Revisiting Rockets and Feathers: New Evidence from the Korean Gasoline Market

Seon-Yong Kim*

Click here for the latest version.

Abstract

Recent studies on "Rocket and Feathers" tend to rely more on high-frequency data to avoid bias arising from the temporal aggregation of data. In this study, I investigate price adjustment patterns by estimating an error correction model using daily station-level data from the Korean gasoline market. I find that compared to those based on weekly data, the estimated adjustment patterns based on daily data exhibit a greater variation, which may be attributed to model misspecification that fails to account for the essential feature of daily-level data: censored responses to cost changes. The empirical findings emphasize the need for careful model specification when investigating the price adjustment pattern with daily-level data. In additional analyses, I explore the effect of consumer search on adjustment patterns and find that consumer search may not be a primary driving factor behind asymmetric price adjustments.

JEL classification: Q40, D40, C80

Keywords: Retail gasoline price, Oil price, Asymmetric adjustments, Data frequency

1 Introduction

Asymmetric price adjustment, commonly known as "Rockets and Feathers," refers to the phenomenon where retail prices of a product, such as gasoline, rise rapidly in response to increases in input costs but decrease slowly when input costs decline. This concept has been extensively studied, particularly in the gasoline market. The majority of studies provide evidence supporting the existence of downstream price asymmetry in response to changes in

*Department of Economics, University of Missouri, E-mail: skxbb@umsystem.edu

upstream prices.[1]

However, there are conflicting findings in several studies that challenge the existence of the "Rockets and Feathers" phenomenon. These studies argue that inconsistencies in results may be attributed to various factors such as differences in data frequency, market characteristics, and modeling approaches.[2] For example, Bachmeier and Griffin (2003) claims that aggregating daily data to a wider interval, such as weekly data, can introduce significant bias when analyzing the dynamics of gasoline prices. As a result, recent studies on the "Rocket and Feathers" phenomenon have increasingly relied on high-frequency data, such as daily station-level data(Faber (2015), Remer (2015), Balaguer and Ripollés (2016), Loy et al. (2018)).[3]

It is true that aggregating daily data to weekly data can introduce bias, especially if the retail price of gasoline exhibits daily responsiveness to changes in the upstream price with a linear relationship between changes in retail price and cost. Moreover, high-frequency data enables us to obtain smaller standard errors when estimating the model, which might lead to the perception that relying on daily data provides more reliable results.

However, Meng and Xie (2014) show that the conventional wisdom (i.e more data assures the better estimates) is not always true and the estimation results can be even worse with larger data. Although the case of the model they presents are not the case of the model in the literature of "Rockets and Feathers", it reminds us to consider the data structure before unquestioningly accepting the conventional wisdom. In a similar vein, Nason, Powell, Elliott, and Smith (2017) emphasize the potential drawbacks of excessive sampling, including unnecessary costs associated with sampling and storing highly detailed information. Their findings

[1]See e.g, Bacon (1991) Karrenbrock et al. (1991), Borenstein, Cameron, and Gilbert (1997), Eckert (2002), Galeotti, Lanza, and Manera (2003), Radchenko (2005), Balmaceda and Soruco (2008), Deltas (2008), Verlinda (2008), Lewis (2011), Lewis and Noel (2011), Remer (2015), Balaguer and Ripollés (2016), Loy, Steinhagen, Weiss, and Koch (2018), Hong and Lee (2020).

[2]Kirchgässner and Kübler (1992), Duffy-Deno (1996), Balke, Brown, and Yucel (1998), Godby, Lintner, Stengos, and Wandschneider (2000), Bachmeier and Griffin (2003), Bettendorf, Van der Geest, and Varkevisser (2003), Da Silva, Vasconcelos, Vasconcelos, and de Mattos (2014), Bumpass, Ginn, and Tuttle (2015), and Faber (2015)

[3]The literature on the "Rocket and Feathers" phenomenon is summarized in Table 7 in Appendix A based on the data structure and data frequency.

offer additional insights into determining the appropriate frequency of data collection.

The data used in this study reveal that, although changes in cost occur daily, retailers do not respond to every daily change in cost. Instead, they adjust their prices infrequently, typically on a weekly basis, suggesting that retailers' responses to cost changes are censored. This characteristic of the data can introduce significant bias when estimating the adjustment patterns within a standard model specification of "Rocket and Feathers."

In this study, I estimate the price adjustment model using different data frequencies and structures, including time series versus panel data, as well as weekly-level versus daily-level data. By comparing the results from these four sets of analyses, I demonstrate how relying on daily data can introduce bias in the estimation process with a typical framework of studying "Rocket and Feathers".

Additional analysis can be conducted to explore the theoretical implications of asymmetric price adjustments. Several studies, such as Tappata (2009), Yang and Ye (2008), and Lewis (2011), provide theoretical frameworks for explaining these asymmetric adjustments based on consumer search intensity. These studies suggest that consumers have a greater incentive to search when cost increases. As a result, retailers may respond faster to cost increases than decreases in order to maximize profits. This leads to asymmetric price adjustments.

Remer (2015) presents empirical evidence to support these hypotheses. He estimates the price adjustment patterns for both premium and regular gasoline and compares them. The findings indicate that the asymmetric adjustment pattern is more pronounced in the case of premium gasoline prices than in regular gasoline prices. This suggests that the asymmetries in consumers' search intensity contribute to the observed asymmetric price adjustments.

I investigate whether differences in search intensity among consumers affect the price adjustment patterns of retailers. Specifically, I assume that the search intensity of consumers for premium gasoline differs from that of regular gasoline, as well as there are variations in search intensity across different types of stations (e.g., full-service stations vs. self-service stations). I compare the estimated adjustment patterns based on these assumptions. Although the pass-through differs by samples (with greater in regular gasoline for self-service stations, but lower in premium gasoline for full-service stations), the adjustment patterns remain similar regardless of the station type or fuel type. This suggests that the hypothesis of search intensity may not be an important contributor to asymmetric price adjustments.

The remaining sections of this chapter are organized as follows: In Section 2, I describe the characteristics of the data used in this study. Next, Section 3 presents the econometric model, and Section 4 provides the results with detailed interpretation. Finally, in Section 5, I conclude the paper by summarizing the findings and offering policy implications related to the conclusions.

2 Data and Market Overview

2.1 Data

The data for this study were obtained from the Oil Price Information Network, which is operated by the Korea National Oil Corporation. The firm collects transaction information from all retailers in Korea and makes the daily price data publicly available on their website. I utilized price information from 709 stations in Seoul, including details about the type of service, brand, and location, spanning the period from 2009 to 2019.

For the variable cost of gasoline, I used wholesale price data from MOPS. This data source reports benchmark prices for petroleum products in the Asian market, based on transactions in Singapore. These prices closely track international oil prices and are employed as a measure of variable cost in this study. Given the size of the Korean market, it is unlikely that the retail price of gasoline in Korea significantly affects the international wholesale price. Therefore, there is no need to consider the issue of endogeneity between retail price and cost in the econometric model.

Additionally, there was a temporary decrease in the oil tax that significantly contributed to the retail gasoline price in Korea. Initially, the total tax amount stood at 745.89 KRW/liter. However, on November 6, 2018, the tax was temporarily reduced to 634.5 KRW/liter for a duration of six months. Subsequently, on May 7, 2019, the tax was increased to 693.72 KRW/liter. Finally, on September 1, 2019, the tax was restored to its original value of 745.89 KRW/liter, and this tax rate remained in effect until the end of the sample period. I control for the impact of these tax changes when estimating the model using the sub-sample of the period 2015-2019, which covers the period of tax change. By doing so, I isolate and remove the effect of tax changes on the retailers' response to cost changes.

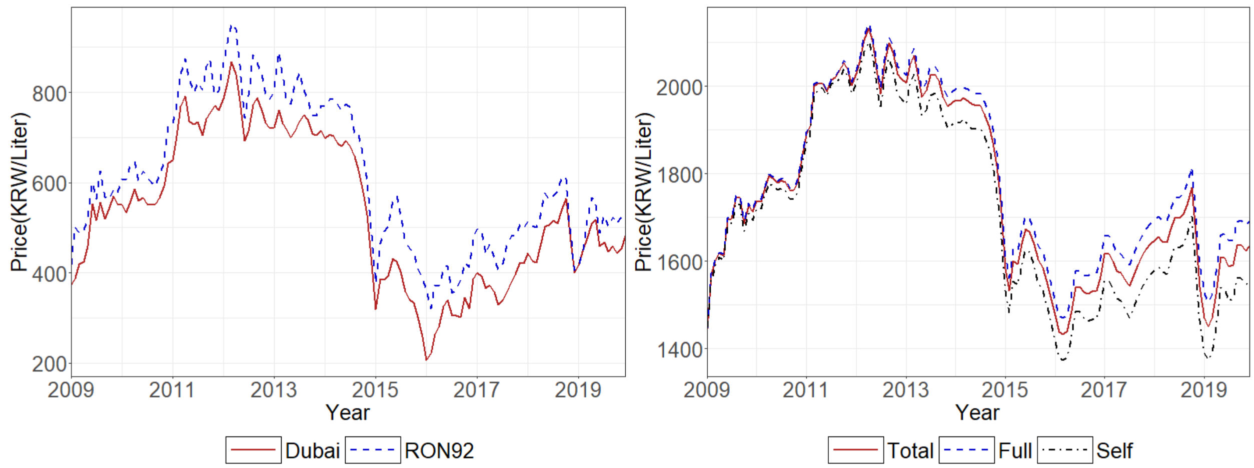
2.2 Market Overview

The pricing behavior of stations in the Seoul retail gasoline market displays an infrequent adjustment pattern, yet they change their prices at regular intervals. Out of a total of 2,275,577 observations, only approximately 10% of them indicate price changes. The mode and median of the frequency of price changes (measured in days) are both 7 days during the 2009-2019 data period. These observed characteristics suggest that retailers typically respond to changes in costs on a weekly basis.

