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Micro Price Dynamics during Japan's Lost Decades

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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, the heterogeneity of frequency and size of price change across products is sizable and maintained throughout the sample period. Fourth, during Japan’s lost decades, temporary sales have played an increasingly important role in households’ consumption expenditure. Fifth, the frequency of upward regular price revisions and the frequency of sales are significantly correlated with the macroeconomic environment in particular indicators associated with a labor market while other components of price changes are not.

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

JEL classification: E31
Notes: The POS is obtained from the POS data. CPI (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. We employ daily scanner or Point of Sales (POS) data from 1988 to 2013 covering over 6 billion records and examine how firms’ price setting has changed over these twenty years; report similarities and differences in micro price dynamics between Japan and the rest of the world; and draw implications for economic theory as well as policy.

This paper provides 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 records about 15% of the products. Second, regular prices are as flexible as those in the U.S. and Euro area. The monthly frequency is around 20%. Third, the heterogeneity of price dynamics across product is substantial and such heterogeneity is maintained. Even under the era of deflation, price has risen for a large number of products and fallen for other products. Asymmetry is observed particularly in the tail end. That is, the magnitude of price drops is greater than that of price jumps for the products that exhibited vast changes in their regular prices during the period. Fourth, temporary sales have played an increasing important role in households’ consumption goods expenditures. They have become more frequent and a ratio of sales sold at the sale price to total sales has augmented in current years. Alongside the number (variety) of products and the price elasticity of consumers’
demand have also increased. Fifth, the frequency of upward regular price revisions and
the frequency of sales are significantly correlated with the macroeconomic environment
including the indicators of the labor market while other components of price changes
are not. 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
conducted by Mackowiak and Smets (2008), Klenow and Malin (2011), and Nakamura
and Steinsson (2013), although Japan’s case is not discussed in details.

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) that employ the same POS data as ours though our
data set is longer than theirs by recent seven years. In addition, the two papers differ
in terms of sales filter and the fact that we explore 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

We employ the POS data collected by Nikkei Digital Media from retail shops located in
Japan. The data are daily ranging from March 1, 1988 to February 28, 2013, excluding
the sample of November and December in 2003. The data consists of records that
amounts to 6 billion and each record contains a number of units sold and sales in yen
for a product \( i \) at a shop \( s \) on a date \( t \). The cumulative number of products appearing
during the sample period is 1.8 million. The data includes processed food and domestic
articles, and unlike CPI, does not include fresh food, recreational durable goods (TVs and PCs), and services (rent and utility). The coverage of the POS in CPI is 170 out of 588 items, which constitutes 17% of household's expenditure according to Family Income and Expenditure Survey. Each product $i$ is identified by 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.

Three advantages are noteworthy regarding our POS data. First, they include quantity information as well as price information. Second, the data frequency is daily, contrasting to the US scanner data that is weekly. Third, they have a long sample period, starting from 1988 up until now, which fully covers the period of lost decades. Table 1 provides the summary statistics. The number of sampled retail shops has increased, reaching 261 in 2012. The number of products has also increased, from 130,000 in the early 1990s to 350,000 in 2012. As shown in Figure 2, this trend increase was robustly observed even when the sampled shops were fixed, suggesting the increase in variety of products and the shortening of product cycles during the sample period.

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

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.
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.\footnote{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.}

As a benchmark, we follow Eichenbaum, Jaimovich, and Rebelo (2011) and define the regular price of a good on a date by the most commonly observed price (mode price) during the 3 months centered on the date.\footnote{They call it a reference price instead of a regular price.} 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 length 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 3 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 3 times in 4 years. The number of units sold occasionally jumps by thousand times.

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\*Figure 3: Price Changes of a Cup Noodle at a Store*
2.3 Aggregating Micro Prices

We below examine various aggregated variables such as the aggregated price index constructed from the POS. As we apply the same aggregation methodology in the rest of the paper unless otherwise noted, we lay out here how we calculate them. First, at the lowest level of JAN codes, we obtain a variable of interest, such as a price, 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. 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 $t$ is January 1, 2012, for instance, we use the sales of January in 2011 as a weight.

