Bank of Japan Working Paper Series

An Empirical Analysis of Price Stickiness and Price Revision Behavior in Japan Using Micro CPI Data

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No.06-E-8
June 2006

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An Empirical Analysis of Price Stickiness and Price Revision Behavior in Japan Using Micro CPI Data[*]

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Abstract

After the collapse of the asset price bubble, especially over the period of declining prices of goods and services from the latter 1990s until recently, it is said that certain Japanese firms have been working to stimulate demand by active price adjustment. Nevertheless, over the same period, inflation persistence has been observed from the year-on-year percent changes in the Consumer Price Index (CPI). How can we interpret this micro and macro information consistently? Motivated by this question, this paper applies a Generalized Dynamic Factor Model to individual CPI item data to examine if it is possible to identify any representative price revision patterns, and if so, to investigate their basic features.

Our findings indicate that in Japan there is a highly representative common component among the item data which means there is the high degree of consistency in the timing of price revisions that is a distinctive feature of Japan, in comparison with the U.S. and the euro area. Also, the common component has the feature of a long period of time between shocks and price reactions. Furthermore, our findings indicate that Japanese price revisions tend to be implemented in specific months rather than having any fixed period between shocks and subsequent price revisions. Finally, comparative analyses dividing the 25 years of time series data from 1980 to 2005 into two terms indicate that in recent years price stickiness has been lowering for goods. However, they also indicate that price

[*] I would like to express my gratitude toYoichi Matsubayashi (Kobe University), Kosuke Aoki (London School of Economics), Hiroshi Ugai (Bank of Japan), Koichiro Kamada (Bank of Japan), and Masahiro Higo (Bank of Japan) for their helpful advice and comments. Regardless, I am solely responsible for any remaining errors in this paper. The views expressed herein are those of the author and do not reflect those of Bank of Japan.

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stickiness has been heightening for services, and the overall price stickiness has not been weakening. This suggests that the increasingly active price adjustment behavior revealed at the microeconomic level may be limited to certain goods only.

Keywords: Price stickiness; Inflation persistence; Price revision behavior; Generalized Dynamic Factor Model; Consumer price index; State-dependent pricing; Time dependent pricing

JEL Classification: C33, C43, D40, E31

1. Introduction

The degree of price stickiness in reaction to exogenous shocks is an important issue for monetary policy. In Japan, even during the recessionary phases of the latter 1990s and 2000-2001, the declines in the year-on-year percent changes in Japan's Consumer Price Index (CPI) have been limited to -1% at most. What is more, despite the ongoing economic recovery since 2001, the year-on-year percent changes of the CPI have remained around 0%. Thus, when viewed from the macroeconomic level, the fluctuations in Japan's CPI show an extremely high level of persistence. On the other hand, when viewed from the microeconomic level, for certain items, it is reported that firms have been working to stimulate demand by active price adjustment, especially during the period of declining prices since the latter 1990s, as price competition with low-priced imported goods has intensified[1] and retailers have been implementing bargain sales more frequently.

This paper purposes to examine how to coherently understand this apparent contradiction of inflation persistence at the macroeconomic level along with high volatility for certain items at the microeconomic level. Possible reasons for the inflation persistence observed at the macro level include: while the shocks that firms react to are not persistent themselves, the speed at which firms react may be slow; and the shocks that firms react to have the feature of persistence themselves. Furthermore, it may be that the speed at which firms revise prices may be fast for some items and slow for others, but it tends to be slow when measured on average. This suggests the possibility that the increasingly active price adjustment behavior revealed at the microeconomic level may be limited to certain items only. This paper examines the basic features of Japanese firms' price revision behavior using individual item data. We apply the Generalized Dynamic Factor Model (GDFM) to identify common patterns among the price changes by item, and closely examine those patterns as well as the different features for goods and services and the changes over time.

There are some prior research papers that have examined the issue of price stickiness using disaggregate data, For example, Bils and Klenow [2002] analyzed the frequency of price changes using individual consumer prices collected by the U.S. Bureau of Labor

[1] See Bank of Japan Research and Statistics Department, "Price Developments in Japan – A Review Focusing on the 1990s", Bank of Japan Research Papers [2000].

Statistics.[2] They found the frequency of price changes varies dramatically across item categories, and reported that the categories which implement relatively short-term price changes of under four months comprise about half of the total CPI. Clark [2003] analyzed the item price data used for the calculation of the U.S. Personal Consumption Expenditures Price Index.[3] He conversely reported that a sizable proportion of disaggregate series are highly persistent, and that the more persistent series tend to represent larger shares of consumer expenditure. Regarding the euro area, Altissimo, Mojon, and Zaffaroni [2004], which use the same analytical method adopted in this paper, analyzed CPI item data from France, Germany and Italy, and found that while price stickiness exists across items to some extent as a common feature, there is high heterogeneity in the propagation mechanism of the common shocks which bring differences in price change timing by item. Regarding Japan, Saita, Takagawa, Nishizaki and Higo [2006] used the average price data by item by sample city from the Retail Price Survey, counted the percentages of cities where prices are changed each month for each item, and found a wide variation in the price change patterns by item. Reviewing all this prior research, even in one country, some papers emphasize that there are a large number of items with price stickiness, while others emphasize the heterogeneity in the price flexibility. This paper clarifies which of these should be emphasized in Japan by attempting to identify highly representative price change patterns and the characteristics.

It would be desirable to use individual product prices rather than item prices to grasp the frequency at which firms actually implement price revisions, but in this paper, the approach is not adopted because it would impose the restriction that it would be difficult to use long term time-series data. Saita, Takagawa, Nishizaki and Higo [2006] also did not use individual product price data, but they used lower-level aggregated data (1989-2003) which may be said to be closer to individual product price data compared with the data analyzed in

[2] Specifically, Bils and Klenow [2002] analyzed the unpublished retail price data ”Commodities and Services Substitution Rate Table for the years 1995 through 2001” surveyed by the Bureau of Labor Statistics for calculating the U.S. CPI. These data are categorized as 388 “Entry Level Items”, and they used 350 of the 388 items which account for approximately 70% of household expenditures, as calculated using the weights under the 1995 Consumer Expenditure Survey.

[3] The data were sourced from the Price Indexes for Personal Consumption Expenditures by Major Type of Product and Expenditure, which is published by the U.S. Bureau of Economic Analysis.

this paper.[4] Accordingly, this paper examines the analytical findings in comparison with those in Saita, Takagawa, Nishizaki, and Higo [2006].

This paper is organized as follows. Section 2 presents an explanation of the Generalized Dynamic Factor Model (GDFM). Section 3 analyzes the price change behavior by item using Japan's CPI item price data. Section 4 presents the analytical findings, and Section 5 is a summary of the conclusions.

