The Monthly Measurement of Core Inflation in Japan

Michael F. Bryan and Stephen G. Cecchetti

This paper considers the use of trimmed means as monthly indicators of Japanese core inflation. As in Bryan, Cecchetti, and Wiggins (1997) for the United States, and Roger (1997) for New Zealand, we find that trimming the tails of the price change distribution substantially improves high-frequency estimates of Japanese core inflation. These estimators yield efficiency gains of roughly two-thirds over the Japanese CPI.

While we find that trimming approximately 35 percent from each tail of the price change distribution produces the most efficient monthly estimator over the full 27-year period, a range of trimmed-mean estimators (between 21 percent and the median price change) provide nearly the same signal. Moreover, we find that these estimators are superior to the standard monthly core inflation estimator in Japan, the CPI less fresh food. At lower frequencies (12-month percent changes and beyond), the differences between the candidate estimators were found to be small, and the trimmed estimators were nearly the same as the CPI less fresh food and energy along many dimensions.

Key words: Inflation measurement; Core inflation; Trimmed means; Median

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I. Introduction

The term "core" inflation is commonly found in the business press as well as the economics literature.[1] Surprisingly, precise definitions of this idea are rarely provided. Few nations *officially* construct such a statistic, although reference to a core inflation measure is commonly made. In many countries, the idea of a core inflation measure has merely evolved from common practice. In the United States, for example, a variety of price statistics have, from time to time, been characterized as the basis for "core" inflation, although recent research applies the term nearly exclusively to the Consumer Price Index (CPI) excluding food and energy items, a measure the Federal Reserve also appears to have adopted in its various policy reports. Indeed, the notion of core inflation often appears to be the product of a central bank, and not that of the statistical agency responsible for producing aggregate price statistics.

In most cases, what has become understood as core inflation is an aggregate measure of retail prices, less items or groups of items presumed to be not representative of the price change distribution.[2] Often, what is excluded from these inflation measures are *ex post*, high-variance components. In most cases, such as in Japan, food items are removed from the retail price index in the construction of core inflation. Commonly excluded components also include certain energy items like gasoline and home heating fuel. Other measures exclude goods with a substantial interest rate component, and still others separate from the price statistics regulated prices, changes in taxes, and subsidies.[3]

In a few cases, central banks have chosen to keep the specific measurement of core inflation somewhat vague, allowing more flexibility in the interpretation of the term. One interpretation of core inflation, by the Reserve Bank of New Zealand, is the CPI adjusted for changes in taxes, government charges, the direct effect of interest rates, and a *significant natural disaster*, a definition that presumably allows the monetary authority to make adjustments to the measured rate if it judges that conditions warrant them. In Sweden, the Riksbank reports three alternative definitions of underlying inflation, the CPI less mortgage interest, taxes, and subsidies (UND1), UND1 excluding petroleum (UND2), and UND1 less mainly imported goods (UNDINH).

In some instances, these *ad hoc* measures of core inflation have become short-run policy gauges for the central bank, and in a growing number of countries, such as Australia, Canada, Finland, France, New Zealand, and the United Kingdom, a core inflation statistic has become a target for the central bank. Table 1 reports a variety of inflation targets by country.

1. Also commonly heard is the term "underlying" inflation. We believe these two terms are, in almost every case, used interchangeably, as in this paper. One exception is noted, however. Archer (1995) suggests that in New Zealand underlying inflation has two meanings that may not always be identical: "The essential or core or trend rate of inflation, and the rate of inflation after adjustment for items covered by Policy Targets Agreement (PTA) caveats."
2. Two exceptions to this are the Bank of India and the Bank of the Philippines, both of which have reported an underlying inflation statistic based on a statistically derived trend line.
3. A survey of the issues confronting the construction of a "core" inflation statistic can be found in Roger (1997) or Taillon (1997).

Table 1 Core Inflation Statistics Used by Selected Central Banks

Country	Core inflation statistic
Australia**	CPI less mortgage interest payments, government controlled prices, and energy items
Belgium	CPI less energy, potatoes, and fruit and vegetables
Canada**	CPI less indirect taxes, food, and energy items
Finland**	CPI less housing capital costs, indirect taxes, and government subsidies
France**	CPI excluding changes in taxes, energy prices, food prices, and regulated prices
Greece	CPI excluding food and fuels
Israel*	CPI less government goods, housing, and fruit and vegetables
Japan	CPI less fresh foods
Netherlands	CPI less vegetables, fruit, and energy
New Zealand**	CPI less commodity prices, government controlled prices, and interest and credit charges
Philippines	A statistical trend line
Portugal	10 percent trimmed mean of the CPI
Spain*	CPI less mortgage interest payments
Sweden*	CPI excluding housing mortgage interest and effects of taxes and subsidies (UND1), UND1 excluding petroleum goods (UND2), and UND1 less mainly imported goods (UNDINH)
United Kingdom**	Retail price index less mortgage interest payments
United States	CPI less food and energy items

Note: * Inflation-targeting countries. ** Core statistic used as a target or objective.
Sources: Various central bank annual reports, 1996.

A few authors have tried to formalize the concept of core inflation, notably Eckstein (1981), who defines core inflation as the trend rate of increase of the price of aggregate supply. He constructs his core inflation estimate from a weighted average of the trend growth rates of unit labor costs and capital costs. In a similar spirit, Quah and Vahey (1995) define core inflation as "that component of measured inflation that has no medium- to long-run impact on real output." Their approach estimates core inflation from a system of VAR equations using monthly retail price and industrial production data. In both cases, the authors have in mind particular, albeit very different, economic concepts, which lead them to produce their core inflation estimates.

In this paper, we impose no theory about what the appropriate inflation statistic should be. We take as given that, over time, the retail price aggregate commonly reported is the appropriate measure; thus, we avoid the more difficult challenges undertaken by others. As in Bryan, Cecchetti, and Wiggins (1997) and Roger (1997), we merely ask if there is a more accurate measure of the population parameter than the commonly reported weighted mean. We think this approach more closely corresponds to the more common use of the term "core" inflation. Moreover, we restrict ourselves to high-frequency statistics (in this case, monthly). This also corresponds more closely to the common definition of the term, and it allows us to retain the timeliness of the inflation measure so as to maximize its usefulness in a monetary policy setting. We briefly consider the more problematic issues at the conclusion of the paper.

We divide our remaining discussion into five chapters. Chapter II outlines the problem of high-frequency inflation estimation. In Chapter III, we introduce trimmed-mean estimators as a potential solution to the measurement problem. Chapter IV investigates the properties of the alternative inflation estimators, and Chapter V follows with checks on the robustness of the results. We conclude in Chapter VI by summarizing the results and suggesting areas for future research.

