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Retail Price Stickiness, Market Structure and Distribution Channels

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Abstract

Using Japanese scanner data of transaction prices and sales for more than 1,600 commodity groups from 1988 to 2008, we find a statistically significant negative correlation between the frequency of price changes and the degree of market concentration. We also find that structural factors of a distribution channel are significantly correlated with rigidity in retail prices. Decomposing the frequency of price changes into the frequency of intraday, sale, and regular price changes, we find that both inter- and intra-brand competition positively affect the frequency of sales. Inter-brand competition among manufacturers has a significant and positive effect on the frequency of regular price changes, whereas intra-brand competition among retailers has no such significant effect. We also document that the term of contracts between manufacturers and retailers has a significant and positive effect on price stickiness.

JEL classification codes: L11, E31, C41

Key words: Sticky prices, Market structure, Distribution channels

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1 Introduction

Price rigidity is evidently an important subject in macroeconomics. This is because the New-Keynesian models often used for analyzing monetary policies can lead to varying results because of changes in assumption of price stickiness. Therefore, researchers have been searching for *how* rigid prices are. Using a wide range of commodities to calculate consumer and wholesale price indexes, recent empirical studies reveal that (1) prices are more flexible than expected in a sticky-price model and (2) there is strong heterogeneity in the degree of price stickiness across commodities (Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008).

The latter finding brings us to the question of why prices of some goods are less flexible than those of others. Searching for *why* prices are sticky is also important because it is useful in verifying sticky-price models. Blinder et al. (1998) classify sources of price stickiness into the following five categories: (1) the nature of cost (menu cost models), (2) the nature of demand (procyclical elasticity of demand), (3) the market structure, (4) the form of contracts, and (5) imperfect information. Our study analyzes the third and fourth reasons.

Many researchers believe that the dichotomy of market structure between perfect and imperfect competition is useful for characterizing firms' pricing behavior. Firms in competitive markets cannot affect the market price, whereas those in imperfectly competitive markets tend to exercise market power and control their product price independent of the changes in marginal cost or market demand. The New-Keynesian models assume that firms in goods markets face monopolistic competition: firms can set optimal prices for their differentiated products. Nominal price rigidity arises when these price setters cannot set optimal prices for reasons such as menu costs and price contracts.¹ In this framework, product differentiation entails firms' market power, which is a rationale of sticky price.

The relationship between price stickiness and market structure has been empirically examined since Gardiner C. Means discussed downward price rigidity during recessions in relation to industrial concentration in a 1935 U.S. Senate Document.² Means' findings implied that prices in less competitive markets tend to be sticky. Known as the administered-price hypothesis, this concept still attracts considerable attention from researchers.³ Conventional wisdom of industrial organizations suggests that the market structure largely determines firms' conducts in the market, and ultimately affects market performance such as market equilibrium price and quantity. Our empirical analysis provides a new insight into this traditional issue because scanner data enables us to quantify both structure (i.e. degree of competition) and performance (i.e. price stickiness) of markets.

An interesting feature of a retail price lies in the multiple pricing decisions made by

¹See Sheshinski and Weiss (1977) and Calvo (1983) for example.

²"Industrial Prices and Their Relative Inflexibility," Senate Document 13, 74th Congress, First Session. Means (1936) classifies the wholesale price index into ten groups according to how many times prices are changed in a given period and shows that price index with low frequency of price changes tends to fall less during the Great Depression of the early 1930s.

³Wolman (2000), for example, discusses the administered prices in the context of theoretical development of menu cost models and provides a historical review of the empirical literature on price rigidity. See Álvarez and Hernando (2007) for recent empirical contribution on this issue. Their analysis is based on a survey concerning pricing behavior of Spanish firms. They found that firms that perceive higher degree of competition tend to reset prices frequently, which is consistent with the administered-price hypothesis.

manufacturers, wholesalers, and retailers. A simple model describing the determination of market prices frequently assumes that consumers purchase goods directly from producers. However, the real process of retail-price determination is more complex. Retailers' temporary price markdowns are certain to affect market-price determination (Gerstner and Hess, 1991). The relationship between manufacturers and retailers is also a relevant factor. Manufacturers tend to control retail prices of their products because, in the absence of downstream competition, retailers exercise market power that lowers manufacturers' profits (Tirole, 1988). The incentive to control retail prices is so strong that manufacturers will reduce the number of channel members even if doing so forfeits opportunities to distribute their products (Coughlan et al., 2006). These considerations suggest the importance of studying the manufacturer-retailer relationship, particularly the structure of distribution channels relating to market power upstream and downstream.

Our scanner data is useful for investigating this issue for two reasons. First, it contains daily transaction prices so that we know how many times prices are changed without severe time-aggregation bias. This is a great advantage for investigating the behavior of retail prices, where retailers' temporary price promotion is a major factor in price change. Second, our specific identification codes for both manufacturers and retailers enable us to infer precisely the effect on price stickiness arising from market structure and channel relationships. As for market structure, we examine the relationship between the frequency of price changes and the degree of market concentration as measured by the Herfindahl-Hirschman index and the four-firm concentration ratio. As for distribution channels, we investigate the source of price stickiness arising from the vertical relationship between retailers and manufacturers by calculating channel-specific variables such as the degree of inter- and intra-brand competition and the term of contracts.

Previous empirical studies of retail-price stickiness commonly found that the frequency of price changes is largely affected by retailers' temporary price markdowns (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008; Abe and Tonogi, 2010). Our own calculation suggests that the frequency of price changes due to sale accounts for about 90% of the frequency of overall price changes. The frequency of sale price changes implies that retailers conduct a price markdown every 7.5 days on average. It is likely that the timing of sale is unrelated to any macroeconomic events, as suggested by Nakamura and Steinsson (2008), but careful analysis of variations in the frequency of sales reveals the relationship between retail-price stickiness and downstream price competition. Therefore, we decompose the original price series into the sale and regular price series, and analyze the determinant of the price rigidity by each series.

