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Micro Price Dynamics during Japan's Lost Decades

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Keywords

Lost decade; deflation; temporary sales; regular prices; scanner data; price stickiness

JEL Classification

E3, E31, E5

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Micro Price Dynamics during Japan's Lost Decades

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1 Introduction

Since the asset price bubble went bust in the early 1990s, Japan has gone through so-called lost decades, experiencing 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 (2009), 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 consist 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 include 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 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. The sample of retail stores spreads across Japan, but it is biased to relatively large stores. According to Abe and Tonogi (2010), even small stores have 2,000 customers a day.

This POS data is useful tool to obtain better understanding of the linkages between macroeconomy and price dynamics, such as possible reasons for sluggish response of aggregate prices to macroeconomic shocks. For instance, Blanchard (1987) shows that individual price adjusts quicker than aggregate price and argues that aggregation bias may be an explanation for the inertia in aggregate price dynamics. Recent study by Boivin et al. (2008) investigate monthly series of prices for products that are disaggregated to the item level of Personal Consumption Expenditure (PCE) and demonstrate that the disaggregated prices respond quickly to idiosyncratic shocks that are specific to each product and respond sluggishly to macroeconomic shocks. They also show that the bulk of disaggregated price variations are attributed to idiosyncratic shocks. From this perspective, POS data contains time series of prices measured in higher frequency and for more disaggregated products compared with official statistics. It also provides ample room for decomposing each price variation in details into various subcomponents, such as temporary sale prices and regular prices, frequency of price change and magnitude of price change, and upward price changes and downward price changes.

Two advantages are also noteworthy regarding our POS data. First, the data frequency is daily, contrasting to the US scanner data that is weekly. Second, they have a long sample period, starting from 1988 up until now, which fully covers the period of lost decades. See Imai and Watanabe (2014) for 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 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]

[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.

As a benchmark, we follow Eichenbaum et al. (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. Temporary sales are identified when the regular price differs from its posted price. We will discuss issues concerning the identification of regular and sale prices in Section 3.3. Here let us just point out two alternative methods. Abe and Tonogi (2010) use a similar method with an alternative mode of one week. Nakamura and Steinsson (2008) conduct a sale filter that makes use of V-shaped patterns to identify sales prices.

Figure 3 depicts a typical pattern of daily price and quantity changes for a certain brand of cup noodle at a certain store at a sampled store. Posted prices are flexible reflecting the presence of temporary sales. Regular prices are revised only 3 times in 4 years. The number of units sold on a day occasionally jumps up by thousand times from that on a previous day.

In this paper, we construct various aggregated variables including the aggregated price index using the POS and examine their time series properties. To do the aggregation, we first obtain a variable of interests, such as a price, for a product i at a shop s on a date t at the lowest level of JAN codes. Second, we aggregate the variables of interests across shops with sales weights to derive weighted mean.[2] Third, up to the 3-digit code level, we aggregate the weighted means across products with sales weights to derive weighted mean. Last, we aggregate the weighted means across 3-digit codes with sales weights to derive weighted mean or weighted median (quantile). Weights are defined by the sale 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. The same construction methodology is applied unless otherwise noted.

Figure 1 illustrates the yearly growth rate (%) of the POS price index (POS-CPI) together with that of official CPI.[3] The POS-CPI series is calculated as the monthly Tornqvist index. Here the 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 in the previous year. The annual inflation rate is measured as a weighted geometric mean of posted price changes from the previous year. For the comparison purpose, we depict a combined series of processed food and domestic articles for official

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

CPI.

The POS-CPI exhibits similar developments as CPI. After experiencing a positive inflation in the early 1990s, they both witnessed a prolonged deflation until 2008 when commodity prices surged. A distinct difference of the POS-CPI from the CPI is its fast decline in the years from 1992 to 1994 following the bust of the asset-price bubble.

2.3 Price Elasticity

An advantage of using the POS data is the availability of both price and quantity series that enables us to investigate their relationships including price elasticity of goods demand. Figure 4 shows a scatter plot for daily quantity changes shown in vertical axis together with corresponding daily price changes shown in horizontal axis for the item of a cup noodle. The slope is clearly negative, which according to the standard theory that assumes supply slopes upward and demand slopes downward, suggests that supply shocks are prevalent in this goods market.

