# Asymmetric Pass-Through in U.S. Gasoline Prices

*Matthew Chesnes**

**ABSTRACT**

This paper presents new evidence of asymmetric pass-through, the notion that upward cost shocks are passed through faster than downward cost shocks, in U.S. gasoline prices. Much of the extant literature comes to seemingly contradictory conclusions about the existence and causes of asymmetry, though the differences may be due to different aggregation (both over time and geographic markets) and the use of different price series including crude oil, wholesale, and retail gasoline prices.

I utilize a large and detailed dataset to determine where evidence of a pass-through asymmetry exists, and how it depends on the aggregation and price series chosen by the researcher. Using the error correction model, I find evidence of pass-through asymmetry based on spot, rack and retail prices, though the largest effect is found in the rack to retail relationship. I find more asymmetry in branded prices compared with unbranded prices, consistent with a consumer search explanation for asymmetry. However, I also find evidence consistent with explanations based on market power as the magnitude of asymmetry is positively associated with retail concentration. On average, retail prices rise three to four times as fast as they fall.

**Keywords:** Gasoline prices, Cost pass-through, Asymmetric adjustment

http://dx.doi.org/10.5547/01956574.37.1.mche

## 1. INTRODUCTION

There is a large literature analyzing the cost to price pass-through in industries ranging from automobiles (Gron and Swenson (1982)), to cheese products (Kim and Cotterill (2008)), to the beef industry (Goodwin and Holt (1999)). The literature has not only focused on the ability of firms to successfully capture rents when input costs change, but also on how the rate of pass-through varies when the costs increase versus decrease. Peltzman (2000) analyzes over 200 consumer and producer products and find asymmetric adjustment in two-thirds of the products. Similarly, Meyer et al. (2004) surveys the literature and finds that symmetric adjustment is rejected in about one-half of the cases. Much of the extant literature comes to seemingly contradictory conclusions about the existence and causes of this phenomenon, though the differences may be due to different data sources, price series, aggregation over time and across geographic areas, as well as misspecified models. In this paper, I examine the dynamics of pass-through in gasoline prices using a detailed dataset available at a high frequency, across many cities, and at several price levels in the vertical distribution process for gasoline.

* Federal Trade Commission, Bureau of Economics, 600 Pennsylvania Avenue, N.W., Washington DC, 20580. E-mail: mchesnes@ftc.gov. Web: http://www.chesnes.com.

 Copyright © 2016 by the IAEE. All rights reserved.

Particularly in the gasoline industry, this asymmetric phenomenon is known as rockets and feathers, reflecting the fact that retail prices tend to increase quickly when costs (say, wholesale gasoline prices) rise, but drift down slowly when they fall.[1] Pass-through in the gasoline industry has been the focus of many studies for several reasons. Gasoline is a fairly homogeneous product and both retail and intermediate wholesale prices are relatively transparent compared with other industries.[2] Much of the variation in gasoline prices is driven by the price of crude oil, the key input into gasoline.[3] Crude oil is traded on a world market and the price is also transparent to market players and to consumers. In spite of the transparency of prices, there are dynamics present in the gasoline industry that are difficult to explain with competitive or oligopolistic economic models.

The literature on rockets and feathers dates back to at least 1991 when Robert Bacon found evidence of an asymmetric response in gasoline prices in the UK. Since that time, others have found evidence of the phenomenon including Borenstein, Cameron, and Gilbert (1997, hereafter BCG), Ye et. al. (2005), Deltas (2008), Tappata (2009) and Lewis (2011). These studies all utilize some form of an error correction model (outlined below) and consider some combination of crude oil prices, wholesale prices (rack or spot), and retail gasoline prices. They also vary by the geography they consider and how the data are aggregated over time. There are also several papers that, due to either a different data source or model, find no evidence of an asymmetric price response including Godby (2000) and Gautier and Le Saout (2012). Bachmeier and Griffin (2003) test the results in BCG using daily data and a different methodology and find no evidence of asymmetric adjustment, however they only focus on the transmission of crude oil to spot gasoline prices.

If it exists, there is little consensus on what causes an asymmetric response. BCG offer three potential explanations for asymmetric adjustment: focal-point pricing as a form of market power, inventory adjustment frictions in the face of positive and negative demand shocks, and differences in consumer search patterns when prices are rising and falling. Deltas (2008) and Verlinda (2008) look at how the asymmetric response varies with the level of retail market power and find more asymmetry in markets with relatively more retail market power.[4]

Lewis (2011) and Tapatta (2009) posit that consumer search behavior could be causing the asymmetric response. If consumers are more likely to search for a low price when prices are rising or expected to rise, then competition will be fierce when costs are rising and margins tight. However, if prices are falling, consumers may search less and this provides retailers with short-term market power and allows them to slowly lower prices and increase their margins. Evidence

1. The production and distribution of gasoline is just one part of the petroleum industry, which produces a whole range of refined products. The rockets and feathers literature has focused primarily on gasoline prices.

2. Rack prices for wholesale gasoline are observable and in 2009, rack sales accounted for 60% of the total gasoline supplied in the U.S. See http://tonto.eia.doe.gov/dnav/pet/pet_cons_refmg_c_nus_epm0_mgalpd_a.htm and http://tonto.eia.doe.gov/dnav/pet/pet_cons_psup_dc_nus_mbbl_m.htm. The rest is sold to lessee-dealer stations at (unobserved) dealer-tank-wagon (DTW) prices and via transfer prices to refiner-operated stations.

3. See The Federal Trade Commission, "Gasoline Price Changes: The Dynamics of Supply, Demand and Competition," 2005.

4. In Deltas, the average markup observed in the market over his sample period serves as a proxy for market power. It is tempting to assume that markets in which firms face less competition will feature firms quickly passing on cost increases to consumers, and only slowly (or possibly never) passing on cost savings. Markets with many competing firms should feature perfect pass-through. For industry-wide cost changes, this is generally true, however the opposite results when the cost change is firm-specific. Bulow and Pfleiderer (1983) show that firm-specific cost changes are more completely passed through the less competitive is the market. (See also, Ten Kate and Niels (2005).) The reason is that when faced with a cost decrease, say, firms with a greater market share will benefit relatively more from the increase in quantity demanded, which more than offsets the lower revenue from passing on the cost decrease in the form of lower prices.

Copyright © 2016 by the IAEE. All rights reserved.

of this explanation could be found in the difference in asymmetry between branded and unbranded gasoline prices. If consumers who purchase unbranded gasoline tend to search more intensively than branded customers who are loyal to a specific brand, cost shocks to unbranded rack prices would be passed on more quickly to retail prices.

The Edgeworth price cycle model of Maskin and Tirole (1988) may also explain the dynamics. They show that competition may lead to relatively slow price undercutting down to cost and a rapid rise or resetting of the cycle initiated by a single firm and quickly followed by all its competitors. Several studies have found evidencing of price cycles in gasoline markets (see Eckert (2002), Noel (2007, 2009), Lewis and Noel (2011), and Zimmerman et al. (2013)). While price cycle models do not deal directly with the response of prices to changes in costs, cycles and asymmetric pass-through may be related. Lewis and Noel (2011) show that cost shocks are passed through faster in markets that feature price cycles. However, the speed of pass-through may be unrelated to the asymmetric response to positive and negative cost shocks. Pass-through rates may be fast, though asymmetric, so cycling cities may show evidence of asymmetric pass-through even if the speed of pass-through is faster than in non-cycling cities.

This paper is similar to BCG in that I analyze several different prices (crude oil, spot gasoline, rack, and retail prices) over a long period of time. However, unlike BCG who use weekly and bi-weekly data from the Lundberg Survey, I have access to daily data on all prices. I also avoid a modeling assumption by BCG (discussed below) which was questioned by Bachmeier and Griffin (2003) and instead use a more standard approach. I also consider how asymmetry varies across different U.S. cities, between branded and unbranded prices, and how asymmetric pass-through is correlated with market concentration and the existence of price cycles.

I find evidence of asymmetry in the crude oil to gasoline spot price, the spot to rack, and the rack to retail price relationships.[5] The rack to retail relationship shows the strongest asymmetry at both the city and national level. On average, retail prices rise three to four times as fast as they fall. Asymmetry varies significantly across cities with the strongest rack to retail asymmetry in Salt Lake City, Louisville (Indiana) and Cleveland. New York shows the least asymmetric pass-through. Estimates based on weekly data show more asymmetric pass-through as retail prices are predicted to increase faster following a cost (rack price) increase and fall slower following a cost decrease. Branded gasoline features significantly more asymmetry compared with unbranded gasoline in response to changes in the rack price, consistent with the consumer search explanation for asymmetric pass-through. Computing the impact of asymmetric pass-through over time shows significant differences by year, though on average, retail prices would be about 2.45 cents per gallon (cpg) lower if they fell as quickly as they rose.

Finally, I find that cities that show more asymmetric pass-through tend to feature more price cycling and have a faster overall speed of pass-through. I also find evidence that asymmetry is positively related to market concentration. The overall brand-level Herfindahl-Hirschman Index is about 14% higher for cities in the top quartile of asymmetry relative to the bottom quartile.

The paper proceeds as follows. In section 2, I outline the model that I employ and specification tests are run to justify its use. I discuss the data and provide basic descriptive statistics in section 3 and present the results of my model in section 4, including asymmetric pass-through results for different geographic areas, at different levels of time aggregation, and for different

5. It is important to note that the model predicts complete pass-through of both positive and negative cost shocks after some period of time, typically around two weeks. Asymmetric pass-through generally occurs in the first week after the cost shock and after which, pass-through of positive and negative shocks is statistically indistinguishable.

Copyright © 2016 by the IAEE. All rights reserved.

products. I also present city-specific factors that may be related to the magnitude of asymmetric pass-through. Section 5 concludes.

## 2. MODEL

I estimate an error correction model (ECM) frequently used in the literature, though in various forms (e.g., Bachmeier and Griffin (2003)). I estimate the model individually for each city (metro area)[6] and for a national specification that allows for different price levels and markups in each city. The latter regression measures the average pass-through rate across all cities, while allowing the long-term relationship to vary by city. I allow for a difference in the pass-through of positive and negative upstream price changes. While I estimate the model for several pairs of upstream and downstream prices, for simplicity, the following is the rack to retail pass-through model for a given city:

$$
\begin{aligned}
\Delta Retail_t = & \sum_{i=0}^{L_1^+} \beta_{1i}^+ \Delta^+ Rack_{t-i} + \sum_{i=0}^{L_1^-} \beta_{1i}^- \Delta^- Rack_{t-i} \\
& + \sum_{i=1}^{L_2^+} \beta_{2i}^+ \Delta^+ Retail_{t-i} + \sum_{i=1}^{L_2^-} \beta_{2i}^- \Delta^- Retail_{t-i} \\
& + \beta_3^+ \underbrace{(Retail_{t-1} - \gamma_0 - \gamma_1 Rack_{t-1})}_{z_{t-1}^+} \\
& + \beta_3^- \underbrace{(Retail_{t-1} - \gamma_0 - \gamma_1 Rack_{t-1})}_{z_{t-1}^-} + \varepsilon_t.
\end{aligned} \tag{1}
$$

Note $\Delta Retail_{t-i} = Retail_{t-i} - Retail_{t-(i-1)}$. Lag lengths are determined by minimizing the Bayesian Information Criterion (BIC):

$$BIC = K * log(N) + N * [Log(RSS/N)], \tag{2}$$

where $K$ is the number of parameters to be estimated, $N$ is the number of observations, and $RSS = \hat{\varepsilon}'\hat{\varepsilon}$ from equation 1. I could allow the lag lengths to vary separately for positive and negative changes as well as for rack and retail prices. However, since determining the optimal lag lengths for each price series, versus using a fixed (and equal) lag length for all, does not affect the qualitative results, in the analysis below I fix the lag length at 21 days in all regressions.[7] This also allows me to compare regressions across cities and over time since I will utilize the same specification in each.

The expression $z_{t-1} = Retail_{t-1} - \gamma_0 - \gamma_1 Rack_{t-1}$ is the error correction term, and it captures the long-run relationship between the upstream and downstream prices. $\beta_3^+$ and $\beta_3^-$ should both be negative: if retail prices are above their equilibrium level ($z_{t-1} > 0$), retail prices should fall and if they are below the level predicted by the rack price ($z_{t-1} < 0$), retail prices should rise.

