Unraveling Price Stickiness: Evidence from Daily Gasoline Prices in Seoul, Korea

Seon-Yong Kim*

Click here for the latest version.

Abstract

Stickiness in retail prices has been well-documented empirically, while economic explanations of the phenomenon are still debated in macroeconomics and industrial organization. This study investigates price stickiness using daily prices of gasoline stations in Seoul, Korea. It finds that stations change prices infrequently and that the infrequent adjustments follow both state-dependent and time-dependent patterns. Stations with greater local market power tend to favor the time-dependent pricing rule, resulting in price changes at regular intervals. These empirical findings contribute to our understanding of price stickiness, offering insights from both the perspectives of industrial organization and macroeconomics.

JEL classification: Q40, D40, L10

Keywords: Retail price, Sticky price, Gasoline market, Time-dependent pricing, State-dependent pricing

1 Introduction

Retail pricing is a topic of significant interest and has been thoroughly examined across various fields of economics due to the direct connection between the retail sector and consumers' purchasing behaviors. One consistent feature of retail pricing is an infrequent and often periodic and lumpy pattern of price adjustments, even when the factors influencing pricing decisions continuously evolve in terms of time and magnitude. Different economic explanations have emerged in distinct areas of research.

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

In macroeconomics studies, concepts like menu costs and information acquisition costs are primarily employed to develop models that demonstrate how costly adjustments lead to price stickiness.[1] The models of periodic retail price changes are grouped into state-dependent (hereafter SD) models (Caplin and Spulber (1987)) and time-dependent (hereafter TD) models (Taylor (1980); Calvo (1983)). In time-dependent models, the probability of a price change in the current period depends on the duration of maintaining the previous price. In state-dependent models, the decision to change the price depends on the cost or demand shocks that the firm is currently facing and anticipates in the future.

In the field of industrial organization, researchers do not generally support the idea that costly adjustments lead to price rigidity and they have focused on the role of market structure and strategic interaction between firms. Many empirical findings in this field suggests that prices tend to be more rigid in concentrated markets compared to competitive ones.[2] Particularly, the gasoline markets have been extensively studied due to their suitability for investigating infrequent price adjustment behavior. These studies collectively support the relationship between price rigidity and strategic interactions among firms in these markets[3]

Because menu cost, information acquisition cost, and strategic interactions between firms are empirically relevant, the question of how retailers change prices is empirical. However, consensus remains elusive in the existing literature.[4] This mixed pattern of pricing may stem from the heterogeneity in unobserved factors that influence pricing. For instance, changes in variable costs may vary among retailers and/or goods, remaining unobserved by researchers. The lack of comprehensive data on the drivers of price changes makes it challenging to

[1]See, e.g., Barro (1972) for menu cost, and Sims (2003) and Reis (2006) for information acquisition cost.

[2]Empirical evidence provided by studies such as Carlton (1986), Dixon (1983), Neumark and Sharpe (1992), and suggests that prices tend to be more rigid in concentrated markets compared to competitive ones. Theoretical frameworks developed by Athey, Bagwell, and Sanchirico (2004) and Garrod (2012) establish connections between price rigidity and collusive behavior.

[3]see e.g., Slade (1999) , Borenstein and Shepard (2002), Davis and Hamilton (2004), Noel (2007), Douglas and Herrera (2010), Jiménez and Perdiguero (2012), and Clark and Houde (2013).

[4]For example, Alvarez, Lippi, and Passadore (2017) note that for profit-maximizing retailers, 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. However, 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 frequency of price changes differs widely by types of goods.

estimate and analyze pricing rules. Furthermore, some of studies primarily focus on the specific market to explore firms' pricing behaviors. This specialization raises concerns about generalizing specific phenomena observed in a particular market to the broader retail market, where distinct features may exist.[5]

This study analyzes the daily prices (in Korean won per liter) of gasoline stations in the Seoul market of Korea from 2009 to 2019. The purpose of this study is to investigate the pricing behavior of retailers, specifically whether they adhere to SD pricing rules or TD pricing rules, in order to explore the relationship between these rules and local market power. There are several key advantages to focusing on the retail price of gasoline in this study. First, gasoline prices are less noisy than prices of retail goods that are occasionally discontinued out of season or exhibit varying quality. Second, the fact that we observe daily variations in the wholesale gasoline price, a key variable cost that gasoline retailers commonly face, makes it easier to contrast SD models against TD models.

I employ a logit model to examine the relationship between the probability of price changes and variables representing both SD and TD pricing rules, as well as factors indicating the level of competitiveness within the local market. The estimation results suggest that gasoline stations do not exclusively adhere to a single pricing rule but instead employ both SD and TD pricing rules in their pricing decisions. Furthermore, the results imply that stations with greater local market power are more inclined to adjust prices on a weekly basis, indicating a stronger preference for the TD pricing rule.

The empirical findings of this paper shed new light on studies related to price stickiness. First, in contrast to most studies in industrial organization, I find evidence supporting the idea that the costs associated with acquiring information for price adjustments do indeed impact price stickiness. Second, in addition to the first implication, the results suggest

[5]For example, Borenstein and Shepard (2002) rejects the menu cost interpretation for sticky prices and attributes infrequent price adjustments to firms' market power. Similarly, Davis and Hamilton (2004) and Douglas and Herrera (2010) dismiss the menu cost and information processing delay theories, proposing that the strategic interaction between buyers and sellers in determining 'fair pricing' is a key factor in explaining the persistence of sticky prices. All three of these studies focused on the wholesale gasoline market, which possesses distinctive characteristics compared to other retail markets.

that stations' inclination toward the TD pricing rule can be influenced by market conditions. These implications bridge the gap between studies in industrial organization and macroeconomics by providing evidence of the relationship between market power and costly adjustments, indicating that both are actually aligned, not conveying different narratives. In summary, this study contributes to our understanding of sticky prices from both an industrial organization and macroeconomics perspective.

The remainder of the paper is structured as follows: I describe the details of the data in this study in Section 2. In Section 3, I first document in detail the empirical patterns of station-level daily gasoline prices. Section 4 presents the estimation model that encompasses variables serving as proxies for both TD and SD pricing rules. In Section 5, I present the estimation results and their interpretation. Finally, I summarize this study and present conclusions in Section 6.

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 Singapore (MOPS)*, which reports benchmark prices for petroleum products in the Asian market based on transactions in Singapore.[6] 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.[7] *MOPS* constitutes a significant portion of the pre-tax price and

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

[7]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

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. Firstly, I take into account the number of stations within a 1-kilometer radius. To make this variable, centered on a station, I calculate the distance for all pair of existing stations using spatial coordinates of stations and count the number of stations within a 1km radius.[8] Additionally, I utilize monthly sales volume as a proxy for evaluating the competitiveness of local markets.[9]

In Table 1, I present summary statistics for the variables used in this study, either as inputs to other variables or directly in the estimation model. The price of station i on date t is represented as p_{it} and the price change is denoted by Δp_{it}. f_{it} is used as a dependent variable in the estimation model, indicating whether stations change their prices, *i.e.*, $f_{it} = 1$ for $\Delta p_{it} \neq 0$ and $f_{it} = 0$ for $\Delta p_{it} = 0$.

One prominent feature of the data is the infrequent price adjustment. Out of a total of 2,000,904 observations, only 187,860 have $f_{it} = 1$, and its mean is 0.09. Despite the knowledge of daily fluctuations in wholesale price levels and the existence of almost zero physical menu costs, retailers adjust prices infrequently, with approximately 90% of the observations showing no price changes. a_{it} represents the duration for which stations maintain their previous price before changing it at time t. It is calculated as $a_{it} = t - k$ where $f_{it} = 1$, $f_{ik} = 1$, and $f_{ij} = 0$ for $k < j < t$. On average, stations change their prices approximately every 9 days, with a median and mode of 7 days. Price changes appear to be infrequent but regular.

The variables $ld1_{it} = \mathbb{1}\{l_1(p_{it-1}) = 8, 9\}$ and $ld2_{it} = \mathbb{1}\{l_2(p_{it-1}) = 9\}$ are indicator

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*.

[8]Stations entered and exited during the period of our data, and 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.

[9]I calculate the monthly sales volume by dividing the district-level sales volume by the number of stations in that district.

