Empirical Regularities of Asymmetric Pricing in the Gasoline Industry

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Abstract

This paper analyzes the various econometric models that have been used to identify asymmetric pricing in the retail gasoline industry, and also documents empirical regularities in the market. I find that a standard error-correction model coupled with daily price data is best suited to analyze asymmetric price adjustments. Moreover, temporally aggregated data can severely bias parameter estimates. Asymmetric pricing is also found to be a market-wide phenomenon, and not the strategy of a firm acting independently of the market. In kind, a host of market characteristics that influence the speed of price adjustments are identified.

1 Introduction

A substantial body of economic literature empirically investigates the presence of asymmetric price movements in the retail gasoline industry. Yet, there is no general agreement as to whether asymmetric pricing is widespread throughout the retail gasoline industry or merely an anomaly of select markets. This paper helps to reconcile the disagreement. In doing so, I also document general properties of rockets and feathers across a diverse set of markets.

One reason for conflicting findings in the rockets and feathers literature is that almost no two studies utilize the same set of data. And, it is likely the case that the magnitude of price asymmetry varies across time and geographic region. Unique data, however, cannot entirely explain the variability in results across asymmetric pricing studies. Bachmeier and Griffin (2003) employ the same price data as BCG and find that identifying the existence of asymmetric pricing is sensitive to the specification of the econometric model. Similar to Bachmeier and Griffin's exploration of

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the speed of transmission of oil price changes to gasoline spot prices, I show that identification of retail gasoline price asymmetry is dependent upon both the choice of econometric model and high time frequency price data. Yet, the findings in this paper differ from Bachmeier and Griffin in that instrumental variable regression, and not simultaneous estimation of long and short-run retail price responses, appears to more severely contaminate estimates of rockets and feathers.

After pinpointing a major source of variation in the empirical documentation of asymmetric pricing and offering a pragmatic solution, I then explore the extent to which the magnitude of asymmetry varies across markets and between firms. The purpose of this examination is to try to distinguish whether rockets and feathers is a market-wide phenomenon or the strategy of an individual firm. In general, rockets and feathers is thought to be a market and not a firm characteristic, and previous research, such as Lewis (2010), Yang and Ye (2009), Tappata (2009), and Remer (2010), showing that consumer search costs play a pivotal role in asymmetric pricing supports this idea. Still, it is informative to glean whether certain firms tend to price more asymmetrically than others. Consequently, I measure the speed of price adjustment of fourteen major gasoline retailers, and find a high degree of dispersion in the magnitude of asymmetry across different brands. However, it does not appear that major brands, such as Exxon or Shell, employ a given degree of asymmetry as a general pricing strategy. Further analysis shows that uniquely branded firms within a market adjust prices more similarly than a single brand across several markets, which reinforces the concept of rockets and feathers as a market-level characteristic.

After establishing evidence of asymmetric pricing as a market trait, I then document which market and population characteristics correlate with the speed of cost to retail price pass-through. The driving and commuting behavior of consumers turns out to play a pivotal role in the magnitude of asymmetry, which again evidences consumer search costs as an important determinant of rockets and feathers. Furthermore, the large number of geographically diverse markets used in the testing helps bring to light the general relationship between market structure and asymmetric pricing in the retail gasoline industry.

The remainder of the paper is organized as follows; section 2 reviews the empirical rockets and feathers literature, section 3 investigates the role data aggregation and modeling technique play in the variation in previous empirical findings, section 4 explores whether rockets and feathers is a market or firm level pricing phenomenon, section 5 documents which market and population characteristics impact the magnitude of price asymmetry, and finally section 6 concludes.

2 Previous Findings of Rockets and Feathers

In the past two decades, a growing number of empirical studies have tested for the presence of asymmetric pricing in the retail gasoline industry. One explanation for continued interest in the topic is that almost no two studies estimate the same magnitude of asymmetry. Moreover, there does not even seem to be a general agreement as to whether the phenomenon even exists; while a majority of the evidence suggests retail gasoline prices react faster to positive than negative cost changes, a significant number of studies fail to reject symmetric price adjustment.

Using biweekly data arising from UK retail gasoline markets Bacon (1991) employs a partial adjustment model to confirm that positive cost changes are fully transmitted to retail prices two weeks faster than negative changes. Borenstein et al. (1997) tracks the speed of transmission of oil and terminal prices[1] to retail prices and finds strong evidence in favor of rockets and feathers. The study utilizes bi-weekly city-average prices as well as a non-standard error-correction model. Therefore, as illustrated in Bachmeier and Griffin (2003) and in detail below, there is reason to view BCG's results with some skepticism.

There are, however, a number of studies that confirm the existence of asymmetric pricing using a standard error-correction model. Eckert (2002), using weekly averaged retail prices from Windsor, Ontario, finds that one week following a cost change retail prices rise almost five times faster following a positive change than they fall after a negative one. Similarly, Verlinda (2008) estimates an error-correction model with once-per-week firm-level price data from South Orange County, CA and finds that three weeks after a cost shock prices rise by 110% of a positive shock, but only fall by 83% of a negative shock. Chesnes (2010) uses a standard error-correction model in conjunction with eight years of daily city-average prices for more than twenty major United States cities, and detects asymmetric pricing in each of the metropolitan areas. To date, Chesnes (2010) is the most comprehensive documentation of the rockets and feathers phenomenon in the retail gasoline industry, and provides solid evidence in favor of asymmetric price adjustments.

Yet, as mentioned above, many studies reject asymmetric pricing as an accurate description of retail gasoline price dynamics. Galeotti et al. (2003) use monthly average prices for European countries to estimate an error-correction model and find that prices respond symmetrically to cost changes. Godby et al. (2000) estimate a threshold regression model with six years of weekly averaged prices for thirteen Canadian cities and find no price asymmetry. Bachmeier and Griffin (2003) use the same data as BCG, but specified at daily instead of bi-weekly intervals, and a standard-error correction model and find no evidence of asymmetric pass-through of oil to spot prices.

While the previously mentioned studies are a small sample of the literature, it should be clear that there persists a general discord amongst the various findings. In addition, the source of the disharmony remains an open question. Bachmeier and Griffin (2003) show that unique data across studies is not solely responsible for the varying results in the literature. They argue that models that estimate long and short-run price adjustments in a single step are misspecified, and generate

[1]The terminal, or rack, price is what gasoline retailers pay at local distribution centers to have the final product delivered to their station.

results different from a correctly specified two-step model. As I show below, however, the single-step estimation may not be a problem, and there are other more serious threats to unbiased estimation of asymmetric pricing models. In the following section, I detail the impact of instrumental variables, temporally aggregated data, city-averaged prices, and non-standard error-correction models on the estimation of rockets and feathers.

3 Data and Modeling Issues in Asymmetric Pricing Models

3.1 Data Description

The data in this paper consists of daily price observations from July 30th, 2008 through July 29th, 2009. In total, over 11,000 individual stations from the states of Maryland, New Jersey, Virginia, and Washington as well as the Philadelphia, PA and Washington, DC metro areas are represented in the data. The data was scraped from the website gasprices.mapquest.com, whose prices are provided by the Oil Price Information Service (OPIS). OPIS obtains their information from credit card transactions, direct feeds, or station self reporting, and therefore the prices are measured with high precision. Mapquest was scraped at daily intervals, however, 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. 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.

As a measure of cost I employ the the daily gasoline spot prices listed on the New York Mercantile Exchange (NYMEX). More specifically, reformulated gasoline delivered from the New York and Los Angeles Harbors are used for firms located in the eastern and western states, respectively. These prices, however, are not the actual wholesale price that individual station owners paid to have gasoline delivered to their station, which is known as the Dealer Tank Wagon (DTW) price. This price is privately negotiated between station owners and their distributer, and thus, is not publicly available. Yet, Chandra and Tappata (2008) find that monthly averaged DTW and NYMEX spot prices have a correlation greater than .99, and as I am concerned with cost changes, not levels, not having DTW prices does not pose a serious problem.

