Bank of Japan Working Paper Series

Does a Higher Frequency of Micro-level Price Changes Matter for Macro Price Stickiness?: Assessing the Impact of Temporary Price Changes

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No.16-E-9
July 2016

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DOES A HIGHER FREQUENCY OF MICRO-LEVEL PRICE CHANGES MATTER FOR MACRO PRICE STICKINESS?

ASSESSING THE IMPACT OF TEMPORARY PRICE CHANGES[*]

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July 2016

Abstract

Even though prices at the macro level in Japan, like in Europe and the United States, are sticky, individual prices as measured in micro data change frequently. The reason for this puzzle, it has been argued in the context of the United States, is the presence of temporary price changes due to sales and other promotions. In other words, the impact of temporary price changes on the inflation rate is negligible, since some price cuts during sales are cancelled out by other price rebounds from the previous sale prices. The hypothesis thus is that what affects macro-level inflation is not temporary price changes but changes in regular prices, which change only infrequently and hence are responsible for sticky prices at the macro level. We investigate this hypothesis using the micro data underlying Japan's consumer price index (CPI) and find that, in general, that the hypothesis is supported in Japan's case. Unlike in the United States, however, the frequency of temporary price changes has trended upward since the 1990s, so that the impact of temporary price changes on the inflation rate has gradually increased. If this development were to continue, it could lead to greater elasticity of the inflation rate in the future.

Keywords: Phillips Curve; Frequency of Price Change; Running Mode Filter

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[*] The authors would like to thank Kosuke Aoki (The University of Tokyo) and the staff of the Bank of Japan for their helpful comments. Any errors or omissions are the responsibility of the authors. The views expressed here are those of the authors and should not be ascribed to the Bank of Japan or its Research and Statistics Department. The English translation was mostly prepared by Chikako Wakasa.

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I. INTRODUCTION

Price stickiness is strongly associated with firms' price-setting behavior and in standard New Keynesian theory, firms' pricing policies are regarded to be an essential determinant of price stickiness. If prices become less sticky due to a higher frequency of price changes, the inflation rate becomes more responsive to the business cycle and cost changes, and monetary policies will have a greater impact on prices. This means that an accurate understanding of firms' pricing behavior is important when considering the transmission mechanisms of monetary policies. Against this background, numerous studies examining the frequency of price change using micro data have shown that individual prices are changed rather frequently. In contrast, macro-level price movements have been much more sluggish, giving rise inconsistency between the price stickiness assumed in standard macro-level New Keynesian theory and the frequent price changes observed at the micro-level. The present paper seeks to investigate the factors underlying this apparent puzzle.

New Keynesian approaches often rely on the Calvo-type New Keynesian Phillips curve. In a standard Calvo-type model, the relationship between inflation and real marginal costs or the output gap depends on the frequency of price changes by firms. This means that it is possible to implicitly obtain the frequency of price changes by estimating the parameters of this model using macro data. Some studies have examined whether the frequency of prices changes obtained from the macro data is consistent with the frequency of price changes of individual products actually sold at stores by directly counting the number of price changes using micro data that contain changes in individual product prices. Micro data commonly used for such analyses are the source data of the Consumer Price Index (CPI) and Point of Sale (POS) data collected by retail stores.

With more and more studies measuring the frequency of price changes from macro and micro data, there is growing evidence of a discrepancy between the estimates of price change frequencies in the two different types of data. For instance, focusing on the United States and employing estimates based on a New Keynesian Phillips curve using macro data, Galí and Gertler (1999) find that the frequency of price changes was about 6% per month (i.e., an average 6% of firms changed their price every month; put differently, on average firms change their prices about once every 1.3 years). In contrast, Bils and Klenow (2004), using CPI micro data, arrive at a figure of 23% per month (once every 4.3 months), indicating that price changes in micro data appear to be more frequent than calculations based on macro data suggest. Estimation results for Japan show a similar pattern to that of the United States: while studies using macro data estimate the frequency of price changes to be between 4 and 13% per month (once every 8 months to 2.4 years), Higo and Saita (2007), using CPI micro data, arrive at an estimate of 21% per month (once every 4.7 months), a frequency that is about two to five times as high as that suggested by macro data.

How to make sense of this inconsistency in price stickiness has been a subject of intense debate among researchers. The most plausible hypothesis is the temporary nature of price changes.[1] In practice, many products are sold at their regular price and, from time to time, at a cheaper sale price. Let us assume that sales take place at different stores at different times, while regular prices change only infrequently. In this case, the frequency of price changes at the micro level will rise with the number of sales. However, at the macro level, price reductions during a sale and price increases once the sale is over will cancel each other out across retailers and products. Put differently, this hypothesis suggests that macro-level price indexes strongly reflect changes in regular prices, so that the price changes measured based on these indexes show

[1] Another strand of the literature seeks to address the inconsistency by including not only temporary price changes but also real rigidities such as strategic complementarities between firms. While the focus of the present study is temporary price changes, these alternative hypotheses cannot be ruled out. For more details on real rigidities, see Eichenbaum and Fisher (2007).

the frequency of changes in regular prices. Thus, according to this hypothesis, the high frequency of price changes at the micro level is consistent with price stickiness at the macro level.

To examine this hypothesis, Nakamura and Steinsson (2008), using data for the United States, split price changes into those due to sales and those due to changes in regular prices and show that (i) price changes are mostly attributable to sales and that the frequency of changes in regular prices is close to the frequency at the macro level, and that (ii) the correlation between the frequency of price changes due to sales and macro-level inflation is low. Furthermore, based on these observations, they build a theoretical model in which sticky regular prices and flexible temporary sale prices coexist. Meanwhile, empirical analyses by Eichenbaum, Jaimovich, and Rebelo (2011), Kehoe and Midrigan (2015), and Guimaraes and Sheedy (2011) based on theoretical models they construct come to the conclusion that temporary price changes have little impact on price stickiness at the macro level.

However, the conclusions of these theoretical models are based on the implicit assumption that the relative volume of transactions based on flexible sale prices and those based on sticky regular prices remains stable over time. If the frequency of sales increases and transactions based on sale price substantially outweigh those based on regular prices, this may exert downward pressure on the inflation rate at the macro level, since, on an aggregate basis, the price reduction may not be cancelled out by the price rebound once the sale has ended. This implies that the relationship between sales and price stickiness depends on the frequency of sales as well as changes in this frequency. Sudo et al. (2014b) argue in this context if the frequency of sales changes over the course of the business cycle, it is likely that price stickiness at the macro level will also change.

Against this background, the purpose of the current study is to examine the inconsistency in price stickiness on a micro and macro basis levels by focusing on the temporary nature of price changes. We approach this issue by extracting temporary price changes from the micro data of the Ministry of Internal Affairs and Communications' Retail Price Survey (RPS), which provides the source data for the CPI. Since the price survey for the CPI excludes sale prices that last no more than seven days, the effects of sales are excluded to some degree. Conversely, since the price survey includes sales that last more than seven days, this study can be regarded as investigating the impact of somewhat longer sales on the CPI.

The remainder of this study is organized as follows. Section II shows that, in Japan, too, the frequency of price changes observed in micro data is higher than the frequency indirectly obtained from the Phillips curve. Section III presents an overview of theoretical research showing that the discrepancy between the micro- and macro-based frequency of price changes is attributable to temporary price changes. Next, Section IV provides our estimates of the frequency of changes in regular prices and of temporary price changes using micro data. Section V then explores the impact of the frequencies of these price changes on macro-level price stickiness. Section VI concludes.

II. THE FREQUENCY OF PRICE CHANGES IN JAPAN'S CPI

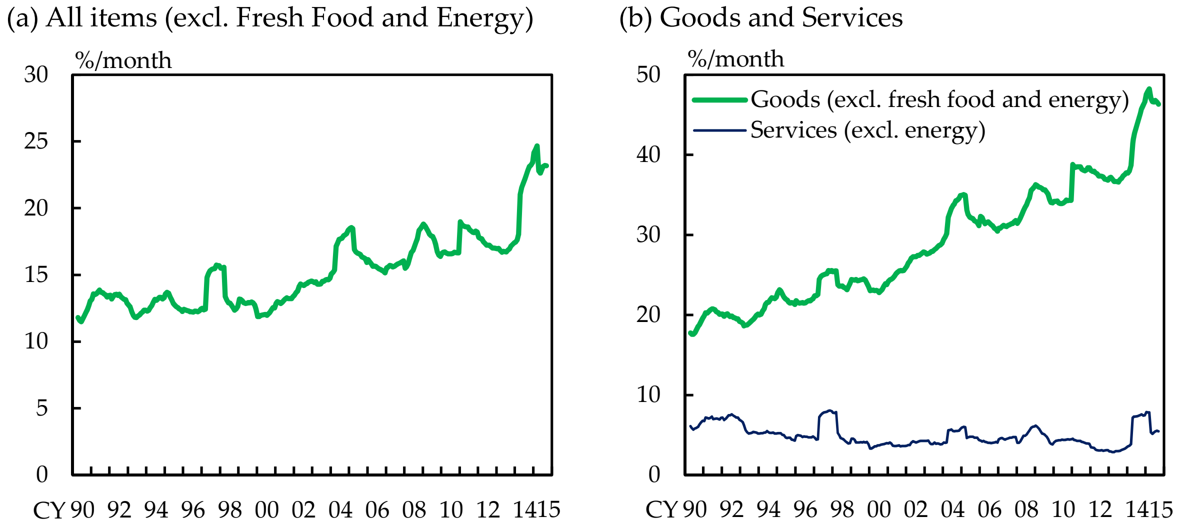
(1) Estimation Results from Micro Data

There are a number of studies examining the frequency of price changes in Japan using micro data either from the RPS or POS data collected at retail stores. An example of a study using the RPS data is that by Higo and Saita (2007), who find that the average frequency of price changes in the period 1999–2003 was 21% (once every 4.7 months) and that the frequency has followed an increasing trend, particularly in the case of goods, since 1995. Figure 1 depicts the frequency of price changes based on the RPS employing the same method as that used by Higo and Saita (2007).[2] As shown in Figure 1(a), the frequency of

[2] For further details on the measurement of the frequency of price changes, see Section IV. The aggregation methods for the frequency of price changes and the inflation rate

price changes on an all items basis (excluding fresh food and energy) has followed a steady upward trend since the 1990s: while the frequency of price changes was 13% per month in 1990 (equivalent to once every 8 months), this rose to 25% per month in 2015 (once every 4 months). This increase is entirely due to the increase for goods, and the frequency of price changes for goods only (excluding fresh food and energy) recently reached almost 50% per month (equivalent to once every 2 months). In contrast, the frequency of the change in prices for services has remained low and essentially unchanged since the 1990s.

Figure 1. Frequency of Price Changes Based on the Retail Price Survey



Notes: 1. The categories are defined as follows (*italics* represent categories used by the Ministry of Internal Affairs and Communications):

All items excluding fresh food and energy: *All items excluding fresh food* less *Energy*.

Goods excluding fresh food and energy: *Goods* less *Electricity, manufactured & piped gas & water charges*, *Fresh food* and *Petroleum products*.

Services excluding energy: *Services* plus *Electricity, manufactured & piped gas & water charges*, less *Electricity* and *Gas, manufactured & piped*.

The same definitions apply to the figures and tables below.