6. Most of the metro areas in my sample are major cities. Some cities near state borders are split across state lines, so for example, Louisville, KY and Louisville, IN are separate metro areas. See figure A1 for an example. This is important because often different types of gasoline (e.g., conventional, RFG, and California Air Resources Board (CARB) gasoline) are sold in different states.

7. The lag length is also three in the weekly specifications.

Copyright © 2016 by the IAEE. All rights reserved.

Following the two-step method proposed by Engle and Granger (1987), I estimate $\gamma_0$ and $\gamma_1$ by running OLS on the following equation:

$$Retail_{t-1} = \gamma_0 + \gamma_1 Rack_{t-1} + z_{t-1}. \tag{3}$$

The residuals, $z_{t-1}$, are then inserted directly into the model.[8] BCG estimate the long-term relationship in the same step as the rest of the parameters and instrument for the upstream prices to control for possible endogeneity. As outlined in Bachmeier and Griffin (2003), this may lead to problems with the resulting estimates.[9] Once I obtain the residuals, I can estimate equation 1 by OLS.[10]

Asymmetric adjustment of downstream prices to changes in an upstream cost (such as a wholesale price) is generally divided into two forms: amount asymmetry and pattern asymmetry. Amount asymmetry occurs when the aggregate change over a period of time is different when costs are rising versus when they are falling. In terms of the model parameters, amount asymmetry would be of the form:

$$\sum_{i=0}^{L_1^+} \beta_{1i}^+ \neq \sum_{i=0}^{L_1^-} \beta_{1i}^-. \tag{4}$$

However, this cannot exist over the long term since upstream and downstream prices do not tend to drift apart.

Pattern asymmetry involves differences in the relative speed of pass-through. As an example, one may find evidence of pattern asymmetry if a 10% increase in wholesale prices leads to a 10% increase in retail prices after one week, but an equivalent decrease in wholesale prices leads to only a 5% decline in retail prices after one week and the full 10% after two weeks. Pattern asymmetry could be found if any one of the following three conditions are met:

$$\beta_{1i}^+ \neq \beta_{1i}^- \text{ for some } i \tag{5}$$

$$|\beta_{3i}^+| \neq |\beta_{3i}^-| \tag{6}$$

$$L_1^+ \neq L_1^- \text{ or } L_2^+ \neq L_2^-. \tag{7}$$

The asymmetry in equation 5 is the one commonly analyzed in the literature. While the aggregate pass-through should be the same for positive and negative rack price changes, the pattern of pass-through may be different. If any of the coefficients on the same lag are different, this is evidence of pattern asymmetry. The coefficients on the first lag, $\beta_{1,1}^+$ and $\beta_{1,1}^-$, are particularly important because they measure the contemporaneous speed of pass-through, assuming the model could be approximated as a first-order difference equation. However, to fully assess the impact of

8. Since the two series are cointegrated, the OLS regression yields super-consistent estimates of the parameters. The estimates can then be inserted into the model as if they were known parameters.

9. BCG run a two-stage least squares regression and instrument for the upstream price with the crude oil price in England and forward prices of crude oil in the U.S. However, while they reject the null that there is no endogeneity in the prices, their 2SLS and OLS estimates are very similar.

10. For the national-level specification, I estimate equation 3 separately for each city and then substitute the residuals (stacked, city by city), into equation 1.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 1: Daily Spot Prices (Cents per Gallon)**

| Spot Price | N | Min | Mean | Max | Std Dev | Date Range | Margin Over WTI |
|---|---|---|---|---|---|---|---|
| Gulf—Conventional | 3,478 | 44.00 | 173.09 | 475.96 | 80.14 | 1/00–12/13 | 23.50 |
| Gulf—RFG | 3,478 | 26.05 | 176.93 | 452.91 | 79.93 | 1/00–12/13 | 27.34 |
| NY—Conventional | 3,478 | 46.75 | 175.96 | 366.50 | 81.67 | 1/00–12/13 | 26.37 |
| LA—RFG/RBOB | 3,478 | 47.00 | 192.73 | 417.70 | 81.03 | 1/00–12/13 | 43.14 |
| Brent | 3,478 | 39.31 | 154.52 | 342.74 | 79.56 | 1/00–12/13 | 4.93 |
| WTI | 3,478 | 41.67 | 149.59 | 345.98 | 68.87 | 1/00–12/13 | 0.00 |

asymmetric adjustment on the downstream price, a full impulse response function will be estimated taking into account all lags of the upstream and downstream price. In principal, any difference in the coefficients is evidence of some form of pattern asymmetry, but the rockets and feathers type of asymmetry implies $\beta_{1i}^{+} > \beta_{1i}^{-}$ for least one lag.

The second pattern asymmetry (noting again that $\beta_3$ should be negative reflecting mean-reversion) involves the speed at which relative prices return to their long-term equilibrium levels. We have evidence of the rockets and feathers type of asymmetry if this mean reversion is slower (closer to zero) when retail prices are above their long-term levels and faster when retail prices should be adjusting upwards toward their long-term levels (i.e., $|\beta_3^{+}| < |\beta_3^{-}|$).

Finally, if I allowed the BIC-optimum lag lengths to vary for positive and negative changes, further evidence of pattern asymmetry is obtained if the optimal lag lengths are different. Though this is often the case, I fix the lag lengths and focus most of my attention on the asymmetries in equations 5 and 6.

## 3. DATA AND DESCRIPTIVE STATISTICS

I combine two datasets to perform the analysis. Spot prices are available from Reuters via the Energy Information Administration (EIA) and rack and retail price data are from the Oil Price Information Service (OPIS). All data are available daily (weekends and missing values discussed below) from 2000 through 2013 though some series are not available for the entire period. Summary statistics are provided in tables 1, 2, and 3.

Spot prices include the price of West Texas Intermediate (WTI) crude oil at Cushing, Oklahoma and Brent crude oil produced in the North Sea region. I also obtain the conventional and reformulated gasoline (RFG) spot prices on the Gulf Coast[11] along with another conventional spot at New York Harbor and RFG/RBOB[12] spot price for Los Angeles. Spot prices are reported as of the close of day, Monday through Friday.

I use rack prices from OPIS for 20 U.S. cities. These rack prices are for the type of gasoline used in each city since many cities utilize different types of gasoline (conventional, RFG, etc.). In some cases, rack prices for different types of gasoline are reported in the same city. In these cases, I use the rack price that corresponds to the type of gasoline that is used in each retail market area. For example, the Fairfax, VA rack reports both conventional and RFG prices. Since I observe retail data for stations in Washington, DC, as well as the Virginia, Maryland, and West Virginia suburbs

11. The Gulf Coast RFG price becomes Gulf RFG with Ethanol in June 2006.

12. RBOB is short for Reformulated Blendstock for Oxygenate Blending. The Los Angeles RFG price is replaced with the RBOB spot price in November 2003.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 2: Daily Branded Rack Prices (Cents per Gallon)**

| Rack | N | Min | Mean | Max | Std Dev | Date Range | Margin Over WTI |
|---|---|---|---|---|---|---|---|
| Atlanta (Conventional) | 4,298 | 50.64 | 182.75 | 354.29 | 81.37 | 1/00–12/13 | 33.08 |
| Boston (RFG) | 4,365 | 56.15 | 187.77 | 362.22 | 82.29 | 1/00–12/13 | 38.54 |
| Chicago (RFG) | 4,365 | 61.64 | 190.28 | 366.60 | 81.16 | 1/00–12/13 | 41.10 |
| Cleveland (Conventional) | 4,365 | 54.22 | 183.90 | 359.30 | 80.55 | 1/00–12/13 | 34.66 |
| Dallas (RFG) | 4,365 | 54.47 | 184.81 | 356.63 | 80.82 | 1/00–12/13 | 35.62 |
| Denver (Conventional) | 4,365 | 52.23 | 183.68 | 364.76 | 80.80 | 1/00–12/13 | 34.65 |
| Detroit (Conventional) | 4,365 | 52.02 | 184.43 | 361.20 | 81.53 | 1/00–12/13 | 35.26 |
| Fairfax (Conventional) | 4,365 | 53.49 | 185.84 | 356.28 | 81.68 | 1/00–12/13 | 36.64 |
| Fairfax (RFG) | 4,365 | 51.22 | 180.84 | 351.70 | 80.28 | 1/00–12/13 | 31.62 |
| Houston (RFG) | 4,364 | 52.44 | 182.77 | 355.03 | 81.14 | 1/00–12/13 | 33.53 |
| Los Angeles (CARB) | 4,062 | 59.28 | 207.39 | 392.91 | 77.66 | 12/00–12/13 | 52.72 |
| Louisville (Conventional) | 4,348 | 52.58 | 183.23 | 355.70 | 80.08 | 1/00–12/13 | 33.74 |
| Louisville (RFG) | 3,563 | 84.89 | 216.85 | 376.64 | 74.38 | 7/02–12/13 | 48.72 |
| Miami (Conventional) | 4,361 | 50.98 | 182.11 | 353.51 | 81.44 | 1/00–12/13 | 32.97 |
| Minneapolis (Conventional) | 4,363 | 51.41 | 184.76 | 363.60 | 79.61 | 1/00–12/13 | 35.60 |
| New Orleans (Conventional) | 4,365 | 50.02 | 178.71 | 350.88 | 80.26 | 1/00–12/13 | 29.52 |
| Newark (RFG) | 2,374 | 98.89 | 245.14 | 355.16 | 54.72 | 5/06–12/13 | 44.60 |
| Phoenix (Conventional) | 4,365 | 61.61 | 195.62 | 366.58 | 79.66 | 1/00–12/13 | 46.61 |
| Salt Lake City (Conventional) | 4,364 | 59.11 | 188.71 | 367.52 | 80.99 | 1/00–12/13 | 39.83 |
| San Francisco (CARB) | 4,158 | 59.23 | 202.17 | 380.51 | 77.82 | 1/00–12/13 | 49.33 |
| Seattle (Conventional) | 4,365 | 56.21 | 190.64 | 364.57 | 80.77 | 1/00–12/13 | 41.60 |
| St Louis (Conventional) | 4,357 | 52.51 | 182.27 | 355.41 | 80.00 | 1/00–12/13 | 33.14 |
| St Louis (RFG) | 4,365 | 57.92 | 188.11 | 364.79 | 79.10 | 1/00–12/13 | 38.97 |

Some racks service multiple states with different types of wholesale gasoline. The Fairfax, VA rack sells RFG to stations in DC, MD, and VA, while it sells conventional gasoline to stations in WV. Similarly Louisville and St. Louis sell conventional gasoline to stations in IN and IL and RFG to stations in KY and MO respectively.

of DC, I match the RFG rack price to DC, VA, and MD since each uses primarily RFG, while the WV retail prices are matched to the conventional rack since that area primarily uses conventional gasoline. Rack prices are reported as of 9AM, Monday through Saturday and are available for both branded and unbranded products.[13]

Some racks service multiple states with different types of wholesale gasoline. The Fairfax, VA rack sells RFG to stations in DC, MD, and VA, while it sells conventional gasoline to stations in WV. Similarly Louisville and St. Louis sell conventional gasoline to stations in IN and IL and RFG to stations in KY and MO respectively.

Finally, I utilize pre-tax retail price data from OPIS for the 27 retail metro areas all within the 20 cities for which I have rack prices. Retail prices are (usually) end of the day prices as they are recorded from the last swipe of a consumer's "fleet-card" on a given day.[14] OPIS averages all the prices they receive each day (at most one from each station) to determine the price for the metro area. After 2001, the prices are reported every day of the week. OPIS samples over 100,000 stations each day and covers branded and unbranded stations. As shown in table 3, (pre-tax) retail prices varied significantly during this period from 53 cents per gallon to over $4 per gallon. The Seattle

13. For racks that report multiple prices for different types of RFG or different types of conventional gasoline on the same day, the lowest price quote is selected.

