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

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Abstract

(Incomplete!)This study explores the price adjustment behavior of retail gasoline stations in Seoul, Korea. The empirical findings indicate that all stations adjust their prices infrequently. However, there are actually two different mechanisms for making these infrequent price adjustments: the state-dependent rule and the time-dependent rule. Retailers employ both pricing rules depending on the situations, and local market power affects this combination of pricing strategies. Stations with more market power are more likely to adjust prices using the time-dependent rule, while those with less market power are more likely to adjust their prices using the state-dependent rule.

JEL classification: Q40, D40

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

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, with changes in its market structure directly impacting consumer welfare. In the industrial organization, extensive research has been dedicated to understanding the dynamics of retail pricing, particularly with a focus on uncovering the role of market structure and strategic interactions among retailers. This body of work serves as a crucial tool for shaping regulatory policies and fostering fair competition in markets. In the field of macroeconomics, the investigation of retail pricing is instrumental in shedding light on

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how retailers transmit cost shocks to retail prices. Such studies contribute to predicting the dynamics of inflation and play an important role in guiding the conduct of monetary policy.

One consistent feature of retail pricing is 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. In the macroeconomics, the term 'sticky prices' was initially introduced, and various theories have been proposed to account for this phenomenon. Models of periodic retail 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.

Alvarez, Lippi, and Passadore (2017) note for profit maximizing retailers, SD models are optimal when there is a fixed cost in changing price (e.g., menu cost, see Barro (1972)), while TD models are optimal when there is a fixed cost in acquiring information (which results in rational inattention, Sims (2003), Reis (2006)). These models depict different mechanisms on how changes in cost pass through into retail price and predict different dynamics of prices.

In the industrial organization, researchers have focused on the role of market structure and strategic interaction between firms. For example, Carlton (1986), Dixon (1983) and Slade (1999) have furnished empirical evidence indicating that prices exhibit greater rigidity in concentrated markets compared to prices in competitive markets. Athey, Bagwell, and Sanchirico (2004) and Garrod (2012) have provided theoretical framework that establish links between price rigidity and collusive behavior. The retail and wholesale gasoline markets have received particular attention in this context, as they offer advantageous settings for investigating infrequent price adjustment behavior. These studies have contributed to building substantial evidence supporting the relationship between price rigidity and the strategic interactions among firms in these markets(Borenstein and Shepard (2002), Davis and Hamilton (2004), Noel (2007), Douglas and Herrera (2010), Jiménez and Perdiguero (2012), and Clark and Houde (2013)).

Because menu cost, information acquisition cost and strategic interactions between firms are empirically relevant, hence how retailer change prices is an empirical question. However, consensus remains elusive in the existing literature. Klenow and Kryvtsov (2008) show that neither SD nor TD models explain all patterns in changes of consumer prices cross products in CPI categories. The frequency of price changes differs widely by types of goods.[1] Most studies in IO literature usually do not accept the interpretation of menu cost and information cost. Specifically, Borenstein and Shepard (2002) reject the menu cost interpretation for sticky price, and attribute the infrequent price adjustment to firms' market power. Moreover, Davis and Hamilton (2004) and Douglas and Herrera (2010) reject the menu cost and information processing delay theories. They propose that the strategic interaction between buyers and sellers in determining 'fair pricing' is a key factor in explaining the persistence of sticky price.[2]

However, 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 in variable costs may differ by retailers and/or by goods, and are unobserved by researchers. The lack of comprehensive data on drivers of price changes makes it difficult to estimate and analyze pricing rules. Furthermore, the three aforementioned studies in the field of Industrial Organization focus primarily on the wholesale gasoline market to explore firms' pricing behaviors. This specialization raises caution against generalizing specific phenomena observed in a particular market. Indeed, the wholesale gasoline market possesses distinct characteristics compared to other retail

[1] Across the retail industry, Nakamura and Steinsson (2008) estimate the median frequency of price changes to be between 7 and 11 months, considering the presence of product substitutes. Without considering product substitutes, the estimate of frequency falls within the range of 8 to 11 months.

[2] Theoretical models that explain how consumers' search behavior and the potential for punishment influence sellers' pricing behavior can be found in Cabral and Fishman (2012).

markets, particularly concerning the number of firms and their customer base.

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 study is to investigate the pricing behavior of retailers, specifically whether they adhere to SD rules or TD rules, to explore the connection between these rules and local market power. There are three key advantages to focusing on the retail price of gasoline in this study. First, the price of gasoline is less noisy than prices of retail goods that are occasionally out-of-season discontinued, or with varying quality. Second, the fact that I observe daily variations in Korean wholesale gasoline price, a key variable cost that gasoline retailers face in common, enhances our ability to contrast SD models against TD models. Lastly, the industry-specific information on the nature of cost of price changes lends additional economic insight in infrequent price change. Unlike most retailers that sell many items, gasoline stations can update prices with practically zero menu cost. To explain infrequent price changes I must identify alternative sources of cost in adjusting price.

I utilize a logit model to investigate how the likelihood of price changes relates to variables representing both SD and TD pricing rules, as well as factors indicating the level of competitiveness within the local market. The estimation results reveal that gas stations do not rely solely on a particular pricing rule but instead use both SD and TD pricing rules in their pricing decisions.

Additional analysis reveals the relationship between market power and these pricing rules. Specifically, I cannot find evidence of different responses to cost changes in various subsamples divided based on variables that proxy market power. This suggests that market power may affect the size of cost pass-through but not the timing of adjustment.[3]

In contrast, stations with more local market power exhibit a more regular pattern of price adjustments, often on a weekly basis, suggesting a stronger inclination toward the TD pricing rule. These findings suggest that TD pricing and strategic interactions between firms, are

[3] Several studies indicate that firms in competitive markets pass on cost changes more(Hong and Li (2017), Pless and van Benthem (2019), Ritz (2019), Genakos and Pagliero (2022)).

not mutually exclusive but are closely interconnected.

