Micro Price Dynamics during Japan's Lost Decades

Nao Sudo

Kozo Ueda

Kota Watanabe

UTokyo Price Project
702 Faculty of Economics, The University of Tokyo,
7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan
Tel: +81-3-5841-5595
E-mail: watlab@e.u-tokyo.ac.jp
http://www.price.e.u-tokyo.ac.jp/english/

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Nao Sudo,[*] Kozo Ueda,[†] and Kota Watanabe[‡]

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Very preliminary

Abstract

We study micro price dynamics and their macroeconomic implications using daily scanner data from 1988 to 2013. We provide five facts. First, posted prices in Japan are ten times as flexible as those in the U.S. scanner data. Second, regular prices are almost as flexible as those in the U.S. and Euro area. Third, heterogeneity is large. Fourth, during Japan's lost decades, temporary sales played an increasingly important role. Fifth, the frequency of upward regular price revisions and the frequency of sales are significantly correlated with the macroeconomic environment like the indicators of labor market.

Keywords: Lost decade; deflation; sales and regular prices; scanner data; price stickiness
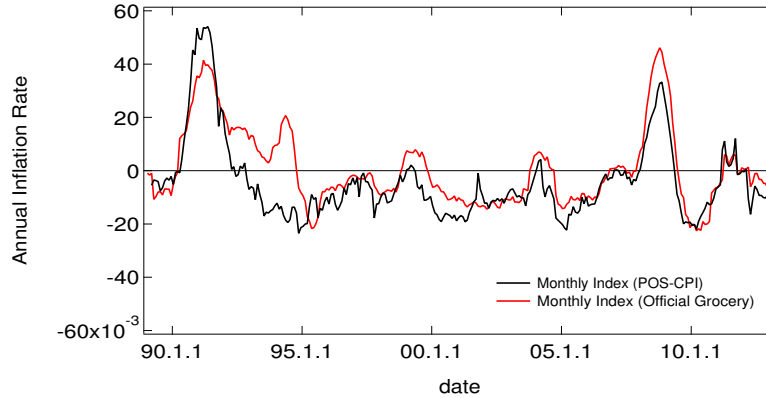
JEL classification: E31

Figure 1: CPI and POS-CPI

Notes: The POS-CPI is obtained from the POS data. Official Grocery represents the CPI price index of the same item category as the POS data. For details, see Section 2.3.

1 Introduction

Since the asset price bubble went bust in the early 1990s, Japan has gone through prolonged stagnation and very low rates of inflation (see Figure 1). To investigate its background, in this paper, we study micro price dynamics at a retail shop and product level. In doing so, we use daily scanner or Point of Sales (POS) data from 1988 to 2013 covering over 6 billion records. From the data, we examine how firms' price setting changed over these twenty years; report similarities and differences in micro price dynamics between Japan and foreign countries; and draw implications for economic theory as well as policy.

This paper provides mainly five facts. First, posted prices in Japan are ten times as flexible as those in the U.S. scanner data. The daily frequency of price changes is about 15%. Second, regular prices are almost as flexible as those in the U.S. and Euro area. The monthly frequency is around 20%. Third, heterogeneity is large. Even under deflation, a large number of products increased their prices. At the same time, asymmetry exists in the tail end. The magnitude of price drops is greater than that of price jumps for the items that exhibited vast changes in their regular prices. Fourth, during Japan's lost decades, temporary sales played an increasingly important role. Both the frequency of temporary sales and a ratio of sales sold at the sale price to total sales increased. Alongside the number (variety) of products and the price elasticity of consumers' demand also increased. Fifth, the frequency of upward regular price revisions and the frequency of

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sales are significantly correlated with the macroeconomic environment like the indicators of labor market. The last two facts may imply the possibility that worsened labor conditions for households during the prolonged recessions caused them to go to bargain hunting. This raised the price elasticity, and by observing this, retail shops raised the frequency of temporary sales.

As for the micro price dynamics, Bils and Klenow (2004) are the seminal empirical paper that studies the case in the United States. Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) conduct further detailed analysis. A good survey is carried out by Mackowiak and Smets (2008), Klenow and Malin (2011), and Nakamura and Steinsson (2013), although Japan's case is hardly discussed.

Japan's micro price dynamics have been studied by the Bank of Japan (2000), Higo and Saita (2007), Ikeda and Nishioka (2007), Mizuno et al. (2010), Abe and Tonogi (2010) and Watanabe and Watanabe (2013) among others. Our closest and complementary work is Abe and Tonogi (2010). Both use the same POS data, but our data are longer by recent seven years. We illustrate the issue of heterogeneity rigorously; impose a different sales filter; and examine the relationship between micro price dynamics and the macro economy.

The structure of this paper is as follows. Section 2 explains the POS data. Section 3 provides stylized facts on price stickiness. Section 4 examines the relationship between micro price dynamics and the macro economy. Section 5 concludes.

2 POS Data

2.1 Data Description

In this paper, we use the POS data gathered by Nikkei Digital Media from various retail shops throughout Japan. The data are daily, ranging from March 1, 1988 to February 28, 2013, but excluding the sample of November and December in 2003. The cumulative number of products during the sample amounts to 1.8 million. The cumulative number of records during the sample amounts to 6 billion, where each record contains the number of units sold and its sales (yen) for a product i at a shop s on a date t. Types of products are processed food and domestic articles. Unlike CPI, neither fresh food, recreational durable goods (TVs and PCs), nor services (rent and utility) are included. The coverage of the
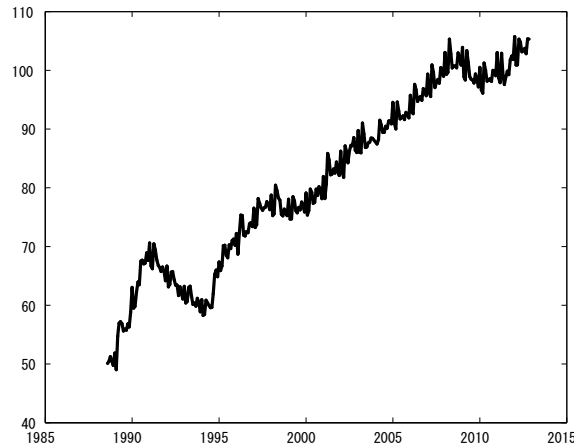
Figure 2: Number of Products Sold at Each Shop
Note: We normalize the number of products in April 2010 as 100.