To see how the demand elasticity of price has changed over time, we calculate the slope of quantity changes against price changes for each product and store and then construct the weighted median of elasticities across products and stores. Figure 5 displays an annual time series of the slop series from the mid-1990s up to the current years. The time series possesses a upward trend, indicating that households become increasingly price-sensitive in the current years.[4]

[4] Here, we assume a simple demand and supply structure such as

$$\begin{aligned}\Delta q(t) &= \beta_s \Delta p(t) + \varepsilon_s(t) \\ \Delta q(t) &= \beta_d \Delta p(t) + \varepsilon_d(t)\end{aligned}$$

where β_s and β_d are supply and demand elasticity and $\varepsilon_s(t)$ and $\varepsilon_d(t)$ are supply and demand shock, respectively. Clearly, under the premise that variance structure of demand and supply shocks are maintained throughout the sample periods, changes in the slope, $\frac{\beta_s var(\varepsilon_d)+\beta_d var(\varepsilon_s)}{var(\varepsilon_s)+var(\varepsilon_d)}$, depicted figure is attributed to either changes in demand elasticity β_d or supply elasticity β_s over time. In order to focus on the demand elasticity, we make two adjustments to the data sampling. First, we drop samples when realization of demand shock may be large by making use of the samples in the second and fourth quadrants in the scatter plot. Second, we employ the data of monthly changes for quantities and prices so as to eliminate effects stemming from temporary sales. Price changes below 3 yen are omitted. Because data are monthly, the number of sample for calculating a slope for a year is at most 12. When the number of sample falls below 6, we omit it. Even when we look at daily changes, we confirm a trend increase in price elasticity.

3 How Sticky are Prices?

In this section, we document stickiness of micro prices by analyzing the two disaggregated components of price changes: frequency and magnitude of price changes. The former (latter) represents extensive (intensive) margin.

3.1 Frequency and Magnitude 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.[5] 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 1 displays the frequency of price changes both for posted and regular prices. Regarding the 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 and report that the average monthly frequency of price changes is around 25% for regular prices based on the analysis using scanner data in the United States.[6] By contrast, 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, 3 months and 1 week.

Next, we turn our attention to posted price changes. Posted prices exhibit far higher

[5]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. (2012) for related discussion.

[6]Klewno and Malin (2011) also reports that the frequency of regular price changes for monthly CPI is around 25% as well in the United States. The frequency in the Euro area tends to be lower, ranging 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%.

frequent price changes than regular prices. In 2000 to 2013, average monthly frequency is above 400%; daily frequency is about 15%, that is about a half of the number reported in Abe and Tonogi (2010), which is 850%, for the data from 2000 to 2005. Note that this difference is attributed to factors other than the window length such as weights for aggregation, data samples, the treatment of missing data, and the treatment of decimal prices. For instance, regarding the last point, Abe and Tonogi (2010) round prices to the nearest integer while we identify a price change only when the price deviates from its previous observation by 3 yen. Irrespective of differences between Abe and Tonogi (2010) and ours, however, common finding is that Japan's posted prices change far more frequently than the United States. Based on the corresponding number for the United States reported in Klenow and Malin (2011), which is around 40%, posted prices in Japan are ten times as flexible as those in the United States.

Last, substantial heterogeneity exists across products and a large part of it comes from temporary sales. For instance, 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 of different products 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. Dashed lines represent weighted quantiles of top 10th and 90th, and a solid line represents weighted median.

The figures reveal three things.[7] First, developments in frequency are not monotonic. The frequency 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

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

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 there are some products change their regular prices highly frequently together with 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.

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. 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 the 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.

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.[8] 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 larger (smaller) idiosyncratic shocks change their prices more (less) frequently by a larger

[8]Wulfsberg (2009) finds a negative relationship between the frequency and the price change in Norwegian data.

(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.

3.2 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 a four days in the current years. The revenue coming from the temporary sale has reached 30% of total 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%.