14. See http://www.opisretail.com/methodology.html for more information on OPIS's retail data. More than one-half of the stations in the OPIS sample report a price each day, though the sample of stations may change from day to day.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 3: Daily Retail Prices (Cents per Gallon)**

| Retail Area | N | Min | Mean | Max | Std Dev | Date Range | Margin Over Rack |
|---|---|---|---|---|---|---|---|
| Atlanta | 4,930 | 60.09 | 196.03 | 360.72 | 80.88 | 1/00–12/13 | 10.42 |
| Boston | 4,930 | 69.82 | 208.63 | 366.50 | 82.60 | 1/00–12/13 | 17.59 |
| Chicago | 4,930 | 67.75 | 208.90 | 378.24 | 83.76 | 1/00–12/13 | 15.43 |
| Cleveland | 4,930 | 63.61 | 200.77 | 369.15 | 81.82 | 1/00–12/13 | 13.72 |
| Dallas | 4,930 | 62.48 | 199.06 | 359.40 | 80.97 | 1/00–12/13 | 11.00 |
| Denver | 4,929 | 61.51 | 200.42 | 360.39 | 80.48 | 1/00–12/13 | 13.54 |
| Detroit | 4,930 | 61.57 | 199.54 | 362.99 | 81.87 | 1/00–12/13 | 11.89 |
| Houston | 4,870 | 75.20 | 221.38 | 380.73 | 84.94 | 1/00–12/13 | 30.70 |
| Los Angeles | 4,930 | 72.16 | 209.72 | 368.13 | 82.53 | 1/00–12/13 | 20.54 |
| Louisville IN | 4,930 | 63.97 | 205.44 | 363.64 | 83.16 | 1/00–12/13 | 16.29 |
| Louisville KY | 4,928 | 65.49 | 203.54 | 362.74 | 85.19 | 1/00–12/13 | 19.25 |
| Miami | 4,930 | 60.97 | 197.19 | 357.66 | 81.08 | 1/00–12/13 | 11.16 |
| Minneapolis MN | 4,929 | 53.85 | 217.29 | 397.34 | 83.44 | 1/00–12/13 | 13.99 |
| Minneapolis WI | 4,928 | 64.57 | 195.74 | 361.26 | 79.62 | 1/00–12/13 | 9.67 |
| New Orleans | 4,929 | 68.79 | 205.52 | 388.44 | 81.15 | 1/00–12/13 | 7.06 |
| Newark | 4,930 | 62.18 | 203.53 | 365.27 | 83.13 | 1/00–12/13 | 17.79 |
| New York City | 4,930 | 59.44 | 201.54 | 385.61 | 79.83 | 1/00–12/13 | 13.69 |
| Pheonix | 4,928 | 63.64 | 201.67 | 369.52 | 80.33 | 1/00–12/13 | 13.68 |
| Salt Lake City | 4,928 | 63.31 | 199.25 | 362.24 | 80.48 | 1/00–12/13 | 17.19 |
| San Francisco | 4,929 | 68.22 | 208.71 | 367.73 | 82.17 | 1/00–12/13 | 19.90 |
| Seattle | 4,930 | 77.39 | 218.26 | 381.63 | 86.64 | 1/00–12/13 | 34.96 |
| St Louis IL | 4,929 | 68.04 | 209.46 | 377.72 | 78.93 | 1/00–12/13 | 10.43 |
| St Louis MO | 4,929 | 62.85 | 200.65 | 373.46 | 81.56 | 1/00–12/13 | 8.62 |
| Washington DC | 4,929 | 87.55 | 228.08 | 401.90 | 79.39 | 1/00–12/13 | 27.03 |
| Washington MD | 4,929 | 78.39 | 215.87 | 384.57 | 83.01 | 1/00–12/13 | 21.83 |
| Washington VA | 4,930 | 57.98 | 192.86 | 350.23 | 79.45 | 1/00–12/13 | 7.23 |
| Washington WV | 4,929 | 59.26 | 199.22 | 363.56 | 81.12 | 1/00–12/13 | 8.00 |

This table shows statistics by “retail market area” as reported by OPIS. Prices are generated using Fleet Card purchases from all stations in the area.

metro area had the highest average margin (retail less rack price) over the sample period while New Orleans had the lowest average margin.

Given the different reporting times of day for each price series, when running regressions using daily data, it is important that lags are used where appropriate. For example, when considering the speed of pass-through from rack to retail, I can consider the effect for the same time stamp since end of day retail prices have a chance to adjust to a change in the rack price observed at the beginning of the day. However, in the spot to rack pass-through regressions, I use the lagged spot price because these two price series are reported at the same time of day.

My data include both branded and unbranded rack prices. Generally, unbranded gasoline is more homogeneous across refiners because it includes only a generic package of additives and lacks a brand name premium. Therefore, in most cases, branded gasoline is about five cents more expensive than unbranded. However, at times the unbranded price exceeds the branded price.[15] Many of these inversions follow supply shocks (e.g., hurricanes and refinery outages) as refiners may be giving priority to their branded customers to maintain the brand image, resulting in a more

15. Across all cities, the unbranded price exceeds the branded price on 12% of the days in my sample. Among cities, this percentage varies from less than 4% in Minneapolis and New Orleans to over 25% in Los Angeles, San Francisco, and St. Louis.

Copyright © 2016 by the IAEE. All rights reserved.

severe supply reduction for unbranded gasoline. Whatever the cause, below I investigate the asymmetric response for branded and unbranded fuel separately.

In addition to data from EIA and OPIS, I also gather information on each city in the sample to assess factors that may be associated with more or less asymmetric pass-through. Some factors, such as the degree of price cycling and the speed of cost pass-through can be calculated using the EIA data. In addition, I calculate brand-level retail market concentration for each city based on sales data from New Image Marketing Research Corporation.[16] These data provide brand-level sales for 22 of the 27 cities in my sample for a single year between 1998 and 2001, which is around the start of my sample period.

### 3.1 Data Issues

Before focusing on the results, there are a few issues with the data that need to be addressed. I run my regressions at both a daily and a weekly frequency. Weekly data is generated both as the simple average of the daily series and by choosing a specific day of each week.[17] Using the daily average means that sometimes the average is over five days, other times six days, four days, etc. Using the weekly price series based on a particular day of the week avoids this issue, though it turns out that the estimates using either method are almost identical.

Due to weekends, holidays, etc, there are some missing values in the daily data. Since the regression equations involve the contemporaneous and lagged change in prices, it is important to make constant the time over which the change is calculated. For over 99.9% of the daily observations, the difference in days between observations is three or less (82.8% of the observations are adjacent). In the results presented in the next section, I linearly interpolate the prices if one or two days are missing between observations and I drop any observation where the change in price is over three or more days. The resulting dataset contains daily observations where the change in prices is always over exactly one day. For robustness, I also consider two alternative methodologies:

1. do not interpolate and drop changes over three or more days;
2. do not interpolate and do not drop multi-day changes.

Each of these alternatives lead to qualitatively similar results. The estimates themselves change only slightly and are never statistically different from each other. For example, using the branded rack-to-retail national specification, the positive and negative contemporary coefficients ($\beta^{+}_{1,1}$ and $\beta^{-}_{1,1}$) using the baseline algorithm are 0.23 and 0.08 respectively. They change slightly to 0.23 and 0.07 using alternative one, and 0.24 and 0.07 using alternative two.

Finally, at one time the spot price for RFG was for reformulated gasoline blended with MTBE, which has now been banned in most states.[18] It has been replaced by the RBOB spot price, which is RFG that will eventually get blended with an oxygenate (typically ethanol). For the LA spot price, there is some overlap in the two series so I create a complete spot price series for RFG using the old RFG spot for the early part of the sample and switching to the RBOB spot as soon as it is reported. The two prices are similar to each other during the overlap period.[19] For the Gulf

16. See http://www.nimresearch.com/.

17. My algorithm selects the price on Wednesday in almost all weeks, though selects the price on Thursday in the few weeks when there is no reported Wednesday price.

18. In some states the liability protection has been removed so refiners are reluctant to use it.

19. A simple regression of the RFG spot on the RBOB spot during the overlap yields a slope coefficient of 0.95.

Copyright © 2016 by the IAEE. All rights reserved.

Coast, there is no overlap (the RFG spot ends on one day and the RBOB spot begins being reported on the very next day) so I concatenate the two series to form my complete Gulf Coast RFG spot price. However, the RBOB price on its first day reported is 38 cents higher than the RFG spot on the previous day.[20] For robustness, I have run the models only using dates where I observe the RFG spot price and the results are qualitatively similar.

## 4. RESULTS

Before analyzing the results, it is important to test for stationarity of the regressors. I run a Dickey Fuller (DF) test on each price series, which show that all have a unit root so first differencing is necessary. I then run the Johansen test on each set of price series together and confirm that the upstream and downstream price series are cointegrated (i.e., the residuals from the long-run regression equation 3 are stationary).[21] Therefore, estimating the long-term relationship in the first stage provides super-consistent estimates that can be entered into the model directly. Durbin Watson tests for autocorrelation correlation are also run and fail to reject the hypothesis that there is no autocorrelation in the residuals for each model.

I divide the results into several sections which consider the differences in pattern asymmetry among different price relationships, across cities and in the national regression, by the time aggregation of the data, for branded versus unbranded wholesale gasoline, and over time. I show formal F-tests of pattern asymmetry for each type of model and provide evidence of city-specific factors that are correlated with the magnitude of asymmetry.

### 4.1 Price Relationships

I investigate pass-through asymmetry for combinations of the crude oil price, the gasoline spot price, the branded and unbranded rack prices, and the retail price series. The following tables and figures summarize the results of the national specification. The long-run coefficients are estimated separately for each city and then equation 1 is estimated for all the cities combined.

The relationships include the following:

1. the crude oil price to the gasoline spot price, the rack prices, and the retail price,[22]
2. the closest gasoline spot price to the rack prices and the retail price, and[23]
3. the rack price to the retail price.

Complete results for one of these regressions (rack to retail) is shown in table 4. In this specification, I include five lags of the rack and retail price changes. Similar results are found using

20. This difference is large compared with the mean absolute day-to-day changes for RFG and RBOB of 2.6 and 5.1 cents respectively.

21. Both tests are carried out assuming a constant term in the polynomial under the null hypothesis. Dickey Fuller tests on each price series confirm the presence of a unit root at the 5% significance level. Johansen tests on each pair of upstream and downstream prices reject the null hypothesis that no cointegrating relationship exists. The tests are significant at the 5% level in all cases except one (WTI/Newark-NJ branded rack), which is significant at the 10% level. Complete statistical results are available from the author upon request.

22. I estimate the crude to spot relationship for each of the six spot prices available on EIA's website: conventional gasoline and RFG in NY, Houston, and LA.

23. I use the NY spot price for Boston and Newark. I use the LA spot price for LA, San Francisco, Phoenix, Salt Lake City and Seattle. For the remaining cities, I use the Gulf Coast spot price.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 4: Regression Results: Branded Rack to Retail Prices, All Cities**

| Variable | Coeff. | t-stat |
|---|---|---|
| + (Rack(t) − Rack(t-1)) | 0.220*** | 102.179 |
| + (Rack(t-1) − Rack(t-2)) | 0.072*** | 29.990 |
| + (Rack(t-2) − Rack(t-3)) | 0.011*** | 4.653 |
| + (Rack(t-3) − Rack(t-4)) | 0.038*** | 15.662 |
| + (Rack(t-4) − Rack(t-5)) | 0.035*** | 14.706 |
| − (Rack(t) − Rack(t-1)) | 0.088*** | 42.023 |
| − (Rack(t-1) − Rack(t-2)) | 0.061*** | 26.775 |
| − (Rack(t-2) − Rack(t-3)) | 0.031*** | 13.472 |
| − (Rack(t-3) − Rack(t-4)) | 0.028*** | 12.088 |
| − (Rack(t-4) − Rack(t-5)) | 0.029*** | 12.904 |
| + (Retail(t-1) − Retail(t-2)) | 0.352*** | 108.684 |
| + (Retail(t-2) − Retail(t-3)) | −0.141*** | −41.429 |
| + (Retail(t-3) − Retail(t-4)) | −0.032*** | −9.257 |
| + (Retail(t-4) − Retail(t-5)) | −0.029*** | −9.080 |
| − (Retail(t-1) − Retail(t-2)) | 0.331*** | 44.340 |
| − (Retail(t-2) − Retail(t-3)) | 0.052*** | 6.566 |
| − (Retail(t-3) − Retail(t-4)) | 0.086*** | 10.890 |
| − (Retail(t-4) − Retail(t-5)) | 0.066*** | 9.241 |
| + EC Term | −0.023*** | −31.896 |
| − EC Term | −0.053*** | −61.667 |
| Observations | 130,421 | |
| Durbin-Watson | 2.01 | |
| $R^2$ | 0.40 | |

Dependent varible: Retail(t) − Retail(t-1). Significant at the 1% (***) level.

a larger number of lags. Though a complete picture of pass-through asymmetry can only be seen from an impulse response graph, the contemporary coefficients on the change in the rack price embodies the speed of pass-through if we think of the model as approximating a first-order difference equation. In this specification, the positive and negative coefficients are 0.22 and 0.09 respectively. This means that based on the contemporary coefficients, retail prices rise 2.4 times as fast when the rack price increases, than they fall when the rack price declines.[24] The asymmetry persists for the other lags, but the difference quickly becomes small. The coefficients on the error correction terms are negative and significant as expected and rockets and feathers asymmetry is evident here as well: when retail prices are above their level predicted by the rack price ($z_{t-1} > 0$), retail prices fall more slowly compared with the speed at which retail prices rise when they are below their predicted level.