POS in CPI is 170 items out of 588, which constitutes 17% of household's expenditure according to Family Income and Expenditure Survey. Each product i is identified by the the Japanese Article Number (JAN) code. In addition, Nikkei Digital Media defines a 3-digit code, from which we classify the types of products such as yogurt, beer, tobacco, and toothbrush.

Japan's POS data are valuable particularly in three respects. First, they include the information about quantity as well as prices. Second, their frequency is daily, while the US scanner data are weekly. Third, data have long samples, ranging from 1988 till now, which covers the whole period of Japan's lost decades.

Table 1 provides the summary of the data. The number of retail shops has been increasing. In 2012, the number of retail shops reached 261. The number of products has also been increasing, from 130,000 in the early 1990s to 350,000 in 2012. This trend increase was robustly observed even when shops were fixed, as Figure 2.1 shows. In other words, the variety of goods has increased and the product cycles have shortened during Japan's lost decades.

2.2 Measuring Prices

From each record of the POS data, we measure the price of a product by its unit price, that is, sales over the number of units sold for a product i at a shop s on a date t. Recorded sales exclude the contribution of consumption tax that was introduced in

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Table 1: Basic Statistics

Year	# of stores	# of products	Sales (yen)	# of records
1988	29	88,207	24,967,387,530	25,397,753
1989	45	118,459	38,848,140,951	39,967,625
1990	50	131,217	47,914,018,985	46,449,145
1991	53	133,201	56,554,113,519	50,762,796
1992	62	135,862	67,325,003,923	56,069,411
1993	65	139,929	75,403,002,651	61,371,512
1994	103	157,148	115,779,158,308	91,670,103
1995	124	169,366	149,242,076,718	119,894,820
1996	132	177,116	180,557,355,210	150,298,311
1997	150	194,522	205,874,958,531	171,939,036
1998	172	218,661	262,631,787,495	218,298,976
1999	172	225,503	265,603,874,575	226,063,598
2000	189	250,497	276,182,400,451	242,140,503
2001	187	264,994	301,163,033,600	274,076,220
2002	198	275,815	313,697,755,019	283,176,100
2003	189	259,242	264,127,818,448	242,227,335
2004	202	278,894	306,121,269,565	281,899,515
2005	187	287,680	328,939,470,128	309,625,996
2006	189	305,223	334,615,509,093	323,381,091
2007	274	347,185	373,166,817,586	378,924,802
2008	261	367,064	407,677,569,675	412,836,053
2009	264	357,928	404,988,058,786	416,290,153
2010	259	358,282	395,223,198,995	415,348,828
2011	249	358,813	380,908,900,263	403,645,269
2012	261	356,587	399,628,611,703	445,046,118
2013	256	244,582	61,426,810,036	71,502,482

Notes: The data range from March 1, 1988 to February 28, 2013, but exclude the sample of November and December in 2003. The number of records in 2013 is small because the sample ends in February.
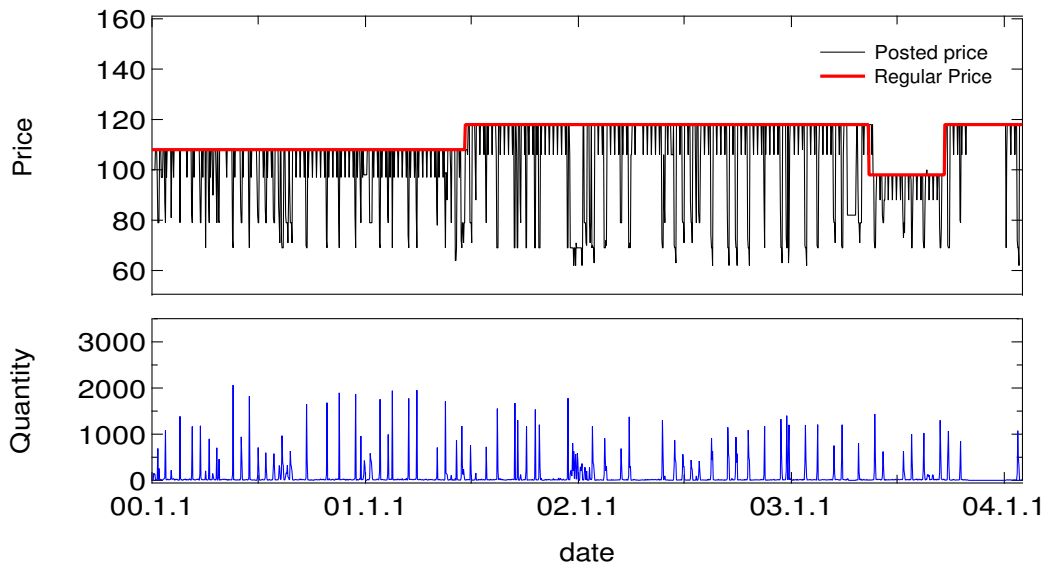
Figure 3: Price Changes of a Cup Noodle at a Store

April 1989 and raised in April 1997.