The trend of oil prices suggests the possibility of two distinct regimes within the data period of 2009-2019. Figure 1 illustrates this trend, showing that oil prices were relatively high during the period of 2009-2014. However, there was a significant drop in oil prices around 2015, leading to a sustained period of relatively low oil prices thereafter.[4]

The retail price exhibits distinct patterns corresponding to these two possible regimes. Generally, the prices of full-service stations are higher than those of self-service stations. However, the difference between these prices was relatively insignificant during the period of 2009-2014. In contrast, the difference between the two prices became more pronounced during 2015-2019. This observation suggests the possibility of a change in retailers' pricing

[4]During the period of 2009-2014, the average positive and negative price changes for 'RON92' were 9.07 and -9.49, respectively. The daily standard deviation for price changes was 10.2. Transitioning to the period of 2015-2019, the average positive and negative price changes for 'RON92' shifted to 7.4 and -7.31, respectively. Similarly, the daily standard deviation for price changes decreased to 7.83.



(a) Crude and Wholesale price

(b) Retail price(by type)

Figure 1: The trend of oil price

Note: (1) The 'Dubai' and 'RON92' represents the Dubai crude oil price and the international wholesale price of RON(Research Octane Number) 92 based on MOPS, while the retail price refers to the average retail price across stations categorized by station type.

behavior after 2015. The presence of a structural break during the data period is examined in Section 4.

The price of gasoline is influenced by two key factors: the type of service provided at stations and the type of fuel. Full-service stations offer the convenience of attendants refueling vehicles while drivers remain in their vehicles, but this convenience comes at a higher cost compared to self-service stations. On the other hand, self-service stations attract price-sensitive consumers who actively search better prices and are willing to forgo the convenience of full-service to save money.

Furthermore, the price of gasoline varies depending on the type of fuel. Premium gasoline, as highlighted in Remer (2015), is commonly used in luxury cars and preferred by higher-income consumers, and it tends to have higher prices compared to regular gasoline. This suggests that users of premium gasoline are generally less responsive to price fluctuations compared to users of regular gasoline. Overall, premium gasoline prices are higher than regular gasoline prices. Within the category of regular gasoline, prices at self-service stations

Table 1: Pairwise t-test by type of fuel and service

	2009-2014		2015-2019	
	Mean Diff.	Std. Error	Mean Diff.	Std. Error
Premium(full) - Premium(self)	45.44***	0.72	161.71***	0.71
Premium(full) - Regular(full)	206.26***	0.52	251.59***	0.56
Premium(full) - Regular(self)	256.71***	0.72	430.66***	0.71
Premium(self) - Regular(full)	160.82***	0.72	89.88***	0.71
Premium(self) - Regular(self)	211.27***	0.88	268.94***	0.83
Regular(full) - Regular(self)	50.45***	0.72	179.07***	0.71

[1] Multiple comparisons were conducted using Tukey's HSD test. The significance level of 1% was denoted by three asterisks (***) to indicate statistical significance based on adjusted p-values, which were corrected for the family-wise error rate.
[2] The term "Premium(full)" refers to the price of premium gasoline sold at full-service stations. In this notation, the first part represents the type of fuel (premium gasoline), and the last part in parentheses indicates the type of service (full-service).

tend to be lower than those at full-service stations.

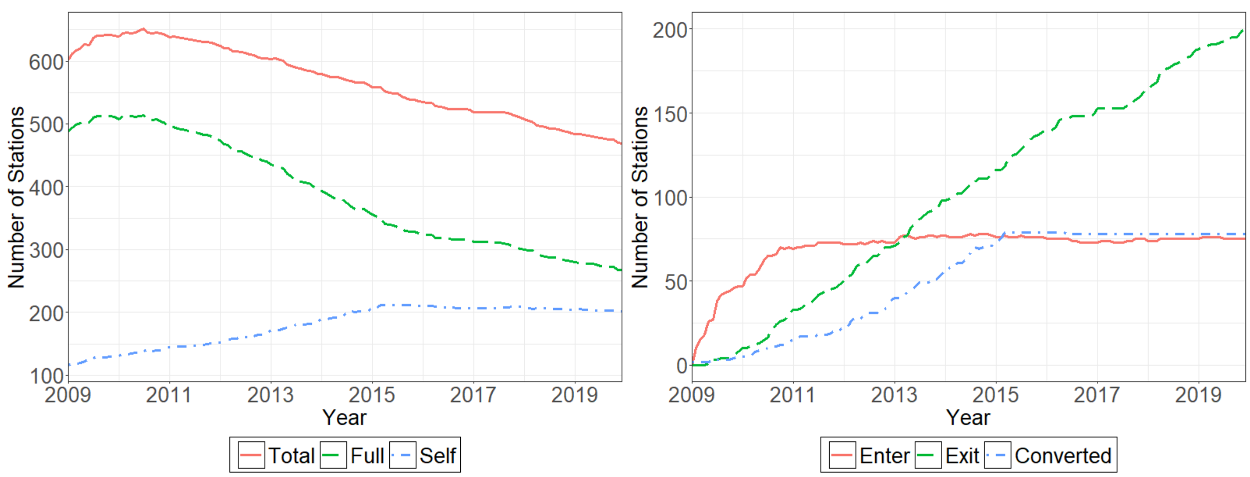
Table 1 displays the results of the multiple mean comparison analysis, which examines the pricing behavior based on the type of fuel and service. The analysis is conducted using data from 375 stations that sell both premium and regular gasoline throughout the data period. To account for the potential presence of a structural break, the data is divided into two sub-samples: 2009-2014 and 2015-2019.

Comparison by rows in Table 1 indicates that throughout the entire sub-sample period, premium gasoline at full-service stations was consistently sold at the highest prices, while regular gasoline at self-service stations was sold at the lowest prices. Comparison by columns of the table shows that the average price differences between the types of gasoline vary in the two periods.

Specifically, the analysis reveals a price difference of approximately 45.44 KRW/liter within the premium gasoline category, while the price difference within the regular gasoline category is around 50.45 KRW/liter. This suggests that the price levels were relatively similar across different types of service and comparable across different types of fuel.

The similarity of prices within the same type of fuel changed during the period of 2015-2019. The price differences within the premium gasoline category and the regular gasoline category increased by approximately 161.71 KRW/liter and 179.07 KRW/liter, respectively. These changes appear to be driven by the divergence in prices between different types of service. As a result, the price difference between premium full-service gasoline and regular self-service gasoline widened. Overall, there was an observable divergence in prices across both types of fuel and service in the period of 2015-2019.

The increased divergence in price between different types of service can be attributed to the changing composition of stations in Seoul. Self-service stations were relatively recently introduced in Korea, so they have not been in operation for an extended period. In certain districts with high real estate and gasoline prices, such as the Gangnam district, self-service stations were not introduced until late 2009.



(a) By type of service

(b) By decision

Figure 2: The number of station by type of station

As seen in Figure 2, the number of self-service stations in the early period of the data was approximately 100, but it gradually increased and exceeded 200 by 2015, primarily due to the conversion of full-service stations to self-service stations. Meanwhile, the number of full-service stations began to decline around 2011, resulting in a decrease in the ratio of full-service to self-service stations over time.

Kim (2018) studies the retail gasoline market in Seoul and finds that as the number

Table 2: The summary statistics of retail and wholesale price

	2009-2014			2015-2019		
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
P	1902.40	189.01	1898	1586.74	179.96	1545
C	724.58	126.24	761.7	473.11	70.95	480.82
ΔP^{+}	21.73	16.82	20	19.17	17.72	14
ΔP^{-}	-20.74	20.25	-16	-22.61	26.98	-16
ΔC^{+}	9.12	7.62	7.15	7.41	5.88	6.19
ΔC^{-}	-9.55	8.70	-7.4	-7.32	6.10	-5.95
Freq.(retail)	9.61	14.12	7	9.13	11.28	7
Freq.(cost)	1.45	0.88	1	1.47	0.90	1
Observation		1,341,062			933,886	

[1] P and C represent the retail price and wholesale price, respectively, while ΔP and ΔC represent the size of price changes for the retail and wholesale prices, respectively. The unit is KRW/liter.
[2] Freq. represents the frequency of price changes measured in days.

of self-service stations increases, the market becomes more segmented. Full-service stations located far from self-service stations tend to maintain their pricing behavior, while the prices of stations near self-service stations becomes less dispersed.

