# ESSAYS ON RETAIL GASOLINE PRICING

A Dissertation

presented to

the Faculty of the Graduate School

at the University of Missouri

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

by

SEON-YONG KIM

Dr. Shawn Ni, Dissertation Supervisor

MAY 2024

The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled

ESSAYS ON RETAIL GASOLINE PRICING

presented by Seon-Yong Kim,

a candidate for the degree of Doctor of Philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

Professor Shawn Ni

Professor David Kaplan

Professor X. H. Wang

Professor Michael Podgursky

Professor Guanyu Hu

# ACKNOWLEDGEMENTS

I would first like to express my appreciation to my advisor, Shawn Ni, for his unwavering support throughout my Ph.D. program. During this time, he not only provided academic guidance but also showed genuine concern for my life at Mizzou. His passion for research and novel insights motivates me deeply to explore new avenues in my academic studies. This valuable experience will undoubtedly contribute to my success in my next steps in Korea Energy Economics Institute.

I also appreciate my committee members (Dr. David Kaplan, X.H. Wang, Michael Podgursky, and Guanyu Hu) for providing me with valuable feedback to complete my thesis. Dr. Kaplan, especially, was always willing to spend time to reviewing my work and provided detailed and insightful comments. I also would thank Dr. Daewook Kim and Sungbong Cho for their support and encouragement even after the graduation of Soongsil University.

I am deeply thankful for my family—my father, mother, and sister. Doing a Ph.D. in the U.S. was sometimes challenging, and whenever I felt frustrated, they trusted me and encouraged me up. Their support was instrumental in completing my Ph.D. degree, and I am truly happy to go back and see my family again in Korea.

Finally, I would like to give thanks to God with all my heart. Whenever I felt like I couldn't finish the race, He enabled me to do things that I couldn't do without Him. Every challenge was not easy to overcome, but now I am thankful that I grew in Him and created a deeper relationship with Him.

"Surely goodness and mercy shall follow me all the days of my life, and I shall dwell in the house of the LORD forever." - Psalm 23:6 -

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ESSAYS ON RETAIL GASOLINE PRICING

Seon-Yong Kim

Dr. Shawn Ni, Dissertation Supervisor

Overview

This dissertation investigates retailers' pricing behavior by focusing on the retail gasoline market in Seoul, South Korea. The study consists of two chapters.

The first chapter presents an empirical analysis of how gasoline stations change prices. One common feature of retail price changes is their periodic and lumpy nature. Various theories have been proposed to explain why retail prices are sticky, each focusing on different factors that influence how retailers set prices. Studies in macroeconomic theory indicate that optimal price adjustment patterns depend on the nature of costs involved in price adjustment. If a price change incurs a fixed cost (e.g., a "menu cost"), optimal price changes occur when the change in state variables exceeds a threshold, resulting in state-dependent price changes. Alternatively, if there is a fixed cost associated with acquiring information, it is optimal to make price adjustments with periodic regularity (time-dependent). Studies in industrial organization emphasize the role of market power and strategic interactions among retailers. Some studies in marketing science argue that retailers are more likely to maintain certain prices based on consumer psychology (e.g., those ending with the digit 9).

Do some or all of these theories explain how Seoul's gasoline retail price changes? In the first chapter, I examine the empirical significance of time-dependent pricing, state-dependent pricing, market power, and psychological pricing in the estimation model and examine how these factors are correlated with each other. The estimation results show that the most dominant factor affecting pricing decisions is the time-dependent pricing rule, and this tendency to follow the time-dependent pricing rule varies with retailers' local market power.

The analysis of how frequently gas stations change prices helps to better understand another common empirical phenomenon concerning asymmetric changes in retail gasoline prices in response to changes in wholesale prices. Many studies find that increases in costs (such as oil prices) are passed through more quickly to retail prices than decreases in costs, a pattern known as "rockets and feathers". This literature is mostly based on the error correction model that assumes retail prices are a linear function of costs. The pricing behavior examined in the first chapter implies that changes in retail prices are nonlinear in changes in costs, as gas stations keep daily prices mostly unchanged despite continuous changes in costs.

In the second chapter, I demonstrate the potential bias arising from using daily data for the "rockets and feathers" study. Recent studies on "rockets 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 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.

# Chapter 1

# How Retailers Change Prices: Daily Data of Gas Stations in Seoul Korea

## 1.1 Introduction

Retail price changes are generally periodic and lumpy, even when the factors that affect pricing decisions change continuously in time and size. Competing theories on sticky prices have been developed in several fields of economics, based on different premises regarding how retailers set prices. A number of studies in industrial organization focus on the role of market power and strategic interactions among retailers.[1] Some studies in marketing science argue that retailers set prices based on consumer psychology (e.g., keeping the last digit of prices at 9).[2]

[1]See e.g., Dixon (1983), Carlton (1986), Neumark and Sharpe (1992), Slade (1999), Athey, Bagwell, and Sanchirico (2004), Renner and Tyran (2004), Noel (2007), Garrod (2012), Jiménez and Perdiguero (2012), and Clark and Houde (2013).

[2]See e.g., Schindler and Kirby (1997), Stiving and Winer (1997), Basu (2006), Levy, Lee, Chen, Kauffman, and Bergen (2011), Lewis (2015), Ater and Gerlitz (2017), Levy, Snir, Gotler, and Chen (2020), Snir, Chen, and Levy (2022).

A voluminous amount of studies in macroeconomics theorize how patterns of price adjustment relate to the nature of costs in price adjustment. They classify price adjustment as state-dependent (SD) or time-dependent (TD). In TD models, the probability of a price change in the current period depends on how long the previous price was held. In SD models, the decision to change the price depends on the current cost or demand shocks and changes in expectations for the future. Alvarez, Lippi, and Passadore (2017) note that SD models are optimal when there is a fixed cost associated with changing prices, while TD models are optimal when there is a fixed cost associated with acquiring information.[3]

How well do these competing theories explain price changes by a given sample of retailers? I address this question by examining daily prices (in Korean won per liter) of all gas stations in the Seoul market of Korea between 2009 and 2019. The data are special in several ways: I observe a large amount of high-frequency data of retail gasoline prices and proxy variables for cost, such as international wholesale prices. Retail prices are measured by four digits in Korean won per liter, which makes them ideal for studying the role of "psychological preference" in changing retail prices.

I proxy the prevalence of TD rules by price changes with regularity in time (e.g., on a particular day of the week), SD rules by the response to changes in wholesale price, "psychological pricing" by the last and second-to-last digit in the price, and local market conditions by the number of stations within a 1km radius and type of service.

I seek to make two contributions to the empirical literature of retail pricing. First, I present evidence in gasoline retail pricing that supports all competing theories (TD

[3]See, e.g., Barro (1972), Caplin and Spulber (1987) for menu cost, and Taylor (1980), Calvo (1983), Sims (2003) and Reis (2006) for information acquisition cost.

and SD rules, local competition, and psychological pricing). Specifically, (i) stations adjust price infrequently, (ii) price changes occur disproportionately weekly and on Tuesdays, (iii) price changes occur less frequently when the last and second to last digit of the previous price ends at 9, (iv) Price changes occur more frequently at stations with a higher number of rival stations.

Second, I gauge the empirical significance of the competing theories by estimating a logit model of price changes that contains the aforementioned proxy variables. I find that in separate regressions, TD, SD, local market condition, and "psychological pricing" are significant. However, in a joint model, the TD model plays a dominating role in explaining the frequency of retail price changes.

The findings that retail gasoline stations adhere to a TD pricing rule make several contributions to previous studies. First, this study investigates the general landscape of retail pricing with a clearer framework. In environments where numerous retailers offer diverse products across various markets, pricing may exhibit a blend of patterns due to underlying heterogeneous factors. However, focusing on the retail pricing of gasoline offers distinct advantages, facilitating a clearer examination of retail pricing dynamics.

Second, all competing theories—namely, TD and SD rules, market power, and psychological pricing—are simultaneously considered in one study. Sticky prices have been studied in various areas, but they often focus on specific factors without considering multiple factors simultaneously. However, it's important to consider these pricing theories within a broader context and not assess them in isolation because all competing theories are correlated with each other. This study contributes to existing research on sticky prices by considering all competing theories simultaneously and examining their correlations with each other.

Finally, this study contributes to the literature on the "rocket and feather" price adjustment pattern, which describes how retailers quickly increase prices in response to cost increases but are slow to decrease them when costs fall. Bachmeier and Griffin (2003) suggests that temporal aggregation can introduce substantial bias in estimation results, advocating for the use of high-frequency data, such as daily data. Consequently, recent research tends to utilize daily data to examine price adjustment patterns more accurately. However, the findings indicate that relying on daily-level data with a standard model for the "rocket and feather" study might introduce a different type of bias.

The remainder of this chapter is structured as follows: Section 1.2 describes the data used in this study and documents the empirical regularity of retail pricing in Section 1.3. Section 1.4 presents the estimation model that encompasses variables serving as proxies for each factor and shows the estimation results. In Section 1.5, I discuss the implications of this study. Finally, Section 1.6 summarizes this study and presents conclusions.

## 1.2 Data

The data for this study were obtained from the *Oil Price Information Network (OPINET)* operated by the *Korea National Oil Corporation.* The firm collects transaction information from all retailers in Korea and publicly posts their daily prices on its website. I use the price information of 708 stations in Seoul, including the station characteristics such as the type of service, brand, and location, for the period between 2009 and 2019.

A key variable cost of gasoline is the wholesale price from *Mean of Platts Singa-*

*pore (MOPS)*, which reports benchmark prices for petroleum products in the Asian market based on transactions in Singapore.[4] The pre-tax wholesale price of the oil refinery company is determined by adding tariffs, mark-up, and distribution costs to the *MOPS* price, which reflects the exchange rate.[5] *MOPS* constitutes a significant portion of the pre-tax price and is therefore used as a variable cost in this study. I consider *MOPS* to be exogenous given the relatively small share of the Korean demand in the global oil market.

I use several variables to represent the level of competitiveness within the local market where a station is situated. I take into account the number of stations within a 1-kilometer radius. To create this variable, centered on a station, I calculate the distance for all pairs of existing stations using the spatial coordinates of stations and count the number of stations within a 1km radius.[6]

### 1.2.1 Proxies for each factor

In this study, I explore competing theories of retail pricing behavior, including: TD, SD, psychological pricing, and market power. To assess how each factor influences pricing behavior, I first define proxies to represent each factor. I summarize the

[4] The original unit is \$/bbl, and it is provided on *OPINET* after being converted into Korean won per liter.

[5] There are four major refinery companies: *SK Energy*, *GS Caltex*, *Hyundai Oil Company*, and *S-OIL*. They operate their own brand retail gasoline stations and also have franchise stations where private owners operate under the supply agreement of the franchisor, the refinery company. The market structure of both retail gasoline stations and the wholesale market is vertically integrated. Although the method of determining the pre-tax wholesale price varies from one company to another, it mostly involves a combination of factors such as the average *MOPS* price over the past week and daily changes in *MOPS*.

[6] Stations entered and exited during the period of our data. Based on their entry and exit dates, determined by their earliest and latest transaction dates, I define a station as 'open' during a particular month if there is at least one transaction occurring in that month. Consequently, this variable exhibits monthly variation for each station.

proxies representing each factor in Table 1.1.

Table 1.1: Proxies of factors for price changes

| Factor | Proxies |
|---|---|
| Time-dependent pricing | Duration of keeping previous price, day of the week |
| State-dependent pricing | Cumulative cost change between price changes |
| Psychological pricing | Last and second-to-last digit of retail price |
| Market power | Number of stations within 1km radius, service type, brand |

The TD rule indicates that retailers change prices at regular intervals. This implies that the probability of a price change increases as the duration of maintaining the previous price reaches a particular length. Thus, I use the duration of maintaining the previous price as a proxy for the TD rule. Additionally, the pattern of price changes in the Seoul gasoline market shows a distinct weekly pattern, where retailers tend to change prices on a weekly basis. Therefore, I add day-of-the-week dummies as proxies for the TD rule.

The SD rule implies that the probability of a price change increases as the state changes, such as a change in costs. I consider the cumulative cost change as the cost shock retailers face when making a decision. Specifically, for station $i$ that changes price at time $t$ and had the previous price change at time $t-k$, the cumulative cost change represents the difference in cost between time $t$ and $t-k$. The underlying assumption behind using cumulative cost change is that stations determine whether to change their price by considering whether the change in their marginal cost exceeds some threshold. This variable serves as a proxy for the SD pricing rule.

Psychological pricing pertains to consumers' limited recognition of price, such as overlooking the last digit, which can affect pricing behavior. Thus, I use the last and second-to-last digits as proxies for this factor.

Retailers with market power influence pricing behavior by setting prices higher than those in competitive markets. Additionally, in terms of the frequency of price changes, retailers with greater market power tend to exhibit more rigid pricing. The most commonly used proxy for local market power is the number of stations within a 1km radius, which I use as a variable. Additionally, the type of service and brand are also used as proxies.

### 1.2.2 Notations

I first denote some notations used in this study. $p_{it}$ represents the retail price for station $i$ at time $t$, and the price change is denoted as $\Delta p_{it}$. The indicator variable $f_{it} = 1\{\Delta p_{it} \neq 0\}$ represents the retailer's decision to change the price at time $t$.

The cost variable is converted to cumulative cost change and used in the analysis to investigate the effect of cost change on the pricing decisions of stations. Specifically, for station $i$ that changes price at time $t$ and had the previous price change at time $t - k$, the cumulative cost change $DC_{it} = c_t - c_{t-k}$ represents the difference in cost between time $t$ and $t - k$ where $f_{it} = 1$, $f_{ik} = 1$, and $f_{ij} = 0$ for $k < j < t$. The underlying assumption behind using cumulative cost change is that stations determine whether to change their price by considering whether the change in their marginal cost exceeds some threshold.

$a_{it} = t - k$ represents the duration of maintaining the previous price change, where $f_{it} = 1$, $f_{ik} = 1$, and $f_{ij} = 0$ for $k < j < t$. For example, $a_{it} = 3$ implies that station $i$ changes the price at time $t$ after keeping the previous price for three days. Therefore, this variable indicates the stickiness of the station's price.

Some statistics representing the frequency of price changes can be denoted as follows. $F_t = \frac{1}{N}\sum_{i=1}^{N} f_{it}$ is the frequency of price changes that occurred at time $t$. If half of the stations change price at the same time at $t$, $F_t$ will be 0.5. This statistic represents how synchronized stations' pricing decision is. $F_i = \frac{1}{T}\sum_{t=1}^{T} f_{it}$ is the frequency of price change for station $i$ during the period of the data. If station $i$ changes price every day during the period, this will be 1. Thus, this statistic represents how frequent station price changes are. $F = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} f_{it}$, without any subscript, represents the pooled statistic over time and station.

$P_i^m = \frac{1}{T}\sum_{t=1}^{T}(p_{it} - p_t^m)$ represents the average adjusted price, where $p_t^m$ is the market average price at time $t$. It calculates the average deviation of the retail price from the market average price. This statistic, on average, indicates whether station $i$'s price is higher or lower than the market average.

### 1.2.3 Summary statistics

In Figure 1.2, I present summary statistics for the variables used in this study, either as inputs to other variables or directly in the estimation model. The statistics are pooled statistics, where the mean is calculated by averaging over time and station.

## 1.3 Empirical Evidence in Retail Gasoline Pricing

### 1.3.1 Stations adjust prices infrequently

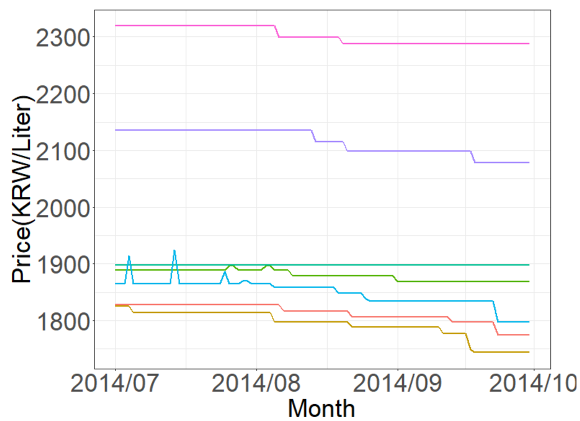
Despite knowing daily fluctuations in wholesale price levels and virtually zero menu cost, retailers adjust price infrequently, with approximately 90% of the observations showing no price changes. Out of the 2,275,577 total observed daily prices, only 199,696 show non-zero price adjustments. Figure 1.1a shows an example of retail

Table 1.2: Summary statistics for variables

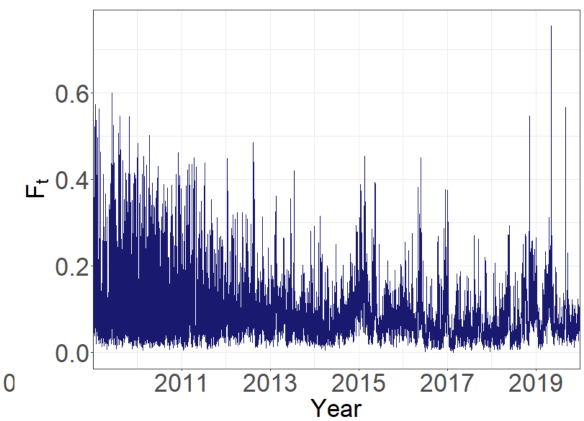
| | Description | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Price** | | | | | |
| $p$ | Retail gasoline price(KRW/liter) | 1766.61 | 242.35 | 1218.00 | 2490.00 |
| $ld1$ | Indicator variable for digits | 0.53 | 0.50 | 0.00 | 1.00 |
| $ld2$ | Indicator variable for digits | 0.19 | 0.40 | 0.00 | 1.00 |
| $f$ | Indicator variable for $\Delta p_{it} \neq 0$ | 0.10 | 0.30 | 0.00 | 1.00 |
| $a$ | Duration of keeping previous $p$ | 8.24 | 7.00 | 1.00 | 35.00 |
| **Cost** | | | | | |
| $c$ | Wholesale price(KRW/liter) | 624.07 | 164.33 | 286.93 | 977.28 |
| $DC^2$ | Squared cumulative cost changes | 7.12 | 15.38 | 0.00 | 341.95 |
| **Station characteristics** | | | | | |
| $N^r$ | Number of stations(within 1km) | 4.06 | 2.16 | 0.00 | 13.00 |
| *Self* | Type of service: self-service | 0.33 | 0.47 | 0.00 | 1.00 |
| *SKE* | Brand: SK Energy | 0.42 | 0.49 | 0.00 | 1.00 |
| *GSC* | Brand: GS Caltex | 0.28 | 0.45 | 0.00 | 1.00 |
| *HDO* | Brand: Hyundai Oil Bank | 0.14 | 0.35 | 0.00 | 1.00 |
| *S-OIL* | Brand: S-OIL | 0.12 | 0.33 | 0.00 | 1.00 |
| *Thrifty* | Brand: Thrifty station | 0.02 | 0.12 | 0.00 | 1.00 |
| *Unbrand* | Brand: Unbranded station | 0.02 | 0.12 | 0.00 | 1.00 |

[1] $ld1$ is an indicator variable that equals 1 if the last digit of the station's price is 8 or 9, and 0 otherwise. Similarly, $ld2$ is an indicator variable that equals 1 if the second-to-last digit of the station's price is 9, and 0 otherwise.
[2] $DC_{it}$ is scaled by 10, making the unit 10 won per liter.
[3] $Self_{it}$ is a dummy variable that indicates self-service stations. While $Self_{it}$ remains time-invariant for most stations, 82 full-service stations transitioned into self-service stations during the data period.

price changes at 7 randomly selected stations during July to September 2014, with an average frequency of price changes of 4.57 over four months.