Table 1: Summary statistics for variables

	Description	Mean	SD	Min	Max
Price					
p_{it}	Retail gasoline price(KRW/liter)	1766.86	242.65	1218.00	2490.00
$ld1_{it}$	Indicator variable for price point	0.53	0.50	0.00	1.00
$ld2_{it}$	Indicator variable for price point	0.20	0.40	0.00	1.00
Cost					
C_t	Wholesale price(KRW/liter)	622.04	164.37	286.93	977.28
$\|\Delta C_t\|$	Wholesale price change	0.62	0.78	0.00	8.92
Decision					
f_{it}	Indicator variable for $\Delta p_{it} \neq 0$	0.09	0.29	0.00	1.00
a_{it}	Duration of keeping previous price	9.31	9.24	1.00	56.00
Station characteristics					
$Self_{it}$	Type of service: self-service	0.32	0.47	0.00	1.00
$SalesVol_{it}$	Monthly sales volume	3.08	1.00	1.04	6.97
N^r_{it}	Number of stations within 1km radius	4.22	2.18	0.00	13.00

[1] $a_{it} = t - k$ where $f_{it} = 1$, $f_{ik} = 1$, and $f_{ij} = 0$ for $k < j < t$. Observations where a_{it} is greater than 56 are omitted because they are outliers.
[2] $|\Delta C_t|$, and $SalesVol_{it}$ are scaled by their respective standard deviations.
[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.

variables that indicate whether the last digit of the previous price is an 8 or a 9-ending digit (9-ending for the second to last), where $l_1(.)$ and $l_2(.)$ are functions that provide the last and second-to-last digits of price, respectively. The mean values for $ld1_{it}$ and $ld2_{it}$ are 0.53 and 0.2, respectively, indicating that a significant portion of price points have either an 8 or 9 as the last or second to last digit. I will discuss this in more detail in Section 3.

The first difference of cost, denoted as ΔC_t, is used in this study to estimate the probability of price changes in response to daily cost shocks. The unit of ΔC_t (Korean won per liter) is approximately 0.001 USD, so I scale ΔC_t by dividing it by its standard deviation to provide a more meaningful interpretation of the marginal effect. Asymmetric responses are not the focus of this study, so it is assumed that the response to both positive and negative cost changes is the same, and the absolute value of cost changes is used.

Other variables are used as proxies for the competitiveness of the local market that station i is facing. $Self_{it}$ is a dummy variable for self-service stations. In the retail gasoline market in Korea, there are two types of services: full-service and self-service. Full-service stations offer more convenience, with an employee refueling the gasoline instead of the driver, and the driver doesn't have to exit the car. However, this convenience comes at a higher price, and the prices at full-service stations are generally higher than those at self-service stations. Users of full-service stations are willing to pay a higher price for this convenience and are less price-sensitive. On the other hand, users of self-service stations are more price-sensitive, and self-service stations have less flexibility in adjusting their prices compared to full-service stations.

$SalesVol_{it}$ represents the monthly sales volume, and the rationale for employing this variable stems from the fact that, under the assumption of consistent demand, the equilibrium quantity is consistently higher in competitive markets compared to oligopoly or monopoly markets.[10] N^r represents the number of stations within a 1km radius, and distance-based measures like this one are typically used as proxies for assessing the competitiveness of local markets in several studies.[11]

3 Stylized Patterns of Retail Pricing

I now summarize several empirical regularities discovered in the data.

3.1 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 price adjustments on a weekly basis. The mode and median of a_{it} are both 7 days during the 2009-2019 data period. Figure 1 illustrates the distribution of the duration at the time of price change, highlighting a concentration of frequencies at multiples of 7.[12] These observed

[10]The original $SalesVol_{it}$ variable ranges from 465.6 to 3125.6, with a mean of 1382.6. To facilitate a meaningful interpretation of the marginal effect, I divide it by its standard deviation of 448.29.

[11]see, e.g., Barron, Taylor, and Umbeck (2004), Hosken, McMillan, and Taylor (2008), Lewis (2008), Houde (2012), Kim (2018)

[12]The duration is capped at 29 days in the plot. Price changes with durations beyond 28 days exhibit a similar pattern.

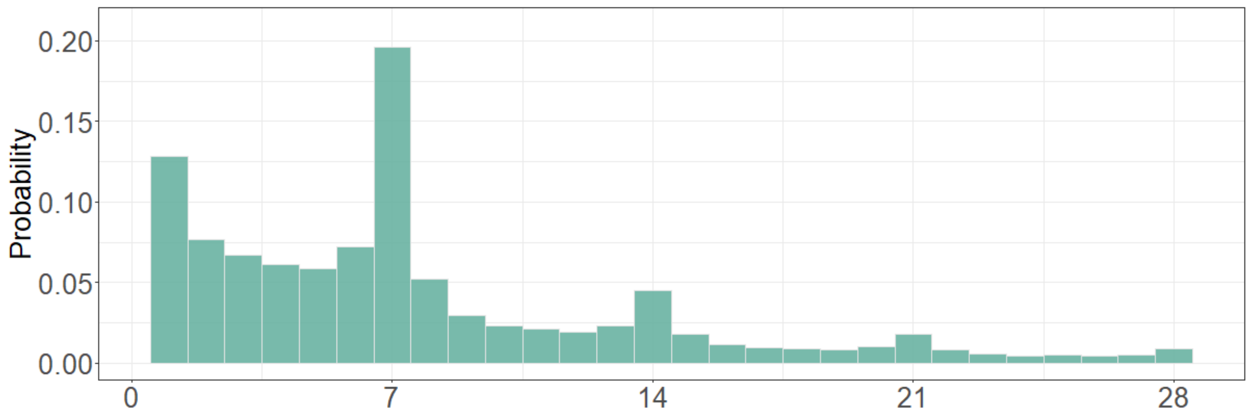


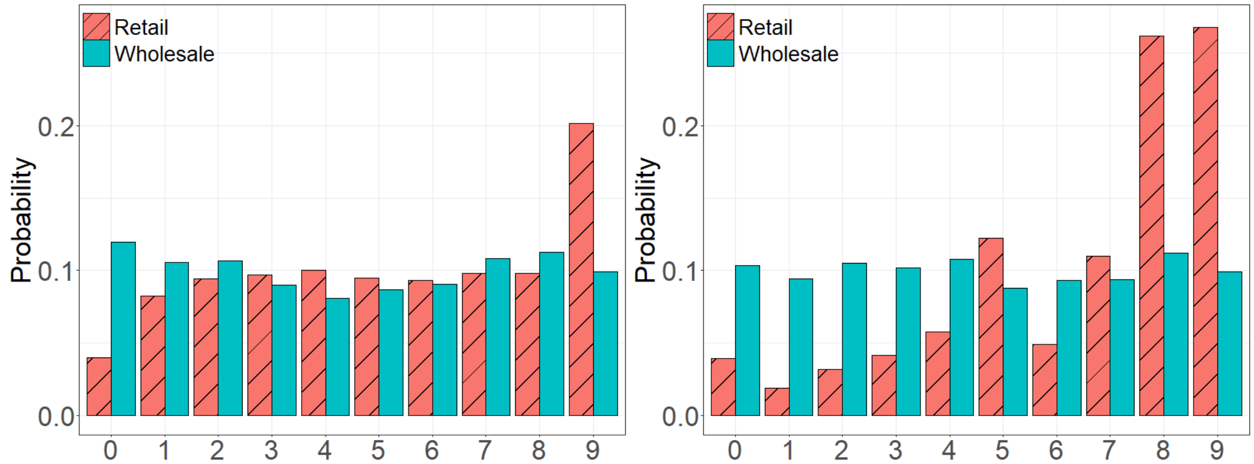
Figure 1: The distribution of a_{it}

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

Furthermore, price changes exhibited a disproportionate occurrence throughout the days of the week. The majority of price changes took place on Tuesday, accounting for 28.3% of all observed price changes. Wednesday followed with 18.3%, Thursday with 15.9%, Friday with 13.6%, and Saturday with 11.4%. In contrast, Monday and Sunday registered lower proportions at 7.8% and 4.7%, respectively. In Figure 1, the sum of the fractions of price changes at weekly frequency (on the 7th, 14th, 21st, 28th day) is about 30%. The disproportional numbers of price changes at the weekly frequency are related to the high numbers of price changes on Tuesdays. This might suggest a cyclicality in price changes and coordination of price adjustments.

3.2 Distribution of prices by last digit and size of price changes

The distribution of numbers in the last and second-to-last digits of retail prices also reveals distinct patterns, with retailers seemingly intentionally choosing prices that end in 8 or 9, as illustrated in Figure 2. This pricing pattern has been documented in both IO and marketing literature. Some studies suggest that odd prices, especially those ending in 5 or 9, are used as focal points for tacit collusion (Lewis (2015)). However, most studies investigate this



(a) Distribution of $l_2(p_{it})$ (b) Distribution of $l_1(p_{it})$

Figure 2: The distribution of price points in last and second-to-last digit

Note: $l_1(.)$ and $l_2(.)$ are functions that output the last and second-to-last digits of price, respectively. In the legend, 'Retail' and 'Wholesale' represent the distribution of price points for retail gasoline prices and wholesale prices respectively.