II. The Problem

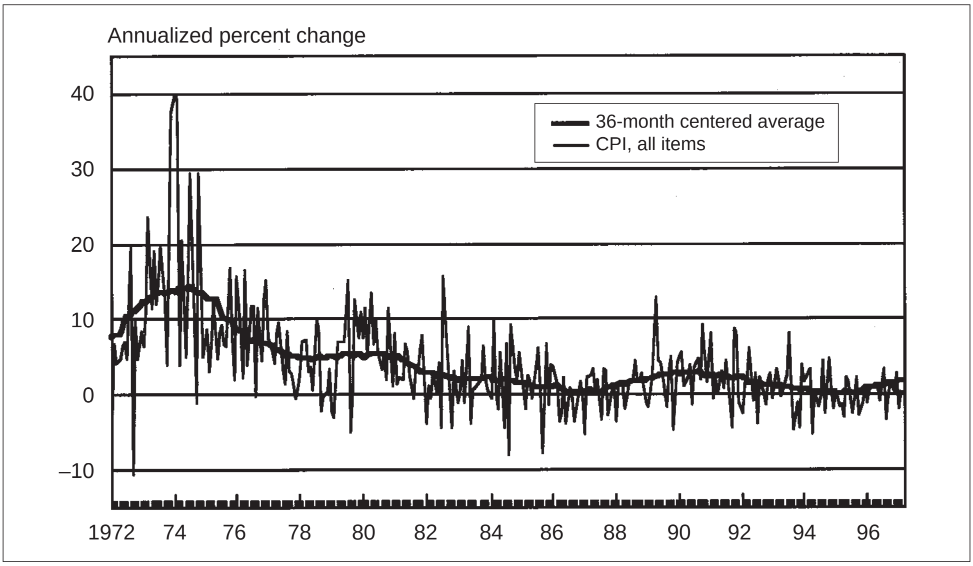
Monthly inflation reports are certainly among the most influential statistics in directing the conduct of central bank policies around the world. Unfortunately, monthly estimates of aggregate retail price changes are extremely volatile, which limits their usefulness as a basis for monetary policy decisions.

How much can we tell about inflation from a single monthly retail price report? Probably not very much. Figure 1 shows the monthly changes in the Japanese CPI during 1972–96, around its long-term growth trend.

A. The Data

To investigate high-frequency inflation estimation, we use monthly data on 88 components of the Japanese CPI, beginning with January 1970. The data are available only on a non-seasonally adjusted basis.[4] All data were seasonally adjusted using a simple X-11 algorithm. The weights were computed from semi-decennial household expenditure surveys for the years 1970, 1975, 1980, 1985, 1990, and 1995. A list of the 88 components and their average weights is reported in the Appendix.

Figure 1 Monthly Changes in Japanese CPI (1972–96)



4. Unlike the U.S. CPI, the Japanese retail price aggregate is seasonally adjusted after aggregation.

B. Characteristics of the Data

We begin our analysis by examining the cross-sectional and time-series properties of Japanese retail prices. Specifically, we calculate the percentage change in the component price data, over varying overlapping horizons k, or

$$\pi_{it}^{k} = \frac{1}{k}\ln(p_{it}/p_{it-k}), \tag{1}$$

and an aggregate consumer price increase,

$$\Pi_{t}^{k} = \sum_{i} w_i \pi_{it}^{k}, \tag{2}$$

which is the weighted average of the components. The cross-sectional moments of the data are computed in the standard way,

$$m_{rt}^{k} = \sum_{i} w_i (\pi_{it}^{k} - \Pi_{t}^{k})^{r}, \tag{3}$$

where m is the r-th cross-sectional moment at time t, for price changes calculated over a k-th horizon. The skewness and kurtosis of the distribution are simply the scaled third and fourth moments of the data, as reflected in equations (4) and (5), respectively.

$$S_{t}^{k} = \frac{m_{3t}^{k}}{(m_{2t}^{k})^{3/2}}. \tag{4}$$

$$K_{t}^{k} = \frac{m_{4t}^{k}}{(m_{2t}^{k})^{2}}. \tag{5}$$

The distributional characteristics of the price change distribution over k horizons of 1, 3, 6, 12, 24, and 36 months are reported in Table 2. The average standard deviation of the monthly data is approximately 22, or more than 500 percent greater than the mean inflation. That cross-section variation diminishes rapidly as k increases from a monthly to a 12-month horizon. Further, while the data are nearly symmetric over the full sample (S_t = 0.45), the standard deviation of the skewness coefficient is quite large, suggesting that for k horizons of 12 months or less, the Japanese retail price data are often highly skewed. Moreover, the data are extremely leptokurtic, or "fat-tailed." As a point of reference, a standard normal distribution has a kurtosis of 3. The kurtosis of the Japanese consumer price data *averages* 31.25.

These distributional characteristics have been reported for many other nations. For monthly U.S. CPI data over the 1970–97 period, the average cross-sectional standard deviation is 170 percent of the inflation rate, with a very slight positive average skewness (0.25), and a kurtosis of 11.44. Using quarterly data for New Zealand, Roger (1997) reports an average cross-sectional standard deviation of 125 percent of the inflation rate, with an average skewness of 0.7 and a kurtosis of 7.2. Similar results are reported for the United Kingdom (Bakhshi and Yates [1997]) and a variety of other nations.

Table 2 Distributional Characteristics of Japanese CPI Data, Seasonally Adjusted (1970–97)

k	Mean	Standard deviation	Skewness	Kurtosis
1	4.12 (6.65)	21.90 (12.72)	0.45 (4.17)	31.25 (28.90)
3	4.13 (5.24)	11.62 (6.12)	0.34 (3.30)	22.06 (17.61)
6	4.16 (4.77)	7.56 (3.78)	0.28 (2.57)	16.10 (10.41)
12	4.19 (4.55)	5.31 (2.51)	0.02 (2.03)	12.21 (7.81)
24	4.25 (4.28)	3.70 (1.53)	–0.24 (1.37)	7.83 (4.51)
36	4.34 (4.06)	3.02 (1.11)	–0.40 (0.93)	5.78 (2.82)
k	**Full sample, 1970–97**			
1	4.12 (6.65)	21.90 (12.72)	0.45 (4.17)	31.25 (28.90)
	High-inflation period, 1970–82			
1	7.27 (7.85)	27.65 (14.25)	0.50 (3.73)	27.04 (26.04)
	Low-inflation period, 1983–97			
1	1.28 (3.41)	16.71 (8.26)	0.41 (4.56)	34.81 (31.01)

Note: Standard deviations in parentheses.

The common observation from these and other investigations is that at high frequencies (periods of 12 months or less), retail price change distributions tend to be volatile, showing large average variation around the trend and very large but often transitory skewness. Moreover, the price change distributions tend to be extremely "fat-tailed," a characteristic that is especially pronounced in Japanese data. These distributional characteristics of the Japanese consumer price data were first noted by Shiratsuka (1997) for 12-month percent changes.

Figures 2 and 3 show the price change distribution for Japanese consumer prices. Figure 2 is a representative monthly distribution, with a very large proportion of the price changes concentrated at the middle of the distribution, and widely scattered, uneven changes on the extreme tails. In this particular case, the distribution is highly negatively skewed (S_t = –3.1). This is a typical consumer price report.

Figure 3 shows the average monthly price change distribution for Japanese consumer prices over the 1970–97 period expressed in terms of standardized deviations from the mean. Relative to a standard normal distribution, Japanese consumer prices have extremely high concentrations on the interior of the distribution, with exceedingly elongated tails. The figure shows price spikes at > 3 and < –3 standard deviations.[5] This is an unavoidably misleading representation, as these spikes reflect the accumulation of very small price changes that extend outward to approximately ±25 standard deviations from the mean!

