Revisiting Rockets and Feathers: How Frequency of Data Affects Estimation Results

Seon-Yong Kim*

October 21, 2023

Abstract

This paper revisits asymmetric price adjustments using daily station-level data from the Korean gasoline market. While recent studies tend to utilize high-frequency data to investigate these adjustments, such an approach can introduce significant biases into estimation results due to the nonlinear relationship between changes in retail prices and variable costs. Specifically, although changes in variable costs occur daily, retailers do not consistently respond to these daily cost variations. This study illustrates how the frequency of data affects estimation results by comparing the outcomes across different data frequencies and highlights the inconsistency of results obtained with daily-level data. Additionally, simulations confirm these findings and emphasize the significance of choosing an appropriate econometric model for accurately describing retailers' pricing behavior.

JEL classification: Q40, D40

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-Columbia, 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 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 4 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, while changes in cost can be observed on a daily basis, retailers do not respond to all daily changes in cost but rather adjust their prices infrequently, typically on a weekly basis. This suggests that the relationship between changes in retail price and wholesale price is nonlinear. This characteristic of the data can introduce significant bias when estimating the adjustment patterns within a linear model framework.

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".

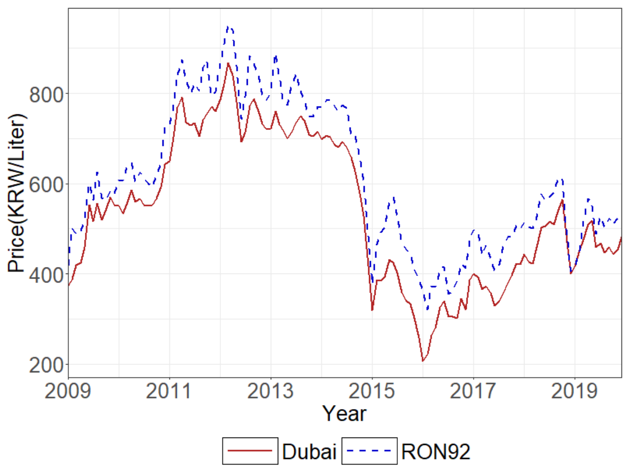
The remaining sections of this chapter are organized as follows. In Section 2, I describe the characteristics of the data used in this study. Section 3 presents an econometric model and the main results with detailed interpretation. Finally, in Section 4, I conclude the paper by summarizing the findings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

2 Data and Market Overview

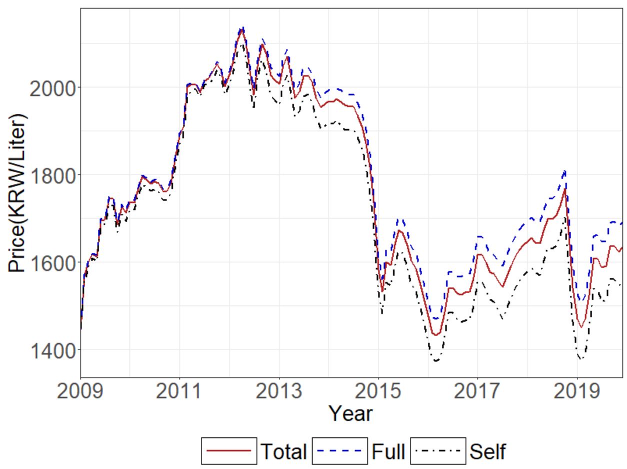
2.1 Data

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 public the price on the website on daily level. Among them I use the price information of 709 stations in Seoul, including the type of service, brand, and location, for the period between 2009 and 2019.

To determine the variable cost of gasoline, I use the wholesale price data from MOPS, which reports benchmark prices for petroleum products in the Asian market based on transactions in Singapore. This price closely tracks international oil prices and are used as a measure of variable cost in the analysis. Given the size of the Korean market, it is unlikely that the retail price of gasoline in Korea would significantly affect the international wholesale price. Therefore, there is no need to consider the issue of endogeneity between retail price and cost in the econometric model.



(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. (2) 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.

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.

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 behavior after 2015. The presence of a structural break during the data period is examined in Section 3.