(a) Example of retail price




(b) Average frequency of price change

Figure 1.1: The retail pricing

Note: (a) shows an example of pricing behavior using 7 randomly selected stations in July 2014 - Sep 2014. (b) Cross-sectional average of frequency of price changes by day

Figure 1.1b shows the fraction of stations that change prices vary daily and exhibit a downward trend during 2009 to 2014. From 2009 to 2014 oil price sharply increase then sharply decrease, while the frequency of price adjustment trends downwards. At the first glance, the data do not suggest a strong correlation between frequency of retail price changes and variations in wholesale price.

### 1.3.2 Frequency of price changes by duration or day of the week

The pricing behavior of retailers in the retail gasoline market reveals a notable pattern of adjusting prices on a weekly basis. The mode and median of the frequency of price changes (measured in days) are both 7 days during 2009-2019. In Figure 1.2, the sum of the fractions of price changes at weekly frequency (on the 7th, 14th, 21st, 28th day) is about 30%. Figure 1.3a shows price changes occur disproportionately more likely at multiples of 7 days.

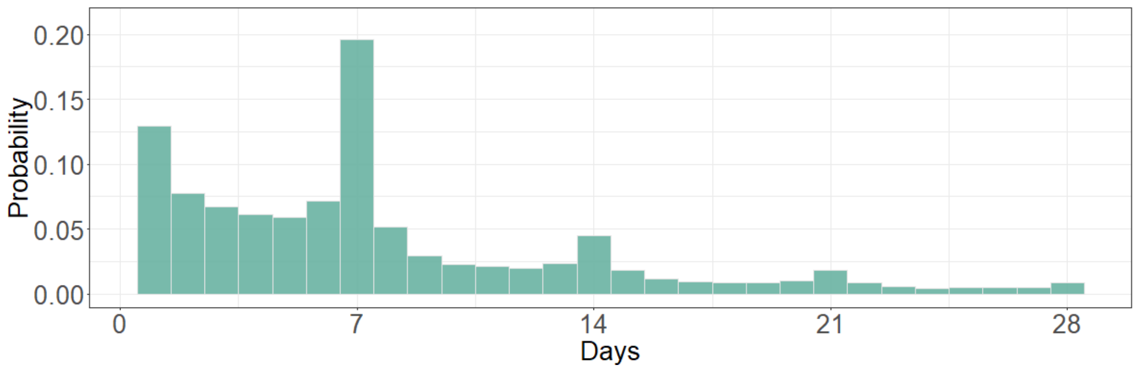
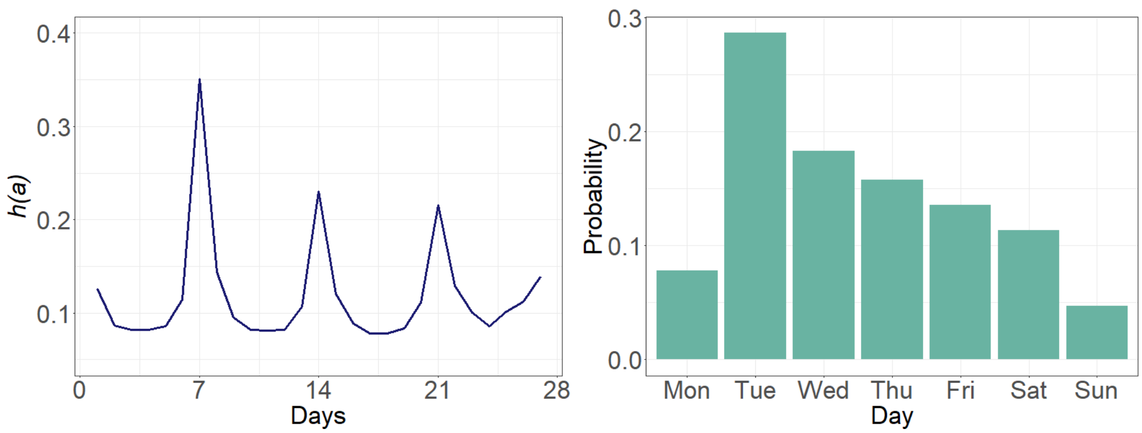



Figure 1.2: The distribution of days between price changes

Note: The fraction of price changes by duration at the time of price change. The duration is capped at 29 days in the plot. Price changes with duration beyond 29 days exhibit a similar pattern.

Figure 1.3b shows that about 27% of all price changes occurred on Tuesdays. The disproportionate numbers of price changes at the weekly frequency are related to the high numbers of price changes on particular days of the week. Price changes most likely occur on Tuesdays, followed by Wednesdays, then Thursdays, and so on.

I report the 7 by 7 transition matrix on how the day of the week of current price change relates to that of the previous price change. Table 1.3 shows the current day of the week of price changes tend to positively related to that of the previous price change. But the persistence is strongest for Tuesday. If the previous price change occurs on a Tuesday then the probability that the current price change also occurs on a Tuesday is 48.9%. By comparison, if the previous price change occurs on a




(a) By duration (b) By day of the week

Figure 1.3: The probability of price change by duration and day-of-week

Note: (a) The probability of price change is defined as follows. For all stations, denoted as $i = 1, .., N$, I have $h(a) = \text{prob}(f_{it} = 1|a_{it} = a)$. When tracking a group of stations since the last price change, if the fraction of remaining stations with $a$ is represented as $S(a)$ (where $S(0) = 1$), then for $a \geq 1$, the hazard rate can be expressed as $h(a) = 1 - \frac{S(a)}{S(a-1)}$, where $S(.)$ denotes the survival rate. (b) The distribution of the day of the week when price changes occurred.

Monday then the probability that the current price change also occurs on a Monday is only 10.9%, much lower than the probability of current price change occurring on a Tuesday (35.2%).

### 1.3.3 Distribution of prices by last digit

Besides the reported regularity in timing of price change, price changes also depend on the digits of previous price. The retail gasoline in KRW per liter are in four digits. Figure 1.4 shows that the last digit of retail prices disproportionately end in 8 or 9, and the second-to-last digits disproportionately end in 9.

The non-uniformity of marginal distributions of the last and second-to-last digits

Table 1.3: Transition matrix of price changes by day of the week

| | $\text{Mon}_t$ | $\text{Tue}_t$ | $\text{Wed}_t$ | $\text{Thu}_t$ | $\text{Fri}_t$ | $\text{Sat}_t$ | $\text{Sun}_t$ |
|---|---|---|---|---|---|---|---|
| $\text{Mon}_{t-\psi}$ | 0.109 | 0.352 | 0.176 | 0.134 | 0.114 | 0.082 | 0.035 |
| $\text{Tue}_{t-\psi}$ | 0.041 | 0.489 | 0.176 | 0.117 | 0.089 | 0.066 | 0.022 |
| $\text{Wed}_{t-\psi}$ | 0.056 | 0.191 | 0.247 | 0.228 | 0.145 | 0.099 | 0.034 |
| $\text{Thu}_{t-\psi}$ | 0.067 | 0.184 | 0.167 | 0.195 | 0.216 | 0.127 | 0.044 |
| $\text{Fri}_{t-\psi}$ | 0.087 | 0.205 | 0.159 | 0.143 | 0.139 | 0.207 | 0.060 |
| $\text{Sat}_{t-\psi}$ | 0.103 | 0.224 | 0.168 | 0.138 | 0.114 | 0.136 | 0.117 |
| $\text{Sun}_{t-\psi}$ | 0.240 | 0.227 | 0.162 | 0.139 | 0.107 | 0.075 | 0.049 |

[1] $t-\psi$ represents the period when a station changed its price in the last period. For example, if a station changed its price the day before $t$, then $t-\psi$ would be equal to $t-1$.

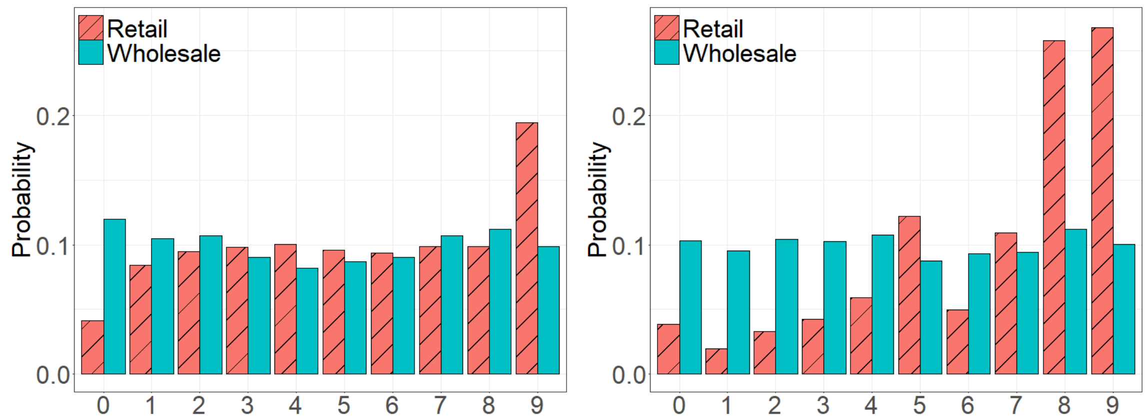
reported in Figure 1.4 suggests that the joint distribution of the last two digits is also nonuniform. To report the joint distribution of the last two digits, I adopt the following notation of dummy variables for the last 2 digits of the price in $t$ as $(ld2, ld1)_t$: with $ld2 = 1$ when the second-to-last digit is 9, and $ld2 = 0$ otherwise; and $ld1 = 1$ when the last digit is 8 or 9, and $ld1 = 0$ otherwise.

Table 1.4: Average fraction of $(ld2, ld1)_t$ over $t$

| | $(0,0)_t$ | $(1,0)_t$ | $(0,1)_t$ | $(1,1)_t$ |
|---|---|---|---|---|
| Uniform dist. | 0.72 | 0.08 | 0.18 | 0.02 |
| Observed | 0.401 | 0.073 | 0.404 | 0.121 |

[1] The uniform distribution of $(ld2, ld1)$ represents a hypothetical ratio assuming that the last two digits are uniformly distributed, while the observed distribution of $(ld2, ld1)$ reports the distribution observed in the sample retail price data.

If the last two digits are uniformly distributed from 0 to 9, then the probability that $ld2 = 1$ is 0.10, and $ld1 = 1$ is 0.2; and the joint distribution of $(ld2, ld1)_t$ is given by the first row of Table 1.4. If the last 2 digits are uniformly distributed, the fractions of (0,0), (1,0), (0,1), (1,1) should be (0.72, 0.08, 0.18, 0.02). The second row of the table shows that the observed sample of Seoul retail gasoline prices differs from




(a) Second to last digit (b) Last digit

Figure 1.4: The distribution of numbers in last and second-to-last digit

this benchmark distribution. For example, the fraction of observed prices with the last digit being 8 or 9 but the second-to-last digit being 0 to 8 is 0.404, much higher than that corresponding to the uniform distribution (0.18). The table also shows that in the data, the second-to-last digit is disproportionately 9 when the last digit is 8 or 9. This suggests that stations making a non-random choice for the second-to-last digit also tend to make a non-random choice for the last digit.

The nonuniform distribution of the end digit in retail pricing has been documented in studies in IO and marketing. Many studies investigate this pattern in relation to psychological pricing that takes advantage of limitations in consumers' cognition. One may theorize that consumers tend to focus on the first two or three digits of the retail price while disregarding the remaining digits (e.g., underestimating the difference between 1459 and 1450 relative to 1460 and 1459). This makes consumers perceive a price ending in 9 to be lower than it actually is.[7] Some studies also suggest

[7]see e.g., Schindler and Kirby (1997), Stiving and Winer (1997), Basu (2006), Levy et al. (2011), Snir, Levy, and Chen (2017), and Levy et al. (2020).

that odd prices, especially those ending in 5 or 9, are used as focal points for tacit collusion(Lewis (2015)).

Retailers' preference for using 8 or 9 as ending digits implies that prices ending with these digits are stickier (e.g., Levy et al. (2020)). I find confirmation of this hypothesis in Table 1.5. The table shows that when both the last and the second-to-last digit are preferred numbers, the probability of a price change is much lower (0.071) than when neither of the digits is a preferred number (0.110).

Table 1.5: The frequency of price change $F_i$ given $(ld2, ld1)_{t-1}$

| | $(0,0)_{t-1}$ | $(1,0)_{t-1}$ | $(0,1)_{t-1}$ | $(1,1)_{t-1}$ |
|---|---|---|---|---|
| $F_i$ | 0.110<br>(747,896) | 0.087<br>(136,275) | 0.096<br>(753,483) | 0.071<br>(226,443) |

[1] In parentheses are the number of observations of prices by different combinations of ending digits.

Looking at the transition of prices by the last and second-to-last digits also confirms the effect of psychological pricing on price rigidity. Table 1.6 reports how the probability of changing to a price with certain ending digits depends on the ending digits of the previous price. For example, the third column indicates that if the last digit of the previous price was 8 or 9, then the probability that the current price will end in 9 (0.713 = 0.573 + 0.140) is higher than the probability of it not ending in 9 (0.287 = 0.251 + 0.036).

This transition pattern suggests that retailers' preference for a specific number as the last digit of their price can influence their pricing strategy, resulting in less frequent price changes. This observation aligns with the results presented in Table 1.5, where the average frequency of price changes is lower when the last digit of the price is either 8 or 9. Thus, the dependence of probability of price change on the ending

Table 1.6: Transition matrix from $(ld2, ld1)_{t-\psi}$ to $(ld2, ld1)_t$

| | $(0,0)_{t-\psi}$ | $(1,0)_{t-\psi}$ | $(0,1)_{t-\psi}$ | $(1,1)_{t-\psi}$ |
|---|---|---|---|---|
| $(0,0)_t$ | 0.632 | 0.622 | 0.251 | 0.277 |
| $(1,0)_t$ | 0.091 | 0.089 | 0.036 | 0.062 |
| $(0,1)_t$ | 0.215 | 0.205 | 0.573 | 0.618 |
| $(1,1)_t$ | 0.062 | 0.085 | 0.140 | 0.042 |

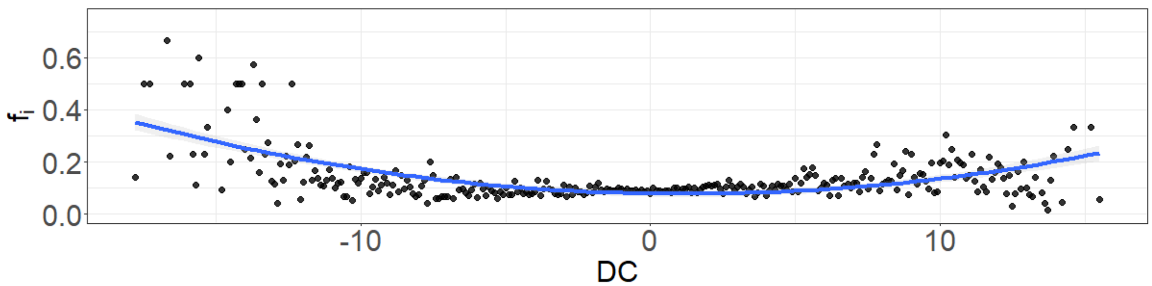
[1] $t - \psi$ represents the period when a station changed its price in the last period. For example, if a station changed its price the day before $t$, then $t - \psi$ would be equal to $t - 1$.

digits indicates "psychological pricing" is a potentially important factor in retail price change.