Our empirical results produce four findings. First, the degree of market concentration has a negative and significant effect on the frequency of price changes for both retailers and manufacturers. Second, structural factors relating to distribution channels correlate significantly with rigidity in retail prices. Third, both inter- and intra-brand competition have a positive effect on the frequency of sales. This means that an increase in competitiveness among channels leads to more flexible price adjustments for retailers. However, inter-brand competition among manufacturers has a significant effect on the frequency of regular price changes, whereas intra-brand competition among retailers does not have a significant effect. Fourth, the term of contracts between manufacturers and retailers has a significant and positive effect on price rigidity.

Group	Total	Manufacturer		Item		Sales	
		Total	Mean	Total	Mean	Total	Share
Food	1,200	19,506	94.6	948,146	790	3,370	82.1
Processed food	748	12,623	84.5	491,764	657	1,994	48.6
Cakes and candies	204	6,034	141.6	273,491	1,341	513.2	12.5
Beverages	317	4,208	74.9	133,898	617	768.5	18.7
Other food	31	3,546	166.0	48,993	1,580	94.2	2.3
Daily necessities	461	4,238	57.7	421,342	914	735.9	17.9
Miscellaneous goods	151	1,845	51.2	73,009	484	290.2	7.1
Cosmetics	96	994	68.5	118,894	1,238	232.1	5.7
Household utensils	100	1,682	61.2	78,394	784	121.6	3.0
Pet accessory	31	404	46.4	20,477	661	32.1	0.8
Other commodities	3	71	30.7	2,146	715	10.3	0.3
Stationery	64	886	66.3	114,239	1,785	30.5	0.7
Car goods	2	56	39.5	670	335	0.2	0.0
Home electronics	14	114	21.4	13,513	965	18.9	0.5
All groups	1,661	23,183	84.4	1,369,488	824	4,106	100.0

Table 1: Number of manufacturers and items and the amount of sales by item group. Mean of the number of manufacturers and items is calculated based on the weighted average across six-digit commodity groups, weighted by total sales. Total sales is reported in billion yen. Sales share is reported in percent. Scanner data collected by Nikkei Digital Media Inc. March 1, 1988–April 30, 2008.

The remainder of this paper proceeds as follows. Section 2 describes the scanner data. Section 3 discusses the variables used in our analysis and introduces the models. Section 4 discusses estimation results. Section 5 concludes.

2 Data

The following analysis is based solely on scanner data collected by Nikkei Digital Media Inc. Our scanner data is a set of records on items, prices and quantities that recorded when consumers buy products in a supermarket. It contains an enormous number of observation. Our data set covers daily retail transactions spanning over 20 years from March 1, 1988 to April 30, 2008, whose corresponding total sales exceed 4 trillion yen. As Table 1 shows, our dataset composition is 82.1% food and 17.9% daily necessities. The largest category in the food sector is processed food, with a share of 48.1%. In the sector of daily necessities, cosmetics and miscellaneous goods, such as shampoo, detergents, tooth paste, and sanitary goods, account for a relatively high proportion.⁴

Our scanner data is a highly disaggregated data and therefore suitable for analyzing behavior of retail prices. This feature of fine classification is owing to the product classification

⁴Our dataset does not contain categories such as fresh food, medicines, and do-it-yourself goods.

system using Japanese Article Number (JAN).⁵ This classification system allows us to identify commodity items in detailed specifications such as volume, color, flavor, and fragrance. For example, we treat the product packaged in 100 gram and 150 gram quantities as different even if their contents are identical. Producers allocate a JAN code every time they introduce a new commercial product, even if it only slightly modifies an existing item.

JAN codes contain a company prefix that provides information about producers. In a 13-digit code, the first two-digit number is a country code (45 or 49 for Japan) and the following seven-digit or five-digit code is a company prefix, assigned to member companies and managed by DSRI in Japan. We take full advantage of JAN codes to identify producers. Table 2 shows the number of manufacturers and items. It is evident that our data includes enormous number of observations—23,183 manufacturers and over 1.3 million items for the entire period observed. We also report the summary statistics by commodity groups in Table 3. For cakes and candies in food sector and for cosmetics, household utensils, and stationary among daily necessities, we observe a relatively large number of manufacturers and items per six-digit commodity group.

Our data set also contains information at the most disaggregated level for the spatial dimension. Raw price data consists of the price of a single unit of a product defined by JAN code sold at a particular store on a specific day. We can distinguish the price of a product according to the supermarket at which it was sold. Table 2 indicates that data covers 373 retailers dispersed throughout Japan.⁶ We identify retailers by the store code provided by Nikkei Digital Media. Combining the producer code and the store code enables us to identify the distribution channel from manufacturers to retailers.⁷ Thus we can study the relationship between price stickiness and the structure of distribution channels.

Statistics calculated at five-year intervals in Table 2 show the growing number of manufacturers, items and stores. Growth is due partly to increases in the number of retailers sampled by Nikkei Digital Media. The disproportionate growth in numbers of items and manufacturers also reflects on the dynamic nature of retail markets, including the introduction of new items and entry or exit of manufacturers.

3 Model

Our aim is to study the relationship between market structure and price stickiness. As mentioned, this issue has long been discussed in the empirical literature of price stickiness. However, the results from recent studies using micro-price data are mixed. Bils and Klenow (2004) examined 231 items in the U.S. CPI and found a statistically significant negative correlation between a four-firm concentration ratio and frequency of price changes. But they concluded that the degree of concentration is not a robust predictor because the effect on the frequency of price changes is no longer significant if controlled for item-group dummies. A

⁵In Japan, commodity items are allocated 13- or eight-digit identification code, which is called JAN code. Distribution System Research Institute (DSRI) manages the database of item information corresponding to JAN code, which is called JICFS/IFDB. The information is available at <http://www.dsri.jp/>.

⁶See Abe and Tonogi (2010) for the number of retailers by location.

⁷Unfortunately, our data does not contain any information of wholesalers. The issues of wholesale distribution is out of our scope. See Dutta, Bergen, and Levin (2002) and Nakamura (2008) for the discussion of this issue.