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.

In this study, 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. This approach allows for a more accurate analysis of the underlying asymmetric price adjustments, controlling for the temporary tax adjustments.

2.2 The Frequency of Price Change

The pricing behavior of retailers in the retail gasoline market reveals an infrequent adjustment pattern. Despite being aware of daily fluctuations in wholesale price levels and absence of menu cost, retailers adjust price infrequently, with approximately 90% of the observations showing no price changes. Out of the 2,275,577 total observations, only 199,696 show non-zero price adjustments.

Another distinctive feature of retailers' pricing behavior is their preference for changing prices on a weekly basis. The mode and median of the frequency of price changes (measured in days) are both 7 days during the 2009-2019 data period. This concentration of frequencies at multiples of 7 is visually illustrated in Figure 2.[4] These observed characteristics suggest

[4]I omit the remaining cases with frequencies greater than 29 days, but they exhibit a similar pattern.

that retailers typically respond to changes in upstream prices on a weekly basis.

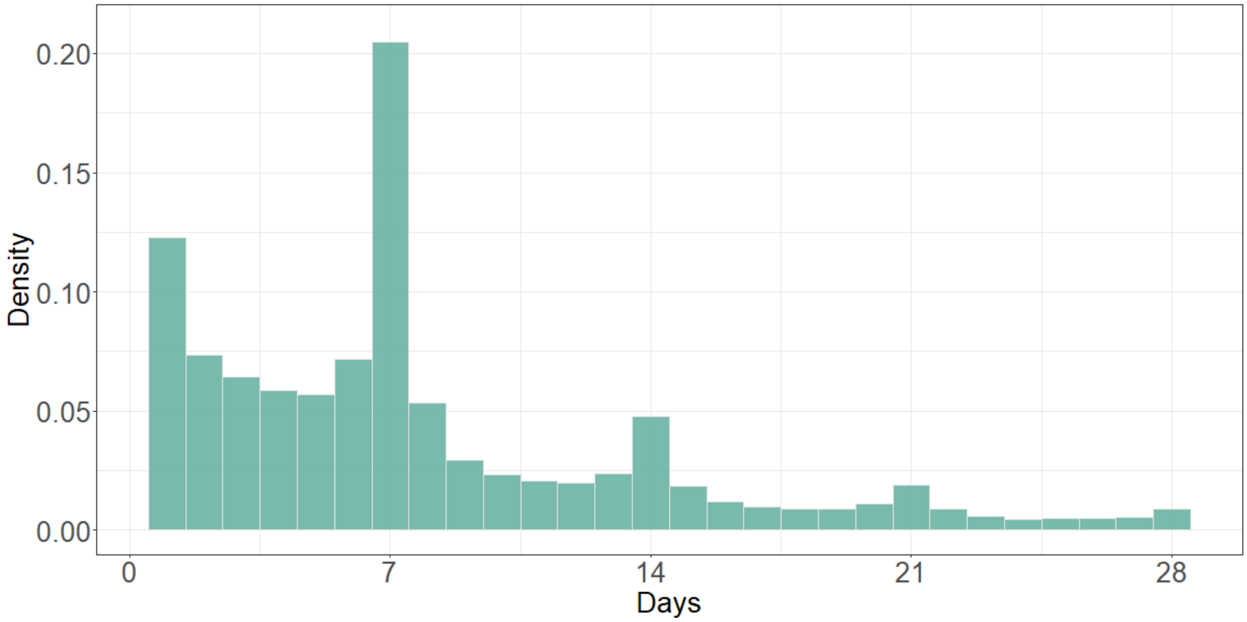


Figure 2: The distribution of days between price changes

Note: The fraction of price changes the age at the time of price change among all price changes.

Table 1 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 75KRW/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,

Table 1: 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.

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 Results

3.1 An error-correction 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]

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

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].

[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($P_t = \phi_0 + \phi_{1t} + \eta_t$). 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.

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

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 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

Balaguer and Ripollés (2016)

[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).

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.

3.2 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

[8]The cumulative adjustments are calculated based on the estimation results in Table 2 and Table 3 in Appendix A

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.

