Working Paper Series

# Downward Price Rigidity of the Japanese CPI —Analysis by Probability Density Functions and Spatial Density Functions

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Working Paper 99-3

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# Downward Price Rigidity of the Japanese CPI —Analysis by Probability Density Functions and Spatial Density Functions*

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August 11, 1999

**Abstract**

We define downward price rigidity as the state in which the speed at which prices fall is slower than that in which they rise. Based on this definition, we examine the downward price rigidity of each item that constitutes the core CPI of Japan. That is, according to the results of fractional integration tests on price changes of individual items, we estimate probability density functions in the stationary case and estimate spatial density functions in the nonstationary case. We also test their skewness. As a result, we found significant downward price rigidity in some items. Roughly speaking, about 20-30% of the core CPI weight shows downward price rigidity.

*Keywords:* CPI, Spatial Density Function, Price rigidity, Fractional integration
*JEL Classification:* E31

## 1 Introduction

Recently, the core CPI of Japan [1] has been falling because of a serious recession. However, the falling speed of the core CPI looks relatively slow.

*Preliminary. Do not quote without permission. I am grateful to Professor Peter C.B. Phillips for helpful suggestions and comments. The views expressed in this paper are those of the author and do not neccessarily reflect those of the Bank of Japan or Research and Statistics Department.

[1] The core CPI of Japan is CPI excluding fresh food.

That is, the speed at which prices change in this deflationary period looks slower than that of past non-deflationary periods. This might be because of downward price rigidity.

However, we can not tell if this is conclusive because the core CPI itself is a aggregate index. That is, there are other hypotheses.

(i) Possible price rises in some items could lessen the falling speed of the core CPI.

(ii) The Japanese economy could not be so weak. This would be consistent with the slow falling speed of the core CPI.

Given these alternative explanations, it is useful to test whether each individual item constituting the core CPI has downward price rigidity. If we find downward price rigidity in many items, there would be support for the downward price rigidity hypothesis. On the other hand, if we do not find it in each item, we should not use the downward price rigidity hypothesis to explain the relatively slow falling speed of the Japanese CPI. We define downward price rigidity as the state in which the speed at which prices fall is slower than that in which they rise. Based on this definition, we examine the downward price rigidity of each item that constitutes the core CPI. That is, we test or observe the skewness in the distributions of price changes of each item.

There are several studies related to price rigidity. That is, price rigidity itself has been used for a number of studies in macroeconomic models. A typical study of price rigidity assumes that some nominal prices are flexible and other prices are rigid. For example, Gordon(1975) assumes that oil prices are flexible and other prices are rigid. Phelps(1978), and Dornbusch-Fischer(1990) assume that nominal wages are rigid and output prices are flexible.

In studies of downward price rigidity, Balvers(1988) solved the firm's maximization problem to show that firms with a high degree of monopoly power display relative downward price rigidity, while the reverse applies to firms with low monopolistic power. Neumark and Sharpe(1992) showed that downward price rigidity and upward price flexibility are a consequence of market concentration by estimating a dynamic pricing function that used a bank deposit interest rate as a dependent variable and inter-market loan rates and market characters as independent variables.

Some studies worked with the cross-sectional skewness of price changes. Ball and Mankiw(1995) and Balke and Wynne(1996a, b) reported the correlation between the mean of price changes and the "cross-sectional" skewness. They also discussed whether their finding is related to price rigidity or another hypothesis. However, Bryan and Cecchetti(1995, 1999) criticized the correlation itself. They showed that the observed correlation between the mean and the cross-sectional skewness could be the result of a small-sample bias.

In analyzing price rigidity, we assume that some nominal prices could be rigid and others might not be, as in typical studies of price rigidity [2]. We also assume that some have downward price rigidity and others do not, although we do not specify the theoretical reasons for downward price rigidity. Our approach is to observe the time-series skewness of the distributions of individual items [3]. Because we are working with time series, we have to solve the problem of the possibility of nonstationarity. In order to solve this problem, we test general nonstationarity by fractional integration tests before estimating probability density functions in the stationary case and spatial density functions in the nonstationary case. Based on those functions, we test or check the skewness of each item.