Variable	Period	Total	Variation across commodity groups						
			Mean	SD	Percentiles				
					10th	25th	Median	75th	90th
Manufacturer	All	23,183	84.4	97.4	15	27	53	103	191
	1988	4,718	14.1	16.4	2	4	9	17	31
	1992	6,958	20.8	23.6	3	6	14	26	47
	1997	8,813	25.9	27.3	4	9	18	32	57
	2002	10,402	31.6	35.4	6	10	21	38	69
	2007	13,740	39.1	50.5	5	11	24	45	88
Item	All	1,369,488	824.5	1813	52	115	305	817	1,874
	1988	88,237	55.7	107.0	4	10	25	58	129
	1992	136,132	84.2	148.9	5	13	36	91.5	206
	1997	194,700	116.9	217.6	9	21	49	124	271
	2002	276,281	165.6	330.4	11	27	66	166.5	393
	2007	347,988	208.8	421.2	12	32	81	205	494
Store	All	373	326.2	64.7	239	309	353	371	373
	1988	29	20.8	9.0	5	14	24	29	29
	1992	62	44.3	19.2	13	30	52	61	62
	1997	150	119.9	40.3	53	103	141	150	150
	2002	198	168.6	45.8	102	158.5	191	198	198
	2007	274	223.3	67.7	117	201	255	273	274
Total sales (in billion yen)	All	4,106	2.47	6.37	0.057	0.197	0.691	2.065	5.904
	1988	25.0	0.016	0.042	0.000	0.001	0.003	0.012	0.039
	1992	67.4	0.042	0.104	0.000	0.002	0.01	0.036	0.106
	1997	206.0	0.124	0.319	0.002	0.01	0.036	0.108	0.288
	2002	313.8	0.188	0.521	0.004	0.014	0.051	0.152	0.449
	2007	373.8	0.224	0.604	0.003	0.014	0.053	0.180	0.559

Table 2: Summary statistics for the number of manufacturers, items, stores, and total sales. Variation across commodity groups is calculated based on the weighted average across six-digit commodity groups, weighted by total sales.

major obstacle for their investigation is that the number of observations is highly restricted because of availability of price data as well as data for market share of individual firms. Carlton (1986) was able to include 27 observations in his OLS equation of average price age regressed on a four-firm concentration ratio. His result is consistent with the administered-price hypothesis that the average duration becomes relatively extended for industries with high concentration. Carlton points out, however, that the result should be regarded with caution because of its relatively few observations.

We largely follow previous study in modeling and statistical inference, but we make an in-depth analysis of this relationship in the following two respects. First, we decompose the

	Variation across commodity groups							
	Total	Mean	SD	Percentiles				
				10th	25th	Median	75th	90th
<i>A. Manufacturer</i>								
Food	19,506	94.6	108.2	16	29	59	117	220
Processed food	12,623	84.5	95.6	16	28	54.5	101.5	201
Cakes and candies	6,034	141.6	128.2	29	52.5	108	183.5	303
Beverages	4,208	74.9	93.7	12	21	45	90	159
Other food	3,546	166.0	201.2	15	22	88	234	429
Daily necessities	4,238	57.7	51.9	13	22	44	75	118
Miscellaneous goods	1,845	51.2	57.6	11	19	33	57	108
Cosmetics	994	68.5	59.4	14	24	47	100.5	147
Household utensils	1,682	61.2	42.6	19	31.5	52	77	113
Pet accessory	404	46.4	32.4	12	18	37	77	99
Other commodities	71	30.7	18.4	15	15	26	51	51
Stationery	886	66.3	48.0	14	27.5	59	89.5	134
Car goods	56	39.5	12.0	31	31	39.5	48	48
Home electronics	114	21.4	11.5	9	13	17.5	28	38
<i>B. Item</i>								
Food	948,146	790	1,813	53	113	303	748	1,794
Processed food	491,764	657	1,883	52	101	254	580	1,301
Cakes and candies	273,491	1,341	2,064	115	279	634	1,425	3,201
Beverages	133,898	617	1,047	37	84	254	602	1,688
Other food	48,993	1,580	1,721	175	361	1,064	2,237	3,888
Daily necessities	421,342	914	1,814	47	122	337	1,008	1,964
Miscellaneous goods	73,009	484	844	39	76	183	494	1,278
Cosmetics	118,894	1,238	2,638	49	136	382	1,268	2,686
Household utensils	78,394	784	921	95	200	496	1,161	1,812
Pet accessory	20,477	661	792	64	121	425	840	1,634
Other commodities	2,146	715	711	132	132	507	1,507	1,507
Stationery	114,239	1,785	2,920	47	249	627	1,476	6,250
Car goods	670	335	54	297	297	335	373	373
Home electronics	13,513	965	1,027	101	272	547	1,348	2,215

Table 3: Number of manufacturers and items by item group. Commodities are classified by their JICFS classification. Variation across commodity groups is calculated based on the weighted average across six-digit commodity groups, weighted by total sales.

frequency of price changes into the frequency of intraday, sale, and regular price changes. Second, we analyze the structure of distribution channels in retail markets. This enables us to conduct a micro-level study into the effect of brand competition both upstream and downstream, the openness of a distribution channel to alternative business entities, and the

term of contracts between retailers and manufacturers.

In this section, we discuss first the definition of price changes and the decomposition of the frequency of price changes. After briefly discussing the regressors that related to market structure, we discuss the characteristics of distribution channels and introduce the corresponding models.

3.1 Frequency of price changes

In our data set, the simplest definition of a price change is that $p_{ijt} \neq p_{ijt-1}$, where the indexes i , j , and t are defined at the most disaggregated level in each dimension and denote the product defined by a JAN code, the store that sold the product, and the date, respectively. A simple calculation of frequency of price changes based on this definition, however, leads to severe upward bias because it includes at least three types of price changes: (1) intraday price changes⁸, (2) temporary price markdowns by retailers, and (3) regular price changes.

Previous empirical literatures reports that estimates of price-change frequency vary drastically according to how a change in sale price is defined (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). The simple way to define a sale price is to filter the original price series and exclude changes due to temporary price markdowns. A temporary price markdown usually is expressed as a V-shape in a price series; that is, when the sale period ends, the price reverts to its regular price. The upper panel of Figure 1 illustrates the pattern, making it evident that most sale prices return to their previous level. Nakamura and Steinsson (2008) define the filter that identifies sale prices by the two patterns of change in prices: (1) a symmetric V-shape pattern and (2) an asymmetric V-pattern in which a sale price does not return to its previous level. Following Nakamura and Steinsson (2008), we also decompose causes of price changes by filtering the original price series.