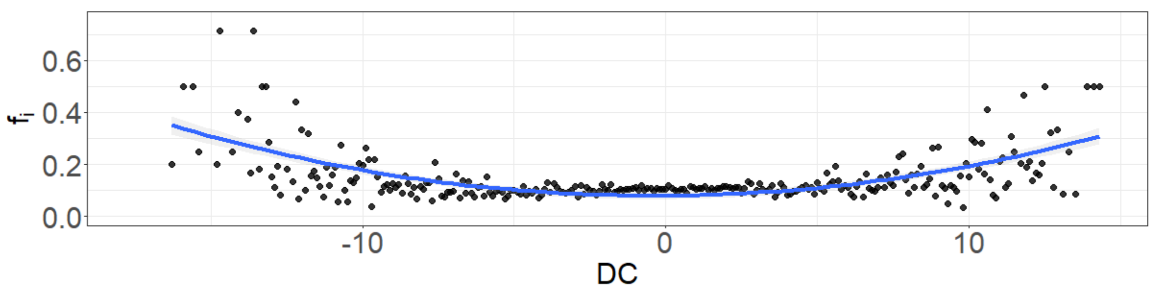
### 1.3.4 Probability of price change in response to cost change

I now examine how the probability of retail price changes relates to the cumulative change in wholesale price since the previous price change. Figure 1.5 plots the probability of price change by full- (self-) service stations against the cumulative change in wholesale price from the previous price change. Both figures show that wholesale price change is weakly correlated with the probability of price change. On average, the probability of price change rises when the cumulative change in wholesale price is substantially large.

These figures suggest a potential role of SD rules in changes of retail gasoline price. They are consistent with the scenario that some stations change prices whenever the desired price, which depends on the wholesale price, substantially deviates from the current price.




(a) Full-service




(b) Self-service

Figure 1.5: Probability of price change by cumulative cost change

Note: (1) The figures show the probability of price change given cumulative change in wholesale price from the previous price change. The horizontal axis is cumulative cost change(KRW/liter divided by 10).

### 1.3.5 Local market condition and price change frequency

Table 1.7 reports how the frequency of price changes relates to two proxies of stations' market power. I theorize that a larger number of rival stations within a 1km radius suggests stronger local competition, and I assume that full-service stations have more pricing power because they serve customers who are less price-sensitive. Thus, I conclude that self-service stations with more local rivals are likely to have lower market power.

Table 1.7: The frequency of price change $F_i$ by the numbers of local rivals

| $N^r$ | 0 | 1 | 2 | 3 | 4 to 6 | 7 and more |
|---|---|---|---|---|---|---|
| $F_i$ (all) | 0.081 | 0.084 | 0.093 | 0.097 | 0.098 | 0.103 |
| $F_i$ (full-serv.) | 0.076 | 0.080 | 0.085 | 0.093 | 0.095 | 0.101 |
| $F_i$ (self-serv.) | 0.088 | 0.088 | 0.110 | 0.108 | 0.106 | 0.110 |

[1] $\bar{F}_i$ (all) represents the average frequency of price changes for all stations regardless of their type. $\bar{F}_i$ (full-serv.) uses only full-service stations to calculate $\bar{F}_i$. Conversely, $\bar{F}_i$ (self-serv.) only includes self-service stations.

These conjectures are consistent with Table 1.7. For all stations, the frequency of price changes is positively correlated with the number of local rivals. Full-service stations with no local rivals change prices least frequently, while self-service stations with two or more local rivals change prices most frequently. The table shows that stations with more market power change prices less frequently. This pattern is consistent with that reported in previous studies.[8]

[8] Previous studies on local competition in retail gasoline markets have investigated several aspects. Hastings (2004) and Houde (2012) demonstrate that changes in vertical relationships within a local market impact the price level. Barron, Taylor, and Umbeck (2004), Lewis (2008), Clemenz and Gugler (2009), and Kim (2018) found empirical evidence that local market conditions can affect price dispersion in a local market. Regarding the frequency of price changes, Athey, Bagwell, and Sanchirico (2004) and Garrod (2012) present theoretical frameworks where market power affects price rigidity. Borenstein and Shepard (2002) show empirical evidence that market power affects price stickiness.

Table 1.8: Fraction of price change by day-of-week (by brand)

| Brand | *MS* | $P_i^m$ | Mon. | Tue. | Wed. | Thu. | Fri. | Sat. | Sun. |
|---|---|---|---|---|---|---|---|---|---|
| *SKE* | 41.2 | 26.30 | 0.071 | 0.378 | 0.155 | 0.148 | 0.108 | 0.098 | 0.042 |
| *GSC* | 28.1 | -5.15 | 0.067 | 0.234 | 0.234 | 0.181 | 0.145 | 0.099 | 0.040 |
| *S-OIL* | 12.9 | -39.64 | 0.099 | 0.189 | 0.177 | 0.164 | 0.174 | 0.135 | 0.063 |
| *HDO* | 14.2 | -49.09 | 0.101 | 0.146 | 0.224 | 0.184 | 0.160 | 0.128 | 0.057 |
| Thrifty | 2.1 | -106.03 | 0.096 | 0.171 | 0.177 | 0.182 | 0.185 | 0.125 | 0.064 |
| unbranded | 1.4 | -89.94 | 0.151 | 0.198 | 0.171 | 0.129 | 0.172 | 0.110 | 0.069 |

[1] $P_i^m$ represents the average deviation of a station's price from the entire market's average price.
[2] *MS* denotes the market share, which is calculated as the number of stations by brand divided by the total number of stations in the market.
[3] The day of the week (Mon., Tue., etc.) represents the fraction of price changes that occurred on each specific day.
[4] There are four major wholesale companies that operate retail gasoline stations: *SK Energy (SKE)*, *GS Caltex (GSC)*, *Hyundai Oil Bank (HDO)*, and *S-OIL*, which retains its name without an abbreviation.

Pricing rules vary by brand. Table 1.8 shows that the market share of a brand is related to how much stations' prices deviate from the market average price. Specifically, *SK Energy* holds the largest market share, and the prices at their stations tend to be, on average, 26.3 KRW/liter higher than those at other stations. Similarly, *GS Caltex*, with the second-largest market share, has stations whose $P_i^m$ ranks second highest.

There is a distinct pattern indicating that stations have varying preferences for choosing the day of the week to change prices, depending on the brand. Generally, stations are inclined to adjust their prices on Tuesday. However, stations belonging to brands with a larger market share, particularly *SK Energy* and *GS Caltex*, which are two of the leading brands, exhibit a higher tendency to select Tuesday for price changes compared to stations of other brands. The market share by brand could mirror overall market conditions, suggesting that this specific pattern of selecting a day of the week indicates that stations with more market power are more inclined to adhere to a TD rule.

## 1.4 Regression Analysis of Retail Gasoline Pricing

The documented empirical evidence suggests that changes in retail gasoline prices may be governed by TD rules and SD rules, influenced by the ending digits of the previous price, and correlated with stations' local market power. These pricing theories should not be evaluated in isolation. For instance, if the wholesale price follows a random walk pattern, then the variance of cumulative change in cost expands over time. Thus, a periodic change in price appears consistent with both a TD and an SD rule. However, the empirical relevance of all these factors does not quantify their individual roles. Therefore, I use a logit model to estimate the effect of these factors collectively.

### 1.4.1 Logit models for price changes

Here's the rationale for using the logit model: On date $t$, station $i$ makes a decision, represented by the indicator variable $f_{it}$. If $f_{it} = 1$, it means station $i$ changes the price (e.g., $\Delta P_{it} \neq 0$), while $f_{it} = 0$ indicates that the station chooses to keep the previous price. The goal of the estimation is to examine the impact of specific predictors that represent pricing rules on the probability of changing the price. I assume a binomial distribution for the outcome variable and model the probability of a price change based on a given set of predictors.

The vector of regressors $\boldsymbol{x_{it}}$ includes variables such as the lags of the station's price, lags of competitors' prices, lags of competitors' decisions on whether to change prices, and aggregate variables. The vector state variables $\boldsymbol{x}_{it} = (\eta_i, \phi_t, \psi_{it})$ consist of three types:

(a) features of station/price: $\eta_i \in$ {type of service (full or self); brand; number of rivals with radius $r$, $N_r$};

(b) aggregate time varying variable: $\phi_t = \{\text{wholesale price } c_t\}$;

(c) station-time state variables: $\psi_{it} \in \{DC_{it}, a_{it}, dw_{it}, L_{it}\}$, where $DC$ is size of the cumulative cost change since the last price change $DC_{it} = c_t - c_{t-k}$ where $f_{ik} = 1$ and $f_{ij} = 0$ for $k < j < t$. $a$ is duration of price (time since the last change) $a_{it} = t - k$ where $f_{ik} = 1$ and $\delta_{ij} = 0$ for $k < j < t$. $DW$ is day of the week as station $i$ makes decision on pricing in day $t$, $dw_{it}$=1 (Monday) to 7 (Sunday). $ld$ is ending digits of previous price $ld1_{it} = 1$ ($ld2_{it} = 1$) if the last (second to last) digit of $p_{it-1}$ is 9, and zero otherwise.

These predictors can be categorized into four factors based on their suitability as proxies for competing theories. When stations adhere to an SD pricing rule, the likelihood of changing prices increases in response to larger cost shocks. The cumulative cost change ($DC$) reflects the cost shocks that retailers face when deciding to adjust their prices.

If stations adhere to a TD pricing rule, the probability of changing prices increases as the duration of maintaining the previous price approaches specific time thresholds. As discussed in Section 1.3, stations tend to change their prices at intervals of 7 days. Given that 7 days can be considered a time threshold for the TD rule, the probability of changing the price will differ between $a_{it} = 1, \ldots, 6$ days and $a_{it} = 7$ days.

I create indicator variables for each $a_{it} = k$, where $I(a_{it} = k)$ implies that station $i$ changed the price on date $t$ after maintaining the price for $k$ days. However, this approach of creating variables to indicate TD rules requires a large number of parameters, so I exclude variables where $a_{it}$ exceeds 28 and focus on pricing behavior during 4 weeks.

Also, the data used for estimating the model omits observations where $a_{it} > 35$ to create the reference variable for $I(a_{it} = k)$ and make the interpretation of the coefficient $I(a_{it} = k)$ easier. Specifically, I set the reference variable for $I(a_{it} = k)$ as $I(a_{it} = 29, ..., 35)$, which equals 1 if stations change their price 29 through 35 days after keeping the previous price, and 0 otherwise. Therefore, the interpretation of the marginal effect of $I(a_{it} = k)$ is how the probability of a price change occurring at $k$ differs from the probability of a price change occurring in the 5th week.

The predictors also include variables serving as proxies for local competition. Previous studies suggest that market power can influence price rigidity, as shown in Section 1.3. To examine the impact of competition on the probability of price changes, I utilize *Self*, $N^r$, and brand dummies as proxies for local market power.

The preference for 9-ending digits is also a factor that can affect price rigidity. In other words, the probability of a price change is lower when the last digit of the price is 9. To account for this 9-ending effect on pricing, I consider an indicator variable that is 1 if the previous price ends with a 9. Specifically, $ld1$ is the indicator variable representing 1 if the price ends with an 8 or 9, and $ld2$ represents 1 if the second-to-last digit ends with a 9.

I have documented above that competing factors are correlated with the frequency of price changes. I now use a regression model to quantify the role of these state variables, as well as station state variables, in the frequency of price changes. The model is constructed by adding variables representing each factor, as shown in Table 1.9. After constructing the full model with all variables, the model is constructed as follows:

The probabilities I seek to estimate is $prob(f_{it} = 1|\boldsymbol{x}_{it}) = \frac{exp(\boldsymbol{x_{it}}'\boldsymbol{b})}{1+exp(\boldsymbol{x_{it}}'\boldsymbol{b})}$, where

$$\boldsymbol{x}'_{iwt}\boldsymbol{\beta} = \sum_{k=1}^{28} b_k I(a_{iwt} = k) + \sum_{j=1}^{6} b_{j+28} DW^j_{iwt} + b_{35} DC^2_{iwt} + b_{36} ld1_{iwt} + b_{37} ld2_{iwt} + b_{38} Self_{iwt} + b_{39} N^r_{iwt} + \sum_{m=1}^{5} b_{m+39} Brand^m_{iwt} + a_i + c_w \quad (1.1)$$

Table 1.9: Constructing models with proxies for factors

| Model | Factor | Regressors |
|---|---|---|
| Model1 | TD | $I(a = k)$, $DW$ |
| Model2 | TD and SD | $I(a = k)$, $DW$, $DC^2$ |
| Model3 | TD, SD, and LD | $I(a = k)$, $DW$, $DC^2$, $ld1$, $ld2$ |
| Model4 | TD, SD, LD, and MP | $I(a = k)$, $DW$, $DC^2$, $ld1$, $ld2$, $Self$, $N^r$, $Brand$ |

[1] 'TD' stands for time-dependent pricing, 'SD' for state-dependent pricing, 'LD' for the last two digits of prices(psychological pricing), and 'MP' for market power.
[2] 'TD' includes includes day-of-week dummies and dummies for the duration since the last price change.
[3] 'SD' includes the square of the cumulative cost change.
[4] 'LD' includes indicator variables to signify whether the last digit, or the second-to-last digit, is 9.
[5] 'MP' includes a self dummy, the number of stations within a 1km radius, and brand-specific dummies.

I include station fixed effects to account for unobserved variations specific to each station and year-week fixed effects to control for time-varying factors that could influence the likelihood of price changes. For instance, local traffic flow and citywide demand for gasoline can vary over time, thus affecting the pricing behavior of all stations. In particular, the year-week fixed effect controls for unobserved factors that can influence price changes within a week when comparing the probability of price changes at $a_{it} = 1, ..., 6$ with that at $a_{it} = 7$. Consequently, I adopt a two-way fixed effects model in the estimation model.

However, it's important to note that there might be an issue with the incidental parameter problem when individual fixed effects are included in nonlinear models like logit and probit. This issue becomes particularly significant when N (the number of entities) and T (the number of time periods) are large. In such cases, the estimators for the variables may become inconsistent. Furthermore, even if the model can be estimated without any fixed effect-induced bias, another problem arises concerning fixed effects: the inability to estimate the average marginal effect.

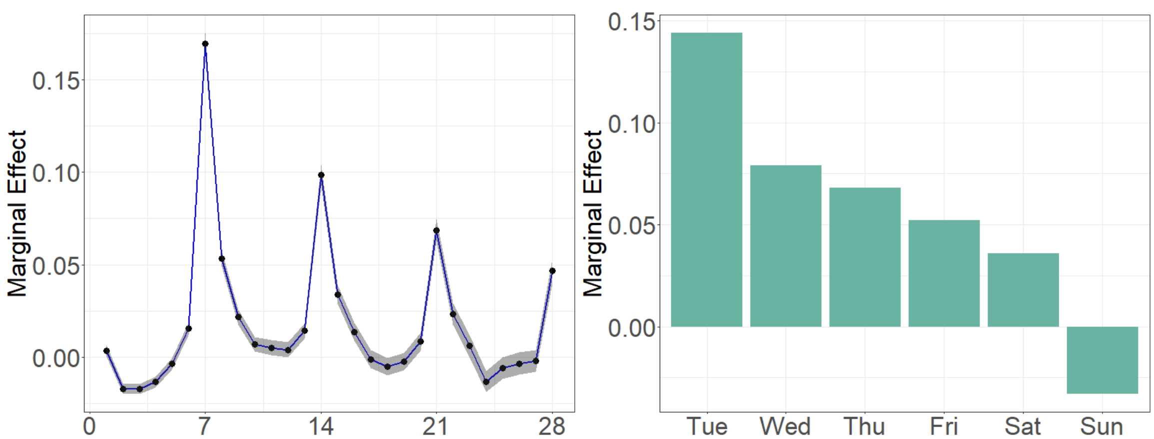
Let's consider the marginal effect for a discrete variable $X_1$ and denote it as $m(\boldsymbol{x}_{it}, \beta, c_i) = F[(x_{1it}+1)\beta_1 + x_{2it}\beta_2 + c_i] - F[x_{1it}\beta_1 + x_{2it}\beta_2 + c_i]$, where $F(.)$ is the link function, and $c_i$ represents the unobserved characteristics for individual $i$. The marginal effect on probability $y$ cannot be estimated unless a value for $c$ is plugged in, the distribution of which is unknown (see Wooldridge (2010) p. 492.) Fernández-Val and Weidner (2016) suggest a bias-correction method for the logit model with two-way fixed effects. The marginal effects are calculated based on bias-corrected estimates. I use their method to obtain the bias-corrected estimates and calculate the average marginal effects.

### 1.4.2 Estimated results

As shown in Table 1.9, the models are sequentially expanded by incorporating each factor, ultimately culminating in Model 4, formulated as Equation (1.1). Models 5 and 6 include year-week fixed effects and two-way fixed effects, respectively. The estimated results are included in the appendix, and I interpret them through the marginal effects calculated from Table A.1.

Table 1.10 reports estimated marginal effects. Columns 1 to 4 correspond to Models 1 to 4 listed in Table 1.9. Column 1 (Model 1) shows an $R^2$ of 0.575. Consequently, adding SD rules, psychological pricing, and market conditions does not improve the model fit and does not significantly change the estimated marginal effects of the previous model. While competing theories of TD, SD, psychological pricing, and market conditions all have some explanatory power for price change frequency, the TD model dominates other theories empirically for the whole sample.

Moreover, the estimated marginal effects are quite large, particularly for the TD rules. Figure 1.6a illustrates the marginal effect of the duration since the last price change based on Model 6, suggesting that the probability of a price change increases sharply whenever $a_{it}$ reaches multiples of 7 days. Figure 1.6b shows that on Tuesdays, the probability of price change is about 7 percentage points (p.p) higher than on Wednesdays, the second most likely day for a price change. These findings imply that retailers tend to follow the TD rule by changing their prices weekly, specifically on Tuesdays.[9]




(a) Duration dummies

(b) Day of week dummies

Figure 1.6: The estimated marginal effects for 'Model6'

[9]This does not necessarily mean that retailers only follow the TD rule and change their prices at fixed intervals deterministically. It's important to remember that the definition of the TD rule is that the "probability" of a price change is dependent on the duration since the last price change.