2. Analytical Method using a Generalized Dynamic Factor Model (GDFM)

In this section we explain the framework of the Generalized Dynamic Factor Model (GDFM)[5] which we use to extract representative price change patterns among the item price changes in Japan's CPI. Let x_{it} equal the price change of item $i(1,...,n)$ in period t. This method extracts the common component χ_t from the data series X_t which is composed of x_{it} and views the portion that cannot be explained by the common component as the idiosyncratic components ε_t that are unique to each item.

$$X_t = \chi_t + \varepsilon_t \qquad \begin{aligned} X_t &= (x_{1t}, x_{2t}, ..., x_{nt})' \\ \chi_t &= (\chi_{1t}, \chi_{2t}, ..., \chi_{nt})' \\ \varepsilon_t &= (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{nt})' \end{aligned}$$

The extraction of the common component by the GDFM is a four-step process which

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4 The CPI item price data used in this paper are calculated using the average price data by item by sample city aggregated by the Retail Price Survey. The average price data collected by Retail Price Survey are changed into indices and compiled in nationwide weighted average indices by item using the weights by item by sample city calculated by the Family Income and Expenditure Survey.

5 In the GDFM, the term "Dynamic" refers to the model's ability to grasp price reactions to shocks not only when the prices of all items react at once but also when individual items react with different timing. The term "Generalized" in the GDFM refers to the modification from the original Dynamic Factor Model, which assumed that the idiosyncratic components of different items are mutually orthogonal. (For details regarding the GDFM see Forni, Hallin, Lippi, and Reichlin [2000]). The Dynamic Factor Model, which expresses a given time series as the sum of common and idiosyncratic components, was proposed by Sargent and Sims [1977] and Geweke [1977].

(1) generates lag covariances from the price changes of individual items, (2) expresses these as spectra, (3) conducts principal component analysis to extract a number of common components, and (4) finally integrates some of the most contributive common components in descending order to estimate a representative common component. We now explain the framework of the GDFM and then present the specific estimation method by each step.

2.1. Framework of the GDFM

The GDFM takes common components which are denominators of observed values such as changes in CPI item price data as the reaction to q principal shocks which affect all items (common shocks) along with their particular lag structures and reaction parameters. Our estimation makes the following assumptions, in line with Forni et al. [2002]. (See the Appendix for the details of the assumptions).

(i) The common shocks have no correlations with one another.

(ii) The lag structures and reaction parameters to the common shocks are symmetrical to the positive and negative lags.

(iii) The idiosyncratic components have no correlations with the common shocks.

(iv) As long as the simultaneous correlation is zero, correlations among the idiosyncratic components are allowed.

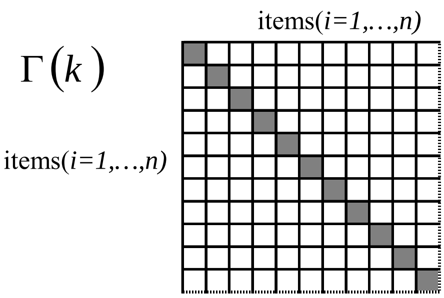
The GDFM is constructed to follow reality by allowing a limited amount of correlation among the idiosyncratic components because in the CPI it is possible that even under shocks that only affect individual items, there is a weak cross-correlation among goods and services that can substitute for one another. While making this assumption may partially diminish the accuracy of the estimate, it is considered an effective modification to allow a model closer to reality.

2.2. Explanation of the Estimation Steps

<Step(1)>

Assume all items are now exposed to a common shock. The shock propagation process is believed to vary by item. Among items that react to the common shock with the same timing, a high simultaneous correlation can be observed. Also, among items that react to the shock with different timing, for example, between the observed prices of items that react quickly and of items that react slowly, the correlation becomes higher as the lag grows longer. These facts can be derived from transforming the observed value matrix into the lag correlation matrix after normalizing the variance of each time series as 1. In so doing, the lag for the lag correlation matrix must be finite because the sample data set is limited. However, considering the purpose of extracting the common components, it is sufficient to take enough lags within the range where the cross-correlation among items is well recognized.

[Covariance matrix]



The correlation matrix $\Gamma(k)$ ($k = 0,1,...,M$) displays the correlation coefficients at lag k as a matrix. The diagonal elements are the autocorrelation coefficients for each time series at lag k, and the off-diagonal elements are the cross-correlation coefficients of each of the two time series at lag k. The cross-correlation among items can be derived from the cross-correlation matrix at all leads and lags from k to $-k$. The correlation matrix at lag k and lag $-k$ are symmetrical since the ij factor of $\Gamma(k)$ equals the ji factor of $\Gamma(-k)$.

<Step(2)>

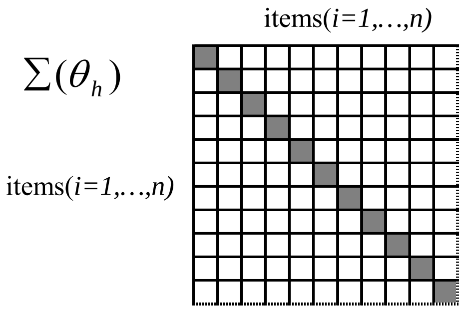
When groups of items with common statistical characteristics of fluctuation are observed in the data matrix, the GDFM takes the fluctuations of these groups as common components. For example, when there are groups of items with a fixed price revision period, high cross-correlations can be observed at the fixed period. Also when most items react to cyclical shocks such as the business cycle, the fluctuations of the groups are viewed as movements with a certain periodicity. Such periodicity can be grasped by viewing the spectrum density of the time-series, which indicates the contribution of each frequency band.[6] So a Fourier transformation is implemented on the correlation matrix $\Gamma(k)$ to seek the spectral density matrix $\sum(\theta_h)$ where frequency θ_h denotes the $(2M+1)$ points for the discrete Fourier transformation as follows.

$$\sum(\theta_h) = \sum_{k=-M}^{M} \Gamma(k) W_k e^{-ik\theta_h}$$

$$\theta_h = \frac{2\pi h}{2M+1} \qquad (h = 0,1,\ldots,2M)$$

$$W_k = 1 - \frac{|k|}{M+1} : \text{ Bartlett lag window}^{7}$$

[Spectral density matrix]



The spectral density matrix $\sum(\theta_h)$ is expressed as the matrix of the cross-spectrum at frequency θ_h so it comprises the diagonal element which is the spectrum of each time series at frequency θ_h and the off-diagonal element which is the cross-spectrum of the two time series at frequency θ_h.