5. A description of the distribution characteristics of Japanese CPI data can also be found in Shiratsuka (1997).

Figure 2 Price Change Distribution of Japanese CPI (March 1997)

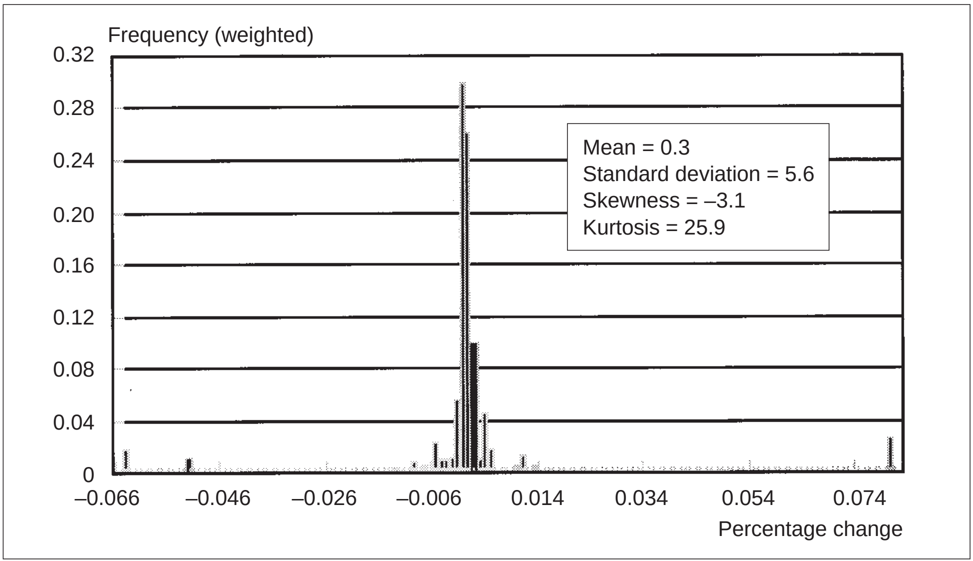
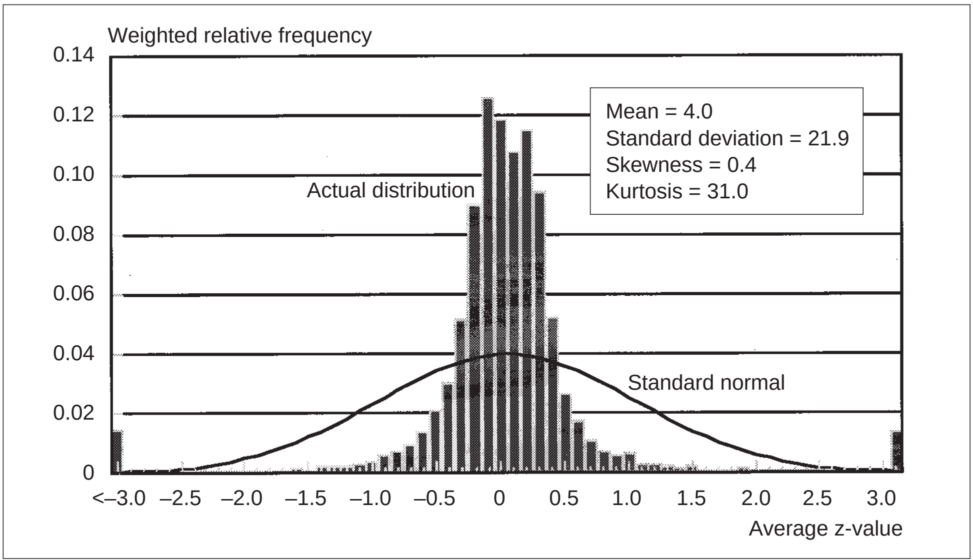


Figure 3 Price Change Distribution of Japanese CPI (Monthly Average, 1970–97)



Furthermore, these monthly distributional characteristics are not particularly sensitive to the sample period (Table 2). If we divide the sample nearly in half (into 1970–82, and 1983–97, corresponding to Japan's high- and low-inflation periods), the low-inflation period exhibits relatively greater cross-sectional variation, nearly the same symmetry, and a marginally higher kurtosis.

A number of authors have attempted to interpret the unusual distributional characteristics of price data by appealing to a particular economic model of pricing behavior. Noteworthy examples include the costly price adjustment models of

Caballero and Engel (1991) or Caplin and Leahy (1991). An alternative view is presented by Balke and Wynne (1996), who show that such characteristics could be derived from a flexible price model in an environment of asymmetric supply shocks.

Bryan, Cecchetti, and Wiggins (1997) suggest a statistical interpretation. Random draws from normal distributions with different variances will produce highly leptokurtic aggregate price change distributions. That is, random draws from the tails of the distribution become more likely. Under these conditions, a simple weighted mean of the data is unlikely to produce an efficient estimator of the population parameter. This insight leads us to calculate estimators that are robust to the presence of fat tails.

III. The Trimmed-Mean Solution

In this chapter, we ask whether, given the distributional characteristics observed in Japanese consumer price data, there are more efficient estimators of the monthly inflation rate than the simple weighted average commonly employed.

To answer this, we consider the family of estimators represented by

$$\bar{x}_{\alpha} = \frac{1}{1-2\left(\frac{\alpha}{100}\right)} \sum_{i \in I_{\alpha}} w_i \pi_{it}. \tag{6}$$

The estimators, $\bar{x}_{\alpha}$, are computed by ordering the component price change data, the π_{it}'s, and their associated weights, w_i. The set of observations to be averaged, I_{α}, is the set of price changes whose cumulative weights, $W_i = \sum_{i=1}^{j} w_i x_i$, are centered between $\alpha/100$ and $1 - \alpha/100$. We refer to these as the α-trimmed mean estimators, for which the weighted mean ($\alpha = 0$) and the weighted median ($\alpha = 50$) are special cases.

To find the efficient estimator within this family of estimators, we proceed along two related lines. First, we conduct Monte Carlo experiments using actual Japanese CPI data in order to gauge the *a priori* efficient estimator from the assumed underlying distributions. Then we examine the *ex post* historically efficient estimator. The two experiments yield solutions that are nearly identical.

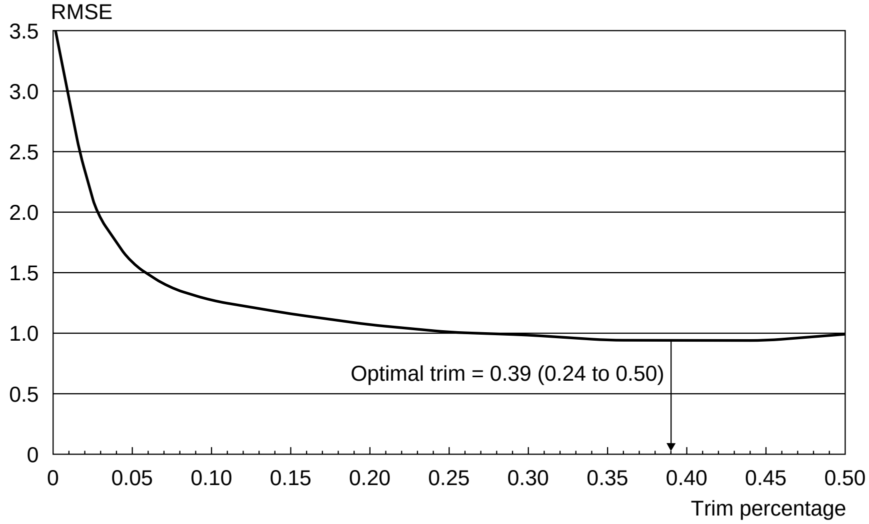
At this point, some judgment must be made concerning the actual, unknown population parameter in question—core inflation. We choose the 36-month centered moving average inflation trend, as in Cecchetti (1997). Sensitivity to this assumption is tested in a subsequent chapter of this paper.

A. Monte Carlo Simulations

We compute each of the 88 components' deviation from the centered inflation trend for all 326 months in the sample. We randomly draw one observation from each component, weighted according to the component's average weight corresponding to the Japanese CPI over the full sample. From each sample, we compute a family of 51 estimators that range from the sample mean to the sample median and compute two measures of efficiency for each—its root mean squared error (RMSE) and its mean absolute deviation (MAD). This experiment is then replicated 10,000 times.