2. Figures are 12-month averages of the monthly frequency of price changes.

Meanwhile, there are a substantial number of studies using POS data collected by retail stores such as supermarkets and convenience stores. Although POS data cover only such goods as food and daily necessities, the data include a million items and provide observations on a daily basis, so that

are presented in Appendix 2.

they allow a more detailed analysis in terms of the number of products and data frequency. One example of a study using daily POS data covering processed food and household products is that by Abe and Tonogi (2010). They show that the frequency of price changes for these products was extremely high, reaching once every 3.6 days (2000-2005 average). However, when these data were converted to a monthly basis in line with the survey period for the CPI, the frequency of price changes fell to only once every 3.9 months, which is much closer to the frequency observed in the RPS.

(2) Price Stickiness Observed from Macro Data

Measuring the frequency of price changes using a Calvo model

The Calvo-type Phillips curves widely used in New Keynesian theory are based on the assumption that price stickiness at the macro level is determined by the probability that firms change their prices. This means that it is possible to indirectly estimate the frequency of price changes by calculating the structural parameters based on this Phillips curve using macro data. In this section, we employ this approach to compare the estimated frequency using macro data with the frequency observed in micro data. Employing a uniform indicator such as the frequency of price changes in order to gain a rough impression of the consistency of micro and macro data is useful to a certain extent. However, it should be noted that the assumptions underlying standard Calvo-models are extremely simple, so that the comparison here may be misleading if there are other factors than the frequency of price changes that strongly affect price stickiness.

The Calvo-type Phillips curve in the simplest form can be written as follows:

$$\pi_t = \beta E_t \pi_{t+1} + \frac{(1-\theta)(1-\theta\beta)}{\theta} mc_t, \tag{1}$$

where π denotes the inflation rate and mc denotes real marginal costs; both are defined in term of the deviation from steady state. β represents the discount rate and θ the probability of no price change. E denotes the expected value and the subscript denotes the time. Based on this equation, we can obtain the value of $(1-\theta)$, that is, the frequency of price changes, by estimating θ using macro data. Table 1 presents the estimation results of earlier studies employing this method to Japan's CPI. The table shows that estimates of the frequency of price changes range from 4 to 13% per month (equivalent to a price change of once every 8 months to 2 years), with the different results reflecting differences in the estimation equation due to alternative model assumptions as well as differences in the data and estimation period used.[3]

Table 1. Probability of Price Change in Japan Obtained from Phillips Curve Estimates

	Authors	Probability of price change (%/month)	Estimation period	Inflation indicator	Explanatory variables
(1)	Koga and Nishizaki (2006)	12-13	1980/Q1 -2004/Q3	CPI (excl. fresh food)	Inflation rate (lag) Expected inflation rate (lead) GDP gap Real wage gap
(2)	Ichiue, Kurozumi, and Sunakawa (2013)	9	1981/Q1 -1995/Q4	CPI (excl. fresh food)	Inflation rate (lag) Expected inflation rate (lead) Real marginal costs
(3)	Iiboshi et al. (2015)	5-8	1981/Q1 -1995/Q4	CPI CPI (excl. fresh food)	Inflation rate (lag) Expected inflation rate (lead) Real marginal costs
(4)	Sugo and Ueda (2008)	4	1981/Q1 -1995/Q4	CPI (excl. fresh food)	Inflation rate (lag) Expected inflation rate (lead) Real marginal costs
(5)	Kaihatsu and Kurozumi (2014)	4	1985/Q1 -2008/Q4	Private consumption deflator	Inflation rate (lag) Expected inflation rate (lead) Real marginal costs

Note: Figures for the monthly probability of price change are calculated as:
(1 - quarterly probability of no price change)/3.

Following these earlier studies, we estimate the probability of price change for the period 1975-2015, and present the results in Table 2 (see Appendix 1 for

[3] The studies listed in Table 1 implicitly assume indexation. Therefore, the probability of price change is interpreted as the "ratio of firms that optimize their price."

details on the estimation). For the estimation, we expanded the model by adding lagged inflation to equation (1).[4] Moreover, to ensure the robustness of the results, we use a number of proxy variables for real marginal costs. The estimation results in Table 2 are almost identical to those in earlier studies: the frequency of price change was between 5.7% and 9.6% per month (equivalent to a price change of once every 10 months to 1.5 years), with an average of 8.2% per month (equivalent to once a year). With the frequency of price change in the RPS micro data having recently reached 25% per month (equivalent to once every 4 months), it may well be said that the frequency of price change indicated by the Phillips curve is clearly lower.

Table 2. Probability of Price Change in Japan's CPI Obtained from Phillips Curve Estimates

Variable	Probability of no price change (%/quarter)	s.e. (%pt)	Probability of price change (%/month)	Average duration of price change (months)
(1)	74.0 ***	[5.4]	8.7	11.5
(2)	76.9 ***	[29.3]	7.7	13.0
(3)	82.9 ***	[8.8]	5.7	17.6
(4)	71.1 ***	[4.3]	9.6	10.4
(5)	71.6 ***	[3.1]	9.5	10.6
Average of variables (1)-(5)			8.2	12.1

Notes: 1. *** indicates statistical significance at the 1 percent level. For details of the estimation, see Appendix 1. For details of variables (1)-(5), see Table A1-1.
2. Figures for the monthly probability of price change are calculated as: (1 - quarterly probability of no price change)/3.
3. Figures for the average duration of price change are calculated as: 1/monthly probability of price change.

Checking for structural breaks

A number of studies suggest that there are structural breaks in Japan's Phillips. A typical argument is that Japan's Phillips curve has flattened since the burst of the bubble economy and that inflation has become less responsive to changes in the output gap and unemployment rate. For instance, based on the results of a

[4] Although the results are not shown here, we also conducted the estimation without lagged inflation and obtained more or less identical estimates.

sliding window estimation of a reduced-form Phillips curve, Kimura, Kurozumi, and Hara (2008), argue that the parameters for the output gap declined from the 1990s to the mid-2000s. Meanwhile, De Veirman (2009) and Kaihatsu and Nakajima (2015), based on estimations of a reduced-form Phillips curve using a time-varying parameter model, suggest that while the slope of the Phillips curve remained largely unchanged between the second half of the 1990s and 2015, the curve flattened between the second half of the 1980s and the first half of the 1990s. On the other hand, Hara, Hiraki, and Ichise (2015), estimating the exchange rate pass-through from a reduced-form Phillips curve, point out that it was likely that the Phillips curve has become steeper since the second half of the 2000s. In sum, while it seems fair to say that the Phillips curve has become flatter after the 1980s, there is no consensus regarding changes in the Phillips curve between the second half of the 1990s and 2000s.

With regard to the slope of the Phillips curve and the frequency of price changes, the Calvo-type Phillips curve expressed by equation (1) implies that the lower the frequency of price changes is, the smaller the coefficient on real marginal costs and therefore the smaller the slope of the Phillips curve will be. Given this, and following Qian and Su (2014, 2016), we attempt to identify structural breaks in the estimation equation.[5] The results we obtain depend on the variable used, with two suggesting a structural break around 1990 and another two indicating structural breaks in 1995 or 1997. Finally, one result

[5] Qian and Su (2016) propose the following approach for detecting the number of structural breaks and their dates using penalized least squares estimation and for selecting the tuning parameter λ based on information criteria:

$$\min_{\{\beta_t\}} \quad \frac{1}{T}\sum_{t=1}^{T}(y_t - \beta_t' x_t)^2 + \lambda \sum_{t=2}^{T} \|\beta_t - \beta_{t-1}\|$$

$$\beta_t = \alpha_j \text{ for } t = T_{j-1}, \dots, T_j - 1 \text{ and } j = 1, \dots, m+1$$

Here, T_j denotes the date of structural breaks ($T_0 = 1, T_m = T + 1$), while m denotes the number of structural breaks. For the case that the variables are endogenously determined, Qian and Su (2014) propose to first specify structural breaks employing the approach above and then using GMM estimation to obtain the parameters for each regime j.

suggests there was no structural break (Table 3). Among the estimates suggesting a structural break, the probability of price change tended to be lower in the period after the break than before the break. Therefore, like previous studies, the results suggest that the Phillips curve flattened after the late 1980s, although the timing – that is, whether it occurred around 1990 or in the middle or second half of the 1990s - is not necessarily clear. On the other hand, none of the results suggest that changes in the slope started around 2000, meaning that we find no evidence of the kind of steepening of the Phillips curve between the second half of the 2000s and recent years found in some of the other studies.

Table 3. Structural Breaks in the New Keynesian Phillips Curve

Variable	Structural break date	Probability of no price change				Probability of price change	
		Before		After		Before	After
		(%/quarter)	s.e. (%pt)	(%/quarter)	s.e. (%pt)	(%/month)	(%/month)
(1)	1989/Q3	37.0 ***	[11.6]	80.3 ***	[6.6]	21.0	6.6
(2)	1997/Q2	65.6 ***	[14.4]	68.8 ***	[16.9]	11.5	10.4
(3)	1990/Q3	68.2 **	[29.4]	87.8 ***	[19.4]	10.6	4.1
(4)	1995/Q2	63.4 ***	[4.9]	83.3 ***	[8.7]	12.2	5.6
(5)	no break						

Notes: 1. *** and ** indicate statistical significance at the 1 and 5 percent level, respectively.
2. Figures for the monthly probability of price change are calculated as (1 - quarterly probability of no price change)/3.
3. The tests for structural breaks and their dates are conducted using the approach proposed by Qian and Su (2014). The probabilities of no price change before and after the structural break are estimated using the corresponding observation periods.

In practice, factors other than the frequency of price change may affect the slope of the Phillips curve. For example, it is well known that if the kind of simple model represented by equation (1) is expanded, the slope of the Phillips curve is determined by a string of factors such as the price elasticity of demand and the degree of strategic complementarity. Therefore, further examination is needed to determine the underlying reasons for the structural breaks in Japan's Phillips curve. However, rather than investigating this issue in more detail here, we focus on the relationship between the slope of the Phillips curve and the frequency of price changes.

III. TEMPORARY PRICE CHANGES AND PRICE STICKINESS

At first sight, the stickiness of price changes implied by the Phillips curve seems to contradict the highly frequent price changes observed in micro data. To understand how these go together, we posit the hypothesis that the difference is due to differences in the change in regular prices and temporary price changes. In practice, products are usually sold at a regular price, but in addition, they are often also temporarily sold at a sale price -- that is, at a certain discount from the regular price. As mentioned earlier, examining price changes of individual products and distinguishing between price changes due to sales and changes in the regular price, Nakamura and Steinsson (2008) found that sales accounted for the majority of price changes and that, moreover, the frequency of changes in regular prices was low and close to the frequency of price change indirectly measured using the Phillips curve.

The reason is that price reductions due to sales are offset by other price increases due to the end of sales, so that the effects of sales on macro-level price indexes are small and it is changes in regular prices that have a stronger impact on macro-level price indexes. This means that while sales lead to a higher frequency of price change at the micro level, but the frequency of price change measured using macro data is close to the frequency of changes in regular prices.