<Step(3)>

Next we extract the common component among items using principle component

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[6] Strictly speaking, this should read “angular frequency” rather than “frequency” ($\omega = 2\pi f$, where f is normally referred to as the frequency). “Frequency” implies “angular frequency” in the remainder of this paper as well.

[7] When estimating the spectrum using Fourier transformations of the autocorrelation function and the cross-correlation function, the variance of estimated spectrum grows large unless the values of k are restricted to those with small coefficient of variation (normalized standard error) of autocorrelation function and cross-correlation function. The Bartlett lag window is one method which, considering that the coefficient of variation of the correlation function expands as $|k|$ increases, adds attenuating weights as the value of k increases to the estimated values of correlation function for smoothing and then computes the Fourier transformation to estimate the spectrum with a low standard error.

analysis. Principal component analysis is a method which expresses the matrix of mutually correlated data using orthogonal hypothetical endogenous factors (the principal component vectors) and weights which indicate their relative importance (principal component scores), and then concisely expresses the data matrix using representative principal component vectors. The common component is assumed to be shocked by q principal shocks, so we seek q principal component vectors in descending order of magnitude to grasp them. Mathematically, seeking highly contributive principal components is identical to seeking highly contributive eigenvectors and eigenvalues. Accordingly, we now seek first q eigenvectors $P_j(\theta_h)$ and eigenvalues $\lambda_j(\theta_h)$ $(j = 1,...,q)$ as follows.

$$P_j(\theta_h) = \left(P_{j,1}(\theta_h),...,P_{j,n}(\theta_h)\right)$$

$$\widetilde{P}_j(\theta_h) = \left(\widetilde{P}_{1,j}(\theta_h),...,\widetilde{P}_{n,j}(\theta_h)\right)'$$: Transpose of complex conjugate

<Step(4)>

Finally, we estimate a filter $K_i(L)$ to extract the common component by integrating the first q principal component vectors based on the following approach. Filtering the data is similar to calculating the principal component scores using orthogonal projections on the principal component vectors. This makes it possible to divide the data into the portion that can be explained using a filter (common component) and the portion that cannot be explained (idiosyncratic component), as follows.

$$\chi_{it} = \underline{K}_i(L)X_t$$

$$K_i(\theta_h) = \widetilde{P}_{i,1}(\theta_h)P_1(\theta_h) + ... + \widetilde{P}_{i,q}(\theta_h)P_q(\theta_h).$$

$$\underline{K}_{i,k} = \frac{1}{2M+1}\sum_{h=0}^{2M} K_i(\theta_h)e^{ik\theta_h}$$

$$\underline{K}_i(L) = \sum_{h=-M}^{M} \underline{K}_{i,k} L^k .$$

3. Analysis of Price Revision Behavior Using Individual Item Data

3.1 Data set

In this section we apply the method explained in Section 2 to Japan's CPI item data to examine the basic features of the price revision behavior of Japanese firms. Out of the 588 items covered by Japan's CPI (year 2000 level = 100), our data set comprises the 360 items with continuous usable data from 1980 through 2004 (excluding alcoholic beverages to remove any influence from changes to the Liquor Tax Law). By weight, these 360 items account for 75% of the CPI overall. These prices are also adjusted for consumption tax and health insurance system factors to eliminate differences not related to price revision patterns.

3.2 Contribution of the common component

We now extract the common component from the CPI item data and measure its relative importance, that is, the extent to which it represents Japan's CPI price revision patterns. To begin with, we consider how many principal components we should focus on to extract the common component. Under the GDFM, the contribution of the common component can be indicated by the eigenvalues. This paper derives a total of 360 eigenvalues, and **Table 1** presents the 10 largest, in order. The table indicates that the relative importance of the first eigenvalue is overwhelmingly stronger than that of the second and subsequent eigenvalues. However, these results are the averages of the eigenvalues at the lags before and after, and depending on the lags it is possible that one of the second or subsequent eigenvalues may actually be more persuasive. Accordingly, we now extract the common component assuming $q=4$.

Figure 1 compares the actually extracted common component with the CPI, to examine the common component's relative importance to the CPI. While the details show that the two come to diverge more frequently after the collapse of the asset price bubble, especially from the late 1990s, overall the common component and the CPI move similarly. **Figure 2** plots the lag autocovariance of the CPI and of the common component. The figure shows that both attenuate as the lag grows longer, and that their levels are approximately equal. These findings suggest that the idiosyncratic component does not significantly influence the fluctuation of the CPI.

3.3 Analysis of the basic features of the common component

The 360 eigenvalues presented in the previous section are important in that they express the characteristics of the common component. Let us now proceed with observing the eigenvalues of the common component, and with examining the representative price change patterns of the item price data in detail. **Figure 3** plots the 10 largest eigenvalues derived from the CPI item data, which is not seasonally adjusted. The horizontal axis shows the frequency.[8] Because the time required for the common component to take all its values (the cyclical period) is $2\pi / I$ (I = the unit time, which are quarters in this paper), when there is a peak at a frequency of π, then the half-year periodical fluctuation is highly contributive, when there is a peak at a frequency of $\pi/2$, then the one-year periodical fluctuation is highly contributive, and when there is a peak at a frequency of $\pi/6$, then the three-year periodical fluctuation is highly contributive to the CPI. The height of the spectrum at lower frequencies can be viewed as the estimated value of the price stickiness, but because this paper estimates at $M = 8$[9], we view the size of the eigenvalue at a comparatively more reliable estimated value of $\pi/8$ (a period of four years) as an index representing the estimated price stickiness.[10] In this paper we use the first four principal component vectors that correspond to the four largest eigenvalues. For that reason, the sum of the first four eigenvalues can be viewed as the spectrum of the common component at

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[8] In fact, we did not conduct principal component analyses for all the frequencies, but rather conducted analyses on fully sufficient numbers of lags before and after (the $2M+1$ from $-M$ to M). Considering $M \to \infty$, the lines connecting the eigenvalues can be expressed by curves. Also, because the size of the eigenvalues is symmetrical to 0, it is actually sufficient only to look up to $[0, \pi]$.

[9] This is because there is a tradeoff between the stability and the estimation error of the size of the eigenvalues, and to moderately meet both requirements, a figure that is about 10% or less of the length of the time series is considered appropriate.

[10] The size of the eigenvalues at a frequency of 0 can also be used as the estimated value of the price stickiness (Altissimo, Mojon, and Zaffaroni [2004]), but that primarily reflects price trends. In this paper, because we need to separate the timing of price changes in reaction to shocks from price changes following the price trend, we interpret the height of the spectrum at a frequency of zero only as the average relative importance of the common component.

each frequency.