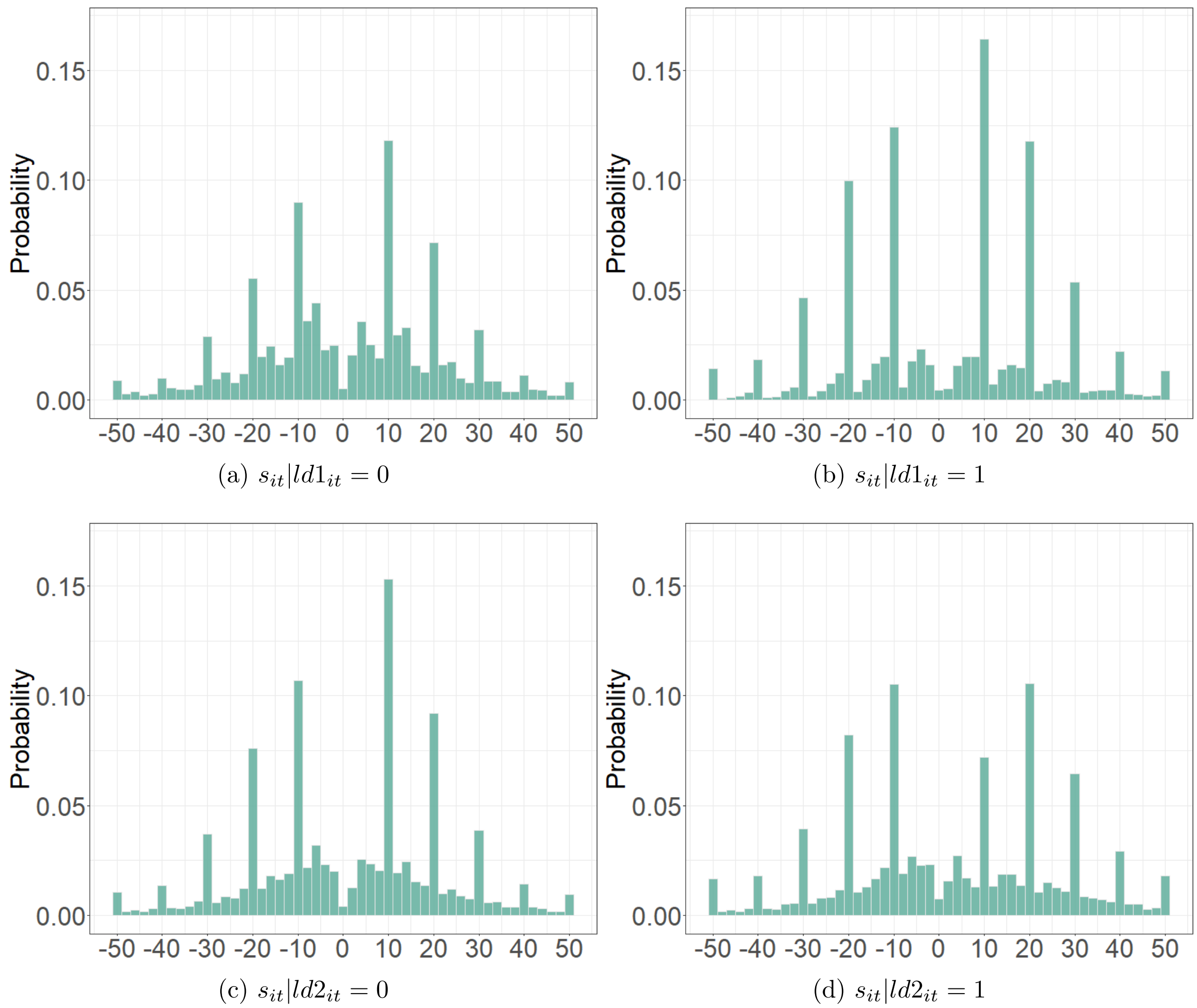
pattern in relation to consumers' cognition.[13]

There are two possible explanations for the use of 9-ending digits in the context of psychological pricing. One is 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). The other explanation is that consumers perceive prices ending in 9 as lower than they actually are.

A retailer's preference for using 9 as the last digit indicates that they are less inclined to change their price when their current price ends with 9. This preference not only impacts the frequency of price changes but also the magnitude of those price changes. As shown in Figure 5a and Figure 5b, when the last digit of the previous price ends in 8 or 9, price changes are more likely to be in increments of 10. However, the case of $ld2$ exhibits slightly different patterns. As demonstrated in Figure 5d and Figure 5c, when the second-to-last digit of the previous price ends in 9, price changes are still likely to be in increments of 10.

[13]see e.g., Schindler and Kirby (1997), Stiving and Winer (1997), Basu (2006), Levy, Lee, Chen, Kauffman, and Bergen (2011), Snir, Levy, and Chen (2017), and Levy, Snir, Gotler, and Chen (2020)

However, retailers are less inclined to change their price by an amount of 10 in this case. In the case of $ld2 = 1$, increasing the price by a magnitude of 10 results in the second-to-last digit becoming zero. This may not convey to consumers a lower price.



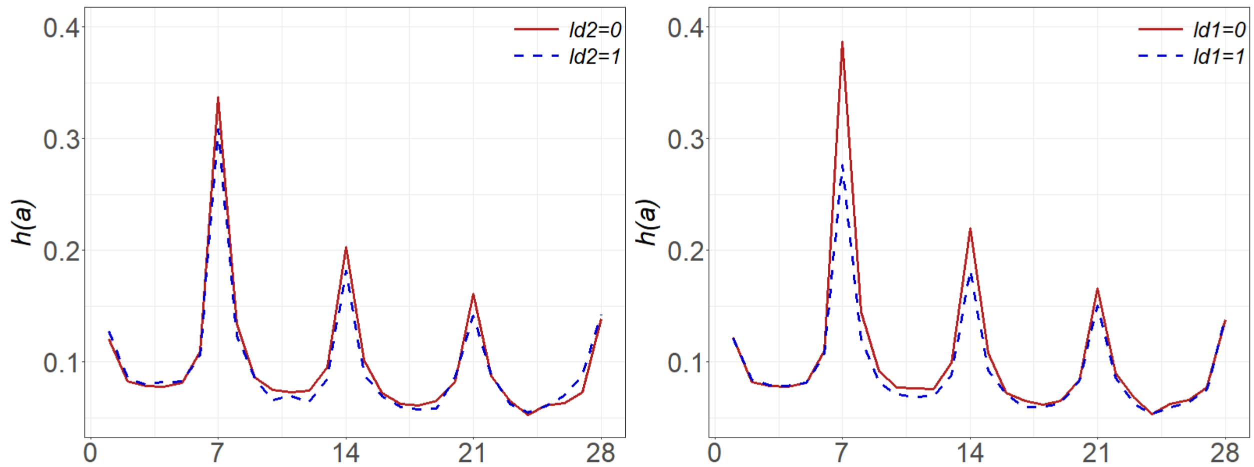
(a) $s_{it}|ld1_{it} = 0$ (b) $s_{it}|ld1_{it} = 1$

(c) $s_{it}|ld2_{it} = 0$ (d) $s_{it}|ld2_{it} = 1$

Figure 3: The distribution of s_{it} (KRW/liter)

Note: $s_{it} = \Delta p_{it}|(f_{it} = 1)$ is the size of the price change. Additionally, $ld1_{it} = 1$ if the last digit of p_{it-1} is 8 or 9, and zero otherwise. Similarly, $ld2_{it} = 1$ if the second to last digit of p_{it-1} is 9, and zero otherwise.

The preference for 9-ending digits for both the last and second-to-last digit makes retailers change their price infrequently, but the reasons behind this preference may vary. Snir and



(a) $h(a|ld2_{it})$ (b) $h(a|ld1_{it})$

Figure 4: Hazard rates conditional on $ld2$ and $ld1$

Note: The hazard rate 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.

Levy (2021) used scanner price data from a large US grocery chain to investigate whether consumers' belief (that 9-ending prices are lower) is accurate. They found that 9-ending prices are actually higher than non-9-ending prices by as much as 18%. This finding aligns with the results obtained from comparing gasoline prices in the cases of $ld2 = 0$ and $ld2 = 1$ where the difference in the mean gasoline price between $ld2 = 1$ and $ld2 = 0$ is 21.84. However, the results from comparing gasoline price in the case of $ld1 = 0$ and $ld1 = 1$ are different; the difference in the mean gasoline price between $ld1 = 1$ and $ld1 = 0$ is -14.25.[14]

A retailer's preference for using 9 as the last digit also affects their regular price change frequency. Figure 4 illustrates how the probability of a price change varies with the duration of maintaining the previous price. As depicted, the hazard rate (probability of changing the price) sharply increases at multiples of 7 days in the duration of keeping the previous price. Furthermore, the hazard rate also exhibits variation based on the last and second-

[14]The t-tests for mean differences in both cases are statistically significant at the 1% significance level.

to-last digits. Figure 4 reveals that when the last and second-to-last digits do not end with a 9, retailers are more inclined to change their price with a regular duration, especially at multiples of 7 days, compared to when the last or second-to-last digit is 9.