A number of studies have sought to build theoretical model for this. Eichenbaum, Jaimovich, and Rebelo (2011) present a model in which firms have a "price plan" consisting of a series of prices. Firms can change prices without incurring menu costs provided that this is done within the price plan, while changing the price plan itself involves menu costs. They show that the impulse response of prices to a monetary policy shock calculated from this model is fairly close to the actual response and argue that the frequency of changes in regular prices provides a better representation of price stickiness.

Meanwhile, Kehoe and Midrigan (2015), propose extensions of Calvo and menu cost models in which sticky regular prices and flexible temporary prices coexist and, calibrating these models using U.S. data, measure price stickiness at the macro level. They argue that their extended models successfully reproduce the coexistence of price stickiness at the macro level and frequent price changes at the micro level, showing that even if prices of individual items change frequently, prices at the macro level can still be sticky.

Finally, Guimaraes and Sheedy (2011) divide households into two types: households less sensitive to prices (loyal customers) and those sensitive to prices (bargain hunters). On this basis, they assume an economy in which firms are only allowed to change their regular price with a certain probability; firms can freely offer sales but not discriminate between household types. They show that in this case the optimal behavior for firms is to offer sales on a regular basis. Furthermore, they show that the slope of the New Keynesian Phillips curve depends on the probability of change in regular prices and not on the frequency of sales.

The above findings, however, implicitly assume that the frequency of price reductions due to sales is about the same as the frequency of subsequent price increases back to the original level. If, say, the frequency of sales increases in a certain period so that the frequency of price reductions significantly exceeds the frequency of subsequent price increases, this may act to lower the inflation rate and change price stickiness both at the macro level accordingly. Based on these considerations, Sudo et al. (2014b) extend the model by Guimaraes and Sheedy (2011) to allow the fraction of each type of household to change endogenously depending on the business cycle and show that the frequency of sales may affect price stickiness at the macro level.

IV. Measuring the Frequency of Temporary Price Changes

Based on the discussion in the previous section, we separate the frequency of changes in regular prices and the frequency of temporary price changes using micro data of the Japanese CPI. The estimation results obtained in this section are then used to examine the consistency of such micro-level price changes with price stickiness at the macro level in the next section.

(1) Data

The price data we use are the data from the RPS, which provides the underlying microdata for the CPI. The RPS collects the actual retail prices (including the consumption tax) of 760 items from 167 cities. Of the data collected, price data by item for 81 cities are released on a monthly basis. In the price survey, prices of sales that last no more than seven days are excluded, meaning that the effects of sales lasting only a short period are not reflected in the price data.

Following Higo and Saita (2007), we exclude items with the following two characteristics from our analysis: (i) items for which price data cannot be obtained on an ongoing basis due their seasonality, and (ii) items for which the frequency of price changes cannot be accurately captured due to the large number of stores covered for the item- and city-level price indexes. Our observation period runs from January 1989 to September 2015. Table 4 presents the coverage of our data in relation to the data underlying the CPI (2010 base year). The table shows that on the basis of their weights in the CPI, our data covers 54.6% of all items, with the coverage being 76.7% for goods and 33.0% for services. In terms of the actual number of items, our dataset covers 77.4% of all items in the CPI, with the coverage being 80.5% for goods and 67.4% for services. The reason for the limited coverage of services in our dataset is that many service items in the CPI are compiled without using the RSP, with house rents -- which represent slightly less than 20 percent of the CPI in terms of weight -- making up the largest share.

Table 4. Data Coverage

	Total				
		Goods	Services		
				Public services	General services
Weights	54.6%	76.7%	33.0%	25.8%	35.3%
Number of items	77.4%	80.5%	67.4%	41.9%	78.6%

Note: Figures are calculated based on 2010-base CPI.

We exclude fresh food and energy prices from the analysis. These prices are highly susceptible to day-to-day fluctuations in the prices of commodities such as agricultural products and crude oil, and most of these prices change on a monthly basis. As will be discussed in more detail below, we define regular prices as the most frequently observed price over a period of several months. For this reason, changes in the prices of fresh food and energy prices, which fluctuate on a monthly basis, would all be regarded as temporary price changes rather than changes in regular prices. Therefore, to avoid the bias that would result from this, fresh food and energy are removed from our analysis.

Following Higo and Saita (2007), when measuring the frequency of price change, we treat (i) price changes due to a change in the brand representing a particular item in the RPS and (ii) price changes due to the consumption tax hike as no price change. Prices in months which saw a consumption tax hike are treated as follows: (i) if the month-on-month rate of change fell within ±0.5 percent of the change due to the increase in the consumption tax rate, prices were regarded as having remained unchanged; (ii) in all other cases, the rate of change was calculated by subtracting the change to the increase in the consumption tax hike from the month-on-month rate of change and the result was regarded as the rate of price change due to a price revision. [6] Finally, the aggregate frequency of price changes is obtained by (i) calculating the frequency of price changes for each item by dividing the number of cities in which the price changed by the number of cities covered in the RPS and then (ii) calculating the weighted average using CPI weights of those items.[7]

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[6] The change due to the increase in the consumption tax rate was 3% for April/1989 (=1.03/1.00), 1.94% for April/1997 (=1.05/1.03), and 2.86% for April/2014 (=1.08/1.05).

[7] Since the frequency of price changes tends to be higher for goods than for services, our data for the frequency of price changes in all items is biased upward, because in our data goods comprise a larger weight than in the CPI. In order to correct for this bias, we inflate the weights of service items so that the weights of goods and services match those of the CPI.

(2) Approach for Identifying Temporary Price Changes

To identify temporary price changes in price data, a number of mechanical filters have been developed. The filter we use in this study is the running mode filter (see Appendix 3 for the algorithm). This approach defines the most frequent price over a certain period as the regular price and identifies the difference between the actual price and the regular price as the temporary price change. This is the approach employed by Eichenbaum, Jaimovich, and Rebelo (2011), Kehoe and Midrigan (2015), Chahrour (2011), Sudo et al. (2014a), among others.

Other filters that have been employed in literature include the V-shaped filter (Nakamura and Steinsson, 2008).[8] Stevens (2015) simulates several patterns of price changes and compares the advantages and disadvantages of different filters. He concludes that the running mode filter shows the best performance in terms of identifying the number and duration of changes in regular prices.

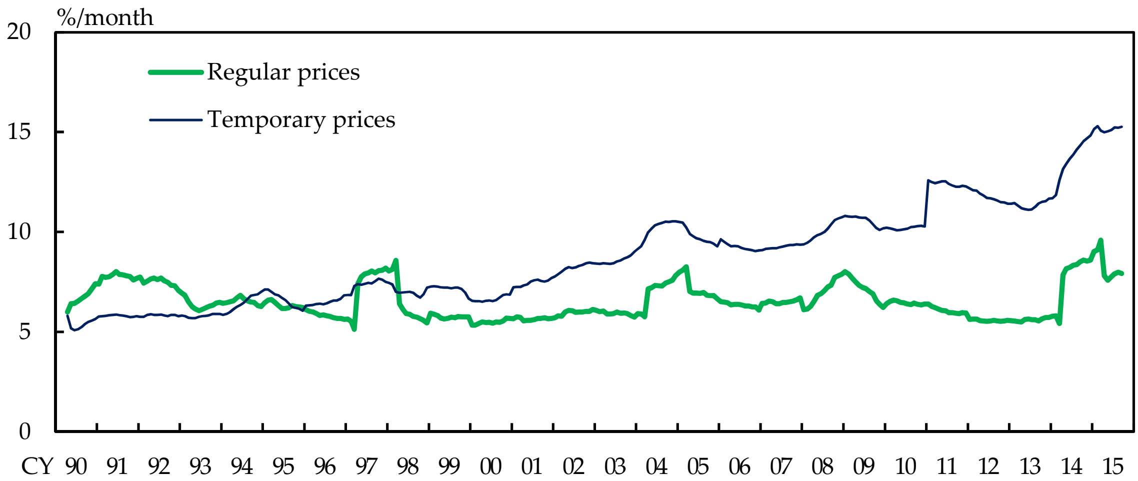
(3) Estimation Results

Figure 2 displays our estimation results using the running mode filter. The figure shows that the frequency of changes in regular prices was about 6.5% per month (equivalent to a change of once every 1.3 years). Since the frequency of all price changes was approximately 25% per month in 2015 (equivalent to a change of once every 4 months), we find that the frequency of changes in regular prices was well below all price changes. The frequency of changes in regular prices has remained almost unchanged since 1990, which contrasts with

[8] In the V-shaped filter, temporary price changes are defined as a temporary price decrease followed by a return to the previous level. This filter derives its name from the fact that price changes form a V-shape around the time of a sale. However, Stevens (2015) argues that the performance of the V-shaped filter is inferior to other filters, since it frequently incorrectly identifies temporary price changes as changes in the regular price.

the uptrend in the frequency for all prices.[9] The key factor behind the upward trend in the frequency of all price changes therefore is the higher frequency of temporary price changes, implying that the frequency of changes in regular prices has remained more or less unchanged over the past 25 years or so. Figure 3(a) indicates that these patterns largely reflect developments in the frequency of price changes for goods. These results are consistent with those obtained by Sudo et al. (2014a), who applied the running mode filter to goods prices based on POS data.[10] Meanwhile, Figure 3(b) showing the results for services indicates that the pattern for regular prices is very similar to that for prices overall, while the frequency of temporary price changes remained low.

Figure 2. Frequency of Changes in Regular Prices



Notes: 1. Figures are for all items excluding fresh food and energy.
2. Figures are the 12-month averages of the monthly frequency of price changes.

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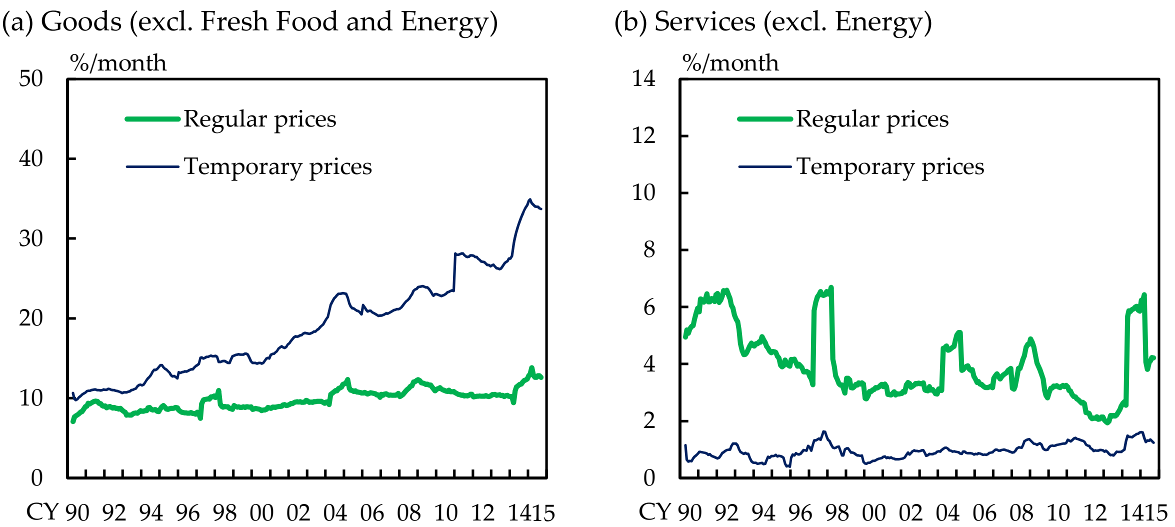
[9] Using again the method by Qian and Su (2016) already employed in Section II, we conduct a test for structural breaks in the frequency of changes in regular prices and find no structural breaks (estimated by regressing the frequency of changes in regular prices on the constant).