2.4 Comparison with official CPI

Figure 1 illustrates the yearly growth rate (%) of the POS price index (POS-CPI) together with that of official CPI. The POS-CPI series is calculated as the monthly Tornqvist index where a weight used for aggregating each good at each store is the average of the corresponding sales share during the month in the current year and 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. The depicted CPI series consists only of processed food and domestic articles for the comparison purpose.

The POS-CPI exhibits similar developments as CPI. After experiencing positive inflation in the early 1990s, they both entered into the period of prolonged deflation until 2008 when commodity prices surged. A distinct difference of the POS-CPI from the CPI is observed in its fast decline in the years from 1992 to 1994 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 dominant in the economy, their relation is considered to be negative. Its slope indicates

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4See Watanabe and Watanabe (2013) for details.
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 increasingly price sensitive.
3 How Sticky are Prices?

In this section, we document stickiness of micro prices by analyzing the two disaggregated components: 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 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 at $t$ differs from that on the previous date at least by 3 yen.\footnote{The reason behind setting the criteria of 3 yen is that a unit price computed from the sale revenue divided by the number of unit sold may otherwise become non-integers reflecting time sales within a day and/or buy-one-get-one-free sales. In addition, the consumption tax plays a certain role. When a household purchases a basket of several products and Nikkei Digital Media reports the corresponding sales excluding the consumption tax by dividing sales by the tax rate, a unit price of each product is likely to be non-integer. Moreover, in April 2004, consumption tax inclusive pricing was introduced, requiring retail shops to post prices including the consumption tax. That statutory change increased the possibility of decimal prices. See also Eichenbaum et al. (2013) for related discussion.} Second, we aggregate the frequency of price changes across products and shops following the aforementioned method. When price data on a certain date are missing due to zero transaction, we assume that its price is the same as that on the last date when transaction is present.

Table 2 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 comparable with that in the most of previous studies. Klenow and Malin (2011) provide the extensive international comparison regarding price stickiness. As for the use of scanner data, several studies exist in the United States and 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%. In Japan, the frequency is 23% according to Higo and Saita (2007). The frequency in high-inflation developing countries such as Brazil, Chile, and Mexico tends to be higher, around 30 to 50%. In contrast to these studies, Abe and Tonogi (2010) report higher frequency: monthly frequency amounts to 80% for regular prices from 2000 until 2005. As we discuss below, such a difference, despite the usage of the same POS data as ours, may have arisen due to the difference in the window length that is adopted in calculating the mode price: we use 3

\footnote{The reason behind setting the criteria of 3 yen is that a unit price computed from the sale revenue divided by the number of unit sold may otherwise become non-integers reflecting time sales within a day and/or buy-one-get-one-free sales. In addition, the consumption tax plays a certain role. When a household purchases a basket of several products and Nikkei Digital Media reports the corresponding sales excluding the consumption tax by dividing sales by the tax rate, a unit price of each product is likely to be non-integer. Moreover, in April 2004, consumption tax inclusive pricing was introduced, requiring retail shops to post prices including the consumption tax. That statutory change increased the possibility of decimal prices. See also Eichenbaum et al. (2013) for related discussion.}
months while they use 1 week.

Next, we turn our attention 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 is attributed to factors other than the window length including weights for aggregation, data samples, the treatment of missing price data, and the treatment of decimal prices. Regarding the third point, while Abe and Tonogi (2010) is unclear, if they omit missing price data, it yields a higher frequency of price changes than our method. Regarding the last point, Abe and Tonogi (2010) round prices to the nearest integer while we identify a price change when the price is different from its previous observation by 3 yen. Irrespective of such differences 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.

Last, 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 6 displays time-series developments in the frequency of regular price changes for upward price revision and downward price revision. In order to underscore the heterogeneity across products, for each period, we compute the distribution of frequency across products that are aggregated up to 3-digit code items and depict the time path for different quantiles. 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. First, developments in frequency are not mono-

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6Around April 2004, a big bump is observed due to the statutory change about consumption tax.
Table 2: Frequency of Price Changes

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

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

The frequency of price changes increased steadily from the early 1990 until 2004 and decreased moderately thereafter. Second, heterogeneity across products is sizable. Even under a deflation period, a large number of products increased their prices. The distribution of frequency across products did not change 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.