3.3 Robustness in Measuring the Frequency of Price Changes

In this section, we discuss three issues in measuring the frequency of price changes. The first concerns the terminology of our mode price, the regular price. One of our benchmark papers, Eichenbaum et al. (2011) call a price identified as a mode price a "reference price" instead of a regular price since non-mode prices are not necessarily the sale prices: Admittedly, related to this point, 24% of non-mode prices in our data are higher than the mode prices. We maintain the terminology "regular price" throughout the current paper, because we intend to capture general developments in regular price by tracking the movements of mode prices. Our mode-price is, however, conceptually no different from reference price in Eichenbaum et al. (2011).[9]

The second issue is the use of 3-month window length to calculate the mode price as a proxy for a regular price. Our regular price looks far stickier than that reported in Abe and Tonogi (2008). To investigate its reason, we follow their method and use the 1-week window length. Table 2 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. Although determining the appropriate filter is beyond the scope of our paper, we choose 3-month window length because in case that the estimated regular price components suffer from measurement errors when short window is applied to the price series for which the corresponding sale lasts long.[10] Under the 1-week window length, the general features of Figure 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.

The third important issue 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 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.

[9]It is also important to note that we omit the products whose price is higher than regular price from from our analysis.

[10]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.

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 macroeconomic variables. As for the micro prices, we make use of 6 variables 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 complied 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.[11] Figure 12 depicts the correlations between the micro price components and the macro indicators. Dotted 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 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

[11] 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.

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.[12] 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) 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.

[12]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.

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.[13]

5.1 Japan's 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) 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.

Another important observation is made on the timing of economic events: That is, several changes have coincidentally occurred around 1995 when deflation started at the aggregate level. Around the same period, the price elasticity and the frequency of sales started to increase, and the magnitude of price changes started to shrink. While Nishizaki et al. (2014) point out that the decline in productivity is a potential candidate explanation for deflation, existing study such as Hayashi and Prescott (2006) indicates that slowdown in technology growth has taken place in the early 1990s and therefore precedes the deflation by several years. Moreover, existing pricing theories are not determined about the relationship between aggregate technology and behaviors of firms' price setting behaviors, such as frequency and magnitude. It is thus left for future research

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

to examine whether such same timing is a just coincidence or stemmed from a common factor.

At the macro level, Nishizaki et al. (2014) reports the flattening Phillips curve in the current years which may look contradictory with a high and increased frequency of price changes found at the micro level. This is because other things being equal a stylized Calvo-type New Keynesian model predicts the flattening Phillips curve in response to an increased frequency of price changes. One potential explanation to reconcile the two findings is to consider changes in marginal cost structures. For instance, though developments in marginal cost are beyond the scope of our paper, changes in production structure may have caused flattening of Phillips curve even when frequency of price change increases. Explicit incorporation of input-output production structures, a rise in the input share of cheap imported goods from overseas, and an increase in labor supply elasticity, all alter the quantitative relationship between output and marginal cost and may serve as potential candidate explanation for the flattening of the slope of the Phillips curve. In addition, it is plausible that frequency of price change differs depending on the type of shocks hitting the firms. For instance, prices may move more sluggishly to the macroeconomic shocks than to micro shocks as discussed in Boivin et al. (2008).

5.2 Sticky-price Models

As stressed in Nakamura and Steinsson (2013), 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 three 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.

Third, flexible prices at a retailer level do not necessarily mean flexible prices at a household level in the following two respects. An economically important price for household should represent the minimized cost of not consumption expenditure, but unit consumption flow. It embeds not just quantity purchased but also home production at a household level, which is strongly related to endogenous bargain hunting stated above. Another respect is the selection of retail shops. Household optimally chooses where to buy products among neighboring shops. To examine this implication for prices, household data are indispensable and Abe and Shiotani (2014) are a pioneering study in Japan.

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.

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Table 1: Frequency of Price Changes

		1988-1999 median	1988-1999 mean	2000-2013 median	2000-2013 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.

Table 2: Window Length and Frequency of Regular Price Changes

Window	1988-1999 median	1988-1999 mean	2000-2013 median	2000-2013 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.

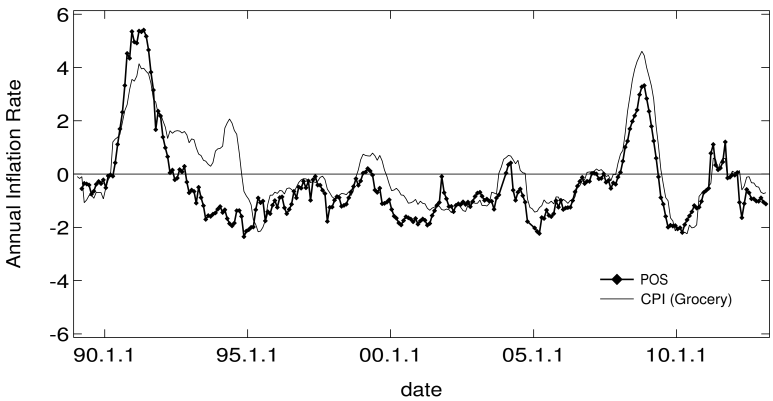

Figure 1: CPI and POS-CPI

Note: 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.