The remainder of the paper is structured as follows. I describe the detail of data in this study in Section 2. In Section 3, I first document in details of empirical patterns of station-level daily gasoline prices. Section 4 presents our estimation of a logit model that encompasses variables serving as proxies for both TD and SD pricing rules. In Section 5, I show the estimation results and interpret them. Finally, I summarize our 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 makes public the price on the website on daily level. I use the price information of 709 stations in Seoul, including the station characteristics such as type of service, brand, and location, for the period between 2009 and 2019.

A key variable cost of gasoline is the wholesale price from MOPS, which reports benchmark prices for petroleum products in the Asian market based on transactions in Singapore. This price closely tracks international oil prices and are used as a measure of variable cost, which I consider to be exogenous given the share of the Korean demand in the global oil market.[4]

I include several variables in the model to gauge 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 1km radius.[5] Additionally, I utilize monthly sales volume as prox-

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

[5]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 being ‘open’ during a

ies for evaluating the competitiveness of local markets.[6]

Table 1: Summary statistics for variables

	Description	Mean	SD	Min	Max
Price					
p_{it}	Retail gasoline price(KRW/liter)	1766.65	242.52	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)	623.14	164.34	286.93	977.28
ΔC_t	Wholesale price change	0.02	9.46	-83.92	65.36
DC_{it}	Cumulative cost change	-0.74	27.49	-207.06	202.34
Duration					
f_{it}	Indicator variable for $\Delta p_{it} \neq 0$	0.10	0.29	0.00	1.00
a_{it}	Duration of keeping previous price	8.74	7.95	1.00	43.00
Station characteristics					
$Self_{it}$	Type of service: self-service	0.33	0.47	0.00	1.00
$Sales\ vol_{it}$	Monthly sales volume(bbl.)	1382.64	449.05	465.63	3125.59
N^r_{it}	Number of stations within 1km radius	4.23	2.18	0.00	13.00

[1] Observations where a_{it} is greater than 42 are omitted when generating summary statistics, and observations where $a_{it} \leq 34$ are used in the actual estimation.
[2] $Self_{it}$ 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.
[3] The total number of stations, including those that exited during the data period, is 708.

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 p_{it} and the price change is denoted by Δp_{it}. One prominent feature of the data is the infrequent price adjustment. The dependent variable in the estimation model, represented by f_i, indicates whether stations change their prices. Out of a total of 2,274,273 observations, only 195,959 have $f_{it} = 1$, and its mean is 0.09. Despite the knowledge of daily fluctuations in wholesale price levels and the absence of menu costs, retailers adjust prices infrequently, with approximately 90% of the observations showing no price changes. a_{it} represents the

particular month if there is at least one transaction occurring in that month. Consequently this variable exhibits monthly variation for each station.

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

duration between the previous price and when stations change their price at time t. It is calculated as $a_{it} = t - k$ where $f_{ik} = 1$ and $f_{ij} = 0$ for $k < j < t$. On average, stations change their price approximately every 9 days, with a median and mode of 7 days and the price changes seem to be infrequent but occur regularly.

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 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 output 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.

Two types of cost changes are utilized in this study: the first is the first difference of cost, denoted as $\Delta C = c_t - c_{t-1}$, and the second is the cumulative wholesale price change, denoted as $DC_{it} = c_t - c_{t-k}$, where $f_{ik} = 1$ and $f_{ij} = 0$ for $k < j < t$. The former is used to estimate the probability of price changes in response to daily changes in cost shocks, while the latter is employed in additional analyses to estimate the probability of price changes at regular intervals. For example, if station i changes prices at regular intervals at time $t - k$ and the next change occurs at time t station i considers the difference in wholesale price changes, $c_t - c_{t-k}$, as cumulative cost change.

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.

Sales vol_{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 when compared to oligopoly or monopoly markets. N^r represents the number of stations within a 1km area, and distance-based measures like this one are typically employed as proxies for assessing the competitiveness of local markets in previous studies(see, for example, Barron, Taylor, and Umbeck (2004), Hosken, McMillan, and Taylor (2008), Lewis (2008), Houde (2012), Kim (2018)).

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 adjusting prices on a weekly basis. The mode and median of the 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.[7] These observed 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