Temporary sales are considered to behave differently from regular prices and play a different role in the macro economy. Therefore, it is important to isolate temporary sales from posted prices. The POS data do not tell explicitly which is the sales or not, however, so we need a certain identification method.[1]

As a benchmark, we follow Eichenbaum, Jaimovich, and Rebelo (2011) and define the regular price of a good on a date by the the most commonly observed price (mode price) during the 3 months centered on the date.[2] Temporary sales are identified when the regular price differs from its posted price. We can think of other methods of identifying a regular price. Abe and Tonogi (2010) use a similar method, but their window for calculating a mode is 1 week instead of 3 months. Nakamura and Steinsson (2008) conduct a sale filter to look for V-shaped patterns in developments in sales prices.

Figure 2.2 depicts a typical pattern of price changes for a certain brand of cup noodle at a certain store. Posted prices are flexible reflecting temporary sales. Regular prices are revised only three times in 4 years. The number of units sold occasionally jumps by thousand times.

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[1]Japan's CPI focuses on the developments in regular prices, not making use of sale prices in constructing its index. Prices with durations of less than seven days are excluded by price surveyors.

[2]They call it a reference price instead of a regular price.

2.3 Aggregating Micro Prices

We below report various aggregated variables such as the aggregated price index constructed from the POS and the aggregated frequency of price changes. Since we use basically the same method of aggregation, we lay out here how we calculate. First, at the lowest level of JAN codes, we obtain a variable of interest for a product i at a shop s on a date t. Second, we aggregate it across shops with sales weights to derive weighted mean.[3] Third, up to the 3-digit code level, we aggregate it across products with sales weights to derive weighted mean. Last, we aggregate it across 3-digit codes with sales weights to derive weighted mean or weighted median (quantile). Weights are, in most cases, defined by the sales during the month in the previous year. If a date is January 1, 2012, then we use the sales of January in 2011 as a weight. In calculating the following POS-CPI, however we use different weights.

2.4 Comparison with CPI

Figure 1 illustrates the time-series annual change in the POS price index (POS-CPI) with that of CPI.[4] The annual change in the POS-CPI is measured based on the monthly Tornqvist index, where a weight of each good at each store equals the average of its sales share during the month and its sales share during the same month of the previous year. The annual inflation rate is measured as a weighted geometric mean of posted price changes from the previous year. As for CPI, we focus on the same item category as the POS data, that is, processed food and domestic articles, for comparison.

The POS-CPI exhibits similar developments as CPI. After experiencing positive inflation in the early 1990s, they entered into the period of prolonged deflation since the mid 1990s. An exception is around 2008, when a surge in commodity prices led to inflation. A distinct difference of the POS-CPI from the CPI is its faster decline in 1992 to 94 after the bust of the asset-price bubble.

2.5 Price Elasticity

An advantage of the POS data is the observation of both prices and quantities. From them, we investigate price changes vis-a-vis quantity changes. If supply shocks are

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[3]Nakamura and Steinsson (2008) use sales weights, while Abe and Tonogi (2010) use quantity weights.
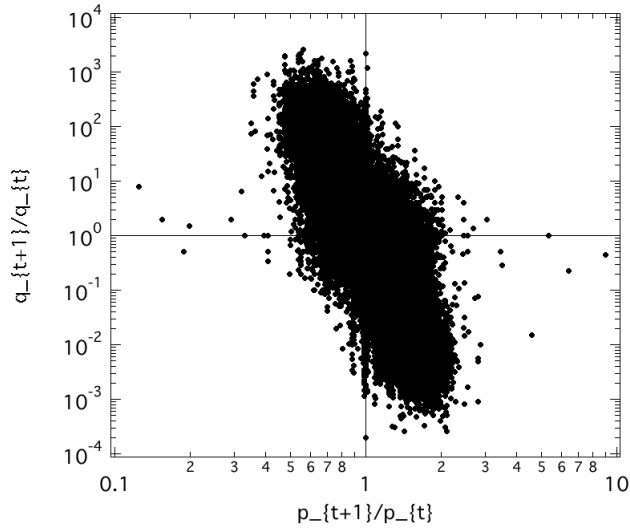[4]See Watanabe and Watanabe (2013) for details.

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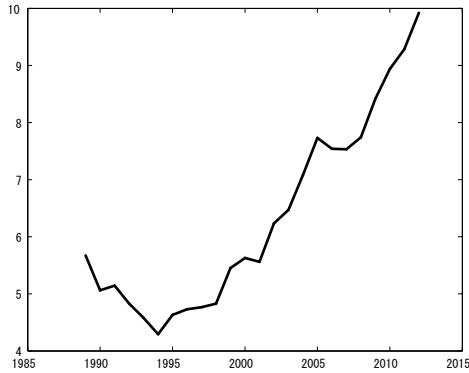Figure 4: Price Changes vis-a-vis Quantity Changes for a Cup Noodle

Figure 5: Price Elasticity

dominant in the economy, their relation is considered to be negative. Its slope indicates the price elasticity of demand. Figure 4 shows a scatter plot regarding quantity changes in response to price changes for the item of a cup noodle. The horizontal and vertical axes indicate daily price changes and daily quantity changes, respectively. The slope is clearly negative.

We next calculate the time-series path of the price elasticity. We draw samples only from the second and fourth quadrants in the above scatter plot to eliminate the effect of demand shock and calculate the price elasticity for each product and store. We then construct the weighted median of elasticities across products and stores. Figure 5 exhibits an upward trend from the early 1990s, suggesting that households become more price

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sensitive.

3   How Sticky are Prices?

In this section, we report price stickiness mainly from two perspectives: frequency and magnitude of price changes. The former (latter) represents extensive (intensive) margin.