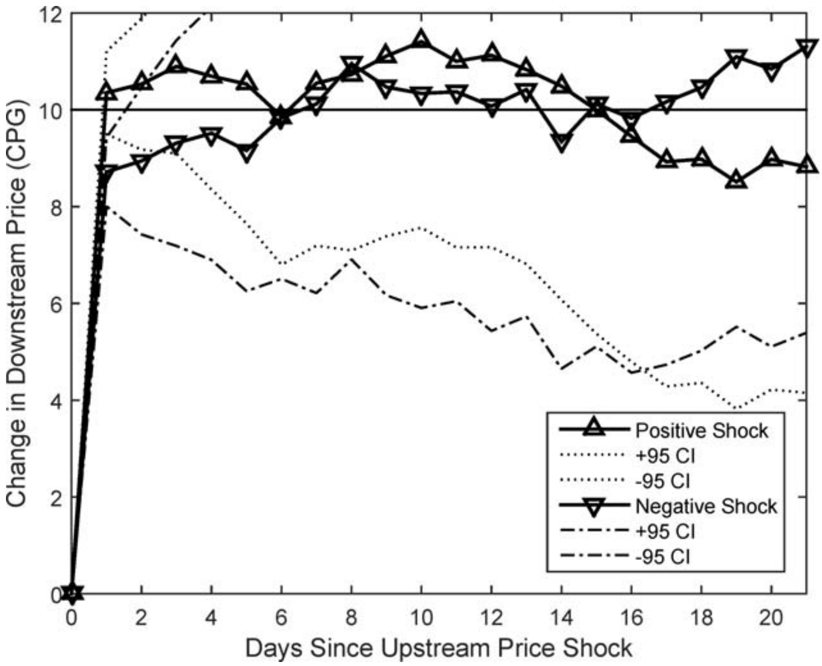
Following the literature on asymmetric pass-through, it is helpful to graphically present the full impact of these results. The reason is that a one-time change in the upstream price will have an immediate effect on the downstream price, but the total effect may be drawn out over a period of days and include both the short-term speed of adjustment (the $\beta_1$ terms in equation 1), the own-lag effects (the $\beta_2$ terms), and the long-term error correction effects (the $\beta_3$ terms). For this reason, I present impulse response functions that trace out the effects of a ten cent per gallon change (positive or negative) in the upstream price on the downstream price over a period of several days following the shock. The 95% confidence bands are also shown in each graph.[25]

24. Adjusting the number of lags included in the regression only slightly affects the results.

25. To account for possible nonlinearities in the relationships between the upstream and downstream prices, I consider an upstream price increase from 200 cpg to 210 cpg and a corresponding decrease from 210 cpg to 200 cpg.

Copyright © 2016 by the IAEE. All rights reserved.

**Figure 1: Impulse Response Function: WTI to Spot, National**




Figures 1, 2, and 3 display the impulse response function tracing out the effect on the downstream price of a 10 cpg change in the upstream price. I have shown the relationships between the crude oil and spot prices, the spot and branded rack prices, and the branded rack and retail prices. The appendix includes impulse response functions for four other price relationships: crude oil to branded rack prices (figure A2), crude oil to retail prices (figure A3), spot to retail prices (figure A4), and unbranded rack to retail prices (figure A5) . All of these impulse response functions reflect a national-level regression with prices from all cities included.

The impulse response functions plot the changes in the downstream price in the 21 days following the change in the upstream price. For a negative shock to the upstream price, the absolute value of the change in the downstream price is shown so a comparison can be made between the two response paths. Figures 1 and 2 show relatively little asymmetric adjustment. The 95% confidence intervals often overlap meaning the response paths are not statistically different from each other. In the case of the spot to branded rack price, the asymmetry disappears after about three days. However, as shown in figure 3, the rockets and feathers type of asymmetry (where the response time of positive shocks exceeds negative shocks) is strongest in the branded rack to retail relationship. The rapid rise in the retail price following a positive shock is reflected in the steep slope of the response path. The asymmetry persists until approximately ten days following the shock at which time the response paths are not statistically distinguishable. Note that full pass-through is achieved for positive and negative shocks after about three weeks so there is no amount asymmetry as was discussed in section 2.

A convenient way to quantify the asymmetry is to calculate the following:

$$Impact = \int_{t \in T^*} \Delta^+ P(t) - \left| \Delta^- P(t) \right| dt, \tag{8}$$

Copyright © 2016 by the IAEE. All rights reserved.

**Figure 2: Impulse Response Function: Spot to Branded Rack, National**

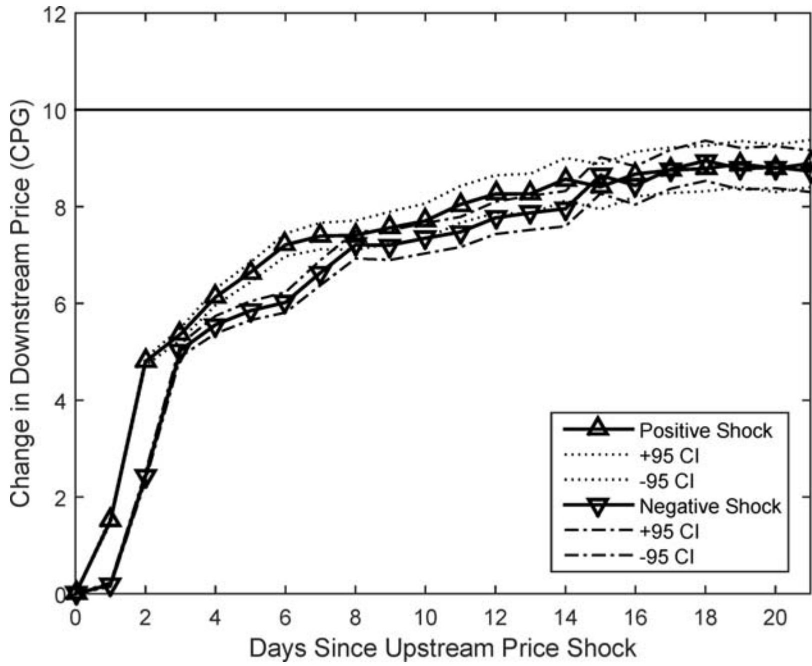
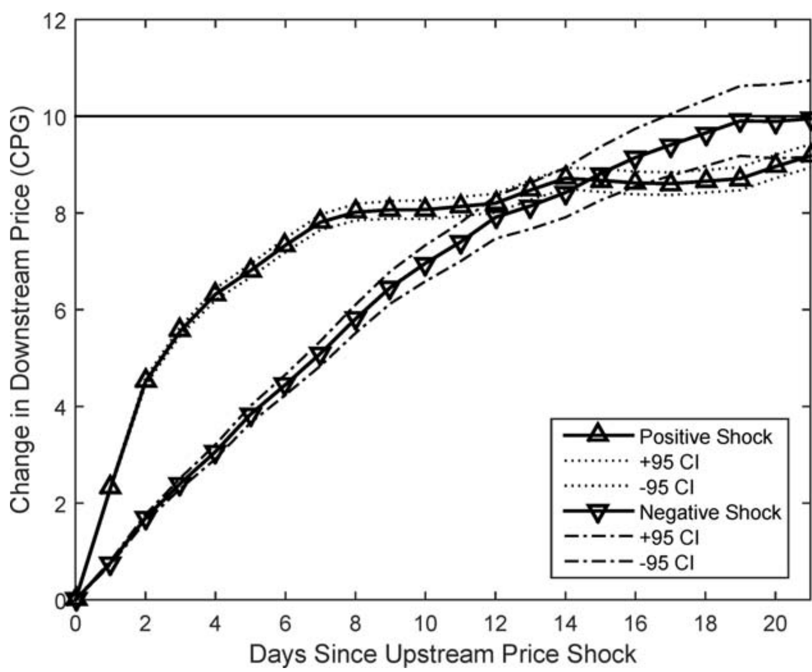
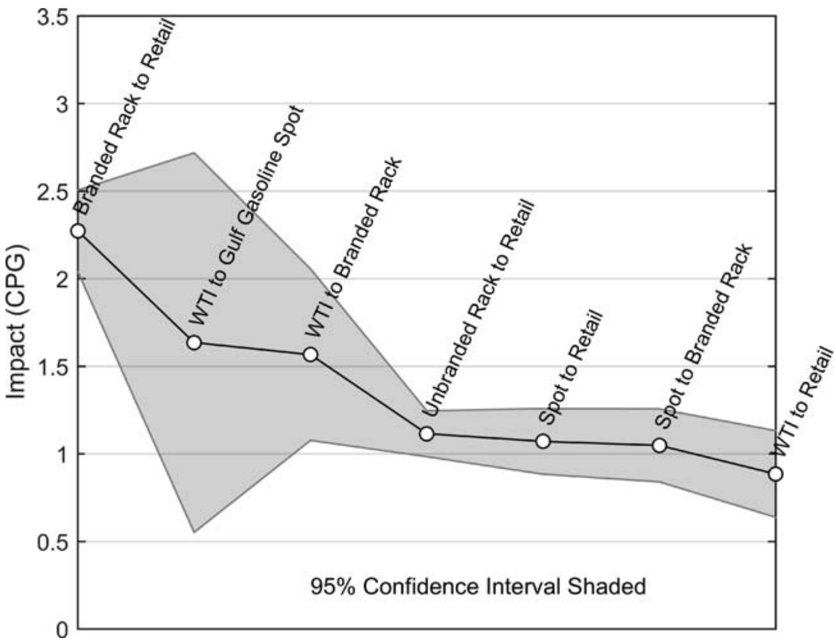



**Figure 3: Impulse Response Function: Branded Rack to Retail Prices, National**




Copyright © 2016 by the IAEE. All rights reserved.

**Figure 4: Impact Estimates**




where $T^*$ defines any time period where the response paths are significantly different from each other. $\Delta^+ P(t)$ and $|\Delta^- P(t)|$ are simply the (absolute) changes in downstream prices at time $t$ following positive and negative shocks respectively. In figure 3, the estimate of impact simplifies to calculating the average price following a positive shock and subtracting the average price following a negative shock where the average is taken over the first ten periods.

Impact estimates for each price series are shown in figure 4. The largest impact of 2.27 cpg is for the branded rack to retail relationship. Other relationships show a positive and significant impact between 1 and 1.5 cpg.[26] The real-world interpretation of this result is as follows. Consider two 3-week periods, one following a one-time rack price increase from 200 cpg to 210 cpg and one following a one-time rack price decrease from 210 cpg to 200 cpg. Assume consumers randomly purchased retail gasoline over the course of each period. With symmetric pass-through, consumers would on average pay the same amount for retail gasoline over both periods. However, with asymmetric pass-through, consumers purchasing retail gasoline following a rack price increase will pay 2.27 cpg more than consumers purchasing retail gasoline following a decrease in the rack price.

Bacon (1991) found a similar asymmetry in rack to retail prices, while Bachmeier and Griffin (2003) find no evidence of asymmetry in the crude oil to gasoline spot price transmission, consistent with my results. BCG (1997) do not find any significant asymmetry in the gasoline spot to rack relationship, but they do find significant asymmetry in the crude to gasoline spot and the rack to retail relationships. Since BCG relies on bi-weekly data, I have also run my specifications using only prices from every other week and my impact results are larger though the estimates are based on different cities over a different period of time.[27]

26. The confidence interval on the WTI to Gulf gasoline spot relationship is larger than the others due to fewer observations. Other specifications estimate the average impact over multiple retail and wholesale market areas.