Figure 3 shows that the first principal component has a peak in the area with a frequency below $\pi/6$, that is with a period longer than 3 years. Moreover, by itself this first principal component explains nearly 50% of the fluctuations (the area surrounded by the dotted line in **Figure 3**). Therefore the size of this eigenvalue shows that it is the common component, and not the idiosyncratic component, which is the source of the price stickiness of Japan's CPI. In other words, this demonstrates that there is a dominant common pattern in the price changes of Japan's CPI, and the role played by the fluctuations of idiosyncratic component is not all that substantial. It is also patently clear that this common component is strong at a frequency around $\pi/2$, that is at a period of one year, and at a frequency around π, that is at a period of a half-year.

Do these findings imply that prices will be revised one year or a half-year after Japan's CPI is exposed to an exogenous shock, or do they indicate that the prices are revised in certain months, once or twice a year, regardless of when shocks occur? To examine this, in **Figure 4** we calculated the eigenvalues using quarter-to-quarter data after making seasonal adjustments to the monthly data. Hypothetically if the price revisions are in fact implemented during certain months, then the eigenvalue at frequency π (price revisions at half-year period) should diminish when using seasonally adjusted data. The results show that the peaks which appear at one year and half-year intervals in **Figure 3** do disappear, and that the only peaks remaining are those in the range of low frequencies. These results imply that rather than changing prices a year or a half-year after exposure to shocks, there is a higher probability that Japanese firms implement price revisions in certain months, once or twice per year.[11] Meanwhile the size of the eigenvalue at a frequency of $\pi/8$ shows no decline following the seasonal adjustment. This result suggests the possibility that the prices of many items are revised all at once, following a long hiatus, after firms pass by several opportunities to revise their prices every year or half-year.

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[11] Bank of Japan Research and Statistics Department, "Price-setting Behavior of Japanese Companies – The Results of the 'Survey of the Price-setting Behavior of Japanese Companies' and its Analysis" [2000] reported that when asked how often they had changed their prices over the past year, for both manufacturing and non-manufacturing firms by far the most common answer was "once or twice." From these results, this paper indicated the possibility that considering the information collection costs and customer relationships, many enterprises probably revise their prices when they settle their accounts.

The second and third sections of **Figure 3** show the sizes of the eigenvalues when separate calculations are made for goods and for services. At a frequency of $\pi/8$ the eigenvalue of the first principle component is around 50% for services and around 30% for goods, indicating much lower price stickiness for goods compared with services. This is consistent with the conclusions of Saita, Takagawa, Nishizaki, and Higo [2006], which compared goods and services and found low price stickiness for goods and high price stickiness for services. Returning to our own analytical findings, we note that like the price revisions for all items, the price revisions for goods and for services are both implemented in certain months, once or twice per year.

3.4 Analysis of changes in price stickiness

The analyses thus far have indicated that many of the items in Japan's CPI have the feature of price stickiness. We now consider how this relates with the microeconomic information of increasingly active price adjustment behavior in recent years. **Figures 5** and **6** divide the sample into the two terms of 1980-1992 and 1993-2004 and extract the common components.

As for all items (the top section), the sum of the eigenvalues for the first and second principal components at a frequency of 0 remains around 50% for both terms. This is also true when the calculations are made at a frequency of $\pi/8$ where the sum of the eigenvalues for the first and second principal components is around 45% for both terms. Basically, the two terms show no major differences in the degree of price stickiness. This corresponds with the macro data which shows continued inflation persistence in Japan's CPI.

However, changes in price stickiness emerge when goods and services are examined separately. For goods, the sum of the eigenvalues for the first and second principal components declined from around 40% in 1980-1992 to about 35% since 1993, showing a slight decline in price stickiness. Indications that Japanese firms have adopted more frequent price revision in recent years may point to this lowering price stickiness for goods. In contrast, for services the sum of the eigenvalues for the first and second principal components rose from about 60% in 1980-1992 to about 70% since 1993, showing a heightening in price stickiness.[12] Thus at the macro level the lowering in the price stickiness for goods has been cancelled out by the heightening in the price stickiness for services, and this resolves the apparent contradiction of price stickiness at the macro level accompanied by more active price revision behavior for certain items. Incidentally, at a glance it seems odd that the heightening in the price stickiness for services has taken place since the 1990s amid the progress of deregulation, primarily in service industries.

3.5 The nature of common shocks which fluctuate the common component

Exactly what kinds of shocks generate fluctuation of the common component? To examine this point, we calculated weighted averages of the common component of each item using the item weights in the CPI, and compared these with several representative macroeconomic variables. Specifically we selected the AR(1) residual of M1[13] as a variable that is strongly influenced by monetary policy shocks, and the natural rate of interest and the GDP gap as variables that are strongly influenced by business conditions.

Table 2 presents the lag correlation coefficients between the common component and these variables. The table shows no clear correlation between the common component and the AR(1) residual of M1. This indicates that monetary shocks do not strongly influence the common component. On the other hand, the table shows strong correlations between the common component and the natural rate of interest, which is strongly influenced by demand shocks[14], and between the common component and the GDP gap, which has a strong correlation with demand shocks. This indicates that the common component has become

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[12] Another feature of services during this term is the high contribution from the second principle component in the area with a frequency smaller than $\pi/6$. The reason for this is not certain, but during this term for goods there is a possibility that the first principal component may have incorporated the shock of rapid appreciation of the yen and the shock of decline in crude oil prices under the same recessionary period. For services, since the influences from the foreign exchange rate and crude oil prices are small, it may be possible to grasp the shocks as the second principal component. Thus it is important to note that the first principal component cannot always grasp a specific shock, and that it may rather indicate the most important common shock depending on the frequency and the data period.

[13] The AR(1) residual of M1 is the $\Delta\log$ M1 residual from the AR(1) model with constant term, including the trend.

[14] See Oda and Muranaga [2003].

more strongly influenced by real shocks since the 1980s.[15]

4. Discussions

4.1 Relationship with macroeconomic pricing models

In this subsection we examine the implications of the conclusions drawn in Section 3 for the construction of macroeconomic models, in relation with recent developments in macroeconomic pricing models.

Two types of pricing models are frequently used in macroeconomics: (1) the state-dependent pricing model, which holds that enterprises revise prices whenever the gap between optimal prices and the actual prices of their own products exceeds a certain level, and (2) the time-dependent pricing model, which holds that price revision opportunities are dependent not on economic conditions, but rather on time. The time-dependent pricing model (2) is further broken down into (a) Taylor-type pricing models, which hold that price revisions are implemented at fixed intervals, such as once every half-year, and (b) Calvo-type pricing models, which hold that enterprises face a given probability of opportunities to revise prices, such as a 25% chance of revising prices each quarter.