Table 1.10: The estimated marginal effects for Logit model(1): Full sample

| | w/o fixed effect | | | | w/ fixed effect | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| $DC^2$ | | 0.0006*** | 0.0006*** | 0.0006*** | 0.0001*** | 0.0001*** |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| $ld1$ | | | -0.011*** | -0.011*** | -0.011*** | -0.010*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $ld2$ | | | -0.021*** | -0.020*** | -0.023*** | -0.021*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| *Self* | | | | 0.012*** | 0.017*** | 0.025*** |
| | | | | (0.000) | (0.000) | (0.001) |
| $N^{1km}$ | | | | 0.001*** | 0.001*** | 0.000 |
| | | | | (0.000) | (0.000) | (0.000) |
| *HDO* | | | | 0.000 | 0.001*** | 0.010*** |
| | | | | (0.001) | (0.001) | (0.002) |
| *S-OIL* | | | | 0.007*** | 0.007*** | 0.027*** |
| | | | | (0.001) | (0.001) | (0.003) |
| *SKE* | | | | 0.005*** | 0.006*** | 0.006** |
| | | | | (0.001) | (0.001) | (0.002) |
| *Thrifty* | | | | 0.035*** | 0.047*** | 0.044*** |
| | | | | (0.002) | (0.002) | (0.003) |
| *unbranded* | | | | 0.016*** | 0.019*** | 0.009** |
| | | | | (0.002) | (0.002) | (0.003) |
| Time-dependent | ○ | ○ | ○ | ○ | ○ | ○ |
| State-dependent | | ○ | ○ | ○ | ○ | ○ |
| $ld1$ and $ld2$ | | | ○ | ○ | ○ | ○ |
| Market power | | | | ○ | ○ | ○ |
| Year-week FE | | | | | ○ | ○ |
| Station FE | | | | | | ○ |
| Pseudo $R^2$ | 0.575 | 0.575 | 0.576 | 0.577 | 0.591 | 0.601 |

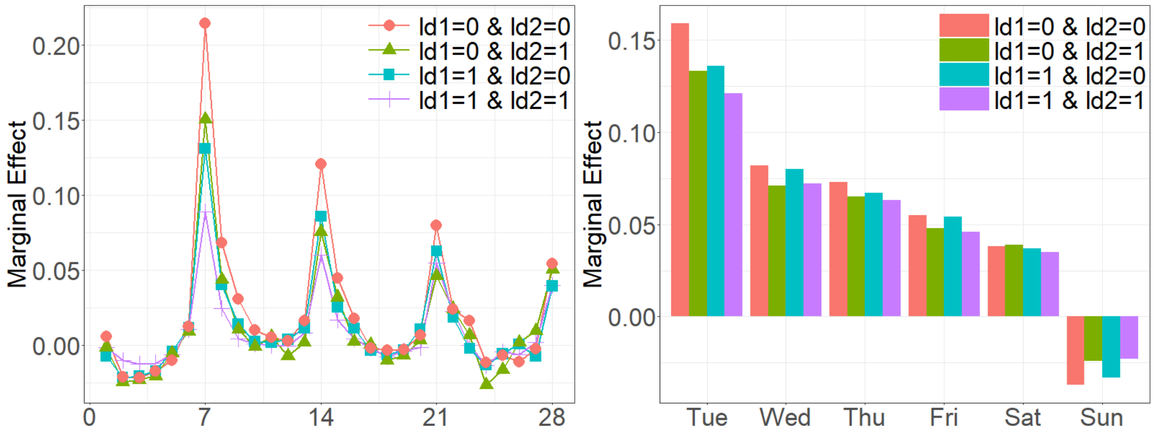
[1] All models include dummies for the duration since the last price change and day-of-week dummies, but these were excluded from the table due to page size limitations.

The non-TD factors are statistically significant but not quite substantial. Especially for the SD rule, the marginal effect of the cumulative cost change $DC$ is not economically significant. The estimated marginal effect of the squared cumulative cost change is 0.0001, as derived from Model 6. This suggests that with a 10 KRW/liter increase in cost, the probability of a price change increases by 0.01 p.p. Considering that the profit margin of retail gasoline stations is approximately 10 Korean won per liter, even if the size of the cost change is nearly equivalent to their margin, it does not significantly influence the probability of changing prices. This implies that cost changes may not be critical in the decision-making process regarding price adjustments.

The marginal effects of the last and second-to-last digits are all significant at the 1% significance level. Specifically, the probability of changing the price decreases by 1.1 p.p. when the last digit of the previous price was 8 or 9. Furthermore, the probability of changing the price decreases by 2 p.p. when the second-to-last digit of the previous price was 9. The marginal effect of the self-service station dummy variable is estimated to be 0.025 at the 1% significance level, indicating that self-service stations are 2.5 p.p. more likely to change their prices than full-service stations. The marginal effect of the number of rival stations within a 1km radius is insignificant, both statistically and economically.

### 1.4.3 How the competing theories correlate with the TD rule

To explore how TD rules interact with other pricing factors, I now estimate Equation (1.1) with sub-samples grouped by ending digits, and brand, and compare the marginal effects of the duration of keeping the previous price and the day of the week.



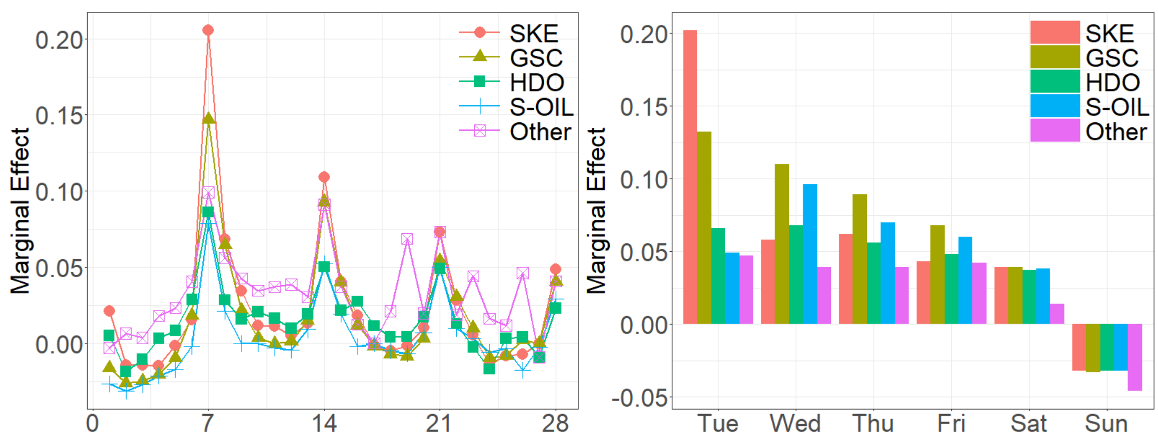
(a) Duration dummies


(b) Day of week dummies

Figure 1.7: The estimated marginal effects by sub-samples ($ld1$ and $ld2$)

First, I examine whether stations change prices based on TD rules depending on the ending digit of the price. Figure 1.7 shows that if the previous price ends with a 9 at its last or second-to-last digit, retailers delay their regular price change, which typically occurs at intervals of 7 days. Additionally, the preference for Tuesday for changing prices is slightly less likely to be observed if the previous price has a 9-ending in its last or second-to-last digit. The combination of these findings is consistent with the scenario where a station is more likely to deviate from its routine procedure of changing prices when the current price has desired ending digits.

The prevalence of TD rules significantly varies across retail station brands. As indicated in Table 1.8, there is a correlation between market share and cost pass-through, which, in turn, appears to be associated with the prevalence of TD rules. Figure 1.8 demonstrates that the estimated results from the sub-samples align with the findings presented in Table 1.8. The figure suggests that stations under the *SK Energy (SKE)* brand, which has the largest market share, are most likely to adjust their prices at multiples of seven days, particularly on Tuesdays, compared to stations of other brands. Similarly, stations under the *GS Caltex (GSC)* brand, holding the second-largest market share, rank second in likelihood to change their prices at multiples of seven days and specifically on Tuesdays when compared to stations of other brands. These results imply that market share influences retailers' pricing strategies, making stations with a larger market share more likely to follow the TD rule.



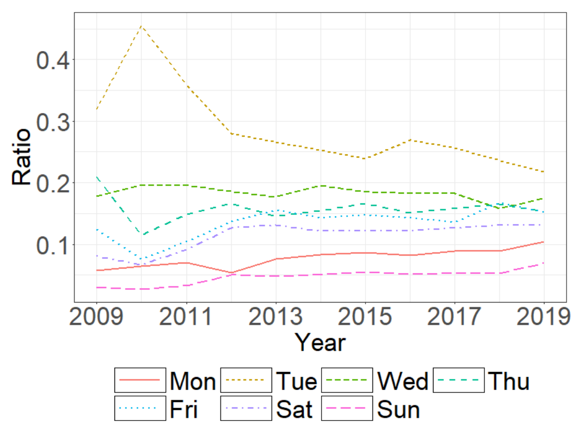

(a) Duration dummies (b) Day of week dummies

Figure 1.8: The estimated marginal effects by sub-samples (by brand)

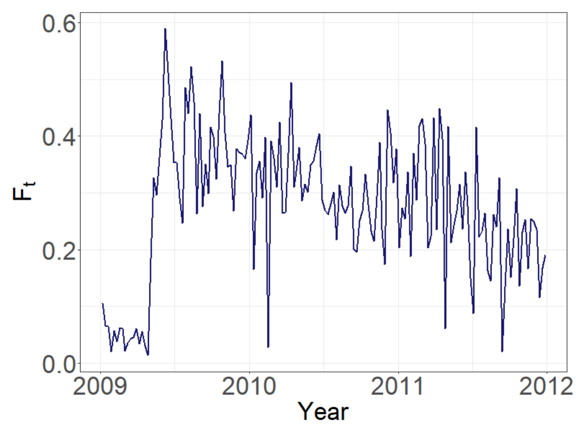
## 1.5 Discussion

### 1.5.1 The time-varying pattern of TD rules

A prominent feature of Seoul gas retail pricing is the high incidence of price changes on Tuesdays. This particular TD rule warrants additional examination. The prevalence of price changes on Tuesdays varies substantially over time. Before May 2009, price changes were relatively evenly spread over the days of the week. From May 2009 to 2011, the percentage of price changes occurring on Tuesdays jumped from about 20% to over 50%. After 2011, the percentage of price changes occurring on Tuesdays trended downwards and averaged about 20%. The distribution of the annual average of price changes by the days of the week plotted in Figure 1.9a captures this general trend.




(a) The distribution of day by year




(b) The $F_t$ on Tuesday from 2009-2011

Figure 1.9: The time-varying pattern of choosing the day of the week

Note: (a) The graph plots the fraction of of price changes occurred by the day of the week for all stations within each year. (b) The graph plots the frequency of price changes $F_t$ that occurred on Tuesday.

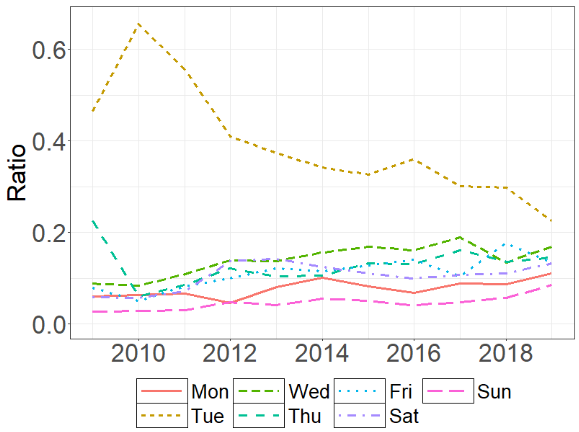
The rapid change in the occurrence of price changes on Tuesdays can be more clearly seen in Figure 1.9b, which represents the daily frequency of price changes on Tuesdays from 2009 to 2011. The $F_t$ remained relatively low before May 12th, 2009 (the average of $F_t$ was 0.07), and it sharply increased on May 12th, 2009 ($F_t = 0.327$), reaching its highest value on June 9th, which was 0.589. After reaching its peak, $F_t$ shows a gradual downward trend over time.

Is the change in the timing of price changes due to a particular brand? Figure 1.10 provides detailed information about the timing of price changes. The figure illustrates the distribution of price changes throughout the week by different companies. On average, stations for *SK Energy* and *GS Caltex* exhibit a preference for changing their prices on Tuesdays. Particularly for *SK Energy*, approximately 40% of their price changes occur on Tuesdays. In contrast, the choice of the day for price changes by stations of the other two brands appears to be relatively evenly distributed across the week. However, all brands show a spike of Tuesday price changes around 2009 to 2011.

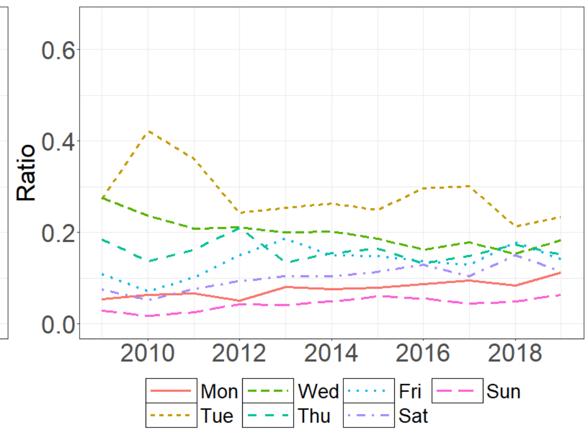
Based on these findings, the preference for Tuesday as the date for price changes correlates with the brand's market share and varies over time. This raises the question: Why do retailers prefer choosing Tuesday as the date for price changes, and why does this preference for Tuesday price changes vary over time? This preference could be due to coordination among stations. Based on the findings of Byrne and De Roos (2019) and Noel (2019), retailers' strategic behavior can establish focal points for tacit collusion, leading to certain days of the week being preferred for price changes.[10]

Two possible factors contributing coordination can be considered. First, the distinct market structure in the Korean gasoline market, where the four major brands account for almost all market share, with the top two brands holding approximately 70%. When a few large firms dominate the market, they can easily send signals, and the limited number of players in the market reduces the risk of any player deviating

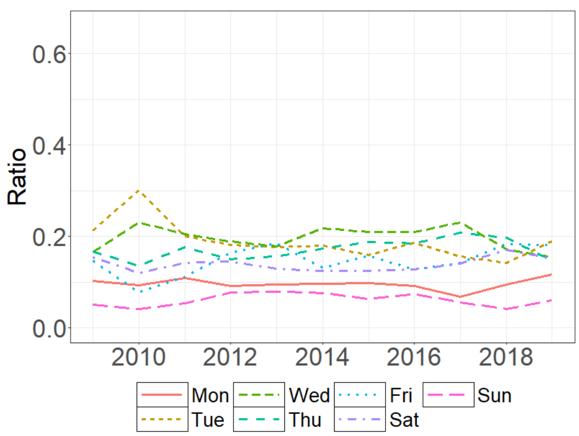
[10] Byrne and De Roos (2019) explore dynamic pricing among retailers in Perth, Western Australia, and present empirical evidence of a transition in coordinated equilibrium. Specifically, dominant firms utilize their market power and price experiments to establish focal points for tacit collusion. Noel (2019) focuses on calendar synchronization in price cycles, where regular price increases occur on the same day of the week every week(e.g., in Perth, Western Australia, troughs consistently occur on Wednesdays and peaks on Thursdays).



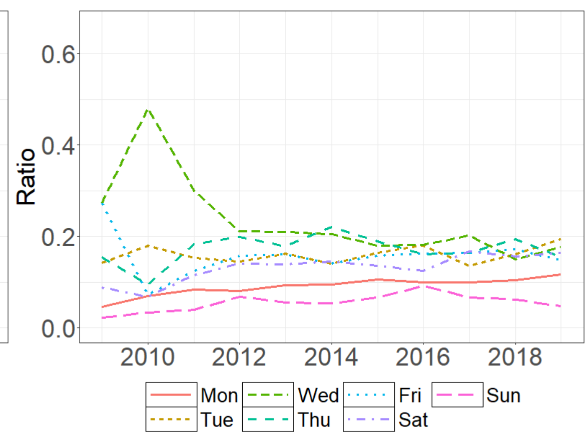

(a) SKE




(b) GSC




(c) S-OIL




(d) HDO

Figure 1.10: The distribution of the day of week by year and brand

Note: For each brand the graph plots the fraction of of price changes occurred by the day of the week within each year.

from the coordinated equilibrium.[11]

Second, stations following time-dependent pricing can also contribute to facilitating the coordination of price changes among stations. In Reis (2006), optimal inattentiveness is determined by the volatility of costs and the elasticity of consumers for each good. Based on the volatility of oil prices and the elasticity of consumers in the gasoline station market, stations' optimal inattentiveness is determined to some extent, and the interval between two consecutive price changes is more likely to be 7 days. What if the interval between price changes is 6 or 8 days? Then the day of the week for price changes will be different every week, even if stations change their prices at a fixed interval, making it difficult for them to send a consistent signal for the price change date.