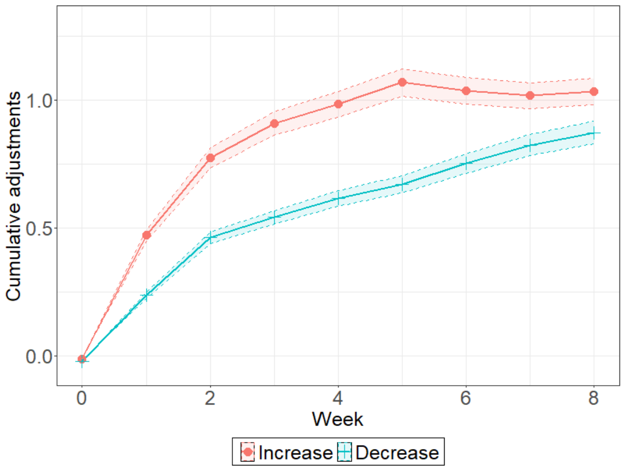
In the 2015-2019 period, the adjustment patterns for weekly data closely resemble those observed in the 2009-2014 period for both time series and panel data cases. Specifically, as depicted in Figure 4, the cumulative adjustments reach their peak around the 5th week. However, it takes more time to complete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

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.

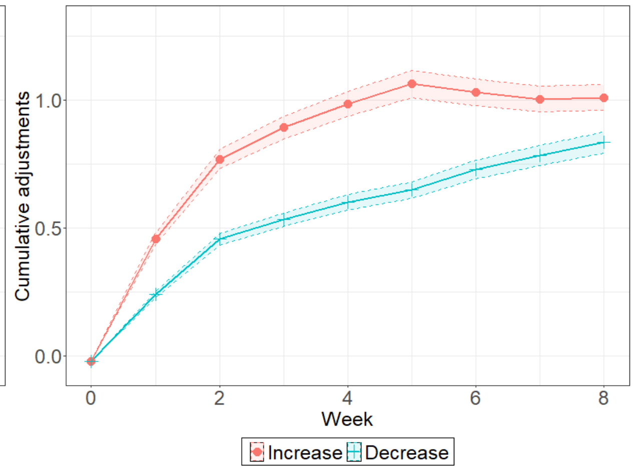
3.3 Explanation of results

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.

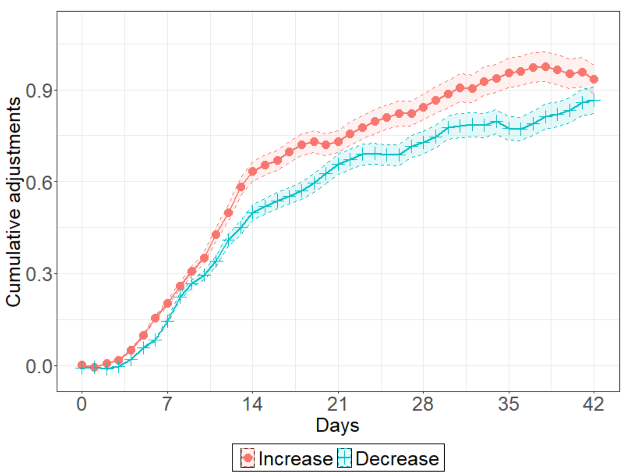
This inconsistency in results when using daily data may be due to the infrequent changes in retail prices compared to daily cost variations. While we may not have precise insight