Our sale filter differs with that of Nakamura and Steinsson in two respects. First, we explicitly calculate the duration of prices since the previous price change. This is necessary because our analysis uses daily data whereas Nakamura and Steinsson use the consumer price index (CPI) and wholesale price index (WPI) research database in which most prices are reported monthly. Second, we use the same sampling method as the Japanese CPI to detect sale prices. The calculation is based on a monthly report of retail prices in which price reporters exclude prices as a sale price if the price is in effect one week or less. Following this definition, we detect sale prices that form a symmetric V-pattern.

Filter for intraday price changes

Our data records daily prices, sales and quantity sold. An item's price is defined as its daily unit value, that is, total sales divided by the quantity of that item sold in the outlet in a day. Following this definition of prices, the unit value of an item may become a decimal when retailers offer time-limited special prices in a day. We can regard decimal prices as evidence of price flexibility due to intraday price changes. Thus we separate this cause of price changes by rounding and adjust the price to the preceding regular price when the difference in prices is less than one yen.

⁸By intraday price changes, we mean price changes due to time-limited special offers in which a retailer sells an identical item at two or more different prices in one day.

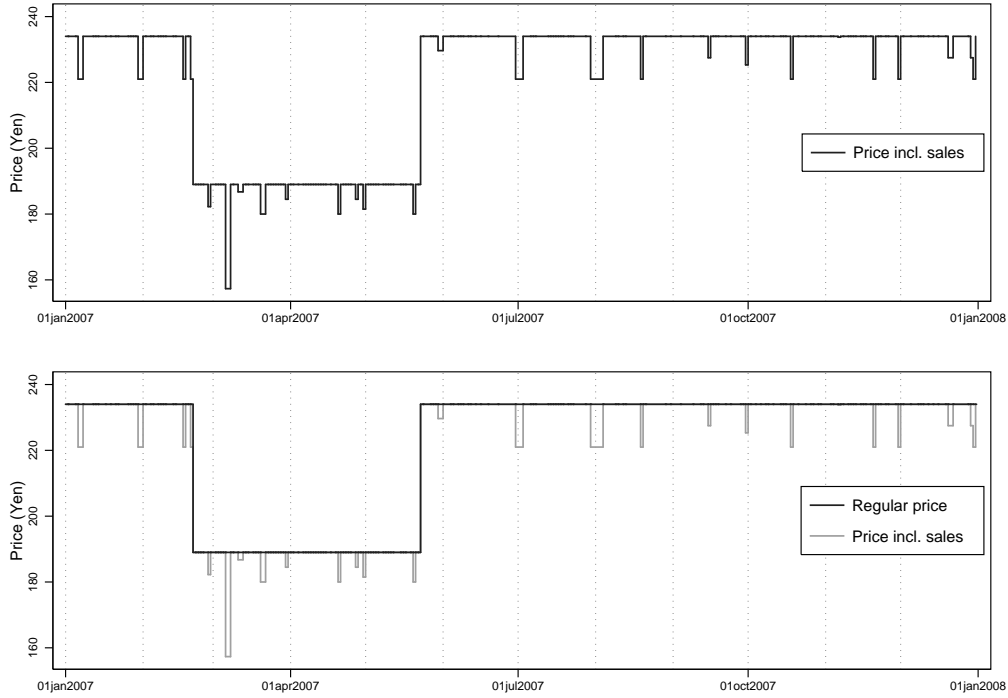


Figure 1: Sale price and regular price. Price series of instant coffee (30 grams) sold at a retail store. Price includes sale prices (above) and the filtered price series (below).

Filter for symmetric V-shaped price series

As mentioned, we identify a sale price if two or more different prices are observed during one week according to the exclusion rule in calculating Japanese CPI. The simplest example of the V-shaped price series is that two different prices are observed in a week, in other words, only one sale price forms the bottom of the "V." In this case, it is necessary only to replace the sale price with the previous regular price. Complications arise when sale prices have different values during the period of sale (i.e., at the bottom of U-shaped price series). To address this problem, we group the different prices while the sale lasts as long as the interval does not exceed eight days. Then we replace the set of different sale prices with the preceding regular price.

Filter for asymmetric V-shaped price series

In the previous case, we easily located the regular price because the series of prices is symmetrical. If the pattern becomes asymmetrical, a price prior to the sale period differs from a price after the period. It becomes more complicated when frequent changes in sale prices continue for an extended time, for such patterns offer no clue for determining the regular price for the period.

Replacing the sale price with the maximum price during the period is reasonable, but

uncritical repetition of that procedure may lead to replacements using an irrelevant historical price. Therefore, we impose two conditions in applying this replacement rule. First, the duration of price spell during the period is less than or equal to one month. Second, the substituted regular price is chosen only from among the four different preceding prices. Satisfying these conditions, we replace sale prices with the maximum price during the period. This rule does not alter the regular prices obtained at the preceding steps.

Figure 1 displays the original price series (above) and the filtered price series (below) for 30 grams of instant coffee sold at a particular store. Visible in the upper panel are several price drops that immediately reclaim their previous level. Our filter regards these spikes as symmetric V-shaped price changes from the retailer’s temporary markdown and it replaces the sale prices with the preceding regular price. Figure 1 exhibits a large price reduction lasting from late February to late May. The sale filter interprets it as a regular price change.