3.2 Biases When Testing For Asymmetric Pricing

With the expansive data set I am well equipped to explore the extent to which aggregated data and misspecified models bias estimates of asymmetric pricing. Geweke (1978) details the various channels through which temporal aggregation may contaminate parameter estimates. Of particular interest to asymmetric pricing models 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 rockets and feathers 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 different 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 (as in Chesnes (2010)), and finally completely disaggregated to station-specific daily prices.[2]

In their critique of BCG, Bachmeier and Griffin note that not only does temporally aggregated data bias estimates of asymmetric price adjustments, but misspecified models can also contaminate estimates. The study evaluates two potential causes for concern. First, they note that in estimating a standard error-correction model:

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

the long-run relationship between retail prices and cost, captured by the parameters ϕ_1 and ϕ_0, should be estimated by OLS first and then substituted into equation (1) as if they were known with certainty.[3] This two-step procedure was first detailed in Engle and Granger (1987); subsequently, its properties have been widely analyzed, and it has become the standard modeling technique used to correct for cointegration. When BCG tested for the presence of rockets and feathers they estimated the following equation:

$$\begin{aligned}\Delta R_t = &\sum_{j=0}^{n}(\beta_j^+ \Delta C_{t-j}^+ + \beta_j^- \Delta C_{t-j}^-) \;+\; \sum_{j=1}^{n}(\gamma_j^+ \Delta R_{t-j}^+ + \gamma_j^- \Delta R_{t-j}^-) \\ &+ \;\vartheta_1 (R_{t-1} - \phi_1 C_{t-1} - \phi_0) + \epsilon_t. \end{aligned} \tag{2}$$

However, they estimate the error-correction term simultaneously with all of the other parameters, and use instrumental variable regression instead of OLS.[4] Thus, it is unknown which properties of

[2]The cost variable is the spot price of regular unleaded fuel delivered at the New York and Los Angeles Harbors for stations located in the east and west, respectively.

[3]The parameters ϕ_1 and ϕ_0 are able to be treated as known with certainty because the retail and cost price series are cointegrated, and therefore, OLS estimation of the relationship is superconsistent.

[4]Also, note that equation (2) does not allow the error-correction term to asymmetrically adjust to retail prices

the standard error-correction model are applicable to the non-standard version used in BCG.

Bachmeier and Griffin show that when analyzing the the pass-through rate of oil to spot prices both temporally aggregated data and simultaneous estimation of the error-correction term with the rest of the model can severely contaminate results, and possibly generate a false-positive of asymmetric pricing. In what follows, I explore the consequences of these two problems, as well as the impact of city-averaged prices and using instrumental variables to estimate equation (2), in testing for asymmetric pass-through of spot to final retail prices.

To do so, each data specification is tested using three different models: the standard-error correction model (equation (1) estimated in two steps), an error-correction model (equation (2)) where the long and short-run components are estimated simultaneously, and equation (2) 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. The estimates oppose Bachmeier and Griffin (2003), however, 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 and Griffin, but as a result of their reliance upon instrumental variable regression.

To begin, the data is aggregated to city-week averages.[5] Figure 1 graphs daily retail and wholesale prices for a single gas station in Washington, DC, and Figure 2 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 gas station daily prices into weekly averages becomes apparent. Figure 1 clearly illustrates the daily comovements of price and cost, which become severely muted when averaged over time and geographic region. Estimates of asymmetric pricing may, therefore, suffer from the problems detailed in Geweke (1978, 2004).

Before estimating each of the models, to increase the accuracy of results, I add city fixed effects to the error-correction term in equation (1). Adding this term allows different cities to have unique long-run relationships between retail price and cost. Also, the log of population and the number and percentage of non-major branded stations in each city is added to equations (2) and (1). BCG proposes estimating equation (2) 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

being above or below its long-run relationship with cost.

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

cost of gasoline. In step, 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 1; column 1 utilizes two-step estimation of equation (1), and columns 2 and 3 employ OLS and 2SLS, respectively, of equation (2).[6] The respective CRF's are depicted in Figure 3, and it appears that none of the estimation techniques are robust to the data 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.

In general, however, the two-step and BCG OLS models do not perform as poorly as the IV model. The BCG OLS model finds symmetric price adjustments, but it does not predict nearly the degree of upwards price stickiness as the IV model nor does it find prices reacting with greater speed to negative cost changes. The two-step error-correction model does uncover evidence of asymmetric pricing two weeks after an initial cost change, but the asymmetry is not apparent until 1.5 weeks following the cost shock. That is, for the first 1.5 weeks retail prices are predicted to react with the same speed to a positive or negative cost change, then for the next 5 days the cumulative response to a positive shock is greater than a negative, and finally the asymmetry disappears. Conversely, using the same data set, Remer (2010) shows that daily firm prices used in conjunction with the two-step model estimates asymmetry immediately following a cost change, and the difference in the speed of adjustment lasts for only eight days. It is likely that when using time and city averaged data the asymmetry becomes dampened and transferred to later in the adjustment process as the

[6] 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.

cost and retail price changes become similarly muted and averaged over longer periods of time.

The contrast in the estimates produced by all three models with the results when daily firm-level data 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 aggregation 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 (2) and (1) are augmented with characteristic data.[7]

Estimated coefficients and standard errors clustered by station and corrected for heteroscedasticity are reported in Table 2. 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 week-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 unrealistically upwardly sticky prices (one week after a positive cost change retail prices incorporate only 4% of the shock). The dynamic adjustment of retail prices predicted by the BCG OLS model are nearly the same as with city-week prices. One distinction, however, is that the model now finds evidence of asymmetry from 1.6 weeks after a cost change until 2.4 weeks. Interestingly, the point estimate of the magnitude of asymmetry is predicted to be less than when the model is estimated with city-week average prices, but using firm-week prices increases the power of the regression to such an extent that statistical significance in favor of asymmetric pricing can now be found. Accordingly, the two-step model now yields estimates of rockets and feathers for up to 5 weeks following an initial cost change. Again, the estimated degree of asymmetry, at any point in time, is nearly identical to when the model is estimated with city-week data, but firm-week data now affords additional power in the significant tests. Thus, the model predicts rockets and feathers for a longer period of time.

The augmented power afforded by disaggregating the data to the firm-level, while maintaining weekly averages, in some sense exacerbates the problem of temporal aggregation. Given that pa-

[7]The additional controls are the log of population of the city of operation for each station, 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, and the percentage of independent stations within .1, between .1 and 1.5 miles, and between 1.5 and 5 miles. Also, station fixed effects are added to the error-correction term in equation (1).

rameter estimates remained nearly identical, and just as unrealistic, measuring them with greater precision serves to increase their bias. Moving from city-week to firm-week average prices leaves the prediction of upward price stickiness unchanged in all three models. In the IV BCG model, using weekly averaged firm prices merely makes the prediction of prices reacting faster to negative cost changes even stronger. In the OLS BCG and the two-step models, disaggregating prices to firm-week averages allows for asymmetry to be detected, but the estimates appear to be biased. Neither model finds any retail price asymmetry in the first week following a cost change. When the two-step model is estimated with the best available data, rockets and feathers is present immediately after a cost shock and persists for eight days. Thus, it appears that estimating the model with weekly averaged data biases the estimates such that the asymmetry appears later in the adjustment process. Consequently, 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.[8] Even though prices are still spatially aggregated the estimates dramatically improve, and both the one and two-step models produce results resembling those found with daily-firm data. Estimates are reported in Table 3 and plotted in Figure 5, 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 5 days after the initial cost change.[9]

Despite the improvement in both the one and two-step error-correction models the IV estimation utilized in BCG does not fare any better,[10] 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,[11] the Hansen J statistic rejects their validity with 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

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

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

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

[11] Both this study and BCG utilize the Brent crude oil price as an instrument. However, where they use oil futures prices as additional instruments I employ the spot price of wholesale gasoline traded at the Singapore harbor.

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 4 reports estimates of the three models, and the corresponding CRF's are charted in Figure 6. 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.[12] 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.[13] 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 in both OLS models.

The disparity 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

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

[13] This is true with 95% confidence.

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.

An additional source of the 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 their temporally aggregated counterparts. 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.