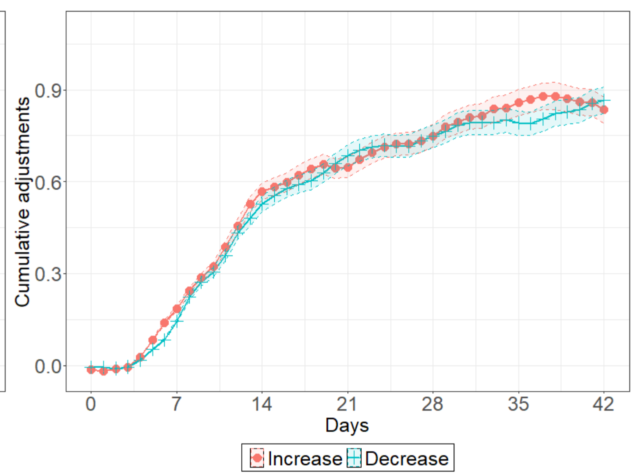
(a) Time series, Weekly data



(b) Panel, Weekly data



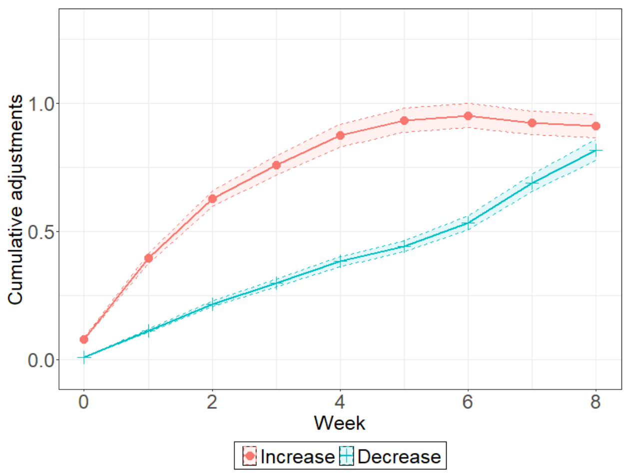
(c) Time series, Daily data



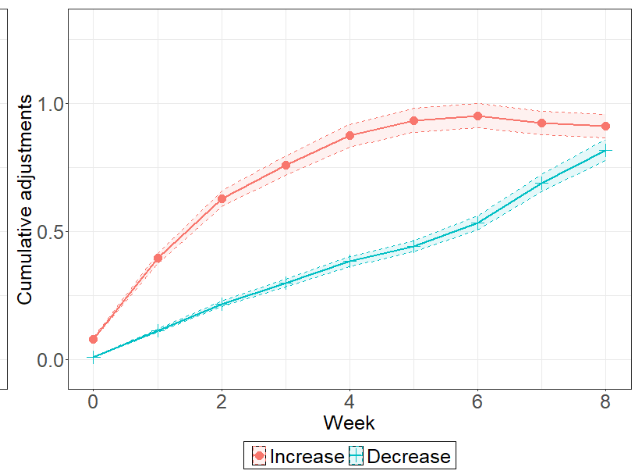
(d) Panel, Daily data

Figure 3: Estimated Cumulative adjustments, 2009-2014

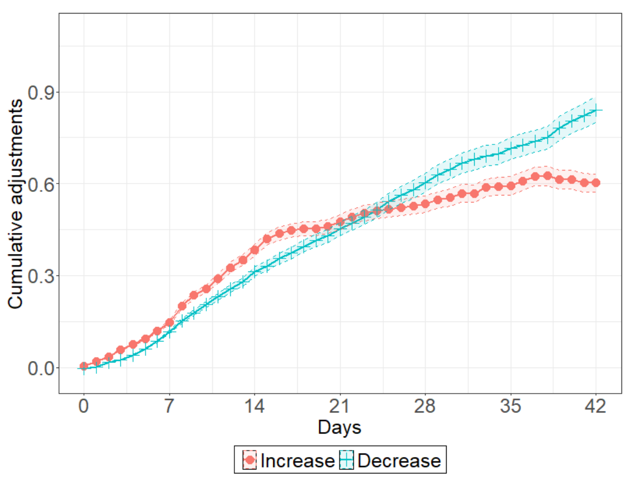
Note: (1) The solid red line represents the cumulative adjustments in response to a one-unit increase in cost, while the solid blue line represents the cumulative adjustments in response to a one-unit decrease in cost. (2) The dashed lines represent the confidence intervals at 5% significance level for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