Under the state-dependent pricing models, when a strong shock simultaneously affects a large number of items, prices are revised all at once, suggesting a high probability of grasping price fluctuations as a common component. It should also be easy to grasp price fluctuations as a common component under Taylor-type time-dependent models whereby prices are revised at fixed intervals. With Calvo-type models, however, when the price revision probability is high (when the flexibility of the price is high), there is a likelihood that fluctuations may be grasped as a short-period common component, or otherwise the fluctuations may be just classified as the idiosyncratic component. Of course, if firms' actual price changing behavior is now less uniform and more complex than imagined by recent macroeconomic theory, the fluctuations will surely be grasped as the idiosyncratic component.

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[15] We suspect that the long stagnation of the Japanese economy during the sample period (from the 1st quarter of 1989 through the 4th quarter of 2002) is the reason why no clear correlation is seen between the monetary policy shock proxy variable and the demand shock proxy variable which are believed to be the principal components of the common component.

Our analyses so far have confirmed the presence of a strongly representative common component, and shown that price revisions tend to be implemented only in certain months. These facts suggest that it would be difficult to explain the price revision behavior of Japanese firms using a Calvo-type model. Moreover, in a strict sense, this behavior does not match the Taylor-type model either, in the sense that that the price revisions are implemented not at fixed intervals, but rather in certain predetermined months. Nevertheless, in constructing economic models the Taylor type does make a close approximation, and is unlikely to greatly diverge from the actual price revision behavior.

Saita, Takagawa, Nishizaki, and Higo [2006] observed the price revision pattern in Japan using a hazard probability distribution.[16] They found that there are absolutely no items with random price-revision patterns, and reported that it would be difficult to use a Calvo-type model to explain Japanese price revision behavior, reaching the same conclusion suggested by the analyses in this paper.

4.2 The harmonization in the timing of price revisions among items

The prior research Bils and Klenow [2002], which analyzed price stickiness using price revision probability data for items used to compile the U.S. CPI, reported substantial differences in price flexibility across item categories.[17] Also, while Altissimo, Mojon, and Zaffaroni [2004], which analyzed price stickiness using CPI item data from France, Germany and Italy, observed common price stickiness characteristics in the aggregated series data and, to some extent, in the disaggregate data as well, they reported great heterogeneity by item in the shock propagation mechanism. In Japan as well, Saita, Takagawa, Nishizaki, and Higo [2006] reported that the price revision pattern has extremely complex characteristics with great differences by item.

Clark [2003] focused on the relationship between macro inflation persistence and micro price stickiness, analyzed item price data used for the compilation of the U.S. personal consumption expenditures price index, and measured how price stickiness changes when the item data is aggregated into higher categories. He reported that the persistence of

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[16] This is the distribution of the conditional probability that prices that are not revised continuously from period 0 to period $t-1$ will be revised in period t.

[17] Bils and Klenow also reported that the prices of half the items are revised at a frequency of 4.3 months or less.

the disaggregate data is lower than that of the aggregated data, but that a sizable proportion of the disaggregate data are highly persistent, and that the more persistent items tend to represent larger shares of consumption expenditures. Similarly, the analyses in our paper extract a highly representative common component from the Japanese price revision patterns by item, and conclude that this common component accounts for a substantial portion of the CPI. These conclusions do not deny the existence of unique price revision patterns by individual item.[18] They do, however, indicate that the variations by item do not have a great impact on the price fluctuations in the total CPI.

The high harmonization in the timing of price revisions in Japan contrasts with the findings reported by Altissimo, Mojon, and Zaffaroni [2004] for the euro area. Compared with the results presented herein in **Figure 3** through **Figure 6**, in the euro area the relative importance of the common component drops dramatically as the frequency moves higher. In other words, in the euro area the relative importance of the idiosyncratic component is extremely high outside the band of low frequency, and this indicates a great difference by item in the speed at which shocks are transmitted. In Japan, the common component retains some relative importance, even in the high frequency band. This indicates a greater uniformity in the timing of price revisions in Japan compared with the euro area.

5. Conclusions

The analyses in this paper conclude that the timing of price revisions is similar among the various items that comprise Japan's CPI. The analyses also reveal that price revisions in Japan are implemented in particular months, rather than taking place a certain period of time after shocks occur. Moreover, our findings indicate a high probability that the prices of many items are revised at long periods of a half-year or more. Additionally, they show that in recent years the characteristic of price stickiness has been lowering slightly for goods, but heightening for services, and that the price stickiness overall remains at a high

[18] It is important to note that because our paper analyzes quarterly data, it does not grasp price revision frequencies with short periods of just one month. Thus the conclusions in our paper do not deny the findings in Saita, Takagawa, Nishizaki, and Higo [2006] that the majority of goods have hazard probability distributions whereby the probability of price revisions peaks at an elapsed period of one month and declines thereafter. Furthermore, it is also important to note that Japan's CPI do not includes short period bargain sale prices which is set for less than 7 days.

level.

Considering the implications of these findings for constructing macroeconomic models, we found that Calvo-type models, which have often been used as standard models in recent years, are not a realistic choice for depicting the Japanese price revision process, and that rather Taylor-type models whereby prices are revised at fixed intervals are likely to better fit the Japanese data. While these facts have also been observed in the U.S. and euro area to some extent, the analyses in this paper indicate that compared with the U.S. and euro area Calvo-type models are more unlikely to match the price setting behavior of Japanese firms.

This paper constitutes one attempt to examine the basic features of price revision behavior in Japan. In Europe and the U.S. research is advancing on price setting behavior with studies using disaggregate data such as item data and even individual price data[19] In Japan, studies of price setting behavior using micro data have also recently begun as well. Studies in this area need to be pursued further, including the perspective of whether Japanese firms' price revision behavior is better characterized as state-dependent pricing or time-dependent pricing.

[19] For example, the European Central Bank (ECB) launched an Inflation Persistence Network which conducts comprehensive research on price characteristics in 2003, and joint research is being conducted by the ECB, the central banks of each country, and academic researchers.

Appendix. Assumptions for the Estimation of the GDFM Model

The GDFM expresses the observed values x_{it} （item $i = 1,...,n$; time $t = 1,...,T$ ） as follows.

$$x_{it} = \underbrace{b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \cdots + b_{iq}(L)u_{qt}}_{\text{Common component } \chi_{it}} + \underbrace{\varepsilon_{it}}_{\text{Idiosyncratic component}},$$

Here $u_{jt}(j = 1,...,q)$ are the common shocks、L is the lag operator, and b_{iq} are the shock response parameters. The following assumptions are made for the estimation.

