that if a market is served by a single firm then prices will respond with equal speed to price increases and decreases. As such, the empirical analysis in this paper shows that monopolies price symmetrically.

In contrast, little evidence in favor of collusion as a consequential determinant of rockets and feathers is uncovered. After isolating firms with the greatest potential to be acting collusively, these businesses are found to exhibit no more asymmetry than firms almost certainly not colluding. Moreover, there is no verifiable relationship between the magnitude of asymmetry and price levels, suggesting that asymmetric pricing is not a means for collusive firms to inflate prices. In total, the data strongly suggests that asymmetric pricing is a rational profit maximizing strategy amongst *non-collusive* firms operating in a market typified by consumer search costs.

Rockets and feathers has long been established as an empirical regularity of a diverse set of product markets. A deep understanding of the pricing phenomenon's cause, however, has lagged behind. Theory based on oligopolistic competition with consumer search recently supplied a rigorous foundation upon which to analyze the properties of asymmetric price adjustments. The econometric results presented in this paper substantiates the theory as an accurate description of the pricing pattern's underlying mechanism. Using data that covers a large range of markets and is disaggregated to the daily-firm level adds further robustness to the empirical findings, and consequently, confidence in the validity of the search theory of rockets and feathers.

The outline of the paper is as follows; section 2 reviews past empirical approaches and introduces the econometric model used to perform the analysis, section 3 discusses the data and its general properties, section 4 presents new evidence of rockets and feathers, section 5 tests search-based theories of price asymmetry, section 6 examines focal price collusion, section 7 concludes, and the appendix provides a robustness check of the econometric model and illustrates the problems inherent in time-averaged data used in most previous studies.

2 A Model of Asymmetric Pricing

When Bacon (1991) first tested for the presence of retail price response asymmetry, he specified the following functional form:

$$R_t - R_{t-1} = \beta_1(\vartheta_0 + \vartheta_1 C_{t-1} - R_{t-1}) + \beta_2(\vartheta_0 + \vartheta_1 C_{t-1} - R_{t-1})^2 + \epsilon_t, \tag{1}$$

where R_t is the retail price at time t, C_t is the price of crude oil, and ϵ_t is a normally distributed iid shock. Bacon estimates the coefficient of the quadratic term, β_2, to be positive and significantly different from zero, and subsequently concludes that there exists response asymmetry. However, this model posits an overly rigid relationship between retail price changes, $R_t - R_{t-1}$, and its long-run relationship with cost, $\vartheta_0 + \vartheta_1 C_{t-1} - R_{t-1}$. Specifically, equation (1) restricts retail prices to have equally proportional adjustments towards the new price equilibrium in each of the periods following the initial cost shock. Further shortcomings are detailed in BCG and Geweke (2004).

In light of the restrictions imposed by Bacon (1991), BCG proposed a more general test which has become the standard identification technique in the rockets and feathers literature. As the model serves an integral role in the empirical work presented in the following sections, it is useful to go through the model's derivation. First, BCG posit a long-run relationship between the price of wholesale gasoline and the retail price charged by firms:

$$R_t = \phi_0 + \phi_1 C_t + \epsilon_t, \tag{2}$$

where the variables are defined as in equation (1). Given the long-run relationship between retail price and the cost of gasoline, BCG then posit the short-run response of retail prices to a cost change. First, $\Delta X_t = X_t - X_{t-1}$ is defined for any variable of interest X. Then, they define the short-run effect of a cost change in period t on retail prices in period t to be:

$$\Delta R_t = \beta_0 \Delta C_t + \epsilon_t. \tag{3}$$

Yet, the adjustment of retail prices to changes in the wholesale cost of gasoline do not occur solely within the period of observation, and may take weeks to fully transmit. Thus, BCG include lagged changes in cost to arrive at the following equation:

$$\Delta R_t = \sum_{j=0}^{n} \beta_j \Delta C_{t-j} + \epsilon_t. \tag{4}$$

Here, n is the number of time periods it takes retail prices to fully adjust to a one time cost shock. Equation (4) restricts retail prices to adjust symmetrically to positive and negative changes in cost. As the aim of the model is to test whether or not this is a valid assumption, the restriction is loosened and then tested to see if it has any bite. Thus, equation (4) is rewritten so that separate coefficients for positive and negative wholesale price changes may be estimated:

$$\Delta R_t = \sum_{j=0}^{n} (\beta_j^+ \mathbf{1}(\Delta C_{t-j} > 0) + \beta_j^- \mathbf{1}(\Delta C_{t-j} < 0)) + \epsilon_t. \tag{5}$$

The indicator function $\mathbf{1}(\cdot)$ takes the value of ΔC_{t-j} if the expression in parenthesis evaluates true and zero otherwise. The appeal of equation (5) is that it not only allows for asymmetric price adjustments, but also places minimal restrictions on the path of adjustment over many time periods to a one time change in wholesale costs. In general, BCG claim that if significant differences between the coefficients for positive and negative cost shocks, β_j^+ and β_j^-, are estimated then the available data supports the existence of rockets and feathers.

Before BCG proceed with the estimation they further enrich the estimated equation. First, lagged changes in retail price are included to allow for the possibility of previous retail price changes affecting current pricing decisions. In the long-run firms fully incorporate cost changes into retail prices; in the short-run, perhaps due to menu costs or competitive considerations, firms may face a tradeoff between changing retail prices today or in the future. More importantly, BCG reconcile the model to deal with a problem found throughout the literature on retail gasoline prices. Namely, retail price and cost series are cointegrated. There exists a common solution to the problem of cointegration – transforming the model into an error-correction form.[3] By adding the one period lagged residual from equation (2) to equation (5), short-run adjustments to price shocks as well as the tendency for retail prices and wholesale costs to revert to their long-run relationship can be separately estimated:

$$\begin{aligned}\Delta R_t = &\sum_{j=0}^{n}(\beta_j^+\mathbf{1}(\Delta C_{t-j}>0)+\beta_j^-\mathbf{1}(\Delta C_{t-j}<0)) \;+\; \sum_{j=1}^{n}(\gamma_j^+\mathbf{1}(\Delta R_{t-j}>0)+\gamma_j^-\mathbf{1}(\Delta R_{t-j}<0))\\ &+\;\vartheta_1(R_{t-1}-\phi_1 C_{t-1}-\phi_0)+\epsilon_t. \end{aligned} \tag{6}$$

Equation (6) serves as the foundation for BCG's empirical investigation, which supports the existence of asymmetric pricing. They find that for up to four weeks following a crude oil price change, retail prices more quickly incorporate a positive shock; 67% of a positive cost change is included in the final price after four weeks, but only 38% of a negative change. Yet, BCG also estimate retail prices to increase for up to two weeks following a price decrease, indicating that their econometric model may be misspecified or suffer from temporally aggregated data.[4]

Accordingly, recent literature has contended that BCG's results critically rely upon data aggregated across time and stations and nonstandard econometric techniques. Galeotti et al. (2003) and Bachmeier and Griffin (2003) each criticize BCG's paper for estimating in one step both the long and short-run adjustments in retail price to cost changes.[5] Furthermore, it is noted that due to BCG's utilization of 2SLS to estimate parameters of interest, their estimates will converge to the true values exponentially slower than when using standard OLS. In the appendix of this paper, the 2SLS technique employed by BCG is found to produce implausible results; retail prices immediately increase by 10% of the size of a cost decrease, and fall by 18% of the size of a cost increase. The problems associated with BCG's 2SLS regression are also shown to become accentuated when used in conjunction with temporally aggregated data.

To correct for the problems thought to exist in BCG, it is proposed to estimate the error-

[3]The solution was first derived in Engle and Granger (1987).

[4]BCG utilize bi-weekly city-averaged retail prices for large metropolitan areas in the USA.

[5]Instead of first estimating equation (2) and substituting the predicted residuals into equation (6), as suggested by Engle and Granger (1987), BCG directly include R_{t-1} and C_{t-1} in equation (6).

correction model in two steps, as originally posited in Engle and Granger (1987). Equation (2) is first estimated using OLS and then the pertinent values are substituted into (6). Additionally, equation (6) is generalized to not only allow retail prices to respond asymmetrically to short-run cost shocks, but also to permit asymmetric adjustments to the new long-run equilibrium. Thus, the following equation has been put forth in the literature as an improvement over the BCG model:

$$\Delta R_t = \sum_{j=0}^{n}(\beta_j^+ \mathbf{1}(\Delta C_{t-j} > 0) + \beta_j^- \mathbf{1}(\Delta C_{t-j} < 0)) \; + \; \sum_{j=1}^{n}(\gamma_j^+ \mathbf{1}(\Delta R_{t-j} > 0) + \gamma_j^- \mathbf{1}(\Delta R_{t-j} < 0))$$
$$+ \vartheta_1^+ \mathbf{1}(R_{t-1} - \phi_1 C_{t-1} - \phi_0 > 0) + \vartheta_1^- \mathbf{1}(R_{t-1} - \phi_1 C_{t-1} - \phi_0 < 0) + \epsilon_t. \quad (7)$$

Here, ϕ_0 and ϕ_1 are estimated via equation (2) and substituted into (7), and ϑ_1^+ and ϑ_1^- capture the tendency for retail prices to revert to their long-run relationship with cost. Analysis in the appendix is in agreement with previous literature in that equation (7) is demonstrated to be the most appropriate model to identify asymmetric pricing, and therefore, the equation serves as the foundation of the econometric analysis in this paper.

Galeotti et al. (2003) employ a standard error-correction model similar to equation (7) and fail to reject symmetric pricing; the study, however, employs monthly averaged prices for entire European countries, and findings presented in the appendix suggest that data aggregated to this level is highly susceptible to bias. Eckert (2002) uses weekly averaged retail prices from Windsor, Ontario in conjunction with equation (6) and finds support for asymmetric pricing; one week after a cost shock retail prices incorporate 120% of a positive change but only 24% of a negative change. Deltas (2008) utilizes monthly averaged data for 47 states in the USA in conjunction with equation (6) and yields evidence in favor of rockets and feathers; one month after an initial price shock retail prices incorporate 17% more of a positive cost change. Using weekly price observations from South Orange County, CA, Verlinda (2008) estimates an error-correction model like equation (7) and finds that three weeks after a cost change retail prices increase by 110% of a positive cost shock, but decrease by only 83% of a negative shock. Conversely, Hosken et al. (2008) utilize weekly averaged data from individual firms in the Washington, DC metro area to estimate equation (7) and find that asymmetric pricing poorly explains the retail price changes in their data.

The aforementioned studies represent only a sample of the empirical asymmetric pricing literature and, by and large, a substantial body of work has coalesced in favor of prices responding in greater magnitude to cost increases than decreases.[6] In the subsequent sections, equation (7) is estimated utilizing the two-step OLS estimation procedure in order to identify the existence of asymmetric pricing in the retail gasoline industry.

[6]Table 1 offers a brief summary of the rockets and feathers literature. Geweke (2004) gives a more detailed summary of the asymmetric pricing literature and identification techniques.

3 Data and Summary Statistics

The econometric analysis in this paper is buoyed by a richly detailed data set consisting of daily price observations from July 30th, 2008 through July 29th, 2009. Included in the data are station specific observations for nearly every gas station in the states of New Jersey, Maryland, Virginia, Washington, as well as the Philadelphia, PA and Washington, DC metro areas. Also included are firms not in these states, but within approximately 15 miles of their border. This amounts to over 11,000 unique stations. The data was culled from the website gasprices.mapquest.com whose information is provided by the Oil Price Information Service (OPIS).[7] According to its website, OPIS collects data "through exclusive relationships with credit card companies, direct feeds, and other survey methods," and therefore price observations are measured with a high degree of accuracy. Every morning at 12:30 a.m. I ran a computer program that gathers the most recent pricing information posted on mapquest. Each price is accompanied by the date it was reported to OPIS. While mapquest was scraped at daily intervals, the website does not report a new price for each station on every day. On average they post new price observations for 72% of stations on weekdays and 48% on weekends.[8]

Previous studies of the retail gasoline market have been constrained by data limitations; prices are averaged across stations (e.g., Eckert (2002), Borenstein and Shepard (1996), Borenstein et al. (1997)), observations only represent small subsections of a market (e.g., Noel (2009), Noel (2003), Slade (1992)), retail prices are averaged across time (e.g., Hosken et al. (2008), Borenstein et al. (1997)), or prices are only collected one day per week (Verlinda (2008), Lewis (2005), and Lewis (2008)). Moreover, studies that do utilize station-specific daily price observations for complete markets take their prices from websites whose data is user reported (e.g., Eckert and West (2004), Lewis and Marvel (2007))[9]. As pointed out in Atkinson (2008), consumer-reported internet data may be subject to a host of biases that can lead to misleading results when high time frequency data or prices for independent stations are needed.

The price data limitations that have hindered previous studies in the rockets and feathers literature pose less of a concern in this paper.[10] The data set is geographically balanced and contains complete markets, observations occur at daily time frequencies, retail prices derive from credit card transactions and station self-reporting, not potentially biased consumer reports, and a host of per-

[7]Figure 2 is a screen shot of the website from where I scraped the data.

[8]These numbers are consistent with those reported in previous studies whose data is directly obtained from OPIS. Thus, there is no reason to believe that the data scraped from mapquest represents an incomplete sample of stations whose prices are reported by OPIS.

[9]A notable exception is Chandra and Tappata (2008). However, the focus of their paper, to test whether price dispersion is a consequence of search costs, is unrelated to this paper.

[10]The appendix confirms that price data aggregated to weekly averages can severely contaminate parameter estimates of equations (6) and (7).

tinent station characteristic information complements the price data. Thus, I am not only well equipped to explore the existence of asymmetric pricing, but also to consider its underlying cause.

The daily gasoline spot prices listed on the New York Mercantile Exchange (NYMEX) is employed as the cost variable. Reformulated gasoline delivered from the New York and Los Angeles Harbors are used for firms located in the eastern and western states, respectively. In reality gas stations purchase gasoline in the wholesale market at the rack price posted at local terminals or at the Dealer Tank Wagon (DTW) price, which is negotiated privately between firms and refineries. While I was unable to obtain this cost data, Chandra and Tappata (2008) note that monthly spot, rack, and DTW prices are almost perfectly correlated.[11] Since retail price responses to changes in cost is what is of interest, utilizing spot instead of terminal or DTW prices should not limit the accuracy of results. Another potential concern is which day's spot price to use for a given day's retail price. Even though wholesale costs change daily, gas stations do not receive a new shipment of gasoline every day. Thus, lagged values of cost reflect the price paid by firms that do not replenish their inventory on a given day. However, the concurrent day's spot price reflects the opportunity cost of holding inventory and is generally the index by which stations set their price.[12] Therefore, in accordance with the literature, I match retail prices with the same day's spot price.[13]

The spatial makeup of individual markets plays an important role in the econometric analysis.[14] In particular, the number of competing stations within given distances of the firm of interest is incorporated into each test. To calculate this I first needed to geocode the data.[15] A variety of software packages facilitated this process. First, the addresses were converted into geographical coordinates by software provided by USC's Department of Geography and cross referenced with coordinates determined by Yahoo maps. Any coordinates that did not match or were unable to be determined with sufficient precision were then geocoded by hand using the Google maps API. Once every station was coded, the distance between all pairs of firms was calculated using the Euclidean distance measure. Given these distance measures, I then calculated market concentration for a variety of market definitions.

Throughout the econometric investigation, a host of control variables supplement the estimated equations. Table 3 reports summary statistics for pertinent station and market characteristic variables that are at times included as additional controls. Also reported in the table are the results

[11] In the appendix of Chandra and Tappata (2008), it is noted that monthly spot, rack, and DTW prices have a correlation greater than .99.

[12] The Association for Convenience and Petroleum Retailing, a lobbying group for gas stations, explains in their 2009 Gas Price Kit that firms set their retail price based on the "replacement cost" of gasoline: the current wholesale price.

[13] Chandra and Tappata (2008), Lewis (2008), and Verlinda (2008) also use this approach.

[14] Houde (2009) finds that both market structure and the commuter paths of consumers significantly impact retail price dynamics.

[15] Geocoding is the process of converting street addresses into longitude and latitude coordinates.

of regressing regular unleaded retail price on those traits.[16] In step with previous studies, such as Eckert and West (2004) and Hosken et al. (2008), independent brand retailers are found to charge significantly lower prices than majors. Additionally, prices increase with the distance to the closest competitor, which indicates that firms are able to exploit available market power. The number of competing firms within a given distance has no significant sway over price levels. This is a consequence of two counteracting effects; the number of firms within a given distance positively correlates with the degree of competition, which decreases prices levels, but also serves as a proxy for demand, which positively correlates with price levels. Therefore, the net effect of the number of firms within a given distance, if no other market characteristics are controlled for, becomes insignificant. Acting as a better representation of local competition is the percentage of competitors that are not major brands. Table 3 indicates that prices decrease if more competitors are independents. A host of previous papers find that independent retailers are more likely to undercut their rivals' prices, thereby increasing market competition.[17] Thus, the basic statistics are consistent with the existing literature.

The time over which I analyze data was a particularly volatile period in the gasoline industry; the price of oil peaked at just over 126¢ per gallon and fell to a low of 31¢. Figure 1 plots the wholesale and average retail price for regular unleaded gasoline over this time period, and Table 2 presents summary statistics for the average daily prices of premium, regular, and wholesale gasoline. The most striking feature of Figure 1 is the rapid decline in gas prices during the autumn of 2008, which coincides with a financial crisis and worldwide slowdown of production. A primary concern, given the lengthy downward trend, is that the price and cost series may not be stationary in first differences. However, augmented Dickey-Fuller tests (Said and Dickey, 1984) assure that both price and cost are stationary in first differences. Actually, a drastic run-up and/or run-down of the price of oil is not atypical of data sets used to identify asymmetric pricing; Borenstein et al. (1997), Bachmeier and Griffin (2003), and Galeotti et al. (2003) all use data encompassing the first Gulf War (when the price of oil more than doubled), and Verlinda (2008) tests for asymmetry with data influenced by two major runs on wholesale prices (caused by the Texas to Arizona pipeline rupture and San Francisco, CA refinery outage). As large swings in the price of oil over short periods of time are fairly common, the effects of the financial crisis in the data should not be viewed as an anomaly or hinderance, but as an opportunity to explore asymmetric pricing with data representative of the inherent volatility of the price of oil.