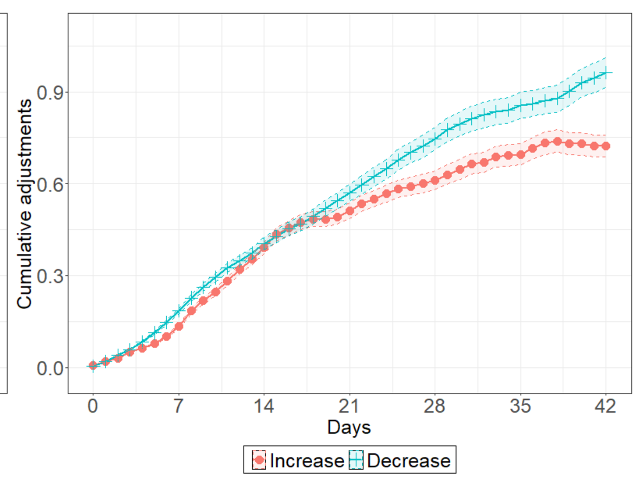
(a) Time series, Weekly data



(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.

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 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

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

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 Concluding Remarks

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

These findings can be explained by the concept of bias resulting from the misspecification of the model when dealing with censored data. This suggests that recent "Rocket and Feathers" studies using linear models with daily data may produce significant biases in estimated adjustment patterns, which could potentially lead to misleading conclusions. Therefore, when working with daily data, it is crucial to develop nonlinear models that can capture the essential features of the data.

These results raise questions about how retailers determine their prices in response to cost changes. We have mentioned two possible hypotheses, but they remain unexplored in this study. In future research, we plan to consider several possible data generating processes that describe retailers' daily pricing under each hypothesis and generate the corresponding datasets. By estimating the model with these simulated datasets and comparing the results with the actual dataset, we aim to unveil the nature of retailers' pricing behavior. We expect that this future study will contribute to a better understanding of asymmetric price adjustments by retailers.

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, 22]

[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, 22]

[3] Balaguer, Jacint and Jordi Ripollés. 2016. "Asymmetric fuel price responses under heterogeneity." *Energy Economics* 54:281–290. [2, 9, 22]

[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, 22]

[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, 22]

[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, 22]

[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, 8, 9, 22]

[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, 22]

[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. [22]

[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, 22]

[11] Deltas, George. 2008. "Retail gasoline price dynamics and local market power." *The Journal of Industrial Economics* 56 (3):613–628. [2, 22]

[12] Duffy-Deno, Kevin T. 1996. "Retail price asymmetries in local gasoline markets." *Energy Economics* 18 (1-2):81–92. [2, 22]

[13] Eckert, Andrew. 2002. "Retail price cycles and response asymmetry." *Canadian Journal of Economics/Revue canadienne d'économique* 35 (1):52–77. [2, 22]

[14] Faber, Riemer P. 2015. "More new evidence on asymmetric gasoline price responses." *The Energy Journal* 36 (3). [2, 22]

[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, 22]

[16] 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, 22]

[17] 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, 22]

[18] 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, 22]

[19] 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, 22]

[20] 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, 22]

[21] 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, 22]

[22] 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, 22]

[23] 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]

[24] 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]

[25] 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, 22]

[26] Remer, Marc. 2015. "An empirical investigation of the determinants of asymmetric pricing." *International Journal of Industrial Organization* 42:46–56. [2, 22]

[27] Tobin, James. 1958. "Estimation of relationships for limited dependent variables." *Econometrica: journal of the Econometric Society* :24–36. [14]

[28] 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, 22]

[29] 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. [9]

A Appendix

The tables below show the estimation results, but due to space limitations, some coefficients and their standard errors are omitted. The estimation results for creating Figure 3c, 3d, 4c, and 4d are presented in Table 3. Similarly, The estimation results for creating Figure 3a, 3b, 4a, and 4b are presented in Table 2. Figure **??** are made based on the Table **??** and **??**. The significance levels are represented with the asterisk($***\ p < 0.01$, $**\ p < 0.05$, and $*\ p < 0.1$).