Table 2 provides an overview of the summary statistics for both retail and wholesale prices, revealing these patterns more closely. The retail prices exhibit higher levels and greater variation when compared to wholesale prices. This difference is evident not only when considering cross-sectional station price data but also when comparing the standard deviation of daily average retail prices to that of wholesale prices. For example, the standard deviation of the average retail price from 2009 to 2014 is 126 KRW/liter, while for the period 2015 to 2019, it is 75 KRW/liter.

The higher level and variation in retail prices are also reflected in the magnitude of price adjustments. During the period 2009-2014, the average size of adjustments in retail prices is approximately 20 KRW/liter for both positive and negative price changes. In contrast, wholesale prices exhibit smaller adjustments, averaging around 9 KRW/liter for both positive and negative changes. This pattern persists during the period 2015-2019, indicating consistent behavior over time.

The frequency of price changes unveils distinct patterns for both retail and wholesale prices. Across all periods, including 2009-2014 and 2015-2019, the mean frequency of price changes is approximately 9 for retail prices and 1.5 for wholesale prices, with medians of 7 and 1, respectively. These findings imply that wholesale prices change daily, while retail prices change infrequently, with most adjustments occurring on a weekly basis.

While the retail price series does reflect changes in the wholesale price series and allows us to track retail price trends by examining wholesale prices, it's crucial to recognize that the underlying nature of these two price types is different. Wholesale prices change daily with relatively smaller fluctuations, whereas retail prices change infrequently but with more substantial adjustments. This highlights the importance of exercising caution when constructing econometric models, taking into account the infrequent adjustments in retail prices and how retailers respond to daily changes in wholesale prices.

3 Econometric model

Most studies investigating asymmetric price adjustments have used the error correction model followed by Borenstein, Cameron, and Gilbert (1997) to capture cointegration relationship between retail gasoline price and its upstream price. The retail price and the wholesale price used in this study also are in cointegration relationship, and thus I use the error correction model with nonstationary time series if two times series have a cointegration relationship.[5]

[5] Using weekly time series data for both the retail and wholesale price series, I performed the Augmented Dickey-Fuller Test of stationarity. The test results indicate that we cannot reject the null hypothesis of a unit root, suggesting that both series are nonstationary. To investigate the cointegration relationship between the retail and wholesale prices, I conducted a cointegration test using the disequilibrium error, η_t from the long-run equation($P_t = \phi_0 + \phi_1 C_t + \eta_t$). The Augmented Dickey-Fuller test on these residuals rejected the null hypothesis at the 1% significance level. This provides evidence of a cointegration relationship between the two series. Similar results were obtained when using daily-level data.

$$
\begin{aligned}
\Delta P_{it} = &\sum_{j=0}^{n}(\beta_j^+ \Delta C_{t-j}^+ + \beta_j^- \Delta C_{t-j}^-) + \sum_{j=0}^{m}(\tilde{\beta}_j^+ \Delta T_{t-j}^+ + \tilde{\beta}_j^- \Delta T_{t-j}^-) \\
&+ \sum_{j=1}^{n}(\gamma_j^+ \Delta P_{it-j}^+ + \gamma_j^- \Delta P_{it-j}^-) + \theta[P_{it-1} - (\phi_0 + \phi_1 C_{t-1} + \phi_3 Trend_t)] + \epsilon_{it}.
\end{aligned} \tag{1}
$$

The model specifies the first difference in the price (ΔP_{it}) of station i at week(day) t as in (1). Here C_t is the wholesale price. I use superscription "+" and "−" to indicate positive or negative values of variable x (*i.e.,* $\Delta x_t^+ = max\{0, \Delta x_t\}$ and $\Delta x_t^- = min\{0, \Delta x_t\}$). Since the model separately considers positive and negative shocks, we can estimate retailers' responses to cost changes independently and observe the asymmetric adjustment patterns.

The error-correction model is based on the assumption of a linear long-run relationship between the retail price and wholesale price, with the implication that the price change of the retail price in t period is determined by how far the retail price is from the long-run equilibrium, by previous cost shocks, and by the lagged changes in retail price.[6].

The data period in this study is from 2009 to 2019. However, the assumption that the long-run relationship remains unchanged throughout the entire period may be too strong. The trend of oil prices, as depicted in Figure 1, shows that oil prices were relatively high from 2009 to 2014 but sharply decreased in the early 2015 and remained consistently low thereafter. This suggests the possibility of a structural break occurring during the data period, affecting the long-run relationship between the retail price and the wholesale price.

To test for a structural break, I employ the approach proposed by Zeileis, Leisch, Hornik, and Kleiber (2002). The null hypothesis of no structural break was rejected at a 1% significance level, and the estimated breakpoint was found to be in the first week of 2015. As a result, I divided the data into two sub-sample periods and estimate them separately using (1): the first period from 2009 to 2014, and the second period from 2015 to 2019.

We use four different types of data structures in this study. First, we employ daily

[6] When using daily-level data, I add the trend and day indicator variables following the suggestion by Balaguer and Ripollés (2016)

station-level data from the original dataset and create daily time series data by averaging the retail prices across stations. Next, we generate weekly station-level data by averaging the daily prices within each week. Finally, we construct weekly time series data by averaging the weekly station-level data across stations.

I set the length of lags as $n = 8$ weeks and the detailed results are provided in the Appendix.[7] Instead of reporting the parameter estimates I calculate the cumulative response to a unit change of wholesale price and compare the response of retail price to positive and negative wholesale price change proposed by Borenstein, Cameron, and Gilbert (1997).

Part of the difference between retail price and wholesale price is the fuel tax. The fuel tax was temporarily reduced in Korea in mid-2018, and was reverted to its original level in mid-2019. This type of cost change is distinct from regular wholesale price changes in that it involves a larger adjustment magnitude and an announced ahead of time. Retailers typically respond promptly to the tax change, and the complete adjustment for this specific shock occurs relatively quickly. I assume that the adjustment process will be completed within a maximum of one month (four weeks). To account for the impact of the tax change on the retail price, I include the variables representing the change in tax (ΔT_t^+ and ΔT_t^-), as well as their respective lags($m = 4$), in Equation 1 when estimating the model using data from 2015-2019. By incorporating the tax variable, I can capture the short-term effects of the tax change on the retail price while also examining the response of the retail price to the wholesale price more accurately.

The estimated cumulative response measures the cumulative pass-through at each week up to the eighth week (42 days when using daily-level data), starting from the occurrence of the shock. These cumulative responses are calculated for two cases: increases and decreases in cost shocks. I compare the adjustment speed by week for evidence of asymmetric responses to cost increases and cost decreases.

[7]The determination of the lag length is based on the Bayesian Information Criterion (BIC). However, to ensure a comprehensive adjustment in response to shocks, I have included an additional 2 lags (2 weeks) in the model. For the daily-level data, the lag length is chosen as 28 days, and I have also added an additional 2 weeks of lags (equivalent to 14 days).

4 Results

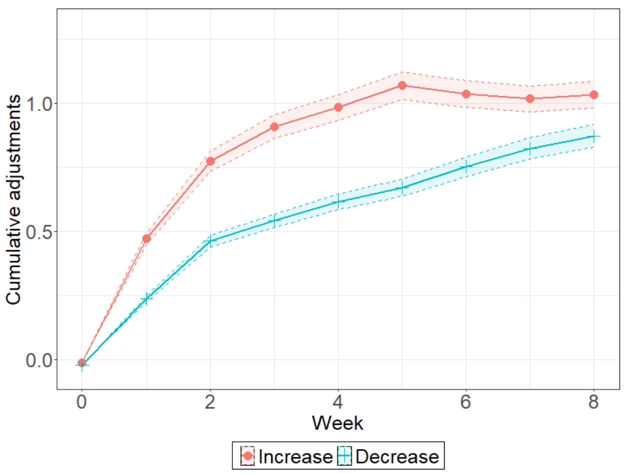
4.1 Estimated Results

Figure 3 displays the results of cumulative adjustments from 2009 to 2014 using four different data frequencies: weekly time series, weekly panel, daily time series and daily panel(Time series data are created by aggregating retail prices across stations for both daily and weekly cases).[8] When using weekly-level data, the adjustment patterns are similar for both time-series and panel data. The adjustment speed is higher in response to an increase of one unit in cost than to a decrease of one unit. Specifically, the cumulative adjustments in response to a one-unit increase in cost reach their peak at approximately the 4th week. However, in the case of a one-unit decrease in cost, it takes more weeks to complete the adjustments.