Decomposition of frequency of price changes

We generate two new price series after filtering the original series: the first series excludes price changes due to a time-limited special offer within a day, and the second is a regular price series. Counting the number of price changes for each series, we can decompose their frequency. Let D_{ij}^0 denote the number of price changes of the i th item ($i = 1, \dots, I$) sold in the j th store ($j = 1, \dots, J$) in the original price data. By using additional price series, we decompose D_{ij}^0 into the number of regular price changes, D_{ij}^1 , of changes in sale price, D_{ij}^2 , and of intraday price changes, D_{ij}^3 . The frequency of price changes is the ratio of the number of price changes to the length of time that we observe the price series. Let F_{ij}^0 be the frequency of price changes. As the length of period is common to all types of price changes, F_{ij}^0 can be written as

$$F_{ij}^0 \equiv \frac{D_{ij}^0}{T_{ij}} = \frac{D_{ij}^1 + D_{ij}^2 + D_{ij}^3}{T_{ij}} \quad (1)$$

We construct the market-level frequency of price changes by taking the weighted average of F_{ij}^0 by weighting the total sales of i th item sold in the j th store q_{ij} . That is,

$$F^0 = \sum_{i=1}^I \sum_{j=1}^J w_{ij} F_{ij}^0, \quad (2)$$

where $w_{ij} = q_{ij} / \sum_{i=1}^I \sum_{j=1}^J q_{ij}$. Substituting (1) into (2), we decompose the frequency of overall price changes as follows

$$\begin{aligned} F^0 &= \sum_{i=1}^I \sum_{j=1}^J w_{ij} \frac{D_{ij}^1}{T_{ij}} + \sum_{i=1}^I \sum_{j=1}^J w_{ij} \frac{D_{ij}^2}{T_{ij}} + \sum_{i=1}^I \sum_{j=1}^J w_{ij} \frac{D_{ij}^3}{T_{ij}} \\ &= F^1 + F^2 + F^3, \end{aligned} \quad (3)$$

where F^1 , F^2 , and F^3 are the weighted mean frequency of regular, sale, and intraday price changes, respectively.

Table 4 presents summary statistics of these decomposed frequencies. The mean frequency of overall price changes, F_0 is 24.8%; it implies that retail prices in our data set

		Mean	SD	Percentile				
				10th	25th	Median	75th	90th
<i>A. Frequency of price changes</i>								
Overall	F_0	0.248	0.135	0.084	0.150	0.227	0.325	0.437
Regular	F_1	0.027	0.012	0.014	0.019	0.024	0.033	0.043
Sale	F_2	0.136	0.088	0.047	0.075	0.111	0.178	0.277
Intraday	F_3	0.085	0.059	0.013	0.045	0.074	0.117	0.176
<i>B. Market structure</i>								
Herfindahl index	HHI	0.235	0.178	0.048	0.106	0.190	0.310	0.467
Concentration ratio	CR4	0.706	0.213	0.334	0.569	0.743	0.884	0.968
<i>C. Channel characteristics</i>								
#channel members	N_j	19.6	22.1	4	7	12	24	44
	N_k	142	113	15	39	114	232	320
Inter-brand comp.	BC_j	0.656	0.216	0.345	0.553	0.713	0.815	0.874
Intra-brand comp.	BC_k	0.929	0.124	0.834	0.927	0.971	0.986	0.991
Term of contracts		3.11	3.67	0.07	0.43	1.53	4.58	8.75

Table 4: Summary statistics of variables for price rigidity, market characteristics, and channel characteristics. The number of observations is 1,661 for panels A and B. Panel C contains 4,171,060 observations. N_j (N_k), the number of manufacturers (retailers) under contract with a retailer (manufacturer); $S_{j(k)}$ ($S_{k(j)}$), sales share of a channel in the total sales of a retailer (manufacturer). The term of contracts is reported in year.

remain unchanged approximately 4 days ($= 1/0.248$). This flexible price change is due to the retailer’s temporary price markdowns. The frequency of regular price changes, F_1 , is 2.7%, which means the regular price remains unchanged for 37 days. It is striking that intraday and sale price changes account for nearly 90% of overall price changes ($= (0.085 + 0.136)/0.248$). As defined by our sale filter, we exclude only price spells lasting fewer than eight days. That implies a large number of prices last only one week due to the retailer’s pricing decision.

Table 5 shows the same summary statistics by item groups. Prices in the food sector are far more flexible than prices for the daily necessities: the weighted mean frequency is 27.8% for food and 11.5% for daily necessities. This sharp contrast is due to differences in the frequency of sale price changes. As expected from the standard deviation of the frequency of price changes in Table 4, the frequency of sales accounts for the large variation of price-change frequency across commodity groups.⁹ For example, the frequency of overall price changes for processed foods is relatively high. Filtering the original series greatly reduces the difference in price-change frequency between processed food and other commodities.

⁹The difference in the standard deviation between the frequencies of changes in regular price, F_1 and sale price, F_2 , may reflect the difference in the mean. Adjusting the difference in the mean, we still maintain that the variation in the frequency of sale price changes is larger than that of regular price changes. The coefficient of variation of F_1 (F_2) is 0.459 (0.649).

3.2 Market structure

This section defines variables related to market structure and shows that all are suitably defined from information in scanner data. In order to study structural factors of a market, one need to determine the boundary of a market. We define a market by its six-digit commodity classification provided by Nikkei Digital Media, and calculate statistics by commodity groups.

Let c ($c = 1, \dots, C$) denote a commodity group defined by the six-digit classification code. The Herfindahl-Hirschman index and n-firm concentration ratio of the c th group are calculated from a firm's sales volume within its group. Let q_k^c be total sales of the k th manufacturer ($k = 1, \dots, K$) in the c th item group. The Herfindahl-Hirschman index is defined as

$$HHI^c = \sum_{k=1}^K (s_k^c)^2, \quad (4)$$

where s_k^c is market share of the k th manufacturer in the c th item group measured by its sales volume, i.e., $s_k^c = q_k^c / \sum_{k=1}^K q_k^c$. The n-firm concentration ratio is defined as follows: Let $r_1^c > r_2^c > \dots > r_K^c$ represent the descending order of $q_1^c, q_2^c, \dots, q_K^c$. The n-firm concentration ratio in the c th item group can be written as

$$CR_n^c = \frac{\sum_{k=1}^n r_k^c}{\sum_{k=1}^K r_k^c}. \quad (5)$$

Table 4 shows the summary statistics of HHI and $CR4$. The mean Herfindahl index across six-digit commodity groups is 0.235. Since the standard deviation of the index takes a value near the mean, we observe large variations across commodity groups, which implies heterogeneity in degree of market concentration. The median $CR4$ is 0.743, suggesting that at the median level of competition, top four manufactures in the market account for nearly three-quarters of sales.