At first glance retail prices in Figure 1 appear to drop simultaneously with wholesale costs, yet

[16] Before regressing retail price on station characteristics all taxes are removed. Also, day of the week controls are included in each of the regressions. For the statistic *% independent competitors* $\leq$ *.1 miles* only stations with at least one competitor within .1 miles are considered. This analogously holds for the subsequent two statistics in Table 3.

[17] See Eckert and West (2004) and Noel (2003) for empirical evidence and Eckert (2002) for a theoretical justification.

upon close inspection there exist many instances when costs drop suddenly and retail prices slowly (or never) follow suit. Around mid-December 2008 and again during mid-July 2009, for example, there are sharp declines in cost, but retail prices exhibit only a gradual decline. Also consistent with asymmetric pricing is the noticeably higher retail margins during the large decline in wholesale prices from mid-September to the end of December. In total, it is not obvious whether retail prices adjust faster to price increases than decreases, and a careful analysis using the model detailed in the previous section is needed.

4 Testing for the Presence of Asymmetric Pricing

Prior to testing theories of asymmetric pricing, I first establish its presence in the data. To the best of my knowledge, no previous study of rockets and feathers has documented the phenomenon with daily firm-level data for such a large number of geographically diverse firms. Previous firm-level studies of asymmetric pricing utilized data detailing only a single metropolitan area. Analysis presented in the appendix illustrates that aggregating data to even weekly averages can contaminate parameter estimates. Therefore, verifying the phenomenon's existence with temporally disaggregated data for firms located in rural and urban markets on both coasts of the USA serves as a useful contribution to the literature.

To ascertain if retail gasoline firms react more quickly to cost increases than decreases, I estimate the error-correction model as recommended in Engle and Granger (1987). That is, I first estimate equation (2) using OLS, then substitute the parameter values into equation (7) and estimate that equation again using OLS. This estimation procedure is appropriate for several reasons. First, employing the standard error-correction technique assures separate identification of short-run responses to cost shocks and the tendency for retail prices to return to their long-run relationship with costs. Also, the stationarity of the regressors in equation (7) enables standard significance tests of the parameters and functions of multiple parameters.[18] As quantifying the degree of price asymmetry involves constructing response functions from multiple parameters, estimating the model in standard error-correction form, as opposed to the non-standard econometric technique employed in BCG, ensures that I am constructing appropriate confidence intervals to test for asymmetry. Finally, in light of the recent critiques of BCG in Bachmeier and Griffin (2003) and Galeotti et al. (2008), I err on the side of caution by following the procedure originally posited in Engle and

[18]In the following sections I test for asymmetry in the pricing of both premium and regular unleaded gasoline. Augmented Dickey-Fuller tests confirm that both price series, as well as the cost series, are stationary in first differences. Estimation of equation (2), using either premium or regular gasoline as the dependent variable, reveals a cointegrating relationship with cost. Therefore, estimates of ϕ_0 and ϕ_1 are superconsistent, and it is appropriate to substitute the residuals of the estimated equation (2) into equation (7) in place of $R_{t-1} - \phi_1 C_{t-1} - \phi_0$, as superconsistency allows the econometrician to act as though ϕ_0 and ϕ_1 were truly known.

Granger (1987), whose properties have been widely studied.

Before proceeding with the econometrics, a host of controls are included to account for differences in local market conditions and firm specific traits. First, station specific fixed effects are added to equation (2) to allow for the possibility that individual firms employ different long-run markups or consistently purchase wholesale gasoline at relatively high or low prices. Additionally, equation (7) is augmented to control for the effect that local competition, demand conditions, and firm traits may have on short-run adjustments. In particular, the log of population of the city of operation for each station,[19] the number of competitors within .1 miles, between .1 and 1.5 miles, and between 1.5 and 5 miles, the distance of the closest competitor, a dummy variable indicating whether the station is a major brand,[20] and the percentage of independent stations within .1, between .1 and 1.5 miles, and between 1.5 and 5 miles are all added to the equation. Finally, day of the week dummies are included in the second step of the econometric procedure to control for predictable changes in demand conditions over the course of the week.[21]

Regression results are reported in Table 4 with standard errors clustered by station and corrected for heteroscedasticity.[22] The regression produces economically plausible results consistent with the existence rockets and feathers. The coefficients for being above or below the long-run equilibrium retail price, ϑ_1^+ and ϑ_1^- respectively, are both negative. This implies that when retail prices are above (below) their long-run equilibrium value there exists downward (upward) pressure guiding retail prices towards their long-run equilibrium relationship with cost. Also, the estimated value for the long-run relationship between retail prices and wholesale costs, ϕ_1 in equation (2), is 1.04.[23] Previous literature, such as Verlinda (2008) and Lewis (2005), has argued that if demand is linear and marginal cost is constant across all quantities then there should be a dollar for dollar pass through of costs to retail prices in the long-run (i.e. $\phi_1 = 1$). While the estimate of ϕ_1 is slightly above one, it is much closer than the values obtained for the same parameter in most studies of asymmetric pricing in the retail gasoline industry.[24]

Supporting the existence of rockets and feathers is that the coefficient on first period positive cost changes, .08, is significantly greater than for negative cost changes, .00.[25] Thus, one day following a

[19] Population data is either the 2007 projections by the United States Census Bureau, or when the projections are unavailable, the 2000 census measure.

[20] I classify Exxon/Mobil, Shell, BP, Texaco, Chevron, Citgo, Amoco, Sunoco, Lukoil, Getty, 76, and Conoco Phillips stations as major brand, and all others as non-majors. The results are robust to changes in the classification.

[21] Generally demand is higher during weekdays when there are a greater number of drivers commuting to work. Also, weekend drivers may be less informed about the market price distribution because they are not necessarily traveling along their usual commuter routes.

[22] For this regression, and all subsequent analysis performed at daily time intervals, the lag lengths for cost and retail price changes are set to ten. I do not report all of the estimated coefficients for lack of room, but they are available upon request.

[23] The parameter is estimated with a standard error of .0004, but is not reported in Table 4.

[24] For example, Verlinda (2008) estimates $\phi_1 = 1.38$ and Lewis (2005) finds $\phi_1 = .48$.

[25] This is true at the 99% confidence level.

10¢ positive cost shock retail prices increase by .8¢, but do not change following a negative shock. This alone, however, is not proof of asymmetric pricing, as I must account for a complicated lag structure and track the entirety of the dynamic price adjustment. To accomplish this, the estimated parameters are used to construct *cumulative response functions* (CRF's), which map the adjustment of retail prices over time in response to a one time, one cent change in wholesale cost. The CRF's are formulated using the equations specified in the appendix of Borenstein et al. (1997).[26] After an initial one cent increase to costs at $t = 0$, the period k change in retail price, B_k^+, is determined by:

$$\begin{aligned} B_k^+ =& B_{k-1}^+ + \beta_k^+ + \vartheta_1^+ \max\{(B_{k-1} - \phi_1), 0\} + \vartheta_1^- \min\{0, (B_{k-1} - \phi_1)\} \\ &+ \sum_{i=1}^{k} (\gamma_i^+ \max\{0, B_{k-i} - B_{k-i-1}\} + \gamma_i^- \min\{0, B_{k-i} - B_{k-i-1}\}). \end{aligned} \tag{8}$$

Then, the CRF is a recursive function which sums n equations, where n is the number of periods it takes retail prices to completely respond to a one time change in cost, and the period $k \in \{1, ..., n\}$ cumulative adjustment is as stated in equation (8). The CRF detailing the response to a cost decrease is defined analogously to equation (8).

Figure 3 plots the CRF's and 95% confidence intervals corresponding to the regression in Table 4, and it is clear that the existence of rockets and feathers is a widespread phenomenon in the retail gasoline industry. Here, the vertical axis plots the percentage of the total cost shock that has been incorporated into the final retail price.[27] For just over eight days following a one time cost shock, the cumulative response is significantly greater for positive than negative shocks. This result is in step with much of the literature, but serves as a stark contrast to the findings of Bachmeier and Griffin (2003) and Galeotti et al. (2008) who employ the same estimation procedure to reject the existence of rockets and feathers. As these studies attribute the rejection of the phenomenon to utilizing a more reliable estimation procedure than BCG, I note that even when employing the more appropriate techniques the data overwhelmingly supports the existence of the pricing behavior.[28]

To highlight the presence of price asymmetry, as well as the cost it presents to consumers, I measure the loss in consumer welfare due to the pricing behavior. Welfare loss is calculated by subtracting the monetary gain consumers enjoy from a cost decrease from the losses accrued by a

[26] I depart from BCG's specification only in that retail prices are allowed to asymmetrically return to their long-run relationship with cost.

[27] In Figure 3, for example, the fourth day after a cost change firms are estimated to have raised retail prices by 38% of the size of a positive shock and to have lowered prices by 18% of the size of a negative shock.

[28] This is not to say that this paper's findings are inconsistent with the other two studies. Bachmeier and Griffin (2003) investigates the connection between oil shocks and wholesale prices. Galeotti et al. (2008) employs monthly averaged price data, and in the appendix temporal aggregation is found to contaminate parameter estimates. It is of note, however, that the aforementioned studies claim their finding of non-existence of price asymmetry is partially attributable to the model choice, yet this paper employs the same model and finds existence.

cost increase:[29]

$$\Delta W_n = \int_{j=0}^{n} (B_j^+ - B_j^-) dj. \tag{9}$$

Here, B_j^+ and B_j^- are defined as in equation (8), and linear interpolation is used to approximate the CRF's at non-integer values. The results are graphed in Figure 4, and the welfare loss to consumers as a result of asymmetric pricing becomes clear; the cumulative cost to consumers increases for up to ten days following a wholesale gasoline price shock. Ten days after the initial one cent cost change consumers lose about 1.3¢ more from an increase than they gain from a decrease, and the difference is significantly different from zero with 99% confidence.

As another gauge of the welfare implication of asymmetric pricing, I calculate how much a typical driver would have saved over the time spanned by the data if retail prices had adjusted symmetrically. To perform this counterfactual, retail prices are predicted under the assumption that they respond with equal speed to positive and negative cost shocks, and compared to the case of asymmetric adjustment. More specifically, symmetric prices are generated using parameter estimates of equation (7), but lagged negative changes in cost parameters, β_j^-, are replaced with the estimates for positive cost changes, β_j^+. Additionally, ϑ_1^+, the effect of price being above its long-run relationship with cost, is replaced with ϑ_1^-, the effect of price being below its long-run relationship with cost, to ensure retail prices descend to their long-run equilibrium following a negative cost shock at the same speed they are estimated to rise to their long-run equilibrium after a positive shock. Asymmetric prices are predicted using the true estimates of equation (7).

Figure 5 plots the predictions of asymmetric and symmetric retail prices using the daily NYMEX spot price for regular unleaded gasoline as the cost data.[30] Symmetrically adjusting prices are always lower, and, on average, are 4.05¢ less than asymmetric prices. The US Department of Transportation reported 205 million licensed drivers in 2007. Using this as an approximation of the number of gasoline consumers, in conjunction with monthly regular fuel gross consumption data, I estimate the gallons of fuel purchased per consumer on each day from August 8th, 2008 through July 29th, 2009.[31] Each driver purchased, on average, .63 gallons of fuel per day. In turn, the typical gasoline consumer would have spent \$9.33 less on fuel over this time if prices had responded symmetrically to cost shocks. This amounts to an additional \$1.91 billion in savings across the entire driving population of the United States. Thus, I find strong evidence in favor of asymmetric pricing and that it poses a real cost to consumers.

[29]This is the same measure of consumer welfare as in BCG.

[30]The spot price used in the predictions is a daily weighted-average of the closing spot price of reformulated gasoline shipped from the Los Angeles, CA and NY, NY Harbors; the weights used to average the cost data reflect the proportion of gas stations in the data set located in the west or east coast of the United States.

[31]Gasoline consumption data is made publicly available by the Energy Information Administration.

5 Search Costs as the cause of Asymmetric Pricing

5.1 Theoretical Background and Testable Hypothesis

The identification of asymmetric pricing in the retail gasoline market is in step with much of the previous empirical literature. Until recently, however, rockets and feathers was thought to be at odds with microeconomic theory. Informal models of focal price collusion were conjectured as the cause, but no rigorous theory or empirical support has surfaced. On the other hand, formal models of asymmetric pricing as a consequence of consumer search costs have been developed in recent years. For the purposes of this paper, I focus on the results of Yang and Ye (2008) and Tappata (2009); the two studies offer unique models with qualitatively similar results. Before the implications of the two papers are tested it is helpful to outline the models and intuition underlying the results.

Both models rely upon the assumption that consumers do not observe firms' marginal cost of production, but may learn this cost through market search and purchase decisions. In each period every firm faces the same marginal cost, which evolves according to a Markov process; the underlying parameters of the Markov process are common knowledge to both firms and consumers. In equilibrium firms use mixed strategies to set prices, and both studies prove that there exists more price dispersion when costs are low. Consumers with nonzero search costs have a greater incentive to search when prices are more dispersed, as the expected gain from obtaining additional price quotes is higher when the distribution of prices is more spread out. Therefore, consumers search more intensely when they believe marginal costs to be low.

Given these preliminary results, both papers consider a dynamic setting whereby marginal costs can take one of two values, high or low. Additionally, costs are assumed to exhibit persistence (i.e. the probability of costs remaining the same next period is greater than $\frac{1}{2}$). First, consider the case when costs transition from a low state in period one to a high state in the next period. Through search and purchase decisions in the first period consumers update their beliefs in favor of marginal costs being low. Due to the persistence of costs, consumers then believe that costs are likely to remain low the next period, and therefore, have a strong incentive to search in period two. However, if the costs become high in period two then consumers are likely to discover the cost change due to their high search intensity. Firms, therefore, adjust prices upwards quickly to reflect updated consumer knowledge.

On the other hand, consider the case when costs are high in period one and transition to low in period two. After period one consumers update their beliefs to reflect the high cost state, and optimally choose a lower search intensity for period two. If, however, costs drop in period two consumers are less likely to discover the change due to their lower search intensity. Firms then have a low incentive to drop prices as consumers' beliefs are less likely to incorporate the cost drop. In total, retail prices adjust slower to cost decreases than increases. While this discussion is a simplification of Yang and Ye (2008) and Tappata (2009) it captures the basic intuition; consumers are less likely to be informed about a cost decrease, and consequently, firms lower prices slowly so as to profitably exploit consumers' lack of knowledge.

The theory developed in Yang and Ye (2008) and Tappata (2009) offers testable predictions, three of which I address in the following subsections. First, Yang and Ye (2008) prove that if the proportion of "shoppers", consumers that face zero search costs, increases then retail prices will adjust downward more slowly in response to a negative cost shock.[32] Intuitively, if the number of shoppers in a market decrease then there is less equilibrium search. Therefore, consumers are generally less informed when costs drop, and consequently, retail prices fall slower. A second verifiable consequence of search-based theory is that greater expected gains from search result in a lower magnitude of price asymmetry. This is true as larger gains from search incentivize more equilibrium search, and thereby, consumers are better informed. Firms are then less able to take advantage of unknowledgable buyers, and prices descend more quickly. A final search theoretic result is that a monopoly will price symmetrically. These firms will not exhibit price asymmetry as they maximize profit by setting the monopoly price each period, and this price responds symmetrically to cost shocks. In the following three subsections I carefully test these three implications of theories based upon competition with consumer search.

5.2 Prices Fall Slower When Consumers Search Less: The Case of Premium Fuel

To empirically examine the consequences of search-based price asymmetry, I rely upon the differences in consumers who purchase regular versus premium unleaded gasoline. Premium gasoline has a higher octane rating[33] than regular fuel, and in my data set, sold for, on average, 25.6¢ more per gallon. However, in cars manufactured since the early 1990's almost all engines have been designed to automatically correct engine knocking, thereby rendering the performance advantage of premium gasoline almost negligible (Ford 2008).[34] In spite of this fact, many luxury vehicles' warranties may be voided if anything but premium fuel is put into the tank. Thus, drivers of more expensive cars are more likely to purchase premium gasoline than owners of less expensive automobiles. Luxury car owners tend to have higher incomes, and Barron et al. (2000) presents convincing evidence that high income consumers that purchase premium fuel are typified by greater search costs. Consumers that are not required by warranty to purchase premium fuel pay a large markup for a product that offers almost no perceptible benefit over regular fuel. Healey (2003) notes, "engineers, scientists and the federal government say there's little need for premium." Consequently, consumers not bound

[32] This claim is explicitly stated and proved in *Proposition 8* of Yang and Ye (2008).

[33] Octane rating measures a fuel's resistance to engine knocking.

[34] Also, premium gasoline neither increases fuel efficiency nor reduces harmful emissions.

by contract to purchase high octane fuel, but still choose to do so, are ill informed. Consumers that do not acquire information pertaining to product value can accurately be described as having a high cost of search for product quality information. Any correlation between consumers' search cost for obtaining product quality information and price information translates into purchasers of premium gasoline having a high cost of price search. Additionally, Manzan et al. (2009) finds that consumers of premium gasoline are exceedingly more demand inelastic than regular buyers across all price levels.

Given that consumers of premium gasoline generally earn higher incomes, are far less price sensitive, and possibly less informed than consumers of regular fuel it appears safe to assume that premium customers are (i) typified by higher search costs and (ii) less likely to be a "shopper" for the lowest possible price.[35] Assumptions (i) and (ii) in conjunction with Yang and Ye's (2008) prediction that a lower proportion of shoppers increases price asymmetry allows the following hypothesis to be tested.

Hypothesis 1 *Firms price premium gasoline with a greater magnitude of asymmetry than regular fuel, and the increased asymmetry is entirely a result of slower adjustment to cost decreases.*

Before undertaking the analysis, an issue in the data must first be dealt with; the data set only contains new premium fuel price observations for, on average, 12% of stations each day. Consequently, if empirical testing is performed on the station-level at daily intervals then a majority of the data will be dropped from the analysis.[36] To ameliorate the problem and maximize the amount of information extracted from the data, the following analysis is performed at the daily market-level (as opposed to firm-level). It is more prudent to spatially aggregate the data than to average it across time because results presented in the appendix convey that temporally aggregating data can severely bias results, but little is changed by averaging prices across cities. Defining a market in the retail gasoline industry can be difficult; firms one mile apart may compete with each other, but the total set of competitors that each faces may not be the same. Essentially the retail gasoline industry consists of a large number of overlapping markets, of which each firm may belong to more than one. This caveat is addressed in the same fashion as Chandra and Tappata (2008) and Lewis (2008); each firm is specified to be operating in a unique market of which they are located at the center. Then, I define a market to be a 1.5 mile radius around each firm.[37]

To test the implications of search-based asymmetry, I first confirm that premium and regular prices respond asymmetrically to cost shocks, and premium and regular prices positively correlate

[35]Here, "shopper" is defined as in the previous subsection: a consumer with zero search cost.