3.3 Market power and frequency of price change

Table 2 reports the average of F_i, A_i and P_i^m for stations with varying values of N^r. Here, F_i stands for the ratio of f_i among all periods for station i indicating how frequently station i changes its price. For instance, if F_i is 0.5, it signifies that station i changes its price every other day. P_{it}^m denotes the average price, adjusted for deviations, across each time period t. This measurement indicates how much station i's price deviates from the average market price. If P_{it}^m is greater than zero, it means that station i's price is relatively higher than the market average price at time t. P_i^m represents the average of P_{it}^m over time, providing an overview of whether station i generally maintains higher or lower prices compared to the market average over a given period. F_i, A_i, and P_i^m are station-level statistics and are aggregated by averaging across different values of N^r, which represents the number of rival stations within a 1km radius.

As the value of N^r increases, there is a notable decrease in the average of A_i (accompanied by an increase in the average of F_i), signifying that stations facing a higher number of competitors within a 1km radius tend to adjust their prices more frequently. Moreover, upon examining the average P_i^m, a consistent decreasing trend is evident as N^r increases. This trend suggests that stations with more competitors are inclined to set their prices lower than the market's average price. This observation aligns with the previously mentioned notion that the number of stations within a specific radius serves as a commonly used proxy for assessing local market competitiveness. Within this context, stations with significant market power are likely to change their prices less frequently. This relationship between market power and the frequency of price changes is further reaffirmed.

Another characteristic of pricing behavior related to market power is that stations with

Table 2: Station average duration and price change frequency by the number of rivals

	A_i		F_i		P_i^m		N
N^r	Mean	SD	Mean	SD	Mean	SD	
0	13.887	12.901	0.067	0.027	30.621	143.141	22
1	12.740	11.824	0.083	0.035	17.222	135.822	96
2	12.567	11.674	0.087	0.048	9.215	113.146	182
3	11.820	10.686	0.096	0.049	10.372	136.021	266
4	11.129	10.233	0.097	0.048	-1.502	119.413	305
5	10.999	9.738	0.104	0.063	-3.924	116.476	309
6	11.218	9.960	0.101	0.054	-8.539	117.786	250
7	10.811	9.805	0.100	0.055	-6.862	116.743	170
8	9.783	8.804	0.105	0.050	-26.109	97.106	106
9	9.518	9.170	0.104	0.038	-49.116	79.987	46
10 $\leq$	9.032	9.085	0.107	0.034	-87.754	23.859	19

[1] $A_i = 1/T \sum_{t=1}^{T} a_{it}$ is the average duration of keeping previous price where $a_{it} = t - k$, $f_{it} = 1$, $f_{ik} = 1$ and $f_{ij} = 0$ for $k < j < t$. $F_i = 1/T \sum_{t=1}^{T} f_{it}$ is the ratio of f_{it} where $f_{it} = \mathbb{1}\{\Delta p_{it} \neq 0\}$. $P_{it}^m = p_{it} - p_t^m$ represents how station i's price deviates from the market average price p_t^m at time t, where $p_t^m = 1/N \sum_{i=1}^{N} p_{it}$. Ultimately, I obtain $P_i^m = 1/T \sum_{t=1}^{T} P_{it}^m$ by averaging over time.
[2] N represents the number of stations included in each category based on N^r.

more market power tend to change their prices at regular intervals and on specific days of the week. In Table 3 the variable $f_i(a_{it} = k) = (1/T) \sum_{t=1}^{T} (f_{it} | a_{it} = k)$ represents the average frequency of price changes occurring with $a_{it} = k$ throughout the entire period for station i. A higher $f_i(k = 1)$ indicates that stations prefer to change their prices mostly within one day of keeping their previous price, while a higher $f_i(k = 7)$ suggests that stations prefer to change their prices every 7 days. Similarly, $f_i(a_{it} = 2, ..., 6) = (1/T) \sum_{t=1}^{T} (f_{it} | a_{it} = 2, ..., 6)$ represents the average frequency of price changes with a_{it} taking on values from 2 to 6.

Summarizing $f_i(a_{it} = 1)$ by quartiles reveals that stations with lower $f_i(a_{it} = 1)$ have, on average, a lower value for N^r compared to stations with higher $f_i(a_{it} = 1)$. A similar pattern is observed in the case of $f_i(k = 2, ..., 6)$. This suggests that stations with more rivals are more likely to change their prices within a duration of less than 7 days. However, this pattern changes in the case of $f_i(a_{it} = 7)$. Specifically, stations with lower $f_i(a_{it} = 7)$ have, on average, a higher value for N^r compared to stations with higher $f_i(a_{it} = 7)$. The same pattern is observed for $f_i(a_{it} = 14)$, $f_i(a_{it} = 21)$, and $f_i(a_{it} = 28)$, indicating that stations

Table 3: Summary statistics by $f_i(k)$

	Quartile	N^r	$Sales\,Vol.$(bbl.)	P_{it}^m	$Tues$
$f_i(a_{it}=1)$	$f_i(.) < q_1$	3.82	1339.67	41.61	0.400
	$q_1 \le f_i(.) < q_2$	4.18	1366.74	-16.04	0.280
	$q_2 \le f_i(.) < q_3$	4.48	1369.98	-22.18	0.280
	$f_i(.) \ge q_3$	4.43	1445.00	-12.34	0.275
$f_i(a_{it}=2,...,6)$	$f_i(.) < q_1$	3.96	1326.12	80.87	0.462
	$q_1 \le f_i(.) < q_2$	4.13	1346.50	20.71	0.325
	$q_2 \le f_i(.) < q_3$	4.27	1406.00	-28.31	0.276
	$f_i(.) \ge q_3$	4.58	1444.11	-76.16	0.206
$f_i(a_{it}=7)$	$f_i(.) < q_1$	4.51	1396.98	-71.72	0.171
	$q_1 \le f_i(.) < q_2$	4.39	1388.23	-49.80	0.222
	$q_2 \le f_i(.) < q_3$	4.15	1421.96	17.11	0.317
	$f_i(.) \ge q_3$	3.93	1319.60	91.61	0.499
$f_i(a_{it}=14)$	$f_i(.) < q_1$	4.46	1421.01	-67.01	0.203
	$q_1 \le f_i(.) < q_2$	4.39	1363.93	-35.78	0.278
	$q_2 \le f_i(.) < q_3$	3.92	1393.43	18.09	0.329
	$f_i(.) \ge q_3$	4.22	1354.51	75.75	0.433
$f_i(a_{it}=21)$	$f_i(.) < q_1$	4.33	1488.16	-37.97	0.254
	$q_1 \le f_i(.) < q_2$	4.44	1401.79	-33.00	0.289
	$q_2 \le f_i(.) < q_3$	4.18	1337.18	14.65	0.331
	$f_i(.) \ge q_3$	4.00	1316.18	42.12	0.338
$f_i(a_{it}=28)$	$f_i(.) < q_1$	4.54	1441.28	-38.87	0.243
	$q_1 \le f_i(.) < q_2$	4.41	1416.26	-20.37	0.295
	$q_2 \le f_i(.) < q_3$	3.99	1358.49	8.28	0.327
	$f_i(.) \ge q_3$	4.10	1324.63	30.88	0.335

[1] If $f_i(.) < q_1$, it indicates that $f_i(.)$ falls below the first quartile. When $q_1 \le f_i(.) < q_2$, it implies that $f_i(.)$ is greater than or equal to the first quartile but still below the median. Similarly, when $q_2 \le f_i(.) < q_3$, it means that $f_i(.)$ is greater than or equal to the median but below the third quartile. Finally, when $f_i(.) \ge q_3$, it signifies that $f_i(.)$ is greater than or equal to the third quartile.
[2] N^r represents the number of stations within a 1km radius, $Sales\ Vol.$ indicates the monthly sales volume per station, and P_{it}^m represents how station i's price deviates from the market average price. All three variables are computed by averaging the corresponding values (price, number of rivals, and sales volume) across stations over time. For example, in the first row, for $f_i(k=1) < q_1$, I begin by calculating $f_i(k=1)$ for each station and categorizing the stations based on the quartile of $f_i(k=1)$. 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.

with more market power are likely to change their prices at regular interval.

The average $SalesVol$ and P^m_{it} support this finding. On average, stations with lower values of $f_i(a_{it} = 1)$ and $f_i(a_{it} = 2, ..., 6)$ tend to have lower sales volume but higher prices (adjusted for deviation). Conversely, stations with lower values of $f_i(a_{it} = 7)$, $f_i(a_{it} = 14)$, $f_i(a_{it} = 21)$, and $f_i(a_{it} = 28)$ have higher sales volume and lower prices (adjusted for deviation).