IV regression performs poorly across all data specifications, and produces especially unrealistic results when paired with daily data. 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.[14] Also note the nearly identical performance of the one and two-step methods, especially when analyzing daily data. Even so, 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

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

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. I, therefore, 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.

4 Asymmetry as a Market or Firm Level Phenomenon?

After establishing the importance of daily and firm-level data in examining the existence and cause of asymmetric pricing, a natural next step is to exploit this data to further document characteristics of rockets and feathers in the retail gasoline industry. In this section, I explore the interaction between firm branding, population characteristics, and asymmetric pricing. Although an extensive literature has tested for the presence of rockets and feathers in retail gasoline markets, a lack of large micro-level data sets has prevented a systematic comparison of markets and the firms operating within those markets.

4.1 Major Brands and Asymmetry

Rockets and feathers is generally believed to be a market-wide phenomenon, and not an equilibrium pricing strategy of isolated firms operating within a market. Indeed, the theories derived in Yang and Ye (2009), Tappata (2009), and Lewis (2010) all contain homogenous firms that, in the long-run, price with the same magnitude of asymmetry. Yet, some empirical literature suggests that firms operating within a single market may exhibit varying degrees of price asymmetry. For example, Verlinda (2008) finds that gas stations in South Orange County, CA price with different magnitudes of asymmetry, and that the speed of price adjustment is correlated with specific firm traits: such as brand and distance of the nearest rival. Faber (2009) uses two years of daily gas station prices from the Netherlands and finds that only 38% of stations price asymmetrically, and concludes that rockets and feathers is a characteristic of individual firms and not entire markets.

Given the dichotomy between the empirical results and the theory and belief of asymmetric pricing as a market characteristic, I now analyze whether major or regional gasoline retailers employ rockets and feathers as a general pricing strategy for regular unleaded gasoline. To do so, I first restrict the data set to only include firms of a particular brand, and then estimate equation (1) using the two-step OLS procedure while including the additional controls detailed in footnote 7. This procedure is carried out for every major brand in the data set, as well as a few independent brands with a strong regional presence.

Table 5 details the estimates of cumulative adjustment asymmetry, the percentage of a positive cost change incorporated into final retail prices, and the percentage of a negative cost change included in final retail prices. Cumulative Adjustment Asymmetry is defined by the following equation:

$$\Delta A_n = \int_{j=0}^{n} (B_j^+ - B_j^-) dj. \tag{3}$$

In words, equation (3) describes the area under the positive CRF minus the area under the negative CRF. It describes the total welfare loss, in dollars, to a consumer following a cost increase minus the gain from a cost decrease over the course of price adjustment. Each column of Table 5 reports estimates for the eighth day following a cost shock. The three statistics are estimated for day eight of the adjustment process because when the model is estimated with the complete data set asymmetry is statistically significant, with 95% confidence, for just over eight days. Still, the choice of using day eight as the barometer is somewhat arbitrary, but results are qualitatively identical from day five through ten.

One striking feature of the table is the disparity in the magnitude of asymmetry with which the different brands price regular fuel. Wawa, a gas and convenience store chain located exclusively in the Mid-Atlantic United States, prices with the highest degree of asymmetry at 2.34. This means that eight days following a cost change WaWa customers lose 2.34¢ more from a cost increase than they gain from a cost decrease. On the other end of the spectrum, 76 and Conoco stations are actually found to react faster to cost decreases than increases; however, their estimated magnitude of asymmetry is not statistically different from zero. In all, five of the fourteen brands can be said, with more than 95% confidence, to react more quickly to cost increases than decreases.

Despite the variability in the estimated degree of asymmetry across brands, it is difficult to claim whether any of these companies employ a specific magnitude of rockets and feathers as a general pricing strategy. Even though the difference in adjustment asymmetry between some of the firms is statistically significant – for example, between WaWa and Texaco/Chevron – the distinction always disappears within the first day after a price change and is economically insignificant. Moreover, even for firms who are found to price asymmetrically with statistical significance, there is enough variance in the estimate so as to make any claim about a specific pricing strategy suspect at best. Further complicating the issue is the ownership structure of the various firms. Some brands are franchised, and prices are set either by local owners or regional managers, and others, such as WaWa, are a family owned and operated company. Finally, even if large corporations were to employ rockets and feathers as a pricing strategy, it is unlikely that they would employ the same magnitude of asymmetry across different markets. As theory predicts, and empirical results in the following section confirm, different types of costumers across markets are associated with different degrees of asymmetry. Thus, even if a large company, like BP, were to maximize profits by reacting faster to cost increases than decreases, the firm should be sophisticated enough to vary the speed of adjustment across markets to account for how much consumers search in those markets. Consequently, finding that a national brand, such as Exxon/Mobil, does not unilaterally price with a significant degree of asymmetry does not negate their reliance upon the pricing mechanism, as they could employ different magnitudes in unique markets. In the following subsection, I estimate the degree of asymmetry of four major brands in different markets, and find evidence suggesting that rockets and feathers is more likely a market phenomenon and not the strategy of a specific firm or brand acting independently.

4.2 The Interaction Between Statewide and Brand-level Asymmetry

In determining whether rockets and feathers is a market or individual firm trait, it is instructive to understand how certain brands' magnitude of asymmetry varies across markets. In this subsection, the magnitude of spot to retail price asymmetry of four major brands is estimated separately in three states. It turns out that unique brands operating in the same state adjust to cost shocks more similarly than the same brand does across different states. Therefore, it is more likely that rockets and feathers exists as a market-wide pricing phenomenon, and is not the strategy of a single firm acting in isolation.[15]

To begin the analysis, I estimate the cumulative adjustment asymmetry of spot to regular unleaded gasoline for the states of Maryland, New Jersey, and Virginia. The parameters are derived by first restricting the data set to only include stations from a particular state, and then equation (1), along with the control variables described in footnote 7, is estimated using the two-step error-correction method. The first three rows of Table 6 present the cumulative adjustment asymmetry, the percentage of a positive cost change incorporated into retail prices, and the percentage of a negative cost change included in retail prices eight days after an initial cost shock. From the table it is clear that gas stations located in different states adjust retail prices with distinct speeds in reaction to changes in cost. Eight days after a cost shock gas stations in Virginia price with approximately 3.5 and 1.75 times more asymmetry than stations in New Jersey and Maryland, respectively. This can be easily seen in Figure 7, where the difference in cumulative asymmetry between the three states appears to be growing for up to two weeks. With more than 95% confidence, the difference in asymmetry between the three states persists for more than four days, and the distinction in the speed of adjustment between New Jersey and Virginia lasts for up to a month. Therefore, strong evidence exists that firms operating in separate markets adjust with different speeds to changes in cost.

[15] Clearly, the pertinent market definition in the retail gasoline industry is smaller than the size of a state. For data reasons, however, the following analysis is performed at the state-level. Discussion below will more clearly address this issue.

Estimating the magnitude of asymmetry in the three states with such a high degree of power, and finding that the asymmetries are statistically distinct, is consistent with the idea of rockets and feathers as a market characteristic. If there were a high variance in the speed of adjustment between firms in the same market, then asymmetry in that market would be estimated with low power. Consequently, it would be difficult to uncover any differences in the magnitude of asymmetry between states. Still, finding unique patterns of dynamic price adjustment between the three states is merely consistent with asymmetry as a market phenomenon, and certainly not proof.

Taking a closer look at individual brands operating in all three states, however, further rules out rockets and feathers as the strategy of an individual firm acting independently of the market. Exxon/Mobil, Shell, BP, and Sunoco are all gasoline retailers with a major presence in Maryland, New Jersey, and Virginia. While individual gas stations branded by the four companies are largely franchised out to individual owners, they are still largely regulated by the parent company. First, owners of the gas stations are required by contract to purchase wholesale fuel from the gasoline brand. Secondly, while individual owners have some leeway to set prices, they are often given a specific range within which they must price. Thus, the parent company exerts a large degree of control over the prices of their franchised stations, and therefore, it would be reasonable for them to enact a uniform pricing strategy across stations in different markets.