27. The rack (wholesale) to retail impact estimate in BCG is 1 cpg while I estimate the impact to be 1.57 cpg. The estimate in BCG is based on 164 bi-weekly observations, while I am fortunate to have over 130,000 daily observations.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 5: Difference in First Coefficients on Lagged Upstream Price**

| | $\beta_1^+$ | t-stat | $\beta_1^-$ | t-stat | $\beta_1^+ - \beta_1^-$ | t-stat |
|---|---|---|---|---|---|---|
| Atlanta | 0.21*** | 30.94 | 0.04*** | 6.15 | 0.17*** | 17.63 |
| Boston | 0.16*** | 33.24 | 0.05*** | 10.92 | 0.11*** | 16.40 |
| Chicago | 0.22*** | 31.84 | 0.07*** | 11.02 | 0.15*** | 14.97 |
| Cleveland | 0.41*** | 27.61 | 0.13*** | 8.73 | 0.29*** | 13.86 |
| Dallas | 0.17*** | 30.79 | 0.07*** | 13.03 | 0.10*** | 12.90 |
| Denver | 0.12*** | 23.78 | 0.03*** | 6.79 | 0.09*** | 12.23 |
| Detroit | 0.42*** | 48.75 | 0.16*** | 19.11 | 0.26*** | 21.53 |
| Washington DC | 0.14*** | 12.76 | 0.03*** | 2.75 | 0.11*** | 7.18 |
| Washington MD | 0.14*** | 29.16 | 0.04*** | 9.05 | 0.10*** | 14.50 |
| Washington VA | 0.13*** | 27.25 | 0.05*** | 9.89 | 0.08*** | 12.48 |
| Washington WV | 0.10*** | 9.76 | 0.06*** | 6.05 | 0.04*** | 2.65 |
| Houston | 0.16*** | 42.73 | 0.05*** | 13.00 | 0.12*** | 21.57 |
| Los Angeles | 0.30*** | 39.24 | 0.06*** | 8.24 | 0.24*** | 22.78 |
| Louisville IN | 0.27*** | 15.42 | 0.07*** | 4.40 | 0.20*** | 8.17 |
| Louisville KY | 0.43*** | 16.60 | 0.12*** | 4.93 | 0.31*** | 8.57 |
| Miami | 0.16*** | 37.19 | 0.04*** | 9.68 | 0.12*** | 20.17 |
| Minneapolis St Paul MN | 0.43*** | 26.51 | 0.12*** | 7.31 | 0.32*** | 14.00 |
| Minneapolis St Paul WI | 0.13*** | 14.73 | 0.06*** | 6.63 | 0.07*** | 5.98 |
| New Orleans | 0.17*** | 30.72 | 0.06*** | 11.77 | 0.11*** | 14.26 |
| Newark | 0.14*** | 24.11 | 0.06*** | 10.96 | 0.08*** | 10.23 |
| New York | 0.09*** | 16.61 | 0.05*** | 9.66 | 0.04*** | 5.61 |
| Phoenix | 0.20*** | 18.65 | 0.06*** | 5.93 | 0.13*** | 8.78 |
| Salt Lake City | 0.16*** | 12.84 | 0.08*** | 6.58 | 0.08*** | 4.73 |
| San Francisco | 0.25*** | 27.70 | 0.08*** | 8.49 | 0.17*** | 13.64 |
| Seattle | 0.21*** | 32.28 | 0.06*** | 9.38 | 0.15*** | 16.65 |
| St Louis IL | 0.24*** | 18.20 | 0.12*** | 8.84 | 0.12*** | 6.57 |
| St Louis MO | 0.37*** | 16.94 | 0.15*** | 7.05 | 0.21*** | 6.97 |
| National Specification | 0.23*** | 100.00 | 0.08*** | 34.13 | 0.15*** | 47.83 |

Estimates from the branded rack to retail specification, by city. Estimates of the first difference in positive and negative rack price coefficients. Positive and significant differences are evidence of rockets and feathers. Significant at the 1% (***) level.

### 4.2 Individual City Results

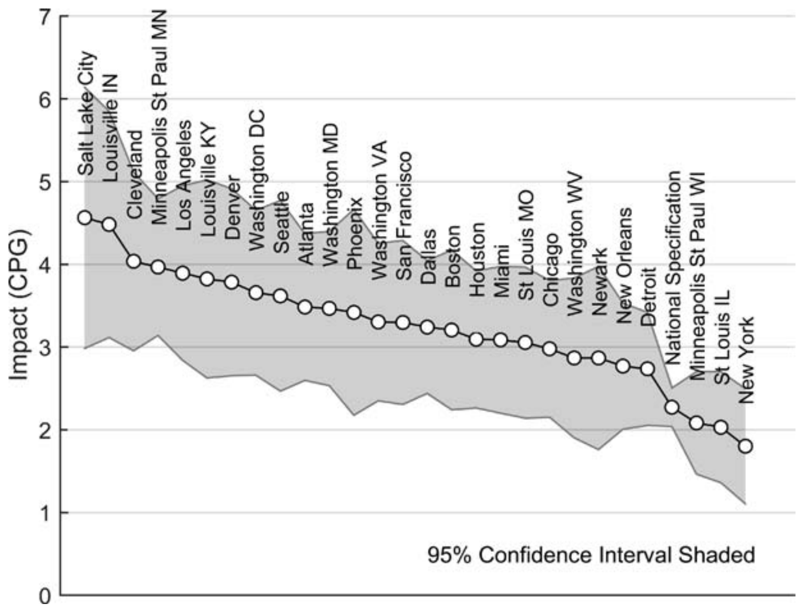
The evidence of asymmetry found in the previous section is mostly confirmed by regressions run at the individual city level. I focus only the branded rack to retail price relationships analyzed in the last section. Table 5 shows the estimates and t-statistics for the contemporaneous coefficients on the positive and negative rack changes. The positive and significant difference between each set of coefficients shows evidence of rockets and feathers asymmetry in every city in the sample.

While I find evidence of asymmetric pass-through from branded rack to retail prices in every city, the overall impact of the asymmetry can only be achieved by estimating the impulse response function and calculating the impact as shown in equation 8. These results are reported in figure 5. Salt Lake City features the largest asymmetry with an impact of about 4.5 cpg (even though the largest differential in the $\beta_1$ estimates was in Minneapolis-MN). Other cities, such as, Louisville-IN, Cleveland, and Minneapolis-MN also show relatively more asymmetry, while Minneapolis-WI, St. Louis-IL, and New York have the least asymmetry.[28] I also calculate the speed of

28. The data feature several periods when the observed retail price is less than the rack price. This may result from short-term shortages at the wholesale level. This happens sporadically and primarily in four areas (Louisville-KY, Phoenix-

Copyright © 2016 by the IAEE. All rights reserved.

**Figure 5: Impact of Asymmetric Adjustment, By City, Branded Rack to Retail**




pass-through by comparing the slopes of the impulse response functions over the first three periods following the cost shock. The speed of pass-through is between three and four times faster when rack prices rise than when they fall.

Interestingly, while three of the retail areas that straddle state lines show similar levels of asymmetry on both sides of the line (Louisville, St. Louis, and Washington), Minneapolis shows significantly more asymmetry west of the Mississippi and less to the east. One potential explanation is due to population density: Minneapolis, WI is much more rural than Minneapolis, MN. The other state-straddling areas are more urban on both sides of the border.[29]

Finally, note that the national-specification impact estimate (2.27 cpg) is not a simple average of the city-level estimates (3.28 cpg) because each impact is calculated as the difference in the impulse response functions over days when they are statistically different. The number of days in this calculation varies from city to city and for the national specification.

### 4.3 Time Aggregation

One of the major differences between the various studies in the extant literature is the frequency of the data used. Many rely on less frequent, bi-weekly or monthly data simply because it it more widely available. In this section, I consider the effect of using daily versus weekly data on the likelihood of finding evidence of pass-through asymmetry.

AZ, StLouis-IL, and StLouis-MO). I have run the national specification and individual city models excluding these periods and the estimates of asymmetry are essentially unchanged.

29. The population density in the Minnesota counties around Minneapolis is over six times the population density in the nearby Wisconsin counties based on the 2010 census. Washington-WV also has a population density less than half that of the other Washington area metro areas, and it also shows relatively less asymmetric adjustment.

Copyright © 2016 by the IAEE. All rights reserved.

**Figure 6: Frequency Analysis: Daily versus Weekly, Rack to Retail**

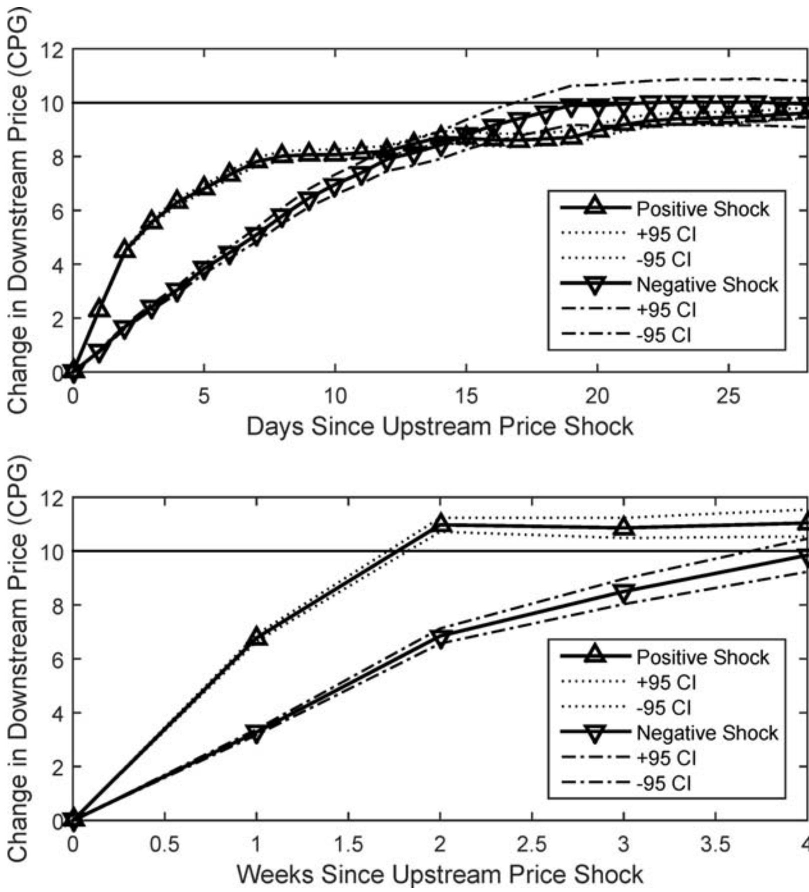



Figure 6 shows the same impulse response function for branded rack to retail, but the top panel uses daily data while the bottom panel uses average weekly prices. While, in general, both show an asymmetric adjustment pattern, the day-to-day variation is being smoothed in the bottom panel, which masks the pass-through dynamics between the two price series. The results are very similar when using weekly prices based on a specific day of each week instead of weekly averages. The impact of asymmetry is 2.80 cpg using average weekly prices and 2.77 cpg using once-per-week prices.[30]

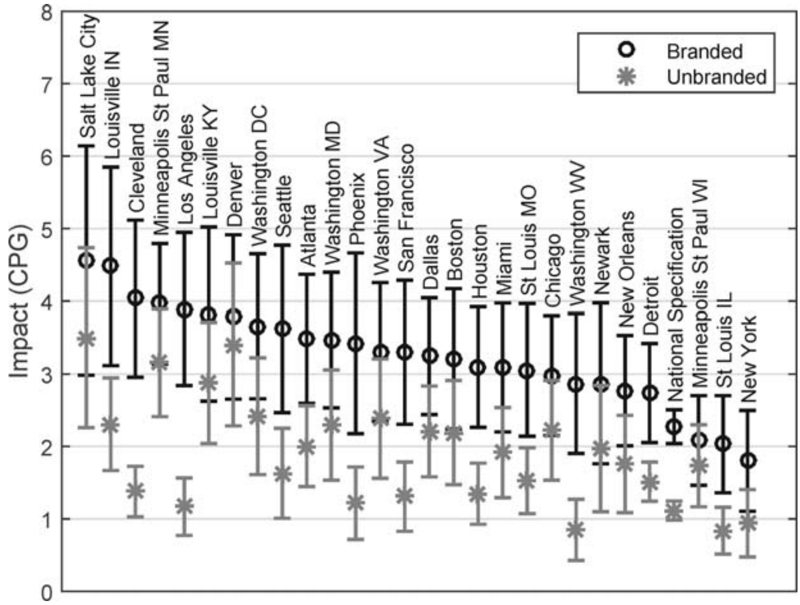
The weekly impact estimate is significantly higher than the impact based on daily price changes (2.27 cpg). Comparing the impulse response functions, it is clear that using daily data, retail prices are predicted to rise slower following a positive cost shock and fall faster following a negative cost shock compared with weekly data.[31] Both of these effects cause the impact estimate

30. The once-per-week specification generally uses the price on Wednesday of each week, though when that price is missing, the Tuesday or Thursday price is selected.