[10] Sudo et al. (2014a) show that the frequency of changes in actual retail prices is high (once every 6.2 days) and follows an upward trend, whereas the frequency of changes in regular prices has fallen to once every 5.1 months and does not show any clear trend over the period as a whole.

Figure 3. Frequency of Changes in Regular Prices: Goods and Services



Note: Figures are the 12-month averages of the monthly frequency of price changes.

One factor underlying the higher frequency of temporary price changes in goods is the increase in sales held. While the RPS excludes the prices of sales that last no more than seven days and uses the normal price as a substitute, sales that last more than seven days are included. Higo and Saita (2007) argue that an increase in the frequency of sales lasting more than seven days may have contributed to the increase in the frequency of price change in the RPS. In terms of the theoretical model presented in Section III, a possible interpretation is that the frequency of sales has increased as a result of a rise in the fraction of price-sensitive consumers. On the other hand, Matsuoka (2012), for instance, based on his analysis using POS data, points out that in Japan the higher the competition among manufacturers and retail stores is, the higher is the frequency of sales, suggesting that greater price competition as a result of deregulation such as the Large-scale Retail Store Act as well as the emergence of discount stores were responsible for the increase in temporary sales. Meanwhile, Tonogi (2013), focusing on the relationship between the cost of storing inventories and the frequency of sales, suggests that the reduction in inventories observed since the burst of the bubble economy as part of efforts by firms to improve their profitability may have pushed up the number of sales held. Yet another possible reason for the increase in temporary sales may have to do with the way price data are collected. In 2004, the rules for the selection of survey districts for the RPS were changed, so that stores with a large turnover were more likely to be selected (the number has subsequently increased at a pace of 5-10 prefectures every year). It is possible that these changes, adding more and more stores such as large discount stores that change their prices more frequently, may also have pushed up the measured frequency of price changes.

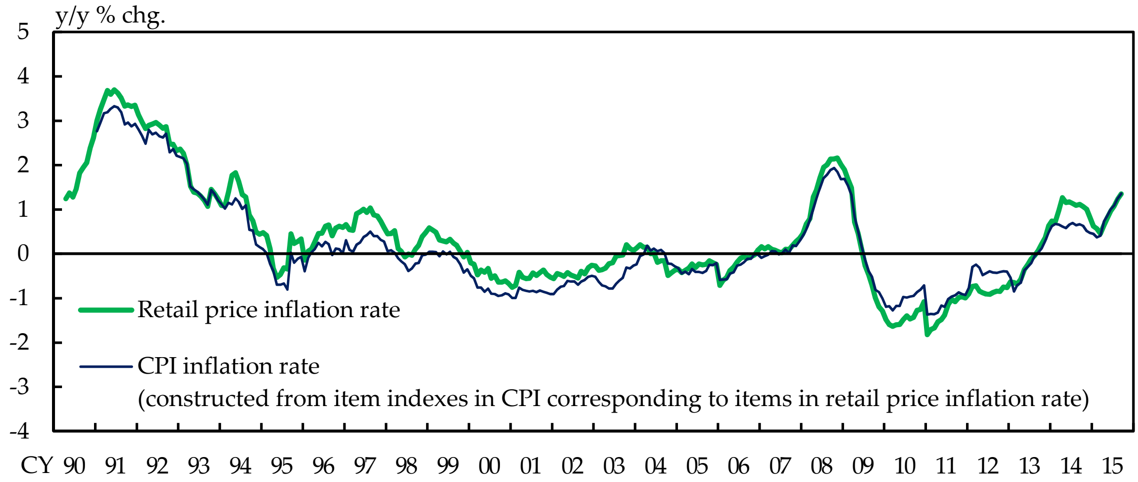
Overall, the develops just described suggest that sales are becoming an increasingly important means for firms to adjust prices. On the other hand, while it is generally assumed that developments in regular prices strongly reflect the macroeconomic environment, the frequency of changes in regular prices has remained virtually unchanged. That being said, a closer look at Figures 2 and 3 suggests that the frequency of changes in regular prices most recently, even with the effects of the consumption tax hike having dissipated, appears to have remained somewhat elevated. While the reason for this is unclear at the moment, economic theory suggests that the frequency of price changes may increase due to a rise in trend inflation and an increase in the costs of leaving prices unchanged (Romer, 1990). It will be interesting to see whether this most recent development in the frequency of changes in regular prices indicates a shift in firms' price-setting behavior.

V. IMPLICATIONS FOR MACRO PRICE STICKINESS

(1) The Relationship between Price Changes and the Macro Inflation Rate

Figure 4 compares developments in the price index constructed by aggregating individual prices in the RPS (referred to as the retail price inflation rate hereafter) and developments in the index constructed from item indexes in the CPI corresponding to the items covered in the retail price inflation rate. The two indexes diverge somewhat , mainly reflecting that (i) while weights for cities are used for compiling the item indexes of the CPI, no city weights are for used for the retail price index (equal weights are used), and (ii) prices of large cities are not reflected in the retail price inflation rate. Overall, however, the two indexes move more or less in tandem.

Figure 4. Retail Price Inflation Rate and CPI Inflation Rate

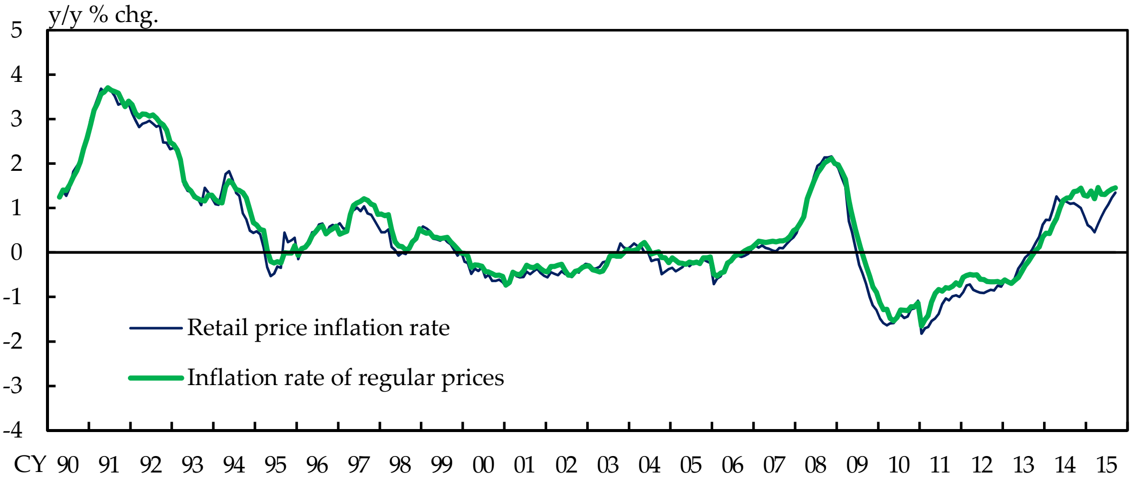


Notes: 1. Figures for the CPI inflation rate are calculated using items which are included in the retail price inflation rate.
2. Figures are adjusted to exclude the estimated effects of the consumption tax hike.

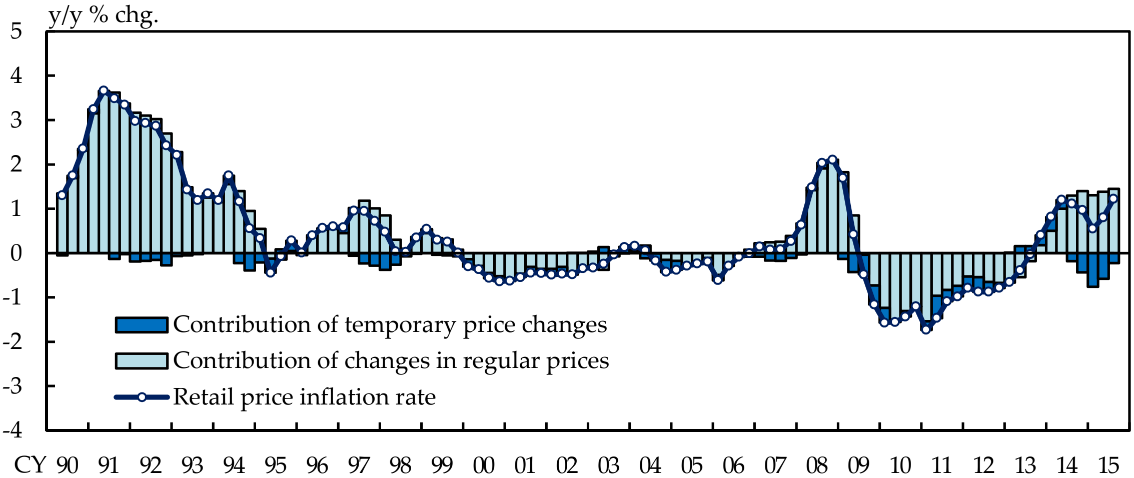
Next, Figure 5 presents a comparison between the retail price inflation rate and the inflation rate of regular prices. The inflation rate of regular prices essentially moves in tandem with the retail price inflation rate. This means that the inflation rate at the macro level, represented by the retail price inflation rate, is largely determined by the relatively infrequent adjustments of regular prices reflecting the macroeconomic environment, while temporary changes, which account for a large fraction of all price changes, have a marginal impact on the inflation rate at the macro level. Calculating the correlation coefficients between changes in regular prices and temporary price changes on the one hand and the output gap and the unemployment rate as indicators of the macroeconomic environment on the other shows that there is a significant correlation between the inflation rate of regular prices and the output gap and unemployment rate, while no significant correlation is observed in the case of temporary price changes (Table 5).

Figure 5. Inflation Rate of Regular Prices

(a) Inflation Rate of Regular Prices and Retail Price Inflation Rate



(b) Decomposition of Retail Price Inflation Rate



Notes: 1. Figures are for all items excluding fresh food and energy.
2. For details on the breakdown for Panel (b), see Appendix 2.

The results in Table 5 thus show that, in contrast with changes in regular prices, temporary price changes have little impact on the inflation rate at the macro level and are less responsive to the business cycle. The reason is that temporary increases and decreases in individual prices tend to offset each other. In fact, when looking at the frequency of price increases and the frequency of price decrease, the two move in opposite directions in response to the business cycle in the case of regular prices, while they tend to move in the same direction in the case of temporary prices (Figure 6).