In the following tests, the magnitude price asymmetry for each of the four brands is estimated separately for their stations in Maryland, New Jersey, and Virginia. Figure 8 plots the resulting CRF's, as defined by equation (3), for the four major gasoline retailers in each of the states. Upon close inspection, it appears that there is a greater correlation between the CRF's of different brands in the same state than there is between the same brand across states. And, statistical tests of significance largely confirm this pattern.

For example, at the 95% confidence level there is no statistical distinction between the CRF's for Shell and BP within any of the three states. Yet, when Shell's CRF's in the states of Virginia and New Jersey (Maryland and New Jersey) are compared, there is a statistical and economically meaningful difference that lasts for more than three (one) days. A similar relationship is revealed when comparing Shell and Sunoco or BP and Sunoco. There is no difference in the CRF's of Shell and Sunoco in Maryland, and in New Jersey and Virginia the difference disappears about one day following a cost change and is not economically meaningful. On the other hand, the difference in asymmetry for BP stations in Virginia and New Jersey last for more than four days and the difference in Maryland and New Jersey persists for just about two days. Similarly, comparing the CRF's for Sunoco stations in Virginia and New Jersey or Maryland and New Jersey reveals a difference in asymmetry that lasts for two days following a cost shock.

The same pattern does not hold, however, for Exxon/Mobil stations. First, there is no significant difference in the degree of asymmetry between Exxon/Mobil stations in different states, which is largely due to the fact that the magnitude of asymmetry is estimated with low power. While the line estimate of the CRF's for Exxon/Mobil stations in different states look distinct, the same can be said when comparing Exxon/Mobil CRF's to different brands in the same state. In fact, Exxon/Mobil CRF's are statistically different from Shell, BP, and Sunoco in Maryland, and the distinction persists for more almost two days.

In total, CRF estimates suggest that there is a stronger relationship in the dynamic price adjustments of firms in the same state than in the same firm across different states. Exxon/Mobil station prices do not completely conform to this pattern, but spot to retail pass-through rates of Shell, BP, and Sunoco do. Thus, the evidence is consistent with the idea that rockets and feathers exists as a market phenomenon and not the strategy of a single firm. If it were the strategy of a firm acting independently of the market, then the CRF's of a single firm across states would be more similar than CRF's of unique firms in the same state. It is true, however, that markets in the retail gasoline industry are much smaller than a single state. The analysis was performed at the state rather than the city-level in order to allow the significance tests to have sufficient power. There are not enough observations for all four major brands, even at the city-level, to allow for meaningful comparisons of CRF's in different cities. Thus, the state-level estimates are only consistent with rockets and feathers as a market phenomenon and not definitive proof. Yet, the evidence is still quite convincing; that the evidence emerges when estimating state-level CRF's means the market-level correlation between brands must be strong.

5 Market Characteristics and Asymmetry

In this section, I explore in more depth the variation in the magnitude of price asymmetry across markets, and which population and city characteristics correlate with the speed of price adjustments. Due to lack of data, there has been little documentation in the rockets and feathers literature as to which market traits are associated with greater asymmetry. Verlinda (2008) details the connection between some firm and market characteristics and the speed of cost to retail price pass-through of gas stations in South Orange County, CA. The study, however, is limited in scope as it only analyzes data for a highly specific geographic region. The following analysis builds on Verlinda (2008) by investigating the issue using an expanse of data stemming from geographically diverse markets. Consequently, I am able to exploit variation in population and market characteristics to reach a more general understanding of how both consumer and market traits influence the speed at which firms incorporate changes in cost into final retail price.

The fist step in the analysis is to estimate the magnitude of asymmetry in the pricing of regular gasoline in the largest cities in the data set. Accordingly, I refine the data set to only include cities whose population is greater than 25,000 and for which I have detailed census data; this parsing of the data leaves information on 140 cities in states of Maryland, New Jersey, Virginia, and Washington, as well as Philadelphia, PA and Washington, DC. The cities range in population from 1,449,634 (Philadelphia, PA) to 25,233 (Salem, VA), and this information is complimented by data from the 2000 United States Census: for example, median income, number of adults that drive to work, and the number of adults that carpool to work. While the year 2000 census data is not concurrent with the price data, it is the best available data, and certainly correlated with the true 2008-2009 values.

Given the restricted data set, equation (1) is separately estimated for each city at the daily firm-level using the typical control variables and the two-step OLS method. Using the unique parameter estimates for each city, I predict cumulative asymmetry response functions for each day of the adjustment process. Then, these daily predictions are employed as dependent variables in a series of OLS regressions; the independent variables are a host of city and firm characteristic variables. This procedure allows for the correlation between market structure and speed of cost pass-through to be quantified.

Before presenting the results, a few technical details must be discussed. The first step of the process, estimating the speed of price adjustments separately for the 140 cities, is performed in the same manner as the econometrics in the previous sections. The second step, using these predictions as dependent variables in a second regression, requires a weighted OLS procedure in order to estimate the correct standard errors. The need for the weighted OLS scheme stems from using predictions, and not true values, as dependent variables in the regressions. Intuitively, more accurate predictions are given more weight in the regression, which increases the efficiency and consistency of the standard errors.

More precisely, let $\hat{y}_i$ be a prediction generated from the estimated parameters of equation (1).[16] The estimate $\hat{y}_i$, however, is only an unbiased predictor of the true value, y_i:

$$\hat{y}_i = y_i + v_i, \tag{4}$$

where v_i is normally distributed with zero mean and finite variance equal to ω_i^2. Therefore, if $\hat{y}_i$ is employed as the dependent variable in an OLS regression it is akin to estimating the model with measurement error:

$$\hat{y}_i = \alpha + X\beta + v_i + \epsilon_i, \tag{5}$$

where X is an n x k matrix of independent variables, β is a k x 1 vector of parameters to be estimated, and ϵ_i is iid and normally distributed with zero mean and finite variance equal to σ^2. While estimates of β in equation (5) will be unbiased, the associated standard errors will be inefficient and inconsistent because the model assumes $v_i + \epsilon_i$ has a common variance across all observations. However, the true variance of $v_i + \epsilon_i$ is $\omega_i^2 + \sigma^2$, which is unique to each observation i.

[16] This weighted OLS econometric technique is based upon a procedure outlined in Lewis and Linzer (2005).

Fortunately, there is an asymptotically efficient correction for measurement error in the dependent variable when the variance of the measurement error is known. First, as detailed in Hanushek (1974) and Lewis and Linzer (2005), there is a simple, straightforward procedure to arrive at an unbiased estimate of $\text{Var}(\epsilon_i)$, denoted $\hat{\sigma}^2$. Then, as $\text{Var}(v_i) = \omega_i^2$ is assumed to be known from the first stage OLS estimation of $\hat{y}_i$, a set of weights can be derived to use in the second stage of the estimation procedure:

$$w_i = \frac{1}{\sqrt{\omega_i^2 + \hat{\sigma^2}}}. \tag{6}$$

Finally, the second stage regression defined in equation (5) is carried out with each observation, i, weighted by w_i:

$$w_i \hat{y}_i = w_i \alpha + \sum_{j=1}^{k} w_i \beta_j X_{ij} + w_i(v_i + \epsilon_i). \tag{7}$$

Notice that both the accuracy of the prediction, $\hat{y}_i$, and w_i are decreasing ω_i^2. Thus, more precise predictions of $\hat{y}_i$ are given more weight in the second stage regression defined in equation (7).

Using this weighted OLS scheme, the results of regressing the predicted degree of cumulative asymmetry eight days after a cost change on population and market characteristic variables are reported in Table 7. Again, estimates are presented for the eighth day following a cost shock, but results are qualitatively similar for days five through ten. Thus, Table 7 documents which population and market traits possibly influence the speed of price adjustments for the first week following a cost shock – the results, however, should be interpreted with caution. It would be asking too much of the data and model to conclude any causal relationship between independent and dependent variables; instead, the estimates should be viewed more as sophisticated correlations.