[36]When lag lengths are set to ten a firm needs to have a run of eleven consecutive price observations to be included in the regression .

[37]Lee (2009) finds that stations compete most heavily with competitors within one mile. I extend the market radius an extra half mile to ensure that I capture all pertinent competitive dynamics.

with wholesale costs.[38] Given these results, I then show that within specific markets premium and regular prices respond at the same speed to positive cost shocks, but premium falls slower after a negative cost change – thus confirming a prediction of search-based rockets and feathers theory.

To begin, equation (7) is estimated using the same cost measures as in the previous section, but firm prices are replaced with market average prices. In estimating the long-run relationship between market price and cost (equation (2)) market-specific fixed effects are included, and a host of controls supplement equation (7): the number of competitors and the percentage of those who are independently branded in the market and between 1.5 and 5 miles of the market center, the log of population of the market, and day of the week controls. Regression results are reported in columns one and two of Table 5 for both premium and regular gasoline, respectively, and Figure 6 plots the corresponding CRF's.[39] Figure 6 illustrates that for more than nine days following an initial price shock premium fuel prices respond in greater magnitude to positive shocks than negative shocks, and this is true with 95% confidence. Also, premium reacts faster than regular to both positive and negative cost shocks. Premium prices do initially act slower in response to a negative cost shock, but by the sixth day after the shock its cumulative response is statistically greater than that of the regular price series. However, premium and regular gasoline exhibit no statistically significant difference in the magnitude of price asymmetry, as measured by equation (9).

While this analysis confirms that premium gasoline prices respond asymmetrically to cost shocks, not much can be said yet in regards to the relationship between consumer search costs and asymmetric pricing. To support the findings in Yang and Ye (2008) and Tappata (2009) I would like to show that premium prices fall slower than regular prices but rise at the same speed. Even though these regressions do not appear to support the theory's predictions, a closer and more careful look at the data reveals estimates largely consistent with search-based theory. The trouble with the tests reported in columns one and two of Table 5 is that the behavior of individual firms is muted. Comparing the premium and regular CRF's in Figure 6, for example, is analogous to measuring how a firm in Seattle, WA prices premium relative to how a firm in Philadelphia, PA prices regular; while this may yield some insight it disregards the fact that the firm in Seattle sets both a premium and regular price, and it is the relative movement of those two prices that should be compared. Nevertheless, it is important to illustrate that when estimating the model with market average prices both types of fuel exhibit a significant degree of price asymmetry and positively correlate with the wholesale cost series.

[38]In the previous section, regular fuel prices were found to exhibit price asymmetry. In this subsection, I show that this still holds when estimating the model with market-level data.

[39]Standard errors reported in Table 5 are clustered by market and corrected for heteroscedasticity. As individual firms belong to multiple markets this remedies the real possibility of error terms in equation (7) being correlated across observations. Also, I only include markets for which I have both premium and regular price data. Again all parameter estimates are not listed due to space constraints, but are available upon request.

A more informative estimation technique is to measure how premium prices move relative to regular prices *within* a given market, and then estimate the behavior of a typical market. Therefore, I now examine the dynamic behavior of the markup of premium over regular gasoline. By estimating the response to cost shocks of market average markups of premium over regular fuel I can isolate how the same firms price the two products over time. To begin, I create a new price series:

$$D_{it} = P_{it} - R_{it}. \tag{10}$$

Here, P_{it} and R_{it} are the premium and regular prices, respectively, set in market i during time period t, and D_{it} represents the markup of premium over regular gasoline. D_{it} then acts as the price variable in equations (2) and (7), and the spot price of WTI crude oil traded on NYMEX is utilized as the cost variable. The spot price of oil is used instead of wholesale regular unleaded fuel to guard against the possibility that cost changes reflect shocks to regular unleaded fuel that are unrelated to premium gasoline.[40] Using the price of crude oil as the cost measure ensures that cost changes only reflect movement in the cost component shared by both types of fuel.

I first estimate equation (2) and obtain economically plausible results. The relationship between the markup of premium over regular fuel and cost (ϕ_1) is found to be .008 and the constant (ϕ_0) is 26.3, both estimated with more than 99% confidence. Thus, the long-run markup of premium fuel over regular gasoline is nearly constant at 26.3¢; it only increases by .8¢ for every dollar increase in the per gallon price of oil. These coefficients are then substituted into equation (7), and the results of estimating the equation are listed in Table 5 and the corresponding CRF's are plotted in Figure 7. The most striking feature of the CRF's plotted in Figure 7 is the distinct negative proportional response to a negative cost shock. This translates into D_{it}, the gap between premium and regular prices, *increasing* when costs *decrease*. Figure 6 illustrates that both premium and regular prices drop in response to negative cost shocks; thereby, premium prices necessarily fall slower than regular prices in any given market in order for the gap to increase. The reaction to positive cost shocks is another story; the markup of premium over regular fuel barely changes. Only on days 2 through 4 after a positive cost shock can it be stated with 95% confidence that the response is greater than zero, and the amount above zero represents an economically meaningless change (less than .05¢ in response to a 1¢ cost change). That the markup does not change in response to a positive shock is highlighted in Table 5 where the only variables that are not significant are D_{it}'s response to lagged positive cost changes of length 1,3, and 4. Figure 6 demonstrates both premium and regular prices increasing in response to a positive cost shock; therefore, premium and regular prices must rise

[40] If there were to be a negative price shock to wholesale unleaded fuel that did not affect the premium market it could cause the price of regular fuel to drop, but leave premium prices unchanged. This would bias results in favor of search-based theory. However, when the wholesale price of unleaded fuel is used as the cost measure the results are qualitatively identical.

at the same rate in a given market for the markup to remain constant. In conclusion, premium prices fall slower than regular prices in response to a negative cost shock, but rise at the same pace following a positive cost change. These estimates confirm hypothesis 1 and support consumer search costs as the mechanism behind rockets and feathers.

5.3 Search Incentives and the Magnitude of Asymmetry

In this subsection, I measure the relationship between the gains from search and asymmetry. In formulating their theory of rockets and feathers, Tappata (2009) and Yang and Ye (2008) both find that consumers increase their search intensity when prices are expected to be more dispersed. The result is a consequence of more varied prices offering consumers greater potential savings, and thereby, an increased incentive to search. And, according to Tappata (2009) and Yang and Ye (2008), a more intensively searching consumer-base implies less market asymmetry.

Hypothesis 2 *Markets with greater price dispersion exhibit less price asymmetry.*

While yielding evidence in favor of hypothesis 2 would be consistent with search-based asymmetric pricing theory, the issue of causality must also be considered. The assumption underlying hypothesis 2 is that markets with more dispersed prices cause consumers to increase their intensity of search; however, a higher degree of search may also serve to drive down price-cost margins, leading to less price dispersion. Therefore, it is not entirely clear whether markets with low price dispersion discourage consumer search, or have low dispersion as a direct result of intensely searching consumers. To distinguish between the two cases, robustness checks are undertaken following the tests of hypothesis 2. Still, note that a direct consequence of search-based theory is that exogenous price dispersion negatively correlates with the magnitude of market price asymmetry.

The econometric tests in this and subsequent subsections will largely follow the same pattern: (i) define a market/firm characteristic that partitions the data and (ii) separately estimate the magnitude of asymmetry for the partitioned markets/firms. More formally, let $d = \{d_1, ..., d_n\}$ be a set of dummy variables such that $d_i = 1$ for a firm if they satisfy some condition (such as their closest competitor is located between 1 and 2 miles away) and $d_i = 0$ otherwise, and for each firm $d_j = 1$ and $d_{-j} = 0$ for some $j \in \{1, ..., n\}$. Then create a new vector of variables $\Omega \equiv \{\alpha_{11}, ..., \alpha_{1n}, ..., \alpha_{mn}\}$, where $n = |d|$ and m is the number of independent variables in equation (7), by interacting each dummy variable with each independent variable in equation (7). Finally, each $\alpha_{ij} \in \Omega$ is added to equation (7), the new equation is estimated, and the estimated parameters are used to separately construct CRF's for each group of markets/firms.[41]

[41]Due to the large number of parameters in each regression the parameter estimates used to construct CRF's throughout this section are not reported. They are available upon request.

In this subsection, markets are partitioned according to their degree of price dispersion, and in accordance with hypothesis 2, CRF's estimated for low dispersion markets exhibit a higher magnitude of asymmetry. As a first proxy for the gains from search, I calculate the average difference between the maximum and minimum price for regular unleaded fuel in each market over the course of the data. This statistic captures, on average, the most a consumer can save by visiting each firm in the market. I then divide the average price range distribution into quintiles and accordingly partition the set of markets. Figure 8 plots the estimated CRF's for firms that fall in either the first or fifth quintile, and the magnitude of asymmetry is greater for markets with a low average price range.[42] The average price range of markets in the first quintile is 4.3¢ compared to 21.9¢ for markets in the fifth quintile. Thus, consumers have a much stronger incentive to search in markets belonging to the upper quintile as apposed to the lower quintile. And, in accordance with search-based theory, there is a greater degree of asymmetry (1.01¢ cumulative difference ten days after a one cent cost shock) in markets with a lower incentive to search.[43]

Similar results are derived when the connection between average price variance in a market and the magnitude of asymmetry is measured. If the variance is close to zero then acquiring price information for an additional firm will yield minimal financial reward; conversely, a high price variance presents the opportunity for consumers to gain substantial surplus by searching for additional price data. Thus, search theory predicts an inverse relationship between the degree of price asymmetry and the average variance of prices in a market. As such, I estimate CRF's for markets in the upper or lower quintile of the price variance distribution, and again find support for search-based asymmetry. While the results are not as strong as with the previous measure of gains from search, the CRF's plotted in Figure 9 illustrate that for more than two days following a cost shock markets with a lower average variance exhibit more asymmetry.[44] Moreover, the difference in asymmetry is almost entirely due to low variance markets reacting more slowly to negative cost shocks. In sum, both measures of search incentives reveal a significant relationship with the rockets and feathers phenomenon, and in the direction posited by search theory.

While these results are consistent with search-based asymmetric pricing, there exists another plausible explanation; markets with low price dispersion are populated by consumers who rigorously search for the lowest price. In other words, it may be that consumers are so well informed that all firms are forced to price near cost. In turn, firms in these markets exhibit a low gap between the highest and lowest price. Thus, it is not known if well informed consumers push the price gap close together or a small price gap provides disincentive for consumers to engage in costly search. To distinguish between the two cases, I test the relationship between market price levels and the

[42]Similar to the previous subsection, this analysis was performed at the daily market level using the same market definition and set of additional controls.

[43]This is true at the 95% confidence level.

[44]This claim is made with 95% confidence.

proxies for search incentives. If a negative correlation between price variance or range and price levels exists then it is unlikely that intense consumer search causes a low price range or variance.

In measuring this relationship it is prudent to remove fixed effects from market price levels. Certain markets may set lower prices because wholesale gasoline is cheaper in that area or the market contains firms selling a lower quality gasoline.[45] Additionally, retail gasoline prices reflect the value of secondary products, such as car repair service or grocery items, also sold at the station. The data set does not allow for the effect these characteristics have over market prices to be directly controlled. Accounting for the impact quality, branding, secondary services, etc., is important in determining which markets set prices higher than the value of the product would normally dictate. Fortunately, in the retail gasoline industry the effect of these factors remains constant over time, and can be controlled for by including a fixed effect variable in equation (2). Thus, to clean price levels of market fixed effects, I estimate the following equation:

$$R_{it} = \phi_0 + \phi_1 C_{it} + FE_i + \epsilon_{it}, \tag{11}$$

and then calculate $G_{it} = R_{it} - FE_i$. Subtracting market fixed effects, FE_i, from the true price allows for market characteristics (and firm traits within the market) that do not vary over time to be controlled. Then, two separate regressions are performed: average price range regressed on average cleaned market price and average price variance regressed on average cleaned market price. Both tests reveal a negative relationship between price levels and the gains from search, which is significant with over 99% confidence.[46] Thus, markets posited to provide a low incentive to search actually set higher prices. It is, therefore, unlikely that the cause of low price dispersion is intense consumer search, which would serve to drive down prices, and in turn, confidence can be instilled in the proxies for the incentive to search. Consequently, a negative correlation between average price range (or variance) and the magnitude of price asymmetry stands as strong evidence in favor of hypothesis 2 and search-based theory of asymmetric pricing.

5.4 Monopolies Price Symmetrically

Next, I test whether firms with substantial monopoly power incorporate positive cost shocks into their final price more quickly than negative shocks. Asymmetric pricing that arises from consumer search costs disappears if consumers are only capable of purchasing from a single firm, which implies the following testable hypothesis.

Hypothesis 3 *Monopolists price symmetrically.*

[45] Even though gasoline is a relatively homogenous good consumers may perceive more heavily advertised brands as selling higher quality gasoline.

[46] The coefficient on G_{it} when range is regressed on it is $-.068$ and is $-.241$ for variance.

To test hypothesis 3, I isolate firms with no nearby competitors and measure the extent to which they react more quickly to positive than negative cost shocks. If rockets and feathers is indeed a competitive phenomenon then there should be no distinction between the rate at which monopolies incorporate positive and negative cost changes into their sale price.

In order to extract firms from the data set who operate as monopolies, or at least have substantial monopoly power, I first estimate the distribution of the "closest competitor" control variable. This variable states, for each firm, the distance between the firm and its nearest rival. Figure 10 plots the distribution, and the goal is to determine whether firms located in the tail, those without a competitor within a few miles, price symmetrically. I estimate the speed of adjustment to cost shocks for firms located in the top 2.5 percentile of the "closest competitor" distribution. The average distance to the nearest competitor for these firms is 3.5 miles and the minimum distance to the closest competitor is 2.2 miles. After estimating equation (7) at the firm-day level for only firms in the top 2.5 percentile of the distribution, the parameters are substituted into equation (9) to measure the magnitude of asymmetry. Equation (9) calculates, for each day following a cost change, the cumulative adjustment of retail prices following a positive cost shock minus the cumulative adjustment after a negative shock. For a firm to exhibit rockets and feathers pricing, the estimated function must be significantly greater than zero.

Figure 11 plots the estimated function and confidence intervals given by equation (9), and it is apparent that firms facing soft competition price with no asymmetry. Here, the estimated function is found to be only slightly above zero, and the upper and lower bounds of the 95% confidence interval are almost symmetric about zero. Thus, there is no reason to suspect that monopolies implement rockets and feathers as a pricing strategy. To ensure that this result is because monopolies indeed price symmetrically, and not that the regression lacked power, I perform the same test for firms in the lowest 2.5 percentile of the "closest competitor" distribution. These are firms whose nearest rival is no more than .013 miles away. The result of estimating equation (9) for these firms is plotted in Figure 12, and firms with a nearby competitor exhibit price asymmetry statistically greater than zero with 95% confidence for up to four days following a cost shock. As there are the same number of observations in this estimation as the monopoly test, it can be assured that the lack of statistical significance for the monopoly group is indeed a consequence of the firms pricing symmetrically. Thus, the empirical results are consistent with hypothesis 3 and the predictions of search-based asymmetry.

6 Focal Price Collusion

6.1 Theoretical Background

The econometrics of the previous section revealed that products whose customers have greater search costs are priced with greater asymmetry, markets with less to gain from search exhibit more asymmetry, and monopoly power translates into symmetric pricing. These finding are all consistent with the theory presented in Yang an Ye (2008) and Tappata (2009). Another common explanation for rockets and feathers is that when prices decrease firms coordinate on the previous period's price in an effort to artificially maintain high prices. In fact, the finding that monopolies exhibit no price asymmetry is consistent with focal price collusion being the underlying mechanism. This section, however, presents sound evidence against collusion being a meaningful determinant of rockets and feathers. After pinpointing firms in the data with the highest potential for collusion, I find that neither the highest priced nor the most cooperative subsets of these firms are more likely to price asymmetrically.

Borenstein, Cameron, and Gilbert (1997) offered a stylized version of the collusion model developed in Green and Porter (1984) as a motivation for the rockets and feathers phenomenon. In BCG's explanation, firms use the previous period's output price as a focal point for collusion. If costs drop then the previous period's price is maintained until a firm cheats on the agreement and triggers a price war. Conversely, if costs increase then firms raise their price to maintain a positive margin and/or not be viewed as cheating on the collusive agreement. In sum, market prices adjust slower to cost decreases than increases. While this brand of focal price collusion generates price asymmetry, BCG only conjecture it to be the cause of the phenomenon and provide no formal model. Subsequent studies that posit focal price collusion to generate asymmetry provide no proof that coordinating on the previous period's price maximizes firms' profits. Despite the lack of formal theory supporting focal price collusion as a profit maximizing strategy, it has become a common explanation for asymmetric pricing, and Lewis (2005) does provide some supporting empirical evidence.

6.2 Empirical Tests of Focal Price Collusion

If collusion is the root cause of asymmetric pricing then firms engaging in the (possibly tacit) agreement, and thereby exhibiting a substantial degree of price asymmetry, should be able to sustain prices at least as high as similar, but non-collusive firms. If the collusive firms set lower prices than their rivals then they would be better off breaking the agreement and setting the price charged by the non-collusive firms. Consequently, if focal price collusion is the cause of rockets and feathers there should exist a positive correlation between the magnitude of asymmetry and price levels.

In making this connection, however, the influence of consumer demand and other pertinent market characteristics over retail prices must be removed. Given the geographic variability in the data, it would make little sense to simply test the correlation between average prices and the degree of asymmetry, as firms in the data set face a wide variety of demand conditions. Therefore, "high priced" ("low priced") firms are defined as those who consistently price above (below) their market's average price. By measuring a firm's price relative to other firms in the same market, both long-run variability in demand across markets and short-run demand shocks can be controlled for in the econometric process. Note, however, that firms that generally price above the market average may do so because they offer a higher quality product. If price levels are largely driven by quality then "high priced" firms may not be those entered in collusive agreements. In essence, the power of the subsequent tests of collusion is dependent upon the extent to which collusion influences price-cost margins relative to other factors, such as product quality. Yet, if focal price collusion does significantly raise price levels and generate price asymmetry then the following hypothesis will hold true.