When firms have market power, they typically increase their prices by reducing their quantity, resulting in a higher equilibrium price and a lower equilibrium quantity. The statistics in Table 3 confirm this common knowledge, and variables such as N^r, $SalesVol$, and P^m_{it} exhibit consistent patterns in representing the competitiveness of the local market. An additional finding suggests that stations with market power tend to change their prices at regular intervals, often every 7 days. I will further explore the relationship between market power and this pricing behavior in the main analysis.

4 Econometric Model

I employ a logit model to investigate whether stations adhere to a SD or TD rule when determining price changes. Here's the rationale for using the logit model: On day 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.

These predictors can be categorized into two groups: SD and TD variables. When stations follow an SD pricing rule, the likelihood of changing prices increases when they face larger cost shocks. All retailers are faced with daily cost changes, and they are more likely to change their price with larger cost shocks, $|\Delta C_t|$. I introduce the variable ΔC_t in absolute value form into the model.

On the other hand, 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 observed in Section 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 $a_{it} = 1, ..., 6$ 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 day 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. Additionally, I group certain durations k into a single indicator variable. For example, I group durations from $a_{it} = 1$ to $a_{it} = 6$ into a single indicator variable, denoted as $I(a_{it} = 1, ..., 6)$, which is equal to one if the duration station i kept the price falls within the range of 1 to 6. The results with the original indicator variables and the reduced indicator variables are similar. For simplicity, I opt to use the reduced indicator variables in the model.

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 can be observed in our data, as shown in Section 3. To examine the impact of competition on the probability of price changes, I utilize *Self*, *SalesVol*, and N^r as proxies for local market power.

It's worth noting that stations tend to keep their prices with a 9-ending digit. In other words, the probability of a price change is lower when the last digit of the price is 9. This behavior affects both SD and TD rules. For instance, if the current price ends with a 9, stations will change their price only in response to larger cost shocks. Conversely, if the current price does not end with a 9, stations may change their price even before 7 days pass if the cost shocks are favorable, leading them to set their price with a 9-ending. To account for this 9-ending effect on pricing, I consider an indicator variable that is one 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.

The probability of price change conditioning on these predictors can be represented as $\pi_{it} = prob(f_{it} = 1|\boldsymbol{x}_{it}) = \frac{exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}{1+exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}$. I seek to estimate the vector of parameter $\boldsymbol{\beta}$ and $\boldsymbol{x}'_{it}\boldsymbol{\beta}$ can be denoted as below.[15]

$$\boldsymbol{x}'_{it}\boldsymbol{\beta} = b_1|\Delta C_t| + b_2 Self_{it} + b_3 N^r_{it} + b_4 SalesVol_{it} + b_5 ld1_{it} + b_6 ld2_{it} + \sum_{k=1}^{28} b_{6+k} I(a_{it} = k) \quad (1)$$

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 change. 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 the price change within a week when comparing the probability of price change 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 biased. Furthermore, even if we can estimate the model without any fixed effect-

[15]This equation represents an extended version where the TD variables are not reduced. In the actual estimation, I employ the reduced version of the equation.

induced bias, we encounter another challenge when it comes to 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. We cannot estimate the marginal effect on probability y unless we plug in a value for c, 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.

5 Estimation Results

I begin by examining the stations' decisions regarding price changes and how they make these decisions by considering SD and TD variables. I estimate the model (1) using four different approaches, each involving the inclusion of station-level fixed effects and year-week fixed effects. There are four sets of estimation results: one without any fixed effect, one with only station-level fixed effects, one with only year-week fixed effects, and one with both station-level and year-week fixed effects. My primary focus is on the two-way fixed effects model, which offers the main interpretation of the results. However, I also use the other specifications to assess the robustness of the findings.

The point estimates of the logit model are provided Table 7 in the appendix. Based on these estimation results, I report the marginal effects for each coefficient in Table 4. When examining the marginal effects of variables $ld1$ and $ld2$, it is evident that they are statistically significant at the 1% level across all four estimation approaches. In particular, within the two-way fixed effects model, the marginal effects for $ld1$ and $ld2$ are estimated to be -0.01 and -0.021, respectively. This implies that the probability of a price change is 1 percentage point lower when the previous last digit of the price is 8 or 9, and 2.1 percentage points lower when the previous second to last digit of the price is 9. This observation aligns with the findings of Ater and Gerlitz (2017), reaffirming that the presence of 9-ending digits contributes to more rigid price changes.

The variables *Self*, N^r, and *SalesVol* are all related to local market power, and their marginal effects are statistically significant at the 1% level, except for N^r. Specifically, in the two-way fixed effects model, the estimated marginal effect of *Self* is 0.024, indicating that self-service stations are 2.4 percentage points more likely to change their prices compared to full-service stations. The marginal effect of *SalesVol* is 0.011, indicating that stations with an increase of one standard deviation in sales volume are 1.1 percentage points more likely to change their prices. While the marginal effect for N^r is relatively modest, its direction corresponds with common expectations. In summary, these findings underscore that competition prompts stations to alter their prices more frequently.

The marginal effect of $|\Delta C|$ is 0.016, statistically significant at the 1% level. This means that the probability of a price change increases by 1.6 percentage points as the absolute size of the cost change increases by one standard deviation in $|\Delta C|$. In other words, stations' decisions to change their prices are influenced by cost shocks, and if stations face larger cost shocks, the probability of a price change becomes higher.

Regarding the marginal effect of indicator variables $I(a_{it} = k)$, the reference variable is $I(a_{it} = 29, ..., 35)$. The interpretation of the marginal effect for $I(a_{it} = k)$ involves comparing the probability of price change at $a_{it} = 29, ..., 35$ to that at $a_{it} = k$. However, I analyze the results by comparing the size of the marginal effect for the first 6 days to that for the 7th day within a week. For example, in the case of the first week, the marginal effect of $I(a_{it} = 1, ..., 6)$ and $I(a_{it} = 7)$ is -0.015 and 0.215, respectively. This implies that the probability of a price change within a duration of less than 7 days is lower than the probability of a price change after maintaining the previous price for a duration of 7 days. A similar pattern can be observed in the 2nd to 4th weeks. These findings suggest that stations tend to change their

Table 4: The estimated marginal effects of Logit model (1): Full sample

	Dependent variable: f_{it}			
	(1)	(2)	(3)	(4)
$\|\Delta C\|$	0.016***	0.015***	0.016***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Self	0.013***	0.018***	0.010***	0.024***
	(0.000)	(0.000)	(0.001)	(0.001)
N^r	0.002***	0.001***	0.007***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
SalesVol	0.006***	0.008***	0.004***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)
$ld1$	-0.011***	-0.011***	-0.011***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
$ld2$	-0.021***	-0.024***	-0.018***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
1st week				
$I(a_{it} = 1, ..., 6)$	0.046***	0.010***	0.027***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
$I(a_{it} = 7)$	0.324***	0.262***	0.286***	0.215***
	(0.004)	(0.004)	(0.004)	(0.003)
2nd week				
$I(a_{it} = 8, ..., 13)$	0.046***	0.031***	0.033***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 14)$	0.178***	0.155***	0.160***	0.131***
	(0.004)	(0.003)	(0.004)	(0.003)
3rd week				
$I(a_{it} = 15, ..., 20)$	0.020***	0.015***	0.014***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 21)$	0.120***	0.109***	0.111***	0.097***
	(0.004)	(0.004)	(0.004)	(0.003)
4th week				
$I(a_{it} = 22, ..., 27)$	0.004***	0.002	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 28)$	0.081***	0.0765***	0.078***	0.072***
	(0.004)	(0.004)	(0.004)	(0.004)
Year-week FE	No	Yes	No	Yes
Station FE	No	No	Yes	Yes

[1] The marginal effects are the averages of the sample marginal effects, which involve calculating a marginal effect for each observation and then averaging them.
[2] The reference for $I(a_{it} = k)$ is $I(a_{it} = 29, ..., 35)$, which is equal to one if the duration of maintaining the previous price falls within the range of 29 to 35 days; otherwise, it is zero.
[3] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

prices at regular interval.

When examining the marginal effects of $|\Delta C|$ and $I(a_{it} = k)$, I have observed distinct pricing patterns that can be summarized as follows: First, the probability of a price change increases with the magnitude of the cost change. This suggests that stations take into account cost conditions and adjust their prices accordingly, indicating adherence to a SD pricing rule. Second, when comparing the indicator variables for $a_{it} = k$, I observed that the probability of a price change is higher when a_{it} is a multiple of 7. This implies that stations consider whether to change their prices at regular intervals, specifically every 7 days, which signifies adherence to a TD pricing rule.

In summary, my findings suggest that stations do not exclusively adhere to a single pricing rule. Instead, they incorporate both SD and TD pricing rules into their pricing decisions. For example, the unique characteristic of gasoline as a non-perishable product, stored in station inventories, leads to the adoption of TD pricing rules. However, significant changes in the state, mostly cost changes, prompt stations to switch to SD pricing rules. The remaining question is whether these pricing rules are related to market power. I explore how stations change their pricing rules as market power changes in the two remaining subsections.