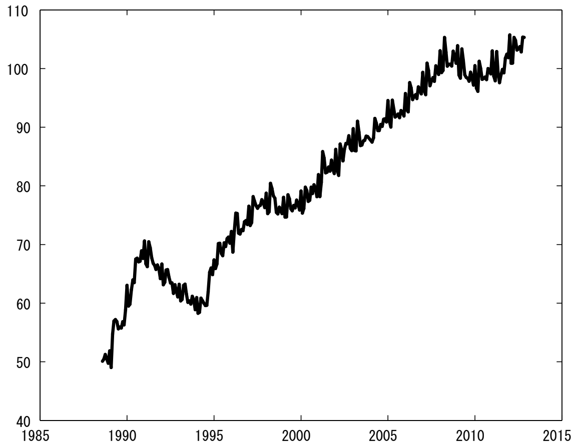

Figure 2: Number of Products Sold at Each Shop
Note: We normalize the number of products in April 2010 as 100.

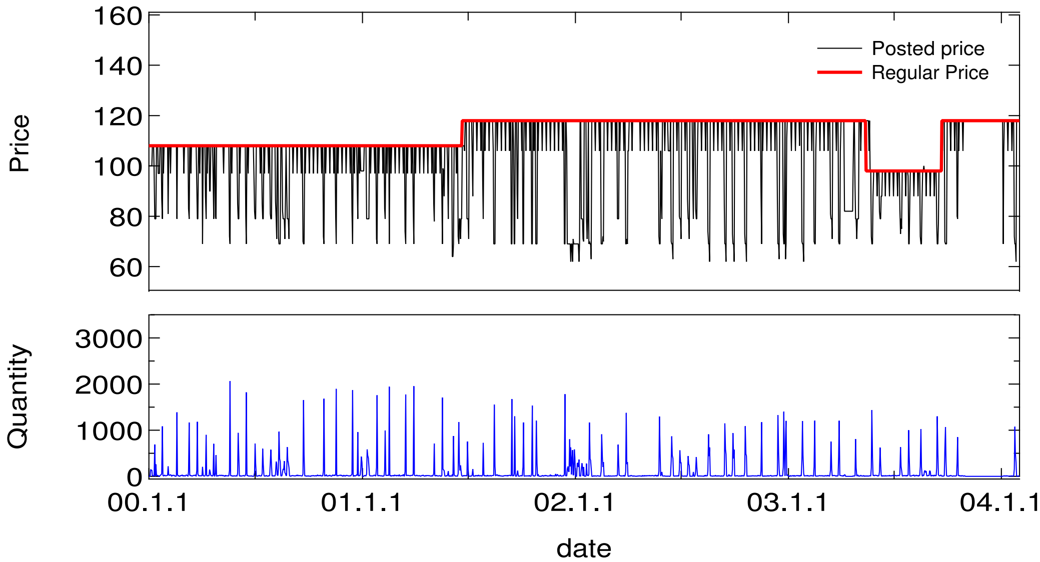

Figure 3: Price Changes of a Cup Noodle at a Store

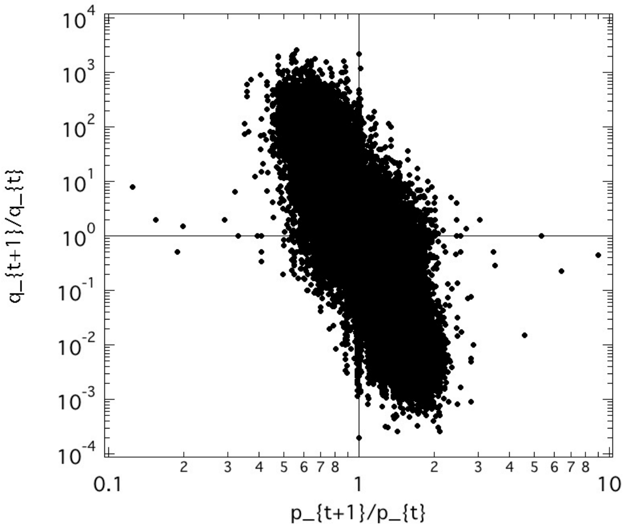

Figure 4: Price Changes vis-a-vis Quantity Changes for a Cup Noodle

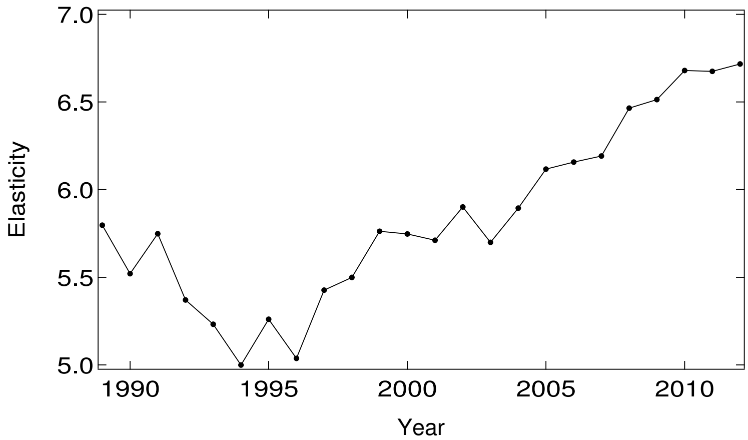

Figure 5: Price Elasticity

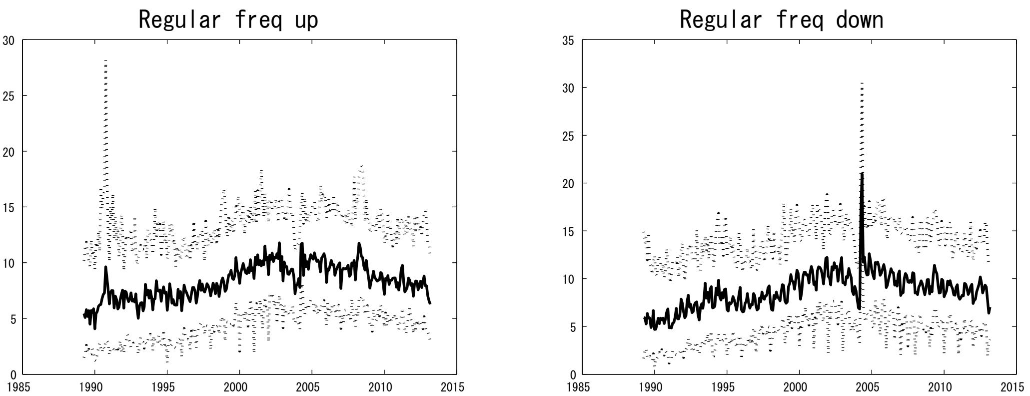