Hypothesis 4 *Groups of closely located firms that consistently price above the market average exhibit more asymmetry than firms that price below the average.*

To test hypothesis 4, I first isolate the set of retailers most likely to be participating in a collusive agreement. Therefore, the data set is refined to only include firms that have exactly one competitor within .1 miles. In general, the ability to maintain collusion decreases in the number of firms entered in the agreement and increases in the ability to monitor behavior. By isolating firms with a single rival whose prices are costlessly observable, only firms with the maximum potential for collusion are included in the analysis. Then, both the average price charged by the two closely located firms, p_{ft}, and the average price charged by all other firms within 1.5 miles, p_{kt}, for each day t, are calculated. Given these values the following dummy variable, d_{pt}, is constructed:

$$d_{pt} = \begin{cases} 1 & \text{if } p_{ft} - p_{kt} > 0 \\ 0 & \text{otherwise} \end{cases} \quad . \tag{12}$$

In words, d_{pt} takes a value of one if and only if the average price of the two firms is greater than the market average on day t. The dummy variable, therefore, distinguishes between retailers who fall above or below the approximate mean of their market's price distribution on a particular day. After partitioning firms according to d_{pt} in each time period, the next step is to isolate firms who consistently fall above, or below, the mean of the the daily price distribution. Specifically, two more dummy variables, indicating "high priced" and "low priced" firms, are created using the following statistic:

$$S = \sum_{t \in T_j} \frac{d_{pt}}{|T_j|}. \tag{13}$$

Here, T_j is the set of days for which I have available price data for the firms in market j. S then calculates the percentage of days such that the average price of the closely located firms is greater than the market average. This statistic allows for a distinction to be made between firms who regularly price above, or below, their competitors. After partitioning the distribution of S values into quintiles, I estimate CRF's for the pairs of firms located in the upper and lower quintile.[47] Firms in the lower quintile price above the market average between 0 and 17% of the time and firms in the upper quintile price above the market average between 72% and 100% of the days. Figure 13 plots the CRF's for pairs of firms that consistently price above or below their market's average, and the line estimates find low priced firms pricing more asymmetrically; they adjust faster to positive cost shocks and slower to negative cost changes. This is a direct contradiction of the prediction of rockets and feathers generated by focal price collusion; high priced firms should price more asymmetrically. Despite the appearance of low priced firms as more asymmetric in Figure 13, at the 95% confidence level, there is no statistical distinction between positive or negative reactions between the two types of firms.[48] Moreover, there is no significant difference in the magnitude of asymmetry as measured by equation (9). Thus, the estimations yield no support for focal price collusion as the determinant of rockets and feathers.

As a robustness check, I classify low and high priced firms using a different definition and estimate their response to cost shocks. First, the analysis is refocused to the market level, and a market is defined as in the previous subsection; each firm exists at the center of a unique market of radius 1.5 miles.[49] Then, equation (11) is estimated using OLS, where R_{it} is the average market price for regular fuel in market i at time t, C_{it} is the wholesale cost, and FE_i is a market specific fixed effect. FE_i captures the extent to which a market's retail price varies, on average, from the price predicted by the long-run relationship between price and cost. Markets with a fixed effect well above zero generally have a higher price than other markets in the data set, and markets with a fixed effect well below zero typically set a lower price. The advantage of defining high and low priced markets in this way is that it enables detection of focal price collusion involving firms throughout an entire market. The previous definition may exclude closely located pairs of firms whose collusive prices are part of a larger agreement across the market. The disadvantage to this new definition is

[47] I estimate equation (7) using the average price of the two closely located firms as the retail price variable. Thus, I am performing a market-level daily analysis where a market is defined as having a firm at the center and the .1 mile radius around the firm. The data is restricted to only include a firm with one competitor within .1 miles.

[48] To say there is no statistical distinction in the magnitude of asymmetry means that this is true from the first day following a price shock until prices have completely adjusted to the new equilibrium.

[49] For this analysis all firms are allowed to be at the center of a unique market, not just those with one competitor within .1 miles.

that differences across markets, like demand conditions, are only controlled for to the extent that the control variables account for them.

CRF's for firms in the lower and upper quintile of the FE_i distribution are graphed in Figure 14. The response functions are qualitatively similar to those estimated for the previous definition of high and low priced markets. Low price markets react faster to positive cost shocks over the first five days following the cost change; however, the difference in the speed of adjustment is not statistically significant. High and low price markets react almost identically to negative cost changes, and thus, there is no meaningful difference in the magnitude of price asymmetry between high and low priced markets. Neither of the definitions, therefore, find a connection between price levels and asymmetric pricing, which contradicts hypothesis 4 and focal price collusion as the motivator of rockets and feathers.[50]

7 Conclusion

In this paper, I identify the existence of rockets and feathers in the retail gasoline industry, but more importantly, provide sound evidence in support of consumer search costs as the underlying cause. By examining the markup of premium over regular fuel, I find that individual firms price premium gasoline with more asymmetry than regular, and the increased asymmetry is entirely a result of premium prices falling slower. As premium consumers are typified by greater search costs, this result supports the theories presented in Tappata (2009) and Yang and Ye (2008). Moreover, the relationship between measures of price dispersion (which serve as a proxy for the incentive to search) and rockets and feathers is consistent with search-based theory.

Conversely, I find little evidence in favor of focal price collusion as a consequential determinant of asymmetric pricing. Even though monopolies price symmetrically (which is also in accordance with search theory) there is no connection between price levels and asymmetry. In addition, firms with the highest probability of being engaged in a collusive agreement price with no more asymmetry than firms that almost certainly are not colluding. Given that there exists no formal theory of focal price collusion that produces asymmetric pricing, and that I find no evidence in favor of the informal hypothesis, there is no reason to suspect that collusion is a relevant factor.

The richness of data used throughout the empirical investigation affords the opportunity to generalize results. The data set includes daily price observations for over 11,000 stations located in the east and west coasts, and in both rural and urban areas. The unique data set also provides a solid foundation for future research. Incorporating firm specific traits and commuter patterns into

[50] Testing of the connection between firm cooperation and asymmetry further undermines collusion as the cause of rockets and feathers. Pairs of firms within .1 miles who often undercut each other price with the same degree of asymmetry as pairs of firms that generally cooperate. Focal price collusion, however, contains periods of price war, and therefore, the theoretical distinction between the types of firms is not entirely clear.

the investigation may paint a clearer picture of asymmetric pricing. US Census data details the driving behavior of cities' population, which may correlate with the propensity to search for the best price. Exploiting this information will facilitate a closer analysis of search-based asymmetric pricing theory.

Additionally, the propensity for collusion amongst closely located firms warrants a closer look. In this study, I illustrate that colluding on the previous period's price is not the mechanism behind asymmetric pricing. This is not to say, however, that collusion is absent from the retail gasoline industry; it only shows that the chosen method of collusion does not generate asymmetric pricing. If, for example, firms agree upon an artificially high markup over wholesale costs then retail prices will adjust symmetrically to cost shocks. More generally addressing the issue of collusion, perhaps by analyzing instances of price wars, offers an avenue for future research. Finally, the data set offers a unique opportunity to address periods of large cost changes. More closely examining which firms led the rundown of retail prices during the financial crisis, or how firms behavior differs during very high and low cost periods may identify some interesting properties of oligopolies.

References

[1] Atkinson, B. (2008) "On Retail Gasoline Pricing Websites: Potential Sample Selection Biases and Their Implications for Empiricle Research", *Review of Industrial Organization*, Vol. 33, pp. 161-175.

[2] Bachmeier, L.J. and J.M. Griffin (2003)] "New Evidence on Asymmetric Gasoline Price Responses", *Review of Economics and Statistics*, Vol. 85, pp. 772-776.

[3] Bacon, R. (1991), "The Asymmetric Speed of Adjustment of UK Retail Gasoline Prices to Cost Changes", *Energy Economics*, Vol. 13, pp. 211-218.

[4] Barron, J.M., B.A. Taylor, and J.R. Umbeck (2000) "A Theory of Quality-Related Differences in Retail Margins: Why there is a "Premium" on Premium Gasoline", *Economic Inquiry*, vol. 38, pp. 550-569.

[5] Barron, J.M., B.A. Taylor, and J.R. Umbeck (2004) "Number of Sellers, Average Prices, and Price Dispersion", *International Journal of Industrial Organization*, Vol. 22, pp. 1041-1066.

[6] Borenstein, S., A.C. Cameron, E. Gilbert (1997), "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?", *The Quarterly Journal of Economics*, Vol. 112, pp. 305-339.

[7] Borenstein, S., and A. Shepard (1996), "Dynamic Pricing in Retail Gasoline Markets", *The RAND Journal of Economics*, Vol. 27, pp. 429-451.

[8] Cabral, L. and A. Fishman (2008) "Business as Usual: A Consumer Search Theory of Sticky Prices and Asymmetric Price Adjustment", Working Paper.

[9] Chandra, A. and M.E. Tappata (2008), "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets", Working Paper, University of British Columbia.

[10] Deltas, George (2008), "Retail Gasoline Price Dynamics and Local Market Power", *The Journal of Industrial Economics*, vol. 57, pp. 613-628.

[11] Eckert, A. (2002), "Retail Price Cycles and Response Asymmetry", *Canadian Journal of Economics*, Vol. 35, pp. 52-78.

[12] Eckert, A. and D.S. West (2004), "Retail Gasoline Price Cycles Across Spatially Dispersed Gasoline Stations", *The Journal of Law and Economics*, Vol. 7, pp. 245-273.

[13] Engle, R. and C.W.J. Granger (1987) "Co-Integration and Error Correction: Representation, Estimation, and Testing", *Econometrica*, Vol. 55(2), pp. 251-276.

[14] Ford, D. "Premium Required? Not Necessarily", *The New York Times* 3 August 2008.

[15] Foros, O. and F. Steen (2008), "Gasoline Prices Jump Up on Mondays: An Outcome of Aggressive Competition?", Discussion Paper NHH SAM.

[16] Galeotti, M., A. Lanza, and M. Manera (2003), "Rockets and Feathers Revisited: An International Comparison on European Gasoline Markets", *Energy Economics*, Vol. 25, pp. 175-190.

[17] Geweke, J.F. (1978), "Temporal Aggregation in the Multiple Regression Model", *Econometrica*, Vol. 46, pp. 643-661.

[18] Geweke, J.F. (2004), "Issues in the Rockets and Feathers Gasoline Price Literature", Report to the Federal Trade Commission, University of Iowa.

[19] Green, E., and R. Porter (1984), "Non-cooperative Collusion Under Imperfect Price Information", *Econometrica* vol. 52, pp. 87-100.

[20] Healey, J.R., "Why Use Premium When Regular Will Do?", *USA Today*, 30 July 2003.

[21] Hosken, D.S., R.S. McMillan, and C.T. Taylor (2008), "Retail Gasoline Pricing: What Do We Know?", *International Journal of Industrial Organization*, Vol. 29, pp. 1425-1436.

[22] Houde, J.F. (2009), "Spatial Differentiation and Vertical Contracts in Retail Markets for Gasoline", Working Paper, University of Wisconsin-Madison.

[23] Lee, S.Y. (2009), "Spatial Competition in the Retail Gasoline Market: An Equilibrium Approach Using SAR Models", Working Paper, San Francisco State University.

[24] Lewis, M.S. (2005) "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market", Working Paper, University of California Energy Institute, Berkeley.

[25] Lewis, M.S. (2008) "Price Dispersion and Competition With Differentiated Sellers", *The Journal of Industrial Economics*, Vol. 57, pp. 654-678.

[26] Manzan, S. and D. Zerom (2009), "A Semiparametric Analysis of Gasoline Demand in the US: Re-examining the Impact of Price", *Econometric Reviews*, Forthcoming.

[27] Maskin, E. and J, Tirole (1988), "A Theory of Dynamic Oligopoly II: Price Competition, Kinked Demand Curves and Edgeworth Cycles", *Econometrica*, vol. 56, pp. 571-599.

[28] National Association of Convenience Stores, "The 2009 Gas Price Kit" www.nacsonline.com, 12 September 2009.

[29] Noel, M. (2003) "Edgeworth Price Cycles: Evidence From the Toronto Retail Gasoline Market", Working Paper, University of California, San Diego.

[30] Noel, M. (2009), "Do Retail Gasoline Prices Respond Asymmetrically to Cost Shocks? The Influence of Edgeworth Cycles", *RAND Journal of Economics*, vol. 40, pp. 582-595.

[31] Peltzman, S. (2000) "Prices Rise Faster Than They Fall", *Journal of Political Economy*, vol. 108, pp. 466-502.

[32] Said, Said E., and D. A. Dickey, "Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order", *Biometrika*, vol. 71, pp. 599-607.

[33] Slade, M.E. (1992) " Vancouver's Gasoline-Price Wars: An Empirical Exercise in Uncovering Supergame Strategies", *Review of Economic Studies*, Vol. 59, pp. 257-276.

[34] Tappata, M. (2009), "Rockets and Feathers. Understanding Asymmetric Pricing", Forthcoming, *RAND Journal of Economics.*

[35] Verlinda, J.A. (2008) "Faster Rockets and Slower Feathers With Local Market Power", *The Journal of Industrial Economics*, Vol. 57, pp. 581-612.

[36] Yang, H. and L. Ye (2008), "Search With Learning: Understanding Aymmetric Price Adjustments", *RAND Journal of Economics*, Vol. 39, pp. 547-564.

8 Appendix

In the appendix I demonstrate that this paper's econometric procedure produces more accurate results than the one utilized in Borenstein et al. (1997), and that studies of asymmetric pricing that do not employ daily price data may produce spurious results. Geweke (1978) details the various channels through which temporal aggregation may contaminate parameter estimates. Of particular interest to this study is Geweke's finding that the potential for temporally aggregated data to bias estimates is increasing in the correlation between explanatory variables. As lagged retail prices and costs are almost perfectly correlated in the data, it follows that any temporal aggregation may seriously limit the ability to accurately measure asymmetric pricing. To gauge the degree to which previous studies may have suffered from temporally aggregated data, I follow the advice of Geweke (1978) and estimate models at various levels of data aggregation and compare the results. I estimate the model specifications using the regular unleaded price data set aggregated to average city-week levels (similar to BCG), refined to station-week average prices (as in Hosken et al. (2008)), then specified as daily city averages, and finally completely disaggregated to station-specific daily prices. Each data specification is tested using three different models: the standard-error correction model employed in the body of the paper, an error-correction model (equation (6)) where the long and short-run components are estimated simultaneously, and equation (6) estimated via two-staged least squares regression as in BCG. It turns out that the BCG framework systematically produces biased results and yields highly implausible estimates when used in conjunction with station-level daily price data. These results are consistent with Bachmeier and Griffin (2003) in that the two-step technique appears to perform with greatest accuracy when used in tandem with the best available data. However, the estimates oppose Bachmeier and Griffin (2003) in that strong evidence in favor of the rockets and feathers phenomenon is produced. That is, even after implementing the technique the previous study used to reject asymmetric pricing I find that when it is employed along with daily price data rockets and feathers pricing exists. The analysis also shows that BCG's econometric technique performs poorly not because of their decision to estimate the error-correction model in a single step, as posited in Bachmeier et al. (2003), but as a result of their reliance upon instrumental variable regression.

To begin, the data is aggregated to city-week averages.[51] Figure 15 graphs daily retail and wholesale prices for a single gas station in Washington, DC, and Figure 16 graphs weekly average retail and wholesale prices for the entire city. In comparing the two graphs, the volume of information lost by aggregating almost 100 hundred gas station daily prices into weekly averages becomes apparent. Figure 15 clearly illustrates the daily comovements of price and cost, which become severely muted when averaged over time and geographic region. Estimates of asymmetric pricing

[51] All cities with a population of less than 25,000 are dropped for the city-week portion of the analysis.

may, therefore, suffer from the problems detailed in Geweke (1978, 2004).

To increase the accuracy of the results, I add city fixed effects to equation (2), and the log of population and the number and percentage of non-major branded stations in each city to equations (6) and (7). BCG proposes estimating equation (6) using two-stage least squares regression to control for the possible endogeneity of C_{it}, which could arise if city-specific demand shocks affected the wholesale cost of gasoline. As such, a set of instruments akin to those used by BCG is identified: lagged changes in the Brent crude oil spot price (the primary index for crude prices in Europe) and in Singapore conventional gasoline prices. The Brent crude oil price is an appropriate instrument, as it is determined on the world market and highly correlated with wholesale gasoline costs for the retail stations included in the data set. It is highly unlikely, however, that any local demand shocks for retail gasoline in the United States would affect the spot price of oil in Europe. The spot price of gasoline in Singapore is similarly correlated with the wholesale price of gasoline in the United States, as both are derived from the globally determined price of crude oil; yet, any unobserved local shocks to demand in the data set will have no effect on the price of gasoline in Singapore.

The results of three separate regressions are reported in Table 6; column 1 utilizes two-step estimation of equation (7), and columns 2 and 3 employ OLS and 2SLS, respectively, of equation (6).[52] The respective CRF's are depicted in Figure 17, and it appears that none of the estimation techniques are robust to the temporal aggregation problem. Particularly problematic is that BCG's IV method implies that one week following a cost increase retail prices increase by only 5% of the size of the initial shock, but incorporate 22% of a negative cost shock into final retail prices. BCG's estimation technique, therefore, predicts that retail gasoline prices are almost entirely sticky for a week following a positive cost shock. Given that firms in this market have a menu cost close to zero, this result seems wholly unrealistic. Moreover, BCG's IV method predicts asymmetric pricing in the opposite direction: prices react more quickly to negative than positive cost shocks. And, while the one and two step models do not predict complete upward price stickiness, they estimate retail prices to increase by 16% and 18%, respectively, of the size of the cost shock, their estimates are unrealistically low. The two-step and BCG OLS models do not perform as poorly as the IV model, however, both fail to identify asymmetric pricing at the 95% confidence level. The seemingly unrealistic estimates produced by all three models may be a consequence of the particularly volatile price of oil over the time period I collected data. According to Geweke's theory, daily volatility in independent variables increases the probability that weekly averaged data will contaminate estimates. Thus, aside from the peculiar result of upward price stickiness, there exists a theoretical basis upon which to view these results with skepticism.