### 3.2 Magnitude of Price Changes

Next we calculate the magnitude of price changes when prices are revised. Here we focus on regular prices. Figure 7 illustrates time-series developments in the magnitude of regular price changes for different quantiles.

Three results are worth noting. First, the magnitude of regular price changes is roughly 15 to 20% on average, which is in line with the past studies. Second, the magnitude of price change has been monotonically decreasing over two decades until its growth rate became almost zero in 2004. As we found above, the frequency of price change has steadily increased until 2004. Other things being equal, such development in frequency together with the decreasing magnitude of price change seems to be consistent with the
implication of a menu cost model that relates a small and frequent price change with a small menu cost. In year 2004 and beyond, the frequency of price changes experienced a decline while the magnitude of price changes was stable, implying that changes in economic environments other than menu cost, such as realizations in marginal cost may have occurred then. Third, asymmetry in the tail end of the distribution plays an important role in regular price dynamics. That is, over the sample period, the magnitude of regular price decline of low-quantile product has been greater (roughly 25 to 30%) than that of regular price rise of high-quantile product (roughly 20 to 25%), contributing to the deflationary price movements.

### 3.3 Relation between Frequency and Magnitude

A number of existing studies emphasize the importance of the relationship between the magnitude and the frequency of price for better understanding of price dynamics. A negative relationship may imply that different items face a different size of menu cost and a similar size of idiosyncratic shocks.\(^7\) Items that entail large (small) nominal rigidity in changing prices exhibit both low (high) frequency and large (small) magnitude. On the other hand, a positive relationship may imply that different items face a similar size of nominal rigidity and a different size of idiosyncratic shocks. Items that face

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\(^7\)Wulfsberg (2009) finds a negative relationship between the frequency and the price change in Norwegian data.
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.

larger (smaller) idiosyncratic shocks change their prices more (less) frequently by a larger (smaller) size.

In Figure 8, we plot a scatter plot across items in the 3-digit codes for the frequency and the magnitude. The correlation coefficient is insignificant. However, if we take a closer look at the graph, a U-shape relationship seems to be present. For items with low frequency, the magnitude is large, suggesting that these items entail large menu cost. For the item with intermediate size of frequency, the magnitude is small, and for the item with high frequency, the magnitude is large. This implies that these items face with large idiosyncratic shocks.

3.4 Temporary Sales

Now we turn our attention to temporary sales. Figure 9 shows time-series of 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 revenue sold at the sale price to total sales revenue in a month (%). All variables are depicted in weighted mean.

This figure suggests that temporary sales have become increasingly important in households’ expenditure activity during the two decades. The frequency of sales has risen from 15 to 25%, indicating that temporary sale take places once in four days in current years. The revenue coming from the temporary sale has reached 30% of total
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.

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.
Table 3: Window Length and Frequency of Regular Price Changes

<table>
<thead>
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<th>Window</th>
<th>1988-1999</th>
<th>2000-2013</th>
</tr>
</thead>
<tbody>
<tr>
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<td>median</td>
<td>mean</td>
</tr>
<tr>
<td>3 months</td>
<td>15.9</td>
<td>15.2</td>
</tr>
<tr>
<td>1 week</td>
<td>65.6</td>
<td>74.3</td>
</tr>
</tbody>
</table>

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

Sales during the 2000s, compared with 20% in the 1990s. While the ratio of quantities sold at the sale price to those at the regular prices has been around 1.6 during the 2000s, smaller than 2.0 during the 1990s, the impact of the quantity variable on the expenditure is dominated by the increase in the sales frequency. Parallel to the increase in the frequency, the magnitude of sales discount has shrunk from 20% to 14%.

3.5 Robustness in Measuring Frequency

Our regular price looks far stickier than that reported in Abe and Tonogi (2008). To investigate its reason, following their method we use the window length of 1 week to calculate the mode price as a proxy for a regular price. Table 3 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.