With this caveat in mind, it is still informative to discuss the estimates within the context of the search-based asymmetric pricing theory presented in Yang and Ye (2008) and Tappata (2009). Of first note, the only population characteristics that are significantly correlated with the magnitude of asymmetry are those pertaining to driving behavior. While neither the log of population nor median income impact the degree of rockets and feathers, the number of people that drive to work or carpool do have significance. For every 1,000 people that drive to work asymmetry increases by 2%, and for every 1,000 people that carpool (share a ride with another commuter) to work asymmetry decreases by 10%. Neither Yang and Ye (2008) nor Tappata (2009) offer models that can relate the magnitude of asymmetry to the size of the consumer population, as both assume a continuum of consumers. Yang and Ye do, however, find that a more intensely searching population decreases asymmetry. It can be argued that people who carpool to work do so largely to save money on the cost of commuting, and thereby, it may be that these consumers are also more likely shop for the lowest price when purchasing gasoline. If this is the case, then more carpoolers in a driving population should serve to decrease price asymmetry – and this is precisely what is found in Table 7.

Perhaps another, albeit weaker, correlate with market search intensity is the proportion of the population that commutes by car to work. Houde (2009) shows that commuting patterns have an important effect over gasoline prices. Here, I find that the proportion of people in the population that drive to work has an important relationship with the speed of price adjustments. Many commuters follow the same general path to work each day, and therefore, may be more informed about, at least a subset, of market prices than the rest of the population. Consequently, a larger proportion of commuters is predicted by search theory to decrease the magnitude of price asymmetry. The estimates, only partially confirm this hypothesis; the direct impact of the proportion of drivers is negative and significant (-12.92), however, the square of this variable is positive and significant (18.93). Taken together, as the proportion of drivers increases from zero to 68% the magnitude of asymmetry decreases, but thereafter the net effect is positive. Theory suggests that if this variable is only picking up search intensity then the effect of the variable should monotonically decrease, yet this is not the case. Therefore, there is either something lacking in the theory, or more likely, the variable is picking up on some other effect.

A similar variable that interplays significantly with asymmetry is the number of commuters per firm, which may be a better proxy of market size than just the number of commuters or even the log of population. This variable may also positively correlate with the degree market power. Thus, it is interesting that with 95% confidence the number of commuters per firm has a positive impact on asymmetry as the value goes from zero to 6.2, and thereafter has a negative effect. It is worth noting that within the sample the variable reaches a maximum of 6.04, and thus always has a positive total effect on cumulative asymmetry. To the extent that commuters per gas station is a proxy for market power, the results are in accordance with Verlinda (2008), which uses a different measure of market power to find a similar relationship.[17]

Two more variables in the regression have interesting implications in regards to the relationship between competition and rockets and feathers. First, relative to all other cities, those located in New Jersey exhibit much less price asymmetry.[18] Gas stations in New Jersey are mandated by law to only set one price per day. Wang (2009) finds that a similar law in Perth, Australia has an important effect on firm pricing strategies within the context of Edgeworth Cycles. Here, the once per day law may serve to drive down the degree of asymmetry. Of final note, the Herfindahl index (HHI)[19] in a city has no significant correlation with asymmetry. This suggests that rockets

[17] Verlinda (2008) uses the number of competitors within a given distance of an individual firm as its measure of market power.

[18] This is true with 99% confidence.

[19] The HHI in a city was not calculated using actual sales as the measure of market share. Instead, market share is defined as the percentage of gas stations that are of a particular brand.

and feathers is not generated by collusion. Firms of the same brand may have an easier time coordinating prices, and therefore, the HHI would have a positive and significant relationship with the magnitude of asymmetry if the pricing phenomenon were caused by collusion.

6 Conclusion

This paper progresses the rockets and feathers literature along a few dimensions. First, it provides clarity as to the most appropriate econometric technique to use when identifying the pricing phenomenon's existence. The standard two step OLS error-correction model is the most robust to different levels of data aggregation, and always performs better than BCG's IV model. The standard error-correction model, however, is not impervious to the ills of temporally aggregated data. When the model is estimated with weekly averaged data prices appear unrealistically upward sticky, and the adjustment process appears much slower than when estimated with daily data. While the problems associated with time-averaged data cannot be overcome with firm specific data, daily city-average data performs almost as well as daily firm data and should be sufficient for identification purposes.

After providing new evidence about modeling and data issues in asymmetric pricing, I exploit a rich data set to more extensively document dynamic pricing regularities in the retail gasoline market. First, I show that different brands of gasoline price with distinct magnitudes of asymmetry. Despite this finding, further testing identifies rockets and feathers as a market-wide phenomenon and not the strategy of a single firm acting in isolation. Finally, I explore which market and population characteristics correlate with the degree of asymmetry in the largest cities in the data set. Most of the factors that significantly interact with asymmetric pricing are those pertaining to consumer characteristics: such as the number of carpoolers and the percentage of the population that drives to work. These results are largely consistent with the search-based asymmetric pricing theory derived in Yang and Ye (2008) and Tapatta (2009). Yet, more research, and possibly more detailed data is needed, to definitively document the major market factors that impact the speed of cost to retail price pass-through. This paper, though, does help explain the differences in previous studies of rockets and feathers, and does uncover some aspects of retail gasoline price adjustments that may be generalizable to the market at large.

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7 Tables

Table 1: Asymmetric Response City-Week Averages

	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)		

Notes: The city-week average change in regular fuel price is the dependent variable. Column 1 reports estimates of equation (1) using the two-step method, Column 2 reports OLS estimation of equation (2), and column 3 is IV estimation of equation (2). All cities with a population less than 25,000 are dropped, and there are 9,393 observations for each model. See notes under next table for variable definitions. Each model was estimated for lag length $n = 5$, but all estimates are not reported due to lack of space. 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 2: 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 (1) using the two-step method, Column 2 reports OLS estimation of equation (2), and column 3 is IV estimation of equation (2). 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 4. 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 3: 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 (1) using the two-step method, Column 2 reports OLS estimation of equation (2), and column 3 is IV estimation of equation (2). 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 5. 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 4: 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 (1) using the two-step method, Column 2 reports OLS estimation of equation (2), and column 3 is IV estimation of equation (2). 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 6. 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: Price Adjustments for Major and Regional Brands After Eight Days

Brand	Asymmetry	Positive Adjustment	Negative Adjustment
Wawa	2.34***	.66***	.34***
	(0.57)	(0.06)	(0.05)
Texaco/Chevron	1.70***	.63***	.39***
	(0.36)	(0.04)	(0.03)
Valero	1.48	.58***	.50***
	(1.05)	(0.12)	(0.09)
BP	1.46**	.62***	.50***
	(0.65)	(0.07)	(0.05)
Exxon/Mobil	1.18	.56**	.46
	(2.74)	(0.23)	(0.29)
Shell	1.10***	.54***	.42***
	(0.41)	(0.05)	(0.04)
Sunoco	.93**	.51***	.38***
	(0.39)	(0.04)	(0.04)
Hess	0.82	.52***	.38***
	(0.83)	(0.08)	(0.08)
Gulf	0.77	.63***	.52***
	(1.00)	(0.10)	(0.10)
Lukoil	0.75	.57***	.39***
	(0.57)	(0.06)	(0.06)
Getty	0.68	.57***	.46***
	(0.71)	(0.07)	(0.08)
Citgo	0.58	.59***	.57***
	(1.46)	(0.16)	(0.13)
711	0.41	.42***	.40***
	(0.43)	(0.04)	(0.04)
76/Conoco	-0.88	.22***	.40***
	(0.84)	(0.08)	(0.10)

Notes: Estimates are derived by first estimating, separately for each brand, equation (1), supplemented with the controls described in footnote 7. Then the parameters are used to calculate the total adjustment asymmetry, the percentage of a positive cost shock passed through to final regular prices, and the percentage of a negative cost shock passed through to final regular prices: which are listed in columns 2, 3, and 4, respectively. 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 6: State and Firm-State Price Adjustments after Eight Days