3.1   Frequency of Price Changes

The frequency of price changes is calculated in the following manner. First, at the lowest (most detailed) level, we identify a change in the price of a product i at a shop s on a date t, when the price is different from that on the previous date by 3 yen.[5] Second, we aggregate the frequency of price changes across products and shops using the aforementioned method of aggregation. When price data on a certain date are missing due to zero sales, we assume that its price is the same as that on the previous date.

Table 3.1 displays the frequency of price changes, both for posted and regular prices. First, we look at regular price changes. Their monthly frequency is around 20%, which is almost comparable with that in the previous literature except for Abe and Tonogi (2010). Klenow and Malin (2011) provide extensive international comparison regarding price stickiness. As for the use of scanner data, several studies exist in the United States. The average monthly frequency of price changes is around 25% for regular prices. As for the monthly CPI data, the frequency of regular price changes is around 25% in the United States as well. The frequency in the Euro area tends to be lower, around 20%. By contrast, the frequency in high-inflation developing countries such as Brazil, Chile, and Mexico tends to be higher, around 30 to 50%. In Japan, the frequency is 23% according to Higo and Saita (2007). By contrast, Abe and Tonogi (2010) report four time higher frequency: monthly frequency amounts to 80% for regular prices in 2000 to 2005. Such a difference, despite the use of the same POS data, arises mainly because the window length to calculate the mode price differs: we use 3 months while they use 1 week. We will distill this later.

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[5]The reason for 3 yen is because on some occasions unit prices are not integers. This reflects time sales within a day, buy-one-get-one-free sales, etc. In particular, the effect of consumption tax seems large. When a household purchases a basket of products and Nikkei Digital Media reports its sales excluding the contribution of consumption tax, a unit price of each product is likely to be non-integer. Moreover, since April 2004, retail shops have been given a mandate to post prices that include the consumption tax. That statutory modification increased the possibility of decimal prices.

Second, we turn to posted price changes. We find far higher frequent price changes than regular prices. In 2000 to 2013, average monthly frequency is above 400%; daily frequency is about 15%. In Abe and Tonogi (2010), monthly frequency is twice as high, 850% in 2000 to 2005. Note that this difference does not come from the window length, implying the importance of other reasons. They are weights for aggregation, data samples, the treatment of missing price data, and the treatment of decimal prices. As for the third, the method of Abe and Tonogi (2010) is unclear; if they omit missing price data, it yields a higher frequency of price changes than our method. As for the last, Abe and Tonogi (2010) round prices to the nearest integer, while we identify a price change when the price is different from that on the previous date by 3 yen. Irrespective of such a difference between ours and Abe and Tonogi (2010), a bottom line result is that Japan's posted prices change extremely frequently compared with the United States. Klenow and Malin (2011) report that the average monthly frequency of price changes is around 40% according to the scanner data. That is, posted prices in Japan are ten times as flexible as those in the United States.

Third, although large heterogeneity exists across products as we will show soon below, a large part comes from temporary sales. Comparison of the frequency between processed food and domestic articles reveals that their difference for regular prices is small, while that for posted prices is twofold. In other words, processed food experiences more frequent temporary sales than domestic articles. Moreover, mean is much higher than median for posted prices, while mean and median are almost at the same level for regular prices. This implies that a small portion of products exhibit highly frequent temporary sales.

Figure 3.1 displays quantile time-series developments in the frequency of regular price changes. We divide the frequency into that of upward price revision and that of downward price revision. Each product is aggregated up to 3-digit code items. To tackle heterogeneity, we plot quantile lines. Nine dashed lines represent weighted quantiles from 10th to 90th, and a black solid line represents weighted median. Weighted mean is expressed in a red solid line with a dot.

The figures reveal three things.[6] First, developments in frequency are not monotonic. The frequency increased steadily from the early 1990 until 2004 and decreased moderately

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[6]Around April 2004, a big bump is observed due to the statutory modification about consumption tax.

Table 2: Frequency of Price Changes

		1988-1999		2000-2013	
		median	mean	median	mean
Posted price					
	All	237.0	306.1	415.3	492.4
	Processed food	275.4	341.6	465.7	544.2
	Domestic articles	106.6	118.0	217.7	233.4
Regular price					
	All	15.9	15.2	19.3	19.8
	Processed food	16.2	15.8	19.0	19.8
	Domestic articles	11.4	12.3	21.1	19.5

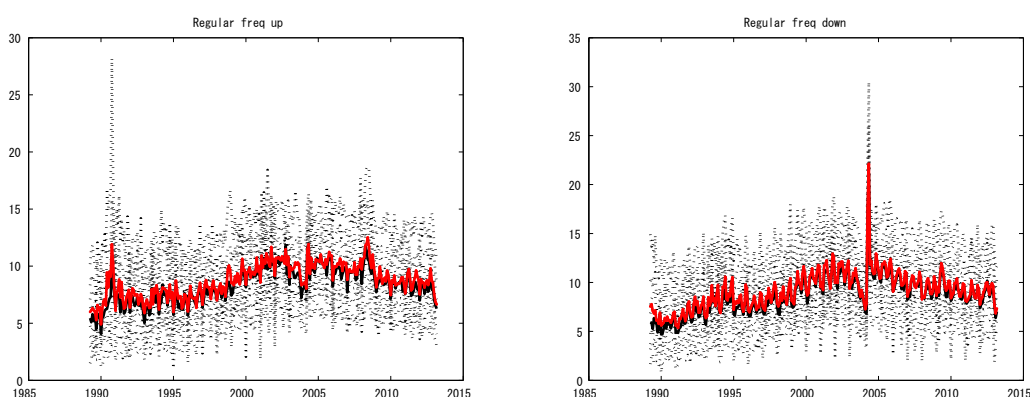Note: Monthly frequency (%) is calculated as daily frequency multiplied by 365/12.