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

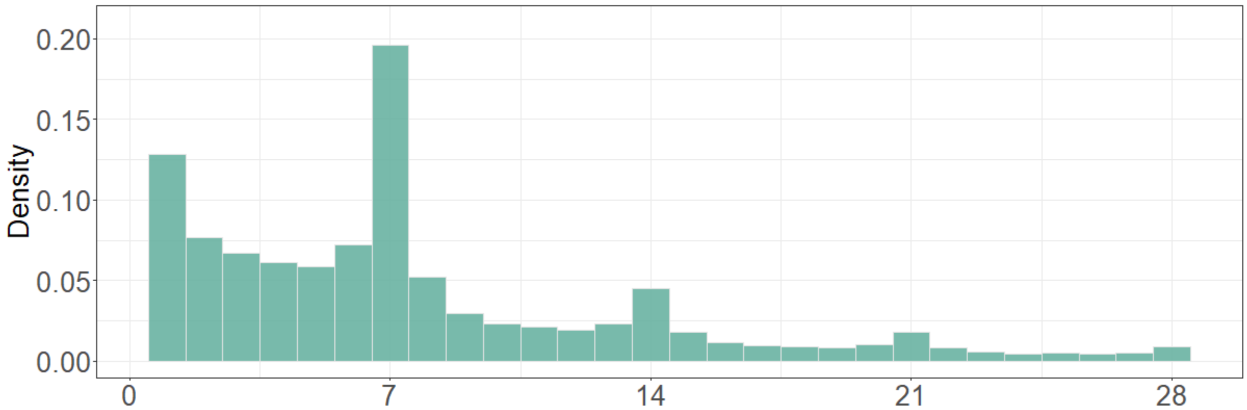


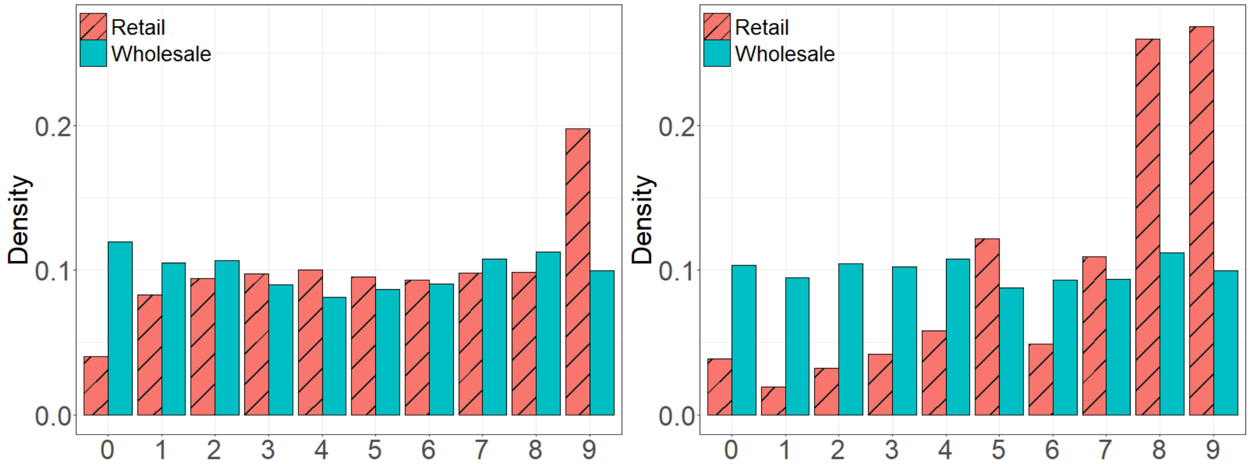
Figure 1: The distribution of a_{it}

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 pattern in relation to consumers' cognition (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)).

There are two possible explanations for the use of 9-ending digits and 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) 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' represents the distribution of price points for retail gasoline prices, and 'Wholesale' represents the distribution of price points for wholesale prices.

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 not only impacts the frequency of price changes but also the magnitude of those price changes. As shown in Figure 3a and Figure 3b, 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 3d and Figure 3c, when the second-to-last digit of the previous price ends in 9, price changes are still likely to be in increments of 10. However, retailers are less inclined to change their price by an amount of 10 or -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. Conversely, decreasing the price by a magnitude of 10 reduces their profits.

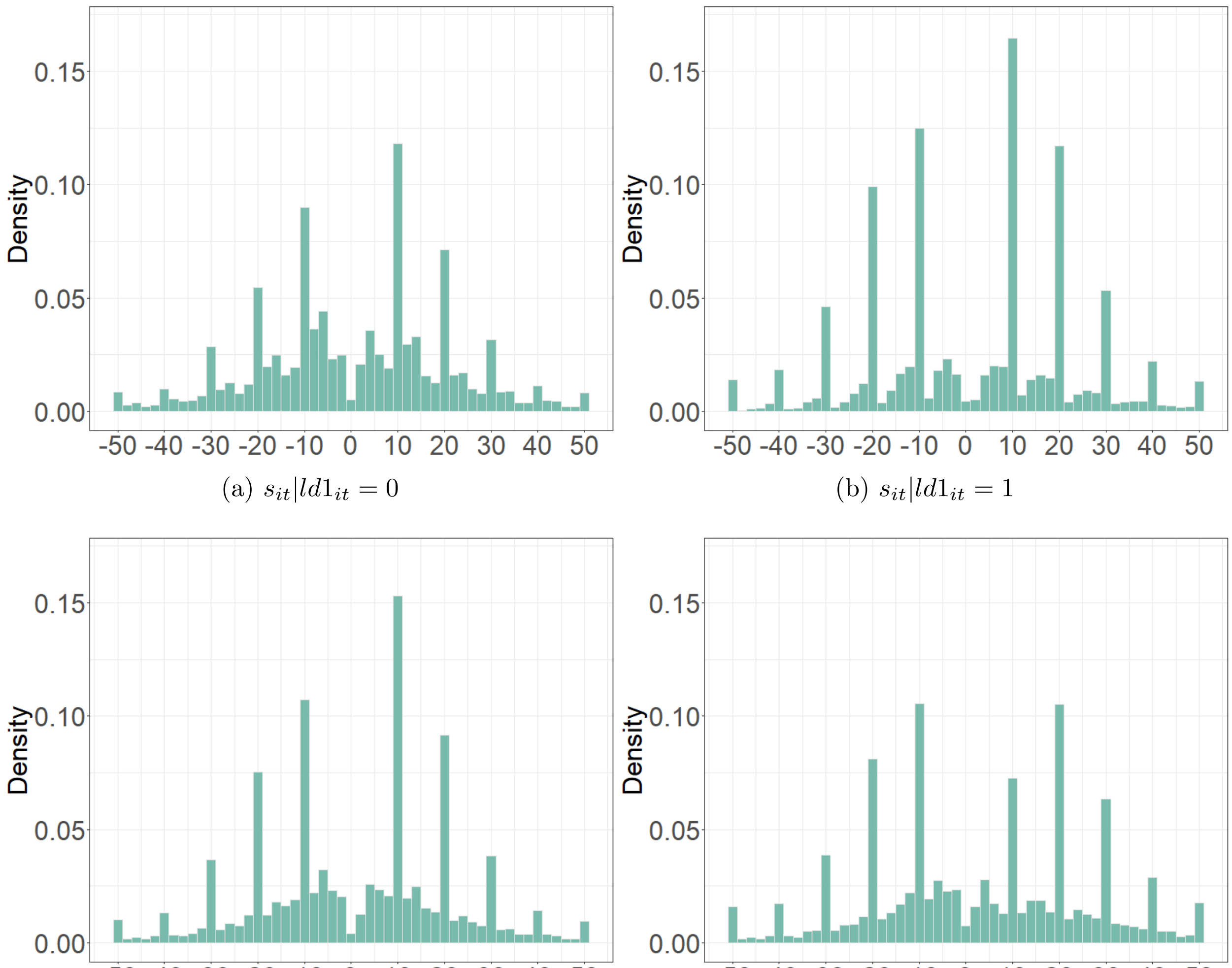
The preference for 9-ending digits for both the last and second-to-last digit makes retailers change their price infrequently, but the reasons behind this preference may vary. Snir and Levy (2021) used scanner price data from a large US grocery chain to investigate whether consumers' belief (that 9-ending 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 $ld2 = 1$. However, the results from comparing gasoline price in the case of $ld1 = 0$ and $ld1 = 1$. Specifically, the difference in the mean gasoline price between $ld1 = 1$ and $ld1 = 0$ is -14.25, whereas the difference in the mean gasoline price between $ld2 = 1$ and $ld2 = 0$ is 21.84.[8]