In order to glean the extent to which the atypical results are a consequence of temporal aggre-

[52]All standard errors are clustered by city and are robust to heteroscedasticity. The lag lengths for past retail and cost changes is set to five.

gation versus averaging prices across firms, I first disaggregate the data to the station level, but leave prices as weekly averages. A share of the recent rockets and feathers literature employs this type of data; Eckert (2002) and Hosken et al. (2008) are prime examples. To improve the accuracy of the estimates, equations (6) and (7) are augmented with the same characteristic data as in the body of the paper.

Estimated coefficients and standard errors clustered by station and corrected for heteroscedasticity are reported in Table 7. The parameters are again measured with a high degree of power, and nearly every coefficient is significant at the 99% confidence level. In fact, the results are strikingly similar to those reported for city averages, suggesting that temporal aggregation poses a greater problem in the estimation of retail gasoline market dynamics than does averaging prices across firms. BCG's IV method still predicts retail prices reacting in greater magnitude to negative cost changes, and the BCG OLS model finds no price asymmetry. The two-step model, however, finds evidence of rockets and feathers for just over 3.5 weeks following an initial cost change. Still, all three models predict almost the same degree of upward price stickiness as with city-week averaged data. Thus, the concerns of Geweke (1978, 2004) hold true; employing weekly data in regressions when variables change on a daily basis can severely bias parameter estimates, especially when multiple right-hand side variables are highly correlated.

The troubles of temporal aggregation are underscored when each of the three models are estimated using city-averaged daily price data.[53] Even though prices are still spatially aggregated the estimates dramatically improve, and both the one and two-step models produce results resembling those found in section 4. Estimates are reported in Table 8 and plotted in Figure 19, and it is clear that prices respond more quickly to price increases than decreases. The upward price stickiness that pervaded the temporally aggregated estimates has completely disappeared from the one and two-step models; one week following a positive cost shock both models find that nearly half of the cost increase has been incorporated into the final price. Yet, this is not true for negative cost shocks as both models detect price asymmetry for more than 6 days after the initial cost change.[54] Despite the improvement in both the one and two-step error-correction models the IV estimation utilized in BCG does not fair any better,[55] and in some respects the parameter estimates have become more implausible. Retail prices are predicted to decrease by 13% of the size of the shock immediately following a cost increase and increase by 8% of the shock immediately after a cost decrease. This spurious finding is a direct consequence of using instrumental variable regression. Although the instruments are similar to those used in BCG,[56] the Hansen J statistic rejects their validity with

[53]I use the same additional controls in these regressions as with the city-week averaged data, but also include day of the week dummies.

[54]This is true at the 95% confidence level.

[55]When using daily data I instrument for concurrent positive and negative cost changes, ΔC^+_{t-1} and ΔC^-_{t-1}.

[56]Both this study and BCG utilize the Brent crude oil price as an instrument. However, where they use oil futures

more than 99% confidence. Thus, there is strong reason to believe the estimated equation is misspecified when using IV regression, which helps to explain the nonsensical results. Of further note is the near statistically identical performance of both OLS methods. This suggests that it is not BCG's decision to simultaneously estimate long and short-run price responses, but their reliance on IV regression that biases estimates.

Refining the daily data to the station level confirms that it is IV regression that contaminates BCG's econometric technique. Using this data, I estimate the same equations as with the weekly station level data, but add additional controls for the day of week. Both Foros and Steen (2008) and Eckert and West (2004) find that the day of the week is an important determinant of retail gasoline prices. For one, demand is greater on weekdays when many people commute to work. Furthermore, certain days of the week may serve as focal points for coordinated price increases. It is these market dynamics that are lost when data is aggregated to the weekly level, and this loss is confirmed by every day of the week dummy being significant at the 99% confidence level in each of the subsequent regressions. Table 9 reports estimates of the three models, and the corresponding CRF's are charted in Figure 20. The results differ markedly from both sets of weekly averaged regressions, but are nearly identical to the daily city estimates. The IV model again predicts that retail prices decrease the first day after a positive cost shock and increase following a negative shock.[57] Bachmeier and Griffin (2003) discuss the potential bias and unclear convergence properties associated with BCG's IV method. Additionally, note that any motivation BCG may have had for employing instrumental variables seems unfounded when estimating their model with daily station level prices and NYMEX commodity prices as a measure of cost. Their concern was that demand shocks affecting the largest US cities may influence the terminal price of gasoline in those respective cities. However, since I use the wholesale prices listed on the New York Mercantile Exchange as a proxy for cost there is no reason to believe that any local demand shocks influence this price over the span of the data. Thus, nothing is gained by including the instrumental variables.

In contrast to the problems with the IV model, both OLS models generate parameters that drastically improve upon the implausible results of their temporally aggregated counterparts. They estimate a smooth pass through of positive cost shocks; 10 days after a 1¢ increase in wholesale cost retail prices increase by .6¢. Moreover, both econometric techniques yield strong evidence in favor of rockets and feathers; for more than 8 days following a cost shock the cumulative retail price response to a positive shock is greater than to a negative shock.[58] Both models predict that ten days after the initial one cent cost change consumers lose about 1.3¢ more from an increase than they gain from a decrease, and the difference is significantly different from zero with 99% confidence

prices as additional instruments I employ the spot price of wholesale gasoline traded at the Singapore harbor.

[57]The Hansen J statistic again rejects the validity of the instruments with more than 99% confidence.

[58]This is true with 95% confidence.

in both OLS models.

The contrast in predictions across levels of data aggregation and econometric models warrants a closer analysis. The difference in results as the data progresses from station level weekly averaged prices to daily prices may partially be attributed to the short time span over which I possess data. Yet, this alone cannot explain the schism; even when prices are analyzed as weekly averages there is still 52 weeks of data for over 11,000 stations. In fact, the high power with which coefficients are estimated, almost every parameter is significant with 99% confidence, suggests that the estimates do not suffer for lack of power. The uniquely volatile price of oil over the time I collected data certainly accentuates the bias of the weekly averaged analysis. Aside from the first Gulf War period, the time over which BCG test for retail price asymmetry contained relatively stable wholesale costs; prices rarely fluctuated more than a cent each day. Conversely, the recent bubble in the oil market and subsequent bursting has translated into a particularly volatile time for the price of gasoline. As such, the problems associated with temporal aggregation detailed in Geweke (1978) have become exaggerated. When prices are relatively stable, and the econometrician possesses data over a long frame of time, weekly averaged prices may not serve as a poor approximation of daily prices. Yet, when costs change by a large magnitude on a daily basis important dynamics are muted by temporally aggregating prices. And, it is precisely the loss of daily dynamics which augments the potential biases that arise in temporally aggregated models. Another source of the large bias associated with the weekly averaged models is the almost perfect correlation between lagged prices and wholesale costs: both explanatory variables. As previously noted, the potential for contaminated estimates in temporally aggregated models is increasing in the degree of correlation between right-hand side variables. Lagged changes in cost and retail price are almost perfectly correlated in the data, and should be in any study of the retail gasoline industry. Thus, it is not surprising that estimating models with daily data produces results unique from the temporally aggregated estimations. Another interesting point is how little is gained by moving from city to firm level data. The results are qualitatively identical for city and station level estimates at the weekly averaged and daily level, respectively. Consequently, spatially aggregated prices may serve just as well as firm specific prices when testing for rockets and feathers – provided the data contains daily price observations. Unfortunately, the econometrician may gain almost nothing by possessing firm specific over city-wide data if prices are weekly averages, as the ills of time averaged data may not be overcome by observing prices at the firm instead of city level.

The use of IV regression appears to accentuate the contamination seen in the first two regressions, and still produces unrealistic results when employed with daily data. However, if one period lagged costs are excluded from the estimated equation the IV model produces estimates similar to both OLS models. Yet, these are precisely the instrumented variables. Given the small probability of endogeneity and the poor performance of IV regression in previous studies of asymmetric pricing, there is no convincing argument in favor of using this technique when investigating rockets and feathers in the retail gasoline industry.[59] Also, note the nearly identical performance of the one and two-step methods, especially when analyzing daily data. Bachmeier and Griffin (2003) are particularly skeptical of estimating long and short-run price responses in a single equation, and do provide evidence that it can bias results. Additionally, Engle and Granger (1987) originally proposed a two-step estimation procedure when they derived the error-correction method of controlling for cointegration. Therefore, I advocate erring on the side of caution and employing a two-step OLS analysis of asymmetric pricing. Finally, I recommend cautiously interpreting any study of the retail gasoline industry that utilizes weekly price data, either at the city or station-level, as temporal aggregation may seriously contaminate results.

[59]Even BCG note that they gain almost nothing over traditional OLS by using the instrumental variable approach.

9 Tables

Table 1: Summary of Previous Literature

Paper	Model	Data	Asymmetry Result
Bacon (1991)	Quadratic Adjustment	City, bi-weekly average	Existence
Borenstein et al. (1997)	IV Error-Correction	City, semi-monthly average	Existence
Godby et al. (2000)	Threshold Regression	City average, weekly	Non-existence
Eckert (2002)	Error-Correction	City, weekly average	Existence
Galeotti et al. (2003)	Error-Correction	Country, monthly average	Non-existence
Lewis (2005)	Error-Correction	Station, weekly	Non-existence
Deltas (2008)	Error-Correction	State, monthly	Existence
Hosken et al. (2008)	Error-Correction	City, weekly average	Existence
Verlinda (2008)	Error-Correction	Station, weekly	Existence

Notes: These studies represent important works in the "Rockets and Feathers" literature, but are only a sample. For a more complete literature review and nice overview of the different econometric models see Geweke (2004).

Table 2: Summary Statistics

	Regular Price	Premium Price	Wholesale Cost
Mean	201.54	227.18	173.08
Std. Dev.	68.77	68.8	62.82
# Increases	156	153	166
Avg. Increase Size	.98	.99	3.62
# Decrease	208	211	198
Avg Decrease Size	-1.42	-1.41	-3.67

Notes: The sample includes price observations from 7/30/08 - 7/29/09 for over 11,000 gas stations, and the units are US ¢. The price observations were scraped daily from gasprices.mapquest.com, whose data is provided by the Oil Price Information Service (OPIS), for all gas stations in the states of NJ, VA, MD, WA and the cities of Philadelphia, PA and Washington, DC. Cost data is a daily weighted-average of the closing spot price of reformulated gasoline shipped from the Los Angeles, CA and NY, NY harbors; the weights used to average the cost data reflect the proportion of gas stations in the data set located in the west or east coast of the United States.

Table 3: Summary Statistics and Results of Regressing Retail Price on Characteristic and Day of Week Controls.

	Mean	Std. Dev.	Coef.	T-stat
Miles to closest competitor	0.65	1.29	.87	21.56
# firms $\leq$ .1 miles	0.34	0.63	0.05	0.48
# firms $>$ .1 miles and $\leq$ 1.5 miles	6.32	5.26	-0.01	0.22
# firms $>$ 1.5 miles and $\leq$ 5 miles	41.51	38.20	0.003	3.05
Independent brand indicator	0.34	0.47	-8.16	-86.89
% independent competitors $<$ 0.1 miles	0.31	0.44	-3.48	-18.25
% independent competitors $<$ 0.1 miles and $\leq$ 1.5 miles	0.35	0.27	-7.33	-41.76
% independent competitors $<$ 1.5 miles and $\leq$ 5 miles	0.34	0.20	-11.42	-48.64
Log of population	10.26	1.91	0.43	17.23
Log of median income	10.64	0.34	4.87	32.93

Notes: Regressions are performed at the daily-firm level. Each row represents a unique regression of price on the specified characteristic and day of the week controls. Before regressing retail price on station characteristics all taxes are removed. For the statistic *% independent competitors $\leq$ .1 miles*, only stations with at least one competitor within .1 miles are considered. This analogously holds for the subsequent two statistics. Population measures are either the 2007 projections by the United States Census Bureau, or the 2000 census measure when the projections are unavailable. Median income data is from the 2000 US census.

Table 4: Asymmetric Response Individual Station Daily Prices

Coef.	Estimate	Coef.	Estimate
ΔC^+_{t-1}	0.08***	ΔR^+_{t-2}	-0.35***
	(0.00)		(0.01)
ΔC^+_{t-2}	0.07***	ΔR^+_{t-3}	-0.07***
	(0.00)		(0.01)
ΔC^+_{t-3}	0.04***	ΔR^+_{t-4}	-0.01
	(0.00)		(0.01)
ΔC^+_{t-4}	0.02***	ΔR^+_{t-5}	0.01**
	(0.00)		(0.00)
ΔC^+_{t-5}	0.03***	ΔR^-_{t-2}	-0.17***
	(0.00)		(0.01)
ΔC^-_{t-1}	-0.00*	ΔR^-_{t-3}	-0.06***
	(0.00)		(0.00)
ΔC^-_{t-2}	-0.05***	ΔR^-_{t-4}	-0.00
	(0.00)		(0.00)
ΔC^-_{t-3}	-0.00	ΔR^-_{t-5}	0.03***
	(0.00)		(0.00)
ΔC^-_{t-4}	0.01***	ϑ^+_1	-0.07***
	(0.00)		(0.00)
ΔC^-_{t-5}	-0.01***	ϑ^-_1	-0.08***
	(0.00)		(0.00)
Observations		609,992	

Notes: The dependent variable is the current period change in the price of regular unleaded fuel. ΔC^+_{t-n} and ΔC^-_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^+_{t-n} and ΔR^-_{t-n} are estimates of lagged retail price changes, and ϑ^+_1 and ϑ^-_1 are parameter estimates of the error-correction term. The model was estimated for lag length $n = 10$, but all estimates are not reported due to lack of space. Also unreported are estimates of the parameters for market characteristic control variables: log of population, the number of competitors within .1 miles, between .1 and 1.5 miles, and between 1.5 and 5 miles, the distance of the closest competitor, the percentage of unbranded stations within .1, between .1 and 1.5 miles, and between 1.5 and 5 miles, and day of the week dummies. All unreported estimates are available upon request. The CRF's constructed from the estimates are graphed in Figure 3. Standard errors are listed in parenthesis below the estimate, clustered by station, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

Table 5: Market Level Asymmetric Response

	Premium	Regular	Premium - Regular
ΔC^{+}_{t-1}	0.03***	0.07***	0.00
	(0.00)	(0.00)	(0.01)
ΔC^{+}_{t-2}	0.02***	0.10***	0.03***
	(0.01)	(0.00)	(0.01)
ΔC^{+}_{t-3}	0.03***	0.05***	0.01
	(0.00)	(0.00)	(0.01)
ΔC^{-}_{t-1}	-0.04***	-0.01***	-0.08***
	(0.00)	(0.00)	(0.01)
ΔC^{-}_{t-2}	-0.11***	-0.04***	-0.05***
	(0.00)	(0.00)	(0.01)
ΔC^{-}_{t-3}	-0.08***	0.01***	-0.09***
	(0.00)	(0.00)	(0.01)
ΔR^{+}_{t-2}	-0.57***	-0.20***	-0.68***
	(0.01)	(0.01)	(0.00)
ΔR^{+}_{t-3}	-0.33***	0.01	-0.56***
	(0.01)	(0.00)	(0.00)
ΔR^{-}_{t-2}	-0.50***	-0.21***	-0.65***
	(0.00)	(0.01)	(0.01)
ΔR^{-}_{t-3}	-0.30***	-0.01	-0.54***
	(0.01)	(0.01)	(0.01)
ϑ^{+}_{1}	-0.13***	-0.05***	-0.20***
	(0.00)	(0.00)	(0.00)
ϑ^{-}_{1}	-0.13***	-0.06***	-0.18***
	(0.00)	(0.00)	(0.01)
Observations	536,584	536,584	503,913
Cost	Wholesale Spot	Wholesale Spot	Crude Oil Spot

Notes: The market average price variables used in the three separate regressions are stated in the first row. Premium - Regular is the average market markup of premium over regular gasoline. ΔC^{+}_{t-n} and ΔC^{-}_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^{+}_{t-n} and ΔR^{-}_{t-n} are estimates of lagged retail price changes, and ϑ^{+}_{1} and ϑ^{-}_{1} are parameter estimates of the error-correction term. The model was estimated for lag length $n = 10$, but all estimates are not reported due to lack of space. Also unreported are estimates of the parameters for market characteristic control variables: the number of competitors and the percentage of those who are unbranded in the market and between 1.5 and 5 miles of the market center, the log of population of the market, and day of the week controls. Unreported estimates are available upon request. CRF's constructed from columns one and two are plotted in Figure 6 and the CRF corresponding to column three is in Figure 7. Standard errors are listed in parenthesis below the estimate, clustered by market, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

Table 6: Asymmetric Response City-Week Averages

	Model		
	Two-Step	BCG OLS	BCG IV
ΔC^{+}_{t-1}	0.18***	0.16***	0.05***
	(0.01)	(0.01)	(0.01)
ΔC^{+}_{t-2}	0.21***	0.19***	0.17***
	(0.01)	(0.01)	(0.01)
ΔC^{+}_{t-3}	0.01	-0.01	-0.02*
	(0.01)	(0.01)	(0.01)
ΔC^{-}_{t-1}	0.16***	0.16***	0.22***
	(0.01)	(0.01)	(0.01)
ΔC^{-}_{t-2}	0.09***	0.09***	0.07***
	(0.01)	(0.01)	(0.01)
ΔC^{-}_{t-3}	0.01	0.01	-0.01
	(0.01)	(0.01)	(0.01)
ΔR^{+}_{t-2}	0.23***	0.22***	0.23***
	(0.02)	(0.02)	(0.02)
ΔR^{+}_{t-3}	0.04**	0.04**	0.04**
	(0.02)	(0.02)	(0.02)
ΔR^{-}_{t-2}	0.33***	0.34***	0.34***
	(0.03)	(0.03)	(0.02)
ΔR^{-}_{t-3}	0.14***	0.14***	0.17***
	(0.02)	(0.02)	(0.02)
R_{t-1}		-0.18***	-0.19***
		(0.01)	(0.01)
C_{t-1}		0.18***	0.20***
		(0.01)	(0.01)
ϑ_1^{+}	-0.20***		
	(0.01)		
ϑ_1^{-}	-0.14***		
	(0.01)		
Observations	9,394	9,394	9,394