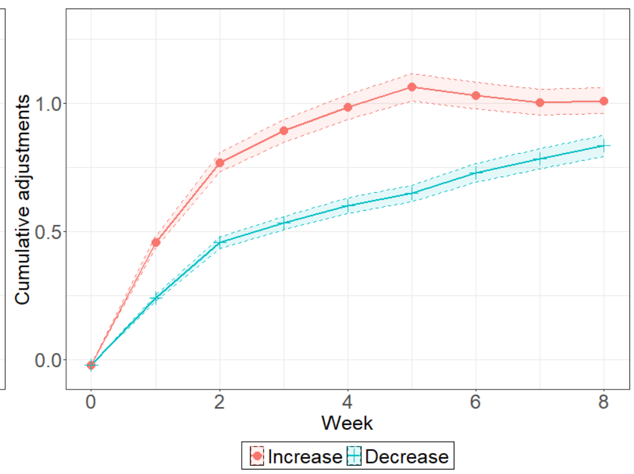
On the contrary, adjustment patterns in daily data are mixed. Based on the estimation results with daily time series data, the cumulative adjustments in response to a one-unit cost increase reach 0.6 around 14 days after a shock occurs. In contrast, the cumulative adjustments in response to a one-unit cost decrease take about 21 days to reach 0.6. Beyond 21 days, it becomes less clear to discern the speed of adjustments, but a weak asymmetric price adjustment pattern can still be observed within the first 21 days. However, in the case of the estimation results with daily panel data, the adjustment patterns in response to both cost increases and decreases are nearly identical. In summary, the price responses to cost changes exhibit asymmetry in daily time series data, but they appear symmetric in daily panel data.

In the 2015-2019 period, the adjustment patterns for weekly data closely resemble those observed in the 2009-2014 period for both time series and panel data cases. Specifically, as depicted in Figure 4, the cumulative adjustments reach their peak around the 5th week. However, it takes more time to complete the cumulative adjustments in response to a decrease in cost, a pattern observed in both time series and panel data cases.

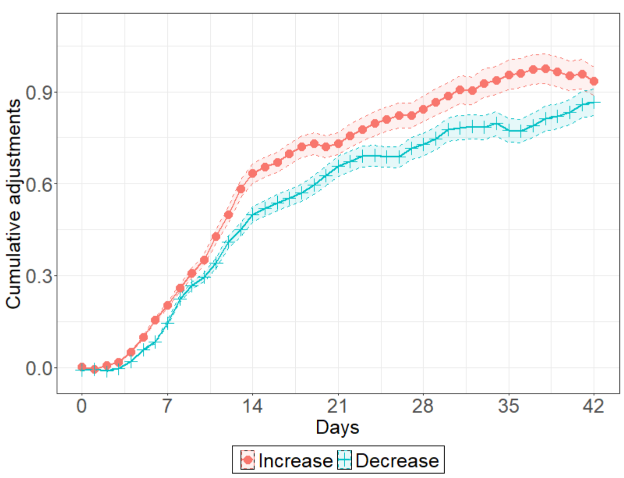
[8] The cumulative adjustments are calculated based on the estimation results in Table 3 and Table 4 in Appendix A



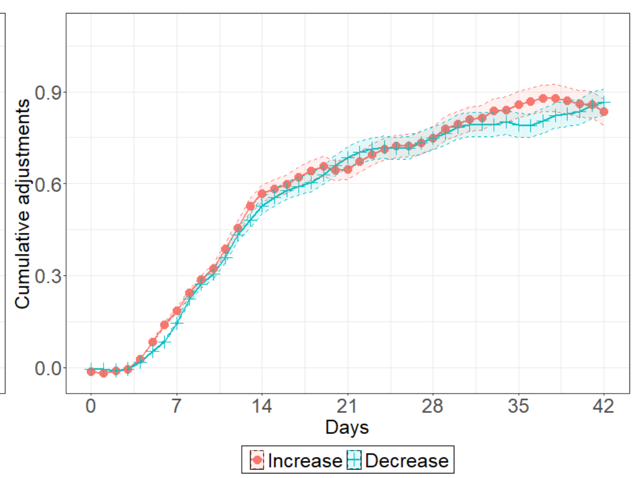
(a) Time series, Weekly data



(b) Panel, Weekly data



(c) Time series, Daily data



(d) Panel, Daily data

Figure 3: Estimated Cumulative adjustments, 2009-2014

Note: (1) The solid red line represents the cumulative adjustments in response to a one-unit increase in cost, while the solid blue line represents the cumulative adjustments in response to a one-unit decrease in cost. (2) The dashed lines represent the confidence intervals at 5% significance level for both the increase and decrease cases, respectively.

However, using daily-level data, the adjustment process differ from those in 2009-14, exhibiting patterns. In daily time series data, retail price responds more strongly to cost increases up to 21 days, but after 21 days, the extent of pass-through of cost decreases exceeds that of cost increase. Moreover, in daily panel data, price responds more strongly to cost decreases than to cost increases, especially beyond 14 days post the cost shock.

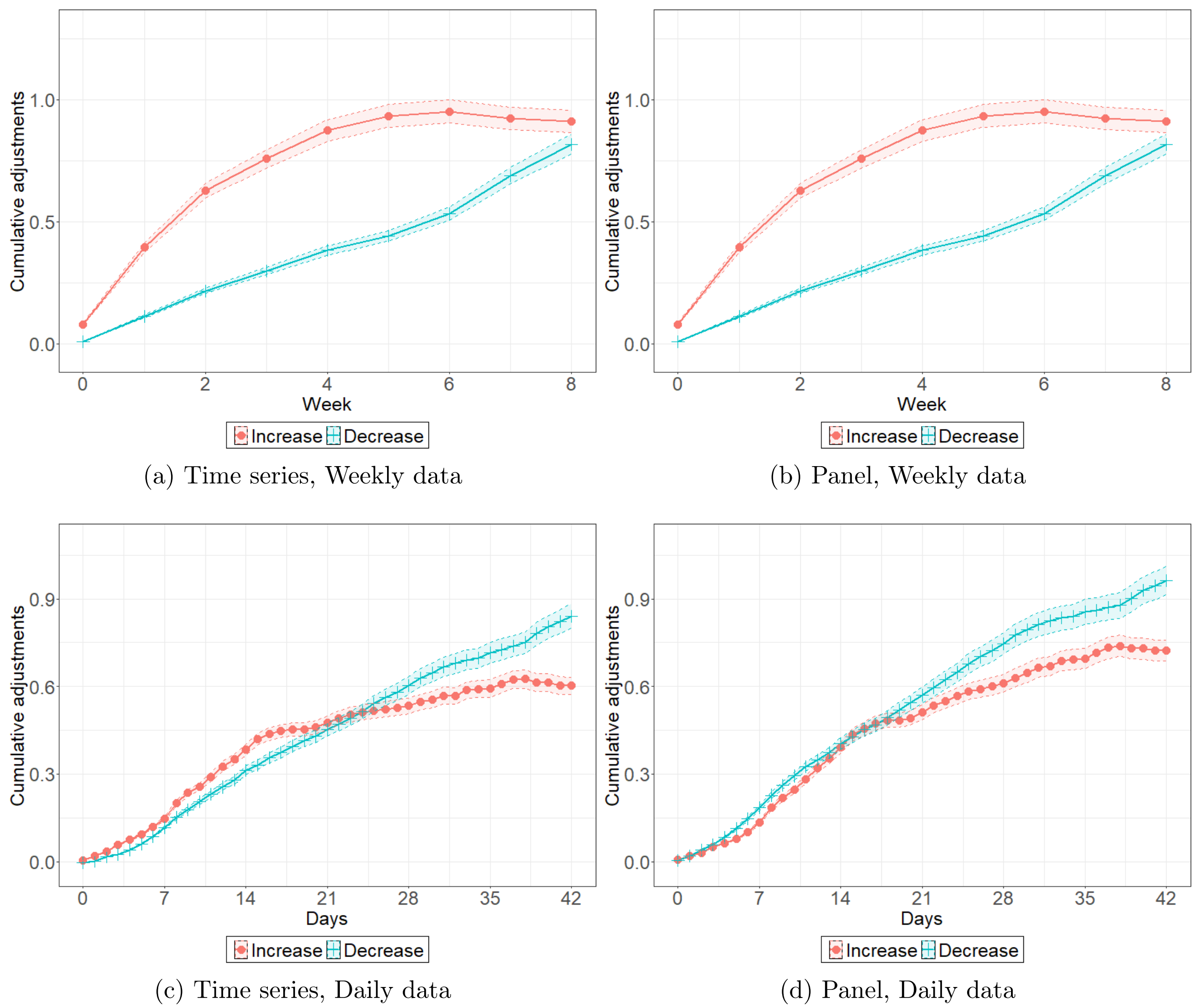
4.2 Explanation of Results

While the estimated adjustment patterns remain robust across different data structures (time series vs. panel) and time periods (2009-2014 vs. 2015-2019) in weekly data, the results are mixed when using the daily-level data. With daily date, the asymmetric adjustment patterns are observed in 2009-2014 with time series data but appear symmetric for panel data. However, in 2015-2019, unusual adjustment patterns are observed for both time series and panel data.