### 1.5.2 Contribution to related literature

This study complements several strands of existing literature. First, it investigates general retail pricing within a clearer framework. Across retail industries, Nakamura and Steinsson (2008) estimate the median frequency of price changes to be between 7 and 11 months. Consequently, one usually does not have enough observations to estimate the pricing rule of each retailer. Furthermore, the frequency of price changes differs widely by types of goods. In a setting in which many retailers sell different bundles of goods in different markets, a mixed pattern of pricing may stem from the heterogeneity in unobserved factors that influence pricing. For instance, changes

[11] The empirical pattern of price change on a specific day of the week, particularly Tuesday, is distinctive for stations with the two leading brands compared to others. Especially $F_t$ on Tuesday by brands shows that at its maximum, approximately 80% of stations with SK Energy change their prices at the same time. The consistent price changes on Tuesday for dominant stations can signal to other stations and lead them to follow suit, creating focal points for coordination.

in variable costs may differ by retailers and/or by goods, and are unobserved by researchers. Extensive empirical research on retail pricing yields mixed results. For example, Klenow and Kryvtsov (2008) show that neither SD nor TD models explain all patterns in changes of consumer prices across products in CPI categories. The lack of comprehensive data on drivers of price changes makes it difficult to estimate and analyze pricing rules.

To learn how retailers change prices, focusing on the retail price of gasoline has three advantages. First, the price of gasoline changes frequently, which permits the study of pricing patterns of each retailer. Second, gasoline prices are less noisy than prices of retail goods that are occasionally out-of-season, discontinued, or with varying quality. Third, the fact that I observe wholesale gasoline prices, a key variable cost that gasoline retailers face in common, enhances our ability to contrast SD models against TD models. Lastly, the spatial data of stations allows for the analysis of local competitors.

This contribution is significant in terms of its policy implications, as the findings assist in predicting inflation dynamics and guiding monetary policy. Gasoline is an essential good, and its weight in the Consumer Price Index (CPI) holds a higher position in most countries.[12] The prediction of inflation dynamics for a specific good can vary by approximately 1% depending on the price adjustment model assumed. Therefore, understanding the pricing rule in the gasoline market enables governments to predict the effects of monetary policy with greater accuracy.

Second, all competing theories, including TD and SD rules, market power, and psychological pricing, are simultaneously examined. While sticky prices have been in-

[12]According to the '2022 CPI Weight Revision' in Korea, gasoline ranks as the fourth highest-weighted item in the CPI.

vestigated across various area, previous studies often focus on isolated factors rather than analyzing multiple factors simultaneously. For example, in macroeconomics, most studies have utilized concepts such as menu costs and information costs to construct theoretical models of price adjustment.[13] On the contrary, in industrial organization, studies focus on strategic behavior and market power, providing empirical evidence of their impact on price rigidity.[14] In marketing literature, studies demonstrate that consumers' psychological factors influence firms' pricing decisions, thereby contributing to price rigidity. However, it's important to consider these pricing theories within a broader context and not assess them in isolation because all competing theories are correlated with each other. This study contributes to existing research on sticky prices by considering all competing theories simultaneously and examining their correlations with each other.

Finally, this study adds to the existing body of research on the "rocket and feather" price adjustment pattern, which characterizes how retailers quickly raise prices in response to cost increases but are slower to lower them when costs decrease. According to Bachmeier and Griffin (2003), temporal aggregation can lead to significant biases in estimation outcomes, advocating for the utilization of high-frequency data, such as daily data. Consequently, recent studies have increasingly turned to daily-level data to more accurately analyze price adjustment patterns. However, the findings suggest that relying on daily data and employing a standard model for studying the "rocket and feather" may introduce a different type of bias. The error correction model that is used as standard for studying asymmetric price adjustment pattern assumes a linear relationship between the retail price changes and cost changes. However, as seen

[13]e.g., Barro (1972), Sims (2003), Reis (2006), and Alvarez, Lippi, and Passadore (2017)

[14]e.g., Noel (2007) and Cabral and Fishman (2012), Clark and Houde (2013), Byrne and De Roos (2019),Borenstein and Shepard (2002),Davis and Hamilton (2004),Douglas and Herrera (2010)

in Section 1.4, retailers' daily response to cost changes is nonlinear, suggesting that estimating the error correction model with daily data may lead to critical bias in the estimation results.

## 1.6 Concluding Remark

This study examines retailers' pricing behavior, particularly focusing on infrequent price adjustments. It confirms several empirical pieces of evidence of sticky prices regarding competing theories (TD and SD, market power, and psychological pricing) using statistical analysis. The estimation results show that the most dominant factor affecting retailers' pricing is TD pricing, and this TD pricing is related to market power.

The contributions of this study are as follows: First, the study investigates general retail pricing within a clearer framework by focusing on the retail price of gasoline. Second, it contributes to existing research on sticky prices by considering all competing theories simultaneously and examining their correlations with each other. Finally, it adds to the literature on the "rocket and feather" price adjustment pattern, suggesting that relying on daily-level data with a standard model for the "rocket and feather" study might introduce a different type of bias.

In summary, this study demonstrates how all competing theories contribute to price stickiness by examining the retail gasoline market. Specifically, TD pricing emerges as the most dominant factor influencing retailers' pricing decisions, and this tendency to adhere to the TD pricing rule can be influenced by market power. Consequently, stations with market power tend to adjust their prices at regular intervals, while those in competitive areas deviate from these regular patterns. Additionally, this result has implications for asymmetric price adjustments, and I suggest further investigation into how using daily data can affect the estimation results in the "rocket and feathers" study for future research.

# Chapter 2

# How Retail Gasoline Responds to Changes in Oil Price: Daily Price of Gas Stations in Seoul Korea

## 2.1 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 upstream prices.[1]

[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).

However, conflicting findings exist 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 wider intervals, such as weekly data, can introduce significant bias when analyzing the dynamics of gasoline prices. As a result, recent studies on the "rockets 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 indeed true that aggregating daily data to weekly data can introduce bias, particularly if the retail price of gasoline demonstrates daily responsiveness to changes in the upstream price with a linear relationship between changes in retail price and cost. Additionally, high-frequency data allows for smaller standard errors when estimating the model, potentially giving the impression that relying on daily data yields more reliable results.

However, Meng and Xie (2014) demonstrate that the conventional wisdom (*i.e.*, more data ensures better estimates) is not always accurate, and estimation results can sometimes be worse with larger datasets. Although the model they present may differ from those in the literature on "rockets and feathers," it serves as a reminder to carefully consider the data structure before unquestioningly accepting conventional wisdom. Similarly, Nason, Powell, Elliott, and Smith (2017) emphasize the poten-

[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 "rockets and feathers" phenomenon is summarized in Table B.5 in Appendix B.1 based on the data structure and frequency.

tial drawbacks of excessive sampling, including unnecessary costs associated with sampling and storing highly detailed information. Their findings provide 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 "rockets 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 within a typical framework for studying "rockets 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 costs increase. 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 for 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 2.2, I describe the characteristics of the data used in this study. Next, Section 2.3 presents the econometric model, and Section 2.4 provides the results with detailed interpretation. Finally, in Section 2.5, I conclude the paper by summarizing the findings and offering policy implications related to the conclusions.

## 2.2 Data and Market Overview

### 2.2.1 Data

The data for this study were obtained from the *Oil Price Information Network*, 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.

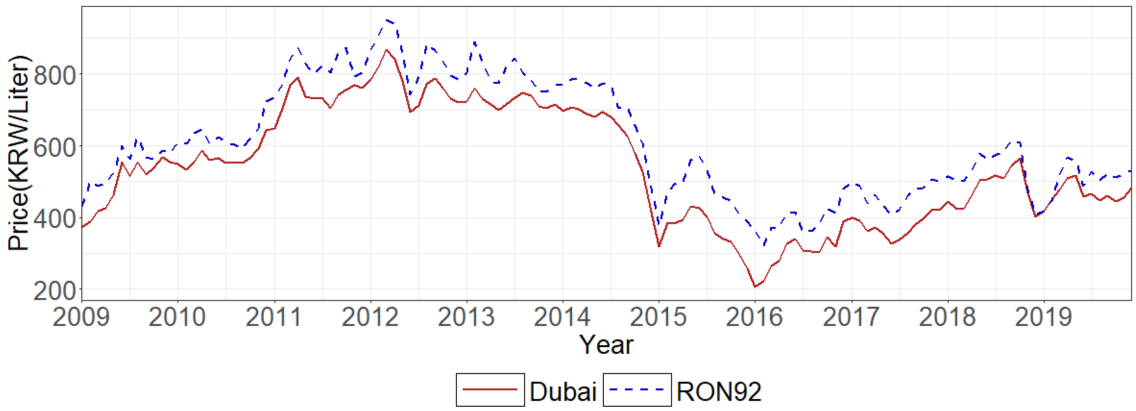
### 2.2.2 Market overview

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.

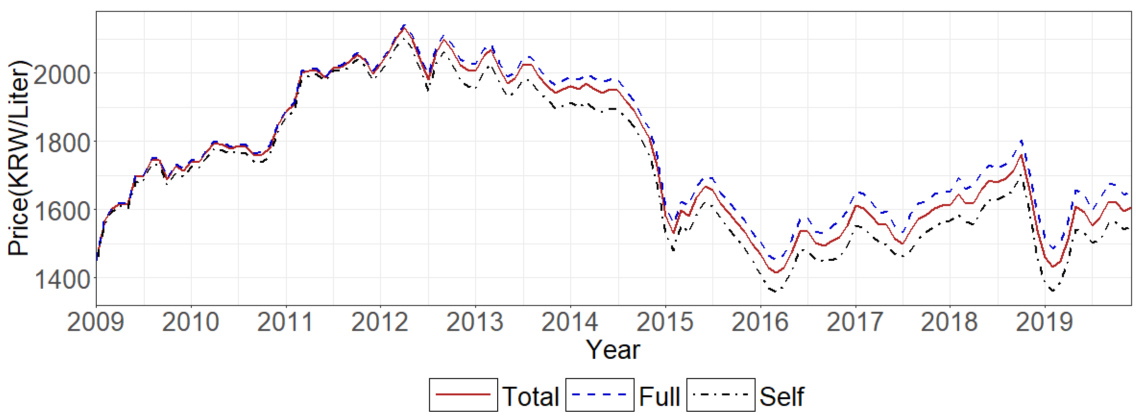
The trend of oil prices suggests two distinct regimes within the data period of 2009-2019. Figure 2.1a illustrates that oil prices were relatively high during the period of 2009-2014, followed by a significant drop in oil prices around 2015 and a sustained period of relatively low oil prices thereafter.

There are two types of stations in the Korean retail gasoline market: full- and self-service stations. Self-service stations attract consumers who prioritize lower prices over full service. Figure 2.1b illustrates that the average prices of full- and self-service stations closely track the oil price and wholesale gasoline price. Generally, the prices of full-service stations are higher than those of self-service stations. The difference between these prices was relatively small during 2009-2014 and became larger during 2015-2019. This observation suggests the possibility of a change in retailers' pricing behavior after 2015. The change in the retail gasoline market coincides with the change in oil price. The majority of stations are full-service, and their number declined throughout the sample period. Meanwhile, the number of self-service stations grew from 2009 to 2014 and remained roughly constant after 2015.

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 for better prices and are willing to forgo the convenience of full-service to save money.




(a) Crude and MOPS price




(b) Retail price(by type)

Figure 2.1: 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.

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

Table 2.1 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 2.1 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

Table 2.1: Pairwise t-test by type of fuel and service

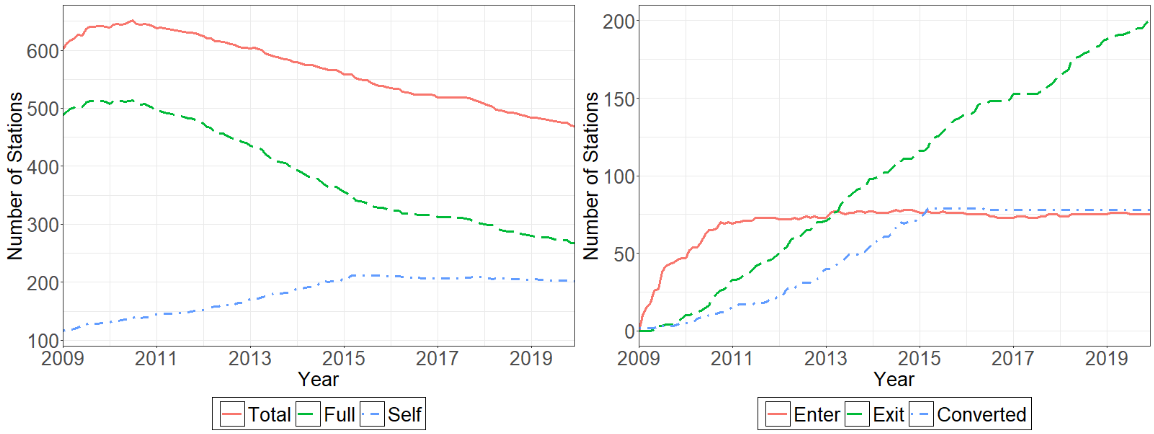
| | 2009-2014 | | 2015-2019 | |
|---|---|---|---|---|
| | Mean Diff. | Std. Error | Mean Diff. | Std. Error |
| Premium(full) - Premium(self) | 45.44*** | 0.72 | 161.71*** | 0.71 |
| Premium(full) - Regular(full) | 206.26*** | 0.52 | 251.59*** | 0.56 |
| Premium(full) - Regular(self) | 256.71*** | 0.72 | 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).

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.

As seen in Figure 2.2, 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.




(a) By type of service (b) By decision

Figure 2.2: The number of station by type of station

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 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 become less dispersed.

Table 2.2 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

Table 2.2: 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 |
| $\Delta P^+$ | 21.73 | 16.82 | 20 | 19.17 | 17.72 | 14 |
| $\Delta P^-$ | -20.74 | 20.25 | -16 | -22.61 | 26.98 | -16 |
| $\Delta C^+$ | 9.12 | 7.62 | 7.15 | 7.41 | 5.88 | 6.19 |
| $\Delta C^-$ | -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 $\Delta P$ and $\Delta C$ 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 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.

## 2.3 Econometric model

Most studies investigating asymmetric price adjustments have used the error correction model proposed by Borenstein, Cameron, and Gilbert (1997) to capture the cointegration relationship between the retail gasoline price and its upstream price. The retail price and wholesale price used in this study also exhibit a cointegration relationship, and thus, I utilize the error correction model with nonstationary time series whenever two time series have a cointegration relationship.[4]

The model specifies the first difference in the price ($\Delta P_{it}$) of station $i$ at week (day) $t$ as in (2.1). Here $C_t$ represents the wholesale price. I use superscripts "+" 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, I can estimate retailers' responses to cost changes independently and observe

[4]Using weekly time series data for both the retail and wholesale price series, I conducted the Augmented Dickey-Fuller Test of stationarity. The test results indicate that I 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, $\eta_t$ 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, providing evidence of a cointegration relationship between the two series. Similar results were obtained when using daily-level data.

the asymmetric adjustment patterns.

$$\Delta P_{it} = \sum_{j=0}^{n}(\beta_j^+ \Delta C_{t-j}^+ + \beta_j^- \Delta C_{t-j}^-) + \sum_{j=0}^{m}(\tilde{\beta}_j^+ \Delta T_{t-j}^+ + \tilde{\beta}_j^- \Delta T_{t-j}^-) + \sum_{j=1}^{n}(\gamma_j^+ \Delta P_{it-j}^+ + \gamma_j^- \Delta P_{it-j}^-) + \theta[P_{it-1} - (\phi_0 + \phi_1 C_{t-1} + \phi_3 Trend_t)] + \epsilon_{it}. \tag{2.1}$$

The error-correction model is based on the assumption of a linear long-run relationship between the retail price and wholesale price. This implies that the price change of the retail price in the $t$ period is determined by how far the retail price is from the long-run equilibrium, previous cost shocks, and the lagged changes in retail price.[5].

The data period in this study spans from 2009 to 2019. However, assuming that the long-run relationship remains unchanged throughout the entire period may be too strong. The trend of oil prices, as depicted in Figure 2.1a, indicates that oil prices were relatively high from 2009 to 2014 but sharply decreased in early 2015 and remained consistently low thereafter. This suggests the possibility of a structural break occurring during the data period, which could affect 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. Consequently, I divided the data into two sub-sample periods and

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

estimated them separately using Equation (2.1): the first period from 2009 to 2014 and the second period from 2015 to 2019.

I use four different types of data structures in this study. First, I employ daily station-level data from the original dataset and create daily time series data by averaging the retail prices across stations. Next, I generate weekly station-level data by averaging the daily prices within each week. Finally, I 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.[6] 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 changes 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 is 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 ($\Delta T_t^+$ and $\Delta T_t^-$), as well as their respective lags ($m = 4$), in Equation 2.1 when estimating the model using data from 2015 to

[6]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).

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.

## 2.4 Results

### 2.4.1 Estimated results

Figure 2.3 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).[7] 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.

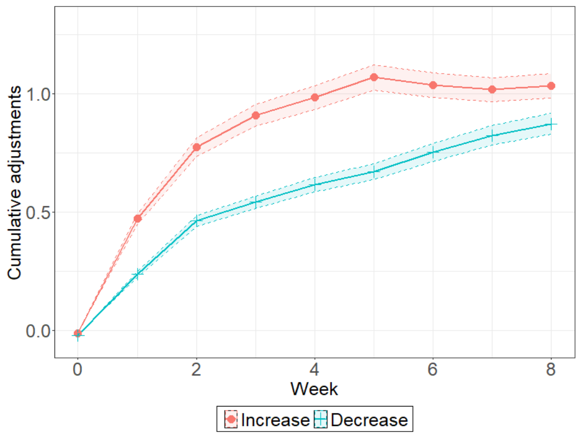
On the contrary, adjustment patterns in daily data are mixed. Based on the estimation results with daily time series data, the cumulative adjustments in response

[7]The cumulative adjustments are calculated based on the estimation results in Table B.1 and Table B.2 in Appendix B.1.