We found significant downward price rigidity at the 5% level in some stationary items, which amount to about 25% of the total core CPI weight. Although we do not have any formal testing tools of skewness for the nonstationary series yet, we casually checked the likelihood of positive skewness by using a modified distribution with 95% upper band in the left-hand side and a 95% lower band in the right-hand side. Even under this modified distribution against the positive skewness hypothesis, some items, which amount to about 4% of the core CPI weight, show positive skewness.

This paper is organized as follows. We discuss the problems of time series analysis and test fractional integration in Section 2. According to the results of those tests, we estimate probability density functions and spatial density functions suggested by Phillips(1998) and Phillips(1999), and calculate skewness in Section 3. Section 4 concludes the paper and discusses its implications.

## 2 Fractional Integrating Tests

In describing the characteristics of an economic time series, a presumption of stationarity helps us greatly. That is, in the case of stationary data, we can use time invariant parameters like the mean, the variance, and the autocorrelogram to build descriptive statistics that can be estimated from the observed data in terms of the sample analogues of these quantities. These

[2]This point is different from the work of Ball and Mankiew(1995).

[3]Our approach is also different from Ball-Mankiw(1995) and Balke-Wynne(1996a, b) on this point. Our approach does not depend on the correlation hypothesis between the mean of inflation and cross-sectional skewness. That is, our approach does not suffer from the small sample positive bias that Bryan and Cecchetti(1995, 1999) pointed out.

parameters are useful in summarizing a particular series and in comparing different series.

Unfortunately, however, we do have trouble working with these descriptive statistics when the presumption of stationarity is removed. This is because the underlying time invariant quantities no longer exist. Of course, the sample analogues are computable in the same way. However, their interpretation is not the same and they typically no longer converge without restandardization as the sample size increases. In many time series that have random wandering characteristics, these sample analogues end up having random rather than nonrandom limits.

In a recent work, Phillips(1998) suggested some methods of spatial density analysis that apply in a fairly natural way to nonstationary data with stochastic trends and are useful as descriptive tools. Even when we do not have a framework of time invariant characteristics to rely on due to nonstationarity, we can use his suggestions to find convenient quantitative representations of sample characteristics without being dependent on the use of a specific model. Thus, whereas we do not have fixed population moments or a time invariant probability density to rely upon, we do have a well-defined concept of spatial location that has meaning beyond the immediate sample data. What changes is not the approach to data analysis, but the interpretation of the empirical quantities that emerge from a nonparametric analysis. For a nonstationary series, these quantities simply reflect variational decompositions across space rather than probability decompositions. In the nonstationary case, the density estimate actually estimates the spatial density of the process at each point over the sample - so the result is path dependent and the function being estimated is itself random. In the stationary case, the density is a constant nonrandom function [4].

As a first step, we test nonstationarity by using fractional integration tests. Although much attention has been focused on comparing unit roots with stationary alternatives, we test a broad range of alternatives that we accommodate by allowing for fractional integration and higher order integration.

$$(1 - L)^d y_t = u_t \tag{1}$$

where $y_t$ is a zero mean stationary process, and $d$ is a long memory parameter. If $d = 1$, $y_t$ is unit root nonstationary and said to be an I(1). However, $d$

[4] If we use the spatial density estimate for nonstationary data in the case of stationary rather than nonstationary data, we will obtain the kernel density estimate for stationary data scaled by $\sqrt{n}$. In that case, we are effectively distributing a non-unitary $\sqrt{n}$ probability across spatial points, rather than the $\sqrt{n}$ sojourn time. See Phillips(1999).

does not have to be a positive integer. When $-\frac{1}{2} < d < \frac{1}{2}$, $y_t$ is stationary but strongly correlated in the sense that its lag-$j$ autocovariance decays at the rate $|j|^{2d-1}$, which is slower than that of stationary linear processes like $u_t$. When $\frac{1}{2} \leq d \leq 1$ , $y_t$ is nonstationary, and the value $d = \frac{1}{2}$ provides the nexus between stationary and nonstationary regions. When $d \geq 2$, it is called higher order integration. A process with $d \geq \frac{1}{2}$ has nonstationary long-memory and a variance that explodes as $t \to \infty$. Such processes are not mean reverting.