Figure 6: Quantile Developments in the Frequency of Regular Price Changes (Up and Down)
Nine dashed lines represent weighted quantiles from 10th to 90th, and a black solid line represents weighted median. Weighted mean is expressed in a red solid line with a dot.

thereafter. Second, heterogeneity is large. Even under deflation, a large number of products increased their prices. However, the distribution of frequency across products has not changed much during the sample period. That is, this time-series pattern was common to all quantiles, increase up until 2004 and decline in the subsequent periods. Consequently, a heterogeneity of frequency across product is maintained throughout the sample period. Third, weighted mean tends to be higher than weighted median, albeit in a small extent. This implies that some products change their regular prices highly frequently while there are products that barely change the prices. For example, 10% of items revised their regular prices about three times as frequently as the average item did around 1991.
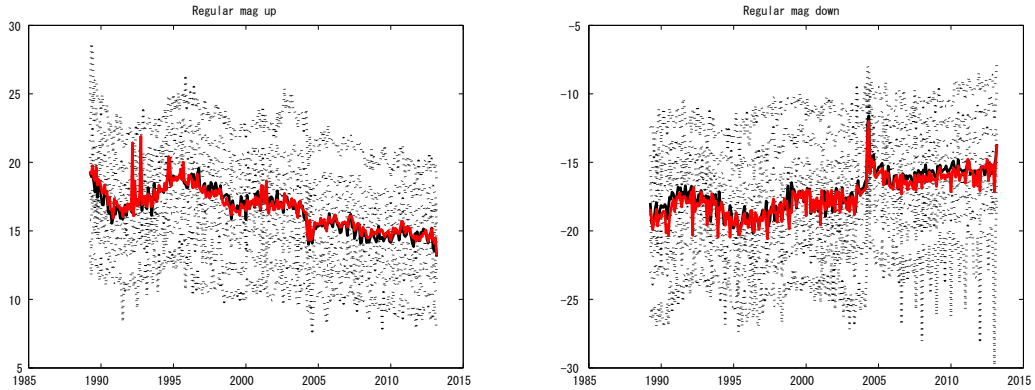
Figure 7: Quantile Developments in the Magnitude of Regular Price Changes (Up and Down)

Nine dashed lines represent weighted quantiles from 10th to 90th, and a black solid line represents weighted median. Weighted mean is expressed in a red solid line with a dot.

3.2 Magnitude of Price Changes

Next we calculate the magnitude of price changes when prices are revised. Here we focus on that of regular prices. Figure 3.2 illustrates quantile time-series developments in the magnitude of regular price changes.

Three results are worth noting. First, the magnitude of regular price changes is roughly 10 to 20% on average. This is consistent with past studies. Second, the magnitude of price change has been monotonically decreasing over two decades, although its growth rate become almost zero since 2004. As we found in the previous subsection, the frequency of price change has steadily increased until 2004. Other things being equal, such developments in frequency together with the decreasing magnitude of price change are consistent with the implication of the menu cost model when menu cost itself is shrinking over time. After year 2004, frequency of price change experiences declining while magnitude of price change is stable, implying that changes in economic environments other than menu cost, such as time series pattern of marginal costs may have occurred during that time. Third, asymmetry exists in the tail end. The magnitude of drops in the regular prices is greater than that of jumps for the items that exhibited vast changes in their regular prices. For example, for the 10th quantile items, their regular prices dropped by around 25 to 30%, while they jumped only by around 20%.
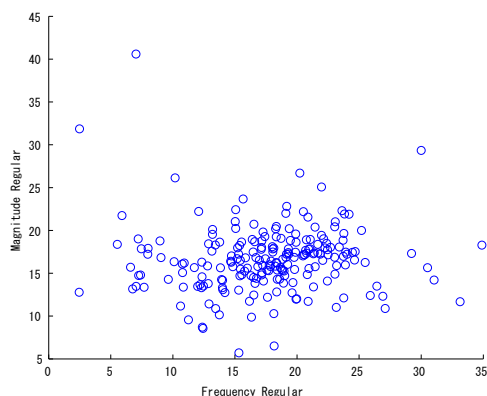
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Figure 8: Frequency versus Magnitude of Regular Price Changes

Note: Each dot represents the frequency and magnitude of regular price changes for an item in the 3-digit code.

3.3 Relation between Frequency and Magnitude

A relation between the magnitude and the frequency of regular price changes provide a clue to refining theory. When we plot a scatter plot across items in the 3-digit codes, two possibilities can be considered as for its slope. A negative slope implies that different items are subject to a different size of menu cost and a similar size of idiosyncratic shocks. Items that entail large (small) menu cost exhibit both low (high) frequency and large (small) magnitude. On the other hand, a positive slope implies that different items are subject to a similar size of menu cost and a different size of idiosyncratic shocks. Items that face larger (smaller) idiosyncratic shocks change their prices more (less) frequently by a larger (smaller) size.