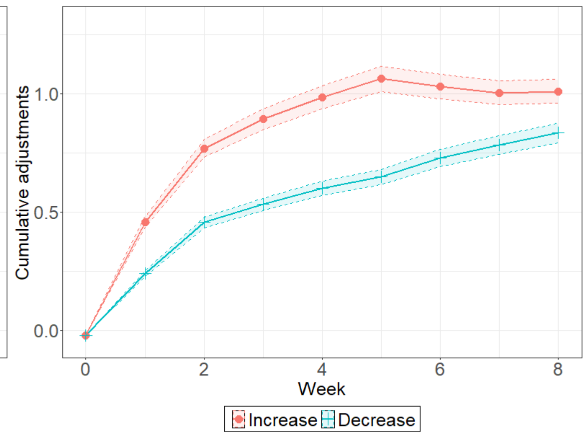
to a one-unit cost increase reach 0.6 around 14 days after a shock occurs. In contrast, the cumulative adjustments in response to a one-unit cost decrease take about 21 days to reach 0.6. Beyond 21 days, it becomes less clear to discern the speed of adjustments, but a weak asymmetric price adjustment 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 2.4, 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.

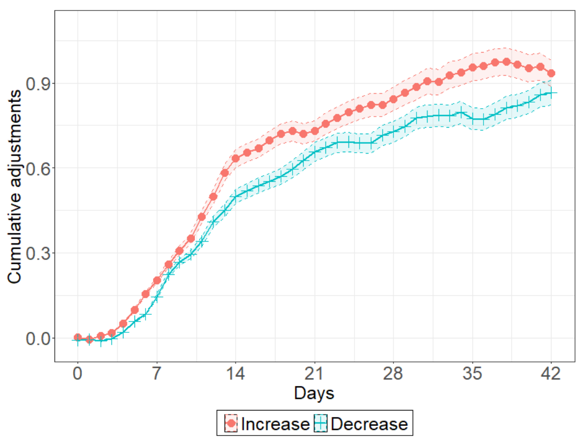
However, using daily-level data, the adjustment process differs from those in 2009-14, exhibiting different patterns. In daily time series data, the retail price responds more strongly to cost increases up to 21 days, but after 21 days, the extent of pass-through of cost decreases exceeds that of cost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



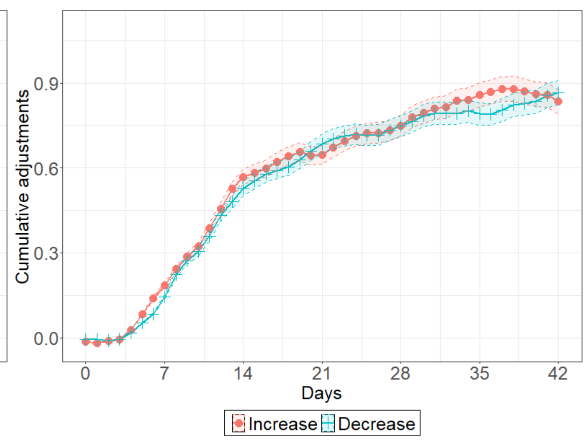

(a) Time series, Weekly data




(b) Panel, Weekly data



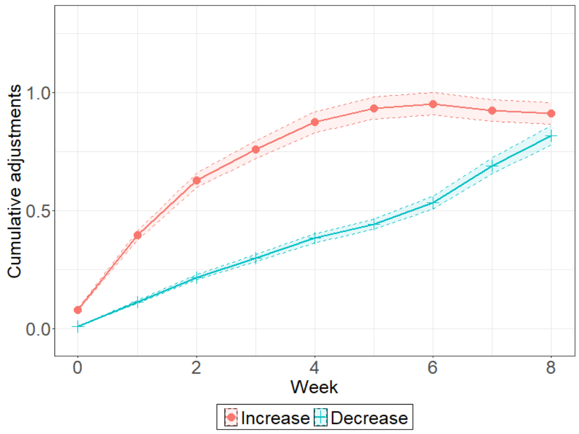

(c) Time series, Daily data



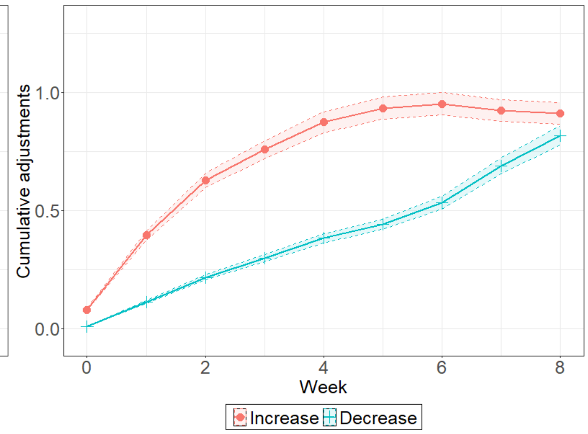

(d) Panel, Daily data

Figure 2.3: Estimated Cumulative adjustments, 2009-2014

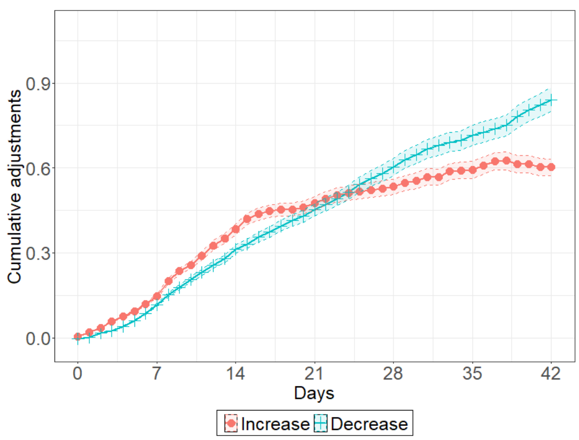
Note: (1) The solid red line represents the cumulative adjustments in response to a one-unit increase in cost, while the solid blue line represents the cumulative adjustments in response to a one-unit decrease in cost. (2) The dashed lines represent the confidence intervals at 5% significance level for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



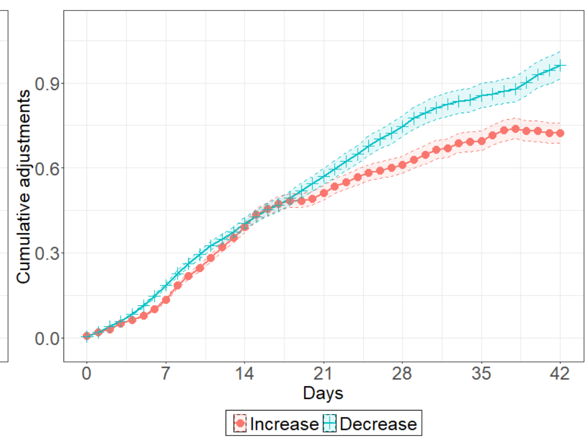

(a) Time series, Weekly data




(b) Panel, Weekly data




(c) Time series, Daily data




(d) Panel, Daily data

Figure 2.4: 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.

### 2.4.2 Why do adjustment patterns with estimated results using daily data vary by period and data structure?

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 data, 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 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). 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 ($\Delta C_t$), $\Delta P_t = \beta \Delta C_t + \epsilon_t$, mis-specifies the data generating process and the estimated coefficient $\beta$ 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 occur 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 the size of retail price change is somewhat averaged out). Therefore, the weekly data is less censored, which is why I obtain relatively consistent results with weekly data.

### 2.4.3 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 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 findings by Remer (2015) lend 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.

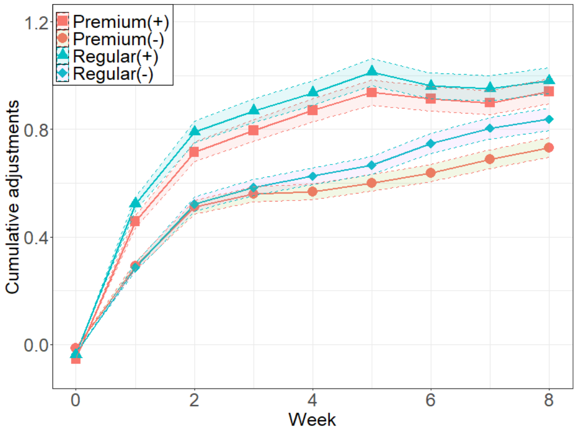
The data samples are divided into four sub-samples based on the type of service and fuel: full-service premium gasoline, full-service regular gasoline, self-service premium gasoline, and self-service regular gasoline. Furthermore, the robustness of the results is examined across two time periods: 2009-2014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

Figure 2.5 presents the cumulative adjustments for the four sub-samples based on fuel type and service type. 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 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.

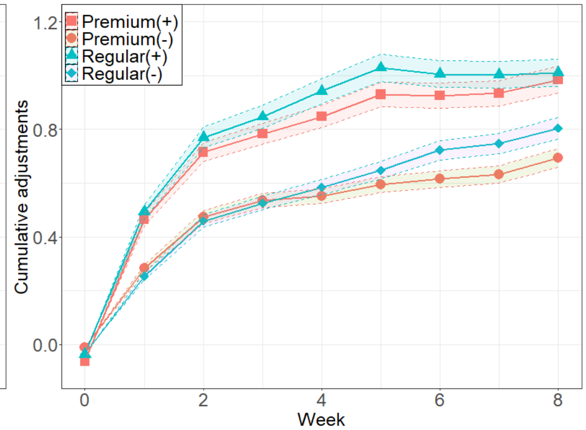
However, the extent of cumulative adjustments varies depending on the type of fuel. For premium gasoline retail price (both full-service and self-service), the complete adjustments in response to an increase of one unit cost reach their peak (around 0.8) at the sixth week. On the other hand, for regular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

Although 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.

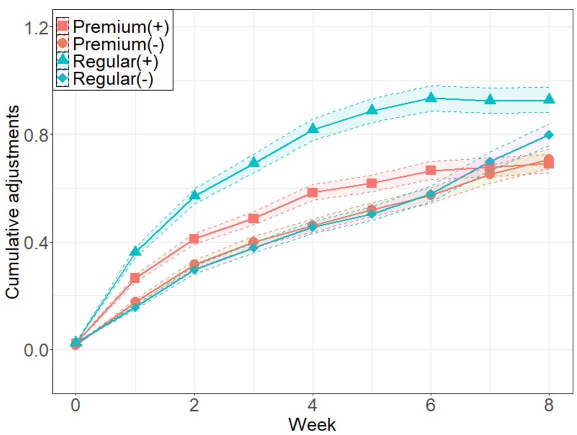
Specifically, the adjustments for the self-service regular gasoline price are completed at around 1 in response to both an increase and a decrease of one unit cost change. However, the pass-through rates for the full-service premium gasoline price are around 0.6 for both an increase and a decrease of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



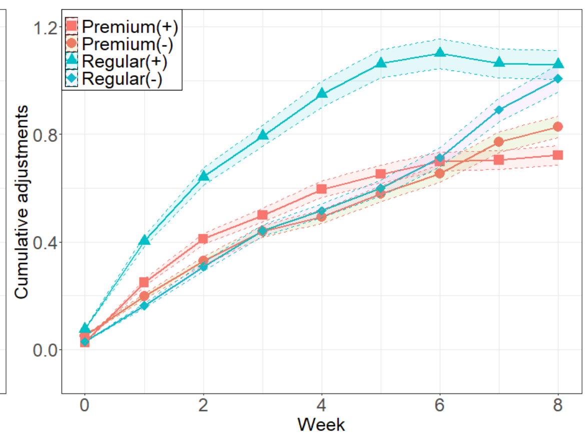

(a) 2009-2014, Full-service




(b) 2009-2014, Self-service




(c) 2015-2019, Full-service




(d) 2015-2019, Self-Service

Figure 2.5: 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).

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.

## 2.5 Concluding Remarks

In this chapter, 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 resulting 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 study 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.

# Appendix A

# Appendix for Chapter 1

## A.1 Appendix

### A.1.1 The estimated results for Logit model

The estimated results for the Logit model imply that the coefficients of all variables are statistically significant at some level in the full model (Model 4), except for the coefficient of the number of stations within a 1km radius after applying fixed effects.

### A.1.2 What drives heterogeneity in pricing?

The findings presented in Section 1.4 suggest that the most dominant factor influencing pricing is the TD rule. The question then arises: How does the tendency to follow the TD rule vary across stations? To answer this question, I sort stations based on the fraction of the duration for which they maintain their previous price. $f_i(a_{it} = k) = \frac{\sum(f_{it}=1|a_{it}=k)}{\sum(f_{it}=1)}$ represents the fraction of price changes where the price has been kept for $k$ days among all price changes that occurred.

Table A.1: The estimated results for Logit model(1): Full sample

| | w/o fixed effect | | | | w/ fixed effect | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| $DC^2$ | | 0.007*** | 0.007*** | 0.008*** | 0.001*** | 0.002*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $ld1$ | | | -0.138*** | -0.132*** | -0.135*** | -0.127*** |
| | | | (0.005) | (0.005) | (0.005) | (0.006) |
| $ld2$ | | | -0.268*** | -0.263*** | -0.312*** | -0.283*** |
| | | | (0.007) | (0.007) | (0.007) | (0.007) |
| *Self* | | | | 0.148*** | 0.208*** | 0.302*** |
| | | | | (0.005) | (0.006) | (0.017) |
| $N^{1km}$ | | | | 0.018*** | 0.010 | 0.002 |
| | | | | (0.001) | (0.001) | (0.004) |
| *HDO* | | | | -0.005 | 0.010 | 0.124*** |
| | | | | (0.009) | (0.009) | (0.027) |
| *S-OIL* | | | | 0.081*** | 0.088* | 0.315*** |
| | | | | (0.009) | (0.009) | (0.027) |
| *SKE* | | | | 0.065*** | 0.074 | 0.074*** |
| | | | | (0.006) | (0.006) | (0.022) |
| *Thrifty* | | | | 0.374*** | 0.494*** | 0.482*** |
| | | | | (0.019) | (0.019) | (0.032) |
| *unbranded* | | | | 0.183*** | 0.217 | 0.111*** |
| | | | | (0.020) | (0.021) | (0.033) |
| Time-dependent | ○ | ○ | ○ | ○ | ○ | ○ |
| State-dependent | | ○ | ○ | ○ | ○ | ○ |
| $ld1$ and $ld2$ | | | ○ | ○ | ○ | ○ |
| Market power | | | | ○ | ○ | ○ |
| Year-week FE | | | | | ○ | ○ |
| Station FE | | | | | | ○ |
| Pseudo $R^2$ | 0.575 | 0.575 | 0.576 | 0.577 | 0.591 | 0.601 |

[1] All models include dummies for the duration since the last price change and day-of-week dummies, but these were excluded from the table due to page size limitations.

Table A.2: Summary statistics by $f_i(.)$

| $f_i(.)$ | Quartile | $N^r$ | $P_i^m$ | $Tues$ | $F_i$ | $ld1$ | $ld2$ |
|---|---|---|---|---|---|---|---|
| $f_i(a = 1..., 6)$ | $f_i(.) < q_1$ | 3.879 | 76.182 | 0.454 | 0.080 | 0.491 | 0.207 |
| | $q_1 \leq f_i(.) < q_2$ | 3.748 | 3.938 | 0.287 | 0.081 | 0.547 | 0.199 |
| | $q_2 \leq f_i(.) < q_3$ | 4.189 | -25.021 | 0.282 | 0.101 | 0.526 | 0.187 |
| | $f_i(.) > q_3$ | 4.407 | -49.131 | 0.236 | 0.133 | 0.523 | 0.171 |
| $f_i(a = 7)$ | $f_i(.) < q_1$ | 4.268 | -68.724 | 0.170 | 0.107 | 0.540 | 0.184 |
| | $q_1 \leq f_i(.) < q_2$ | 4.170 | -47.091 | 0.222 | 0.095 | 0.557 | 0.189 |
| | $q_2 \leq f_i(.) < q_3$ | 4.021 | 19.627 | 0.317 | 0.099 | 0.523 | 0.197 |
| | $f_i(.) > q_3$ | 3.823 | 93.717 | 0.499 | 0.098 | 0.467 | 0.191 |
| $f_i(a = 8..., 13)$ | $f_i(.) < q_1$ | 4.006 | 59.767 | 0.413 | 0.129 | 0.486 | 0.190 |
| | $q_1 \leq f_i(.) < q_2$ | 4.205 | -3.963 | 0.296 | 0.101 | 0.546 | 0.184 |
| | $q_2 \leq f_i(.) < q_3$ | 4.108 | -30.435 | 0.215 | 0.092 | 0.519 | 0.191 |
| | $f_i(.) > q_3$ | 3.942 | -36.257 | 0.184 | 0.074 | 0.542 | 0.198 |
| $f_i(a = 14)$ | $f_i(.) < q_1$ | 4.221 | -64.117 | 0.202 | 0.121 | 0.519 | 0.175 |
| | $q_1 \leq f_i(.) < q_2$ | 4.198 | -33.035 | 0.278 | 0.102 | 0.527 | 0.181 |
| | $q_2 \leq f_i(.) < q_3$ | 3.764 | 20.568 | 0.329 | 0.093 | 0.529 | 0.201 |
| | $f_i(.) > q_3$ | 4.120 | 77.945 | 0.433 | 0.084 | 0.514 | 0.203 |

[1] Station-specific statistics are first calculated and then summarized by pooling them by quartile band.
[1] If $f_i(.) < q_1$, it indicates that $f_i(.)$ falls below the 1st quartile. When $q_1 \leq f_i(.) < q_2$, it implies that $f_i(.)$ is greater than or equal to the 1st quartile but still below 2nd quartile. Similarly, when $q_2 \leq f_i(.) < q_3$, it means that $f_i(.)$ is greater than or equal to 2nd quartile but below 3rd quartile.
[2] $N^r$ represents the number of stations within a 1km radius, and $P_i^m$ represents how station $i$'s price deviates from the market average price. These variables are computed by averaging the corresponding values across stations over time. For example, in the first row, for $f_i(a = 1) < q_1$, I begin by calculating $f_i(a = 1)$ for each station and categorizing the stations based on the quartile of $f_i(a = 1)$. Then, using this categorization, I summarize the values by calculating their averages.
[3] $Tues$ represents the ratio of Tuesdays among the days of the week, taking into account cases where all price changes are not zero. In other words, it indicates how often stations are likely to change their prices on Tuesdays.
[4] $F_i$ represents the average fraction of price changes, while $ld1$ and $ld2$ denote the proportion of times retailers use 8 or 9 as the last digit of their price, with $ld2$ specifically referring to the use of 9 as the second-to-last digit.