This inconsistency in results when using daily data may be due to the infrequent changes in retail prices compared to daily cost variations. While we may not have precise insight into retailers' pricing rules, it is evident that retailers do not consistently adjust their prices in response to daily cost fluctuations. This indicates a non-linear relationship between retail price changes and cost changes.

Two possible hypotheses for this infrequent pricing can be considered. One suggests that retailers follow an (s,S) rule for their pricing, while the other proposes that retailers manage their inventory with maximum and minimum thresholds. In either case, retailers do not adjust their prices daily but rather respond to cost changes on the day when the cost change exceeds their (s,S) thresholds or their inventory reaches the minimum threshold. In other words, retailers' responses to cost changes on other days are censored.

The error correction model used in the 'Rocket and Feathers' studies assumes a linear relationship between changes in retail prices and costs. Recent studies using daily data have adopted a similar framework for their models. The misspecification of the model has led to



(a) Time series, Weekly data

(b) Panel, Weekly data

(c) Time series, Daily data

(d) Panel, Daily data

Figure 4: Estimated Cumulative adjustments, 2015-2019

Note: (1) The solid red line represents the cumulative adjustments in response to a one-unit increase in cost, while the solid blue line represents the cumulative adjustments in response to a one-unit decrease in cost. (2) The dashed lines represent the confidence intervals at 5% significance level for both the increase and decrease cases, respectively.

inconsistent results, particularly when analyzing daily data.

This type of bias is similar to the inconsistency issue encountered when estimating a linear model with censored data using ordinary least squares (OLS).[9] For example, suppose station i changes its price at time t and then changes it again after 7 days at $t+7$ for some reason. During the period from t to $t+7$, the wholesale price changes on a daily basis, but the retail price for station i remains unchanged during the time period $t+1$ to $t+6$ (i.e., $\Delta P_{it} = 0$). A linear regression with the retail price change as the dependent variable and the wholesale price change as the independent variable (ΔC_t), $\Delta P_t = \beta \Delta C_t + \epsilon_t$, mis-specifies the data generating process and the estimated coefficient β does not capture the nonlinear price response.

The reason why the results with weekly data are relatively consistent compared to the ones with daily data can be explained with this concept. As previously mentioned, only about 10% of the total observations for retail price changes are non-zero in the daily data. On the contrary, in the weekly data, approximately 67% of the observations for retail price changes are non-zero. Additionally, changes in retail price predominantly occurs at 7 days and weekly station-level data can still contain the variation of retail price change in response to cost change(although the magnitude of size of retail price change are somewhat averaged out). Therefore, the weekly data is less censored, which is why we obtain relatively consistent results with weekly data.

4.3 Additional Analysis

In the additional analysis, I examine the influence of consumers' search intensity on retailers' asymmetric price adjustments in response to cost increases vs. cost decreases. Previous studies such as Yang and Ye (2008), Tappata (2009), and Lewis (2011) have explored the "rocket and feathers" phenomenon by considering consumers' search behavior.

These studies assume consumers' search more intensively when costs increase. This

[9] A detailed illustration of this bias in the context of censored data can be found in Tobin (1958).

suggests that consumers take more time to realize the true state of costs, leading to retailers having less motivation to immediately lower prices in response to cost decreases. This leads to asymmetric price adjustments.

Empirical finding by Remer (2015) lends support to this hypothesis. Remer (2015) assumes premium gasoline users, who generally have higher incomes, exhibit lower search intensity than regular gasoline users. He finds that the response of premium gasoline prices to cost decreases is slower than that of regular gasoline prices.

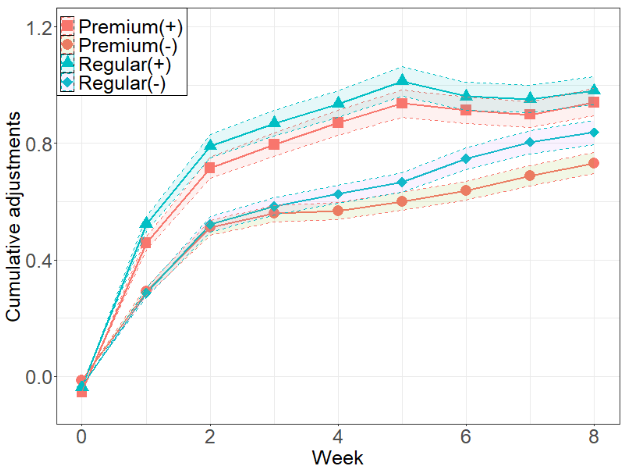
A similar comparison can be made between consumers who use full-service stations and those who use self-service stations. While both types of stations sell the same quality of regular gasoline, full-service stations offer the convenience of allowing drivers to remain in their vehicles while an attendant fuels their vehicle. This added convenience comes at a higher price compared to self-service stations, and consumers who choose full-service stations tend to be less price-sensitive as they are willing to pay higher prices for the enhanced service experience.

I revisit the potential influence of consumer search intensity on asymmetric price adjustments using weekly data from the Korean gasoline market. This analysis involves comparing the results across different types of service and different types of fuel, allowing for a comprehensive investigation of the effect of search intensity on price adjustments.

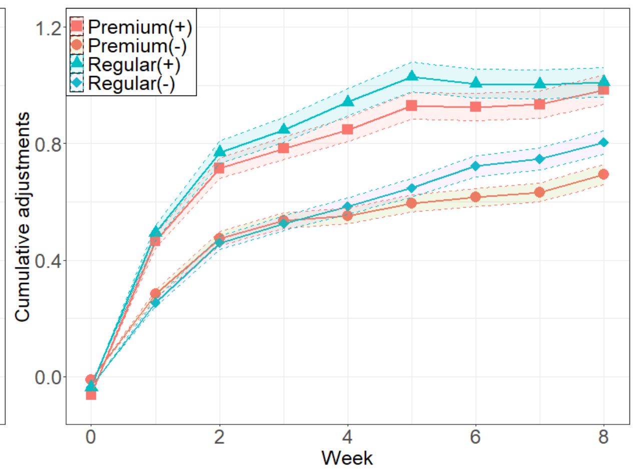
The data samples were divided into four sub-samples based on the type of service and fuel: full-service premium gasoline, full-service regular gasoline, self-service premium gasoline, and self-service regular gasoline. Furthermore, the robustness of the results is examined across two time periods: 2009-2014 and 2015-2019.

Figure 5 presents the cumulative adjustments for the four sub-samples based on fuel type and service type.[10] In the period of 2009-2014, the speed of adjustments in response to both an increase and a decrease of one unit cost is similar across all four cases, with the level of cumulative adjustments starting to diverge slightly after two weeks. These findings are

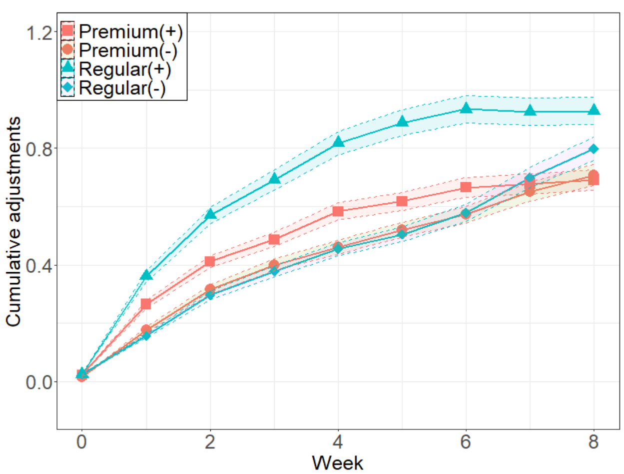
[10]The table of results are in appendix.