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 price change varies with the duration of maintaining the previous price. As depicted, the hazard rate (probability of changing 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-to-last digits. Figure 4 reveals that when the last and second-to-last digits do not end with a 9, retailers are less 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. F_i is the ratio of f_i among all periods for station i, which represents how frequently station i changes its price. If F_i is 0.5, then station i changes its price every other day. P_{it}^m is 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 is the average of P_{it}^m over time, providing insight into whether station i generally maintains higher or lower prices compared to the market average over a period. F_i, A_i, and P_i^m are station-level statistics and they are summarized by calculating their averages with respect to N^r, which represents the number of rivals within a 1km radius.

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

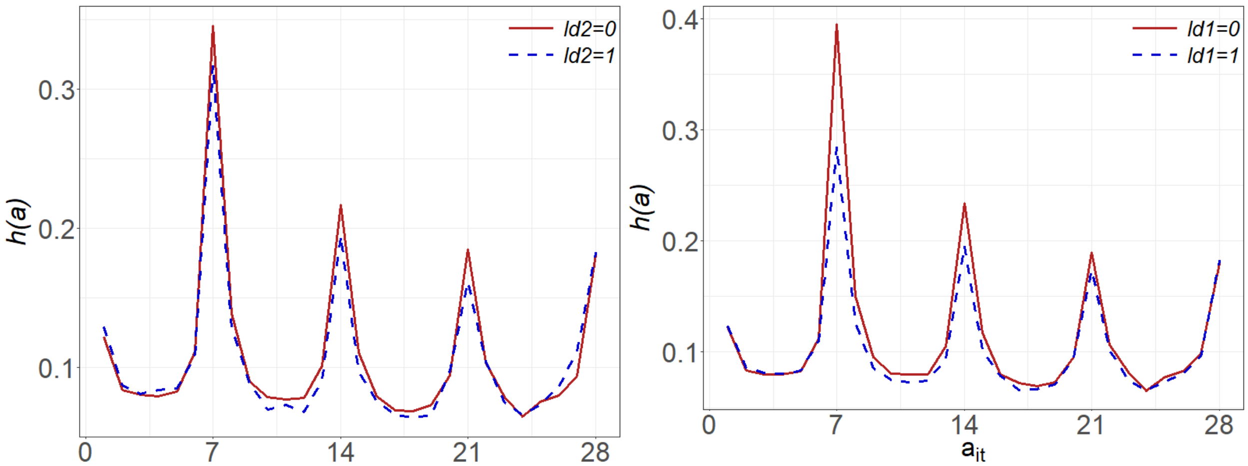


(a) $s_{it}|ld1_{it} = 0$ (b) $s_{it}|ld1_{it} = 1$

(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.



(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 (the probability of making a price change given that the price has remained unchanged since the last 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 price age of 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.

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	13.25	11.30	0.068	0.027	31.85	141.85	22
1	12.08	10.42	0.085	0.035	16.59	135.43	96
2	11.96	10.34	0.088	0.048	10.45	112.68	182
3	11.23	9.60	0.097	0.048	9.46	131.48	265
4	10.72	9.26	0.098	0.048	-0.45	118.98	305
5	10.53	8.79	0.104	0.063	-3.06	116.17	309
6	10.76	9.05	0.102	0.054	-7.75	117.54	250
7	10.42	8.92	0.101	0.055	-6.15	116.54	170
8	9.71	8.12	0.106	0.050	-25.27	97.18	105
9	9.28	8.50	0.105	0.038	-48.62	79.53	46
10≥	8.88	8.50	0.108	0.033	-87.62	23.96	19

[1] A_i is the average duration of keeping previous price where $a_{it} = t - k$ and $f_{ik} = 1$ and $f_{ij} = 0$ for $k < j < t$ and $A_i = 1/T \sum_{t=1}^{T} a_{it}$. F_i is the ratio of f_i where $f_i = \mathbb{1}\{\Delta p_{it} = 1\}$ and $F_i = 1/T \sum_{t=1}^{T} f_{it}$. $P_{it}^m = p_{it} - p_t^m$ 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.
[3] N represents the number of stations included in each category based on N^r.

As the value of N^r increases, the average of A_i decreases (the average of F_i increase), indicating that stations with a greater number of competitors within a 1km radius tend to adjust their prices more frequently. Additionally, when examining the average P_i^m, I observe a decreasing trend as N^r increases. This decreasing trend in average P_i^m with increasing N^r suggests that stations with more competitors tend to set their prices lower than the market average price. This supports the previously mentioned premise that the number of stations within a specific radius is commonly used as a proxy for assessing local market competitiveness. In this context, stations with significant market power are likely to change their prices infrequently. This relationship between market power and the frequency of price changes is reaffirmed.

Another characteristic of pricing behavior related to market power is that stations with more market power tend to change their prices at regular intervals and on specific days of the week. The variable $f_i(a_{it} = k) = 1/T \sum_{t=1}^{T}(f_{it}|a_{it} = k)$ represents the ratio 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 ratio of price changes with a_{it} taking on values from 2 to 6.