Table 5. Correlation with Macroeconomic Indicators

		Inflation rate		
		Retail prices	Regular prices	Temporary prices
Output gap	Full observation period	0.84 [0.05]	0.85 [0.05]	0.09 [0.10]
	1990/Q2-1999/Q4	0.91 [0.07]	0.91 [0.07]	0.11 [0.16]
	2000/Q1-2015/Q3	0.70 [0.09]	0.70 [0.09]	0.01 [0.13]
Unemployment rate	Full observation period	-0.50 [0.09]	-0.51 [0.09]	0.02 [0.10]
	1990/Q2-1999/Q4	-0.35 [0.15]	-0.39 [0.15]	0.04 [0.16]
	2000/Q1-2015/Q3	-0.68 [0.09]	-0.69 [0.09]	0.07 [0.13]

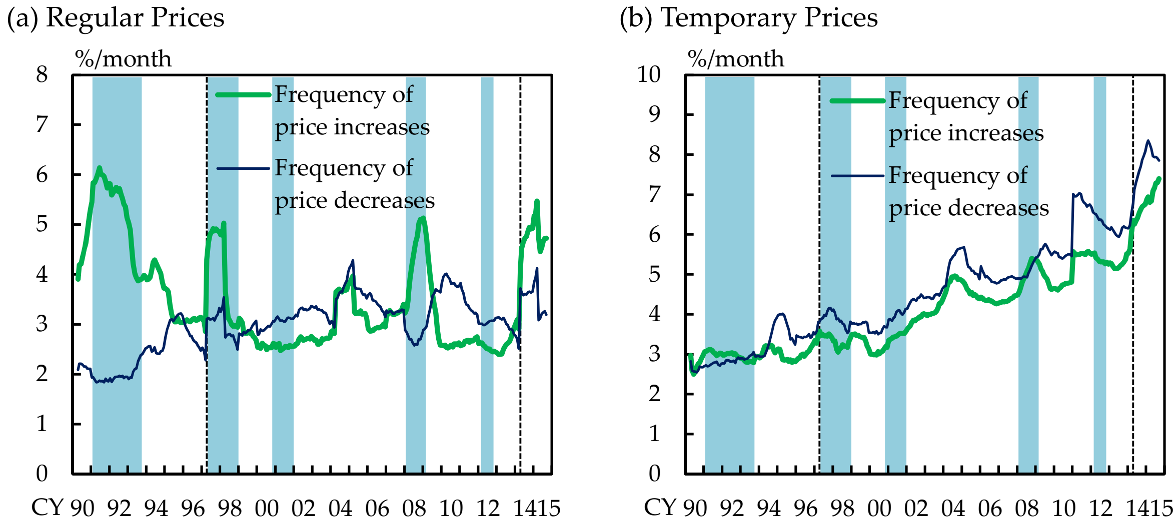
Notes: 1. Figures for inflation rates are for all items excluding fresh food and energy.
2. The full observation period is 1990/Q2 to 2015/Q3. Figures in [ ] are standard errors.
3. The output gap is estimated by the Research and Statistics Department, Bank of Japan. The unemployment rate is HP-filtered (lambda=1,600).

Since the second half of the 2000s, however, temporary price changes have been having a greater effect on the macro-level inflation rate. For instance, in the period between 2009 and 2012 after the financial crisis, temporary price decreases have acted to push macro-level prices downward (Figure 5(b)). Moreover, in 2014, partly in response to the consumption tax hike, temporary price decreases weighed down on inflation at the macro level, with the impact being greater than in the wake of the consumption tax hike in 1997. A possible reason is that -- against the background of the rising trend in the frequency of temporary price changes -- the frequency of price falls through sales has come to exceed the frequency of price rises bringing prices back to the original level, so that there is a growing divergence between the two. [11] As mentioned previously, negative demand shocks such as weakness in consumption during this period may have led to greater price competition and inventory

[11] Existing studies have not reached a consensus on the relationship between temporary price changes and the macroeconomic environment. Anderson et al. (2015), Nakamura and Steinsson (2008), and Coibion, Gorodnichenko, and Hong (2015) show that the frequency of sales in the United States is not sensitive to macroeconomic dynamics such as the unemployment rate, while Berardi, Gautier, and Bihan (2015) obtain similar results for France. In contrast, Kryvtsov and Vincent (2014) find that, in the U.K., the frequency of sales is correlated with the unemployment rate. Moreover, Sudo et al. (2014a), focusing on Japan, find a statistically significant correlation between the frequency of sales derived from POS data collected by retail stores and labor market indicators.

adjustments across the entire economy, which in turn may have exerted downward pressure on inflation rates at the macro level through a higher frequency of sales.

Figure 6. Frequency of Price Increases and Price Decreases: Regular Prices and Temporary Prices



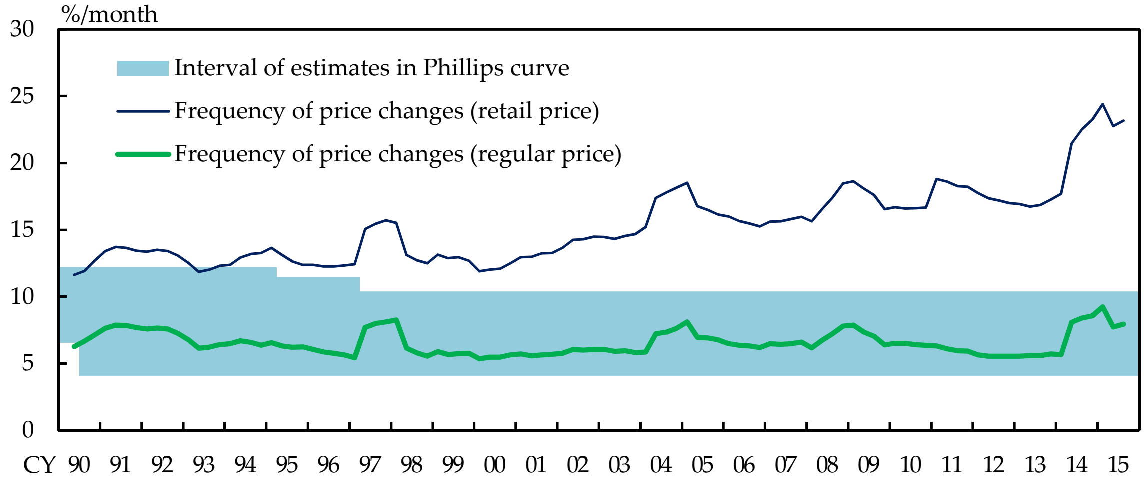
Notes: 1. Figures are for all items excluding fresh food and energy.
2. Figures are 12-month averages of the monthly frequency of price changes.
3. Shaded areas indicate recession periods. Vertical lines indicate periods of consumption tax hikes.

(2) The Impact of Temporary Price Changes on Macro Price Stickiness

Reflecting the debate in the United States, we start by examining whether the frequency of micro-level price changes measured from the RPS is consistent with the macro-level price stickiness estimated from the Phillips curve.

In the discussion in Section III, we highlighted the recent argument that the frequency of price changes estimated from the Phillips curve is close to the frequency of changes in regular prices at the microeconomic level. With this in mind, Figure 7 presents a comparison of the frequency of price changes in the RPS and the estimation results from the Phillips curve. In the figure, the probability of price change derived from the Phillips curve is shown as an interval based on the five indexes of real marginal costs in Section II to represent the frequency of price changes. The figure indicates that while the frequency of all price changes is higher than this interval, the frequency of changes in regular prices remained more or less within the interval, a finding which is consistent with the discussion in Section III.

Figure 7. Frequency of Changes in Regular Prices and Probability of Price Change in the Phillips Curve



Notes: 1. Figures are for all items excluding fresh food and energy.
2. The shaded area indicates the interval of the maximum and minimum estimates of the probability of price change in Tables 2 and 3. When there were structural breaks in the estimates, we used the estimates for the corresponding period.

This argument, however, is premised on the assumption that the Phillips curve is affected solely by changes in regular prices and that the impact of temporary price changes is minimal. To examine this point, we consider the impact of the frequency of temporary price changes on the Phillips curve based on the extended Calvo model developed by Kehoe and Midrigan (2015) mentioned in Section III. This model assumes that when the opportunity comes for firm i to change its pricing policy, it sets price $P_{i,t}$ at time t either as a regular price, $P^L_{i,t}$, or as a temporary price, $P^T_{i,t}$. It is further assumed that the temporary price is flexible and is set by multiplying the marginal cost in the current period and the markup rate. Opportunities for the respective price change are assumed to come with a certain probability:

$$P_{i,t} = \begin{cases} P_{i,t}^{L} & with\,probability\;\alpha_L \\ P_{i,t}^{T} & with\,probability\;\alpha_T \\ P_{i,t-1} & with\,probability\;1-\alpha_L-\alpha_T \end{cases}, \qquad (2)$$

where α_L denotes the probability of a change in the regular price and α_T the probability of a temporary price change. The model assumes that when prices change on a temporary basis, they either return to the regular price in the next period or undergo further temporary changes. When the probability of temporary price change is zero percent, it matches the standard Calvo model. On the other hand, when the probability of temporary price change is 100 percent, prices are perfectly flexible at the macro level. Thus, other things being equal, the higher the probability of temporary price change is, the more flexible prices at the macro level become. However, since usually the probability that a temporary price will return to the regular price in the following period is also high, the impact on price stickiness at the macro level is smaller than that of changes in the probability of a change in the regular price. Details of the model are provided in Appendix 4.

Based on this model, we calibrate α_L and α_T so as to replicate the frequency of price changes obtained from the RPS (average for the 1990-2015 period) to obtain our baseline model. In addition, we calibrate the probability of price change in the corresponding standard Calvo model (without temporary price changes). Furthermore, setting α_L in the baseline model as fixed, we conduct simulations assuming changes in α_T.

Figure 8 depicts the probability of price change in the standard Calvo model for different values of α_T. The point indicated on the line corresponds to the baseline, where α_L and α_T are computed as 7.2 percent per month and 4.3 percent per month, respectively.[12] The simulated probability of price change in

[12] Using U.S. data, Kehoe and Midrigan (2015) calculate values of 7.5 percent per month for α_L and 7.9 percent per month for α_T. Note that α_T represents the probability of temporary price cuts alone, while the frequency of temporary price changes derived from micro data includes both price increases and decreases.

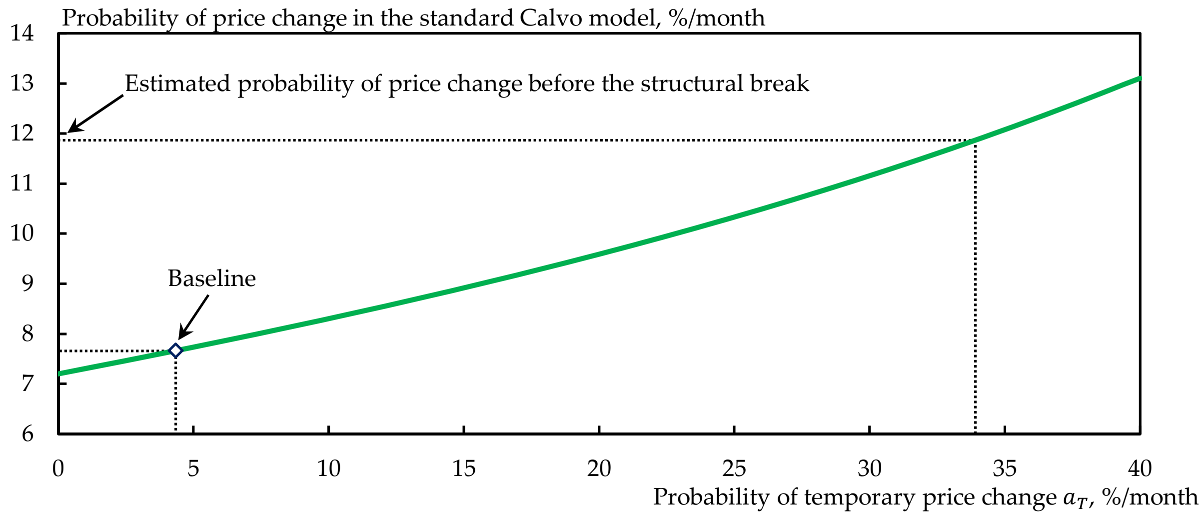
the corresponding standard Calvo model is 7.7 percent per month. This value is broadly consistent with the value obtained from the Phillips curve estimation using macro data, which was 8.2 percent (Table 2). Moreover, the increase in frequency of temporary price changes between 1990 and 2015 seen in the micro data is more or less captured by the increase in α_T from 2.5 percent to 7.8 percent per month. The probability of price change on the basis of the corresponding standard Calvo model is calculated to increase from 7.5 percent per month (once every 13 months) to 8.0 percent per month (once every 12 months). While this would imply that temporary price changes led to greater price flexibility at the macro level, the rate of increase is fairly limited compared to the rise in α_T. Therefore, the upward trend in the frequency of temporary price changes may have had a negligible impact on price stickiness at the macro level.