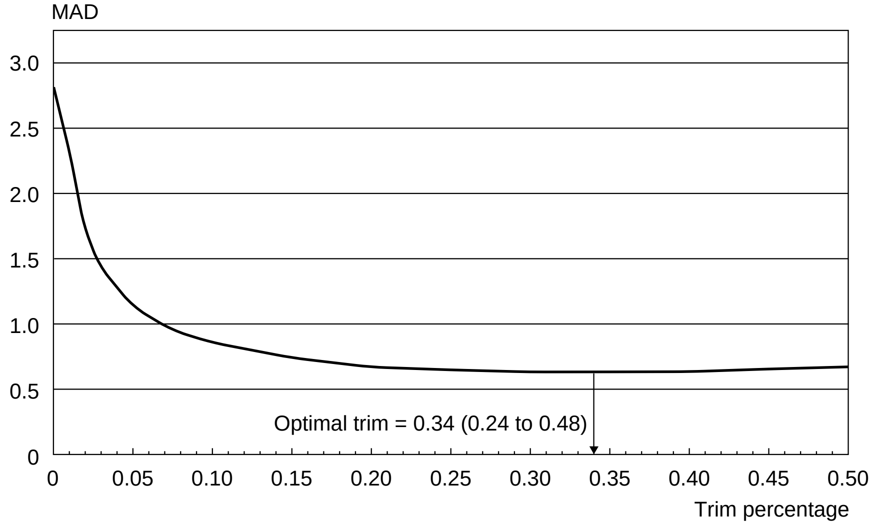
The results of this experiment are shown in figures 4 and 5 and reported in Table 3. We also show the results of two competing estimators, the CPI less fresh food, which is the standard benchmark of core inflation in Japan, and the CPI less fresh food and energy, a common alternative in the United States and elsewhere.

Figure 4 Efficiency of Trimmed Estimators: RMSE (Monte Carlo Results, 10,000 Replications)



Note: Seasonally adjusted data.

Figure 5 Efficiency of Trimmed Estimators: MAD (Monte Carlo Results, 10,000 Replications)



Note: Seasonally adjusted data.

Table 3 Monte Carlo Simulation Results (10,000 Replications)

Seasonally adjusted data	RMSE	MAD
CPI, all items	3.67	2.84
CPI less fresh food	2.22	1.55
CPI less fresh food and energy	2.04	1.47
Minimum: 39 percent trimmed mean (24 percent to 50 percent)	0.94	—
Minimum: 34 percent trimmed mean (24 percent to 48 percent)	—	0.62

Note: Numbers in parentheses are the range of trims within 5 percent of the minimum.

Not surprisingly, by both the RMSE and the MAD criteria, the weighted mean of the data produced the least efficient estimate of the Japanese inflation trend. Indeed, simply subtracting out fresh food prices every month resulted in an efficiency gain of nearly 40 percent on a RMSE basis, and 35 percent on a MAD basis. The most efficient estimator was found to occur at α = 39 on a RMSE basis, and α = 34 on a MAD basis. These resulted in efficiency gains of approximately 74 percent and 78 percent, respectively. In other words, the Monte Carlo experiments suggest that trimming between 34 percent and 39 percent from each tail of the price change distribution monthly reduces the sampling noise of the core inflation estimator by a substantial margin.

Moreover, the results suggest that even small trims of the tails can produce dramatically improved high-frequency inflation estimators. Merely trimming 5 percent from each tail of the price change distribution improves the efficiency of the inflation estimator by 57 percent and 60 percent, respectively. Furthermore, the estimators within 5 percent of the optimal range from 24 percent to the median on a RMSE basis, and from 24 percent to 48 percent on a MAD basis.

B. Historical Experiments

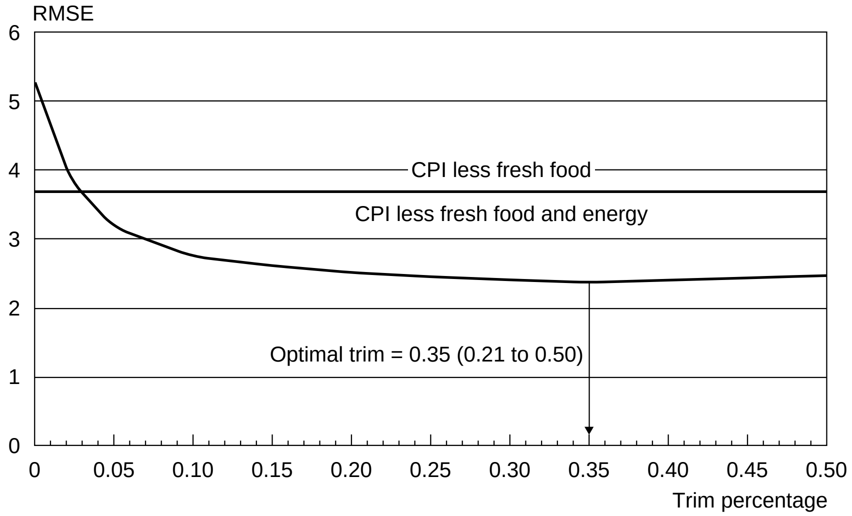
Next, we examine the *ex post* outcomes from trimming the component CPI data over the 1970–97 period. Again, we use as our benchmark for the population parameter in question the 36-month centered moving average trend inflation. These experiments are shown in figures 6 and 7, and summarized in Table 4.

Table 4 Historical Results (1970–97)

Seasonally adjusted data	RMSE	MAD
CPI, all items	5.29	3.72
CPI less fresh food	3.71	2.06
CPI less fresh food and energy	3.66	2.01
Minimum: 35 percent trimmed mean (21 percent to 50 percent)	2.37	—
Minimum: 38 percent trimmed mean (17 percent to 50 percent)	—	1.39

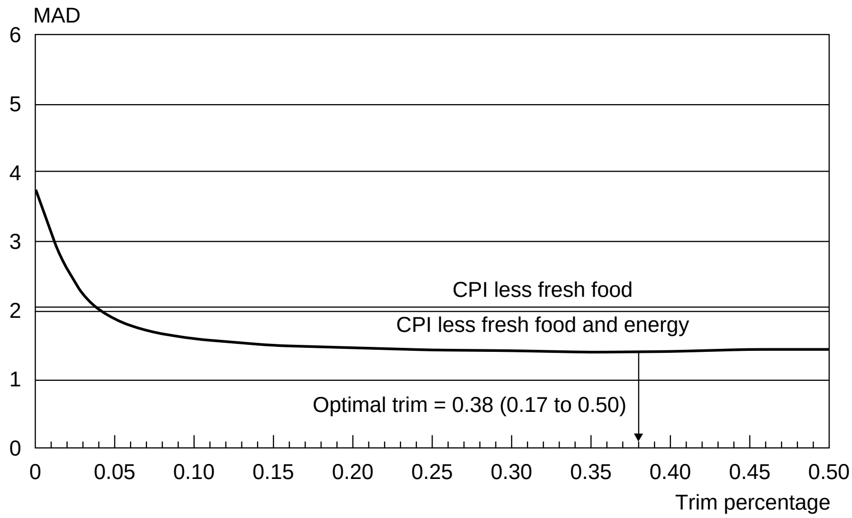
Note: Numbers in parentheses are the range of trims within 5 percent of the minimum.

Figure 6 Efficiency of Trimmed Estimators: RMSE (Historical Simulations, 1970–97)



Note: Seasonally adjusted data.