1. The common shocks u_{qt} which form χ are principal macroeconomic shocks such as demand shocks, supply shocks and policy shocks, and there are q types of such shocks. Moreover, their q-dimensional vectors $U_q = (u_{1t,...,}u_{qt})'$ are orthonormal white noise.

   i.e. For all j and t, $E(u_{jt}) = 0$, $\mathrm{var}(u_{jt}) = 1$,

   For all j, t and $k \neq 0$, $u_{jt} \perp u_{jt-k}$,

   For all $s \neq j$, t and k, $u_{jt} \perp u_{st-k}$,

2. Each u_{jt}, x_{it} has a particular lag structure and reaction coefficient $b_{ij}(L)$. Also, $b_{ij}(L)$ is symmetrical to the positive and negative lags (it is one-sided in L).

3. $\varepsilon_n = (\varepsilon_{1t},...,\varepsilon_{nt})'$ is a stationary process and $E(\varepsilon_{jt}) = 0$, for all n, and has no correlation with macro shocks.

   i.e. For all i, j, t, and k, $\varepsilon_{it} \perp u_{jt-k}$,

4. $\mathrm{X}_{nt} = (x_{1t},...,x_{nt})'$ is a stationary process and $E(\varepsilon_{jt}) = 0$, for all n. Moreover, for all i, the spectral densities $\sigma_{ii}(\theta)$ are bounded in modulus.

   i.e. For all i and for all $\theta \in [-\pi, \pi]$ there exists a real $c_i > 0$ such that $\sigma_{ii} \leq c_i$.

5. Regarding the correlations among the idiosyncratic components, as long as $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{i+h,t}) = 0$ （$h > 1$）, $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{i+1,t}) \neq 0$ is allowed.

6. We denote the j^{th} non-negative real eigenvalue calculated from the spectral

density matrix $S(\theta)$ by λ_{nj}, and by $\lambda^{\varepsilon}_{nj}$ for the idiosyncratic component. For all i and all $\theta \in [-\pi, \pi]$, there exists a real Λ such that $\lambda^{\varepsilon}_{n1}(\theta) \leq \Lambda$ ($\lambda^{\varepsilon}_{n1}$ is the largest $\lambda^{\varepsilon}_{nj}$).

7. Similarly when denoting λ^{χ}_{nj} for the common component, for all i and all $\theta \in [-\pi, \pi]$, there exists a real M such that $\lambda_{nq+1}(\theta) \leq M$, even when the first q diverge.

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Table1. The 10 largest eigenvalues[20]

1	2	3	4	5	6	7	8	9	10
0.225	0.084	0.062	0.054	0.047	0.042	0.038	0.035	0.032	0.029

Table2. The lag correlation coefficients between the common component and macroeconomic variables[21]

	Lags	Natural rate of interest[1]	GDPgap[2]	Monetary policy[3]
Common component is leading	−4	0.35	0.37	−0.14
	−3	0.36	0.44	−0.06
	−2	0.42	0.50	0.01
	−1	0.43	0.57	−0.30
	0	0.49	0.62	−0.26
Common component is lagging	1	0.58	0.63	−0.10
	2	0.55	0.61	−0.40
	3	0.58	0.58	0.01
	4	0.62	0.59	−0.16

Correlation coefficients over |0.5| are shadowed

Notes. 1. Natural rate of interest is difined as the real interest rate where the effect of the interest rate channel to the GDPgap is neutral in IS equation.
2. Operating ratio index of Indices of Industrial Production(IIP).
3. The ΔlogM1 residual from the AR(1)model with constant term, including the trend.

[20] These are averages of the lags from -8 to +8.

[21] Data period is from the 1st quarter of 1989 through the 4th quarter of 2002.

Figure1. The CPI and its common component[22]

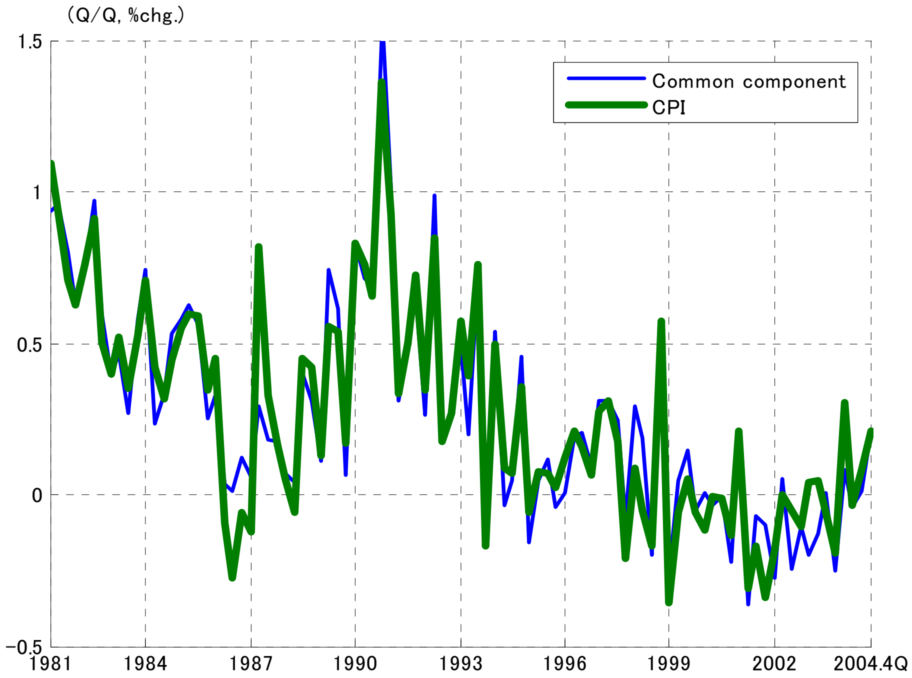
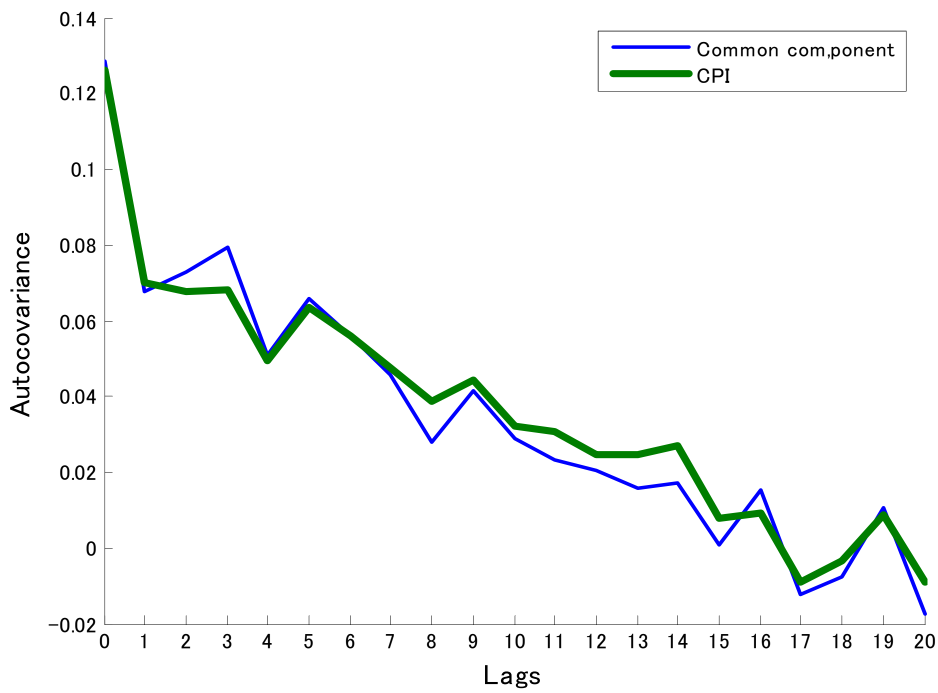