In order to estimate parameter $d$, we use the method proposed by Phillips(1998). That is, we estimate $d$ by maximizing a local Gaussian likelihood in the frequency domain (see Appendix A). The data of our analysis are price changes of individual items that constitute the consumer price index, monthly from January 1991 to March 1999[5]. Although the total number of items is 580, we can use 558 for our analysis due to missing data [6]. The result is shown in table 1. According to the results of our stationarity tests, we classify items by point estimates of $d$ into two groups: stationary items with $-0.5 < d < 0.5$, and nonstationary items with $-1 < d \leq -0.5$ or $0.5 \leq d < 1.0$ [7] In the stationary group of 528 items, 457 items are significantly stationary. That is, 95% lower band of $d \geq -0.5$ and 95% upper band of $d \leq 0.5$.

# 3 Density Functions and Skewness

Based on our grouping of the previous section, we estimate density functions (see Appendix B). As for stationary items, we can estimate time invariant probability density by the kernel estimate that follows.

$$\hat{pdf}_X(s) = \frac{1}{n}\sum_{t=1}^{n} K_{h_n}(s - X_t) \tag{2}$$

where $h_n$ is the bandwidth parameter $\sqrt{n}\epsilon$ , $s$ is the spatial point, $K(.)$, $K_\epsilon = \frac{1}{\epsilon}K(\frac{\cdot}{\epsilon})$ is a symmetric, nonnegative kernel function that integrates to unity. After estimating the probability density function, we test the positive skewness by using a conventional test for stationary data. That is, skewness $S_k$ is

$$S_k = \frac{3rdm}{(se)^3}, \tag{3}$$

[5]The consumption tax was introduced in April 1989 and the tax rate was lifted in April 1997. In order to avoid this effect, we started the data in January 1991 and omitted the consumption tax hike of April 1997.

[6]By using x12ARIMA, we seasonally adjusted 435 series which require seasonally adjustment.

[7]There is no $|d| \geq 1$ although for some estimates of $d$ we cannot reject the possiblity.

where $se$ is a standard error and $3rdm$ is the third moment. The test statistic of the null hypothesis that $S_k = 0$ is as follows.

$$\frac{N}{6}S_k^2 \to \chi^2 \ of \ degree \ 1 \tag{4}$$

Table 2 shows the result of skewness tests for the significant stationary group of 457 items. In this category, items with significant positive skewness amount to 22% of the core CPI weight. Table 3 shows the result of skewness tests for the stationary group of 528 items, which have point estimates $|d| < 0.5$. In this category, items with significant positive skewness amount to 25% of the core CPI weight.

For a nonstationary series, there is no time invariant probability measure and it is no longer sensible to think of decomposing probability into densities of different spatial regions. Instead, we estimate spatial density functions. Roughly speaking, we can think of spatial density functions as the proportion of time that the standardized series spends in the vicinity of a spatial point. That is, in this case, we think sojourn time instead of probability. And the total amount of sojourn time is set to $\sqrt{n}$(the number of samples). We estimate spatial density functions by using the kernel that follows.

$$\hat{L}_B\,(1, s) = \frac{1}{\sqrt{n}}\sum_{t=1}^{n} K_{h_n}(\sqrt{n}s - y_t) \tag{5}$$

The quantity $\hat{L}_B(r, s)$ is a kernel estimate of local time in the sense that it measures sojourn time at the spatial point $s$. The reason for this restandardization is that, in the nonstationary case, the process wanders away from the location. To analyze downward price rigidity as skewness statistically, it is helpful to test the skewness of the density function. But we cannot use the usual skewness test for nonstationary data because the usual test is only for a stationary time series. If a process is nonstationary, that is, its density is random, then one would expect disorder in the density function. However, there may indeed be evidence of longer tails in one direction than in another. So there is probably some basis for analyzing skewness although we do not have the formal testing tools yet. In a nonstationary case, we examine positive skewness by the "modified" distribution, which consists of the 95% upper band in the left hand side and the 95% lower band in the right hand side. This "modified" distribution would be against the hypothesis of skewness$> 0$. So if skewness$> 0$ in the case of this modified distribution, the true skewness is more likely to be positive, although this procedure is not a formal test.

Table 4 shows the result of this preliminary examination, in which 4% of the total core CPI weight shows positive skewness in spite of the modified distribution against positive skewness.