Summarizing $f_i(a_{it} = 1)$ by quartlies 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 with fewer rivals are likely to change their prices after keeping their previous price for a duration of multiples of 7.

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	36.91	0.400
	$q_1 \leq f_i(.) < q_2$	4.18	1366.74	-21.21	0.280
	$q_2 \leq f_i(.) < q_3$	4.48	1369.98	-27.70	0.280
	$f_i(.) \geq q_3$	4.43	1445.00	-18.06	0.275
$f_i(a_{it}=2,...,6)$	$f_i(.) < q_1$	3.96	1326.12	76.41	0.462
	$q_1 \leq f_i(.) < q_2$	4.13	1346.50	15.67	0.325
	$q_2 \leq f_i(.) < q_3$	4.27	1406.00	-33.92	0.276
	$f_i(.) \geq q_3$	4.58	1444.11	-82.15	0.206
$f_i(a_{it}=7)$	$f_i(.) < q_1$	4.51	1396.98	-77.65	0.171
	$q_1 \leq f_i(.) < q_2$	4.39	1388.23	-55.34	0.222
	$q_2 \leq f_i(.) < q_3$	4.15	1421.96	11.82	0.317
	$f_i(.) \geq q_3$	3.93	1319.60	87.16	0.499
$f_i(a_{it}=14)$	$f_i(.) < q_1$	4.46	1421.01	-72.77	0.203
	$q_1 \leq f_i(.) < q_2$	4.39	1363.93	-41.49	0.278
	$q_2 \leq f_i(.) < q_3$	3.92	1393.43	12.97	0.329
	$f_i(.) \geq q_3$	4.22	1354.51	71.19	0.433
$f_i(a_{it}=21)$	$f_i(.) < q_1$	4.33	1488.16	-43.32	0.254
	$q_1 \leq f_i(.) < q_2$	4.44	1401.79	-38.66	0.289
	$q_2 \leq f_i(.) < q_3$	4.18	1337.18	9.35	0.331
	$f_i(.) \geq q_3$	4.00	1316.18	37.27	0.338
$f_i(a_{it}=28)$	$f_i(.) < q_1$	4.54	1441.28	-43.93	0.243
	$q_1 \leq f_i(.) < q_2$	4.41	1416.26	-25.99	0.295
	$q_2 \leq f_i(.) < q_3$	3.99	1358.49	3.01	0.327
	$f_i(.) \geq q_3$	4.10	1324.63	25.70	0.335

[1] If $f_i(.) < q_1$, it indicates that $f_i(.)$ falls below the first quartile. When $q_1 \leq f_i(.) < q_2$, it implies that $f_i(.)$ is greater than or equal to the first quartile but still below the median. Similarly, when $q_2 \leq f_i(.) < q_3$, it means that $f_i(.)$ is greater than or equal to the median but below the third quartile. Finally, when $f_i(.) \geq q_3$, 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.

The average $Sale\ Vol.$ 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. In this context, the variables N^r, $Sale\ vol.$, and P^m_{it} exhibit consistent patterns. This implies that stations with more market power tend to change their prices at regular intervals, often every 7 days.

4 Econometric Model

I employ the logit model to investigate whether stations adhere to a SD or TD rule when determining price changes. The rationale for using the logit model is as follows: At day t, station i makes a decision. The indicator variable f_{it} represents this decision. Specifically, $f_{it} = 1$ if station i changes the price (e.g., $\Delta P_{it} \neq 0$), and $f_{it} = 0$ if the station chooses to maintain the previous price. The goal of the estimation is to examine the impact of specific predictors that represent pricing rules on the likelihood 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.

Predictors can be categorized into two groups: SD and TD variables. If stations follow a SD pricing rule, the likelihood of changing prices increases when they face larger cost shocks. The daily cost shock ΔC_t is aggregate and common to all retailers and I introduce the ΔC_t variable in the form of absolute value in the model.

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, denoted as a_{it}. As I 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 $a_{it} = 1, ..., 6$ 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 in the model. To reduce the number of parameters, I exclude variables where a_{it} exceeds 28 and focus on pricing behavior during 4 weeks. Also, 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 the sake of simplicity, I opt to use the reduced indicator variables in the model.

The predictors also include some variables that serve as proxies for local competition. Previous studies suggest that market power can influence infrequent price adjustments, which is also confirmed in our data as shown in Section 3. To examine the impact of competition on the probability of price changes, I utilize $Self_{it}$, $Sales\ Vol$, and N^r as proxies for local market power.

Note that stations tend to keep their price 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. I consider an indicator variable that is one if the previous price ends with 9 to control this 9-ending effect on pricing. Specifically, $ld1$ is the indicator variable representing 1 if the price ends with a 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 $\pi_{it} = prob(\delta_{it} = 1|\boldsymbol{x}_{it}) = \frac{exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}{1+exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})}$. I seek to estimate the vector of parameter $\boldsymbol{\beta}$ and $\boldsymbol{x}'_{it}\boldsymbol{\beta}$ can be denoted as below.[9]

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

I include station fixed effects to account for unobserved variations specific to each station and year fixed effects to control for time-varying factors that could influence the likelihood of price change. For instance, temporary changes in traffic flow due to nearby construction near station i might impact local demand, subsequently affecting the pricing behavior of that station. Eventually, I adopt a two-way fixed effects model in our analysis. However, it's important to note that there might be an issue with 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-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 discrete variable X_1 and denote it $m(\boldsymbol{x}_{it}, \beta, c_i) = F[(x_{1it} + 1)\beta_1 + x_{2it}\beta_2 + c_i] - F[x_{1it}\beta_1 + x_{2it}\beta_2 + c_i]$ where $F(.)$ is the link function and c_i is 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 c_i is unknown, and we are uncertain about what to use for c_i.[10] For these reasons, some researchers prefer to use Linear Probability Model but the LPM estimator is biased and inconsistent.