Figure 7 Efficiency of Trimmed Estimators: MAD (Historical Simulations, 1970–97)

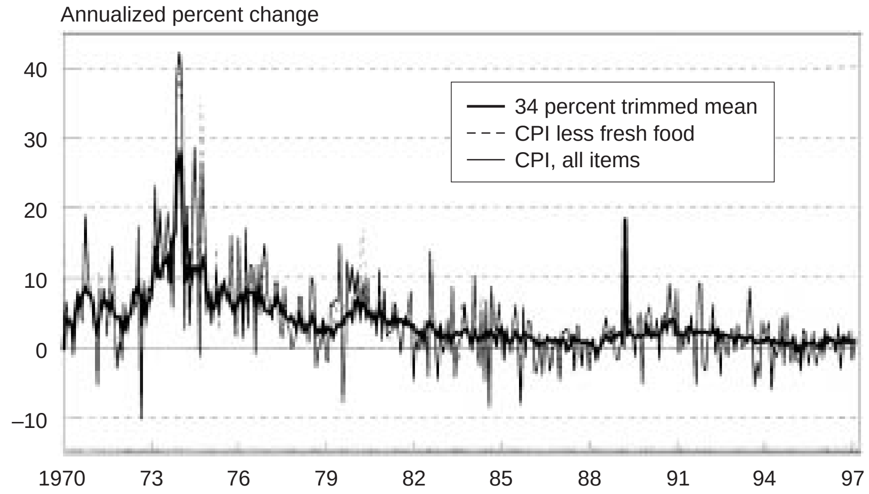


Note: Seasonally adjusted data.

The historical outcomes from trimming component price data are nearly identical to that suggested by the Monte Carlo simulations. The most efficient estimators trimmed 35 percent from each tail of the price change distribution monthly on a RMSE basis, and 38 percent on a MAD basis. These produced efficiency gains of about 55 percent and 63 percent, respectively.

Also as suggested by the Monte Carlo experiments, trims of 21 percent median on a RMSE basis and 17 percent median on a MAD basis resulted in estimators with nearly the same efficiency. And again, even small trims appear to produce substantial efficiency gains. While the more conventional approaches—CPI less fresh food and CPI less fresh food and energy—were substantial improvements over the standard CPI estimator, the trimmed estimators examined here were qualitatively superior monthly inflation statistics. A comparison of the monthly CPI, the 35 percent trimmed-mean estimator, and the more common CPI less fresh food core statistic is reproduced in Figure 8.[6]

Figure 8 Monthly Changes in Japanese CPI (1970–97)



IV. Money and Forecasting Properties

The next question we consider is the informational content of the alternative estimators. That is, we wish to know what information has been gained, or perhaps more accurately, what has been lost by discarding the tails of the price change distribution. We consider this question in two ways. First, we check if the statistics we produce improve or worsen the information about inflation for monetary policymakers by examining contemporaneous correlations between money growth and inflation. Then, we consider the alternative estimators' ability to forecast the future inflation rate as measured by the aggregate CPI.

A. Money Correlations

Among the properties generally attributed to an inflation estimate is its underlying association with the growth rate of the money stock. We therefore check the contemporaneous correlations between the growth rate of alternative measures of the money

6. The April 1989 data spike in all of the estimators results from the implementation of a consumption tax.

stock and the several candidate monthly inflation measures. The measures of money include currency, M1, M2, and M2+CDs. The candidate inflation statistics include the aggregate CPI, the CPI less fresh food, the CPI less fresh food and energy, and three trimmed estimators—the 35 percent trimmed mean, the 21 percent trimmed mean, and the median. These three trimmed estimators represent the optimal trim as suggested by the RMSE criteria from historical observations, and the range of trims within 5 percent of the optimal.

The correlations were computed for overlapping frequencies ranging from k = 1 (monthly percent changes), to k = 48 (48-month percent changes). The results are reported in Table 5. For each money measure and for all frequencies up to 48 months, the trimmed mean estimators yield larger contemporaneous correlations with money growth than either the CPI or the CPI excluding various items. At a monthly frequency, the difference between the 35 percent trimmed mean/money growth correlation was statistically superior to the CPI/money growth correlation at the 90 percent confidence level (using the currency measure) and at the 95 percent confidence level (using the M2 and M2 plus money measures). At 48 months, the CPI less fresh food and energy generally showed correlations that were marginally superior.

The improved money correlations were more significant at higher frequencies than at lower ones, reinforcing our belief that the signal-to-noise ratio of the standard inflation measures is especially low at these frequencies. For example, the contemporaneous correlation between the monthly growth rate of M2+CDs and the Japanese CPI is 0.259. That correlation rises to 0.326 for the CPI less fresh food and to 0.387 for the 35 percent trimmed mean. Similar results were found for other money measures, with the possible exception of the M1 aggregate, where the gains were smaller and only marginally better than the CPI less fresh food or the CPI less fresh food and energy.

Contemporaneous correlations between money growth and inflation, even over relatively long horizons, may be less than forward-looking correlations, because monetary policy is sometimes presumed to affect the price level only after a substantial lag. To accommodate that view, we also considered the simple regression

$$\frac{1}{k}(\ln\pi^r_{t+k} - \ln\pi^r_t) = \alpha + \sum_{i=-1}^{-24}\beta_i(\ln M_i - \ln M_{i-1}) + \varepsilon_t, \qquad (7)$$

where future inflation as measured by the various alternative estimators (π^r), over forward horizons k, are a linear function of monthly money growth (M) over the previous 24 months. These results are reported in Table 6.

The R2's for these experiments were less conclusive. At very high frequencies, monthly and quarterly, the trimmed estimators showed substantial gains relative to the standard CPI and the CPI less fresh foods estimators, and relative to the CPI less fresh food and energy for the monthly data. This result appears robust to the choice of money measure. However, for lower frequencies, k = 6 and above, the differences between the candidate estimators were very small, with a very small preference in favor of the CPI less fresh food and energy estimator for the case where k = 12.[7]

7. The relative standing of these results was also found to be robust for the sample period, although the R2's are considerably lower in the post-1982 sub-period than during the pre-1983 sub-period.

Table 5 Contemporaneous Money Growth Correlations

Currency						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.193	0.257	0.253	**0.304***	0.298	0.299
3	0.389	0.419	0.429	0.467	0.464	**0.469**
12	0.566	0.575	0.603	0.619	**0.622**	0.620
24	0.658	0.663	0.690	0.698	**0.703**	0.697
36	0.737	0.740	0.763	0.761	**0.766**	0.759
48	0.796	0.795	**0.816**	0.807	0.812	0.805
M1						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.140	0.175	0.172	**0.183**	0.183	0.181
3	0.219	0.245	0.259	**0.276**	0.273	**0.276**
12	0.365	0.378	0.411	0.437	0.434	**0.440**
24	0.527	0.540	0.569	0.588	**0.589**	0.588
36	0.690	0.698	0.722	0.728	**0.732**	0.726
48	0.806	0.809	0.828	0.823	**0.828**	0.820
M2						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.256	0.315	0.325	**0.380****	0.371	0.373
3	0.355	0.379	0.396	**0.436**	0.425	**0.436**
12	0.450	0.458	0.480	0.516	0.507	**0.521**
24	0.572	0.579	0.598	0.624	0.620	**0.628**
36	0.707	0.708	0.725	0.733	0.734	**0.735**
48	0.789	0.787	**0.800**	0.796	0.798	0.796
M2+CDs						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.259	0.326	0.335	**0.387****	0.379	0.379
3	0.360	0.385	0.399	**0.438**	0.428	**0.438**
12	0.450	0.458	0.478	0.515	0.505	**0.520**
24	0.572	0.578	0.596	0.623	0.618	**0.626**
36	0.706	0.708	0.723	0.732	0.732	**0.734**
48	0.787	0.786	**0.798**	0.794	0.796	0.794

Note: Seasonally adjusted data, 1970–97, with maximum correlations in bold type. Statistically significant difference from the CPI correlation at 10 percent (*) or 5 percent (**).