For example, $f_i(a = 1)$ denotes the fraction of times station $i$ changes its price after maintaining the previous price for just one day over the entire period. Stations are then ranked and sorted based on this fraction, and summary statistics are generated from this ranking. Therefore, if station $i$ exhibits a relatively high value in $f_i(a = 1, ..., 6)$, it is less likely to adhere to the TD pricing rule. Conversely, a relatively low value in $f_i(a = 1, ..., 6)$ suggests that station $i$ is more inclined to follow the TD pricing rule. As for $f_i(a = 7)$, the interpretation is reversed: a relatively high value implies that station $i$ is more likely to follow the TD pricing rule.

Table A.2 reveals that station statistics, averaged by the quartile of the fraction of times prices are maintained for $k$ days over the entire period, highlight several key insights. First, there is a negative correlation between the inclination to adhere to the TD rule and the average frequency of price changes (along with a positive correlation with the proportion of price changes occurring on Tuesdays).[1] Second, the tendency to follow the TD rule is negatively correlated with the number of stations within a 1km radius (and positively correlated with the degree to which the average price deviates from the market average). Third, the tendency to follow the TD rule is not significantly correlated with the preference for prices ending in 9, both in the last and second-to-last digits of the retail price. In summary, the TD rule may be linked to cost pass-through and the frequency of changes, reflecting market power. Therefore, the heterogeneity in retailers' pricing strategies could arise from the local market conditions they face.

How does local market power influence TD pricing among retailers? To explain

[1]Specifically, for $f_i(a = 1, ..., 6)$, as the quartile band moves to the upper quartile, the average frequency of price changes $F_i$ increases. However, for $f_i(a = 7)$, as the quartile band ascends to the upper quartile, the average frequency of price changes $F_i$ decreases. A similar pattern is observed for $f_i(a = 8, ..., 13)$ and $f_i(a = 14)$.

the empirical findings, I compare them with existing theories that consider rational inattention as optimal behavior.

Following the model presented in Reis (2006), where infrequent adjustments are optimal, let's consider a profit maximization problem under imperfect information, where acquiring the necessary information for price decision-making is costly. There are no physical menu costs, allowing firms to change prices every period at no cost except for the information acquisition cost. In this economy, firms then decide to be rationally inattentive and update their information sets infrequently. The optimal level of inattentiveness is deterministic and can be represented as shown in (1.2), and retailers change their prices at some fixed interval.[2] In this scenario, there is no strategic interaction between retailers that affects their level of inattentiveness.

$$d^* = \sqrt{\frac{4\kappa}{\sigma^2\theta(\theta-1)}} \tag{1.2}$$

Consider a case in which strategic interaction affects the retailers' inattentiveness. This concept is similar to that in Maćkowiak and Wiederholt (2009), where their model allows for heterogeneity in inattentiveness. They consider two types of shocks: one related to aggregate conditions and the other more like firm-specific shocks. Their model predicts that firms are more responsive to idiosyncratic shocks when idiosyncratic conditions are more volatile and important than aggregate conditions. In this case, the choices regarding attention are characterized by strategic complementarity, which implies that a firm becomes more attentive when other firms are also becoming

[2]This is the baseline case described in Reis (2006), where the demand follows an iso-elastic function with a price elasticity parameter $\theta > 1$, the marginal cost follows a geometric Brownian motion with variance $\sigma^2$, and planning costs account for a fixed share $\kappa$ of profits.

more attentive.

For example, let's consider a scenario with a monopoly retail station in an isolated local market, and let $d_m$ represent the retailer's level of inattentiveness in this case. Now, let's assume the same conditions but with two retail stations. In this scenario, each station considers the pricing behavior of the other station, and the optimal inattentiveness will be less than $d_m$. As the number of stations increases under the same conditions, the firm-specific shocks become more volatile and significant, making stations pay more attention to the information and change price more frequently.

Most stations tend to change their prices at regular intervals following the TD pricing rule, typically every 7 days according to my empirical findings. However, some stations facing a more competitive environment have an incentive to be less inattentive, leading them to change their prices even before 7 days have elapsed. In summary, market power affects inattentiveness and, consequently, influences retailers' inclination toward the TD pricing rule.

### A.1.3 Time-dependent rule and type of service

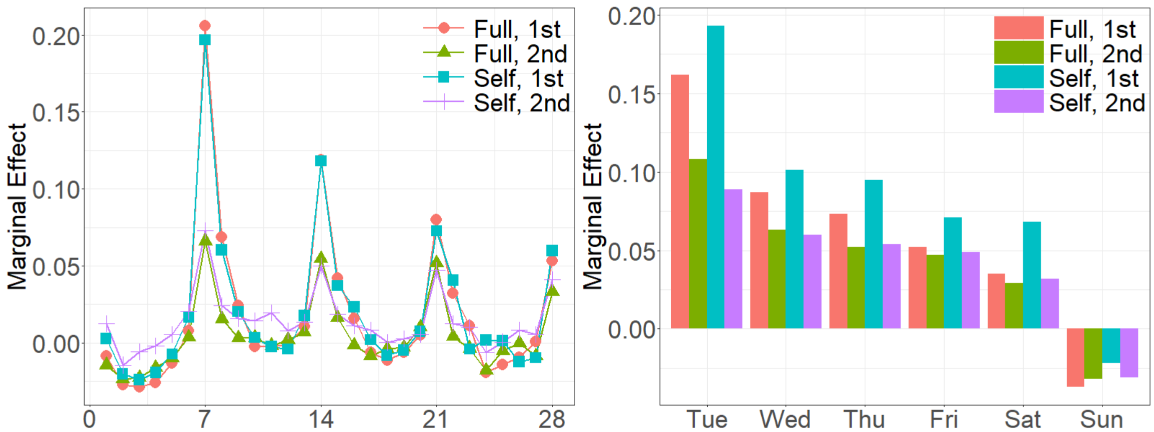
The prevalence of TD rules varies with market conditions. To examine the impact of market conditions on retail pricing, I divided the sample based on the type of service and time period. Typically, self-service stations target more price-sensitive customers, leading them to adjust prices more frequently than full-service stations. However, the competition among stations can also be influenced by the market composition. From 2009 to 2014, the number of self-service stations in the Seoul gasoline market was relatively small, resulting in less intense competition among them compared to that among full-service stations. However, with approximately 200 full-service stations exiting the market or transitioning to self-service stations until 2015, the ratio of full-service to self-service stations decreased. This shift suggests that while competition among self-service stations may have intensified, competition among full-service stations may have lessened compared to the earlier period (2009-2014).

Figure A.1 reflects these changes in market composition from 2009 to 2019. For both periods (2009-2014 and 2015-2019), both full-service stations and self-service stations tended to change their prices at 7-day intervals. However, the figure implies that the preference for the day of the week changed significantly after 2015. In the first period, self-service stations showed a greater preference for changing their prices on Tuesdays compared to full-service stations. However, after 2015, this preference of self-service stations shifted significantly, making them less likely to exhibit a preference for changing prices on Tuesdays compared to full-service stations. Considering that market conditions became less favorable for self-service stations after 2015, this shift in their preference for changing prices on Tuesdays may reflect the changing market dynamics.

### A.1.4 Changes in the market composition

The peak in Tuesday price changes coincides with the peak of number of stations in Seoul. Figure A.2a shows that the total number of stations peaked in the middle of 2010. After 2010, some stations exited the market or switched from full and self-service. The number of self-service station increased while the number of full-service stations decreased due to exits and conversion.

Figure A.2b shows that the decrease in the number of full-service stations and the increase in the number of self-service stations are correlated with the dispersion



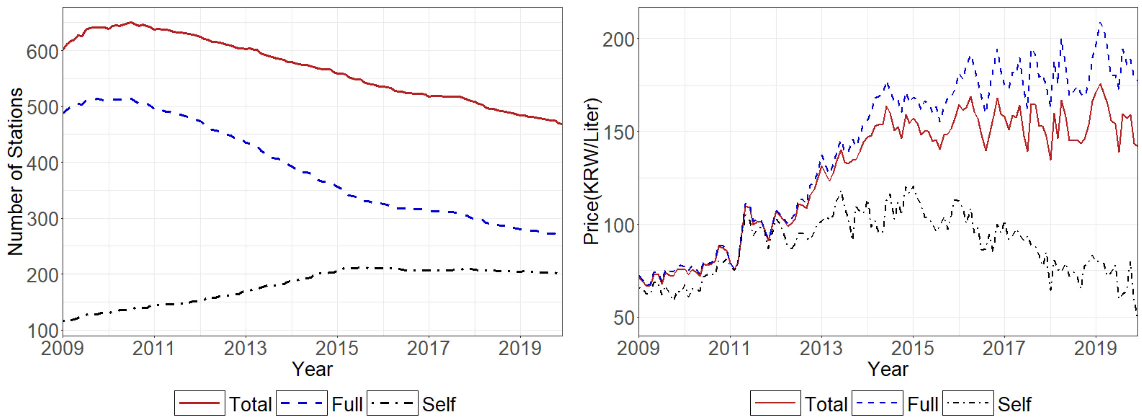

(a) Duration dummies

(b) Day of week dummies

Figure A.1: The estimated marginal effects by sub-samples (Full and Self) in 1st period (2009-2014) and 2nd period (2015-2019).

of price levels. The dispersion of prices among full-service stations diverges, while the dispersion among self-service stations decreased. The decrease in the number of full-service stations increases the price dispersion, while conversely, the increase in the number of self-service stations decreases the price dispersion. This aligns with Borenstein and Rose (1994), where they conclude that competition reduces the price dispersion.

Table A.3 shows that changes in the number and composition of stations are correlated with the frequency of price changes. The average duration of keeping the price unchanged ($A_i$) is at a similar level for both full-service and self-service stations in 2009-2014. In 2015-2019, stations of both types changed prices much less frequently than before, which may be attributed to the decline in the number of stations in the entire market. However, there are significant changes in full-service stations in 2015-2019. Considering that exiting or converting stations are all full-service stations, this




(a) The number of stations by type of service (b) The standard deviation of price across station

Figure A.2: The changes in market composition and price dispersion

significant increase in $A_i$ makes sense.

Another aspect of changes in pricing behavior can be observed in Table A.3. The fraction of price changes that occurred on Tuesday ($Tues$) is similar for both types of service in 2009-2014, but there is a significant drop for self-service stations after 2014 (from 0.321 to 0.233), which implies that the market condition for self-service stations is not as favorable compared to full-service stations.[3]

[3]The fraction of price changes that occurred on Tuesday also dropped for full-service stations, but the decrease is relatively small compared to that of self-service stations(from 0.299 to 0.268).

Table A.3: The summary of the frequency of price changes

| | | 2009-14 | | | | 2015-19 | | |
|---|---|---|---|---|---|---|---|---|
| | | Mean | Std. Dev. | N | | Mean | Std. Dev. | N |
| Full | $F_i$ | 0.098 | 0.038 | 478 | $F_i$ | 0.072 | 0.037 | 349 |
| | $A_i$ | 12.508 | 6.058 | | $A_i$ | 18.195 | 8.387 | |
| | $f_i(7)$ | 0.326 | 0.198 | | $f_i(7)$ | 0.227 | 0.170 | |
| | *Tues* | 0.299 | 0.213 | | *Tues* | 0.268 | 0.183 | |
| Self | $F_i$ | 0.106 | 0.037 | 137 | $F_i$ | 0.097 | 0.061 | 142 |
| | $A_i$ | 11.409 | 5.062 | | $A_i$ | 14.275 | 5.918 | |
| | $f_i(7)$ | 0.310 | 0.199 | | $f_i(7)$ | 0.174 | 0.121 | |
| | *Tues* | 0.321 | 0.208 | | *Tues* | 0.233 | 0.127 | |

[1] Station-specific statistics are first calculated and then summarized by pooling them by type of service and period.
[2] Stations that converted their type of service are omitted to clearly compare the statistics by type of service.
[3] $F_i$ represents the frequency of price changes for each station, and the values in the table are averaged by periods and types of service.
[4] $A_i = \sum_{t=1}^{T} a_{it}$ is the average duration of days keeping the previous price before a change.
[5] $f_i(7)$ is the fraction of price changes made weekly ($a_{it} = 7, ..., 28$).
[6] *Tues* is the fraction of price changes that occurred on Tuesday among all price changes.

# Appendix B

# Appendix for Chapter 2

## B.1 Appendix

The estimation results for creating Figure 2.3c, Figure 2.3d, Figure 2.4c, and Figure 2.4d are presented in Table B.2. Similarly, The estimation results for creating Figure 2.3a, Figure 2.3b, Figure 2.4a, and Figure 2.4b are presented in Table B.1. Figure 2.5 are made based on the Table B.3 and Table B.4.

Table B.1: The estimated results(weekly)

| | Time series | | Panel | |
|---|---|---|---|---|
| | 2009-2014 | 2015-2019 | 2009-2014 | 2015-2019 |
| $\Delta P^+_{t-1}$ | 0.436*** | 0.680*** | 0.153*** | 0.237*** |
| | (0.065) | (0.074) | (0.004) | (0.005) |
| $\Delta P^+_{t-2}$ | -0.094 | -0.118 | -0.087*** | -0.029*** |
| | (0.072) | (0.089) | (0.004) | (0.005) |
| $\vdots$ | | | | |
| $\Delta P^-_{t-1}$ | 0.686*** | 0.777*** | 0.240*** | 0.161*** |
| | (0.086) | (0.111) | (0.003) | (0.004) |
| $\Delta P^-_{t-2}$ | -0.219** | -0.002 | -0.081*** | -0.023*** |
| | (0.100) | (0.135) | (0.003) | (0.004) |
| $\vdots$ | | | | |
| $\Delta C^+_t$ | -0.011 | 0.079*** | -0.022*** | 0.061*** |
| | (0.025) | (0.021) | (0.003) | (0.004) |
| $\Delta C^+_{t-1}$ | 0.382*** | 0.246*** | 0.445*** | 0.264*** |
| | (0.032) | (0.024) | (0.003) | (0.005) |
| $\Delta C^+_{t-2}$ | 0.031 | 0.011 | 0.211*** | 0.134*** |
| | (0.040) | (0.029) | (0.004) | (0.005) |
| $\vdots$ | | | | |
| $\Delta C^-_t$ | -0.021 | 0.006 | -0.022*** | 0.012** |
| | (0.022) | (0.025) | (0.003) | (0.005) |
| $\Delta C^-_{t-1}$ | 0.168*** | 0.080*** | 0.231*** | 0.092*** |
| | (0.029) | (0.027) | (0.003) | (0.006) |
| $\Delta C^-_{t-2}$ | -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 |
| 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 B.2: The estimated results(daily)

| | Time series | | Panel | |
|---|---|---|---|---|
| | 2009-2014 | 2015-2019 | 2009-2014 | 2015-2019 |
| $\Delta P^+_{t-1}$ | 0.257*** | 0.287*** | -0.202*** | -0.282*** |
| | (0.029) | (0.031) | (0.001) | (0.002) |
| $\Delta P^+_{t-2}$ | -0.003 | 0.060* | -0.090*** | -0.086*** |
| | (0.031) | (0.032) | (0.001) | (0.002) |
| $\vdots$ | | | | |
| $\Delta P^-_{t-1}$ | 0.215*** | 0.236*** | -0.136*** | -0.135*** |
| | (0.039) | (0.051) | (0.001) | (0.001) |
| $\Delta P^-_{t-2}$ | -0.057 | -0.051 | -0.065*** | -0.083*** |
| | (0.041) | (0.054) | (0.001) | (0.001) |
| $\vdots$ | | | | |
| $\Delta C^+_{t}$ | 0.0003 | 0.005 | -0.013*** | 0.007*** |
| | (0.008) | (0.006) | (0.002) | (0.002) |
| $\Delta C^+_{t-1}$ | -0.025*** | 0.010* | -0.018*** | 0.004* |
| | (0.009) | (0.006) | (0.002) | (0.002) |
| $\Delta C^+_{t-2}$ | -0.001 | 0.008 | -0.004*** | 0.004** |
| | (0.009) | (0.006) | (0.002) | (0.002) |
| $\vdots$ | | | | |
| $\Delta C^-_{t}$ | -0.01 | -0.003 | -0.007*** | 0.004* |
| | (0.008) | (0.006) | (0.001) | (0.002) |
| $\Delta C^-_{t-1}$ | -0.011 | 0.002 | -0.011*** | 0.004* |
| | (0.008) | (0.006) | (0.001) | (0.002) |
| $\Delta C^-_{t-2}$ | -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 |
| 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 B.3: The estimated results(2009-2014)