	Asymmetry	Positive Adjustment	Negative Adjustment
Maryland	1.56***	.60***	.45***
	(0.44)	(0.05)	(0.04)
New Jersey	0.78***	.58***	.47***
	(0.25)	(0.03)	(0.03)
Virginia	2.74***	.77***	.46***
	(0.39)	(0.04)	(0.03)
MD - Exxon/Mobil	0.02	.48**	.52*
	(2.67)	(0.24)	(0.30)
MD - Shell	1.65	.62***	.47***
	(1.01)	(0.10)	(0.10)
MD - BP	1.08	.60***	.60***
	(1.57)	(0.17)	(0.14)
MD - Sunoco	1.51	.54***	.35***
	(1.13)	(0.12)	(0.12)
NJ - Exxon/Mobil	0.79	.58**	.52*
	(2.60)	(0.23)	(0.27)
NJ - Shell	0.67	.52***	.48***
	(0.67)	(0.07)	(0.06)
NJ - BP	0.60	.49***	.48***
	(0.75)	(0.07)	(0.08)
NJ - Sunoco	0.60	.47***	.36***
	(0.57)	(0.05)	(0.06)
VA - Exxon/Mobil	4.30	.83	.54
	(13.41)	(1.35)	(1.54)
VA - Shell	2.22**	.73***	.50***
	(1.03)	(0.11)	(0.09)
VA - BP	3.26**	.86***	.55***
	(1.53)	(0.17)	(0.12)
VA - Sunoco	1.56	.63***	.45***
	(1.04)	(0.11)	(0.09)

Notes: The total adjustment asymmetry, the percentage of a positive cost shock passed through to final regular prices, and the percentage of a negative cost shock passed through to final regular prices are listed in columns 2, 3, and 4, respectively. Estimates are derived by first estimating equation (1), supplemented with the controls described in footnote 7, at the daily firm level. The first block reports the estimates for the states of MD, NJ, and VA. The next three blocks report estimates for only the listed brand in the given state. 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% = *.

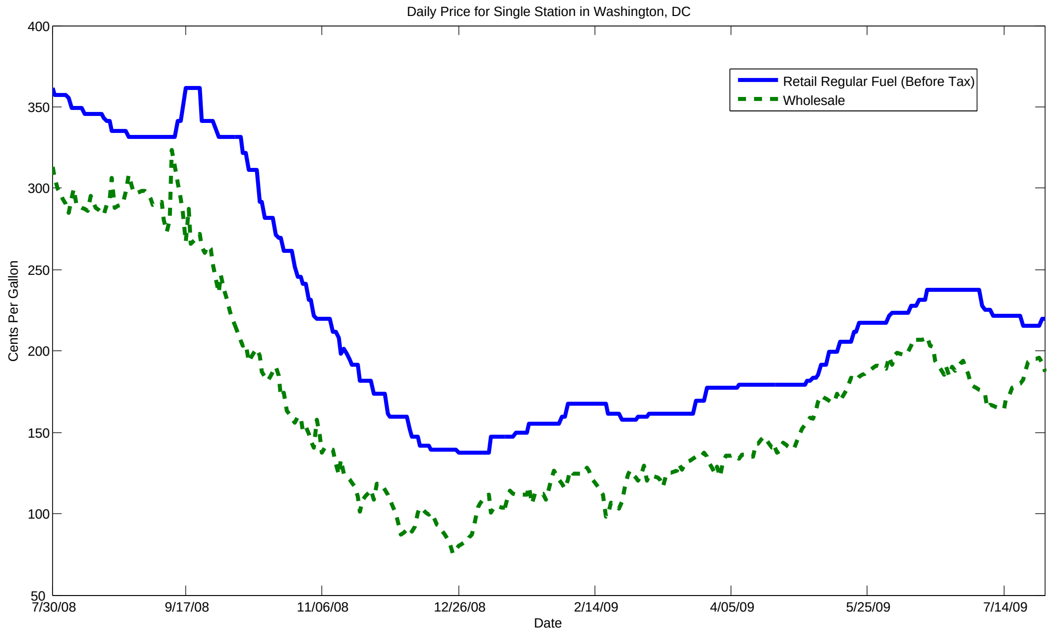
Table 7: The Effect of Population and Market Traits on City-Level Asymmetry

Dependent Variable: Cumulative Asymmetry Eight Days After Cost Change			
Drivers	0.02***	New Jersey	-0.75***
	(0.01)		(0.26)
Carpool	-0.10***	Percent Exxon	0.62
	(0.03)		(1.01)
Log of Population	-0.19	Percent Shell	-1.54
	(0.22)		(1.21)
Log of Median Income	-0.39	Percent BP	4.18***
	(0.38)		(1.35)
Firms	0.00	Percent Sunoco	-0.48
	(0.00)		(1.05)
Percent of Independents	0.64	Percent 76	-7.53***
	(0.72)		(1.27)
$\frac{Firms}{Population}$	2.80	Percent Conoco Phillips	-10.78***
	(1.99)		(1.98)
$(\frac{Firms}{Population})^2$	-1.16	HHI	0.18
	(0.84)		(6.48)
$\frac{Drivers}{Firms}$	1.36**	HHI^2	-8.38
	(0.66)		(15.44)
$(\frac{Drivers}{Firm})^2$	-0.22**	$\frac{Drivers}{Population}$	-12.92**
	(0.09)		(5.10)
		$(\frac{Drivers}{Population})^2$	18.93**
			(7.48)
Observations	140		

Notes: Estimates are the result of regressing the predicted magnitude of asymmetry, for cities with a population greater than 25,000, eight days after a cost shock on city characteristic variables. The econometric model is a weighted OLS procedure detailed in section 5. HHI is the Herfindahl index in the city of operation, Drivers is the number of people that drive to work, Carpool is the number of people that carpool to work, Firms is the number of gas stations in the city, Percent "Brand Name" is the percentage of gas station are of that particular brand in the city, and New Jersey is a dummy variable indicating if a city is in the state of New Jersey. Drivers and Carpool are per 1000 people. Significant at 1% = ***, significant at 5% = **, significant at 5% = *.