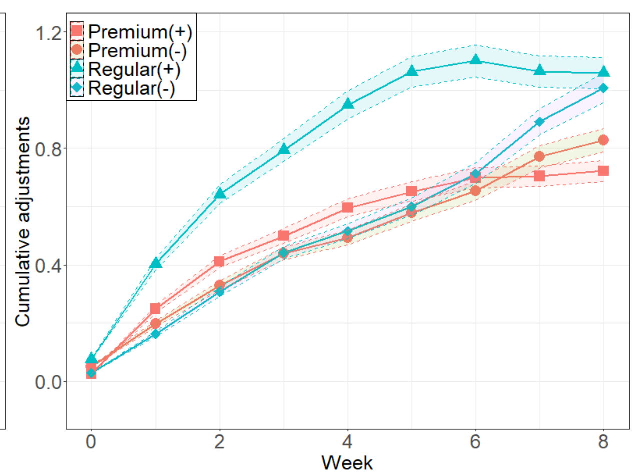
(a) 2009-2014, Full-service



(b) 2009-2014, Self-service



(c) 2015-2019, Full-service



(d) 2015-2019, Self-Service

Figure 5: Estimated cumulative adjustments by fuel and service type, using weekly data

Note: The term "Premium(+)" refers to the cumulative adjustments of premium gasoline in response to one unit cost increase. The first part represents the type of fuel (premium gasoline/regular), and the last part in parentheses indicates the type of shocks("+" for increase/ "-" for decrease).

consistent with the results observed in the period of 2015-2019. Specifically, the complete adjustments in response to an increase of one unit cost reach their peak at the sixth week for all four cases. Similarly, the adjustment patterns during the weeks following a decrease of one unit cost exhibit similarities across the sub-samples.

However, the extent of cumulative adjustments varies depending on the type of fuel. For premium gasoline retail price (both full-service and self-service), the complete adjustments in response to an increase of one unit cost reach their peak (around 0.8) at the sixth week. On the other hand, for regular gasoline (both full-service and self-service), the adjustments are almost completed at around 1 by the sixth week.

Although we have observed that the adjustment patterns are similar across the types of fuel and service, suggesting no significant effect of search intensity on asymmetric price adjustments, there are variations in the cost pass-through among the different sub-samples based on fuel type and service type. These variations are particularly pronounced in the period of 2015-2019.

Specifically, the adjustments for the self-service regular gasoline price are completed at around 1 in response to both an increase and a decrease of one unit cost change. However, the pass-through rates for the full-service premium gasoline price are around 0.6 for both an increase and a decrease of one unit cost. This suggests that there might be an influence of consumers' search intensity on the pass-through rate.

According to Genakos and Pagliero (2022), the pass-through rate varies depending on the level of competition in the market. Their empirical evidence reveals that the pass-through rate increases as the level of market competitiveness increases, ranging from 0.44 in monopoly markets to 1 in markets with four or more competitors. This implies that as firms have less control over their prices, the pass-through rate of cost changes tends to increase.

The results indicating different pass-through rates for full-service premium gasoline and self-service regular gasoline align with the findings presented in Genakos and Pagliero (2022). Retailers catering to consumers with high search intensity (e.g., users of self-service regular gasoline) find it difficult to control their prices because these consumers actively search for lower prices and are more likely to switch to competitors.

In contrast, retailers catering to consumers who use full-service premium gasoline can more easily control their prices because these consumers search less and are less likely to switch to competitors unless the prices are increased excessively. Therefore, the pass-through rate for full-service premium gasoline is lower than that for self-service regular gasoline.

5 Concluding Remarks

In this study, I investigate asymmetric price adjustments using various frequencies and datasets. The results obtained from the analysis of weekly data are robust across different data structures (time series and panel) and data periods (2009-2014 and 2015-2019). However, the results from the analysis using daily data exhibit variations depending on the data structure and sample period.

These findings can be attributed to bias resulted from model mis-specification of daily data. This suggests that recent "Rocket and Feathers" studies using linear models with daily data may introduce significant biases in estimated adjustment patterns, potentially leading to misleading conclusions. Therefore, when working with daily data, it is crucial to model data censoring.

Additional analysis sheds light on the impact of search intensity on asymmetric price adjustments by examining sub-samples based on different fuel types and service categories. The estimates indicate that while search intensity is not the primary determinant of asymmetric price adjustments, it may influence the pass-through rate of costs to prices.

In summary, this paper underscores the importance of considering the nuances of data frequencies in understanding asymmetric price adjustments. The difference in results based on weekly vs. daily data motivates revisiting analysis of other factors that influence retail pricing, such as spatial competition and nonlinear models of price setting.

References

[1] Bachmeier, Lance J and James M Griffin. 2003. "New evidence on asymmetric gasoline price responses." *Review of Economics and Statistics* 85 (3):772–776. [2, 31]

[2] 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. [2, 31]

[3] Balaguer, Jacint and Jordi Ripollés. 2016. "Asymmetric fuel price responses under heterogeneity." *Energy Economics* 54:281–290. [2, 11, 31]

[4] Balke, Nathan S, Stephen PA Brown, and Mine K Yucel. 1998. "Crude oil and gasoline prices: an asymmetric relationship?" *Economic Review-Federal Reserve Bank of Dallas* . [2, 31]

[5] Balmaceda, Felipe and Paula Soruco. 2008. "Asymmetric dynamic pricing in a local gasoline retail market." *The Journal of Industrial Economics* 56 (3):629–653. [2, 31]

[6] Bettendorf, Leon, Stephanie A Van der Geest, and Marco Varkevisser. 2003. "Price asymmetry in the Dutch retail gasoline market." *Energy Economics* 25 (6):669–689. [2, 31]

[7] Borenstein, Severin, A Colin Cameron, and Richard Gilbert. 1997. "Do gasoline prices respond asymmetrically to crude oil price changes?" *The Quarterly Journal of Economics* 112 (1):305–339. [2, 10, 12, 31]

[8] Bumpass, Donald, Vance Ginn, and MH Tuttle. 2015. "Retail and wholesale gasoline price adjustments in response to oil price changes." *Energy Economics* 52:49–54. [2, 31]

[9] Chen, Li-Hsueh, Miles Finney, and Kon S Lai. 2005. "A threshold cointegration analysis of asymmetric price transmission from crude oil to gasoline prices." *Economics Letters* 89 (2):233–239. [31]

[10] Da Silva, André Suriane, Cláudio Roberto Fóffano Vasconcelos, Silvinha Pinto Vasconcelos, and Rogério Silva de Mattos. 2014. "Symmetric transmission of prices in the

retail gasoline market in Brazil." *Energy Economics* 43:11–21. [2, 31]

[11] Deltas, George. 2008. "Retail gasoline price dynamics and local market power." *The Journal of Industrial Economics* 56 (3):613–628. [2, 31]

[12] Duffy-Deno, Kevin T. 1996. "Retail price asymmetries in local gasoline markets." *Energy Economics* 18 (1-2):81–92. [2, 31]

[13] Eckert, Andrew. 2002. "Retail price cycles and response asymmetry." *Canadian Journal of Economics/Revue canadienne d'économique* 35 (1):52–77. [2, 31]

[14] Faber, Riemer P. 2015. "More new evidence on asymmetric gasoline price responses." *The Energy Journal* 36 (3). [2, 31]

[15] Galeotti, Marzio, Alessandro Lanza, and Matteo Manera. 2003. "Rockets and feathers revisited: an international comparison on European gasoline markets." *Energy Economics* 25 (2):175–190. [2, 31]

[16] Genakos, Christos and Mario Pagliero. 2022. "Competition and pass-through: evidence from isolated markets." *American Economic Journal: Applied Economics* 14 (4):35–57. [20]

[17] Godby, Rob, Anastasia M Lintner, Thanasis Stengos, and Bo Wandschneider. 2000. "Testing for asymmetric pricing in the Canadian retail gasoline market." *Energy Economics* 22 (3):349–368. [2, 31]

[18] Hong, Woo-Hyung and Daeyong Lee. 2020. "Asymmetric pricing dynamics with market power: investigating island data of the retail gasoline market." *Empirical Economics* 58 (5):2181–2221. [2, 31]

[19] Karrenbrock, Jeffrey D et al. 1991. "The behavior of retail gasoline prices: symmetric or not?" *Federal Reserve Bank of St. Louis Review* 73 (4):19–29. [2, 31]

[20] Kim, Taehwan. 2018. "Price competition and market segmentation in retail gasoline: New evidence from South Korea." *Review of Industrial Organization* 53 (3):507–534. [8]

[21] Kirchgässner, Gebhard and Knut Kübler. 1992. "Symmetric or asymmetric price

adjustments in the oil market: an empirical analysis of the relations between international and domestic prices in the Federal Republic of Germany, 1972–1989." *Energy Economics* 14 (3):171–185. [2, 31]

[22] Lewis, Matthew and Michael Noel. 2011. "The speed of gasoline price response in markets with and without Edgeworth cycles." *Review of Economics and Statistics* 93 (2):672–682. [2, 31]

[23] Lewis, Matthew S. 2011. "Asymmetric price adjustment and consumer search: An examination of the retail gasoline market." *Journal of Economics & Management Strategy* 20 (2):409–449. [2, 3, 17, 31]

[24] Loy, Jens-Peter, Carsten Steinhagen, Christoph Weiss, and Birgit Koch. 2018. "Price transmission and local market power: empirical evidence from the Austrian gasoline market." *Applied Economics* 50 (53):5728–5746. [2, 31]

[25] Meng, Xiao-Li and Xianchao Xie. 2014. "I got more data, my model is more refined, but my estimator is getting worse! Am I just dumb?" *Econometric Reviews* 33 (1-4):218–250. [2]

[26] Nason, Guy P, Ben Powell, Duncan Elliott, and Paul A Smith. 2017. "Should we sample a time series more frequently?: decision support via multirate spectrum estimation." *Journal of the Royal Statistical Society. Series A (Statistics in Society)* :353–407. [2]

[27] Radchenko, Stanislav. 2005. "Oil price volatility and the asymmetric response of gasoline prices to oil price increases and decreases." *Energy Economics* 27 (5):708–730. [2, 31]

[28] Remer, Marc. 2015. "An empirical investigation of the determinants of asymmetric pricing." *International Journal of Industrial Organization* 42:46–56. [2, 3, 6, 18, 31]

[29] Tappata, Mariano. 2009. "Rockets and feathers: Understanding asymmetric pricing." *The RAND Journal of Economics* 40 (4):673–687. [3, 17]

[30] Tobin, James. 1958. "Estimation of relationships for limited dependent variables."