B. The Forecasting Experiments

We also conduct two forecasting experiments, both designed to answer the question, Given a monthly inflation statistic, which is likely to be the more reliable measure of the Japanese CPI's future course?

Table 6 Money Forecast Equations

Currency						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.394	0.490	0.483	**0.564**	0.556	0.545
3	0.584	0.608	0.625	**0.637**	0.622	0.624
6	0.661	0.658	**0.678**	0.675	0.663	0.673
12	0.720	0.708	**0.723**	0.719	0.710	0.719
M1						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.527	0.570	0.574	**0.591**	0.585	0.582
3	0.556	0.600	0.617	**0.622**	0.614	0.613
6	0.659	0.675	0.697	**0.700**	0.693	0.698
12	0.762	0.764	**0.783**	0.782	0.778	0.779
M2						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.422	0.564	0.562	0.634	**0.636**	0.625
3	0.628	0.675	**0.702**	**0.702**	**0.702**	0.699
6	0.710	0.728	**0.757**	0.745	0.744	0.748
12	0.758	0.766	**0.790**	0.780	0.780	0.784
M2+CDs						
k	CPI	CPI less fresh food	CPI less fresh food and energy	35 percent trimmed mean	21 percent trimmed mean	Median
1	0.426	0.568	0.568	**0.636**	0.639	0.625
3	0.633	0.682	**0.709**	**0.709**	0.708	0.705
6	0.713	0.731	**0.763**	0.750	0.748	0.752
12	0.754	0.762	**0.788**	0.777	0.777	0.781

Note: Seasonally adjusted data, 1970–97. R2's from equation (7), with maximum correlations in bold type.

The first experiment, specified by equation (8), forecasts average CPI growth measured over the next *k*-month horizon, using the growth rates of the trimmed estimators over the previous *k*-month period:

$$\frac{1}{k}\Pi^{k}_{t+k} = \beta_0 + \beta_1\left(\frac{1}{k}\bar{x}^{k}_{\alpha,t}\right) + \varepsilon_t . \tag{8}$$

The R2's from this regression are reported in Table 7, along with those obtained from similar forecasts made using the CPI less fresh food and the CPI less fresh food and energy. As in the money correlations reported earlier, there is an improvement in the forecasting strength of the trimmed estimators. That is, the trimmed estimators (in this case, the 35 percent trimmed mean and the median), provided superior forecasts of future CPI increases compared with those the CPI provided for itself. Further, the forecasting records of the CPI less fresh food and the CPI less fresh food and energy measures were not as good, although both were generally superior to the CPI all items measure.

Table 7 Simple Univariate Forecasts of CPI Inflation

Full sample, 1970–97					
k	**CPI**	**CPI less fresh food**	**CPI less fresh food and energy**	**35 percent trimmed mean**	**Median**
1	0.184	0.375	0.333	0.430	**0.449**
3	0.423	0.535	0.514	**0.586**	0.578
12	0.468	0.460	0.472	0.502	**0.506**
24	0.260	0.275	0.287	**0.310**	0.309
1970–82					
k	**CPI**	**CPI less fresh food**	**CPI less fresh food and energy**	**35 percent trimmed mean**	**Median**
1	0.133	0.315	0.269	0.378	**0.420**
3	0.278	0.368	0.353	**0.433**	0.426
12	0.179	0.173	0.196	0.221	**0.227**
24	0.020	0.028	0.038	0.058	**0.062**
1983–97					
k	**CPI**	**CPI less fresh food**	**CPI less fresh food and energy**	**35 percent trimmed mean**	**Median**
1	0.012	0.000	0.001	0.018	**0.021**
3	0.003	0.113	0.069	**0.116**	**0.116**
12	0.255	0.263	**0.273**	0.256	0.258
24	0.057	0.044	0.042	0.068	**0.074**

Note: R2's from equation (8), seasonally adjusted data, with maximum correlations in bold type.

This result seems to be generally robust for the sample period. When we split the sample into high- and low-inflation sub-periods, the trimmed estimators provide superior forecasts of the future CPI increase over all horizons *k*, although the differences diminish at the lower frequencies. For the low-inflation (post-1982) sub-period, the results were largely the same, although the CPI less fresh food and energy provided the strongest forecasts over 12-month horizons. However, differences in forecast accuracy over this sub-period were generally quite small for all the candidate regressors.

A second, similar forecasting experiment was conducted using a Granger-style approach. Specifically, we estimate two equations. In the first, equation (9), the CPI over a *k*-month horizon is estimated from past *k*-horizon values of the CPI and past *k*-horizon values of the 35 percent trimmed mean estimator. An F-test is conducted on the hypothesis that the sum of the $\beta_{2,L}$ coefficients of the trimmed estimator are jointly zero. The same regressions are estimated using the 35 percent trimmed mean as the dependent variable and testing the sum of the $\beta_{1,L}$ coefficients (equation [10]). Simply, we are asking the question, Is it more likely that the 35 percent trimmed mean is "predicting" the future course of the CPI, or that the CPI is "predicting" the future course of the 35 percent trimmed mean? We conduct these Granger tests for monthly (k = 1), three-month (k = 3), and six-month (k = 6) price changes, and for lag structures that run from 3 months to 12 months. The results are reported in Table 8.

Table 8 Granger-Style Causality Tests, Seasonally Adjusted Data

Full sample, 1970–97						
	$k = 1$		$k = 3$		$k = 6$	
l	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI
3	0.342	0.000	0.867	0.001	0.465	0.005
6	0.703	0.000	0.914	0.012	0.458	0.021
12	0.817	0.000	0.405	0.006	0.634	0.000
1970–82						
	$k = 1$		$k = 3$		$k = 6$	
l	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI
3	0.071	0.000	0.279	0.007	0.283	0.001
6	0.179	0.000	0.307	0.031	0.047	0.001
12	0.452	0.000	0.137	0.051	0.003	0.000
1983–97						
	$k = 1$		$k = 3$		$k = 6$	
l	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI	CPI does not cause 35 percent trim	35 percent trim does not cause CPI
3	0.822	0.000	0.065	0.023	0.058	0.020
6	0.374	0.000	0.073	0.005	0.083	0.007
12	0.067	0.000	0.420	0.002	0.419	0.000

Note: F-statistic p-values from equations (9) and (10), overlapping observations. (The sample p-value is computed using the Newey-West procedure with bandwidth parameter equal to 1.4*k*.)

$$\frac{1}{k}\Pi_t^k = \beta_0 + \sum_L \beta_{1,L}\left(\frac{1}{k}\Pi_{t-L}^k\right) + \sum_L \beta_{2,L}\left(\frac{1}{k}\bar{x}_{\alpha,t-L}^k\right) + \varepsilon_t . \tag{9}$$

$$\frac{1}{k}\bar{x}_{\alpha,t}^k = \beta_0 + \sum_L \beta_{1,L}\left(\frac{1}{k}\Pi_{t-L}^k\right) + \sum_L \beta_{2,L}\left(\frac{1}{k}\bar{x}_{\alpha,t-L}^k\right) + \eta_t . \tag{10}$$

Over the full sample, we can reject the hypothesis that the 35 percent trimmed mean does not predict the CPI for all inflation horizons *k*, a result that is not sensitive to the lag structure we impose. In none of the tests could we reject the hypothesis that the CPI does not cause the 35 percent trimmed mean estimator at the 95 percent confidence level.

The results of the Granger tests in the sub-sample experiments were similar. In the pre-1983 sub-period, we accept the hypothesis that the 35 percent trimmed mean Granger causes the CPI at the 95 percent confidence level in all the monthly experiments except the 3-months-ahead forecast with 12 lags. In this case, the p-value is 0.051. In two cases, the experiments suggest the potential for causality running in both directions ($k = 6$, with 6 and 12 lags). In the post-1982 sub-period, causality from the 35 percent trimmed mean to the CPI was again found to run in only one direction at the 95 percent level of confidence, from the optimal trimmed estimator to the CPI.