Table 2: 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

Table 3: The estimated results(daily)

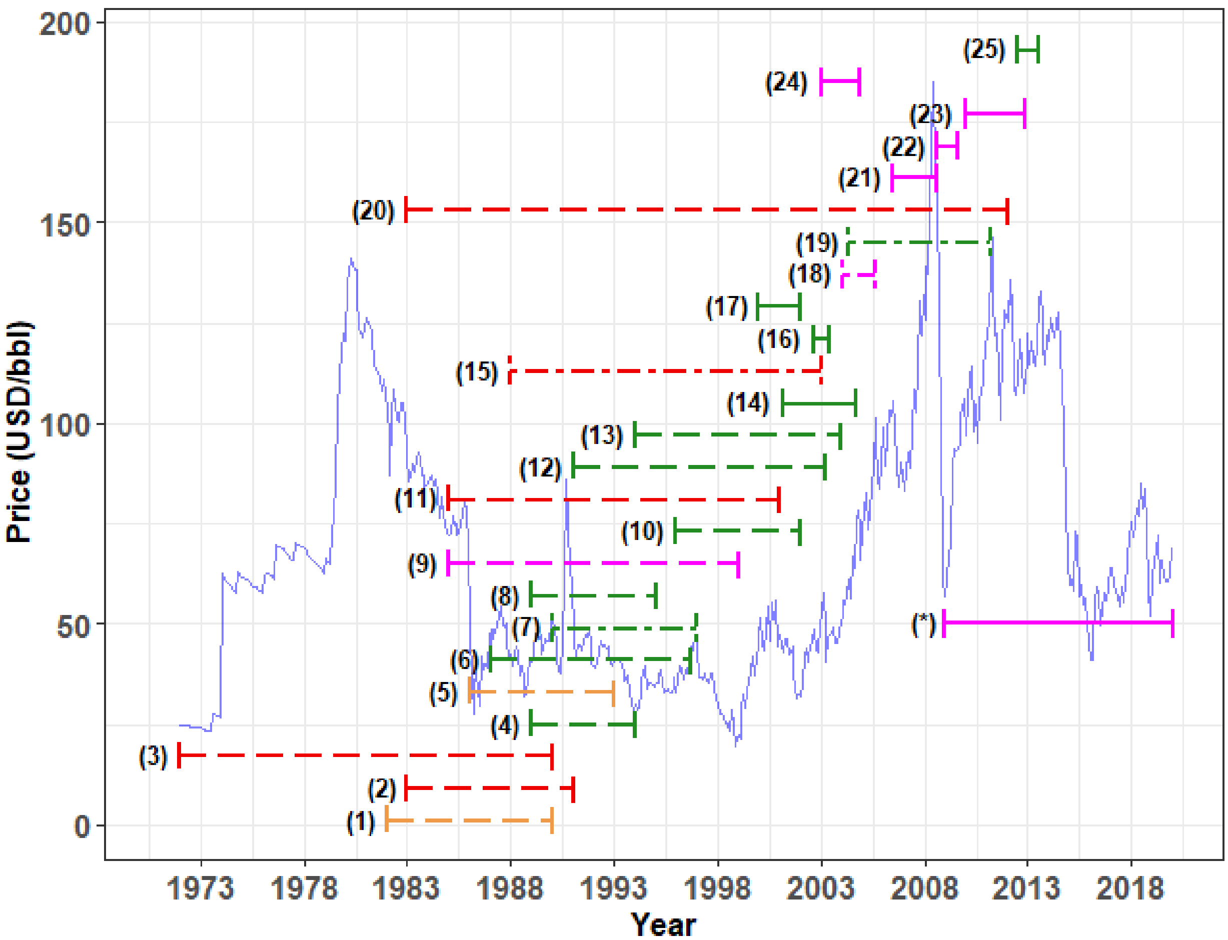
	Time series		Panel	
	2009-2014	2015-2019	2009-2014	2015-2019
ΔP^{+}_{t-1}	0.257***	0.287***	-0.202***	-0.282***
	(0.029)	(0.031)	(0.001)	(0.002)
ΔP^{+}_{t-2}	-0.003	0.060*	-0.090***	-0.086***
	(0.031)	(0.032)	(0.001)	(0.002)
$\vdots$				
ΔP^{-}_{t-1}	0.215***	0.236***	-0.136***	-0.135***
	(0.039)	(0.051)	(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

Table 4: 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 5 with corresponding numbers.

Figure 5: 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 **??**. (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.