Figure 6: Quantile Developments in the Frequency of Regular Price Changes (Up and Down)
Note: Dashed lines represent weighted quantiles of top 10th and 90th, and a solid line represents weighted median.

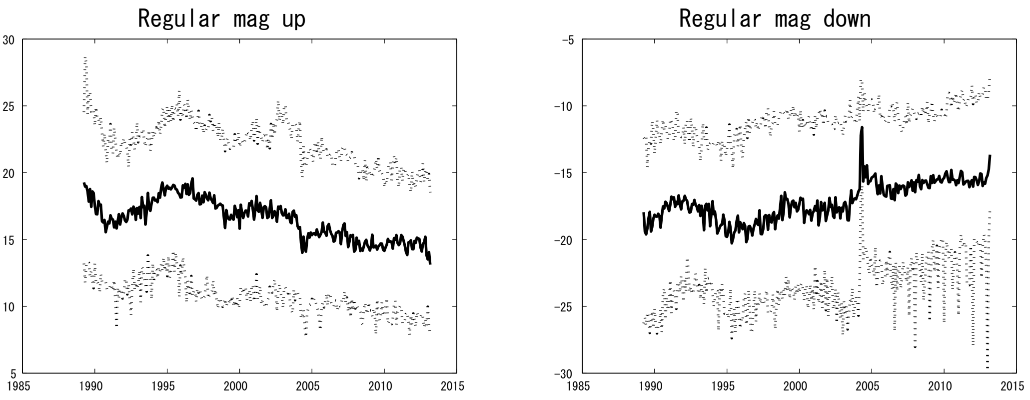

Figure 7: Quantile Developments in the Magnitude of Regular Price Changes (Up and Down)
Note: Dashed lines represent weighted quantiles of top 10th and 90th, and a solid line represents weighted median.