In the cross section analysis, we regress the average frequency of price changes on explanatory variables for market concentration specific to the commodity group. Here, we regard a commodity group as the unit of observation (the number of observations is equal to the number of the six-digit commodity groups, i.e., 1,661). Since Table 1 shows strong heterogeneity in market size, we conduct a weighted least squares (WLS) regression weighted by total sales of a commodity group and use a cluster-robust variance clustered on the three-digit item group.

In the panel data analysis, we construct a panel of 1,661 six-digit commodity groups over the 21 years, 1988–2008. By incorporating the panel data, we can control for the group-specific unobserved factor affecting price stickiness. Specifically, we estimate the following regression:

$$F_{ct} = \beta X_{ct} + \gamma W_{ct} + \alpha_c + \epsilon_{ct}, \quad (6)$$

where X_{ct} represents either HHI or $CR4$ of the commodity group c for the year t depending on the specification. The covariates W_{ct} include the annual sales and the number of items of the group. Tables 2 and 6 indicate an upward trend in total sales and frequency of price changes and a downward trend in the series of HHI and $CR4$ during the observation period. This implies that errors in (6) likely will correlate within a commodity group over time. In the panel estimation, we use cluster-robust standard errors that clustered on the six-digit

Group	Mean frequency of price changes				HHI	CR4
	Overall	Regular	Sale	Intraday		
Food	0.278	0.028	0.152	0.097	0.225	0.686
Processed food	0.287	0.030	0.168	0.089	0.218	0.669
Cakes and candies	0.226	0.024	0.116	0.087	0.198	0.654
Beverages	0.311	0.029	0.147	0.135	0.270	0.757
Other food	0.083	0.016	0.046	0.021	0.140	0.615
Daily necessities	0.115	0.021	0.062	0.032	0.282	0.802
Miscellaneous goods	0.153	0.023	0.088	0.042	0.281	0.829
Cosmetics	0.068	0.025	0.039	0.004	0.213	0.776
Household utensils	0.137	0.013	0.054	0.070	0.414	0.797
Pet accessory	0.104	0.020	0.059	0.025	0.222	0.738
Other commodities	0.067	0.017	0.040	0.010	0.560	0.960
Stationery	0.062	0.012	0.037	0.013	0.252	0.762
Car goods	0.045	0.015	0.029	0.000	0.645	0.956
Home electronics	0.100	0.015	0.068	0.017	0.293	0.837
All groups	0.248	0.027	0.136	0.085	0.235	0.706

Table 5: Mean frequency of price changes and the degree of market concentration by item group. Commodity classification is based on the JICFS classification.

item group. Concerning the group-specific effect α_c , it is necessary to check the assumption that α_c is uncorrelated with the regressors. We conduct the Hausman’s specification test on the assumption that errors are allowed to be heteroskedastic and correlated within a group.¹⁰

3.3 Channel characteristics

We observe the set of manufacturers and retailers in our data set and denote them by $m_k \in M$ ($k = 1, \dots, K$) and $r_j \in R$ ($j = 1, \dots, J$), respectively. Here, K and J are the total number of manufacturers and retailers. According to Table 2, they are respectively equal to 23,183 and 373 for the entire observation period. In order to study price rigidity arising out of channel-specific factors, we focus on pairings or relations of manufacturers and retailers, not on each business entities.

We express *potential* pairings of manufacturers and retailers as the following ordered pairs in the Cartesian product

$$M \times R = \{(m_k, r_j) : m_k \in M, r_j \in R, k = 1, \dots, K, j = 1, \dots, J\}. \quad (7)$$

¹⁰We conduct the asymptotically equivalent version of Hausman test by estimating the following auxiliary OLS regression

$$y_{ct} - \hat{\lambda}\bar{y}_c = \text{const.} + (x_{ct} - \hat{\lambda}\bar{x}_c)'\beta + (x_{ct} - \bar{x}_c)'\gamma + v_{ct},$$

where the regressors are respectively transformed by random-effects (fixed-effects) transformation in the second (third) term of the right hand side. The asymptotically equivalent test statistic is obtained by a Wald test of $H_0 : \gamma = 0$. See Wooldridge (2002) and Cameron and Trivedi (2005).

Variable	Period					
	All	1988	1992	1997	2002	2007
Mean frequency of:						
overall price changes	0.248	0.157	0.167	0.173	0.249	0.450
regular price changes	0.027	0.030	0.029	0.029	0.038	0.036
sale price changes	0.136	0.110	0.124	0.131	0.176	0.182
Intraday price changes	0.085	0.011	0.010	0.012	0.035	0.232
Median frequency of:						
overall price changes	0.130	0.078	0.087	0.087	0.141	0.284
regular price changes	0.016	0.015	0.015	0.019	0.023	0.023
sale price changes	0.069	0.053	0.065	0.065	0.111	0.107
Intraday price changes	0.039	0.000	0.001	0.001	0.005	0.131
HHI	0.235	0.280	0.259	0.244	0.226	0.220
CR4	0.706	0.770	0.730	0.707	0.702	0.704

Table 6: Mean and median frequency of price changes by year. Weighted average across six-digit commodity groups, weighted by total sales for the period, are reported.

This product includes all potential manufacturer-retailer pairings (m_k, r_j) regardless of whether parties actually have been related to one another, but we observe only pairings between which actual transactions have occurred. These *realized* pairings constitute the subset of $M \times R$ denoted by \mathcal{R} . Using this notation, we express the observed pairings of manufacturers and retailers as

$$m_k \mathcal{R} r_j \Leftrightarrow (m_k, r_j) \in \mathcal{R}. \quad (8)$$

The notation $m_k \mathcal{R} r_j$ means that the k th manufacturer *is related to* the j th retailer in the sense that an actual transaction between them has been observed in our data set. To simplify notation, we define the index $l, (l = 1, \dots, L)$ stand for the pairing $(m_k, r_j) \in \mathcal{R}$. Based on this unit of observation, we calculate the frequency of price changes that is specific to the l th distribution channel.