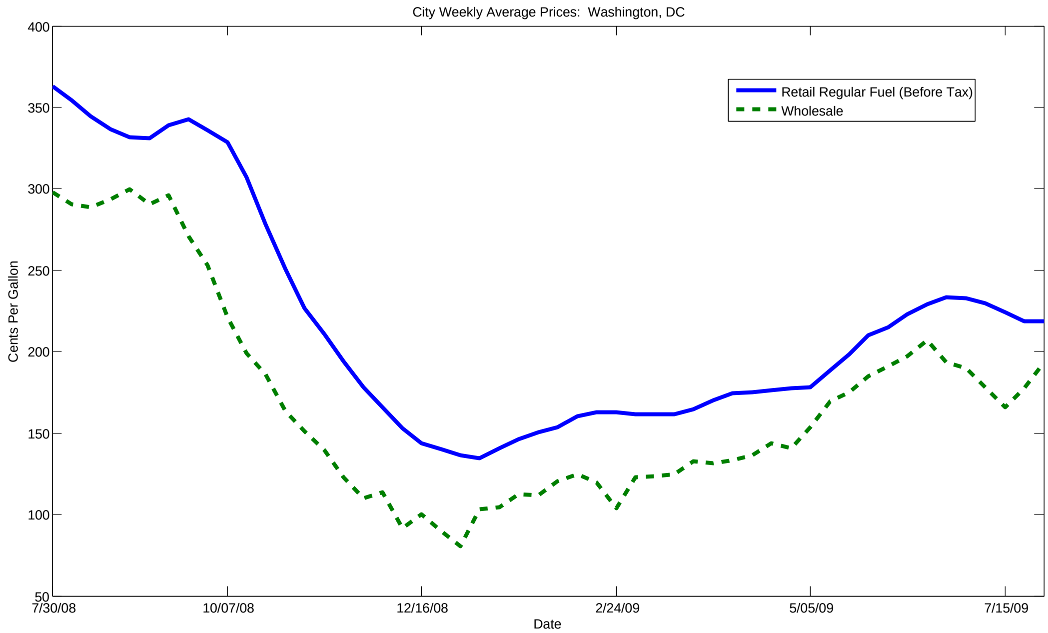
8 Figures

Figure 1



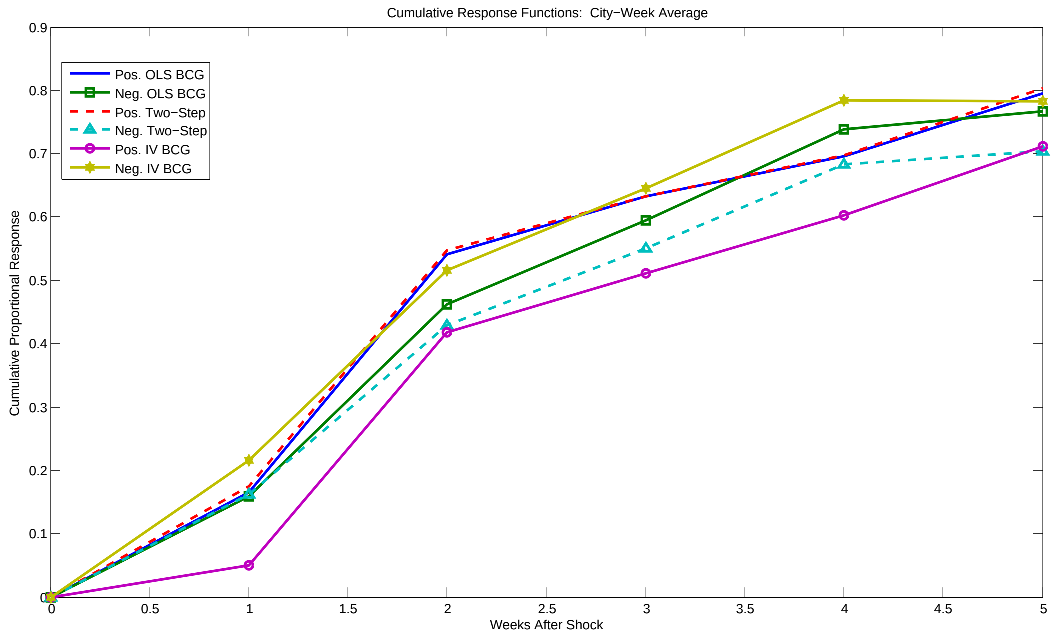
Notes: The retail regular unleaded price and wholesale cost for a single gas station in Washington, DC is depicted in this figure. The NYMEX spot price for reformulated regular gasoline delivered from the NY Harbor is used as the wholesale cost measure.

Figure 2



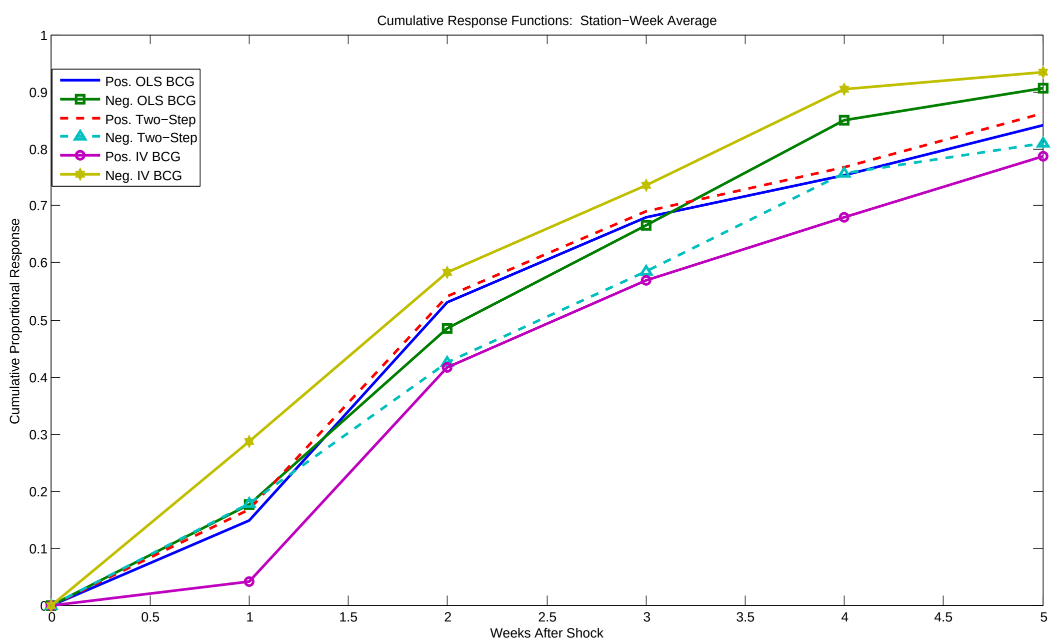
Notes: The daily average retail regular unleaded gasoline price for the city of Washington, DC is graphed along with the wholesale cost. The NYMEX spot price for reformulated regular gasoline delivered from the NY Harbor is used as the wholesale cost measure.

Figure 3



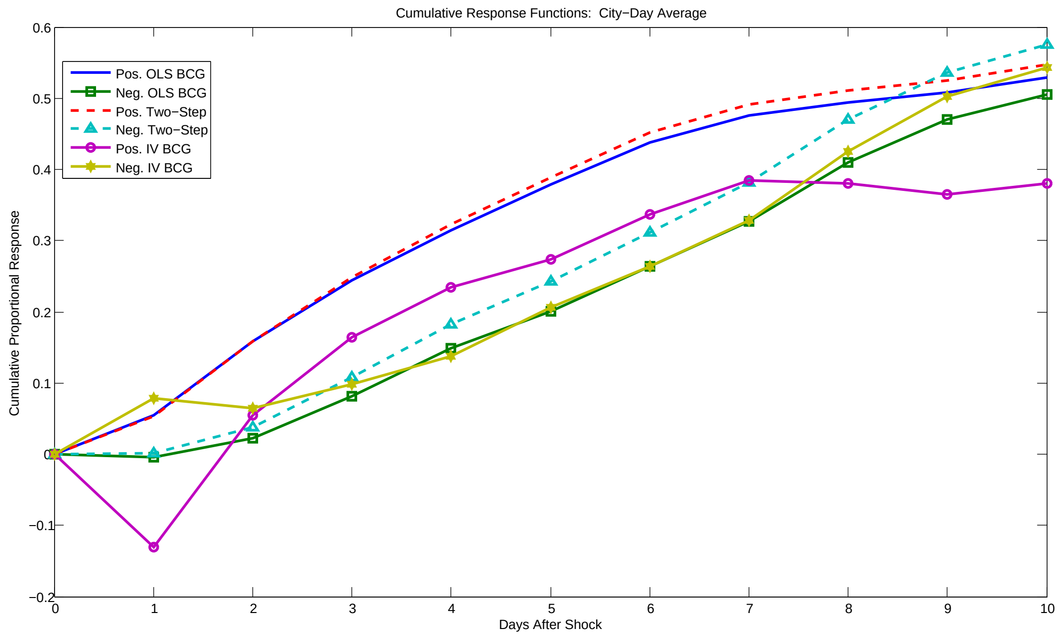
Notes: CRF's are constructed from parameter estimates listed in Table 1 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating the error-correction term using OLS then plugging parameters into equation (1), which is again estimated with OLS; "OLS BCG" is OLS estimation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