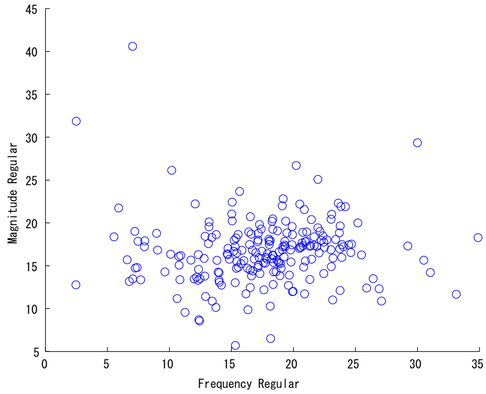

Figure 8: Frequency versus Magnitude of Regular Price Changes

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

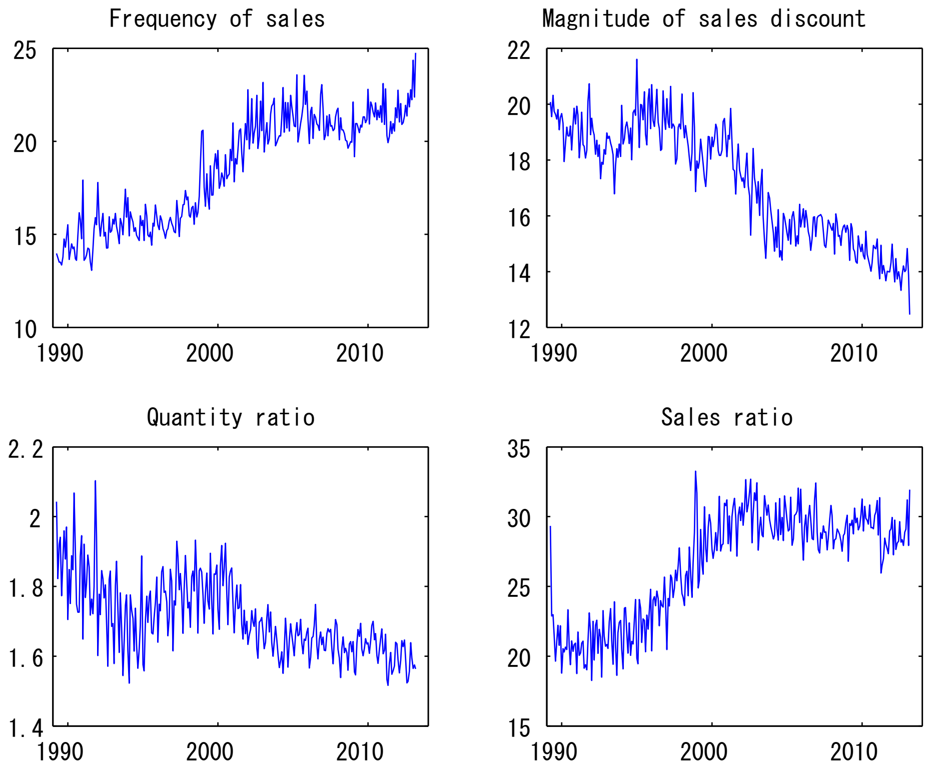

Figure 9: Variables Associated with Temporary Sales

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.

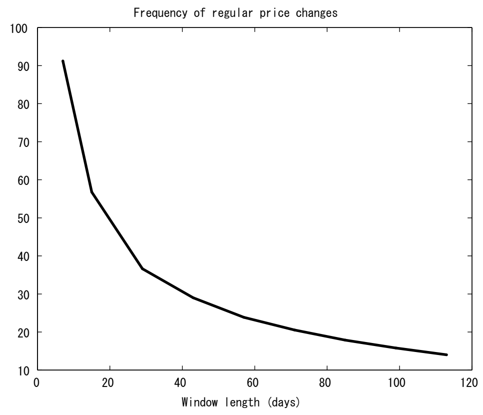

Figure 10: Window Length and Frequency of Regular Price Changes
Note: Monthly frequency (%) is calculated as daily frequency multiplied by 365/12. Samples are from March 1988 to February 2013.