Clearly, determining the appropriate filter is beyond the scope of our paper. It is important to point out, however, that the estimated regular price components may suffer from measurement errors in case that short window is applied to the price series for which the corresponding sale lasts long. Under the window of 1 week, the general features of Figures 6 are maintained, but the frequency of regular price changes exhibits clearer upward trend, indicating the trend increase in the frequency of temporary sales is reflected in the estimated regular price frequency.

Another important issue in measuring the frequency of price change is time scale. Our data are daily, while the US scanner data are weekly and the CPI is monthly. Such time-scale differences may yield differences in the measured frequency. To check this, following Abe and Tonogi (2008), we take prices on one representative date, that is, on the Wednesday of the week that includes 15th day of the month, so as to be consistent

\[8\] Admittedly, when window is substantially longer compared with length of sales in actual practice, then the estimated regular price component may also include measurement errors through the same mechanism.
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.

with the official CPI. Figure 11 illustrates the result. Each line represents the frequency of price changes in each time scale. For example, the “quarterly” represents the quarterly frequency of price changes.

This figure illustrates that as prices are recorded more frequently, the frequency of price changes increases. In the recent few years, frequencies are about 0.2 daily, 0.25 weekly, 0.3 monthly, 0.4 quarterly, and 0.5 yearly. Transformed to monthly frequencies, they amount to about 600% for daily data, 100% for weekly data, 30% for monthly data, 13% for quarterly data, and 4% for annual data. In this respect, the time scale is extremely important. Nevertheless, we can continue to argue that Japan’s posted prices are far more flexible than the US’s. For the same weekly time scale, the monthly frequency of price changes is about 100% for Japan, while it is 40% for the United States.

4 Relation between Micro Price Dynamics and Macro Economy

In this section, we ask if Japan’s prolonged stagnation have altered retail shops’ price setting behaviors and price dynamics. In addition to the univariate time series analysis provided above, we examine how micro price components are statistically correlated with the macroeconomic variables. As for the micro prices, we make use of 6 variables
Figure 11: Frequency of Price Changes Measured in Different Time Scale
Note: Each line represents the frequency of price changes in each time scale. For example, the “quarterly” represents the quarterly frequency of price changes.

for 3-digit code items: 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. Among macroeconomic indicators, we focus on 10 variables all expressed in logarithm: the unemployment rate, total hours worked, the new job openings ratio to applicants, the index of industrial production, the monthly growth rate of CPI, the leading index, the coincident index, the lagging index (these three are the components of Composite Indexes compiled by Cabinet Office), the consumer confidence index, and monetary base. The CPI series is constructed from the same item as those of micro prices. We then distill the business-cycle components with a period of 1.5 to 8 years using the Baxter-King band pass filter and compute contemporaneous correlations for 3-digit code items.\(^9\) Figure 12 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 upward regular price revisions and the frequency of sales, are significantly correlated

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\(^9\)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 12: 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.
with the macroeconomic environment like the indicators of the 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. The CPI inflation rate is also correlated with the frequency of upward regular price revisions positively. The consumer confidence index and monetary base are insignificantly correlated with the frequency of regular prices up. As for the frequency of downward regular price revisions, a smaller number of 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 inflation rate is correlated with both the frequency of upward and downward regular price revisions.

With the magnitude of upward regular price changes, the CPI inflation rate and monetary base are correlated. When the CPI inflation rate is high or monetary base is large, the magnitude declines, somewhat counter-intuitively. This is probably understood in combination with the previous result on the frequency of regular price revisions. When the CPI inflation rate rises, regular prices are revised upward more frequently, which contributes to smaller incremental adjustment of prices. Such a significantly 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 temporary 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. 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 contrasts with Nakamura and Steinsson (2008).

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10 This result is robustly observed when we use the window of 1 week following Abe and Tonogi (2010). A difference is observed for the frequency of downward regular price revisions. It comes to resemble that for the frequency of sales. In other words, the use of 1-week window leads to embedding the components of temporary sales as regular prices.
and Anderson et al. (2012) and is 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 except for monetary base.