Figure2. Lag autocovariance of the CPI and of its common component



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[22] The weighted average of the common components of 360 items.

Figure3. The 10 largest eigenvalues derived from the CPI item data (<u>not</u> seasonally adjusted)

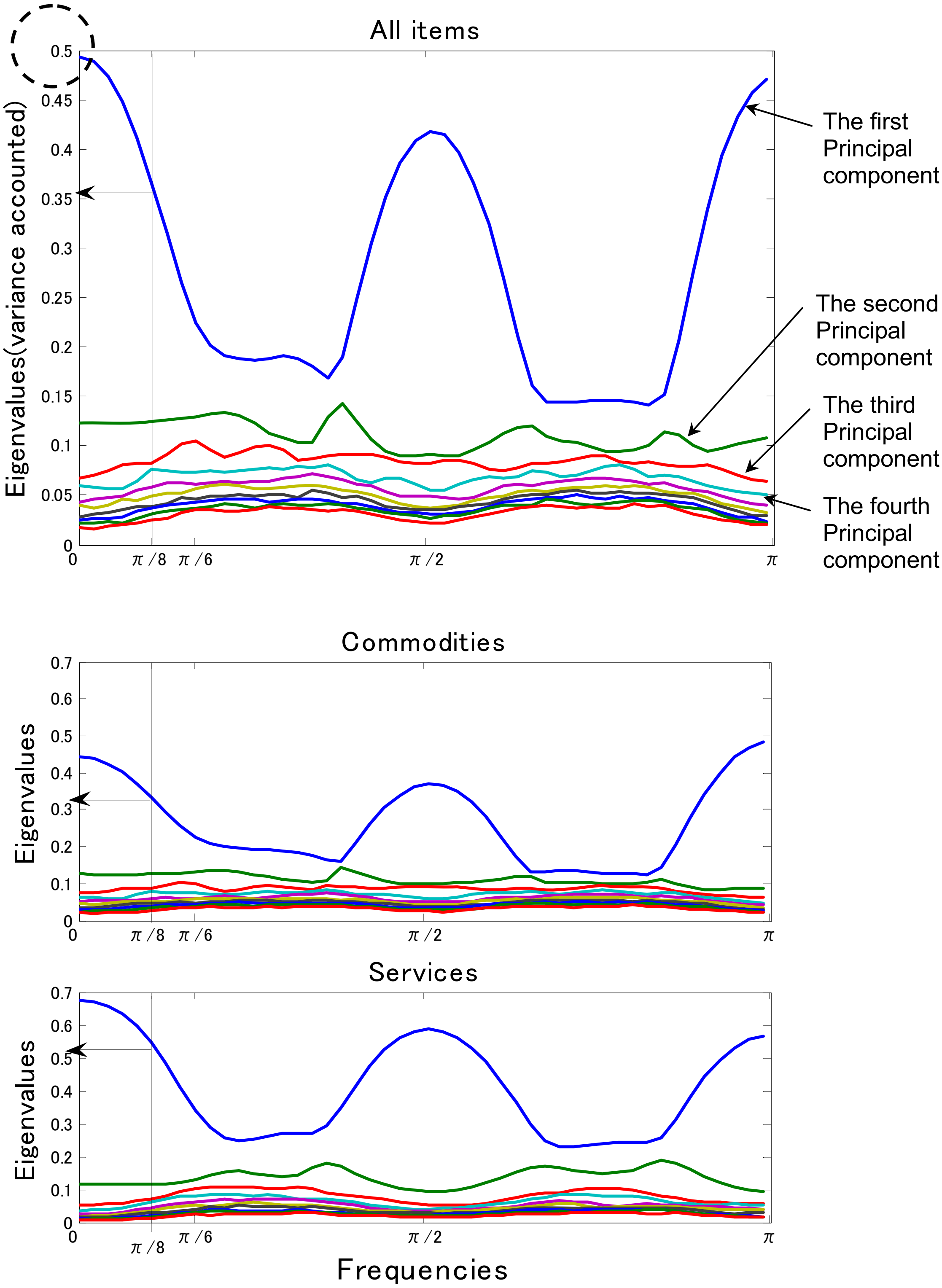

Figure4. The 10 largest eigenvalues derived from the CPI item data (seasonally adjusted)