Of course, if this α_T rises even further, this may have noticeable effects on stickiness at the macro level. For example, if, other things being equal, α_T were to rise to 34 percent per month, the probability of price change in the standard Calvo model would rise to 12% per month (equivalent to a change of once every 8 months), which would be on par with level in the 1970s and 1980s, when prices were more flexible. Therefore, as highlighted in the studies on the United States mentioned above, it is not the case that there is no link between sales and price stickiness at the macro level and a sharp rise in the frequency of sales may potentially affect the shape of the Phillips curve.

VI. CONCLUSION

This study examined why prices at the macro level are sticky despite the high frequency of price changes observed in micro data. Furthermore, we investigated how the increasing trend in the frequency of price changes at the micro level affected the Phillips curve. Our findings can be summarized as follows.

Figure 8. Probability of Temporary Price Change and Probability of Price Change in the Standard Calvo Model



Notes: 1. The baseline shows the values obtained from the model in which a_L and a_T are calibrated to replicate the frequency of price changes in the micro data. The green solid line shows the values obtained for the probability of price change in the standard Calvo model when a_T takes the values on the horizontal axis.

2. Figures for the probability of price change in the standard Calvo model are calibrated to replicate the impulse response of prices to money supply shocks in the model with temporary price changes. The impulse response of prices is normalized by the money supply. For details on the calibration, see Appendix 4.

3. The figure for the probability of price change before the structural break is the average of estimates of the probability of price change before the structural break in Tables 2 and 3.

(1) Using micro data to gauge the frequency of price changes, we distinguished between the frequency of temporary price changes and the frequency of changes in regular prices using the running mode filter and found that the increase in the frequency of price changes overall was due to an increase in the frequency of temporary price changes, while the frequency of changes in regular prices has remained more or less unchanged since the 1990s.

(2) Because temporary price changes reflect price reductions due to sales and other promotions as well as subsequent price increases when the sale ends, they tend to cancel each other out across retailers and products, they have little impact on the macro-level inflation rate. On the other hand, macro-level inflation is highly sensitive to changes in regular prices, and the frequency of changes in regular prices we found was roughly consistent with the probability of macro-level price changes estimated from the New

Keynesian Phillips curve. These estimation results are generally in line with those obtained for the United States.

(3) Unlike in the United States, however, in Japan, with the frequency of temporary price change on the rise, the frequency of price decreases in recent years has clearly exceeded that of price increases, so that their impact on macro-level inflation has gradually increased. Estimations based on the Phillips curve and model-based simulation results together suggest that although the impact of the increased frequency of temporary price changes on the Phillips curve so far is limited, should this trend continue in the future, temporary price changes may lead to greater volatility of macro-level inflation. Added to this, the frequency of changes in regular prices, which had remained unchanged for most of the observation period, appears to have slightly increased even after the dissipation of the effects of the consumption tax hike in 2014. Whether this indicates a change in firms' price-setting behavior needs to be carefully watched.

This study investigated the shape of and structural breaks in the Phillips curve by focusing on the frequency of price changes. However, further research on the presence and timing of structural breaks and their causes from a variety of angles – regarding the assumptions underlying the Phillips curve model and selection of appropriate variables – are needed. Moreover, the present study employed the running mode filter to distinguish changes in regular prices and temporary price changes, and although this filter is currently widely used, employing it represents a simplification, so that it is necessary to examine other methods to distinguish price changes. We leave these issues for future research.

APPENDIX 1: ESTIMATION OF PHILLIPS CURVE

The probabilities of price change in Table 2 are estimated using the following standard hybrid New Keynesian Phillips curve (Galí and Gertler, 1999):

$$\pi_t = \gamma_f E_t \pi_{t+1} + \gamma_b \pi_{t-1} + \lambda \xi mc_t,$$

$$\begin{aligned} \phi &= \theta + \omega\big(1 - \theta(1-\beta)\big) \\ \gamma_f &= \beta\theta/\phi \\ \gamma_b &= \omega/\phi \\ \lambda &= (1-\omega)(1-\theta)(1-\beta\theta)/\phi \\ \xi &= (1-\alpha)/\big(1+\alpha(\varepsilon-1)\big) \end{aligned},$$

where π denotes the inflation rate and θ represents the probability of no price change (therefore $1-\theta$ represents the probability of price change), and ω, β, α, ε, and mc are the fraction of backward-looking firms, the subjective discount factor, the share of capital costs, the elasticity of substitution, and real marginal costs, respectively. This model allows the existence of backward-looking firms who set their prices based on the previous inflation rate.

We use the CPI (all items excluding fresh food and energy) for the inflation rate. Following earlier studies, we construct five measures for real marginal costs such as the output gap and real unit labor costs, which are shown in Table A1-1. The reason is that, as pointed by Rudd and Whelan (2005), estimates of the New Keynesian Phillips differ considerable depending on the variable for real marginal costs selected.

We use the Generalized Method of Moments (GMM) for the estimation and select a 12-period lag for the covariance matrix based on Newey and West (1987). Instruments include the constant and lags of up to four periods of the inflation rate and marginal costs. Following Galí and Gertler (1999), we set $\beta = 1$ and $\xi = 0.15$ to identify the structural parameters θ and ω. $\beta = 1$ means that we assume $\gamma_f + \gamma_b = 1$ in equation (A1). $\xi = 0.15$ is based on the steady state values of the labor share and the markup. The steady state labor share is set to 62%, the long-term average in the "National Accounts," and the steady state markup rate is set to 20% as in previous studies.[13] The data are quarterly time-series data and the observation period is 1975/Q1-2015/Q3, for a total of 163 observations.

Table A1-1. Measures of Real Marginal Cost

	Calculation	Study
Output gap		
(1)	(1 - labor share) × capital input gap + labor share × labor input gap	Nishizaki, Sekine, and Ueno (2014)
(2)	log(real GDP) - HP filter trend	Lindé (2005), Koga, and Nishizaki (2006)
(3)	log(real GDP) - quadratic trend	Galí and Gertler (1999), Muto and Tsuruga (2008)
Real unit labor costs		
(4)	log(nominal compensation of employees / nominal GDP) - mean	Galí and Gertler (1999), Lindé (2005)
(5)	log(nominal compensation of employees / (nominal GDP - (indirect taxes - subsidies) - households' operating surplus)) - mean	Batini, Jackson, and Nickell (2000), Muto (2009)

Notes: 1. Lambda is set to 1,600 in the HP filtering.
2. Variable (1) is estimated by the Research and Statistics Department, Bank of Japan. For details, see Hara et al. (2006).

The estimation results are displayed in Table A1-2. The table shows that most of the estimates of the fraction of backward-looking firms ω are not statistically significant and tend to be small. This result is consistent with earlier studies such as Muto and Tsuruga (2008).[14] Meanwhile, the estimates of the probability of no price change θ are statistically significant and fall within a range of 0.7-0.9. The J-statistic for overidentifying restrictions is not significant in any of the specifications.

[13] We also estimated the model using different values for the steady state markup rate ranging from 10% to 40%; however, the estimation results remained essentially unchanged.

[14] It should be noted, however, that many earlier studies find that the coefficient on the backward-looking term in the reduced-form Phillips curve is quite high.

Table A1-2. Estimation Results of New Keynesian Phillips Curve

Variable	θ			ω			γ_f	γ_b	λ	J-statistic	
		s.e.	p-value		s.e.	p-value					p-value
(1)	0.740	[0.054]	0.000	0.303	[0.142]	0.034	0.710	0.290	0.045	1.468	0.690
(2)	0.769	[0.293]	0.010	0.342	[0.402]	0.396	0.692	0.308	0.032	1.819	0.611
(3)	0.829	[0.088]	0.000	0.394	[0.281]	0.164	0.678	0.322	0.014	1.657	0.647
(4)	0.711	[0.043]	0.000	0.051	[0.198]	0.798	0.933	0.067	0.104	3.789	0.285
(5)	0.716	[0.031]	0.000	0.022	[0.217]	0.918	0.970	0.030	0.107	3.057	0.383

Notes: 1. Figures are GMM estimates using the variables in Table A1-1 for real marginal costs.
2. Following the approach of Newey and West (1987), 12-period lags are used for the estimation of the covariance matrix. Instruments include the constant and lags of up to four periods of the inflation rate and marginal costs. $\beta = 1$ and $\xi = 0.15$ are used for identification.

APPENDIX 2: CALCULATION METHOD

(1) Aggregation of the Frequencies of Price Changes

The aggregate frequency of price changes based on the RPS data and used in Figure 1 and elsewhere is calculated as follows:

$$fr_t = fr_t^+ + fr_t^-,$$

$$fr_t^+ = \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} I_{i,c,t}^+ P_{i,c,t-1}}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t-1}},$$

$$fr_t^- = \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} I_{i,c,t}^- P_{i,c,t-1}}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t-1}},$$

where fr_t denotes the frequency of price change and superscripts "+" and "-" respectively represent a price increase or decrease. w_i denotes the weight of item i in the CPI,[15] $n_{i,c,t}$ is the number of cities surveyed for item i, $P_{i,c,t}$ is the price index for item i in city c, and $I_{i,c,t}^+$ ($I_{i,c,t}^-$) is an indicator function that takes 1 if the price index for item i in city c increases (decreases).

(2) Aggregation of Inflation Rates

The year-on-year inflation rates π_t for retail prices and regular prices shown in Figures 4 and 5 are calculated using the following formula:

$$\pi_t = \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t}}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}} - 1,$$

where price index $P_{i,c,t}$ for the retail price inflation rate is obtained from the

[15] We set the weights for each period by employing the corresponding base year weights of the CPI. Specifically, we use the 1990 weights for 1990-1995, the 1995 weights for 1996-2000, the 2000 weights for 2001-2005, the 2005 weights for 2006-2010, and the 2010 weights for 2011-2015.

price data in the RPS (yen basis) and that for the inflation rate of regular prices is based on changes in regular prices identified using the running mode filter.