31. Based on daily (weekly) data, complete pass-through is achieved in 28 (12) days following positive shocks and 17 (25) days following negative shocks.

Copyright © 2016 by the IAEE. All rights reserved.

**Figure 7: Impact of Asymmetric Adjustment, By City, Branded versus Unbranded**




to be larger based on the weekly data, but complete pass-through is achieved for both positive and negative shocks by about four weeks using either frequency of data.

### 4.4 Branded versus Unbranded

Branded wholesale gasoline is generally a few cents more expensive than unbranded gasoline given the former has proprietary additives (and a brand-name premium) included. However, at times, the unbranded price will exceed the branded price, and this occurs especially following negative supply shocks. As shown in figure 7, the asymmetry for branded gasoline is significantly higher than for unbranded gasoline in about one-half of the retail market areas.[32]

Therefore, while the unbranded price "rockets up" more quickly than the branded price following a supply shock, the unbranded price also retreats back to equilibrium levels at a faster pace than the branded price. In some cities, such as, Seattle, Cleveland, and Los Angeles, the difference in asymmetry is very large with branded prices being more than twice as asymmetric compared with unbranded prices. The result that unbranded gasoline prices exhibit less asymmetry is consistent with the literature that claims heterogeneous consumer search costs are the cause of asymmetric adjustment (e.g., Lewis (2011)). Consumers who buy branded gasoline are likely more loyal to a single brand, while unbranded buyers are more likely to shop around for the best price. A negative cost shock would be passed on more quickly to unbranded prices than to branded prices, reducing the asymmetry in the unbranded price relationship.

32. The impulse response function for the unbranded rack to retail relationship is shown in figure A5. The impact estimate for the unbranded rack to retail national specification is 1.12 cpg, about half that found in the branded rack to retail relationship (2.27 cpg).

Copyright © 2016 by the IAEE. All rights reserved.

### 4.5 Differences Over Time

While the previous results display the differences in asymmetry in different price relationships and cities for a single permanent change in the upstream price, the actual impact of the rockets and feathers phenomenon depends on how the variability of the price series being analyzed changes through time. More data are required to identify how the pass-through relationship has changed over time (i.e. the coefficients in equation 1), so in this section I quantify the amount of asymmetry in each year of the sample using the same set of estimated coefficients. The extreme cases, when prices always rise or always fall, result in complete rockets behavior or complete feathers behavior respectively. If prices are fairly stable or upstream prices generally rise, the impact of asymmetric pass-through will be small, while the feathering effect will be large if prices generally fall during the sample period.

To quantify the impact of asymmetric pass-through over time, I use the actual upstream (rack) price and estimate the downstream (retail) price under two regimes. First, I calculate the predicted price using the estimates of my model (i.e., those that reflect the asymmetric pass-through or the rockets and feathers regime). Assuming the model fits the data well, the predicted prices will be very close to the actual retail prices. In the second regime, I estimate the retail prices if they respond to negative shocks in the rack price at the same rate that they respond to positive shocks. In practice, this means simply replacing the $\hat{\beta}_{1i}^{-}$ coefficients with the $\hat{\beta}_{1i}^{+}$ coefficients for $i = 1, \ldots, L_1$. I call this the rockets and rockets regime (abbreviated RR in the figures). I can then estimate the average downstream price under each regime and determine how much higher prices are under rockets and feathers as compared with rockets and rockets.

Simulation based on the national specification for branded rack and retail prices, January-December 2013. The mean RF price was 301.72 and the mean RR price was 298.37, a difference of 3.35 cpg.

Figure 8 shows the results of the simulation for 2013. I run the national model over the entire sample period from 2000 to 2013 and then simulate prices under the two regimes during 2013 alone. The red dashed line shows the predicted retail price under the rockets and feathers regime and the blue dashed line shows the predicted prices under the rockets and rockets regime. The graph shows that the retail prices increase at approximately the same rate when the rack price is increasing, while the blue line falls back much slower than the red line. Overall the average retail price is 301.72 cpg under rockets and feathers and 298.37 cpg under rockets and rockets, a difference of 3.35 cpg. The reason this difference is larger than the impact estimate in section 4.1 is that rack prices were volatile in 2013 with frequent periods of slowly falling retail prices.

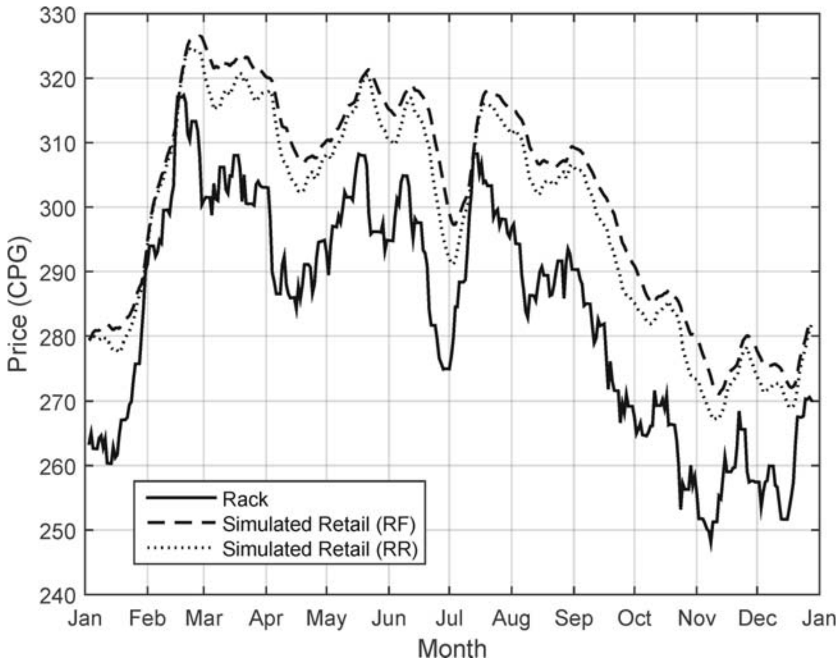
Figure 9 shows the difference in the average retail price under the two regimes for each year from 2000 to 2013. Again, these results are all based on the same set of coefficients (i.e., the model run on all cities/years and not separate models for each year). The year-by-year variation is due to the differences in the volatility of rack prices in each year. The spike in 2008 is due to a long decline in rack prices in the second half of the year, which means there is significant feathering of retail prices and the impact is large. All else equal, based on the average across all years, retail prices would be about 2.45 cpg lower if retail prices fell as quickly as they rose.[33]

It is important to note that the simulated prices under the rockets and rockets regime may not be the outcome one would expect under any model of competition. The simulation is simply a counterfactual experiment to determine how much higher are prices when they feather down instead

33. The 95% confidence interval for the 14-year average impact is (1.18 cpg, 3.72 cpg).

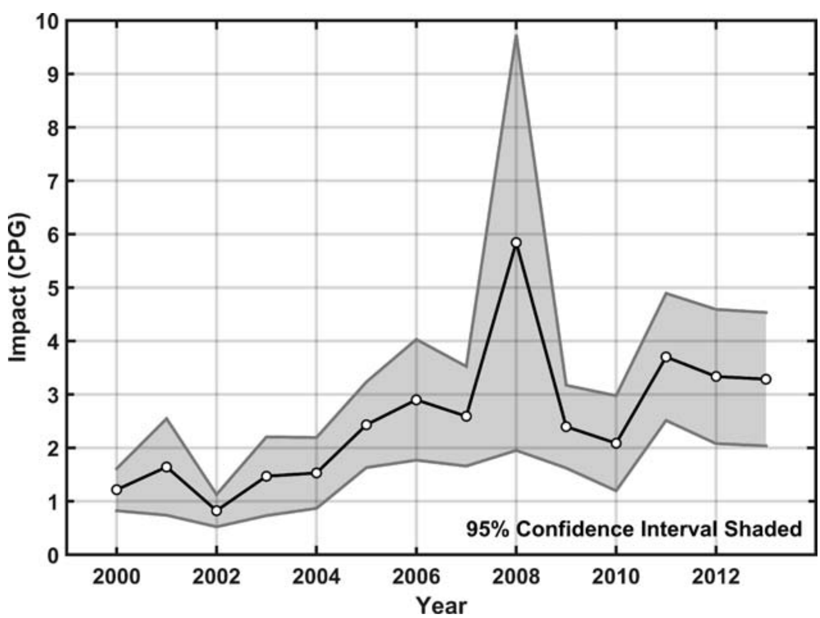
Copyright © 2016 by the IAEE. All rights reserved.

**Figure 8: Simulation: Rockets and Feathers vs Rockets and Rockets, 2013**




Simulation based on the national specification for branded rack and retail prices, January–December 2013. The mean RF price was 301.72 and the mean RR price was 298.37, a difference of 3.35 cpg.

**Figure 9: Simulation: Rockets and Feathers vs Rockets and Rockets, By Year**




Copyright © 2016 by the IAEE. All rights reserved.

of rocket down. If symmetric pass-through or a constant markup over the wholesale price was in some way required, retail station owners may respond by changing their pricing strategy so the average markup is the same under asymmetric or symmetric pass-through. In other words, by requiring symmetric pass-through, it is not clear that consumers would necessarily benefit from lower average retail prices. In fact, under the rockets and rockets counterfactual, the average markup drops by 2.45 cpg, which may cause firms to exit. Thus the welfare consequences of eliminating asymmetric pass-through are ambiguous and the counterfactual serves as an experiment to estimate the magnitude of the impact that feathering has on retail prices, all else equal.

### 4.6 Formal Tests of Asymmetry

In order to formally test for asymmetry, I report F-statistics for the pattern asymmetry in equation 5. I test the following hypothesis:

$$H_0\colon \beta_{1i}^{+} = \beta_{1i}^{-} \ \forall \ i$$

$$H_1\colon \beta_{1i}^{+} \neq \beta_{1i}^{-} \text{ for some } i.$$

Note this is a two-sided test, so includes the possibility that the asymmetry is both the rockets and feathers type and the opposite. To implement the test, I save the residual sum of squares, $RSS_u$, from the full (unrestricted) model where the coefficients are allowed to vary separately for positive and negative shocks. I then estimate a symmetric (restricted) model, with only one set of $\beta_{1i}$ coefficients and save $RSS_r$. Note that minimizing the BIC separately for each model would mean that a different number of lags is included in each.[34] Therefore, I again restrict the number of lags to be 21 days in both regressions so the only difference between the models is the restriction on the parameters.[35] Results are reported in table 6.

The statistics reported in the tables confirm what has been shown in the impulse response functions in the previous sections. There is strong evidence of asymmetry in all national specifications and in the rack to retail specifications for each city. The evidence is slightly weaker when the upstream price is the crude oil price though I still reject the null hypothesis of symmetric pass-through. The branded rack to retail price relationship again shows stronger evidence of asymmetry compared with unbranded rack to retail prices.

### 4.7 Factors Related to Asymmetric Pass-through

I have shown that asymmetric pass-through appears strongest in the rack to retail price relationship and the amount of asymmetry varies by city. In this section, I further investigate factors that may be associated with more or less asymmetry. Table 7 summarizes the results for a three select factors. I report the average value of each factor for cities in the top and bottom quartile in terms of asymmetry as well as the correlation between the factor and the impact estimate for all cities in my sample.[36]

34. See Ye, et. al. (2005) for a discussion of this issue.

35. Formally, the test statistic is of the usual form, $\tilde{F} = \dfrac{(RSS_r - RSS_u)/(K_u - K_r)}{RSS_u/(N - K_u)}$, where $K_u$ and $K_r$ are the number of parameters to be estimated in the unrestricted and restricted models respectively.

36. The top and bottom quartiles correspond to the seven cities in figure 5 that show the largest and smallest impact estimates, respectively.

Copyright © 2016 by the IAEE. All rights reserved.