V. Robustness and Other Considerations

In identifying the efficient trimmed estimators and the forecasting properties discussed earlier, we made several checks on the robustness of the results. In this chapter, we expand on that analysis, first by testing the sensitivity of the analysis to alternative definitions of the assumed population parameter (the 36-month, centered-inflation benchmark) and then by calculating optimal trim percentages over moving sample periods. Finally, we consider the frequency of component exclusion from the trimmed estimators.

A. Benchmark Sensitivity

The choice of a 36-month, centered-average CPI inflation rate as the benchmark for this study was somewhat arbitrary. In this chapter, we consider alternative centered-average benchmarks, from 12 months to 60 months. We recomputed both the Monte Carlo simulations and the historical experiments outlined in sections III.A and III.B, respectively. The results of these experiments are summarized in Table 9.

We find that the results reported earlier are not sensitive to the choice of benchmark. In the Monte Carlo experiments, the optimal trim ranges from a low of 0.36 to a high of 0.39 on a RMSE basis, and from 0.31 to 0.35 on a MAD basis. The range of estimators within 5 percent of the optimal is similar and quite large, generally extending from about 0.25 to the median.

The historical results are also essentially identical to the Monte Carlo results and to the historical calculations presented earlier, although the range of estimators within 5 percent of the optimal values was found to be a bit larger for the higher-frequency benchmarks. In the case of a 12-month centered-average inflation benchmark, trims of between 11 percent and the median were found to be largely the same.

B. Sample Period Sensitivity

Next, we compute the historically efficient trimmed estimator for rolling 10-year periods, beginning with 1971–81 and ending with 1985–95. Figure 9 shows the optimal trimmed estimator on a RMSE basis for each sub-period, along with the

Table 9 Optimal Trims for Alternative Benchmarks

Seasonally adjusted data	Monte Carlo experiments (10,000 replications)		Historical experiments (1970–97)	
Benchmark (centered moving average)	RMSE	MAD	RMSE	MAD
12 months	0.36 (0.25 to 0.50)	0.31 (0.22 to 0.44)	0.30 (0.11 to 0.47)	0.33 (0.11 to 0.50)
24 months	0.37 (0.26 to 0.50)	0.33 (0.23 to 0.46)	0.33 (0.17 to 0.49)	0.36 (0.14 to 0.50)
36 months	0.39 (0.24 to 0.50)	0.34 (0.24 to 0.48)	0.35 (0.21 to 0.50)	0.38 (0.17 to 0.50)
48 months	0.39 (0.26 to 0.50)	0.35 (0.24 to 0.47)	0.36 (0.23 to 0.50)	0.40 (0.20 to 0.50)
60 months	0.39 (0.26 to 0.50)	0.34 (0.23 to 0.47)	0.36 (0.24 to 0.50)	0.41 (0.20 to 0.50)

Note: Numbers in parentheses are the range of trims within 5 percent of the minimum.

range of estimators found to be within 5 percent of the optimal. The same results are shown in Figure 10 using the MAD criteria.

Judged on a MAD-deviation basis, the efficient trimmed estimators appear to be generally stable over time. While the optimal trim falls from around 40 percent to 45 percent for 10-year periods up to 1988, the efficient trims drops to roughly 25 percent to 30 percent beginning in 1989. Still, the optimal trim of 38 percent identified for the full sample remains in the range that is very close to the period-specific optimums.

Figure 9 Efficient Estimators at 10-Year Intervals: RMSE

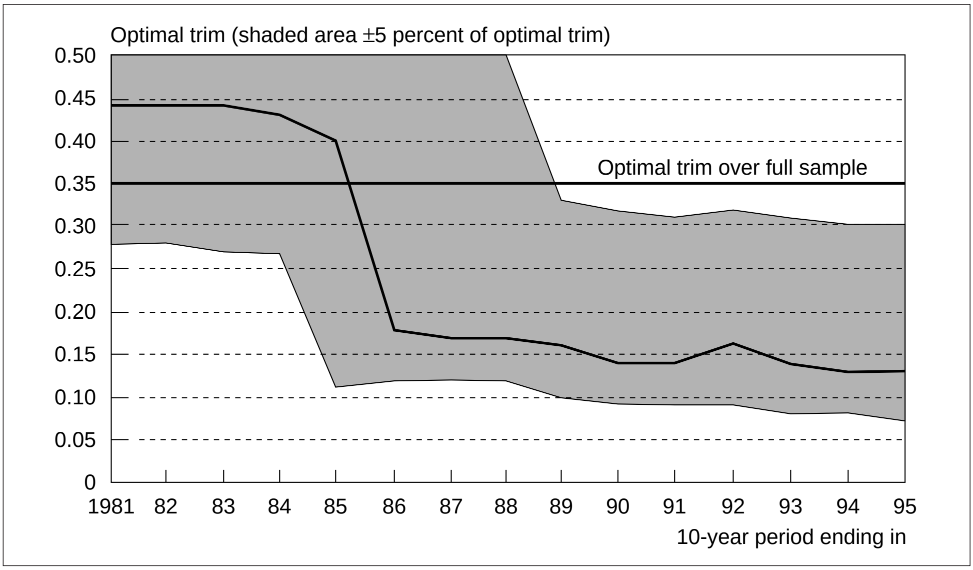
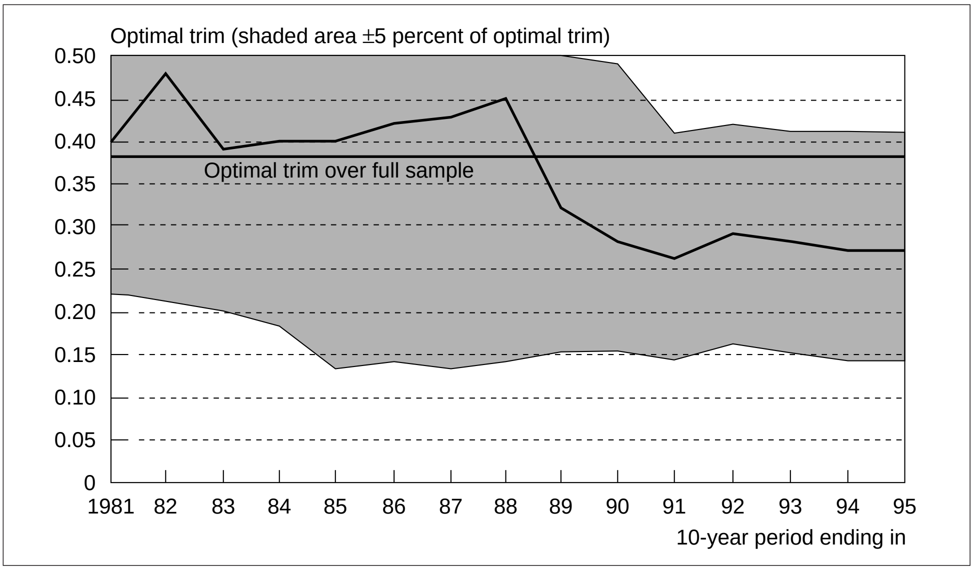


Figure 10 Efficient Estimators at 10-Year Intervals: MAD



On a RMSE basis, however, the drop in the efficient estimate is more pronounced, occurring discretely within the period ending in 1986. Moreover, the optimal trim for the full sample, 35 percent, is just outside the range of estimators found to be within 5 percent of the optimal trim for the 10-year horizons that end in 1989 and beyond. In other words, these results suggest some potential instability in the computation of the efficient estimator, at least between the pre-1986 and the post-1989 sub-periods.