| | Premium | | Regular | |
|---|---|---|---|---|
| | Full | Self | Full | Self |
| $\Delta P^+_{t-1}$ | 0.107*** | 0.056*** | 0.119*** | 0.108*** |
| | (0.008) | (0.013) | (0.008) | (0.014) |
| $\Delta P^+_{t-2}$ | -0.043*** | -0.005 | -0.061*** | -0.066*** |
| | (0.008) | (0.013) | (0.008) | (0.015) |
| $\Delta P^-_{t-1}$ | 0.162*** | 0.094*** | 0.280*** | 0.264*** |
| | (0.007) | (0.011) | (0.006) | (0.010) |
| $\Delta P^-_{t-2}$ | -0.092*** | -0.087*** | -0.083*** | -0.064*** |
| | (0.007) | (0.012) | (0.007) | (0.011) |
| $\vdots$ | | | | |
| $\Delta C^+_{t}$ | -0.054*** | -0.062*** | -0.039*** | -0.037*** |
| | (0.008) | (0.013) | (0.007) | (0.011) |
| $\Delta C^+_{t-1}$ | 0.476*** | 0.486*** | 0.527*** | 0.491*** |
| | (0.008) | (0.014) | (0.007) | (0.011) |
| $\Delta C^+_{t-2}$ | 0.177*** | 0.194*** | 0.175*** | 0.190*** |
| | (0.009) | (0.015) | (0.008) | (0.013) |
| $\vdots$ | | | | |
| $\Delta C^-_{t}$ | -0.014** | -0.012 | -0.034*** | -0.034*** |
| | (0.007) | (0.012) | (0.006) | (0.010) |
| $\Delta C^-_{t-1}$ | 0.268*** | 0.252*** | 0.292*** | 0.253*** |
| | (0.007) | (0.012) | (0.006) | (0.010) |
| $\Delta C^-_{t-2}$ | 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 |
| 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 B.4: The estimated results(2015-2019)

| | Premium | | Regular | |
|---|---|---|---|---|
| | Full | Self | Full | Self |
| $\Delta P^{+}_{t-1}$ | 0.165*** | 0.221*** | 0.255*** | 0.242*** |
| | (0.009) | (0.016) | (0.010) | (0.015) |
| $\Delta P^{+}_{t-2}$ | 0.005 | -0.009 | -0.032*** | -0.039** |
| | (0.009) | (0.016) | (0.010) | (0.016) |
| $\vdots$ | | | | |
| $\Delta P^{-}_{t-1}$ | 0.156*** | 0.250*** | 0.184*** | 0.213*** |
| | (0.007) | (0.010) | (0.007) | (0.010) |
| $\Delta P^{-}_{t-2}$ | -0.037*** | -0.060*** | -0.049*** | -0.029*** |
| | (0.007) | (0.011) | (0.007) | (0.010) |
| $\vdots$ | | | | |
| $\Delta C^{+}_{t}$ | 0.022** | 0.026* | 0.024*** | 0.075*** |
| | (0.010) | (0.013) | (0.009) | (0.013) |
| $\Delta C^{+}_{t-1}$ | 0.208*** | 0.189*** | 0.302*** | 0.278*** |
| | (0.010) | (0.013) | (0.010) | (0.013) |
| $\Delta C^{+}_{t-2}$ | 0.082*** | 0.089*** | 0.103*** | 0.136*** |
| | (0.010) | (0.014) | (0.010) | (0.014) |
| $\vdots$ | | | | |
| $\Delta C^{-}_{t}$ | 0.014 | 0.051*** | 0.025** | 0.029* |
| | (0.012) | (0.017) | (0.011) | (0.016) |
| $\Delta C^{-}_{t-1}$ | 0.130*** | 0.106*** | 0.099*** | 0.096*** |
| | (0.013) | (0.017) | (0.012) | (0.016) |
| $\Delta C^{-}_{t-2}$ | 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 |
| Adjusted $R^2$ | 0.267 | 0.316 | 0.367 | 0.443 |

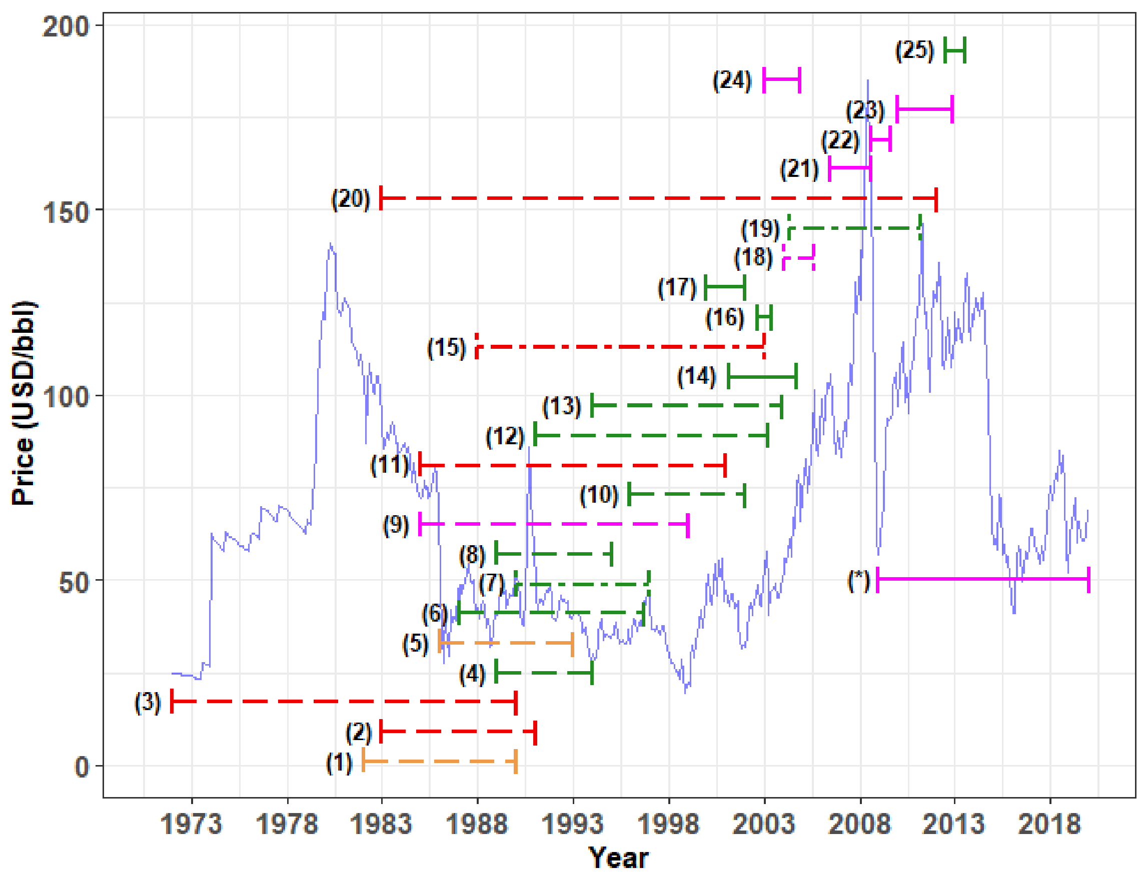
[1] Due to space limitations, some coefficients and their standard errors are omitted.
[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Table B.5: 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 et al. (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 B.1 with corresponding numbers.

Figure B.1: 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 B.5. (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.

## BIBLIOGRAPHY


Alvarez, Fernando, Francesco Lippi, and Juan Passadore. 2017. "Are state-and time-dependent models really different?" *NBER Macroeconomics Annual* 31 (1):379–457. [2, 35]

Ater, Itai and Omri Gerlitz. 2017. "Round prices and price rigidity: Evidence from outlawing odd prices." *Journal of Economic Behavior & Organization* 144:188–203. [1]

Athey, Susan, Kyle Bagwell, and Chris Sanchirico. 2004. "Collusion and price rigidity." *The Review of Economic Studies* 71 (2):317–349. [1, 18]

Bachmeier, Lance J and James M Griffin. 2003. "New evidence on asymmetric gasoline price responses." *Review of Economics and Statistics* 85 (3):772–776. [4, 35, 39, 78]

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. [38, 78]

Balaguer, Jacint and Jordi Ripollés. 2016. "Asymmetric fuel price responses under heterogeneity." *Energy Economics* 54:281–290. [38, 39, 50, 78]

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* . [39, 78]

Balmaceda, Felipe and Paula Soruco. 2008. "Asymmetric dynamic pricing in a local gasoline retail market." *The Journal of Industrial Economics* 56 (3):629–653. [38, 78]

Barro, Robert J. 1972. "A theory of monopolistic price adjustment." *Review of*

*Economic Studies* 39 (1):17–26. [2, 35]

Barron, John M, Beck A Taylor, and John R Umbeck. 2004. "Number of sellers, average prices, and price dispersion." *International Journal of Industrial Organization* 22 (8-9):1041–1066. [18]

Basu, Kaushik. 2006. "Consumer cognition and pricing in the nines in oligopolistic markets." *Journal of Economics & Management Strategy* 15 (1):125–141. [1, 14]

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. [39]

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. [38, 49, 51, 78]

Borenstein, Severin and Nancy L Rose. 1994. "Competition and price dispersion in the US airline industry." *Journal of Political Economy* 102 (4):653–683. [70]

Borenstein, Severin and Andrea Shepard. 2002. "Sticky Prices, Inventories, and Market Power in Wholesale Gasoline Markets." *The RAND Journal of Economics* 33 (1):116–139. [18, 35]

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. [39, 78]

Byrne, David P and Nicolas De Roos. 2019. "Learning to coordinate: A study in retail gasoline." *American Economic Review* 109 (2):591–619. [31, 35]

Cabral, Luís and Arthur Fishman. 2012. "Business as usual: A consumer search theory of sticky prices and asymmetric price adjustment." *International Journal of Industrial Organization* 30 (4):371–376. [35]

Calvo, Guillermo A. 1983. "Staggered prices in a utility-maximizing framework." *Journal of monetary Economics* 12 (3):383–398. [2]

Caplin, Andrew S and Daniel F Spulber. 1987. "Menu costs and the neutrality of money." *The Quarterly Journal of Economics* 102 (4):703–725. [2]

Carlton, Dennis W. 1986. "The Rigidity of Prices." *The American Economic Review* 76 (4):637–658. [1]

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. [78]

Clark, Robert and Jean-François Houde. 2013. "Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case." *American Economic Journal: Microeconomics* 5 (3):97–123. [1, 35]

Clemenz, Gerhard and Klaus Gugler. 2009. *Locational choice and price competition: some empirical results for the Austrian retail gasoline market*. Springer. [18]

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. [39, 78]

Davis, Michael and James Hamilton. 2004. "Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices." *Journal of Money, Credit and Banking* 36 (1):17–37. [35]

Deltas, George. 2008. "Retail gasoline price dynamics and local market power." *The Journal of Industrial Economics* 56 (3):613–628. [38, 78]

Dixon, Robert. 1983. "Industry structure and the speed of price adjustment." *The Journal of Industrial Economics* 32 (1):25–37. [1]

Douglas, Christopher and Ana María Herrera. 2010. "Why are gasoline prices sticky?

A test of alternative models of price adjustment." *Journal of Applied Econometrics* 25 (6):903–928. [35]

Duffy-Deno, Kevin T. 1996. "Retail price asymmetries in local gasoline markets." *Energy Economics* 18 (1-2):81–92. [39, 78]

Eckert, Andrew. 2002. "Retail price cycles and response asymmetry." *Canadian Journal of Economics/Revue canadienne d'économique* 35 (1):52–77. [38, 78]

Faber, Riemer P. 2015. "More new evidence on asymmetric gasoline price responses." *The Energy Journal* 36 (3). [39, 78]

Fernández-Val, Iván and Martin Weidner. 2016. "Individual and time effects in non-linear panel models with large N, T." *Journal of Econometrics* 192 (1):291–312. [24]

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. [38, 78]

Garrod, Luke. 2012. "Collusive price rigidity under price-matching punishments." *International Journal of Industrial Organization* 30 (5):471–482. [1, 18]

Genakos, Christos and Mario Pagliero. 2022. "Competition and pass-through: evidence from isolated markets." *American Economic Journal: Applied Economics* 14 (4):35–57. [61]

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. [39, 78]

Hastings, Justine S. 2004. "Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California." *American Economic Review* 94 (1):317–328. [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. [38, 78]

Houde, Jean-François. 2012. "Spatial differentiation and vertical mergers in retail markets for gasoline." *American Economic Review* 102 (5):2147–82. [18]

Jiménez, Juan Luis and Jordi Perdiguero. 2012. "Does rigidity of prices hide collusion?" *Review of industrial organization* 41:223–248. [1]

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. [38, 78]

Kim, Taehwan. 2018. "Price competition and market segmentation in retail gasoline: New evidence from South Korea." *Review of Industrial Organization* 53 (3):507–534. [18, 47]

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. [39, 78]

Klenow, Peter J and Oleksiy Kryvtsov. 2008. "State-dependent or time-dependent pricing: Does it matter for recent US inflation?" *The Quarterly Journal of Economics* 123 (3):863–904. [34]

Levy, Daniel, Dongwon Lee, Haipeng Chen, Robert J Kauffman, and Mark Bergen. 2011. "Price points and price rigidity." *Review of Economics and Statistics* 93 (4):1417–1431. [1, 14]

Levy, Daniel, Avichai Snir, Alex Gotler, and Haipeng Allan Chen. 2020. "Not all price endings are created equal: Price points and asymmetric price rigidity." *Journal of Monetary Economics* 110:33–49. [1, 14, 15]

Lewis, Matthew. 2008. "Price dispersion and competition with differentiated sellers." *The Journal of Industrial Economics* 56 (3):654–678. [18]

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. [38, 78]

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. [38, 40, 57, 78]

———. 2015. "Odd prices at retail gasoline stations: focal point pricing and tacit collusion." *Journal of Economics & Management Strategy* 24 (3):664–685. [1, 15]

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. [38, 39, 78]

Maćkowiak, Bartosz and Mirko Wiederholt. 2009. "Optimal sticky prices under rational inattention." *American Economic Review* 99 (3):769–803. [67]

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. [39]

Nakamura, Emi and Jón Steinsson. 2008. "Five facts about prices: A reevaluation of menu cost models." *The Quarterly Journal of Economics* 123 (4):1415–1464. [33]

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. [39]

Neumark, David and Steven A Sharpe. 1992. "Market structure and the nature of price rigidity: evidence from the market for consumer deposits." *The Quarterly Journal of Economics* 107 (2):657–680. [1]

Noel, Michael D. 2007. "Edgeworth price cycles, cost-based pricing, and sticky pricing in retail gasoline markets." *The Review of Economics and Statistics* 89 (2):324–334. [1, 35]

———. 2019. "Calendar synchronization of gasoline price increases." *Journal of Economics & Management Strategy* 28 (2):355–370. [31]

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. [38, 78]

Reis, Ricardo. 2006. "Inattentive producers." *The Review of Economic Studies* 73 (3):793–821. [2, 33, 35, 67]

Remer, Marc. 2015. "An empirical investigation of the determinants of asymmetric pricing." *International Journal of Industrial Organization* 42:46–56. [38, 39, 40, 45, 58, 78]

Renner, Elke and Jean-Robert Tyran. 2004. "Price rigidity in customer markets." *Journal of Economic Behavior & Organization* 55 (4):575–593. [1]

Schindler, Robert M and Patrick N Kirby. 1997. "Patterns of rightmost digits used in advertised prices: implications for nine-ending effects." *Journal of Consumer Research* 24 (2):192–201. [1, 14]

Sims, Christopher A. 2003. "Implications of rational inattention." *Journal of monetary Economics* 50 (3):665–690. [2, 35]

Slade, Margaret E. 1999. "Sticky prices in a dynamic oligopoly: An investigation of (s, S) thresholds." *International Journal of Industrial Organization* 17 (4):477–511. [1]

Snir, Avichai, Haipeng Allan Chen, and Daniel Levy. 2022. "Zero-ending prices, cognitive convenience, and price rigidity." *Journal of Economic Behavior & Organization* 203:519–542. [1]

Snir, Avichai, Daniel Levy, and Haipeng Allan Chen. 2017. "End of 9-endings, price recall, and price perceptions." *Economics Letters* 155:157–163. [14]

Stiving, Mark and Russell S Winer. 1997. "An empirical analysis of price endings with scanner data." *Journal of Consumer Research* 24 (1):57–67. [1, 14]

Tappata, Mariano. 2009. "Rockets and feathers: Understanding asymmetric pricing." *The RAND Journal of Economics* 40 (4):673–687. [40, 57]

Taylor, John B. 1980. "Aggregate dynamics and staggered contracts." *Journal of political economy* 88 (1):1–23. [2]

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. [38, 78]

Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data.* MIT press. [24]

Yang, Huanxing and Lixin Ye. 2008. "Search with learning: understanding asymmetric price adjustments." *The RAND Journal of Economics* 39 (2):547–564. [40, 57]

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. [50]

VITA

Seon-Yong Kim was born in Anyang, Gyeonggi, South Korea, on April 4th, 1988. He entered Soongsil University in 2007 and completed his Bachelor's degree in 2014 and his Master's degree in 2017.

He began his Ph.D. studies in Economics at the University of Missouri in Fall 2018. During his time at the University of Missouri, he was under the guidance of Dr. Shawn Ni, focusing on topics in applied microeconomics, particularly studying the retail pricing behavior in the Korean gasoline market. In addition to his academic pursuits, he also served as a research assistant in the Department of Agricultural Economics, studying topics related to food demand elasticity and the effects of climate change on the basis levels of soybean and corn.

After graduation, he will commence his new position as a research fellow at the Korea Energy Economics Institute.