Econometrica: journal of the Econometric Society :24–36. [17]

[31] Verlinda, Jeremy A. 2008. “Do rockets rise faster and feathers fall slower in an atmosphere of local market power? Evidence from the retail gasoline market.” *The Journal of Industrial Economics* 56 (3):581–612. [2, 31]

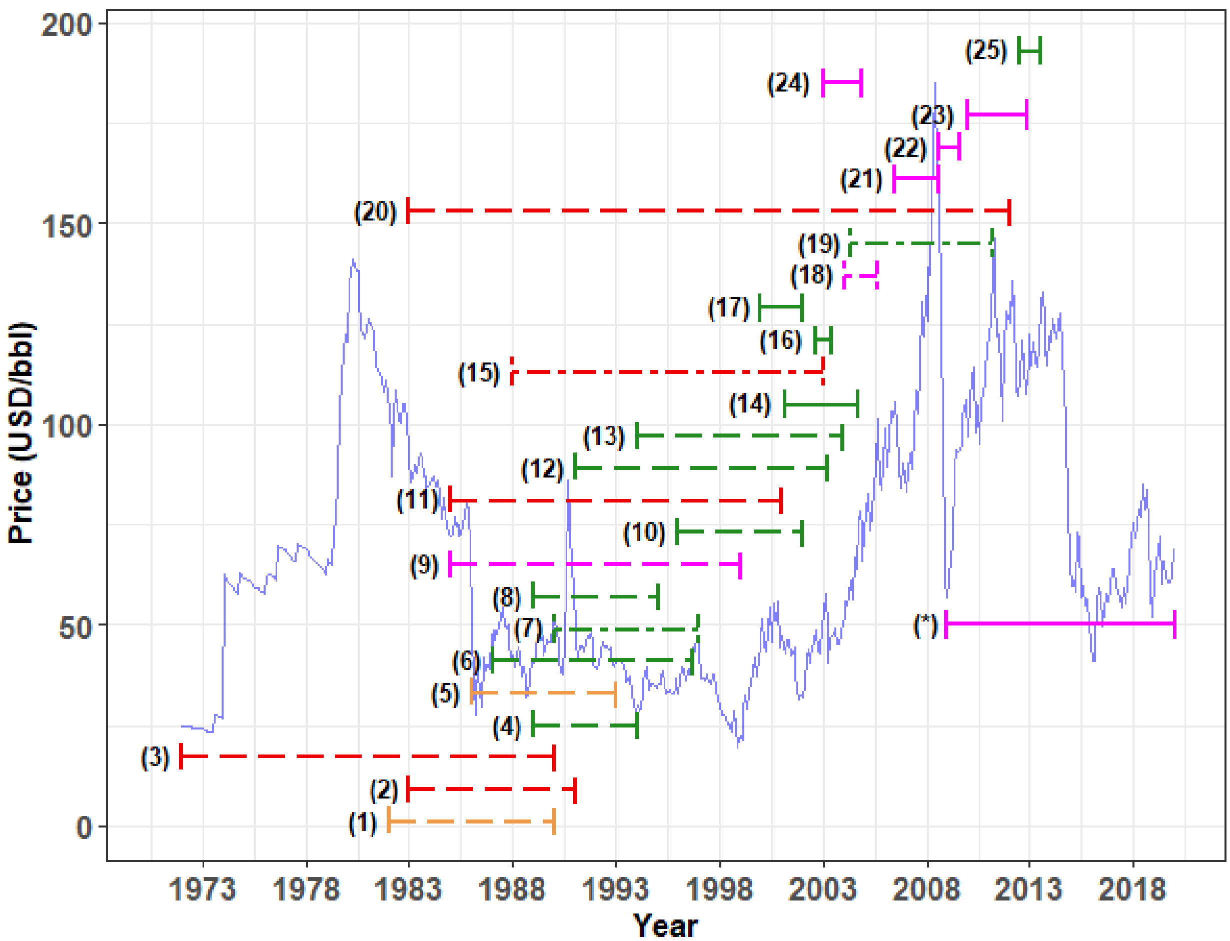
[32] Yang, Huanxing and Lixin Ye. 2008. “Search with learning: understanding asymmetric price adjustments.” *The RAND Journal of Economics* 39 (2):547–564. [3, 17]

[33] Zeileis, Achim, Friedrich Leisch, Kurt Hornik, and Christian Kleiber. 2002. “strucchange: An R package for testing for structural change in linear regression models.” *Journal of statistical software* 7:1–38. [11]

A Appendix

The estimation results for creating Figure 3c, Figure 3d, Figure 4c, and Figure 4d are presented in Table 4. Similarly, The estimation results for creating Figure 3a, Figure 3b, Figure 4a, and Figure 4b are presented in Table 3. Figure 5 are made based on the Table 5 and Table 6.

Figure 6: Sample period of studies on gasoline price response to oil price shocks



Note (a): Monthly crude oil price (thin blue line) is adjusted for CPI inflation to May 2022 price. (b): The numbers in parentheses reference the studies in Table 7. (c): The type of lines represents type of data ('long-dashed': country or city-level time series, 'dot-dashed': city-level panel, and 'solid': station-level panel). (d): The color of lines shows the frequency of data ('red': monthly, 'orange': biweekly, 'green': weekly, and 'purple': daily). (e): (*) represents data used in this study.

Table 3: The estimated results(weekly)

	Time series		Panel	
	2009-2014	2015-2019	2009-2014	2015-2019
ΔP^+_{t-1}	0.436***	0.680***	0.153***	0.237***
	(0.065)	(0.074)	(0.004)	(0.005)
ΔP^+_{t-2}	-0.094	-0.118	-0.087***	-0.029***
	(0.072)	(0.089)	(0.004)	(0.005)
$\vdots$				
ΔP^-_{t-1}	0.686***	0.777***	0.240***	0.161***
	(0.086)	(0.111)	(0.003)	(0.004)
ΔP^-_{t-2}	-0.219**	-0.002	-0.081***	-0.023***
	(0.100)	(0.135)	(0.003)	(0.004)
$\vdots$				
ΔC^+_{t}	-0.011	0.079***	-0.022***	0.061***
	(0.025)	(0.021)	(0.003)	(0.004)
ΔC^+_{t-1}	0.382***	0.246***	0.445***	0.264***
	(0.032)	(0.024)	(0.003)	(0.005)
ΔC^+_{t-2}	0.031	0.011	0.211***	0.134***
	(0.040)	(0.029)	(0.004)	(0.005)
$\vdots$				
ΔC^-_{t}	-0.021	0.006	-0.022***	0.012**
	(0.022)	(0.025)	(0.003)	(0.005)
ΔC^-_{t-1}	0.168***	0.080***	0.231***	0.092***
	(0.029)	(0.027)	(0.003)	(0.006)
ΔC^-_{t-2}	-0.039	0.012	0.119***	0.090***
	(0.034)	(0.029)	(0.003)	(0.005)
$\vdots$				
P_{t-1}	-0.091***	-0.016**	-0.030***	-0.023***
	(0.018)	(0.006)	(0.001)	(0.001)
C_{t-1}	0.103***	0.018**	0.037***	0.034***
	(0.020)	(0.008)	(0.001)	(0.001)
Tax var.	No	Yes	No	Yes
Station FE	No	No	Yes	Yes
Observations	304	252	173,170	126,332
R^2	0.91	0.956	0.459	0.413
Adjusted R^2	0.897	0.945	0.457	0.41

[1] Due to space limitations, some coefficients and their standard errors are omitted.

[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**\,p < 0.05$; and $***p < 0.01$.