5.1 State-dependent rule and market power

The SD pricing rule suggests that stations decide whether to change prices based on cost changes. If some stations are more likely to change prices in response to relatively small cost changes, indicating greater price sensitivity, they appear to rely more on the SD pricing rule compared to stations that are less sensitive to price changes.

To explore the relationship between SD pricing and market power, I segment the data into subsamples based on several variables: the type of service, the number of stations within a 1km radius, and monthly sales volume. Specifically, I estimate the model within subsamples for self-service and full-service categories and then compare the results between these two groups. If market power affects the SD pricing rule, differences in the marginal effect of $|\Delta C|$

Table 5: The estimated marginal effects of Logit model (1): Sub-samples

	Sales volume		Type of service		Number of station	
	Low	High	Full	Self	$N \leq 4$	$N > 4$
Marginal	0.0139***	0.0165***	0.0147***	0.0153***	0.0156***	0.0145***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coef.	0.173***	0.203***	0.191***	0.176***	0.196***	0.176***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
95% CI	[0.165,0.182]	[0.193,0.212]	[0.183,0.198]	[0.165,0.187]	[0.187,0.205]	[0.166,0.185]

[1] The marginal effects are calculated based on the estimates found in Table 8, and the estimate of the model and corresponding standard errors and confidence intervals are provided in the same table.

are expected based on the results for different service types. Additionally, I divide the data into two subsets using the median values of the number of stations within 1km and monthly sales volume, respectively.[16] For each case, I conduct the estimation and compare the results similarly to the type of service analysis.

The marginal effects of cost changes for each subsample can be found in Table 5. In the case of results by subsamples based on sales volume, the marginal effect of $|\Delta C|$ is 0.0139 for stations with 'low' sales volume and 0.0165 for 'high' sales volume. The confidence intervals for the coefficient of $|\Delta C|$ do not overlap, indicating that stations with 'high' sales volume have a higher probability of price change in response to the same amount of cost shocks compared to stations with 'low' sales volume.

However, comparing the marginal effects for different subsamples is somewhat unclear in the case of the type of service because the coefficients of $|\Delta C|$ overlap. Therefore, the hypothesis that the marginal effect of cost change is different between full-service and self-service stations cannot be rejected. Even in the subsamples based on the number of rival stations, the marginal effect of $|\Delta C|$ is greater for stations with a number of rival stations within a 1km radius less than or equal to 4.

The results of two subsamples by sales volume suggest that stations in more competitive areas tend to respond more sensitively to cost changes, indicating that market power makes

[16] The median number of stations within a 1km radius is 4, while the median for monthly sales volume is 2.84

stations less inclined to follow the SD pricing rule. However, the results of two subsamples by the number of rivals tell a different story; market power makes stations more inclined to follow the SD pricing rule. In summary, comparing the marginal effects of the two subsamples in each case does not show a consistent pattern, implying that market power might not actually affect stations' inclination to follow the SD pricing rule. It's important to note that cost shocks are treated as random events and are given to stations exogenously. This implies the response of stations at time t to cost shocks at time t is individually determined without considering the responses of others.

5.2 Time-dependent rule and market power

The definition of a TD pricing rule is that the probability of a price change for stations depends on the duration of maintaining the previous price, implying that stations decide whether to change their prices at regular intervals. I conduct additional analysis to investigate whether the TD pricing rule is related to market power. The outcome of interest in this analysis is the probability of stations changing their prices at regular intervals. Therefore, among all observations with price changes, I only use observations where price changes occurred in the 1st week and examine how the probability of retailers choosing $a_{it} = 7$ depends on the predictors that serve as proxies for the market.[17] I define $\tau_{it} \equiv I(a_{it} = 7)$ and use it as the dependent variable. In detail, the probability of price change at $a_{it} = 7$, given predictors $\boldsymbol{x}_{it}$, can be expressed as $\pi_{it} = prob(\tau_{it} = 1|\boldsymbol{x}_{it}) = \frac{exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}{1+exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}$, where

$$\boldsymbol{x}'_{it}\boldsymbol{\beta} = b_1 N^r_{it} + b_2 SalesVol_{it} + b_3 ld1_{it} + b_4 ld2_{it} + b_5 Self_{it} + \sum_{j=6}^{8} b_j Brand_{jit} + \sum_{k=9}^{14} b_k Day_{kit} \quad (2)$$

Figure 4 suggests that the preference of stations for prices ending in 9 in their last and second-to-last digits might influence the TD pricing rule. To account for this, I have included $ld1$ and $ld2$ as control variables. My primary focus is on variables like N^r, $SalesVol$, and $Self$.

[17] Some observations with the brand labels 'Unbranded' or 'Thrifty' were omitted since they make up a negligible portion of the entire dataset.

If greater market power leads stations to be more inclined to change their prices at regular intervals, we would expect the coefficients of these variables to be negative.

The brand of a station may also influence the TD pricing rule, particularly in terms of the market share of SK Energy (*SKE*), which holds the predominant share, followed by GS Caltex (*GSC*) in the second position. The market shares of the other two brands, Hyundai Oil Bank (*HDO*) and S-Oil (*S-OIL*), are relatively smaller in comparison to the top two companies.[18] Additionally, dummy variables for each day of the week are included in the model, and the estimated coefficients for these variables can help determine whether stations have a preferred day for price changes at regular intervals.

The estimated coefficients are presented in the appendix in Table 9, based on which I compute the marginal effects summarized in Table 6. I now focus on the estimated marginal effect as shown in equation (4) of Table 6. Both the marginal effects of $ld1$ and $ld2$ are negative, which aligns with the findings in Figure 4. The signs of the marginal effects for *Self*, $SalesVol$, and N^r are as expected and statistically significant at the 1% level.

To provide more details, self-service stations are approximately 8.2 percentage points less likely to change their prices regularly. Concerning the marginal effects of sales volume, an increase of one standard deviation in sales volume corresponds to about a 2.5 percentage points reduction in the probability of changing prices regularly. The marginal effect of N^r is -0.016, indicating that having one more rival leads to a roughly 1.6 percentage points decrease in the probability of changing prices with regular intervals.

Based on the marginal effects of the three variables representing competitiveness in the neighborhood, it can be concluded that stations in more competitive local markets are less likely to change their prices at regular intervals. These findings suggest that market power plays a role in the TD pricing rule, making firms in concentrated markets more inclined to adopt the TD pricing rule. To explain the empirical findings, I compare them with existing theories where rational inattention is considered optimal behavior.

[18] The average market shares are 41.2% for *SKE*, 28.1% for *GSC*, 14.2% for *HDO*, and 12.9% for *S-OIL* over the period of the data.

Table 6: The estimated marginal effects of Logit model (2): Reduced sample

	Dependent variable: τ_{it}			
	(1)	(2)	(3)	(4)
N^r	-0.006***	-0.010***	0.021***	-0.016***
	(0.001)	(0.001)	(0.002)	(0.002)
SalesVol	-0.030***	-0.023***	-0.032***	-0.025***
	(0.001)	(0.001)	(0.003)	(0.003)
*ld*1	-0.052***	-0.036***	-0.034***	-0.022***
	(0.003)	(0.002)	(0.002)	(0.002)
*ld*2	-0.012***	-0.011**	-0.011**	-0.008*
	(0.004)	(0.004)	(0.003)	(0.003)
Self	-0.082***	-0.049***	-0.166***	-0.082***
	(0.003)	(0.003)	(0.008)	(0.008)
Brand dummies	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes
Year-week FE	No	Yes	No	Yes
Station FE	No	No	Yes	Yes

[1] The marginal effects are the averages of the sample marginal effects, which involve calculating a marginal effect for each observation and then averaging them.
[2] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

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 (3).[19]

$$d^* = \sqrt{\frac{4\kappa}{\sigma^2\theta(\theta-1)}} \tag{3}$$

In Reis (2006), it is mentioned that the energy retail sector exhibits relatively frequent

[19] 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 σ^2, and planning costs account for a fixed share κ of profits.

price adjustments due to the frequent input cost shocks (high σ^2) and highly price-sensitive consumers (high θ) and thus the result as shown in (3) aligns well with the pricing behavior of retailers in the retail gasoline station industry. For certain parameter values, retailers change their prices every d^* days. In this case, all retailers have the same degree of rational inattentiveness, and there is no strategic interaction between retailers that affects their inattentiveness.

Now, 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 more attentive.

For example, let's consider a scenario with a monopoly retail station in an isolated local market. In this case, the station updates its information set every d_m^* days without considering other stations. 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.

6 Concluding Remarks

This study examines retailers' pricing behavior, with a particular focus on infrequent price adjustments. I confirm several stylized patterns of sticky prices in figures and statistics of this paper. These patterns include price changes at regular intervals, a preference for prices ending with the digit 9, and less frequent adjustments for stations with fewer local rivals.