Although "significant positive skewness at the 5% level in stationary data" is statistically different from "positive skewness in the modified distribution by using 95% confidence intervals in nonstationary data", it would be practically useful for us to summarize our result. Table 5 shows the summary of our analysis, which is just the sum of each cell of Table 3 and Table 4. According to Table 5, about 29% of the total core CPI weight is more likely to be positive skewness (downward price rigidity) as a whole. As for categories of commodities, housing, transportation & communication, education, and food[8] show a relatively higher share of the core CPI weight although we could not specify reasons for downward price rigidity.

# 4 Conclusions

We analyzed downward price rigidity of the core CPI components in Japan. As a result, we found about 20-30 % of the core CPI weight shows downward price rigidity. That is, according to point estimates of memory parameters in fractional integration tests, we classified items into two groups: stationary items, which include significant stationary data, and nonstationary items. In significant stationary data, about 22 % in terms of the core CPI weight shows significant positive skewness at the 5% level. In stationary data, which have stationary memory point estimates $|d| < 0.5$, about 25% in terms of the core CPI weight shows significant positive skewness at the 5% level. In nonstationary data, about 4% in terms of the core CPI weight shows positive skewness in the modified density distribution against the positive skewness hypothesis.

These results imply that price rigidity could, partly, explain the relatively slow falling speed of the core CPI in Japan. It would be more useful to see an extreme case as an upper band of its effect. If every item went into a falling phase with the same potential falling speed, and 20%-30% of the core CPI weight hardly fell, price rigidity would slow the falling speed of the core CPI at a rate of 20% -30%, which means the potential falling speed would be the actual falling speed times $\frac{1}{0.8} \sim \frac{1}{0.7}$.

[8] Premium rice, school lunch and so on.

## 5 Appendix A: Fractional Integration Tests

The following explanation of fractional integration is from Phillips(1998), Phillips and Xiao(1999), and Robinson(1995). We now consider a model for price change process as follows.

$$(1-L)^d y_t = u_t \tag{6}$$

where $u_t$ is a zero mean stationary process with spectral density $f_{uu}$ and d is the long memory parameter. By virtue of equation (6), the spectrum of $y_t$ has the following asymptotic form in the vicinity of the origin

$$f_{yy}(\lambda) \sim \frac{f_{uu}(0)}{\lambda^{2d}},\ \lambda \sim 0. \tag{7}$$

The operator $(1-L)^d$ is defined by the formal binominal expansion

$$(1-L)^d = 1 + \sum_{j=1}^{\infty} \frac{(-d)_j}{j!} L^j, (-a)_j = (-a)(-a+1), ..., (-a+j-1) \tag{8}$$

whose convergence properties depend on the value of $d$. When $d$ is a positive integer, the process $y_t$ is said to be an $I(d)$ process. With this general model, there may be one or several unit roots ($d$ integer $\geq 1$) or fractional integration ($0 < d < 1$).

When $0 \leq d \leq 1/2$ , $y_t$ is stationary but strongly correlated in the sense that its lag-$j$ autocovariance $\gamma_j$ decays at rate $|j|^{2d-1}$ , which is slower than that of a stationary linear process like $u_t$. When $1/2 \leq d \leq 1$ , $y_t$ is nonstationary, and the value $d = 1/2$ provides the nexus between stationary and nonstationary regions. When $d$ is an integer $\geq 2$ , it is called higher order integration. In this case, $y_t$ has two or more real autoregressive unit roots and is stationary after differencing $d$ times. A process with $d \geq 1/2$ has nonstationary long-memory and a variance that explodes as $t \to \infty$. Such processes are, in fact, not mean reverting, although their impulse responses, which are obtained from the expansion

$$(1-L)^{-d} = 1 + \sum_{j=1}^{\infty} \frac{(d)_j}{j!} L^j \tag{9}$$

and have the form

$$\frac{(d)_j}{j!} = \frac{1}{,(d)} \frac{,(d+j)}{,(j+1)} \simeq \frac{1}{,(d)} \frac{1}{j^{1-d}}\ as\ j \to \infty, \tag{10}$$

decay to zero provided $d \leq 1$ , and so shocks in equation (6) are not persistent in this case.

Within the family (6), it is possible to test for 'unit root' nonstationarity by estimating $d$ and testing the null hypothesis $d = 1$ against the alternative $d \leq 1$, or to test for stationarity $d \leq 1/2$.