Figure 3.3 shows the ambiguous relationship between the frequency and the magnitude. Their correlation is insignificant. However, if we look at the graph closely, a U-shape seems to be observed. For the item whose frequency is low, the magnitude is large. This implies that these items entail large menu cost. For the item whose frequency is intermediate, the magnitude is small. And for the item whose frequency is high, the magnitude is large. This implies that these items are faced with large idiosyncratic shocks.
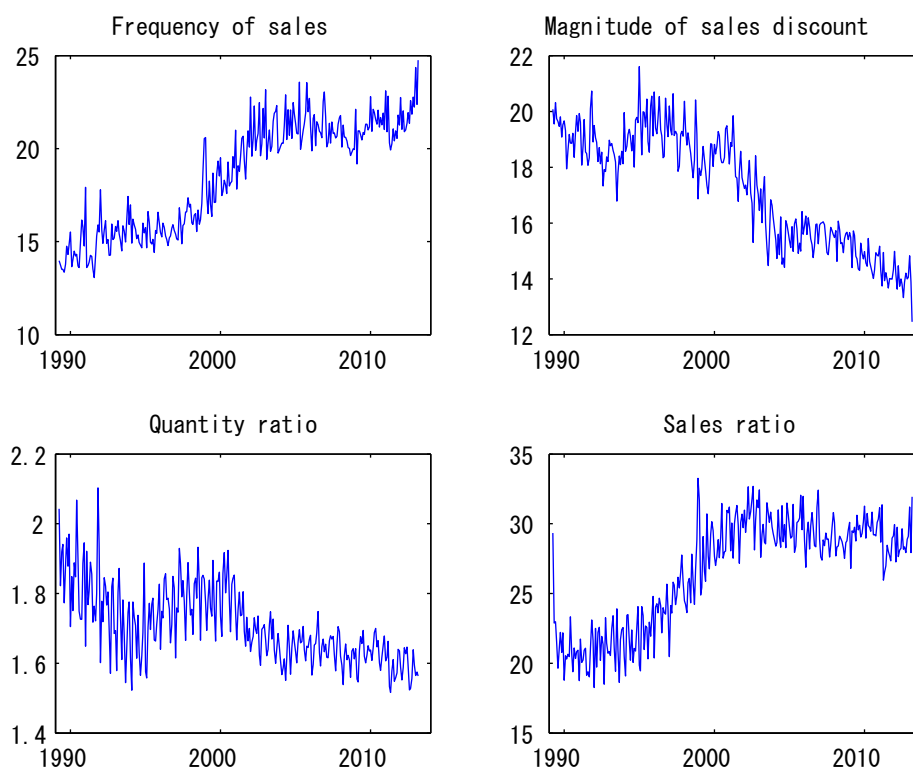
Figure 9: Variables Associated with Temporary Sales

Note: The bottom left panel indicates a ratio of quantities sold at the sale price to those at the regular price. The bottom right panel indicates a ratio of sales sold at the sale price to total sales in a month in percent.

3.4 Temporary Sales

Now we turn our attention to temporary sales from regular prices. Figure 9 shows time-series changes in four variables associated with temporary sales: the frequency of sales (%), the magnitude of sale discount (%), a ratio of quantities sold at the sale price to those at the regular price, and a ratio of sales sold at the sale price to total sales in a month (%). All variables are weighted mean. In Guimaraes and Sheedy (2010), the first three constitute key variables for a DSGE model.

We can find clear trend during Japan's lost decades, which suggests that sales have become increasingly important. The frequency of sales is now 25%, increasing from 15%. In other words, temporary sales are observed once in four days. Sales sold at the sale price account for about 30% of total sales, increasing from 20%. The ratio of quantities sold at the sale price to those at the regular prices is 1.6. This variable exhibits a

Table 3: Window Length and Frequency of Regular Price Changes

| | 1988-1999 | | 2000-2013 | |
Window	median	mean	median	mean
3 months	15.9	15.2	19.3	19.8
1 week	65.6	74.3	95.2	101.9

Note: Monthly frequency (%) is calculated as daily frequency multiplied by 365/12.

decrease from 2.0, but considering the increases in the previous two variables, such a decrease is moderate. Parallel to the increase in the frequency of sales, the magnitude of sales discount shrank from 20% to 14%.

3.5 Robustness to Sales Filter

The regular price looks far stickier than that reported in Abe and Tonogi (2008). To investigate its reason, we follow their method and use the window length of 1 week to calculate the mode price as a proxy for a regular price. Table 3.5 and Figure 10 show that the window length matters for the frequency of regular price changes. By using the window of 1 week, the frequency increases almost by five times.

Which method is more appropriate is difficult to judge, but we think that too short window involves the contribution of temporary sales. True, we confirm that the general features of Figures 3.1 are robust to this modification, but the frequency of regular price changes comes to exhibit clearer upward trend, reflecting the trend increase in the frequency of temporary sales. If the behavior and economic role of temporary sales differ from those of regular priced items, which is believed to be true, then moderately long window can be justified.

4 Relation between Micro Price Dynamics and Macro Economy

Japan's prolonged stagnation may have altered retail shops' price setting. In order to address this point, in this section, we investigate how micro price components are related with the macroeconomic environment. In the previous section, we have reviewed developments in micro price components by simply drawing time-series graphs. This exercise was helpful in searching for a long-run trend, such as the trend increase in the
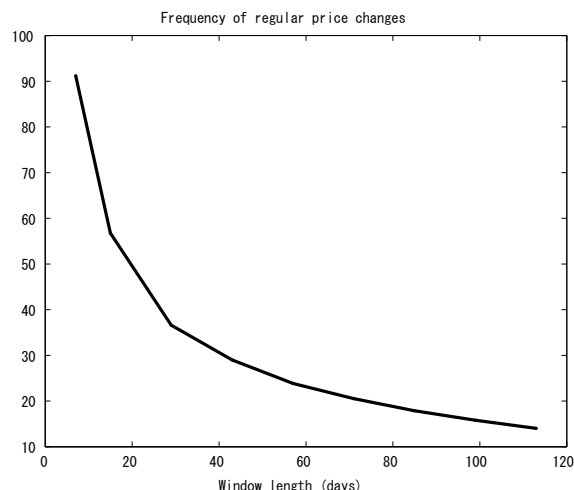
Figure 10: Window Length and Frequency of Regular Price Changes
Note: Monthly frequency (%) is calculated as daily frequency multiplied by 365/12.
Samples are from March 1988 to February 2013.

frequency of temporary sales, under Japan's lost decades.