The contributions of this study, based on the primary analysis, are as follows. First, I investigate sticky pricing through the lens of both SD and TD pricing rules within the retail gasoline market. Retail gasoline market data offers specific advantages for the study of sticky prices, leading to clearer and more robust results. My estimation results reveal that stations do not strictly adhere to a single pricing rule but instead utilize both SD and TD pricing rules. Second, additional analysis indicates that market power does influence the TD pricing rule. Specifically, stations with greater market power tend to change their prices at regular intervals. This empirical result can be explained within the context of a model framework where firms' inattentiveness affects each other.

In summary, this study demonstrates how costly adjustments lead to price stickiness by examining the adherence to both SD and TD pricing rules. In particular, the tendency to follow the TD pricing rule can be influenced by market power. As a result, stations with market power tend to adjust their prices at regular intervals, whereas those in competitive areas deviate from these regular patterns.

However, this study does not explain why stations choose a 7-day interval as the regular pattern. It is worth noting that stations of different brands tend to change price on different days of the week. This pattern changes as the market structure changes (see Figure 5 in the appendix), which may suggest price coordination or price synchronization in the timing of price adjustments. I will explore this topic in future research.

References

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

[2] Ater, Itai and Omri Gerlitz. 2017. "Round prices and price rigidity: Evidence from outlawing odd prices." *Journal of Economic Behavior & Organization* 144:188–203. [19]

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

[4] Barro, Robert J. 1972. "A theory of monopolistic price adjustment." *Review of Economic Studies* 39 (1):17–26. [2]

[5] 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. [7]

[6] Basu, Kaushik. 2006. "Consumer cognition and pricing in the nines in oligopolistic markets." *Journal of Economics & Management Strategy* 15 (1):125–141. [9]

[7] 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. [2, 3]

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

[9] 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]

[10] Carlton, Dennis W. 1986. "The Rigidity of Prices." *The American Economic Review* 76 (4):637–658. [2]

[11] Clark, Robert and Jean-François Houde. 2013. "Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case." *American Economic Journal: Microeco-*

nomics 5 (3):97–123. [2]

[12] 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. [2, 3]

[13] Dixon, Robert. 1983. "Industry structure and the speed of price adjustment." *The Journal of Industrial Economics* 32 (1):25–37. [2]

[14] 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. [2, 3]

[15] Fernández-Val, Iván and Martin Weidner. 2016. "Individual and time effects in nonlinear panel models with large N, T." *Journal of Econometrics* 192 (1):291–312. [18]

[16] Garrod, Luke. 2012. "Collusive price rigidity under price-matching punishments." *International Journal of Industrial Organization* 30 (5):471–482. [2]

[17] Hosken, Daniel S, Robert S McMillan, and Christopher T Taylor. 2008. "Retail gasoline pricing: What do we know?" *International Journal of Industrial Organization* 26 (6):1425–1436. [7]

[18] Houde, Jean-François. 2012. "Spatial differentiation and vertical mergers in retail markets for gasoline." *American Economic Review* 102 (5):2147–82. [7]

[19] Jiménez, Juan Luis and Jordi Perdiguero. 2012. "Does rigidity of prices hide collusion?" *Review of industrial organization* 41:223–248. [2]

[20] Kim, Taehwan. 2018. "Price competition and market segmentation in retail gasoline: New evidence from South Korea." *Review of Industrial Organization* 53 (3):507–534. [7]

[21] 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. [2]

[22] 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. [9]

[23] 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. [9]

[24] Lewis, Matthew. 2008. “Price dispersion and competition with differentiated sellers.” *The Journal of Industrial Economics* 56 (3):654–678. [7]

[25] Lewis, Matthew S. 2015. “Odd prices at retail gasoline stations: focal point pricing and tacit collusion.” *Journal of Economics & Management Strategy* 24 (3):664–685. [8]

[26] Maćkowiak, Bartosz and Mirko Wiederholt. 2009. “Optimal sticky prices under rational inattention.” *American Economic Review* 99 (3):769–803. [26]

[27] 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. [2]

[28] 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. [2]

[29] Reis, Ricardo. 2006. “Inattentive producers.” *The Review of Economic Studies* 73 (3):793–821. [2, 25]

[30] 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. [9]

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

[32] 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.

[2]

[33] Snir, Avichai and Daniel Levy. 2021. "If you think 9-ending prices are low, think again." *Journal of the Association for Consumer Research* 6 (1):33–47. [10]

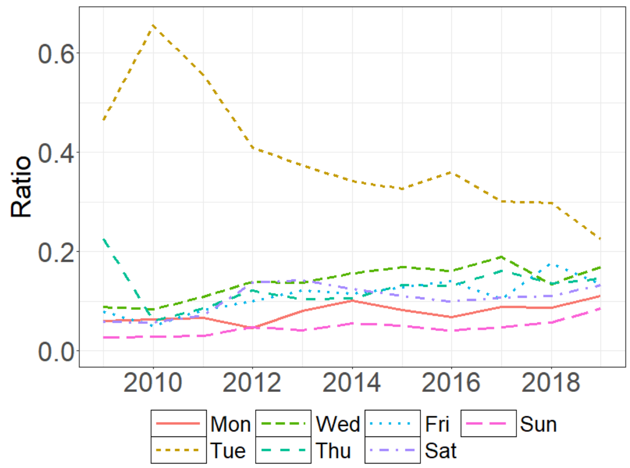
[34] Snir, Avichai, Daniel Levy, and Haipeng Allan Chen. 2017. "End of 9-endings, price recall, and price perceptions." *Economics Letters* 155:157–163. [9]

[35] Stiving, Mark and Russell S Winer. 1997. "An empirical analysis of price endings with scanner data." *Journal of Consumer Research* 24 (1):57–67. [9]

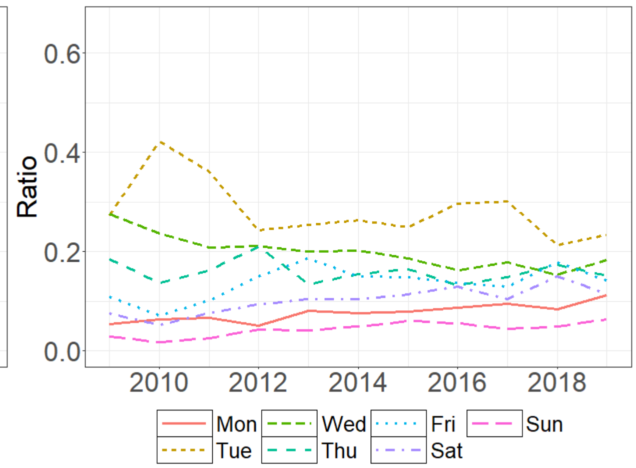
[36] Taylor, John B. 1980. "Aggregate dynamics and staggered contracts." *Journal of political economy* 88 (1):1–23. [2]

[37] Wooldridge, Jeffrey M. 2010. *Econometric analysis of cross section and panel data.* MIT press. [18]

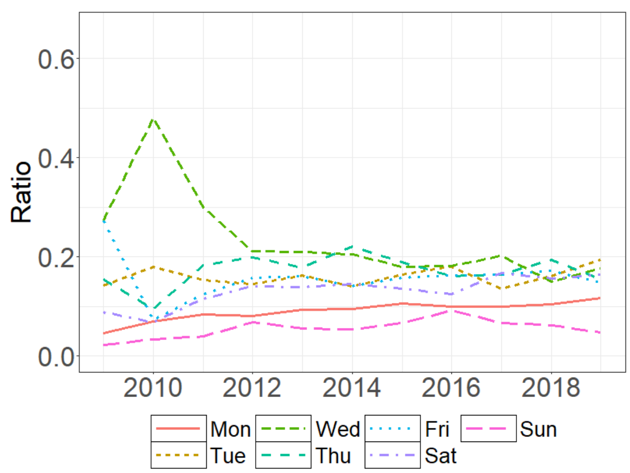
7 Appendix: Additional Tables and Figures



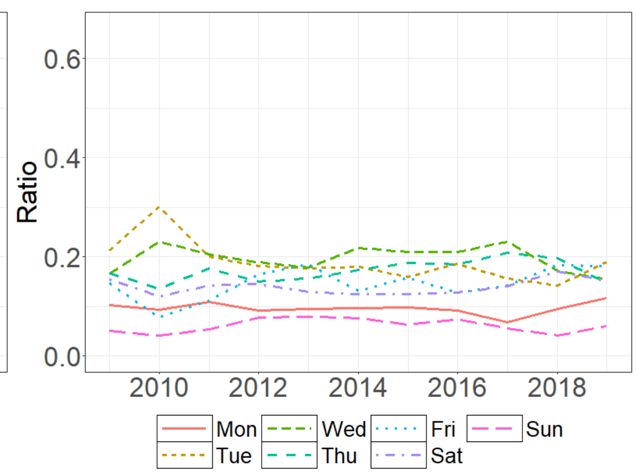
(a) *SKE*



(b) *GSC*



(c) *HDO*



(d) *S-OIL*

Figure 5: The ratio of day of week for price change

Note: The figures show the ratio of each day of the week among all days of price change. Each day of the week is abbreviated (e.g., 'Mon' represents Monday).