Phillips(1998) proposed to estimate $d$ in (6) by maximizing a local Gaussian likelihood. Following Kunsch(1987), he suggests a Gaussian objective function, defined in terms of the parameter $d$ and $G = f_{uu}(0)$,

$$Q_m(G, d) = \frac{1}{m} \sum_{j=1}^{m} \left( log(G\lambda_j^{-2d}) + \frac{\lambda_j^{2d}}{G} I_y(\lambda_j) \right) \tag{11}$$

where $I_y(\lambda_j) = w_y(\lambda_j) w_y(\lambda_j)^*$ is periodgram, $\lambda_j = \frac{2\pi j}{n}, j = 0, 1, ..., n-1$ are the harmonic frequencies, and $w_y(\lambda_j) = \frac{1}{\sqrt{2\pi n}} \sum_{t=1}^{n} y_t e^{i(t-1)\lambda_j}$ is discrete Fourier transform of $y_t$. The integer $m$ is less than $n$ and defines the number of frequencies in the vicinity of the origin that are being used in the estimation of the parameter $d$.

The local Gaussian estimates of $G$ and $d$ are obtained by minimizing $Q_m(G, d)$, so that

$$(\hat{G}, \hat{d}) = \arg \min_{0<G<\infty, d>0} Q_m(G, d), \tag{12}$$

which involves numerical optimization. Concentrating equation(11) with respect to $G$, we find that the estimated $\hat{d}$ satisfies

$$\hat{d} = \arg \min_{d} R(d) \tag{13}$$

where

$$R(d) = log\hat{G}(d) - 2d \frac{1}{m} \sum_{j=1}^{m} log\lambda_j, \quad \hat{G}(d) = \frac{1}{m} \sum_{j=1}^{m} \lambda_j^{2d} I_y(\lambda_j). \tag{14}$$

Recently, Robinson(1995) analyzed the above estimators in the stationary case where $d \in (-\frac{1}{2}, \frac{1}{2})$. Under rather weak regularity conditions, Robinson showed that $\hat{d} \rightarrow_p d_0$ and $\hat{G}(\hat{d}) \rightarrow_p G_0$ where $d_0$ and $G_0$ are the true values of the parameters. Under a slight strengthening of these conditions, Robinson also established that $\hat{d}$ is asymptotically normally distibuted with the limit distribution

$$m^{\frac{1}{2}}(\hat{d} - d) \xrightarrow{d} N(0, \frac{1}{4}). \tag{15}$$

This limit theory makes possible statistical testing and the construction of confidence intervals for $d_0$ in the stationary case.

Phillips(1998) has dealt with the nonstationary case where $d \in (\frac{1}{2}, 1]$ and, under regularity conditions that are broadly similar to those of Robinson(1995), has established that

$$\hat{d} \xrightarrow{p} d, \hat{G}(\hat{d}) \xrightarrow{d} G_0 + C(d), \tag{16}$$

and

$$m^{\frac{1}{2}}(\hat{d}-d_0) \Rightarrow MN\left(0, \frac{1}{4}\frac{G_0^2}{(G_0+C(d_0))^2}\right), \tag{17}$$

where $C(d) > 0$ is a random and depends on the true value of $d$. Since the variance in equation (17) is smaller than $1/4$, conservative confidence intervals can be constructed for $d$ that utilize the limit theory (15) and apply for both stationary and nonstationary $d$.

# 6 Appendix B: Spatial Densities for Nonstationary Series

The following explanation is from Phillips(1998) and Phillips(1999). We concentrates on a unit root time series $y_t = \sum_1^t u_s$, whose increments $u_t$ form a stationary time series with zero mean and finite absolute moments to order $p > 2$, and which satisfies the functional law

$$Y_n(.) = \frac{y_{[n.]}}{\sqrt{n}} \Rightarrow B(.) \equiv BM(\sigma^2). \tag{18}$$

$L_B(r,s)$ is called the local time of Brownian motion $B$ at a spatial point $s$. We define the local time of fractionall Brownian motion

$$L_{B_{d-1}}(r,s) = |B_{d-1}-s| - |B_{d-1}(0)-s| - \int_0^r sgn(B_{d-1}(t)-s)dB_{d-1}(t). \tag{19}$$