Notes: The city-week average change in regular fuel price is the dependent variable. Column 1 reports estimates of equation (7) using the two-step method employed in section 4, Column 2 reports OLS estimation of equation (6), and column 3 is IV estimation of equation (6). All cities with a population less than 25,000 are dropped. ΔC^{+}_{t-n} and ΔC^{-}_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^{+}_{t-n} and ΔR^{-}_{t-n} are estimates of lagged retail price changes, R_{t-1} and C_{t-1} are lagged price and cost levels, and ϑ_1^{+} and ϑ_1^{-} are parameter estimates of the error-correction term. Each model was estimated for lag length $n = 5$, but all estimates are not reported due to lack of space. Corresponding CRF's are plotted in Figure 17. Standard errors are listed in parenthesis below the estimate, clustered by city, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

Table 7: Asymmetric Response Individual Station Weekly Averages

	Model		
	Two-Step	BCG OLS	BCG IV
ΔC^{+}_{t-1}	0.17***	0.15***	0.04***
	(0.00)	(0.00)	(0.00)
ΔC^{+}_{t-2}	0.21***	0.17***	0.13***
	(0.00)	(0.00)	(0.00)
ΔC^{+}_{t-3}	0.05***	0.03***	-0.00
	(0.00)	(0.00)	(0.00)
ΔC^{-}_{t-1}	0.18***	0.18***	0.29***
	(0.00)	(0.00)	(0.00)
ΔC^{-}_{t-2}	0.07***	0.08***	0.07***
	(0.00)	(0.00)	(0.00)
ΔC^{-}_{t-3}	0.03***	0.02***	-0.01***
	(0.00)	(0.00)	(0.00)
ΔR^{+}_{t-2}	0.09***	0.09***	0.11***
	(0.00)	(0.00)	(0.00)
ΔR^{+}_{t-3}	0.04***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)
ΔR^{-}_{t-2}	0.16***	0.17***	0.17***
	(0.00)	(0.00)	(0.00)
ΔR^{-}_{t-3}	0.15***	0.16***	0.18***
	(0.00)	(0.00)	(0.00)
R_{t-1}		-0.23***	-0.24***
		(0.00)	(0.00)
C_{t-1}		0.24***	0.25***
		(0.00)	(0.00)
ϑ^{+}_{1}	-0.27***		
	(0.00)		
ϑ^{-}_{1}	-0.17***		
	(0.00)		
Observations	373,205	373,205	373,205

Notes: Firm weekly-average changes in regular fuel price is the dependent variable. Column 1 reports estimates of equation (7) using the two-step method employed in section 4, Column 2 reports OLS estimation of equation (6), and column 3 is IV estimation of equation (6). ΔC^{+}_{t-n} and ΔC^{-}_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^{+}_{t-n} and ΔR^{-}_{t-n} are estimates of lagged retail price changes, R_{t-1} and C_{t-1} are lagged price and cost levels, and ϑ^{+}_{1} and ϑ^{-}_{1} are parameter estimates of the error-correction term. Each model was estimated for lag length $n = 5$, but all estimates are not reported due to lack of space. Corresponding CRF's are plotted in Figure 18. Standard errors are listed in parenthesis below the estimate, clustered by station, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

Table 8: Asymmetric Response Daily City Prices

	Model		
	Two-Step	BCG OLS	BCG IV
ΔC^+_{t-1}	0.05***	0.05***	-0.13***
	(0.01)	(0.01)	(0.01)
ΔC^+_{t-2}	0.07***	0.07***	0.09***
	(0.01)	(0.01)	(0.01)
ΔC^+_{t-3}	0.04***	0.04***	0.05***
	(0.00)	(0.00)	(0.00)
ΔC^-_{t-1}	0.00	-0.00	0.08***
	(0.00)	(0.00)	(0.01)
ΔC^-_{t-2}	-0.02***	-0.03***	-0.04***
	(0.00)	(0.00)	(0.01)
ΔC^-_{t-3}	0.01***	0.01*	-0.01**
	(0.00)	(0.00)	(0.01)
ΔR^+_{t-2}	-0.28***	-0.28***	-0.28***
	(0.04)	(0.04)	(0.04)
ΔR^+_{t-3}	-0.04**	-0.04**	-0.04**
	(0.02)	(0.02)	(0.02)
ΔR^-_{t-2}	-0.26***	-0.26***	-0.26***
	(0.02)	(0.02)	(0.02)
ΔR^-_{t-3}	-0.05***	-0.05***	-0.05***
	(0.02)	(0.02)	(0.02)
R_{t-1}		-0.05***	-0.05***
		(0.00)	(0.00)
C_{t-1}		0.05***	0.05***
		(0.00)	(0.00)
ϑ^+_1	-0.04***		
	(0.00)		
ϑ^-_1	-0.06***		
	(0.00)		
Observations	65,982	65,982	65,982

Notes: The city averaged daily changes in regular fuel price is the dependent variable. Column 1 reports estimates of equation (7) using the two-step method employed in section 4, Column 2 reports OLS estimation of equation (6), and column 3 is IV estimation of equation (6). All cities with a population less than 25,000 are dropped. ΔC^+_{t-n} and ΔC^-_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^+_{t-n} and ΔR^-_{t-n} are estimates of lagged retail price changes, R_{t-1} and C_{t-1} are lagged price and cost levels, and ϑ^+_1 and ϑ^-_1 are parameter estimates of the error-correction term. Each model was estimated for lag length $n = 10$, but all estimates are not reported due to lack of space. Corresponding CRF's are plotted in Figure 19. Standard errors are listed in parenthesis below the estimate, clustered by city, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

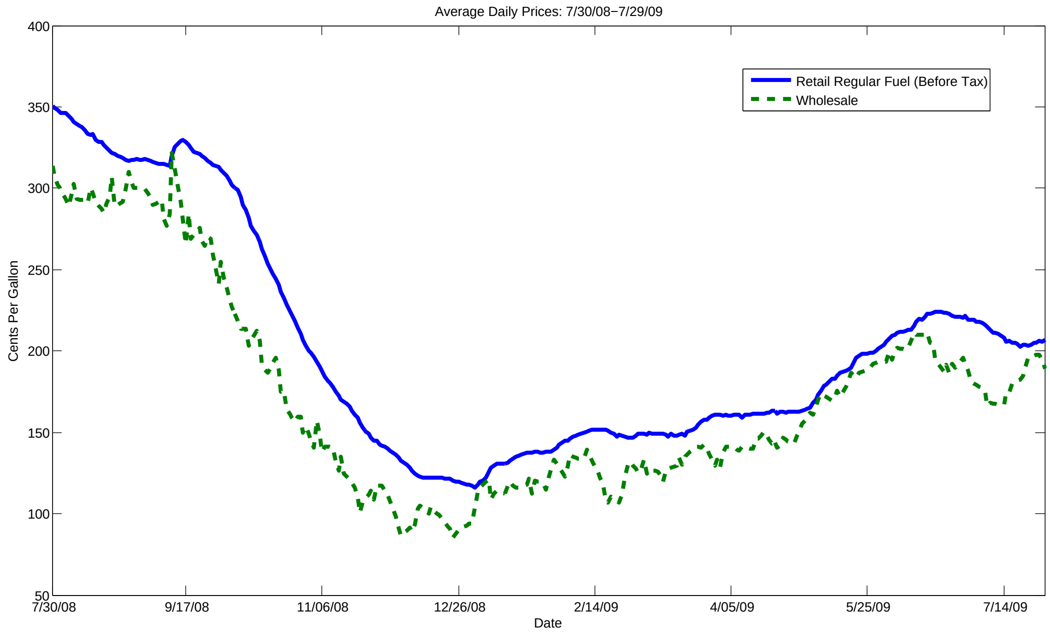
Table 9: Asymmetric Response Individual Station Daily Prices

	Model		
	Two-Step	BCG OLS	BCG IV
ΔC^{+}_{t-1}	0.08***	0.08***	-0.16***
	(0.00)	(0.00)	(0.01)
ΔC^{+}_{t-2}	0.07***	0.07***	0.10***
	(0.00)	(0.00)	(0.00)
ΔC^{+}_{t-3}	0.04***	0.04***	0.05***
	(0.00)	(0.00)	(0.00)
ΔC^{-}_{t-1}	-0.00*	-0.01***	0.10***
	(0.00)	(0.00)	(0.01)
ΔC^{-}_{t-2}	-0.05***	-0.05***	-0.07***
	(0.00)	(0.00)	(0.00)
ΔC^{-}_{t-3}	-0.00	-0.01***	-0.05***
	(0.00)	(0.00)	(0.00)
ΔR^{+}_{t-2}	-0.35***	-0.34***	-0.35***
	(0.01)	(0.01)	(0.01)
ΔR^{+}_{t-3}	-0.07***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)
ΔR^{-}_{t-2}	-0.17***	-0.17***	-0.17***
	(0.01)	(0.01)	(0.01)
ΔR^{-}_{t-3}	-0.06***	-0.06***	-0.05***
	(0.00)	(0.00)	(0.00)
R_{t-1}		-0.08***	-0.08***
		(0.00)	(0.00)
C_{t-1}		0.08***	0.08***
		(0.00)	(0.00)
ϑ^{+}_{1}	-0.07***		
	(0.00)		
ϑ^{-}_{1}	-0.08***		
	(0.00)		
Observations	609,992	609,992	609,992

Notes: Firm daily changes in regular fuel price is the dependent variable. Column 1 reports estimates of equation (7) using the two-step method employed in section 4, Column 2 reports OLS estimation of equation (6), and column 3 is IV estimation of equation (6). ΔC^{+}_{t-n} and ΔC^{-}_{t-n} are estimates of the parameters on positive and negative cost changes, respectively, of lag length n, ΔR^{+}_{t-n} and ΔR^{-}_{t-n} are estimates of lagged retail price changes, R_{t-1} and C_{t-1} are lagged price and cost levels, and ϑ^{+}_{1} and ϑ^{-}_{1} are parameter estimates of the error-correction term. Each model was estimated for lag length $n = 10$, but all estimates are not reported due to lack of space. Corresponding CRF's are plotted in Figure 20. Standard errors are listed in parenthesis below the estimate, clustered by station, and robust to heteroscedasticity. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

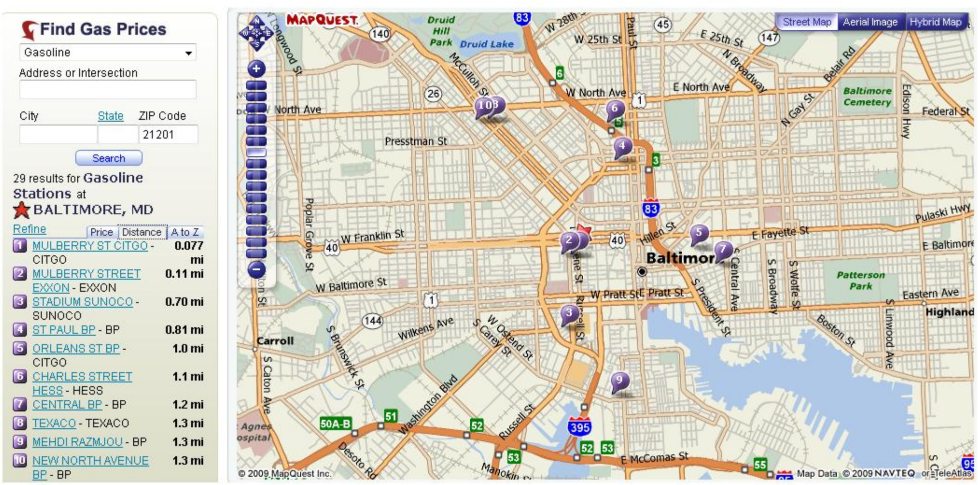
10 Figures

Figure 1



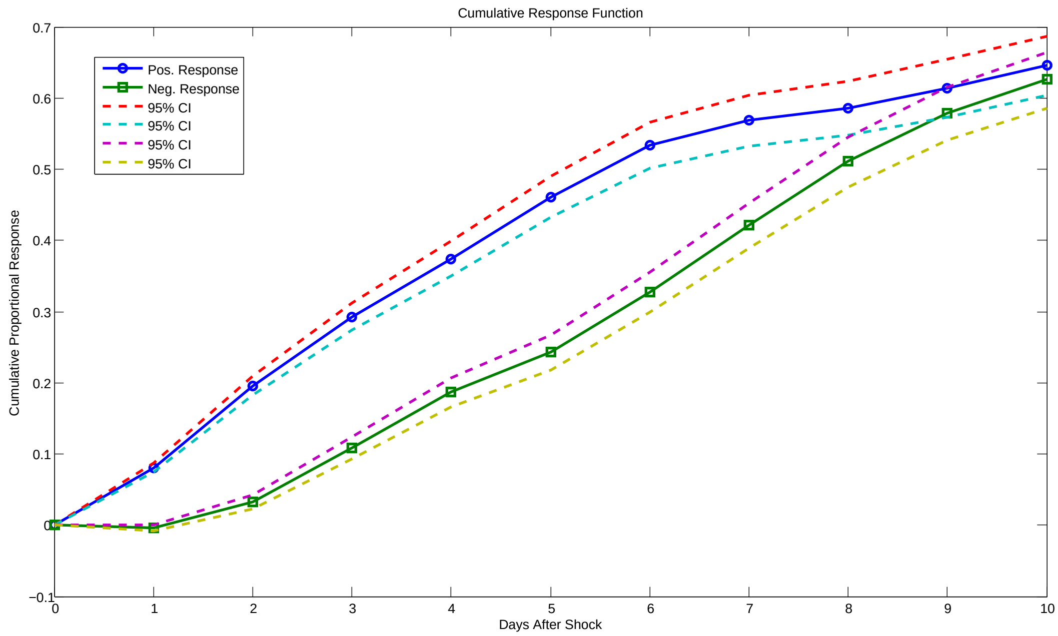
Notes: Retail price is the daily average price for regular unleaded fuel for all firms in the data set. Wholesale is a daily weighted-average of the closing spot price of reformulated gasoline shipped from the Los Angeles, CA and NY, NY Harbors; the weights used to average the cost data reflect the proportion of gas stations in the data set located in the west or east coast of the United States.

Figure 2: Screen Shot: Baltimore, MD



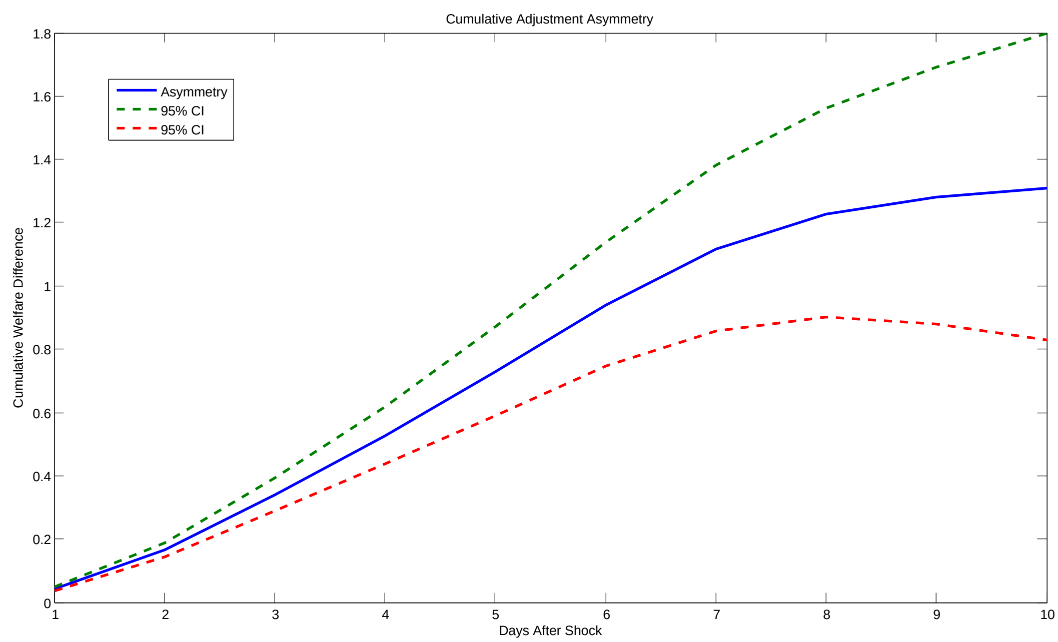
Notes: This figure is a screen shot of gasprices.mapquest.com. The picture shows a map of Baltimore, MD and the location of the ten gas stations closest to the city's center.

Figure 3



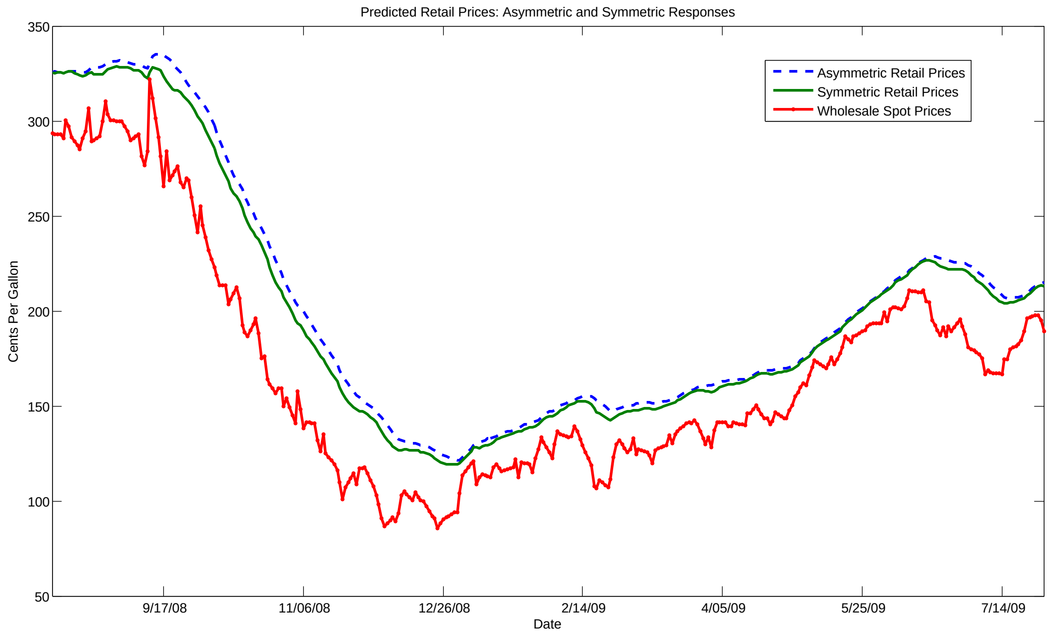
Notes: CRF's are constructed from the parameters estimated in Table 4. The positive (negative) cumulative response function measures, on each day, the proportion of a one unit positive (negative) cost shock at $t = 0$ that has been incorporated into a firm's retail price.