(3) Decomposition of the Retail Price Inflation Rate

The retail price inflation rate in Figure 5 is decomposed into the contribution of temporary price changes and of changes in regular prices as follows:

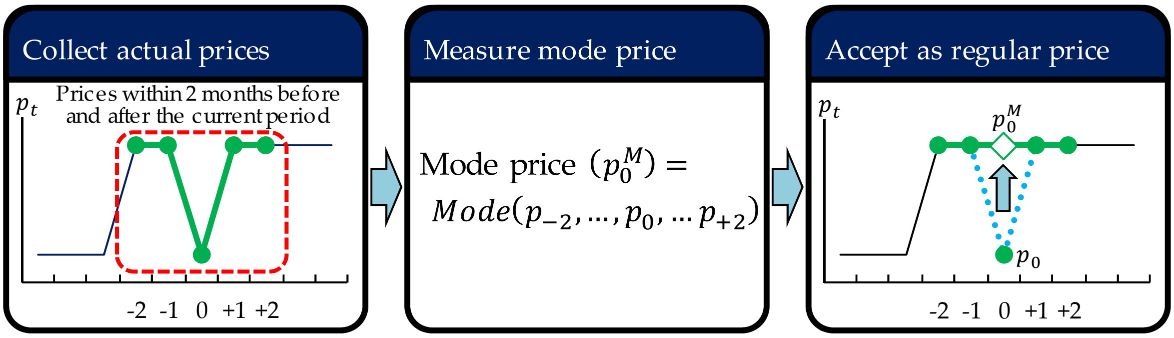
$$\pi_t^P = \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t}^P}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^P} - 1$$

$$= \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^R}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}} \times \left(\frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t}^R}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^R} - 1 \right)$$
$$+ \left(1 - \frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^R}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}} \right) \times \left(\frac{\sum_i w_i \sum_c \frac{1}{n_{i,c,t}} P_{i,c,t}^T}{\sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^T} - 1 \right)$$
$$= \alpha \times \pi_t^R + (1 - \alpha) \times \pi_t^T,$$

where $P_{i,c,t}$ with superscript P denotes retail prices, that with superscript R denotes regular prices, and that with superscript T denotes temporary prices, and $\alpha = \sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}^R / \sum_i w_i \sum_c \frac{1}{n_{i,c,t-12}} P_{i,c,t-12}$.

Appendix 3: Algorithm of the Running Mode Filter

In the running mode filter proposed by Kehoe and Midrigan (2015), the mode price for a certain period is defined as the regular price.

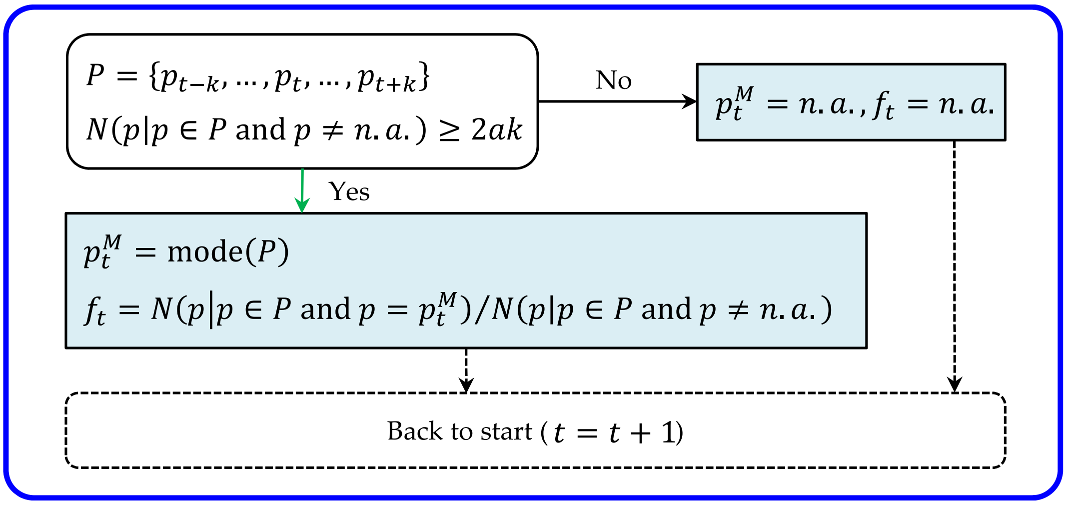


The algorithm of the running mode filter consists of the following three steps: (1) measuring the mode price; (2) measuring the regular price; (3) correcting the time point of the price change. Here, k represents the size of the window for measuring a mode price, a represents the minimum value of the number of periods in the window with the available price to measure the mode price, and c represents the cutoff-rate to accept the mode price as the regular price. Following earlier studies, we set these parameter exogenously as follows: $k = 2,\ a = 0.5,\ c = 1/3$.[16]

Step 1

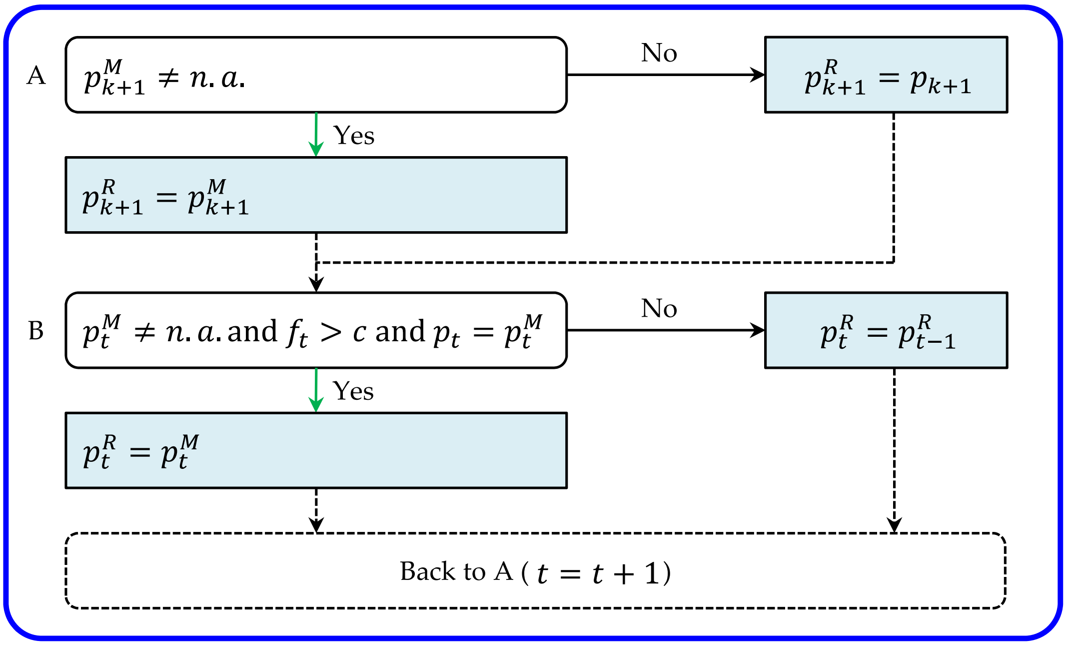
For each period $(k + 1 \leq t \leq T - k)$, we repeat the step to measure the mode price. T indicates the final observation period. Here, function $N(\cdot)$ calculates the number of observations which satisfy the conditions in the parentheses, p_t represents the actual price, p_t^M denotes the mode price of p_t within the period $t - k \leq t \leq t + k$, and f_t is the fraction of p_t^M in p_t in the period $t - k \leq t \leq t + k$.

[16] We also measured regular prices using different parameter values ($k = 2, 3, 4$, $c = 1/2, 1/3, 1/4$). However, although the frequency of changes in regular prices varies somewhat (4-7%), the trend over time -- that is, the fact that the frequency of changes in regular prices has been almost flat since 1990 -- remains unchanged.



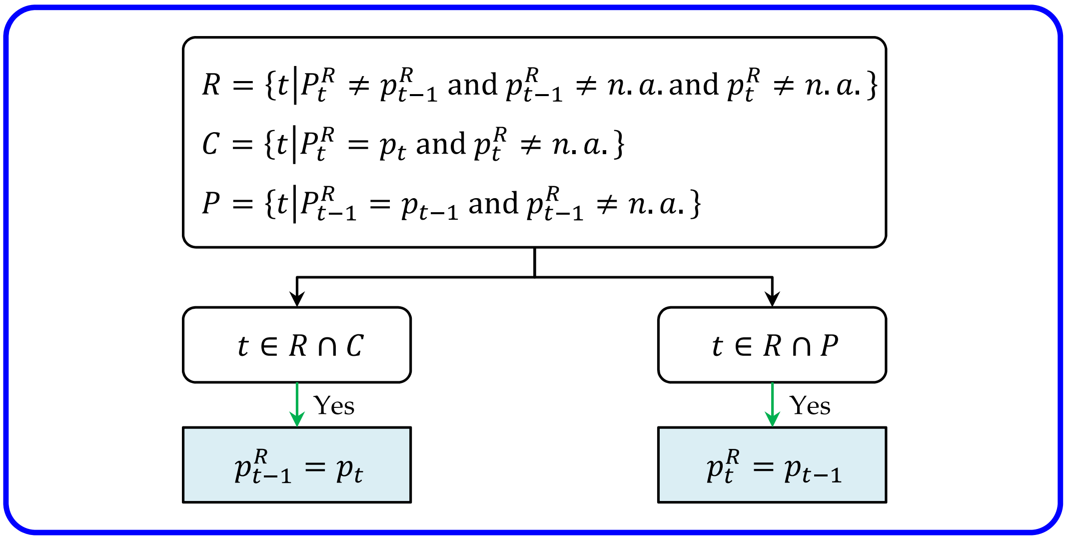
Step 2

We first define the regular price in the initial period ($t = k + 1$) in step (2.A). Then, for each period after the initial period ($k + 2 \leq t \leq T - k$), we measure regular prices by repeating step (2.B). Here, p_t^R denotes the regular price.



Step 3

We repeat the calculation below $k - 1$ times, and then correct p_t^R in which the change in regular price coincides with the actual price change.


$R = \{t | P_t^R \neq p_{t-1}^R$ and $p_{t-1}^R \neq n.a.$ and $p_t^R \neq n.a.\}$
$C = \{t | P_t^R = p_t$ and $p_t^R \neq n.a.\}$
$P = \{t | P_{t-1}^R = p_{t-1}$ and $p_{t-1}^R \neq n.a.\}$
$t \in R \cap C$
$t \in R \cap P$
Yes
Yes
$p_{t-1}^R = p_t$
$p_t^R = p_{t-1}$

APPENDIX 4: MODEL OUTLINE

In Section V, we perform a simulation analysis based on the model with extended Calvo-type price setting proposed by Kehoe and Midrigan (2015). Here we provide a brief description of the model.