Fernández-Val and Weidner (2016) suggests a bias correction method for the logit model with two-way fixed effects. The marginal effects are calculated based on bias corrected

[9]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.

[10]see Wooldridge (2010) p. 492.

estimate. I use their method to get 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 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 fixed effects, and one with both station-level and year 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 results of the estimation are provided in the appendix.[11] Based on these estimation results, I calculate the marginal effects for each coefficient and present them 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 -0.019, respectively. This implies that the likelihood of a price change is 1% lower when the previous last digit of the price is 8 or 9, and 1.9% 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 $\log(Sales\ Vol.)$ all relate to local market power, with their marginal effects being statistically significant at the 1% level. Specifically, in the two-way fixed effects model, the marginal effect of $Self$ is estimated at 0.022, indicating that self-service stations are 2.2% more inclined to change their prices compared to full-service sta-

[11]See Table 7

tions. The marginal effect of $\log(Sales\ Vol.)$ is calculated to be 0.017, signifying that stations with a 1% increase in sales volume are 1.7% 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 0.002 and statistically significant at the 1% level. This indicates that the probability of a price change increases by 0.1% as the absolute size of the cost change increases by one unit. 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 $I(a_{it} = 29, ..., 34)$. The interpretation of the marginal effect for $I(a_{it} = k)$ involves comparing the probability of price change at $a_{it} = 29, ..., 34$ 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 0.039 and 0.32, 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 prices every 7 days.

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

Table 4: The estimated marginal effects

	Dependent variable: f_{it}			
	(1)	(2)	(3)	(4)
$\|\Delta C\|$	0.002***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
$Self$	0.012***	0.016***	0.010***	0.021***
	(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)
$log(Sales\ Vol.)$	0.017***	0.022***	0.012***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
$ld1$	-0.011***	-0.010***	-0.011***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
$ld2$	-0.021***	-0.021***	-0.018***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
1st week				
$I(a_{it} = 1, ..., 6)$	0.054***	0.047***	0.035***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 7)$	0.344***	0.329***	0.306***	0.291***
	(0.004)	(0.004)	(0.004)	(0.004)
2nd week				
$I(a_{it} = 8, ..., 13)$	0.056***	0.050***	0.043***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 14)$	0.195***	0.187***	0.176***	0.169***
	(0.004)	(0.004)	(0.004)	(0.004)
3rd week				
$I(a_{it} = 15, ..., 20)$	0.029***	0.027***	0.023***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 21)$	0.134***	0.131***	0.126***	0.122***
	(0.004)	(0.004)	(0.004)	(0.004)
4th week				
$I(a_{it} = 22, ..., 27)$	0.012***	0.011***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
$I(a_{it} = 28)$	0.094***	0.093***	0.091***	0.090***
	(0.005)	(0.005)	(0.005)	(0.005)
Year 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 $I(a_{it} = 29, ..., 34)$, 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.
[3] Numbers in Parentheses are standard errors and statistical significance levels are represented as $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

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 certain stations are more inclined to change their prices even in response to relatively small cost changes, indicating greater price sensitivity, it seems that these stations 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. More specifically, I estimate the model within subsamples for self-service and full-service and then compare the results between these two categories. If market power affects the SD pricing rule, we would expect to see differences in the marginal effect of $|\Delta C|$ based on the results for different types of service. Additionally, I divide the data into two subsets using the median values of the number of stations within 1km and monthly sales volume, respectively.[12] For each case, I conduct the estimation and compare the results in a similar manner to the type of service analysis.

The marginal effects of cost changes for each subsample can be found in Table 5. First, in the case of type of service, the marginal effect of cost change for full-service stations is 0.001, while for self-service stations, it is 0.002. Although the marginal effects are statistically

[12]The median number of stations within a 1km radius is 4, while the median for monthly sales volume is 1268.4.

Table 5: The estimated marginal effects

	Marginal effect	Coefficient	Std. error	95% Confidence interval
Type of service				
Full	0.001***	0.018***	0.000	[0.018, 0.019]
Self	0.002***	0.018***	0.001	[0.017, 0.019]
Sales volume				
Low	0.001***	0.017***	0.000	[0.016, 0.018]
High	0.002***	0.020***	0.000	[0.019, 0.021]
Number of stations				
$N \leq 4$	0.002***	0.019***	0.000	[0.018, 0.020]
$N > 4$	0.001***	0.017***	0.000	[0.016, 0.018]

[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.

significant at the 1% level for both cases, the confidence intervals of the coefficients for cost change for both cases overlap. Thus, the hypothesis that the marginal effect of cost change is different between full-service and self-service stations cannot be rejected.

Similar results are evident when comparing subsamples divided based on sales volume and the number of stations within a 1km radius. Specifically, the 95% confidence intervals of the coefficients for both stations with 'Low' sales volume and stations with 'High' sales volume overlap. Moreover, similar results are observed for stations with $N \leq 4$ and stations with $N > 4$. These findings lead us to conclude that market power does not affect the probability of price change for stations in response to cost shocks

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 (multiples of 7 days). Therefore, I only use observations where price changes occurred.[13] I define $\tau_{it} \equiv I(a_{it} = 7, 14, 21, 28)$ and use it as the dependent variable. In detail, the probability of price change at $a_{it} = 7, 14, 21, 28$, 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

$$\begin{aligned}\boldsymbol{x}'_{it}\boldsymbol{\beta} = b_1 I(DC_{it} = 0) + b_2 N^r_{it} + b_3 log(Sales\,Vol.) + b_4 ld1_{it} + b_5 ld2_{it} + b_6 Self_{it} \\ + \sum_{j=7}^{9} b_j Brand_{jit} + \sum_{k=10}^{15} b_k Day_{kit}\end{aligned} \tag{2}$$

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, $log(Sales\,Vol.)$, and $Self$. 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. Additionally, I've introduced the indicator variable $I(DC = 0)$, which takes the value of 1 if stations change prices when $DC = 0$, and 0 otherwise. In this context, $DC = 0$ signifies no changes in state over the short run, and price changes under this condition might be a response to station-specific idiosyncratic shocks. This variable also reflects the local market's conditions.