Figure 4



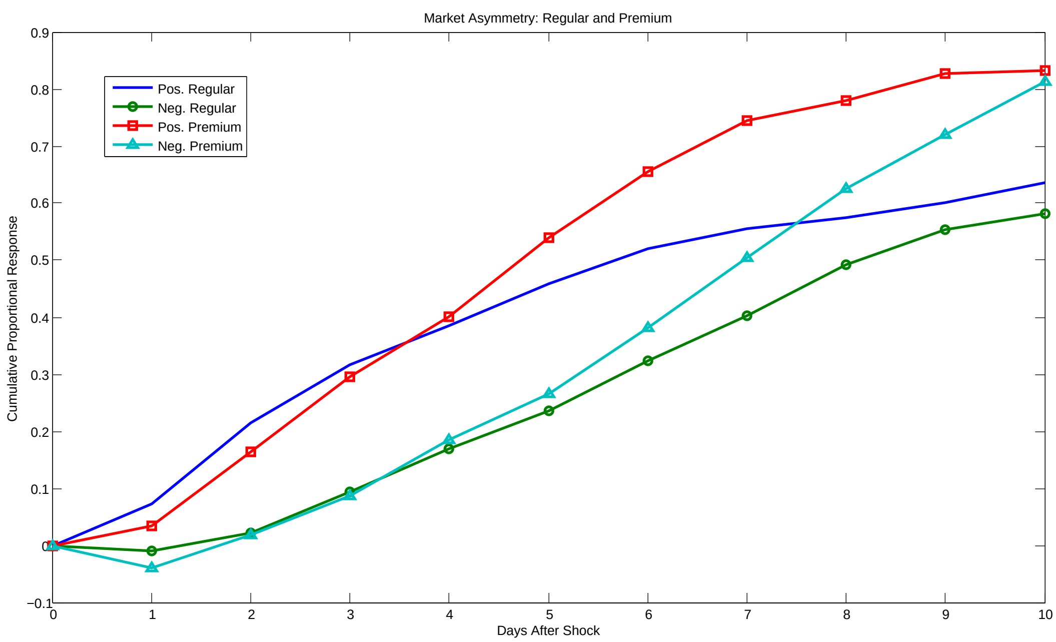
Notes: Parameters from Table 4 are used to estimate equation (9), which measure, on each day, the cumulative speed of adjustment to a positive shock minus the adjustment to a negative shock. The estimated function being greater than zero evidences asymmetric pricing.

Figure 5



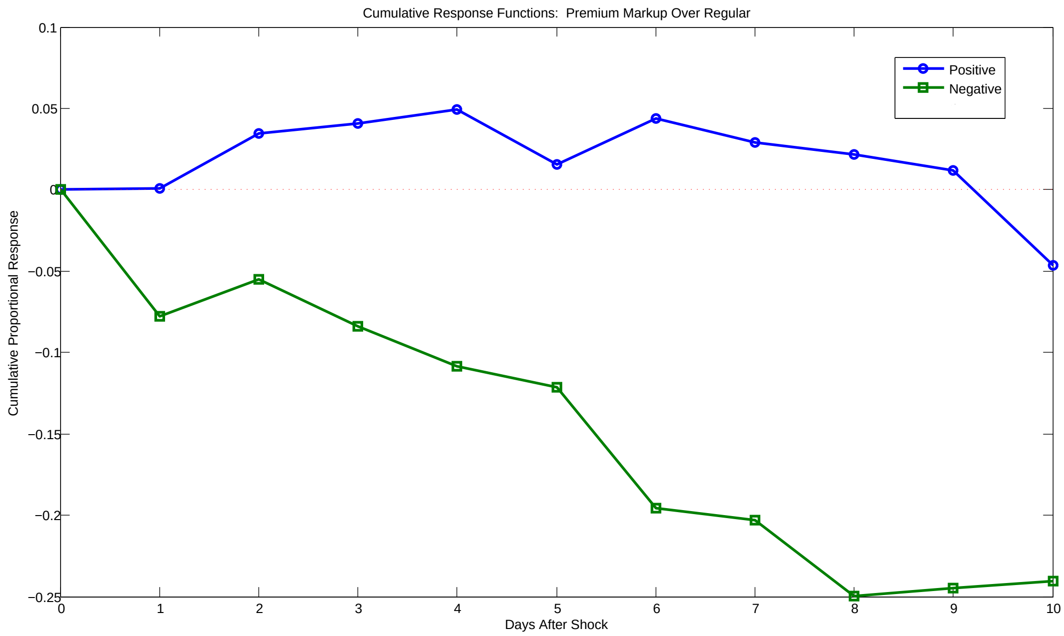
Notes: Retail price predictions are regular octane fuel pre-tax estimates. Asymmetric prices are predicted using parameter estimates of equation (7) for lag length n=10. Symmetric prices are predicted using parameter estimates of equation (7), but the lagged negative changes in cost parameters, C^{-}_{t-n}, are replaced with the estimates for positive cost changes, C^{+}_{t-n}, and the estimate of ϑ^{+}_{1}, the effect of retail prices being above its long-run relationship with cost, is replaced with ϑ^{-}_{1}, the effect of retail prices being below its long-run relationship with cost.

Figure 6



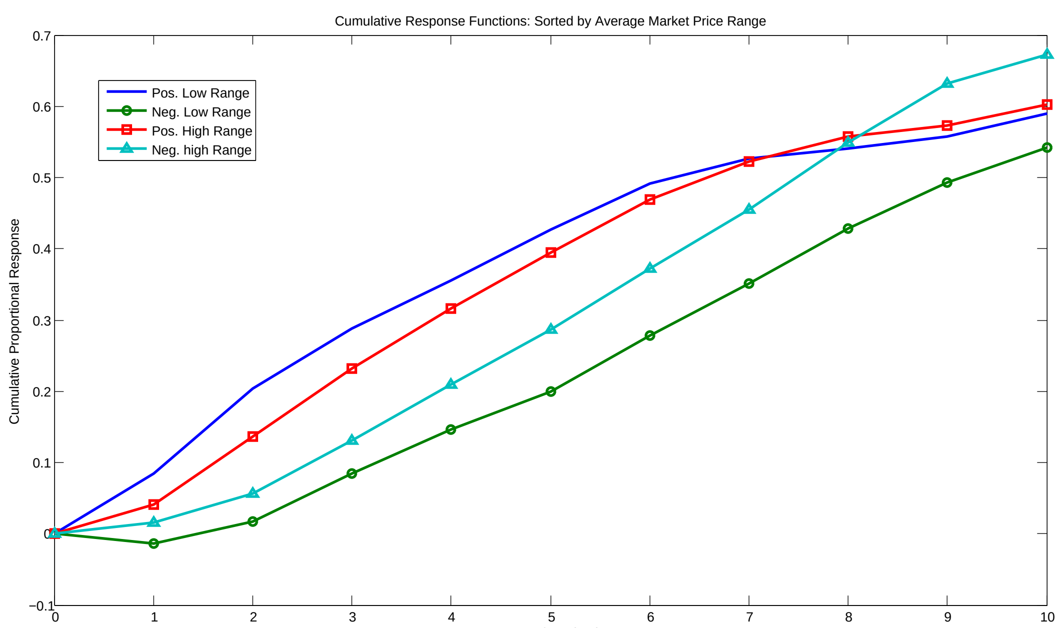
Notes: Parameters from column 1 and column 2 of Table 5 are used to estimated the CRF's for market average premium and regular gasoline prices, respectively. Both price series exhibit price asymmetry with more than 95% confidence.

Figure 7



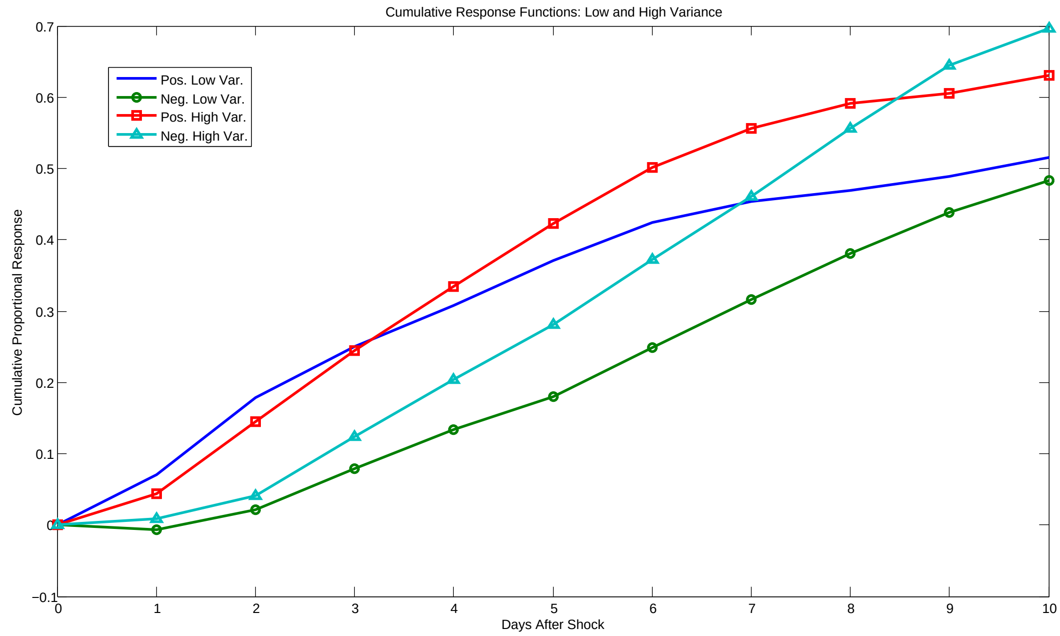
Notes: Parameters from column 3 of Table 5 are used to estimate the CRF's, which track the response of the markup of premium over regular gasoline to positive and negative cost shocks. The markup has a negative proportional response to a negative shock (meaning the gap increases), and has a response close to zero to a positive shock.

Figure 8



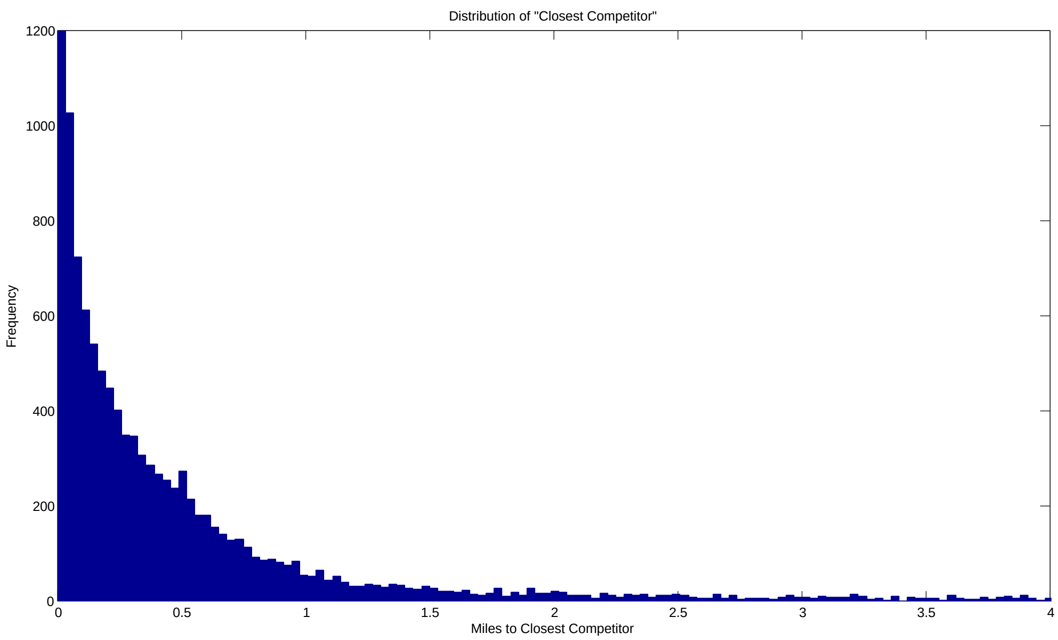
Notes: CRF's are estimated for markets with an average price range in the lower or upper quintile of average price range distribution. Markets with a low average price range exhibit more price asymmetry (1.1¢ cumulative difference ten days after a one cent cost shock) with 95% confidence level.

Figure 9



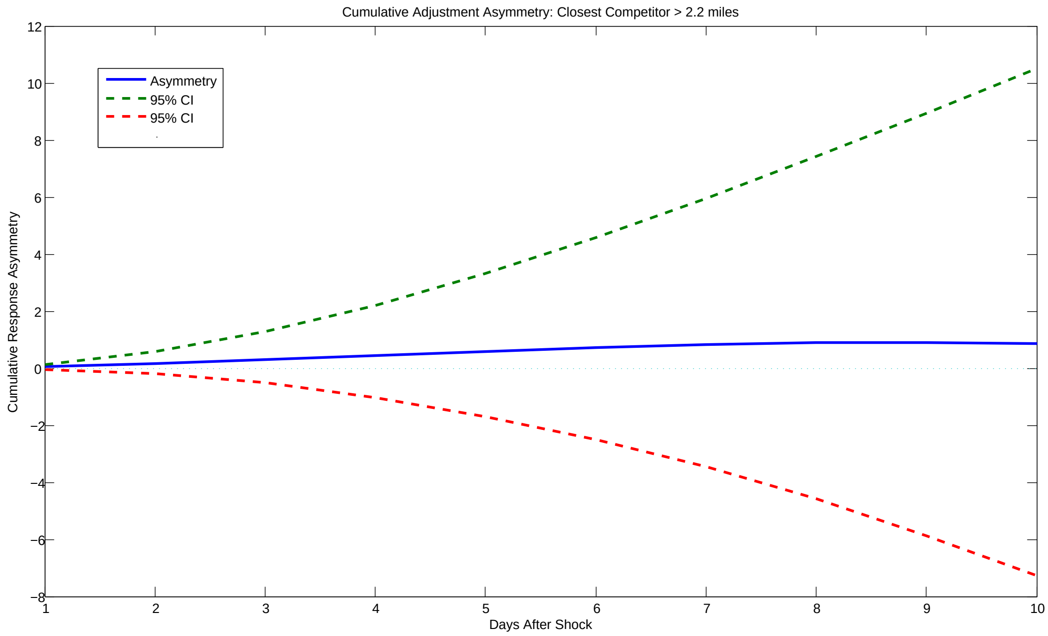
Notes: CRF's are estimated for markets with an average price variance in the lower or upper quintile of the average price variance distribution. Markets with a high average price variance have less price asymmetry at the 95% confidence level.

Figure 10



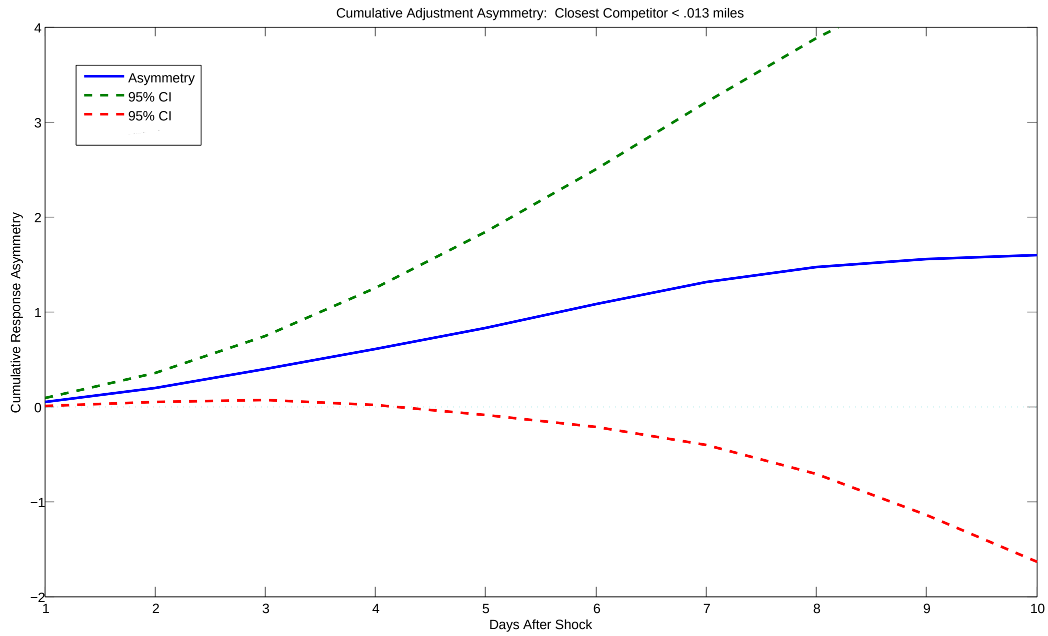
Notes: This figure plots the distribution of the "closest competitor" variable, which for each firm gives the distance, in miles, of the nearest rival.

Figure 11



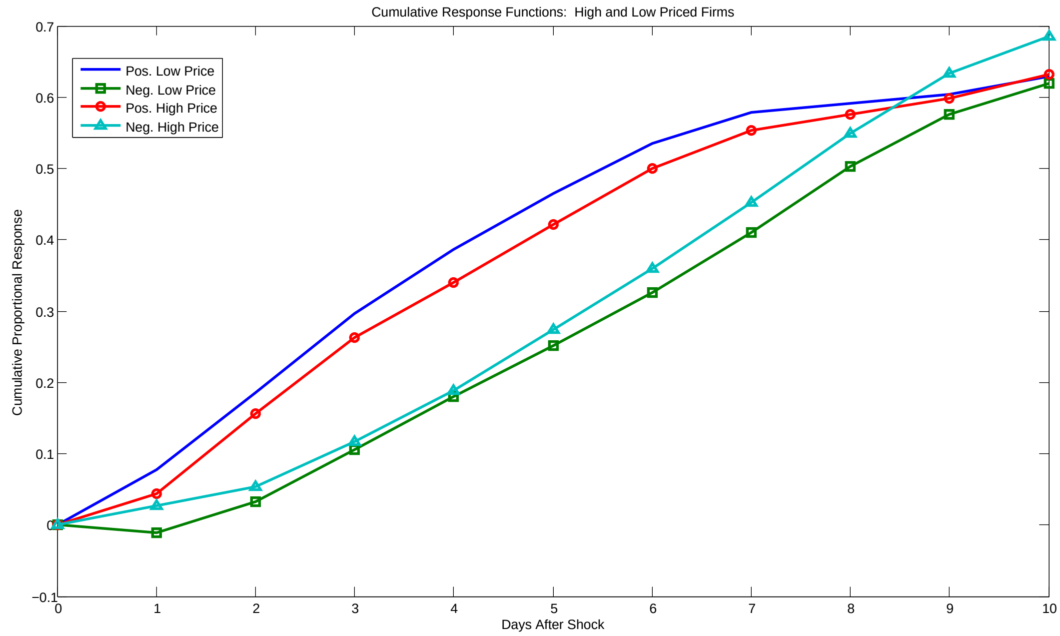
Notes: This plots the estimate of equation (9), which measures, on each day, the cumulative speed of adjustment to a positive shock minus the adjustment to a negative shock, for firms whose closest competitor is at least 2.2 miles away. These firms, which have a substantial degree of monopoly power, show no price asymmetry.