Having defined the observed channels, we now discuss the channel-specific factors. We first calculate two sets of variables: (1) the number of channel members and (2) the degree of brand competition. These variables take different values between a manufacturer and a retailer. From the manufacturer’s point of view, the number of channel members is that of retailers under contract. We define these variables on both sides of a distribution channel and calculate four variables for each channel. In addition, we calculate the term of contract between a manufacturer and retailer.

These channel-specific factors affect the price-setting behavior within a particular boundary of a market; therefore, we calculate these variables per commodity group. Let c ($c = 1, \dots, C$) denote a commodity group defined by the six-digit classification code. Then we denote by \mathcal{R}^c the set of pairings (m_k, r_j) that are under contract within a market c . In the following, we first discuss a manufacturer’s statistics and then a retailer’s. The latter is easily obtained because we assume a symmetric channel structure.

The number of channel members for the k th manufacturer is

$$N_k^c = \sum_{j=1}^J 1[(m_k, r_j) \in \mathcal{R}^c], \quad (9)$$

where $1[\cdot]$ is an index function. In order to quantify the degree of downstream competition, we first calculate the channel's share of total sales for the k th manufacturer—the ratio of sales yielded by the channel (m_k, r_j) to the manufacturer's total sales. It is defined as

$$S_{k(j)}^c = q_{k(j)}^c / \sum_{j \in \{j: (m_k, r_j) \in \mathcal{R}^c\}} q_{k(j)}^c, \quad (10)$$

where $q_{k(j)}^c$ is total sales of the k th manufacturer's products sold by the j th retailer. By aggregating the sales share for each retailer, we can calculate the degree of competition at the downstream stage, which is known as intra-brand competition. We measure the degree of brand competition by the quantity that is in inverse relation to the Herfindahl index:

$$BC_k^c = 1 - \sum_{j \in \{j: (m_k, r_j) \in \mathcal{R}^c\}} (S_{k(j)}^c)^2. \quad (11)$$

We obtain statistics unique to a retailer in the same manner. Competition among manufacturers at the j th retailer is inter-brand competition and is defined as

$$BC_j^c = 1 - \sum_{k \in \{k: (m_k, r_j) \in \mathcal{R}^c\}} (S_{j(k)}^c)^2, \quad (12)$$

where $S_{j(k)}^c = q_{j(k)}^c / \sum_{k \in \{k: (m_k, r_j) \in \mathcal{R}^c\}} q_{j(k)}^c$, that is, the ratio of sales yielded by the channel (m_k, r_j) to the total sales of the j th retailer. Finally, we obtain the number of channel members for the j th retailer as $N_j = \sum_{k=1}^I 1[(m_k, r_j) \in \mathcal{R}^c]$. We show the summary statistics of these variables in Table 4.

The population regression model applied to the data (y_l, X_l) may produce an inconsistent estimation, partly because we omit some unobserved factor that is specific to a commodity group and partly because we fail to control for error correlation within a group. Taking these into consideration, we estimate the effect of channel structure on price rigidity using the cluster-specific effects model

$$y_{cl} = X'_{cl}\beta + \alpha_c + \epsilon_{cl}. \quad (13)$$

We assume that the error ϵ_{cl} is independent across commodity groups, but correlates within a group. In the course of statistical inference, we test the model based on the cluster-robust standard errors.¹¹

4 Result

In this section, we first report the results on the relationship of price stickiness and market structure, where we use the WLS regression and the panel regression model in (6). Then we document the estimation results on channel characteristics using the regression equation in (13).

¹¹The model in (13) is the same as that in (6) except for the difference in the dimension of time. We conduct the same Hausman's specification test according to the procedure shown in Footnote 10.

Specification	Model	Variable	Dependent variable			
			Frequency of price changes:			
			Overall	Regular	Sale	Intraday
No covariates	(1)	#firm	0.014*	0.002**	0.013**	-0.001
			(0.008)	(0.001)	(0.005)	(0.003)
	(2)	CR4	-17.53**	-1.655***	-15.19***	-0.694
			(6.865)	(0.607)	(4.101)	(2.921)
	(3)	HHI	-16.11**	-1.785***	-15.20***	0.872
			(6.272)	(0.581)	(3.839)	(2.608)
With commodity group dummies	(4)	#firm	0.013*	0.002***	0.012***	-0.001
			(0.007)	(0.001)	(0.005)	(0.003)
	(5)	CR4	-14.42**	-1.509**	-12.82***	-0.102
			(7.189)	(0.594)	(4.691)	(2.655)
	(6)	HHI	-16.04**	-1.617***	-14.38***	-0.054
			(6.214)	(0.531)	(4.127)	(2.263)
With commodity group dummies, and #item	(7)	#firm	0.010	0.002**	0.009*	0.000
			(0.008)	(0.001)	(0.005)	(0.003)
		#item	0.022*	0.004***	0.025***	-0.007
			(0.012)	(0.001)	(0.007)	(0.005)
	(8)	CR4	-13.10*	-1.241**	-11.29**	-0.572
			(7.686)	(0.598)	(5.043)	(2.709)
		#item	0.021	0.004***	0.024***	-0.007
			(0.013)	(0.001)	(0.009)	(0.005)
(9)	HHI	-14.45**	-1.288**	-12.54***	-0.624	
		(6.649)	(0.531)	(4.427)	(2.344)	
		#item	0.021*	0.004***	0.024***	-0.007
			(0.011)	(0.001)	(0.007)	(0.005)

Table 7: Degree of market concentration and the frequency of price changes for the six-digit commodity groups. Weighted least squares regression with weights given by the group's total sales for the observation period: 1988- 2008. All equations are based on 1,661 observations. Coefficients are reported in percentage. Cluster robust standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

4.1 Price rigidity and market structure

Table 7 illustrates the result from the cross-section regression, where the dependent variable and regressors are calculated using all data covering the entire observation period. This regression is based on the 1,661 observations of the average frequency of price changes and the average degree of market concentration across items within a group. We have four dependent variables: the frequency of overall, regular, sale, and intraday price changes. For each dependent variable, we estimate models with nine sets of regressors. We report

Dependent variable Frequency of:	Right-hand-side variable		
	#firm	CR4	HHI
Overall price changes	0.191*** (0.030)	-19.91*** (1.716)	-9.121*** (0.984)
Regular price changes	0.012*** (0.002)	-1.307*** (0.227)	-0.754*** (0.131)
Sale price changes	0.051*** (0.011)	-6.404*** (0.710)	-2.808*** (0.456)
Intraday price changes	0.127*** (0.019)	-12.37*** (1.121)	-5.626*** (0.640)

Table 8: Degree of market concentration and the frequency of price changes for the six-digit commodity groups. Results from a panel of 1,661 six-digit commodity groups over 21 years, 1988–2008. Coefficients are reported in percentage. Cluster robust standard errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the coefficient estimate of the variables of interest—the number of firms, HHI and $CR4$ —incorporated in a model separately.