Table 4: The estimated results(daily)

	Time series		Panel	
	2009-2014	2015-2019	2009-2014	2015-2019
ΔP^+_{t-1}	0.257***	0.287***	-0.202***	-0.282***
	(0.029)	(0.031)	(0.001)	(0.002)
ΔP^+_{t-2}	-0.003	0.060*	-0.090***	-0.086***
	(0.031)	(0.032)	(0.001)	(0.002)
$\vdots$				
ΔP^-_{t-1}	0.215***	0.236***	-0.136***	-0.135***
	(0.039)	(0.051)	(0.001)	(0.001)
ΔP^-_{t-2}	-0.057	-0.051	-0.065***	-0.083***
	(0.041)	(0.054)	(0.001)	(0.001)
$\vdots$				
ΔC^+_{t}	0.0003	0.005	-0.013***	0.007***
	(0.008)	(0.006)	(0.002)	(0.002)
ΔC^+_{t-1}	-0.025***	0.010*	-0.018***	0.004*
	(0.009)	(0.006)	(0.002)	(0.002)
ΔC^+_{t-2}	-0.001	0.008	-0.004***	0.004**
	(0.009)	(0.006)	(0.002)	(0.002)
$\vdots$				
ΔC^-_{t}	-0.01	-0.003	-0.007***	0.004*
	(0.008)	(0.006)	(0.001)	(0.002)
ΔC^-_{t-1}	-0.011	0.002	-0.011***	0.004*
	(0.008)	(0.006)	(0.001)	(0.002)
ΔC^-_{t-2}	-0.025***	0.009	-0.014***	0.014***
	(0.008)	(0.006)	(0.001)	(0.002)
$\vdots$				
P_{t-1}	-0.015***	-0.003***	-0.008***	-0.006***
	(0.003)	(0.001)	(0.000)	(0.000)
C_{t-1}	0.017***	0.003***	0.010***	0.010***
	(0.003)	(0.001)	(0.000)	(0.000)
Tax var.	No	Yes	No	Yes
Station FE	No	No	Yes	Yes
Observations	2,147	1,783	1,119,380	868,329
R^2	0.561	0.884	0.088	0.134
Adjusted R^2	0.521	0.866	0.087	0.134

[1] Due to space limitations, some coefficients and their standard errors are omitted.
[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Table 5: The estimated results(2009-2014)

	Premium		Regular	
	Full	Self	Full	Self
ΔP^{+}_{t-1}	0.107***	0.056***	0.119***	0.108***
	(0.008)	(0.013)	(0.008)	(0.014)
ΔP^{+}_{t-2}	-0.043***	-0.005	-0.061***	-0.066***
	(0.008)	(0.013)	(0.008)	(0.015)
ΔP^{-}_{t-1}	0.162***	0.094***	0.280***	0.264***
	(0.007)	(0.011)	(0.006)	(0.010)
ΔP^{-}_{t-2}	-0.092***	-0.087***	-0.083***	-0.064***
	(0.007)	(0.012)	(0.007)	(0.011)
$\vdots$				
ΔC^{+}_{t}	-0.054***	-0.062***	-0.039***	-0.037***
	(0.008)	(0.013)	(0.007)	(0.011)
ΔC^{+}_{t-1}	0.476***	0.486***	0.527***	0.491***
	(0.008)	(0.014)	(0.007)	(0.011)
ΔC^{+}_{t-2}	0.177***	0.194***	0.175***	0.190***
	(0.009)	(0.015)	(0.008)	(0.013)
$\vdots$				
ΔC^{-}_{t}	-0.014**	-0.012	-0.034***	-0.034***
	(0.007)	(0.012)	(0.006)	(0.010)
ΔC^{-}_{t-1}	0.268***	0.252***	0.292***	0.253***
	(0.007)	(0.012)	(0.006)	(0.010)
ΔC^{-}_{t-2}	0.137***	0.129***	0.113***	0.094***
	(0.007)	(0.013)	(0.007)	(0.011)
$\vdots$				
P_{t-1}	-0.033***	-0.039***	-0.030***	-0.035***
	(0.001)	(0.002)	(0.001)	(0.002)
C_{t-1}	0.040***	0.043***	0.038***	0.043***
	(0.001)	(0.003)	(0.001)	(0.003)
Tax var.	No	No	No	No
Station FE	Yes	Yes	Yes	Yes
Observations	46,151	16,054	46,151	16,054
R^2	0.349	0.333	0.454	0.45
Adjusted R^2	0.346	0.328	0.451	0.446

[1] Due to space limitations, some coefficients and their standard errors are omitted.
[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Table 6: The estimated results(2015-2019)

	Premium		Regular	
	Full	Self	Full	Self
ΔP^+_{t-1}	0.165***	0.221***	0.255***	0.242***
	(0.009)	(0.016)	(0.010)	(0.015)
ΔP^+_{t-2}	0.005	-0.009	-0.032***	-0.039**
	(0.009)	(0.016)	(0.010)	(0.016)
$\vdots$				
ΔP^-_{t-1}	0.156***	0.250***	0.184***	0.213***
	(0.007)	(0.010)	(0.007)	(0.010)
ΔP^-_{t-2}	-0.037***	-0.060***	-0.049***	-0.029***
	(0.007)	(0.011)	(0.007)	(0.010)
$\vdots$				
ΔC^+_{t}	0.022**	0.026*	0.024***	0.075***
	(0.010)	(0.013)	(0.009)	(0.013)
ΔC^+_{t-1}	0.208***	0.189***	0.302***	0.278***
	(0.010)	(0.013)	(0.010)	(0.013)
ΔC^+_{t-2}	0.082***	0.089***	0.103***	0.136***
	(0.010)	(0.014)	(0.010)	(0.014)
$\vdots$				
ΔC^-_{t}	0.014	0.051***	0.025**	0.029*
	(0.012)	(0.017)	(0.011)	(0.016)
ΔC^-_{t-1}	0.130***	0.106***	0.099***	0.096***
	(0.013)	(0.017)	(0.012)	(0.016)
ΔC^-_{t-2}	0.087***	0.072***	0.091***	0.086***
	(0.012)	(0.017)	(0.011)	(0.016)
$\vdots$				
P_{t-1}	-0.024***	-0.020***	-0.022***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
C_{t-1}	0.031***	0.029***	0.029***	0.034***
	(0.002)	(0.002)	(0.002)	(0.003)
Tax var.	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes
Observations	32,720	14,419	32,720	14,419
R^2	0.271	0.322	0.371	0.448
Adjusted R^2	0.267	0.316	0.367	0.443

[1] Due to space limitations, some coefficients and their standard errors are omitted.

[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Table 7: Summary of literature

No.	Authors	Data structure, Frequency	Patterns
1	Bacon (1991)	Time-series, Biweekly	$+ > -$
2	Karrenbrock et al. (1991)	Time-series, Monthly	$+ > -$
3	Kirchgässner and Kübler (1992)	Time-series, Monthly	Mixed
4	Duffy-Deno (1996)	Time-series(city), Weekly	Mixed
5	Borenstein, Cameron, and Gilbert (1997)	Time-series, Biweekly	$+ > -$
6	Balke, Brown, and Yucel (1998)	Time-series(city), Weekly	Mixed
7	Godby et al. (2000)	Panel(city), Weekly	$+ \approx -$
8	Eckert (2002)	Time series(city), Weekly	$+ > -$
9	Bachmeier and Griffin (2003)	Time-series(city), Daily	$+ \approx -$
10	Bettendorf, Van der Geest, and Varkevisser (2003)	Time-series, Weekly	Mixed
11	Galeotti, Lanza, and Manera (2003)	Time-series, Monthly	$+ > -$
12	Chen, Finney, and Lai (2005)	Time-series, Weekly	$+ > -$
13	Radchenko (2005)	Time-series, weekly	$+ > -$
14	Balmaceda and Soruco (2008)	Panel(station), Weekly	$+ > -$
15	Deltas (2008)	Panel(city), Monthly	$+ > -$
16	Verlinda (2008)	Panel(station), Weekly	$+ > -$
17	Lewis (2011)	Panel(station), Weekly	$+ > -$
18	Lewis and Noel (2011)	Panel(city), Daily	$+ > -$
19	Da Silva et al. (2014)	Panel(city), Weekly	Mixed
20	Bumpass, Ginn, and Tuttle (2015)	Time-series, Monthly	$+ \approx -$
21	Faber (2015)	Panel(station), Daily	Mixed
22	Remer (2015)	Panel(station), Daily	$+ > -$
23	Balaguer and Ripollés (2016)	Panel(station), Daily	$+ > -$
24	Loy et al. (2018)	Panel(station), Daily	$+ > -$
25	Hong and Lee (2020)	Panel(station), Weekly	$+ > -$

[1] $+ > -$ means the gas price responses faster to oil price increase than oil price decrease.
[2] $+ \approx -$ means the speed of gas price responses to oil price increase and decrease is roughly the same.
[3] "Mixed" means that the adjustment patterns may be asymmetric and symmetric, depending on sample period, econometric model, and sample of stations.
[4] The periods of the studies are represented in Figure 6 with corresponding numbers.