Table 7: Estimates of Logit model (1): Full sample

	Dependent variable: f_{it}			
	(1)	(2)	(3)	(4)
$\|\Delta C\|$	0.107***	0.186***	0.186***	0.187***
	(0.003)	(0.003)	(0.003)	(0.003)
Self	-0.029***	0.215***	0.118***	0.282***
	(0.005)	(0.006)	(0.016)	(0.017)
N^r	-0.065***	0.011***	0.082***	0.006
	(0.001)	(0.001)	(0.004)	(0.004)
Sales Vol.	-0.238***	0.098***	0.044***	0.131***
	(0.002)	(0.003)	(0.005)	(0.006)
$ld1$	-0.346***	-0.136***	-0.133***	-0.130***
	(0.005)	(0.005)	(0.005)	(0.006)
$ld2$	-0.412***	-0.313***	-0.234***	-0.283***
	(0.007)	(0.007)	(0.007)	(0.007)
1st week				
$I(a_{it} = 1, ..., 6)$	-1.183***	0.123***	0.328***	-0.181***
	(0.007)	(0.017)	(0.017)	(0.017)
$I(a_{it} = 7)$	0.367***	1.857***	1.936***	1.650***
	(0.009)	(0.018)	(0.017)	(0.018)
2nd week				
$I(a_{it} = 8, ..., 13)$	-1.235***	0.348***	0.369***	0.175***
	(0.009)	(0.017)	(0.017)	(0.018)
$I(a_{it} = 14)$	-0.358***	1.260***	1.268***	1.138***
	(0.014)	(0.021)	(0.020)	(0.021)
3rd week				
$I(a_{it} = 15, ..., 20)$	-1.497***	0.169***	0.159***	0.072***
	(0.011)	(0.019)	(0.019)	(0.019)
$I(a_{it} = 21)$	-0.712***	0.958***	0.961	0.897***
	(0.020)	(0.025)	(0.025)	(0.025)
4th week				
$I(a_{it} = 22, ..., 27)$	-1.682***	0.029	0.013	-0.014
	(0.015)	(0.021)	(0.021)	(0.021)
$I(a_{it} = 28)$	-0.979***	0.723***	0.727***	0.705***
	(0.028)	(0.032)	(0.031)	(0.032)
Year-week FE	No	Yes	No	Yes
Station FE	No	No	Yes	Yes
Observation	1,867,724	1,867,724	1,867,724	1,867,724
Pseudo R^2	0.016	0.082	0.067	0.103
AIC	1,175,921	1,096,590	1,114,841	1,072,470

[1] The reference for $I(a_{it} = k)$ is $I(a_{it} = 29, ..., 35)$, which is equal to one if the duration of maintaining the previous price falls within the range of 29 to 35 days; otherwise, it is zero.
[2] The estimated results in column (2) - (4) are bias corrected estimates.
[3] Pseudo R^2's are calculated based on McFadden Pseudo R^2.
[4] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Table 8: Estimates of Logit model (1): Sub-samples

	Service		N^r		Sales Vol.	
	Full	Self	$N^r \leq 4$	$N^r > 4$	Low	High
$\|\Delta C\|$	0.191***	0.176***	0.196***	0.176***	0.173***	0.203***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
Self			0.400***	0.199***	0.313***	0.306***
			(0.026)	(0.025)	(0.025)	(0.030)
N^r	0.006	0.002			0.045***	-0.046***
	(0.006)	(0.007)			(0.007)	(0.007)
Sales Vol.	0.110***	0.140***	0.119***	0.097***		
	(0.008)	(0.011)	(0.008)	(0.011)		
$ld1$	-0.127***	-0.126***	-0.123***	-0.131***	-0.131***	-0.120***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
$ld2$	-0.313***	-0.221***	-0.293***	-0.266***	-0.276***	-0.282***
	(0.009)	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)
1st week						
$I(a_{it} = 1, ..., 6)$	-0.279***	-0.071*	-0.206***	-0.224***	-0.323***	-0.130***
	(0.021)	(0.030)	(0.023)	(0.027)	(0.025)	(0.024)
$I(a_{it} = 7)$	1.733***	1.418***	1.616***	1.644***	1.670***	1.565***
	(0.022)	(0.032)	(0.024)	(0.028)	(0.026)	(0.025)
2nd week						
$I(a_{it} = 8, ..., 13)$	0.164***	0.176***	0.164***	0.154***	0.141***	0.167***
	(0.022)	(0.031)	(0.023)	(0.027)	(0.025)	(0.025)
$I(a_{it} = 14)$	1.204***	0.974***	1.119***	1.138***	1.155***	1.088***
	(0.025)	(0.037)	(0.028)	(0.032)	(0.030)	(0.029)
3rd week						
$I(a_{it} = 15, ..., 20)$	0.056*	0.095**	0.040	0.097**	0.042	0.081**
	(0.023)	(0.033)	(0.025)	(0.029)	(0.027)	(0.027)
$I(a_{it} = 21)$	0.955***	0.757***	0.884***	0.905***	0.923***	0.859***
	(0.031)	(0.046)	(0.034)	(0.039)	(0.036)	(0.036)
4th week						
$I(a_{it} = 22, ..., 27)$	-0.045	0.041	-0.013	-0.021	-0.037	0.000
	(0.026)	(0.037)	(0.028)	(0.033)	(0.031)	(0.030)
$I(a_{it} = 28)$	0.721***	0.667***	0.712***	0.691***	0.791***	0.615***
	(0.038)	(0.057)	(0.041)	(0.050)	(0.045)	(0.046)
Observation	1,257,629	610,095	1,061,281	806,443	933,475	934,249
Pseudo R^2	0.114	0.089	0.106	0.104	0.114	0.099
AIC	695,451	373,232	598,916	470,462	529,549	538,082

[1] The reference for $I(a_{it} = k)$ is $I(a_{it} = 29, ..., 34)$, which is equal to one if the duration of maintaining the previous price falls within the range of 29 to 34 days; otherwise, it is zero.
[2] All estimated results are TWFE estimates and have been bias corrected.
[3] Pseudo R^2's are calculated based on McFadden Pseudo R^2.
[4] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**\,p < 0.05$; and $***p < 0.01$.

Table 9: Estimates of Logit model (2): Reduced sample

	Dependent variable: τ_{it}			
	(1)	(2)	(3)	(4)
N^r	-0.077***	-0.061***	0.143***	-0.115***
	(0.003)	(0.004)	(0.012)	(0.014)
Sales Vol.	-0.299***	-0.141***	-0.213***	-0.181***
	(0.006)	(0.008)	(0.018)	(0.021)
$ld1$	-0.383***	-0.227***	-0.227***	-0.160***
	(0.014)	(0.015)	(0.016)	(0.017)
$ld2$	-0.108***	-0.066**	-0.071**	-0.059*
	(0.021)	(0.022)	(0.022)	(0.024)
Service				
Self	-0.578***	-0.306***	-1.142***	-0.592***
	(0.015)	(0.017)	(0.053)	(0.056)
Brand				
SKE	0.431***	0.804***	1.036***	0.712***
	(0.023)	(0.028)	(0.083)	(0.087)
GSC	0.320***	0.725***	0.575***	0.367***
	(0.025)	(0.030)	(0.092)	(0.095)
HDO	0.036	0.554***	0.411***	0.394***
	(0.030)	(0.034)	(0.106)	(0.109)
Day of week				
Mon	-0.776***	0.843***	0.635***	0.588***
	(0.043)	(0.075)	(0.078)	(0.079)
Tue	1.434***	3.015***	2.681***	2.671***
	(0.028)	(0.068)	(0.068)	(0.070)
Wed	0.412***	2.045***	1.813***	1.831***
	(0.030)	(0.069)	(0.070)	(0.071)
Thu	0.143***	1.674***	1.674***	1.618***
	(0.032)	(0.069)	(0.070)	(0.072)
Fri	-0.385***	1.261***	1.206***	1.225***
	(0.035)	(0.071)	(0.072)	(0.073)
Sat	-0.475***	1.205***	0.958***	1.023***
	(0.037)	(0.072)	(0.074)	(0.075)
Year-week FE	No	Yes	No	Yes
Station FE	No	No	Yes	Yes
Observation	112,915	112,915	112,915	112,915
Pseudo R^2	0.138	0.212	0.253	0.304
AIC	119,765	109,408	103,665	96,570

[1] The estimated results in all columns are bias corrected estimates.
[2] Pseudo R^2's are calculated based on McFadden Pseudo R^2.
[3] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.