Remarkable finding is that the variables for market structure significantly affect on both the frequency of changes in regular and sale prices. The sign of coefficient is positive, for the number of firms, and negative for HHI and $CR4$, suggesting retail prices become sticky as the market becomes less competitive. This finding supports the administered-price hypothesis. For the frequency of regular (sale) price changes, the coefficient of HHI in Model (9) is -1.288 (-12.54), respectively. Variables for market structure have no significant effect on frequency of intraday price changes in these cross section models.

Table 8 shows results from panel estimation models in (6). Conducting the asymptotically equivalent version of the Hausman test described in footnote 10, we select the fixed-effects model for all specifications in Table 8. We model three specifications for each dependent variables. We include the yearly number of items and total sales for a commodity groups as control variables for each specification.

Because the fixed-effects model controls the unobserved effect specific to a commodity group, the difference in coefficient estimates may reflect omitted-variables bias in the previous cross section analysis. We obtain, however, qualitatively the same result as from WLS regression. The variables on market concentration (HHI and $CR4$) have statistically significant negative effects on the frequency of regular and sale price changes. The fixed-effects model lowers the coefficient of HHI compared to the cross section model (9) in Table 7. For the frequency of regular (sale) price changes, the coefficient of HHI is -0.754 (-2.808), respectively, which means that unit increase in Herfindahl index—a ceteris paribus change from a perfectly competitive to a monopoly market reduces the frequency of regular price changes by 0.75% points and the frequency of sale 2.8% points.

4.2 Price rigidity and channel characteristics

Table 9 illustrates the estimation result for the relation between price stickiness and the structure of distribution channels. Here, we employ the aggregated data on a channel basis.

Dependent variable	Right-hand-side variable				Term of contracts
	#channel members		Brand competition		
	N_j	N_k	BC_j	BC_k	
Frequency of sale price changes	0.036*** (0.007)	0.003*** (0.000)	2.195*** (0.157)	2.342*** (0.268)	-0.058*** (0.007)
Frequency of regular price changes	0.009*** (0.002)	0.001*** (0.000)	0.097* (0.052)	0.041 (0.075)	-0.140*** (0.006)
					-0.130*** (0.006)

Table 9: Channel structure and the frequency of price changes. Estimation by the cluster-specific fixed effects model. All equations are based on 4,171,060 observations. Coefficients are reported in percentage. Cluster robust standard errors are given in parentheses. N_j (N_k), the number of manufacturers (retailers) under contract with a retailer (manufacturer); BC_j , inter-brand competition; BC_k , intra-brand competition. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

As Table 4 shows, the regression equation in (13) is based on 4,171,060 observations. The same specification test in footnote 10 leads us to select the fixed-effects model in every specification shown in Table 9. We examine two dependent variables: the frequency of sale and regular price changes. For each dependent variable, we specify two sets of regressors relating to the number of channel members and brand competition. For each specification, we include the term of contracts as a regressor.

The term of contracts for a channel has a significant and negative effect on price flexibility. For example, a manufacturer decreases its frequency of regular price changes by about 0.13% points, if its contract with a retailer is extended one year. The number of channel members for both manufacturer and retailer has a significant and positive effect on frequency of both sale and regular price changes. For the dependent variable of sale frequency, the coefficient of N_j is 0.036, which means a retailer can increase the sale frequency by 0.36% if it contracts 10 additional manufacturers in a commodity group, other things being equal.

Intra- and inter-brand competition positively affect the frequency of sale price changes. In other words, increased competitiveness among channels leads to more flexible price adjustments for retailers. For example, the coefficient of intra-brand competition on the frequency of sale price changes is 2.342%. A unit increase in intra-brand competition can be interpreted as a retailer switching from a monopoly to perfectly competitive manufacturers. The coefficient estimate of inter-brand competition means, therefore, that the frequency of sale price changes increases 2.3% points if they contract with perfectly competitive manufacturers, rather than a monopolistic manufacturer. According to the robust standard errors, the significance of these regressors differs between sale price and regular price. Inter-brand competition significantly affects manufacturers' price adjustments, whereas intra-brand competition does not have a significant effect. This result seems reasonable, because manufacturers' price-setting behavior is related to competition upstream rather than downstream.

5 Conclusion

In this paper, we examine the relationship among market concentration, structural factors of distribution channels, and price stickiness. Drawing inferences using the Japanese scanner data covering 1,661 markets over 20 years, we establish four empirical findings.

First, the degree of market concentration negatively and significantly affects price adjustments by retailers and manufacturers. The unit increase in the Herfindahl index leads to increase the frequency of sale price changes by 2.8% points and the frequency of regular price changes by 0.75% points. The degree of concentration upstream has a twofold relevance for retail-price stickiness. Prices become sticky partly because manufacturers would maintain regular prices for a long time and partly because they would influence the retailer's pricing decision.

Second, we find that structural factors of distribution channels are significantly correlated with rigidity in retail prices. The number of channel members for both a manufacturer and a retailer has a significant and positive effect on frequency of both sale and regular price changes. As the channel opens to other business entities, retail prices become more flexible.

Third, both inter- and intra-brand competition have a positive effect on the frequency of sale price changes. The increase in competitiveness among channels leads to more flexible price adjustments for retailers. However inter-brand competition among manufacturers has a significant effect on their price-setting behavior, whereas intra-brand competition among retailers has no significant effect.

Fourth, the term of contracts between manufacturers and retailers has significant and positive effect on price rigidity. This implies that long-term relationships among channel members can be a source of retail-price rigidity.

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