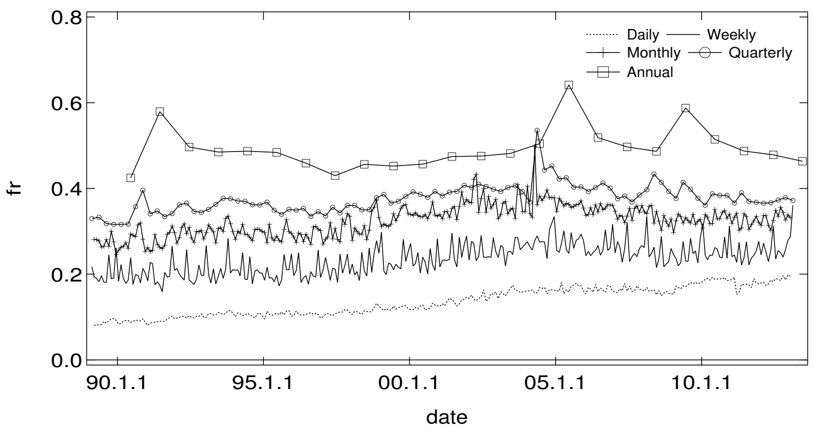

Figure 11: Frequency of Price Changes Measured in Different Time Scale
Note: Each line represents the frequency of price changes in each time scale. For example, the "quarterly" represents the quarterly frequency of price changes.

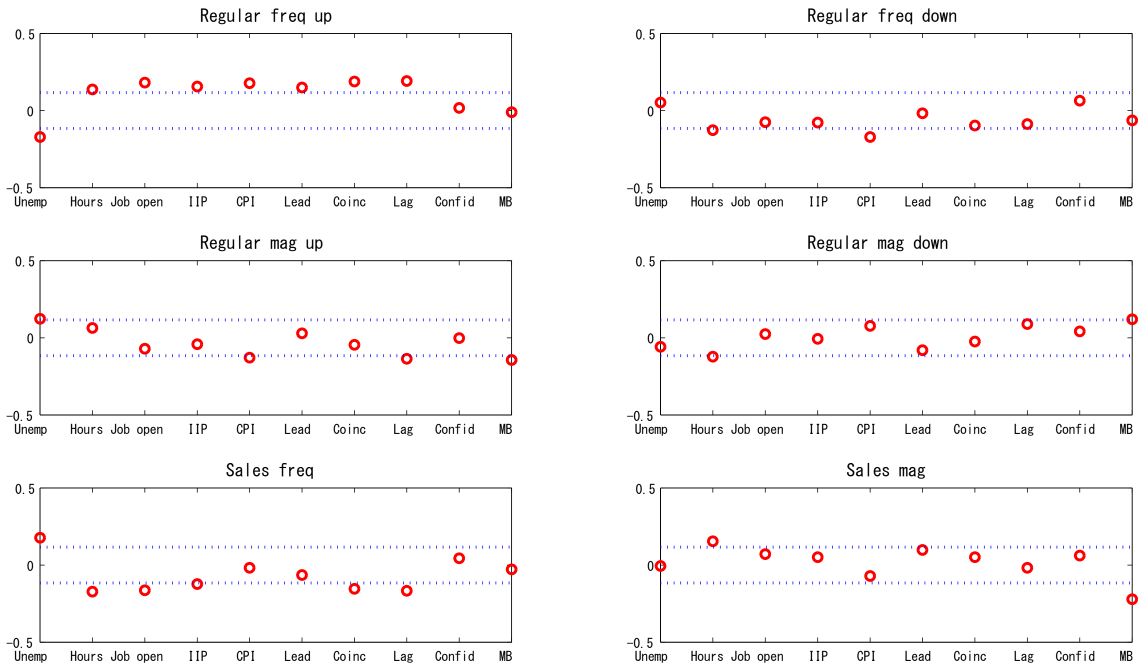

Figure 12: Correlation between Micro Prices and Macro Economy

Note: Correlations between micro price components and macro economy indexes. All series are filtered using the Baxter-King band pass filter. Dotted lines represent 5% significant levels.