(1) Agents' Maximization Problem

We assume that the representative household in this economy determines consumption C_t, bond holdings B_t, money holdings M_t, and labor supply N_t to maximize the following utility function:

$$E_t \sum_{s=0}^{\infty} \beta^s \left(log(C_{t+s}) + log\left(\frac{M_{t+s}}{P_{t+s}}\right) - \psi N_{t+s} \right), \tag{A1}$$

where β and P_t represent the subjective discount factor and the aggregate price level, respectively. The budget constraint of the representative household is given by

$$P_t C_t + M_t + B_t \leq W_t N_t + M_{t-1} + (1 + i_{t-1}) B_{t-1} + D_t, \tag{A2}$$

where i_t, W_t, and D_t represent the nominal interest rate, the nominal wage, and dividends received from firms, respectively. Then, the first order conditions (FOCs) of this maximization problem are:

$$C_t^{-1} = \beta(1 + i_t) E_t \left[\frac{P_t}{P_{t+1}} C_{t+1}^{-1} \right], \tag{A3}$$

$$M_t = \frac{1 + i_t}{i_t} P_t C_t, \tag{A4}$$

$$W_t = \psi P_t C_t. \tag{A5}$$

It is assumed that there are intermediate goods-producing firms and final goods-producing firms in the economy. It is further assumed that intermediate goods-producing firm i ($i \in [0, 1]$) produces differentiated intermediate goods under monopolistic competition, while final goods-producing firms produce final goods using intermediate goods under perfect competition. Final goods-producing firms produce final goods Y_t using intermediate goods $Y_{i,t}$ employing the following production technology:

$$Y_t = \left(\int_0^1 \left(Y_{i,t}\right)^{(\theta-1)/\theta} di \right)^{\theta/(\theta-1)}, \tag{A6}$$

where θ denotes the elasticity of substitution among intermediate goods. Subject to this production function, final goods-producing firms determine their input of intermediate goods $Y_{i,t}$ to maximize profits:

$$P_t Y_t - \int_0^1 P_{i,t} Y_{i,t}\, di. \tag{A7}$$

The FOC of this maximization problem and the zero profit condition are:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\theta} Y_t, \tag{A8}$$

$$P_t = \left(\int_0^1 {P_{i,t}}^{1-\theta} di \right)^{1/(1-\theta)}. \tag{A9}$$

Next, it is assumed that the production technology of intermediate goods-producing firm i is given by the following production function:

$$Y_{i,t} = A N_{i,t}, \tag{A10}$$

where $N_{i,t}$ is the input of labor services by the household and A is the level of technology. Intermediate goods-producing firm i determines the input of labor services $N_{i,t}$ to minimize production costs $W_t N_{i,t}$ subject to its production function. The FOC of this problem gives the marginal costs of intermediate goods-producing firm i:

$$MC_{i,t} = \frac{1}{A} W_t. \tag{A11}$$

Further, it is assumed that intermediate goods-producing firm i faces nominal price rigidities as in Kehoe and Midrigan (2015). Specifically, although intermediate goods-producing firm i has to charge the price charged in the previous period, $P_{i,t} = P_{i,t-1}^{L}$, with probability $1 - \alpha_L - \alpha_T$, the firm can change its regular price $P_{i,t}^{L}$ with probability α_L. Moreover, it is assumed that with probability α_T, the firm can set temporary price $P_{i,t}^{T}$ only for the current period. If intermediate goods-producing firm i sets a temporary price, it sets $P_{i,t}^{T}$ to maximize its profit,

$$\left(P_{i,t}^{T} - MC_{i,t}\right)Y_{i,t}, \tag{A12}$$

subject to (A8). Based on the FOC, temporary price $P_{i,t}^{T}$ is given by

$$P_{i,t}^{T} = \frac{\theta}{\theta - 1} MC_{i,t}. \tag{A13}$$

If intermediate goods-producing firm i changes its regular price, it sets its regular price $P_{i,t}^{L}$ to maximize its profit,

$$\left(P_{i,t}^{L} - MC_{i,t}\right)Y_{i,t} + \sum_{s=t+1}^{\infty} E_t \left(\prod_{r=0}^{s-(t+1)} \frac{1}{1 + i_t} \right) (1 - \alpha_L)^{s-(t+1)} (1 - \alpha_T - \alpha_L) \left(P_{i,t}^{L} - MC_{i,s}\right)Y_{i,s} \tag{A14}$$

subject to (A8). Based on the FOC, regular price $P_{i,t}^{L}$ is:

$${P_{i,t}^{L}}^{-1} = \frac{\theta - 1}{\theta} \frac{1 - (1 - \alpha_L)\beta}{1 - \alpha_T \beta} \left({MC_{i,t}}^{-1} - \alpha_T \beta E_t {MC_{i,t+1}}^{-1} \right) + (1 - \alpha_L)\beta E_t P_{i,t+1}^{L}. \tag{A15}$$

Normalizing all nominal variables by the money supply and log-linearizing around the steady state yields the following equations:

$$p_t = \alpha_L p_t^L + \alpha_T p_t^T + (1 - \alpha_L - \alpha_T)(\bar{p}_{t-1}^L - \mu_t), \tag{A16}$$

$$p_t^T = mc_t, \tag{A17}$$

$$p_t^L = (1 - \alpha_L)\beta E_t p_{i,t+1}^L + \frac{1 - (1 - \alpha_L)\beta}{1 - \alpha_T \beta} \left(mc_{i,t} - \alpha_T \beta E_t mc_{i,t+1} \right) + \frac{1 - \alpha_L - \alpha_T}{1 - \alpha_T \beta} \beta E_t \mu_{t+1}, \tag{A18}$$

$$\bar{p}_t^L = \alpha_L p_t^L + (1 - \alpha_L)(\bar{p}_{t-1}^L - \mu_t), \tag{A19}$$

$$\mu_t = \rho_\mu \mu_{t-1} + \varepsilon_{\mu,t}, \qquad \varepsilon_{\mu,t} \backsim N\left(0, \sigma_\mu\right), \tag{A20}$$

where mc_t, p_t, p_t^L, and p_t^T denote the log-deviations of MC_t/M_t, P_t/M_t,

P_t^L/M_t, and P_t^T/M_t from their steady state, respectively. The growth rate of the money supply is defined as $\mu_t = \ln(M_t/M_{t-1})$ and it is assumed that μ_t follows an AR(1) process. If $\alpha_T = 0$, the model is identical to the standard Calvo model.

(2) Calibration and Impulse Responses

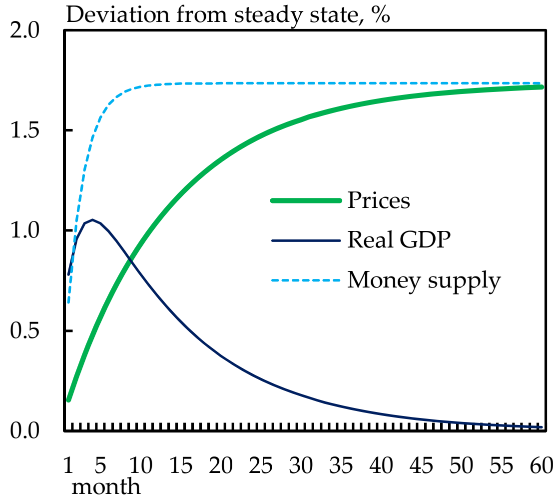
We calibrate parameters α_L and α_T of the above model to replicate the frequency of price changes measured from the RPS and the frequency of changes in regular prices measured by applying the running mode filter. We then use the model as the baseline model in Section V. Table A4-1 presents the result of the calibration. Parameter β is set to $0.96^{(1/12)}$ as in earlier studies. Based on Kano and Nason's (2014) estimation result, we set ρ_μ and σ_μ to 0.6278 and 0.0064, respectively. Figure A4-1 displays the impulse response of major variables to a one standard deviation money supply shock in the baseline model.

Table A4-1. Calibration Result

		Data	Model
Frequency of price changes			
Retail prices (%/month)		15.32	15.32
Regular prices (%/month)		6.51	6.51
Parameter			
Probability of regular price change (%)	α_L		7.20
Probability of temporary price change (%)	α_T		4.35
Subjective discount factor	β		0.9966
AR(1) growth rate of money supply	ρ_μ		0.6278
S.D. of shocks to growth rate of money supply	σ_μ		0.0064

Notes: 1. Figures for the frequency of price changes in the first column are averages of 1990 to 2015 data.
2. The figure for the frequency of changes in regular prices in the second column is calculated by applying the running mode filter to the simulated price data from the extended Calvo model with the calibrated parameters.

Figure A4-1. Impulse Response



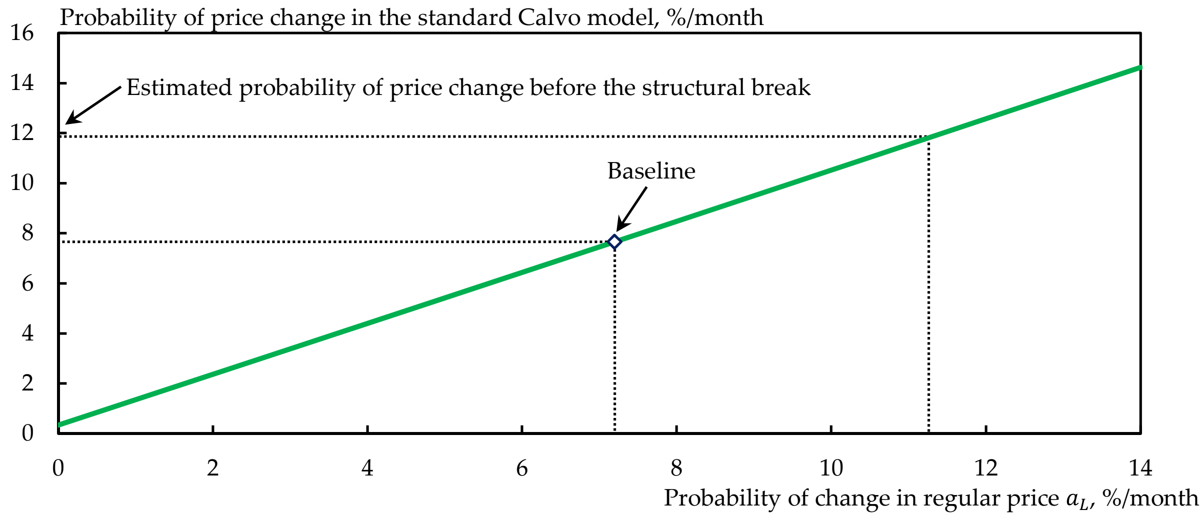
Note: The figure displays the impulse responses to a one standard deviation money supply shock (0.64 percentage point).

Following Kehoe and Midrigan (2015), to calculate the probability of price change in the standard Calvo model corresponding to the baseline model, we calibrate the parameters to replicate the impulse response of prices to the money supply shock as shown below:

$$\sum_{t=1}^{24} \frac{1}{24} \frac{Response\ of\ money\ supply_t - Response\ of\ prices_t}{Response\ of\ money\ supply_t}.$$

The probabilities of price change in the standard Calvo model for different α_T in Figure 8 are calculated by employing the same procedure. In Figure A4-2, we also show the probabilities of price change in the standard Calvo model for different α_L parameters.

Figure A4-2. Probability of Change in Regular Price and Probability of Price Change in the Standard Calvo Model



Notes: 1. The baseline shows the values obtained from the model in which a_L and a_T are calibrated to replicate the frequency of price changes in the micro data. The green solid line shows the values obtained for the probability of price change in the standard Calvo model when a_L takes the values on the horizontal axis.

2. Figures for the probability of price change in the standard Calvo model are calibrated to replicate the impulse response of prices to money supply shocks in the model with temporary price changes. The impulse response of prices is normalized by the money supply.

3. The figure for the probability of price change before the structural break is the average of estimates of the probability of price change before the structural break in Tables 2 and 3.

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