Figure 4



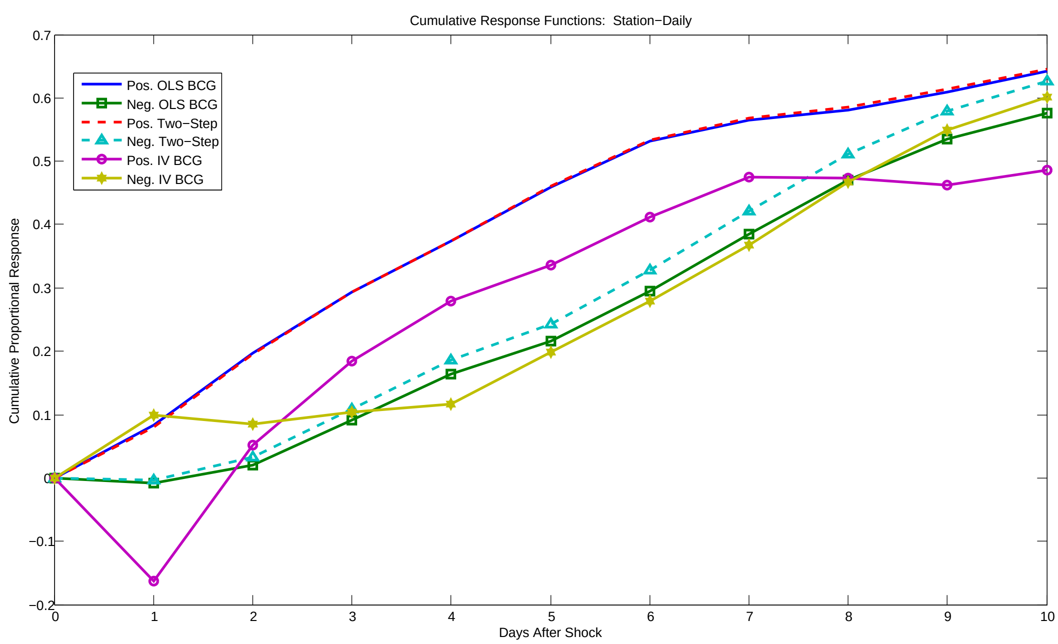
Notes: CRF's are constructed from parameter estimates listed in Table 1 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating the error-correction term using OLS then plugging parameters into equation (1) which is again estimated with OLS; "OLS BCG" is OLS estimation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

Figure 5



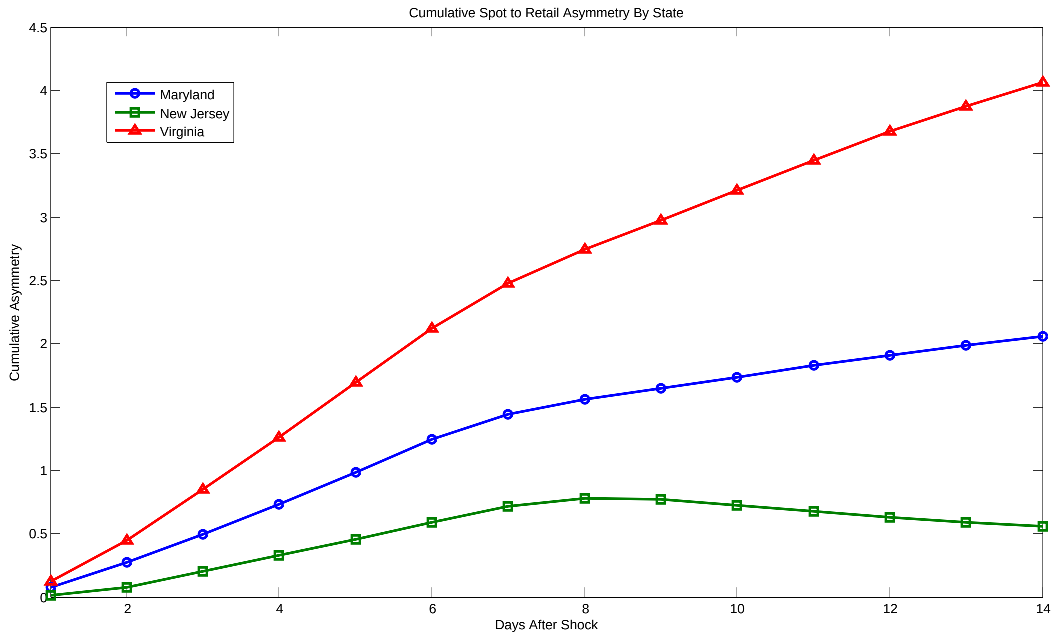
Notes: CRF's are constructed from parameter estimates listed in Table 1 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating the error-correction term using OLS then plugging parameters into equation (1) which is again estimated with OLS; "OLS BCG" is OLS estimation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

Figure 6



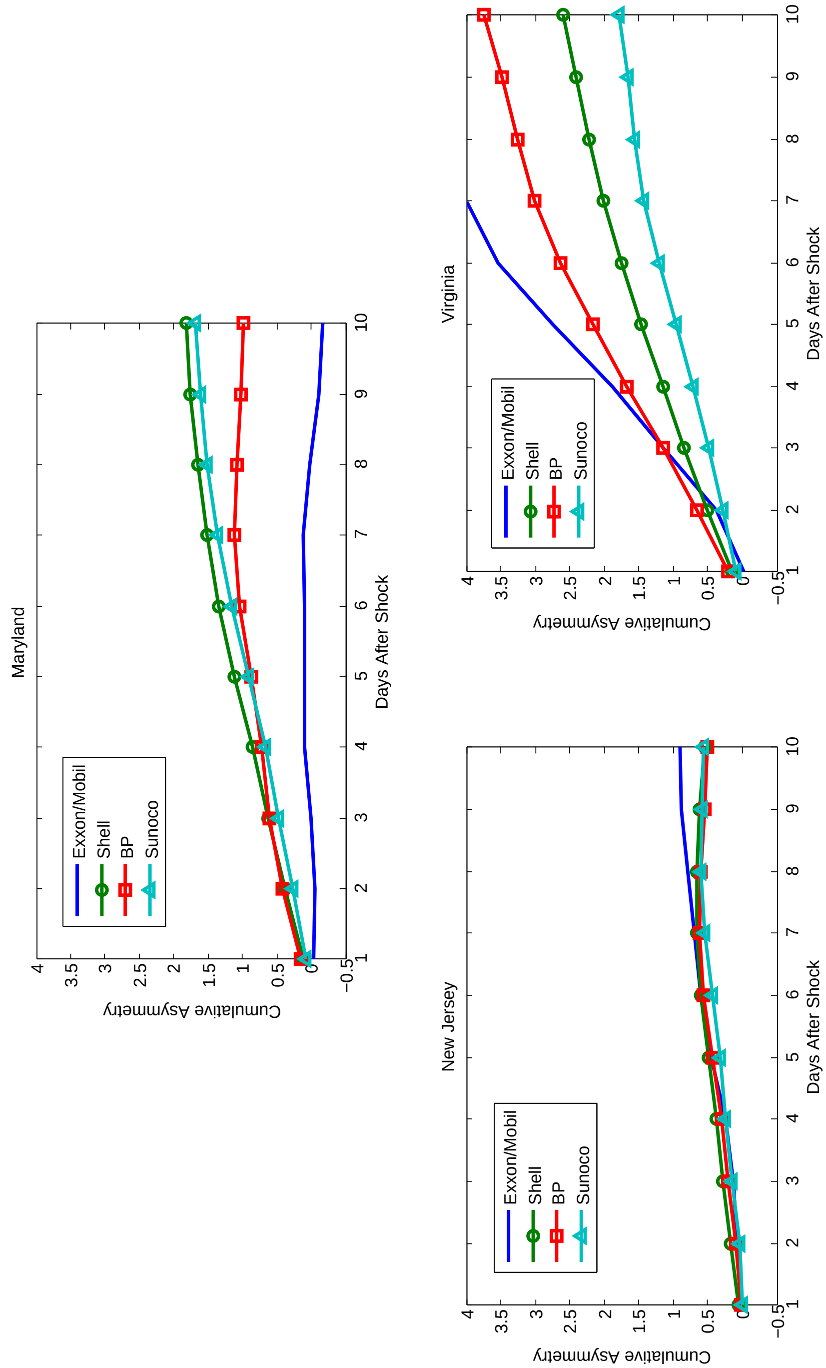
Notes: CRF's are constructed from parameter estimates listed in Table 1 for columns 1 (Two-Step), 2 (OLS BCG), and 3 (IV BCG). "Two-Step" refers to estimating the error-correction term using OLS then plugging parameters into equation (1) which is again estimated with OLS; "OLS BCG" is OLS estimation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

Figure 7: State Level Asymmetry



Notes: Each line plots the cumulative adjustment asymmetry for the given state. The lines are constructed by first estimating equation (1) for all stations in the state. Then the parameter estimates are used to calculate equation (3).

Figure 8: Asymmetry of Four Brands Grouped By State



Notes: Each line plots the cumulative adjustment asymmetry for a given brand in a given state. The lines are constructed by first estimating equation (1) for all stations of a the given brand and state. Then the parameter estimates are used to calculate equation (3).