Here, we conduct a bit more empirical analysis by calculating correlations. As the micro prices consisting of 3-digit code items, we look at 6 variables: the frequency of upward and downward regular price revisions, the magnitude of upward and downward regular price revisions, the frequency of sales, and the magnitude of sales discount. As macro indicators, we look at 10 variables in log: the unemployment rate, total hours worked, the new job openings ratio to applicants, the index of industrial production, CPI, the leading index, the coincident index, the lagging index (these three are the components of Composite Indexes complied by Cabinet Office), the consumer confidence index, and monetary base. Samples are the same as those of micro prices. We then take their business-cycle components using the Baxter-King band pass filter from 1.5 to 8 years.[7] Using these filtered variables, we calculate correlations for 3-digit code items. Figure 4 depicts the correlations between the micro price components and the macro indicators. Red lines with dots (dashed lines) indicate the correlation when we take the weighted mean (quantiles) from micro price components. Blue solid lines represent 5% significant levels.

The figure suggests that micro price components, in particular, the frequency of

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[7]Among the macro indicators, the consumer confidence index was quarterly before March 2004. We filled missing data by linear interpolation. Since we take its business-cycle components, we believe that this problem hardly matters.
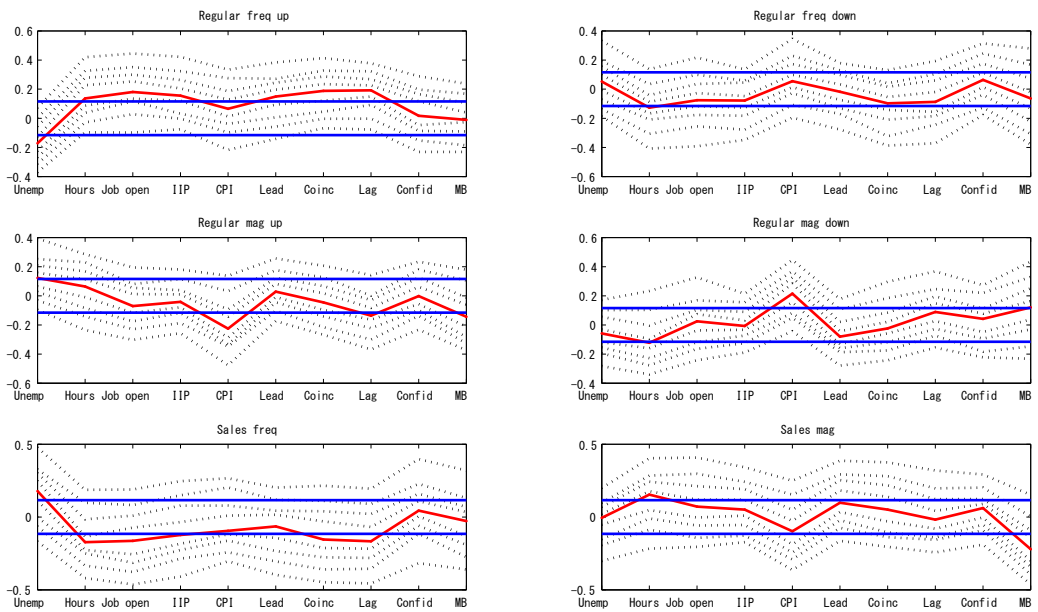
Figure 11: Correlation between Micro Prices and Macro Economy

Note: Correlations between micro price components and macro economy indexes. All series are filtered using the Baxter-King band pass filter. Blue solid lines represent 5% significant levels. Nine dashed lines represent weighted quantiles from 10th to 90th, and a red solid line represents weighted mean.

upward regular price revisions and the frequency of sales, are significantly correlated with the macroeconomic environment like the indicators of labor market. Let us look panels in order. As for the frequency of upward regular price revisions, it tends to be higher when the macro economy is in a good shape: the unemployment rate is low; total hours worked, the new job openings ratio to applicants, and the index of industrial production are high; the leading index, the coincident index, and the lagging index are high. CPI and the consumer confidence index, and monetary base are insignificantly correlated with the frequency of regular prices up. As for the the frequency of downward regular price revisions, no macro indicators are significantly correlated, when we look at the weighted mean of micro prices. Such a difference between upward and downward revisions seems in line with Nakamura and Steinsson (2008) and Gagnon (2009), who report that only the frequency of upward price revisions is correlated with the rate of aggregate inflation. However, inconsistent is the fact that the CPI is uncorrelated with the frequency of upward regular price revisions in our data.

With the magnitude of regular price changes, only CPI and monetary base are correlated. When CPI is high or monetary base is large, the magnitude declines, somewhat counter-intuitively. This high correlation makes a contrast with Nakamura and Steinsson (2008) and Klenow and Krystov (2008). Although weak, the unemployment rate and the lagging index seem some correlation with the magnitude. The magnitude tends to decline, when the unemployment rate falls or the lagging index improves.