The brand of a station may also have an influence on the TD pricing rule, particularly with regard to the market share of SK Energy (SKE), which holds the largest 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. 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 results are presented in the appendix, and I have calculated the marginal

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

effects based on these results, which are summarized in ??.[14] I interpret the results of the estimated marginal effect as shown in (4) in the table. Both the marginal effects of $ld1$ and $ld2$ are negative, consistent with the findings in Figure 4.

The signs of the marginal effects for $Self$, $log(Sales\ Vol.)$, and N^r are in line with expectations and statistically significant at the 1% level. To provide more details, self-service stations are approximately 2% less likely to change their prices regularly. When it comes to the marginal effects of sales volume, an increase of 1% in sales volume corresponds to about a 7% reduction in the likelihood of changing prices regularly. The marginal effect of N^r is -0.008, indicating that having one more rival leads to a roughly 1% decrease in the likelihood of changing prices regularly.

Table 6: The estimated marginal effects

	Dependent variable: τ_{it}			
	(1)	(2)	(3)	(4)
$I(DC = 0)$	-0.269***	-0.268***	-0.268***	-0.268***
	(0.002)	(0.002)	(0.002)	(0.002)
N^r	-0.004**	-0.008***	-0.003***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
$log(Sales\ Vol.)$	-0.075***	-0.049***	-0.139***	-0.067***
	(0.003)	(0.003)	(0.006)	(0.006)
$ld1$	-0.043***	-0.034***	-0.038***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)
$ld2$	-0.014***	-0.013***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
$Self$	-0.063***	-0.039***	-0.043***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
Brand dummies	Yes	Yes	Yes	Yes
Day of week dummies	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
District 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 $***p < 0.01$.

The marginal effect for $I(DC = 0)$ is -0.268, indicating that when stations change their

[14] See Table 9.

prices without any changes in cumulative cost, they are less likely to do so at regular intervals. In essence, idiosyncratic shocks result in irregular price adjustments. This observation aligns with the implications of the model presented in Maćkowiak and Wiederholt (2009), which suggests that when idiosyncratic shocks are more volatile or have a greater impact than aggregate shocks, firms tend to focus more on the idiosyncratic shocks.

For retailers, changes in prices by their rivals can be considered idiosyncratic shocks, and the response to such shocks implies that stations have less market power. This is in contrast to monopoly firms, which only consider their marginal cost when deciding on quantity and price. In this context, the findings also indicate that competition leads to price adjustments at irregular intervals. This is further supported by the fact that among all price changes at $DC = 0$ approximately 96% of them have $a_{it} = 1, 2$.

So far, I have observed that stations with less market power are less likely to change their prices at irregular intervals. In summary, these findings suggest that market power plays a role in the TD pricing rule. To explain these findings, I consider the concept of rational inattention, in which information costs influence decision-making, and firms are more likely to make decisions based on incomplete information.

Let's consider that information costs occur each time stations make a decision regarding whether to maintain their current price or change it. In a dynamic profit-maximizing problem, firms choose how frequently they change their prices, which incurs information costs. In the case of stations with local market power, making daily decisions is not profit-maximizing. Instead, they make decisions at regular intervals, incurring a single information cost. Conversely, in the case of stations in competitive areas, there is an incentive for them to gather the necessary information for decision-making by paying information costs, even before regular intervals. Consequently, stations with less market power sometimes tend to change their prices on an irregular basis.

6 Concluding Remarks

This study examines retailers' pricing behavior, with a particular focus on infrequent price adjustments. I begin by confirming several stylized patterns of sticky prices using figures and statistics. 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 main 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

Furthermore, 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 finding can be explained in terms of rational inattention; stations with market power do not need to acquire the information needed for decision-making every day but at regular, fixed intervals.

Nonetheless, I couldn't find the evidence for difference of probability of price change in response to cost shocks between subsamples based on market power proxy variables. This implies that while market power might influence the extent of cost pass-through, it doesn't seem to impact the timing of adjustments.

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7 Appendix

Table 7: The estimated results

	Dependent variable: f_{it}			
	(1)	(2)	(3)	(4)
$\|\Delta C\|$	0.018***	0.018***	0.020***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
$Self$	0.130***	0.184***	0.116***	0.249***
	(0.005)	(0.005)	(0.016)	(0.017)
N^r	0.011***	0.011***	0.083***	0.012**
	(0.001)	(0.001)	(0.004)	(0.004)
$log(Sales\ Vol.)$	-0.383***	0.262***	0.149***	0.212***
	(0.002)	(0.009)	(0.017)	(0.017)
$ld1$	-0.157***	-0.123***	-0.134***	-0.117***
	(0.005)	(0.005)	(0.005)	(0.005)
$ld2$	-0.277***	-0.268***	-0.235***	-0.240***
	(0.007)	(0.007)	(0.007)	(0.007)
1st week				
$I(a_{it} = 1, ..., 6)$	0.329***	0.554***	0.421***	0.347***
	(0.016)	(0.018)	(0.018)	(0.018)
$I(a_{it} = 7)$	1.862***	2.101***	2.030***	1.969***
	(0.016)	(0.019)	(0.019)	(0.019)
2nd week				
$I(a_{it} = 8, ..., 13)$	0.274***	0.527***	0.461***	0.415***
	(0.016)	(0.019)	(0.019)	(0.019)
$I(a_{it} = 14)$	1.139***	1.402***	1.361***	1.326***
	(0.020)	(0.022)	(0.022)	(0.022)
3rd week				
$I(a_{it} = 15, ..., 20)$	0.015	0.288***	0.252***	0.225***
	(0.018)	(0.020)	(0.020)	(0.020)
$I(a_{it} = 21)$	0.792***	1.074***	1.053***	1.036***
	(0.024)	(0.026)	(0.026)	(0.026)
4th week				
$I(a_{it} = 22, ..., 27)$	-0.165***	0.121***	0.106***	0.093***
	(0.020)	(0.022)	(0.022)	(0.022)
$I(a_{it} = 28)$	0.529***	0.823***	0.819***	0.815***
	(0.031)	(0.032)	(0.032)	(0.032)
Year FE	No	Yes	No	Yes
Station FE	No	No	Yes	Yes
Observation	1,857,576	1,857,576	1,857,576	1,857,576
Pseudo R-square	0.047	0.054	0.067	0.070
AIC	1,133,466	1,125,111	1,109,008	1,105,461