**Table 6: F-Statistics on the Existence of Pattern Asymmetry, By Price Relationship**

| City-Specific Rack to Retail | F-Stat Branded | F-Stat Unbranded |
|---|---|---|
| Atlanta | 16.82*** | 14.56*** |
| Boston | 16.92*** | 12.12*** |
| Chicago | 11.32*** | 8.27*** |
| Cleveland | 9.73*** | 5.30*** |
| Dallas | 11.45*** | 9.44*** |
| Denver | 9.17*** | 7.16*** |
| Detroit | 20.35*** | 10.17*** |
| Washington DC | 6.83*** | 6.29*** |
| Washington MD | 14.44*** | 11.97*** |
| Washington VA | 14.87*** | 14.10*** |
| Washington WV | 5.05*** | 8.67*** |
| Houston | 19.74*** | 10.01*** |
| Los Angeles | 24.25*** | 9.56*** |
| Louisville IN | 5.28*** | 4.63*** |
| Louisville KY | 4.92*** | 6.27*** |
| Miami | 17.03*** | 11.51*** |
| Minneapolis MN | 8.65*** | 7.61*** |
| Minneapolis WI | 6.19*** | 5.47*** |
| New Orleans | 9.15*** | 4.73*** |
| Newark | 5.94*** | 4.26*** |
| New York | 4.65*** | 3.19*** |
| Phoenix | 5.88*** | 2.61*** |
| Salt Lake City | 8.37*** | 4.47*** |
| San Francisco | 10.76*** | 4.11*** |
| Seattle | 14.66*** | 5.14*** |
| St Louis IL | 4.31*** | 3.76*** |
| St Louis MO | 5.78*** | 5.31*** |

| National | F-Stat |
|---|---|
| WTI to Spot | 6.26*** |
| WTI to Branded Rack | 22.14*** |
| WTI to Retail | 9.81*** |
| Spot to Branded Rack | 204.49*** |
| Spot to Retail | 40.40*** |
| Branded Rack to Retail | 123.27*** |
| Unbranded Rack to Retail | 70.49*** |
| Branded Rack to Retail (W) | 75.37*** |

National and city specifications with daily data and 21 lags. Significant at the 1% (***) level.

For each city in the sample, I estimate a statistic on price cycling measured as the median first difference of daily changes in the retail price. Larger (absolute) values of this statistic are evidence of price cycling: if increases in price are relatively large and occur quickly while decreases tend to be small and last for many periods, the median first difference will be more negative. Asymmetry is negatively associated with this statistic, which implies that cities that show more asymmetric adjustment also are more likely to cycle.[37] Asymmetry is also negatively related to the

37. Minneapolis, MN is in the top quartile of cities and shows evidence of cycling (median first difference = $-0.77$) while Minneapolis, WI show relatively less asymmetry and little evidence of cycling (median first difference = $-0.08$).

Copyright © 2016 by the IAEE. All rights reserved.

**Table 7: Factors Related to Asymmetric Pass-through**

| | Factor | | |
|---|---|---|---|
| | Cycling | Speed | Concentration |
| Top Quartile Asymmetric | −0.52 | 9.79 | 1,620 |
| Bottom Quartile Asymmetric | −0.17 | 13.29 | 1,419 |
| Correlation(Asymmetry, Factor) | −0.26 | −0.23 | 0.18 |

Notes: Cycling is measured by the median first difference of retail price changes. Cycling is more prevalent in cities with larger (negative) estimates. Speed is calculated as the number of days to reach 90% pass-through for positive and negative wholesale cost shocks. Concentration is the brand-level HHI based on the total revenue sales by gas stations in each city.

speed of pass-through, measured as the number of days to pass-through 90% of a cost shock (positive or negative). In fact, cycling and pass-through speed are strongly correlated ($\rho = 0.88$), consistent with the findings in Lewis and Noel (2011).

Finally, I calculate a brand-level concentration index for cities in my sample based on data from New Image Marketing Research Corporation. I calculate the Herfindahl-Hirschman Index (HHI) for each city based on the total dollar sales at all stations in a city around the first year in my sample.[38] Concentration is positively correlated with asymmetric pass-through, consistent with the findings in Deltas (2008) and Verlinda (2008). The HHI is about 14% higher for cities in the top quartile of asymmetry relative to the bottom quartile. Other factors, such as gasoline tax levels, median household income, and percent of sales by channel (e.g., rack versus DTW), are uncorrelated with the amount of asymmetric pass-through observed in each city.

## 5. CONCLUSION

The purpose of this study was to understand why so many researchers have studied asymmetric pass-through in the gasoline industry and have come to varying conclusions about its existence and causes. Many of the discrepancies can be explained by variations in the data and the model specification. I find that pass-through asymmetries do exist in all price relationships from the price of crude oil, to spot, rack and retail gasoline prices. Pass-through asymmetry in the branded rack to retail price relationship is shown to be larger than its unbranded counterpart, consistent with the explanation that consumer search costs drive asymmetric pass-through. Averaging daily data to obtain a weekly price series leads to a larger estimate of asymmetry as retail prices are predicted to increase faster following a cost increase and fall slower following a cost decrease.

Estimating the model separately for each city in the sample shows that some cities experience more asymmetric pass-through than others, but in every city, the speed of pass-through is between three and four times faster when rack prices rise than when they fall. I find that asymmetry in pass-through rates is positively correlated with both the degree of price cycling and overall speed of pass-through in a city. I also find evidence consistent with explanations of asymmetry based on market power as the amount of asymmetry is positively associated with retail concentration.

38. I have data on 22 of the 27 cities in the sample for one of the years between 1998 and 2001. Using total sales by all gas stations that sell under each brand name, I calculate $HHI = \sum_i s_i^2$, where $s_i$ is the share of brand $i$.

Copyright © 2016 by the IAEE. All rights reserved.

The magnitude of the impact of asymmetric pass-through is economically significant. I find that retail prices would be about 3.35 cpg lower in 2013 if retail price fell as quickly as they rose. This is about 1% of the retail gasoline price, though it is 15.2% of the average markup of retail over branded rack prices seen in the data.[39] While significant, it is important to keep these findings within the scope of the model, as estimating the welfare implications of eliminating asymmetric pass-through would require a fully structural model of wholesale and retail gasoline pricing. Determining the general equilibrium effects is an appropriate extension to this line of research and may provide important insights into the effects of asymmetric pass-through in gasoline prices as well as other markets.

## ACKNOWLEDGMENTS

The opinions expressed here are those of the author and not necessarily those of the Federal Trade Commission or any of its Commissioners. I thank Michael Noel, Matthew Lewis, Chris Taylor, Louis Silvia, David Meyer, Doug Herman, and participants at the 2010 International Industrial Organization Conference for their suggestions and comments. Elisabeth Murphy and Elizabeth Miles provided excellent research assistance. All remaining errors are my own.

## REFERENCES

Bachmeier, Lance and James Griffin (2003). "New Evidence on Asymmetric Gasoline Price Responses." *The Review of Economics and Statistics* 85(3): 772–776. http://dx.doi.org/10.1162/003465303322369902.

Bacon, Robert W. (1991). "Rockets and Feathers: The Asymmetric Speed of Adjustment of UK Retail Gasoline Prices to Cost Changes." *Energy Economics* 13(3): 211–218. http://dx.doi.org/10.1016/0140-9883(91)90022-R.

Bonnet, C. and S. B. Villas-Boas (2013). "An Analysis of Asymmetric Consumer Price Responses and Asymmetric Cost Pass-Through in the French Coffee Market." TRANSFOP Working paper N. 10.

Borenstein, S., C. A. Cameron and R. Gilbert (1997). "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* 112(1): 305–339. http://dx.doi.org/10.1162/003355397555118.

Borenstein, S. (1991). "Selling Costs and Switching Costs: Explaining Retail Gasoline Margins." *The RAND Journal of Economics* 22(3): 354–369. http://dx.doi.org/10.2307/2601052.

Borenstein, S., Andrea Shepard (1996). "Dynamic Pricing in Retail Gasoline Markets." *The RAND Journal of Economics* 27(3): 429–451. http://dx.doi.org/10.2307/2555838.

Bulow, Jeremy and Paul Pfleiderer (1983). "A Note on the Effect of Cost Changes on Prices." *Journal of Political Economy* 91(1): 182–185. http://dx.doi.org/10.1086/261135.

Deltas, George (2008). "Retail Gasoline Price Dynamics and Local Market Power." *The Journal of Industrial Economics* 56(3): 613–628. http://dx.doi.org/10.1111/j.1467-6451.2008.00350.x.

Eckert, Andrew (2002). "Retail Price Cycles and Response Asymmetry." *Canadian Journal of Economics* 35(1): 52–77. http://dx.doi.org/10.1111/1540-5982.00120.

Energy Information Administration, U.S. Department of Energy (2007). "Refinery Outages: Description and Potential Impact on Petroleum Product Prices."

Energy Information Administration, U.S. Department of Energy (2008). "A Primer on Gasoline Prices." Online: http://www.eia.gov/energyexplained/print.cfm?page = gasoline_factors_affecting_prices [Downloaded: 1/13/2015].

Engle R. and C.W.J. Granger (1987). "Co-Integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55(2): 251–276. http://dx.doi.org/10.2307/1913236.

Espey, Molly (1996). "Explaining Variation in Elasticity of Gasoline Demand in the United States: A Meta Analysis." *The Energy Journal* 17(3): 49–60. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol17-No3-4.

39. The average retail price across all cities in 2013 was 305 cpg and the average rack price was 284 cpg.

Copyright © 2016 by the IAEE. All rights reserved.

Federal Trade Commission (2006). "Investigation of Gasoline Price Manipulation and Post-Katrina Gasoline Price Increases." Available at http://www.ftc.gov/reports/federal-trade-commission-investigation-gasoline-price-manipulation-post-katrina-gasoline.

Federal Trade Commission (2005). "Gasoline Price Changes: The Dynamics of Supply, Demand and Competition." Available at http://www.ftc.gov/reports/gasprices05/050705gaspricesrpt.pdf.

Gautier, E. and R. Le Saout (2012). "The dynamics of gasoline prices: evidence from daily French micro data." Banque de France Working Paper No. 375.

Godby, R, A.M. Lintner, T. Stengos, and B. Wandschneider (2000). "Testing for Asymmetric Pricing in the Canadian Retail Gasoline Market." *Energy Economics* 22(3): 349–368. http://dx.doi.org/10.1016/S0140-9883(99)00030-4.

Goldberg, Pinelopi K. and Rebecca Hellerstein (2008). "A Structural Approach to Explaining Incomplete Exchange-Rate Pass-Through and Pricing-to-Market." *The American Economic Review* 98(2): 423–429. http://dx.doi.org/10.1257/aer.98.2.423.

Goodwin, Barry, and Matthew Holt (1999). "Price Transmission and Asymmetric Adjustment in the U.S. Beef Sector." *American Journal of Agricultural Economics* 81(3): 630–637. http://dx.doi.org/10.2307/1244026.

Government Accountability Office (2006). "Energy Markets: Factors Contributing to Higher Gasoline Prices." GAO-06-412T.

Gron, Anne, and Deborah Swenson (2000). "Cost Pass-Through in the U.S. Automobile Market." *The Review of Economics and Statistics* 82(2): 316–324. http://dx.doi.org/10.1162/003465300558704.

Hastings, Justine, Jennifer Brown, Erin Mansur, and Sofia Villas-Boas (2008). "Reformulating Competition? Gasoline Content Regulation and Wholesale Gasoline Prices." *Journal of Environmental Economics and Management* 55(1): 1–19. http://dx.doi.org/10.1016/j.jeem.2007.04.002.

Hosken, Daniel, Robert McMillan and Christopher Taylor (2008). "Retail Gasoline Pricing: What Do We Know?" *International Journal of Industrial Organization* 26(6): 1425–1436. http://dx.doi.org/10.1016/j.ijindorg.2008.02.003.

Kim, Donghun and Ronald Cotterill (2008). "Cost Pass-Through in Differentiated Product Markets: The Case of U.S. Processed Cheese." *The Journal of Industrial Economics* 56(1): 32–48. http://dx.doi.org/10.1111/j.1467-6451.2008.00331.x.

Knittel, Christopher, Jonathan E. Hughes, and Daniel Sperling (2008). "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand." *The Energy Journal* 29(1): 113–134. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol29-No1-9.

Lewis, Matthew (2011). "Asymmetric Price Adjustment and Consumer Search: an Examination of Retail Gasoline Market." *Journal of Economics and Management Strategy* 20(2): 409–449. http://dx.doi.org/10.1111/j.1530-9134.2011.00293.x.

Lewis, Matthew and Howard P. Marvel (2011). "When Do Consumers Search?" *Journal of Industrial Economics* 59(3): 457–483. http://dx.doi.org/10.1111/j.1467-6451.2011.00459.x.

Lewis, Matthew, and Michael Noel (2011). "The Speed of Gasoline Price Response in Markets with and without Edgeworth Cycles." *The Review of Economic Studies* 93(2): 672–682.