The frequency of sales increases, when the economy is in a recession. When the unemployment rate rises, hours worked falls, the new job openings ratio to applicants falls, the coincident index worsens, or the lagging index worsens, retail shops tend to offer more frequent temporary sales.[8] That suggests a possibility that sale decision by retail shops is sensitive to the macroeconomic environment. Such significant sensitivity of sales to the macro indicators is opposite to Nakamura and Steinsson (2008) and Anderson et al. (2012), but in line with Klenow and Willis (2007) and Coibon et al. (2012). Although consumer confidence is considered to matter for retail shops' price setting, no significant correlation is observed. Monetary base is uncorrelated with variables associated with frequency. The magnitude of sales discount is uncorrelated with the macro indicators

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[8]This result is robustly observed when we use the window of 1 week following Abe and Tonogi (2010). Moreover, the pattern for the frequency of sales resembles that for the frequency of downward regular price revisions. In other words, the use of 1-week window leads to embedding the components of temporary sales as regular prices.

except for monetary base.

Our analysis is, however, still tentative. It is silent about causality and economic rationale. No structural shock is identified. To understand the relation between micro price dynamics and macro economy more deeply, Sudo et al. (2011) and our subsequent paper are continuing further theoretical and empirical analyses.

5   Concluding Remarks: Three Implications

We have studied micro price dynamics using Japan's POS data and provided mainly five facts. First, posted prices in Japan are ten times as flexible as those in the U.S. scanner data. Second, regular prices are almost as flexible as those in the U.S. and Euro area. Third, heterogeneity is large. Fourth, during Japan's lost decades, temporary sales played an increasingly important role. Fifth, the frequency of upward regular price revisions and the frequency of sales are significantly correlated with the macroeconomic environment like the indicators of labor market.

In concluding the paper, we draw implications for three important issues: Japan's deflation, sticky-price models, and policy effects.[9]

5.1   Japan's Deflation

While the aggregated CPI provides strong evidence of chronic deflation in Japan, what the POS data reveal is the presence of large heterogeneity. Even during Japan's chronic deflation, many prices were revised upward. This suggests the importance of idiosyncratic shocks compared with macro shocks including monetary policy shocks. We also find that asymmetry exists in the tail end. The magnitude of price drops is greater than that of price jumps for the items that exhibited vast changes in their regular prices. This appears coherent with deflation.

One question is why Japan has simultaneously experienced various changes in micro price dynamics such as the rise in the frequency of regular price changes, the fall in the magnitude of regular price changes, the increase in the number of products, the increase in the price elasticity, and the rise in the frequency of sales. Answering this question in a unified model is an important research agenda. As one attempt, Sudo et al. (2011)

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[9]Another issue is the measurement error in the consumer price index. See Abe and Tonogi (2010) and Watanabe and Watanabe (2013).

construct a model where decreased hours worked of households lead to more bargain hunting. This raises the price elasticity, and by observing this, retail shops raise their sales frequency. According to the model, an adverse demand shock during Japan's lost decades is the driving force of the decrease in hours worked, and in turn, the changes in micro price dynamics like the ones stated above.

5.2 Sticky-price Models

The accumulation of empirical works on micro price dynamics refines sticky-price models. Over the past decade, numerous papers have examined the validity of time-dependent pricing models such as Calvo and Taylor, state-dependent pricing models such as menu cost models, and sticky information models, and pointed out both consistent and inconsistent features to the stylized facts of micro price dynamics. In this paper, we do not make detailed discussions, simply encouraging readers to refer to the papers cited in Introduction, because they are good surveys on their own and our findings are mostly in line with them. Table 8 in Klenow and Kryvtsov (2008) and Table 14 in Klenow and Malin (2011) are particularly a clear summary. Any single model does not fit the data, and as Nakamura and Steinsson (forthcoming) argue, simple statistics such as the frequency of price changes is misleading guide to the flexibility of aggregate price level.

Here let us make one remark on the fact that micro prices move more flexibly than standard macro DSGE models assume. This fact is not necessarily contradictory. It is pointed out that high flexibility arises from temporary sales and the quick response to idiosyncratic shocks. In comparison, regular (or reference) prices are sticker, and in response to macro shocks such as monetary policy shocks, prices move more sluggishly. In other words, strategic complementarity is strong for macro shocks and weak for micro shocks. If it is the case, the real effects of aggregate demand shocks may be large, even though micro prices are flexible. Guimaraes and Sheedy (2011) construct a DSGE model with temporary sales and show that the real effects of monetary policy hardly diminish in the presence of sales, because sales are strategic substitutes.

This argument rests on the presumption that temporary sales are orthogonal to macroeconomic developments. Kehoe and Midrigan (2010), Eichenbaum et al. (2011), and Anderson et al. (2012) as well as Guimaraes and Sheedy (2011) are its proponents. On the other hand, this paper and Sudo et al. (2011) suggest the opposite possibility, that is, the frequency of temporary sales is influenced by macro business cycles. Klenow

and Wills (2007) and Coibon et al. (2012) provide similar evidence. If so, the real effects of monetary policy may be small.

5.3 Policy Effects

Finally, we discuss policy implications. As for monetary policy, the Bank of Japan's standard instrument has diminished its role due to the zero lower bound of nominal interest rates. It led the Bank of Japan to quantitative easing or unconventional monetary policy. This April new Governor Kuroda initiated Quantitative and Qualitative Monetary Easing policy, announcing the increase in government bond purchases twice in two years and the extension of their maturity from three to seven years. This aggressive monetary accommodation was intended to increase the inflation rate to the target of two percent with a time horizon of about two years. Immediately responding to the policy, stock prices boosted, the currency depreciated, and confidences improved.

Its effect on the inflation rate remains to be seen. Despite the improvement in the consumer confidence survey from the late 2012 to the early 2013, it has insignificant correlations with micro price dynamics, as was shown in Figure 4. Monetary base, which is expected to increase twice, also has insignificant correlations with frequencies both for regular price revisions and temporary sales. Sustainable economic recovery that activates the labor market may play an important role in raising the inflation rate up to the target by increasing the frequency of upward regular price revisions and decreasing the frequency of temporary sales.

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