Our current analysis is, however, still tentative as it is silent about causality and economic rational behind the correlation. To better understand the relationship between micro price dynamics and macroeconomic environments, Sudo et al. (2011) and our subsequent paper conduct further theoretical and empirical analyses.

5 Concluding Remarks: Three Implications

In this paper, we have studied micro price dynamics using Japan’s POS data and provided 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 across product 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 including the indicators of labor market.

In concluding the paper, we draw implications of our findings for three important issues: Japan’s deflation, sticky-price models, and policy implications.\textsuperscript{11}

5.1 Japan’s Deflation

While the aggregated CPI exhibits deflation in Japan, the analysis of POS data displays the presence of a large heterogeneity across products. Even during Japan’s chronic deflation, many prices were revised upward, indicating the importance of idiosyncratic shocks compared with macro shocks in explaining price dynamics. This is in line with existing studies such as Boivin et al. (2008) who discuss that on average only 15% of price variations is accounted for by macroeconomic shocks.

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

\textsuperscript{11}Another issue is the measurement error in the consumer price index. See Abe and Tonogi (2010) and Watanabe and Watanabe (2013).
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) construct a model where household allocates time endowment between working, bargain hunting, and leisure. When households spend more time for cheaper products, the price elasticity rises and retail shops increases their sales frequency.

5.2 Sticky-price Models

As stressed in Nakamura and Steinsson (forthcoming), the current accumulation of empirical works on micro price dynamics has substantially helped developments of sticky-price models, revealing a number of features of price setting in practice that have not been known among the macroeconomists such as cross-product heterogeneity of price dynamics. Along this line, existing studies have examined the validity of time-dependent pricing models such as Calvo and Taylor model, state-dependent pricing models, and sticky information models, by asking the consistency of their models’ implications with the observed micro price dynamics. This paper does not explore these issues in details since there are ample studies that provide related discussions and our findings are mostly in line with theirs. In particular, Table 8 in Klenow and Kryvtsov (2008) and Table 14 in Klenow and Malin (2011) comprehensively summarize the recent developments of the literature.

Here let us make two remarks on the fact that micro prices changes more flexibly than standard macro DSGE models need to assume so as to yield plausible price sluggishness in response to shocks that is observed in the macro data. The first concerns heterogeneity. As is discussed in Golosov and Lucas (2007), this fact is not necessarily contradictory if idiosyncratic shock is embedded in the model. Observed heterogeneity across products illustrated in Figures 6 and 7 are consistent with their view.

The second concerns temporary sales, whose importance has increased in retail shops’ selling activities. In the presence of temporary sales, endogenous responses of retail shops to exogenous shocks may emerge as compositional changes between regular and temporary sales, leaving regular price relatively irresponsive. Regarding the role of temporary sale in macroeconomic dynamics, 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. Their argument rests
on the presumption that choice of temporary sales is orthogonal to changes in 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 Implications

Finally, we discuss implications of the current study to economic policy implementation including monetary policy. Since the latter half of the 1990s, the Bank of Japan’s standard instrument has diminished its role due to the zero lower bound of nominal interest rates. Under such an economic environment, the Bank of Japan has undertaken the quantitative easing and/or unconventional monetary policy. This April, new Governor Kuroda initiated Quantitative and Qualitative Monetary Easing policy, announcing the increase in government bond purchases twice within two years and the extension of the maturity from three to seven years. Such aggressive monetary easing intended to bring the inflation rate to the target of two percent with a time horizon of two years. Immediately responding to the policy, stock prices has boosted, the currency has depreciated, and confidences have improved.

Despite such improvement of sentiment in households and investors, the policy effect on the inflation rate is yet to be seen. According to the analysis above, households’ confidence and/or monetary base are not positively correlated in statistically significant manner with the dynamics of price components when considered in a short horizon. Instead, a full-fledged economic recovery that is accompanied by tight labor market conditions and higher production activities is likely to launch the positive movements of price dynamics.

References