Lewis, Matthew (2009). "Temporary Wholesale Gasoline Price Spikes have Long Lasting Retail Effects: The Aftermath of Hurricane Rita." *Journal of Law and Economics* 52(3), 581–605. http://dx.doi.org/10.1086/592056.

Lewis, Matthew (2012). "Price Leadership and Coordination in Retail Gasoline Markets with Price Cycles." *International Journal of Industrial Organization* 30(4): 342–351. http://dx.doi.org/10.1016/j.ijindorg.2011.12.002.

Lidderdale, Tancred (1999). "Environmental Regulations and Changes in Petroleum Refining Operations." United States Energy Information Administration Report. Online: http://www.eia.doe.gov/emeu/steo/pub/special/enviro.html [Downloaded: 1/13/2015].

MacKinnon, James (2010). "Critical Values for Cointegration Tests." Queen's Economics Department Working Paper No. 1227.

Müller, Georg and Sourav Ray (2007). "Asymmetric Price Adjustment: Evidence from Weekly Product-Level Scanner Price Data." *Managerial and Decision Economics* 28(7): 723–736. http://dx.doi.org/10.1002/mde.1377.

Noel, Michael D. (2007). "Edgeworth Price Cycles, Cost-Based Pricing, and Sticky Pricing in Retail Gasoline Markets." *Review of Economics and Statistics* 89(2): 324–334. http://dx.doi.org/10.1162/rest.89.2.324.

Noel, Michael D. (2009). "Do Gasoline Prices Respond Asymmetrically to Cost Shocks? The Effect of Edgeworth Cycles." *RAND Journal of Economics* 40(3): 582–595. http://dx.doi.org/10.1111/j.1756-2171.2009.00078.x.

Peterson, D. J. and Sergej Mahnovski (2003). *New Forces at Work in Refining: Industry Views of Critical Business and Operations Trends.* Santa Monica, CA: RAND Corporation.

Tappata, Mariano (2009). "Rockets and Feathers: Understanding Asymmetric Pricing." *The RAND Journal of Economics* 40(4): 673–687. http://dx.doi.org/10.1111/j.1756-2171.2009.00084.x.

Ten Kate, Adriaan and Gunnar Niels (2005). "To What Extent are Cost Savings Passed on to Consumers? An Oligopoly Approach." *European Journal of Law and Economics* 20(3): 323–337. http://dx.doi.org/10.1007/s10657-005-4199-3.

Copyright © 2016 by the IAEE. All rights reserved.

United States Senate (2002). "Gas Prices: How are they Really Set?" Online: http://www.hsgac.senate.gov/download/report_gas-prices-how-are-they-really-set [Downloaded 1/13-2015].

Verlinda, Jeremy (2008). "Do Rockets Rise Faster and Feathers Fall Slower in an Atmosphere of Local Market Power? Evidence from the Retail Gasoline Market" *Journal of Industrial Economics* 56(3): 581–612. http://dx.doi.org/10.1111/j.1467-6451.2008.00351.x.

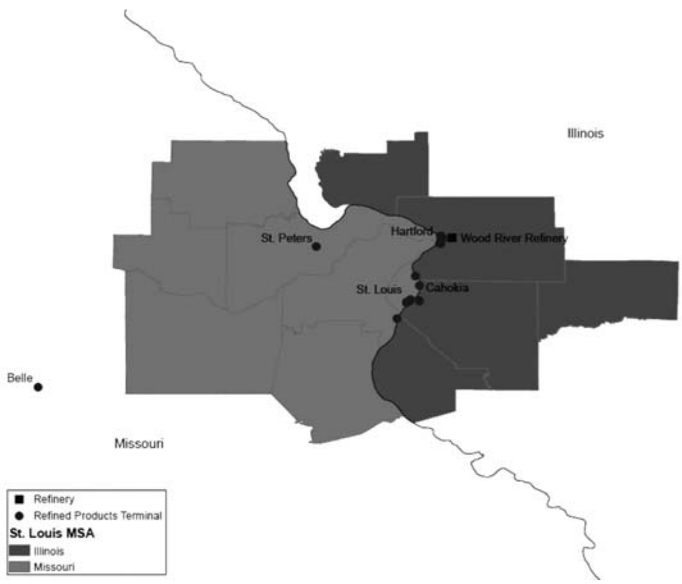
Yang, H. and L. Ye L. (2008). "Search with Learning: Understanding Asymmetric Price Adjustments." *The RAND Journal of Economics* 39(2): 547–564. http://dx.doi.org/10.1111/j.0741-6261.2008.00027.x.

Ye, Michael, John Zyren, Joanne Shore, and Michael Burdette (2005). "Regional Comparisons, Spatial Aggregation, and Asymmetry of Price Pass-Through in U.S. Gasoline Markets." *Atlantic Economic Journal* 33(2): 179–192. http://dx.doi.org/10.1007/s11293-005-3761-2.

Zimmerman, Paul R., John M. Yun, and Christopher T. Taylor (2013). "Edgeworth Price Cycles in Gasoline: Evidence from the United States." *Review of Industrial Organization* 42(3): 297–320. http://dx.doi.org/10.1007/s11151-012-9372-6.

## APPENDIX A: ADDITIONAL FIGURES AND TABLES

**Figure A1: St. Louis Retail Market Areas**




Copyright © 2016 by the IAEE. All rights reserved.

**Figure A2: Impulse Response Function: WTI to Branded Rack, National**

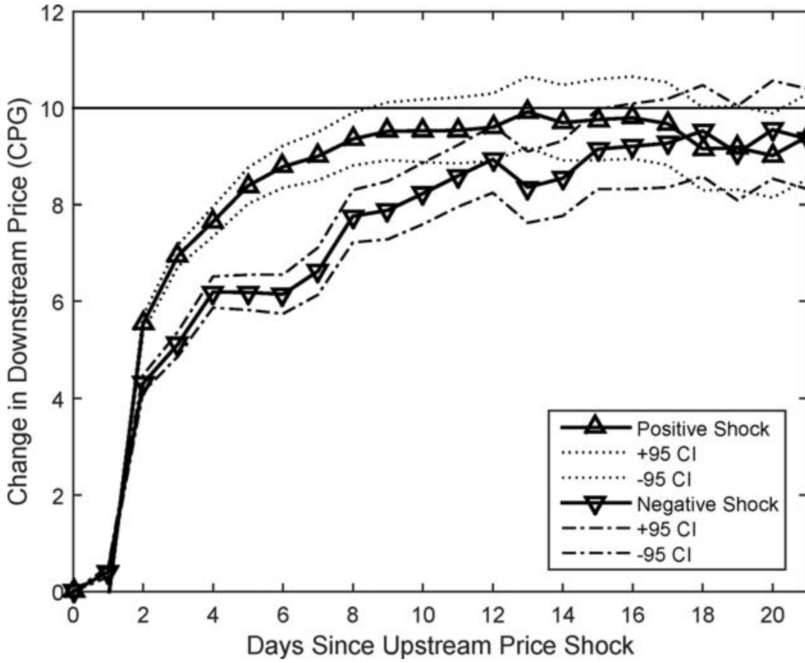
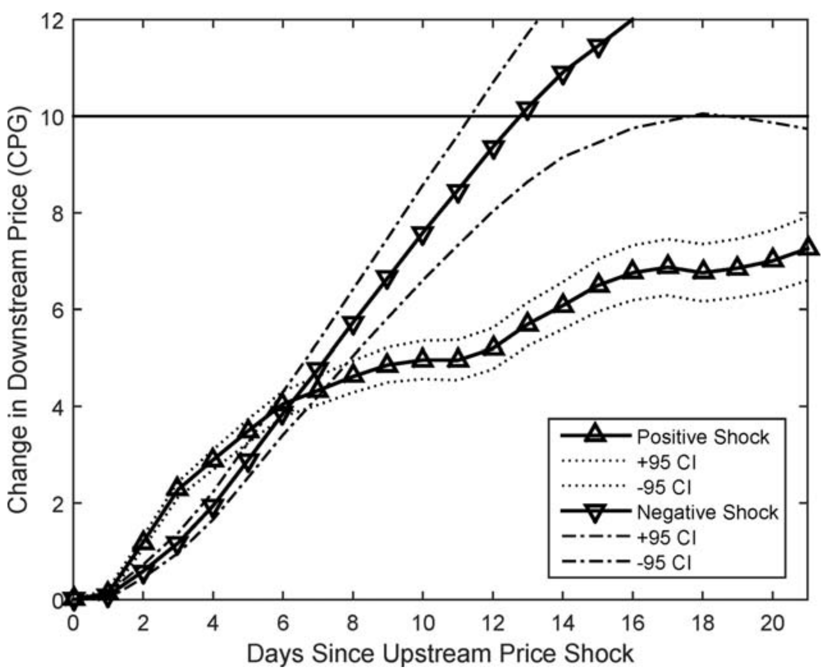



**Figure A3: Impulse Response Function: WTI to Retail, National**




Copyright © 2016 by the IAEE. All rights reserved.

**Figure A4: Impulse Response Function: Spot to Retail, National**

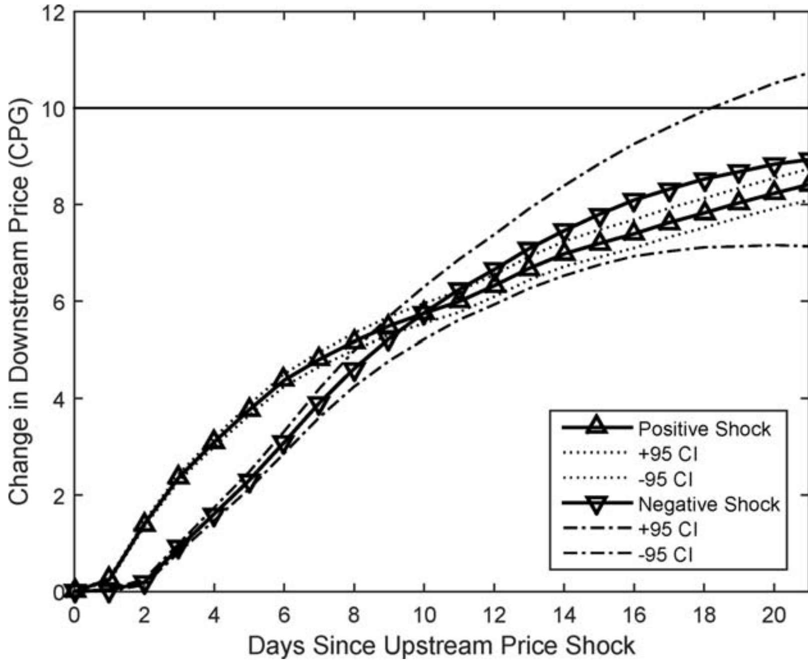
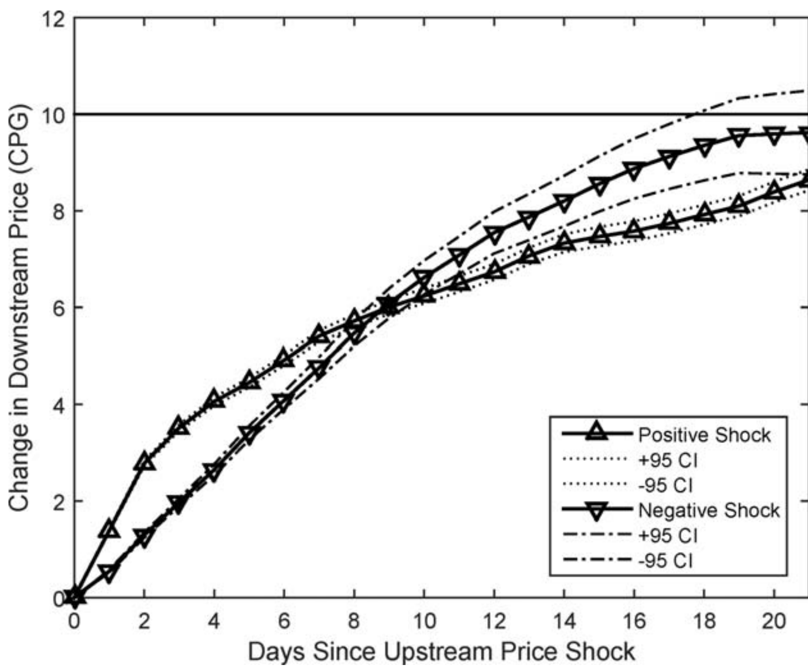



**Figure A5: Impulse Response Function: Unbranded Rack to Retail Prices, National**




Copyright © 2016 by the IAEE. All rights reserved.