Figure 12



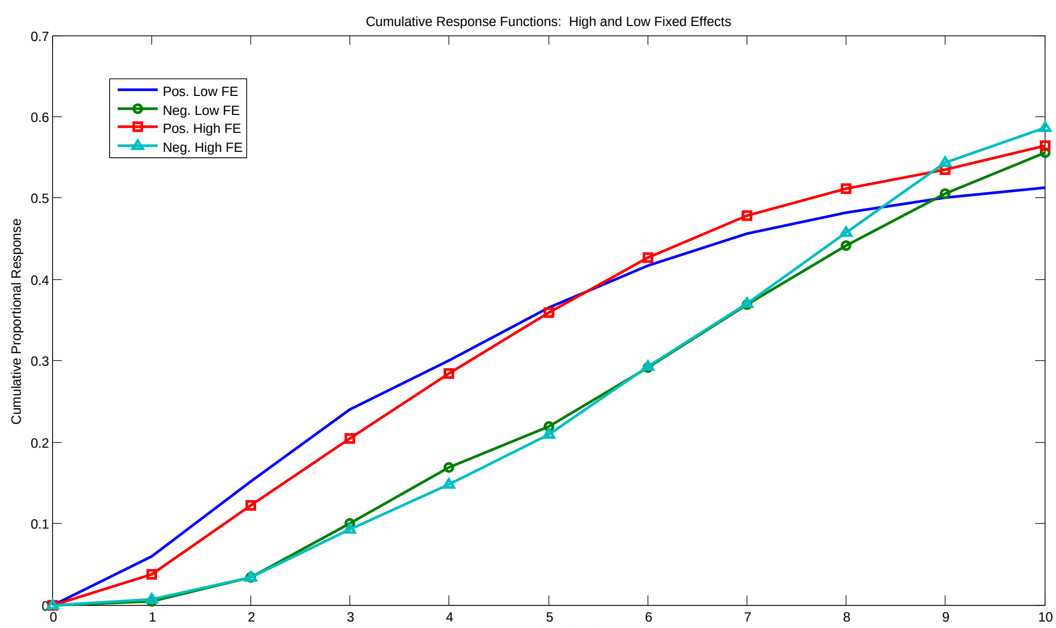
Notes: This plots the estimate of equation (9) for firms whose closest competitor is no more than .013 miles away. With 95% confidence these firms price asymmetrically for up to 4 days following a cost shock.

Figure 13



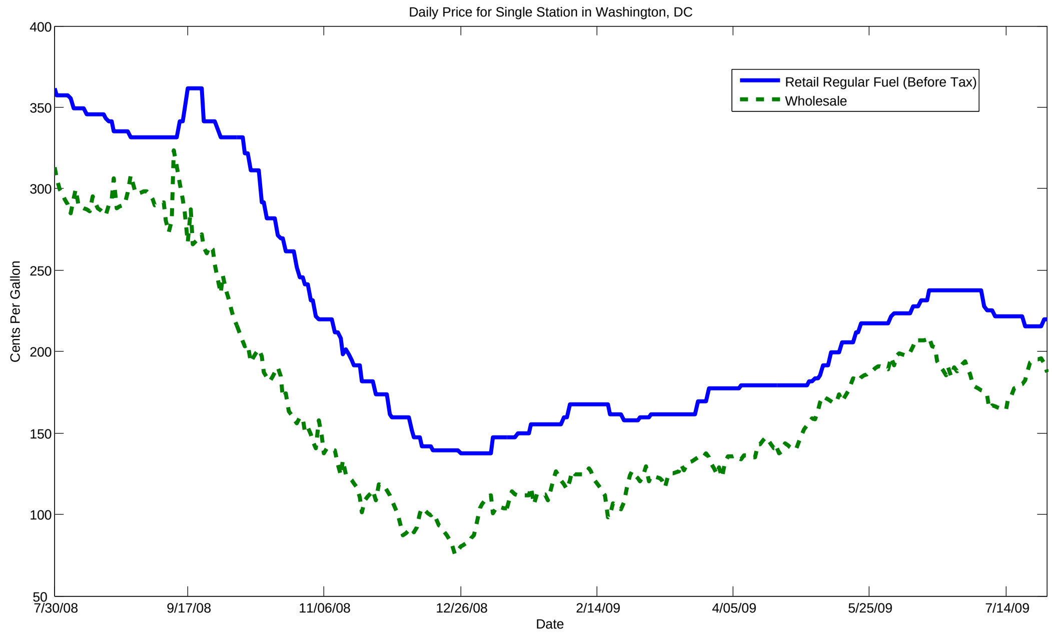
Notes: CRF's are graphed for pairs of firms within .1 miles that generally price above or below their market's average price ("high" and "low", respectively, are defined on page 23.). Throughout the course of adjustment there is no statistically significant distinction in the degree of asymmetry of the two groups.

Figure 14



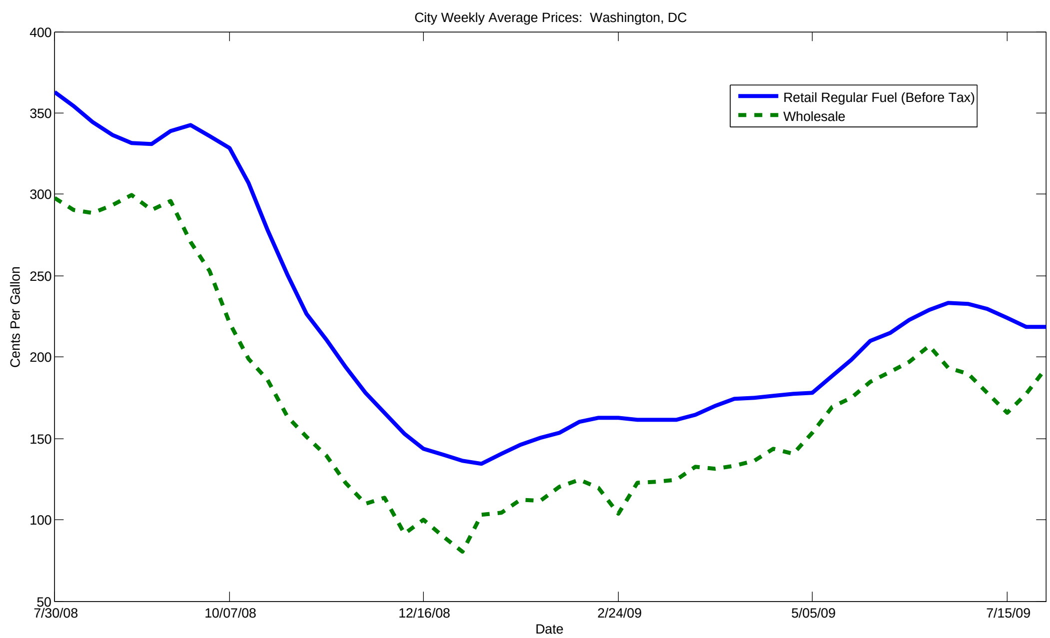
Notes: CRF's are estimated for markets whose average price is in the top or lower quintile of the average market price distribution ("High FE" and "Low FE", respectively). Throughout the course of adjustment there is no statistically significant distinction in the degree of asymmetry of the two groups.

Figure 15



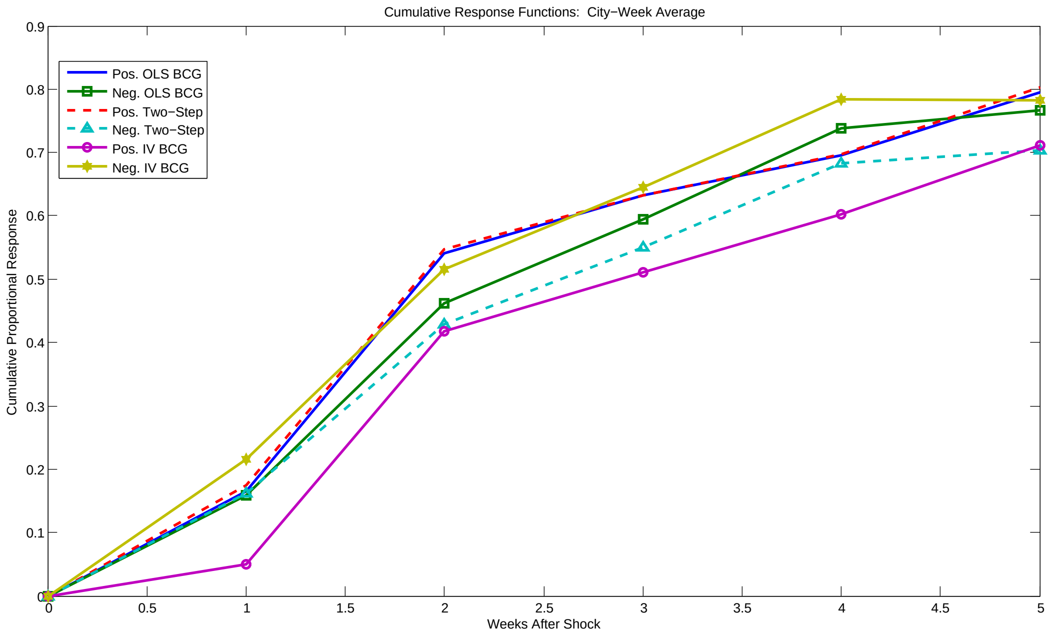
Notes: The retail regular unleaded price and wholesale cost for a single gas station in Washington, DC is depicted in this figure. The NYMEX spot price for reformulated regular gasoline delivered from the NY Harbor is used as the wholesale cost measure.

Figure 16



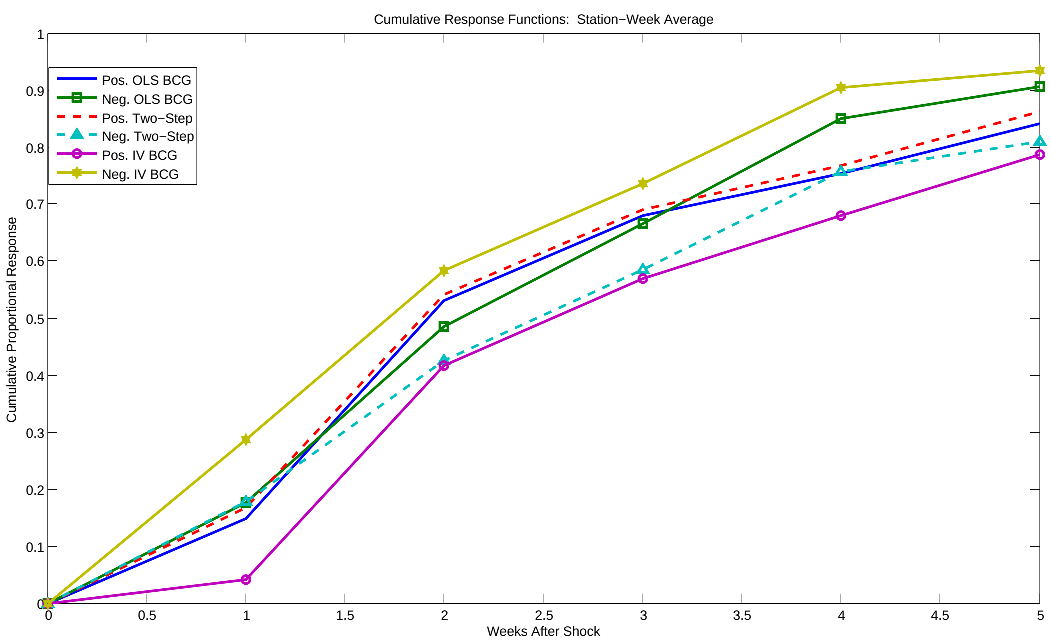
Notes: The daily average retail regular unleaded gasoline price for the city of Washington, DC is graphed along with the wholesale cost. The NYMEX spot price for reformulated regular gasoline delivered from the NY Harbor is used as the wholesale cost measure.

Figure 17



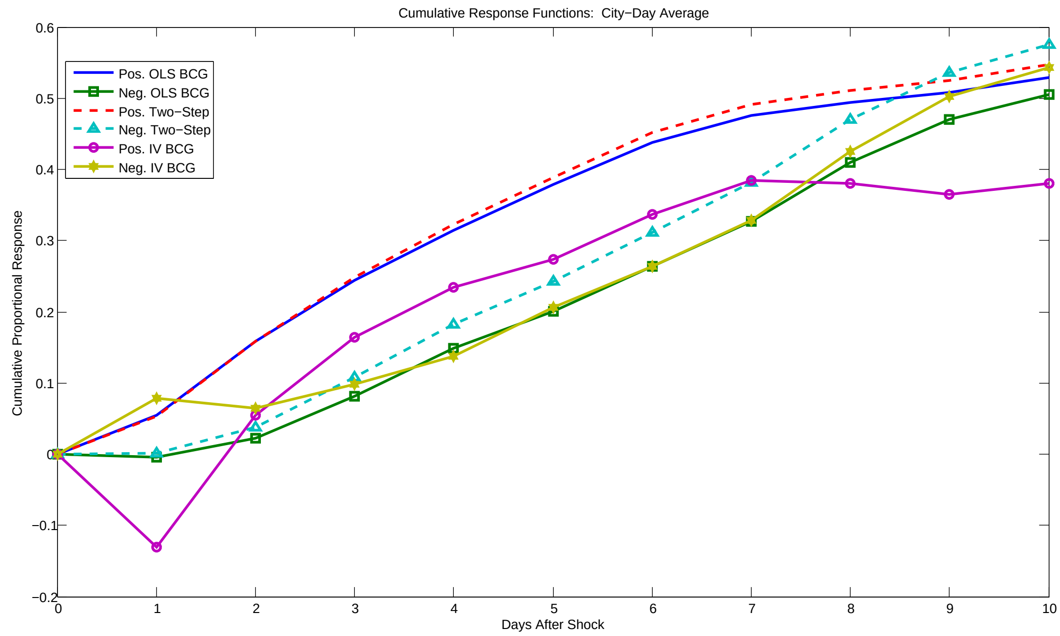
Notes: CRF's are constructed from parameter estimates listed in Table 6 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating equation (2) using OLS then plugging parameters into equation (7), which is again estimated with OLS; "OLS BCG" is OLS estimation of equation (6); IV BCG is instrumental variable regression of equation (7). Data is weekly averaged for all cities with a population greater than 25,000.

Figure 18



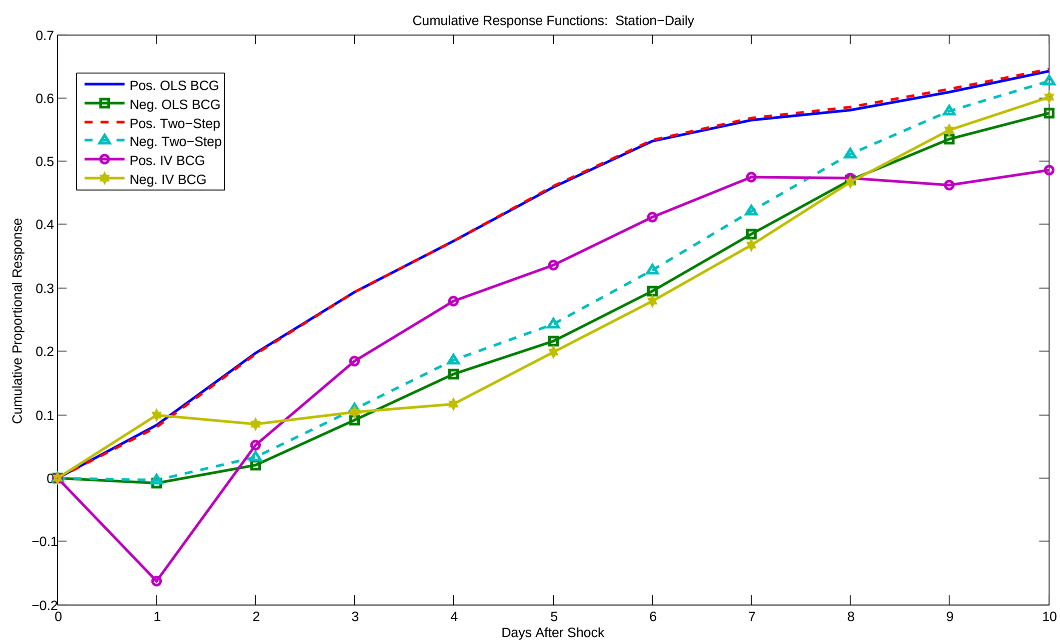
Notes: CRF's are constructed from parameter estimates listed in Table 6 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating equation (2) using OLS then plugging parameters into equation (7) which is again estimated with OLS; "OLS BCG" is OLS estimation of equation (6); IV BCG is instrumental variable regression of equation (7). Data is weekly averages for individual stations.

Figure 19



Notes: CRF's are constructed from parameter estimates listed in Table 6 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating equation (2) using OLS then plugging parameters into equation (7) which is again estimated with OLS; "OLS BCG" is OLS estimation of equation (6); IV BCG is instrumental variable regression of equation (7). Data is daily averages for all cities with a population greater than 25,000.

Figure 20



Notes: CRF's are constructed from parameter estimates listed in Table 6 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating equation (2) using OLS then plugging parameters into equation (7) which is again estimated with OLS; "OLS BCG" is OLS estimation of equation (6); IV BCG is instrumental variable regression of equation (7). Data is daily observations for individual stations.