A natural candidate for estimating the local time of the limit process of $n^{-\frac{1}{2}}X_{[nr]}$ at $s$ is the scaled kernel estimate

$$\hat{L}_B\left(r, \frac{s}{\sqrt{n}}\right) = \frac{1}{\sqrt{n}}\sum_{t=1}^{n} K_{h_n}(a-y_t) \tag{20}$$

where $K(.)$ is a symmetric, nonnegative kernel function that integrates to unity, $K_\epsilon(.) = \frac{1}{\epsilon}K(\frac{\cdot}{\epsilon})$, $a = \sqrt{n}s$, $h_n = \sqrt{n}\epsilon_n$, $\hat{\omega}$ is a consistent estimate of $\omega^2 = 2\pi f_{\delta x}(0)$.

The definition of $\hat{L}_B\left(r, \frac{s}{\sqrt{n}}\right)$ involves scaling the conventional kernel estimator given in equation (20) by $\sqrt{(n)}$. The reason for this standardization is that in the nonstationary case the process $X_t$ wanders away from the location $s$ at the rate $\sqrt{n}$ and, for such departure from $s$, $K(h_n^{-1}(s-X_t))$ is negligibly small. In effect, the stochastic trend property of $X_t$ reduces the order of magnitude of the kernel estimate compared with the stationary case.

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Table 1: Fractional Integration Tests

| memory parameter $d$ | number of items |
|---|---|
| $d \leq -1$ | 0 |
| $-1 < d \leq -0.5$ | 17 |
| $-0.5 < d < 0.5$ | 528 |
| $-0.5 <$ 95% *lower band* *and* 95% *upper band* $< 0.5$ | 457 |
| $0.5 \leq d < 1.0$ | 13 |
| $1.0 \leq d$ | 0 |
| total | 558 |

Table 2: Skewness Tests of Price Changes: significant Stationary Time Series[a]

| commodities | total number of items | number of items with significant positive skewness at 5% level | total weight of items | total weight of items with significant positive skewness at 5% level |
|---|---|---|---|---|
| Food | 222 | 30 ( 14 %)[b] | 2850 | 329 ( 12 %)[c] |
| Housing | 21 | 4 ( 19 %) | 1981 | 99 ( 5 %) |
| Fuel, light and water charges | 6 | 2 ( 33 %) | 590 | 119 ( 20 %) |
| Furniture and household utensils | 61 | 7 ( 11 %) | 411 | 60 ( 15 %) |
| Clothing and footwear | 82 | 20 ( 24 %) | 679 | 122 ( 18 %) |
| Medical care | 26 | 7 ( 27 %) | 329 | 183 ( 56 %) |
| Transportation and communication | 39 | 18 ( 46 %) | 1216 | 454 ( 37 %) |
| Education | 13 | 11 ( 85 %) | 13 | 417 ( 92 %) |
| Reading and recreation | 77 | 18 ( 23 %) | 1090 | 254 ( 23 %) |
| Miscellaneous | 33 | 13 ( 39 %) | 398 | 142 ( 36 %) |
| CPI | 580 | 130 ( 22 %) | 10000 | 2179 ( 22 %) |
| CPI(excluding fresh food) | 518 | 124 ( 24 %) | 9504 | 2135 ( 22 %) |

[a] $-0.5 < 95\%$ *lower band and* $95\%$ *upper band* $< 0.5$.
[b] The value in parenthesis means the percentage of the number in the total number of commodities.
[c] The value in parenthesis means the percentage of the weight in the total weight of commodities.

Table 3: Skewness Tests of Price Change: Stationary Time Series[a]

| commodities | total number of items | number of items with significant positive skewness at 5% level | total weight of items | total weight of items with significant positive skewness at 5% level |
|---|---|---|---|---|
| Food | 222 | 40 (18 %)[b] | 2850 | 477 (17 %)[c] |
| Housing | 21 | 4 (19 %) | 1981 | 99 (5 %) |
| Fuel, light and water charges | 6 | 3 (50 %) | 590 | 198 (34 %) |
| Furniture and household utensils | 61 | 8 (13 %) | 411 | 66 (16 %) |
| Clothing and foot wear | 82 | 21 (26 %) | 679 | 124 (18 %) |
| Medical care | 26 | 9 (35 %) | 329 | 195 (59 %) |
| Transportation and communication | 39 | 18 (46 %) | 1216 | 454 (37 %) |
| Education | 13 | 12 (92 %) | 13 | 442 (97 %) |
| Reading and Recreation | 77 | 20 (26 %) | 1090 | 272 (25 %) |
| Miscellaneous | 33 | 13 (39 %) | 398 | 142 (36 %) |
| CPI | 580 | 148 (26 %) | 10000 | 2469 (25 %) |
| CPI(excluding fresh food) | 518 | 141 (27 %) | 9504 | 2421 (25 %) |