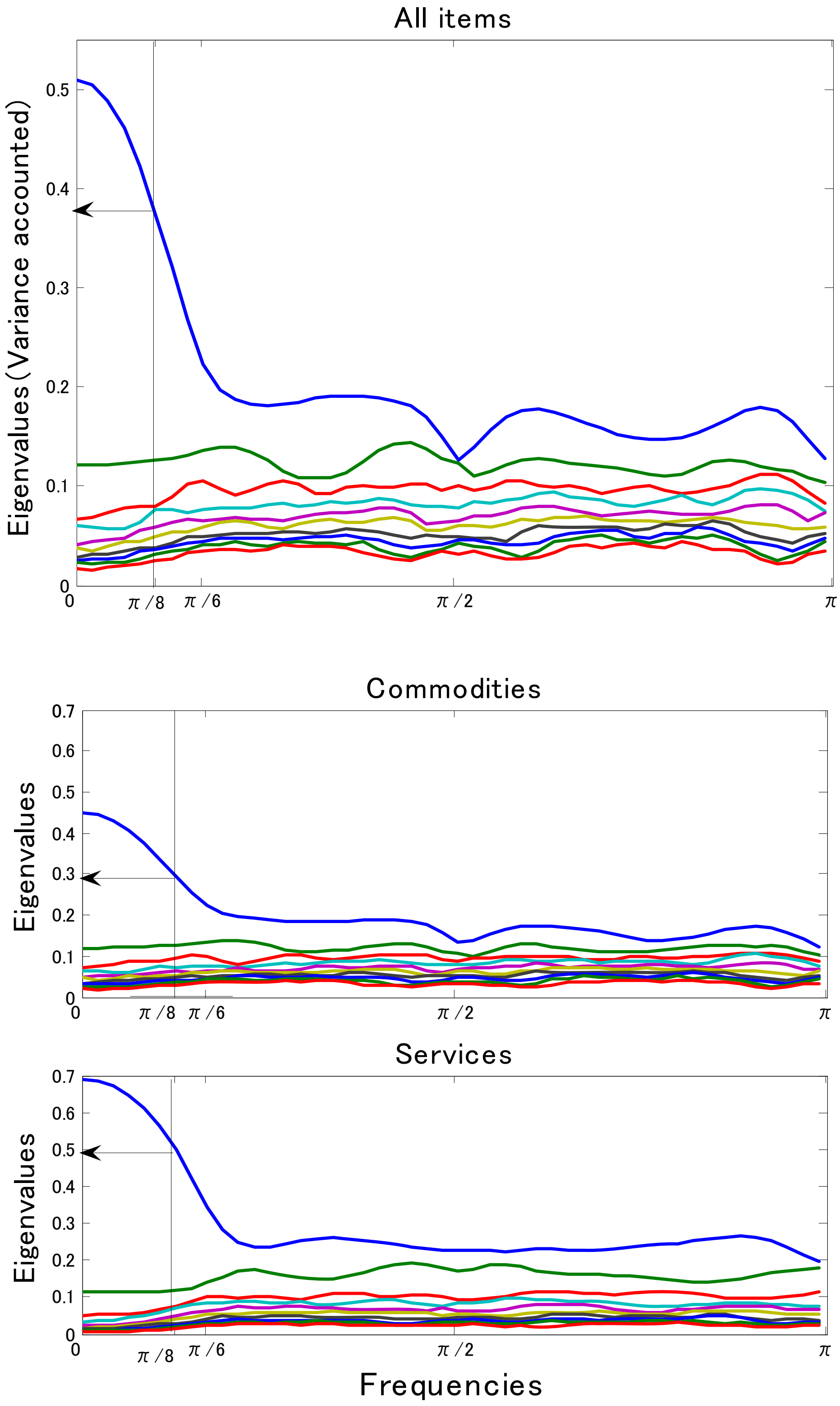

Figure5. The 10 largest eigenvalues derived from the CPI item data (Sample Period: 1980-1992, Seasonally adjusted)

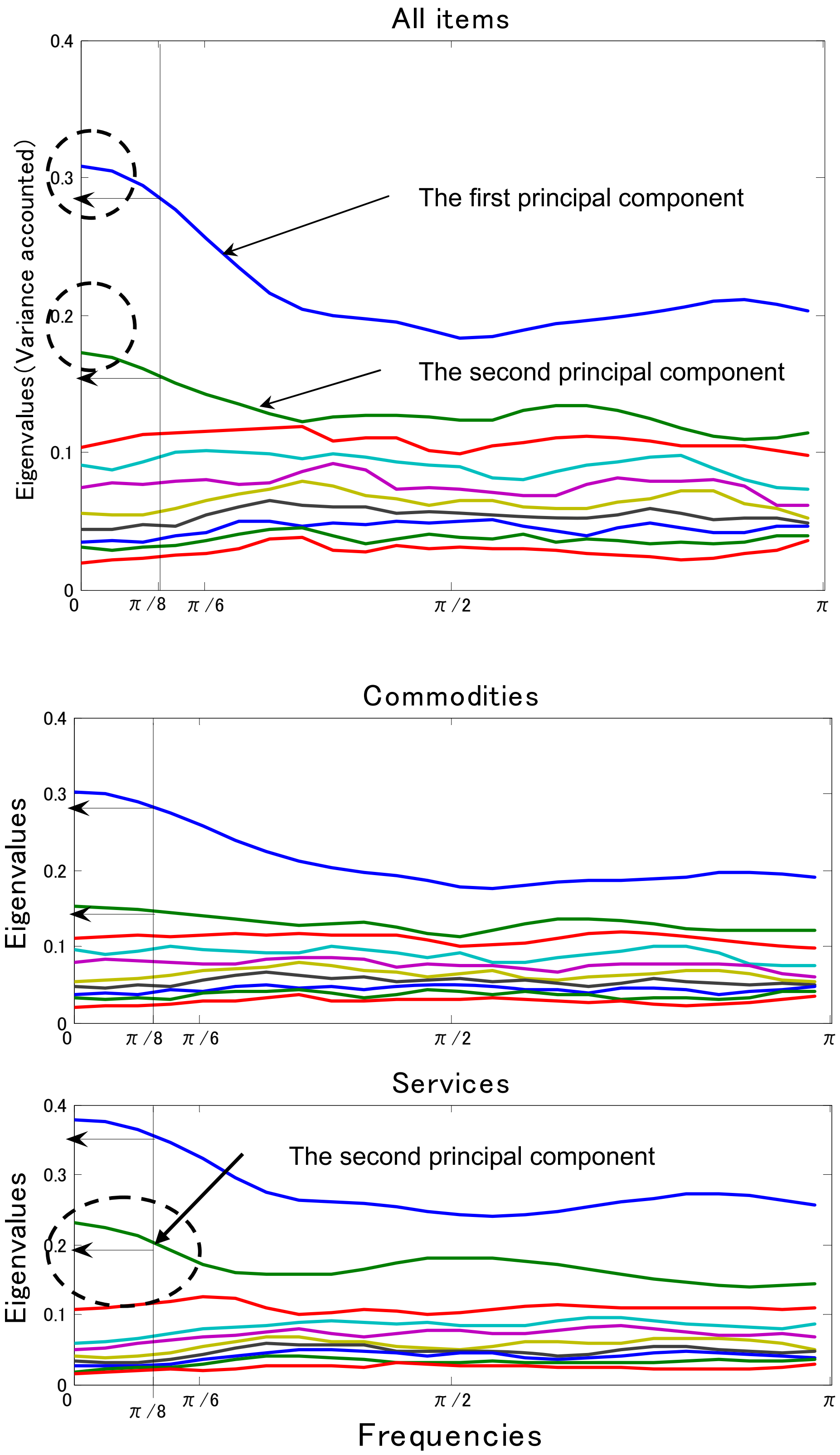

Figure6. The 10 largest eigenvalues derived from the CPI item data (Sample Period: 1993-2004, seasonally adjusted)