[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] 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: The estimated results

	Service		Sales Vol.		N^r	
	Full	Self	Low	High	$N^r < 4$	$N^r > 4$
$\lvert\Delta C\rvert$	0.018***	0.018***	0.017***	0.020***	0.019***	0.017***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$Self$			0.276***	0.281***	0.346***	0.193***
			(0.024)	(0.030)	(0.025)	(0.025)
N^r	0.011*	0.010	0.059***	-0.043***		
	(0.005)	(0.007)	(0.007)	(0.007)		
$log(sales\ vol)$	0.143***	0.250***			0.215***	0.052
	(0.022)	(0.031)			(0.023)	(0.029)
$ld1$	-0.113***	-0.116***	-0.115***	-0.109***	-0.115***	-0.113***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
$ld2$	-0.263***	-0.193***	-0.229***	-0.243***	-0.250***	-0.224***
	(0.009)	(0.012)	(0.010)	(0.010)	(0.010)	(0.011)
1st week						
$I(a_{it} = 1, ..., 6)$	0.226***	0.521***	0.214***	0.407***	0.343***	0.303***
	(0.022)	(0.032)	(0.027)	(0.025)	(0.024)	(0.028)
$I(a_{it} = 7)$	2.031***	1.784***	1.986***	1.892***	1.956***	1.949***
	(0.023)	(0.034)	(0.028)	(0.027)	(0.025)	(0.029)
2nd week						
$I(a_{it} = 8, ..., 13)$	0.387***	0.451***	0.374***	0.415***	0.422***	0.380***
	(0.023)	(0.033)	(0.027)	(0.026)	(0.025)	(0.029)
$I(a_{it} = 14)$	1.385***	1.176***	1.334***	1.285***	1.321***	1.312***
	(0.026)	(0.039)	(0.031)	(0.031)	(0.029)	(0.033)
3rd week						
$I(a_{it} = 15, ..., 20)$	0.205***	0.254***	0.195***	0.232***	0.207***	0.233***
	(0.025)	(0.035)	(0.029)	(0.028)	(0.027)	(0.031)
$I(a_{it} = 21)$	1.097***	0.891***	1.072***	0.985***	1.034***	1.029***
	(0.032)	(0.047)	(0.037)	(0.037)	(0.034)	(0.040)
4th week						
$I(a_{it} = 22, ..., 27)$	0.065*	0.143***	0.080*	0.096**	0.102***	0.075*
	(0.027)	(0.039)	(0.032)	(0.031)	(0.029)	(0.034)
$I(a_{it} = 28)$	0.836***	0.767***	0.910***	0.716***	0.840***	0.780***
	(0.039)	(0.057)	(0.045)	(0.046)	(0.042)	(0.050)
Observation	1,250,584	606,992	928,033	929,543	1,055,121	802,455
Pseudo R^2	0.082	0.053	0.080	0.067	0.074	0.070
AIC	716,585	386,178	546,942	555,085	617,487	486,169

[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] 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 9: The estimated results

	Dependent variable: τ_{it}			
	(1)	(2)	(3)	(4)
$I(DC = 0)$	-4.548***	-4.558***	-4.547***	-4.562***
	(0.289)	(0.288)	(0.288)	(0.288)
N^r	-0.021***	-0.050***	-0.019***	-0.049***
	(0.003)	(0.003)	(0.003)	(0.003)
$log(Sales\ Vol.)$	-0.387***	-0.302***	-0.846***	-0.420***
	(0.008)	(0.020)	(0.037)	(0.039)
$ld1$	-0.253***	-0.208***	-0.232***	-0.183***
	(0.012)	(0.012)	(0.012)	(0.012)
$ld2$	-0.081***	-0.083***	-0.087***	-0.086***
	(0.016)	(0.017)	(0.017)	(0.017)
Service				
$Self$	-0.380***	-0.242***	-0.266***	-0.141***
	(0.013)	(0.013)	(0.014)	(0.014)
Brand				
SKE	0.780***	0.724***	0.653***	0.611***
	(0.022)	(0.022)	(0.022)	(0.022)
GSC	0.591***	0.563***	0.485***	0.473***
	(0.023)	(0.023)	(0.023)	(0.024)
HDO	0.375***	0.417***	0.374***	0.424***
	(0.026)	(0.027)	(0.027)	(0.027)
Day of week				
Mon	0.460***	0.346***	0.376***	0.320***
	(0.060)	(0.062)	(0.062)	(0.062)
Tue	2.449***	2.287***	2.306***	2.207***
	(0.053)	(0.055)	(0.055)	(0.056)
Wed	1.451***	1.303***	1.331***	1.247***
	(0.054)	(0.056)	(0.056)	(0.056)
Thu	1.176***	1.008***	1.079***	0.976***
	(0.054)	(0.057)	(0.057)	(0.057)
Fri	0.750***	0.647***	0.680***	0.642***
	(0.056)	(0.058)	(0.058)	(0.058)
Sat	0.935***	0.859***	0.850***	0.843***
	(0.056)	(0.059)	(0.059)	(0.059)
Year FE	No	Yes	No	Yes
District FE	No	No	Yes	Yes
Observation	174,689	174,689	174,689	174,689
Pseudo R^2	0.134	0.154	0.147	0.167
AIC	176,027	171,903	173,325	169,375

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