[a] $-0.5 < d < 0.5$.
[b] The value in parenthesis means the percentage of the number in the total number of commodities.
[c] The value in parenthesis means the percentage of the weight in the total weight of commodities.

Table 4: Skewness Examination by Modified Distribution[a]: Nonstationary Time Series

| commodities | total number of items | number of items with positive skewness in the modified distribution | total weight of items | total weight of items with positive skewness in the modified distribution |
|---|---|---|---|---|
| Food | 222 | 0 ( 0 %)[b] | 2850 | 0 ( 0 %)[c] |
| Housing | 21 | 2 ( 10 %) | 1981 | 369 ( 19 %) |
| Fuel, light and water charges | 6 | 0 ( 0 %) | 590 | 0 ( 0 %) |
| Furniture and household utensils | 61 | 0 ( 0 %) | 411 | 0 ( 0 %) |
| Clothing and foot wear | 82 | 1 ( 1 %) | 679 | 6 ( 1 %) |
| Medical care | 26 | 0 ( 0 %) | 329 | 0 ( 0 %) |
| Transportation and communication | 39 | 0 ( 0 %) | 1216 | 0 ( 0 %) |
| Education | 13 | 0 ( 0 %) | 13 | 0 ( 0 %) |
| Reading and recreation | 77 | 0 ( 0 %) | 1090 | 0 ( 0 %) |
| Miscellaneous | 33 | 0 ( 0 %) | 398 | 0 ( 0 %) |
| CPI | 580 | 3 ( 1 %) | 10000 | 375 ( 4 %) |
| CPI(excluding fresh food) | 518 | 3 ( 1 %) | 9504 | 375 ( 4 %) |

[a]Modified distribution have the 95% upper band in the left hand side and 95 % lower band in the right hand side.
[b]The value in parenthesis means the percentage of the number in the total number of commodities.
[c]The value in parenthesis means the percentage of the weight in the total weight of commodities.

Table 5: Roundup Table of Skewness Tests and Examination : Stationary and Nonstationary Cases

| commodities | total number of items | number of items with more likely positive skewness[a] | total weight of items | number of items with more likely positive skewness[b] |
|---|---|---|---|---|
| Food | 222 | 40 ( 18 %) [c] | 2850 | 477 ( 17 %)[d] |
| Housing | 21 | 6 ( 29 %) | 1981 | 468 ( 24 %) |
| Fuel, light and water charges | 6 | 3 ( 50 %) | 590 | 198 ( 34 %) |
| Furniture and household utensils | 61 | 8 ( 13 %) | 411 | 66 ( 16 %) |
| Clothing and footwear | 82 | 22 ( 27 %) | 679 | 130 ( 19 %) |
| Medical care | 26 | 9 ( 35 %) | 329 | 195 ( 59 %) |
| Transportation and communication | 39 | 18 ( 46 %) | 1216 | 454 ( 37 %) |
| Education | 13 | 12 ( 92 %) | 13 | 442 ( 97 %) |
| Reading and recreation | 77 | 20 ( 26 %) | 1090 | 272 ( 25 %) |
| Miscellaneous | 33 | 13 ( 39 %) | 398 | 142 ( 36 %) |
| CPI | 580 | 151 ( 26 %) | 10000 | 2844 ( 28 %) |
| CPI(excluding fresh food) | 518 | 144 ( 28 %) | 9504 | 2796 ( 29 %) |

[a]Items with significant positive skewness at 5% level in the stationary case and items with positive skewness in the modified distribution in the nonstationary case.

[b]Items with significant positive skewness at 5% level in the stationary case and items with positive skewness in the modified distribution in the nonstationary case.

[c]The value in parenthesis means the percentage of the number in the total number of commodities.

[d]The value in parenthesis means the percentage of the weight in the total weight of commodities.