C. Trim Frequencies by Component

Finally, we consider the nature of the items excluded from the calculation of the efficient inflation estimator. Table 10 reports the frequency with which each component is trimmed out of the calculation of the 35 percent trimmed mean, its expected trim frequency computed from Monte Carlo simulations by drawing from a uniform distribution (n = 10,000) and given the same distribution of weights found in the Japanese CPI. We also record the proportion of times each component is trimmed from the upper tail of the price change distribution and the lower tail of the distribution.

Five components are found to be trimmed from the calculation of the 35 percent trimmed estimator at more than twice their expected frequency: fresh vegetables, fresh fruits, eggs, cut flowers, and fresh fish and shellfish. With the exception of eggs and cut flowers, these are the components excluded from the calculation of the more traditional measure of core inflation in Japan, the CPI less fresh foods. We also note that these five components are nearly as likely to be found in the upper tail of the price change distribution as in the lower tail, an indication of their highly transitory influence on the aggregate inflation measure. At the very least, then, we would suggest that these latter two components also be considered for inclusion in that measure.

Moreover, five components are less than half as likely to be trimmed in producing the efficient monthly inflation estimate than their unconditional probability: services related to clothing, eating out, cakes and candies, footwear, and medicines. These commodities are likely to fall in the center of the price change distribution an unusually high proportion of the time.

As a final observation, we merely report the components that, while not necessarily trimmed an unusually large number of times, are nevertheless likely to be found on one of the tails of the price change distribution an unusually large share of the time. Three components were found to be 10 times more likely to be trimmed from the upper tail of the price change distribution than from the lower tail: personal care services, service charges for repairs and maintenance, and lesson fees. Conversely, three components were more than 10 times more likely to be trimmed from the lower tail than the upper tail of the price change distribution: domestic durables, other recreational services, and TV sets and audio devices.

Table 10 Trim Frequencies by Component

Item	Trim frequency	Expected frequency	Ratio	Left-tail trim frequency	Right-tail trim frequency	Ratio	Average weight
54	0.068	0.376	0.180	0.006	0.061	10.000	0.007
28	0.114	0.401	0.283	0.025	0.089	3.625	0.069
22	0.147	0.381	0.386	0.068	0.080	1.182	0.026
49	0.156	0.369	0.424	0.052	0.104	2.000	0.009
55	0.175	0.383	0.456	0.071	0.104	1.478	0.007
67	0.209	0.372	0.561	0.086	0.123	1.429	0.004
68	0.209	0.373	0.559	0.086	0.123	1.429	0.007
48	0.212	0.389	0.544	0.080	0.132	1.654	0.008
29	0.218	0.396	0.550	0.028	0.190	6.889	0.113
52	0.221	0.390	0.567	0.129	0.092	0.714	0.003
40	0.221	0.375	0.589	0.123	0.098	0.800	0.004
80	0.230	0.377	0.610	0.000	0.230	n.a.	0.013
65	0.233	0.375	0.621	0.172	0.061	0.357	0.003
39	0.233	0.375	0.621	0.129	0.104	0.810	0.003
2	0.236	0.373	0.633	0.132	0.104	0.791	0.007
86	0.242	0.371	0.654	0.117	0.126	1.079	0.001
59	0.245	0.380	0.645	0.190	0.055	0.290	0.015
26	0.249	0.372	0.668	0.166	0.083	0.500	0.009
57	0.249	0.368	0.676	0.153	0.095	0.620	0.018
24	0.249	0.377	0.660	0.101	0.147	1.455	0.003
27	0.255	0.377	0.675	0.184	0.071	0.383	0.017
82	0.258	0.370	0.696	0.218	0.040	0.183	0.002
51	0.261	0.379	0.688	0.101	0.160	1.576	0.001
10	0.267	0.378	0.706	0.190	0.077	0.403	0.006
31	0.267	0.380	0.703	0.015	0.252	16.400	0.018
23	0.267	0.376	0.710	0.117	0.150	1.290	0.016
44	0.276	0.385	0.717	0.034	0.242	7.182	0.003
3	0.282	0.372	0.758	0.144	0.138	0.957	0.006
60	0.285	0.373	0.765	0.224	0.061	0.274	0.001
56	0.288	0.381	0.758	0.184	0.104	0.567	0.004
69	0.295	0.382	0.770	0.172	0.123	0.714	0.004
38	0.295	0.369	0.799	0.043	0.252	5.857	0.003
83	0.298	0.371	0.803	0.215	0.083	0.386	0.009
78	0.298	0.384	0.775	0.083	0.215	2.593	0.016
84	0.304	0.374	0.812	0.117	0.187	1.605	0.005
7	0.310	0.369	0.841	0.114	0.196	1.730	0.004
36	0.313	0.383	0.818	0.209	0.104	0.500	0.005
58	0.313	0.393	0.796	0.123	0.190	1.550	0.031
17	0.322	0.377	0.854	0.064	0.258	4.000	0.005
81	0.322	0.361	0.891	0.224	0.098	0.438	0.001
11	0.322	0.374	0.861	0.252	0.071	0.281	0.009
37	0.322	0.389	0.828	0.252	0.071	0.281	0.006
35	0.334	0.375	0.891	0.175	0.160	0.912	0.005
76	0.337	0.383	0.881	0.025	0.313	12.750	0.015

Note: Seasonally adjusted data, optimal trim = 35 percent. (The expected trim frequencies were approximated from a Monte Carlo simulation of 5,000 replications.)
n.a.: Not applicable.

Item	Trim frequency	Expected frequency	Ratio	Left-tail trim frequency	Right-tail trim frequency	Ratio	Average weight
9	0.337	0.385	0.876	0.224	0.114	0.507	0.026
30	0.341	0.371	0.919	0.172	0.169	0.982	0.004
1	0.350	0.390	0.898	0.199	0.150	0.754	0.027
15	0.350	0.373	0.938	0.147	0.203	1.375	0.005
50	0.359	0.374	0.960	0.196	0.163	0.828	0.005
87	0.359	0.374	0.960	0.301	0.058	0.194	0.013
53	0.359	0.380	0.946	0.135	0.224	1.659	0.003
71	0.362	0.369	0.981	0.258	0.104	0.405	0.005
21	0.371	0.383	0.969	0.221	0.150	0.681	0.012
43	0.377	0.369	1.021	0.276	0.101	0.367	0.002
45	0.377	0.387	0.974	0.110	0.267	2.417	0.008
16	0.390	0.384	1.015	0.163	0.227	1.396	0.004
42	0.393	0.375	1.046	0.331	0.061	0.185	0.003
62	0.411	0.384	1.070	0.334	0.077	0.229	0.020
32	0.429	0.392	1.096	0.273	0.156	0.573	0.054
74	0.436	0.368	1.184	0.227	0.209	0.919	0.006
77	0.442	0.371	1.191	0.331	0.110	0.333	0.004
85	0.448	0.378	1.185	0.313	0.135	0.431	0.004
8	0.472	0.376	1.257	0.184	0.288	1.567	0.004
19	0.476	0.363	1.308	0.291	0.184	0.632	0.001
33	0.500	0.381	1.312	0.479	0.022	0.045	0.009
72	0.500	0.386	1.296	0.276	0.224	0.811	0.011
20	0.525	0.381	1.378	0.390	0.135	0.347	0.002
12	0.525	0.380	1.380	0.313	0.212	0.677	0.003
79	0.534	0.380	1.406	0.515	0.018	0.036	0.003
6	0.543	0.380	1.429	0.255	0.288	1.133	0.009
4	0.549	0.375	1.463	0.282	0.267	0.946	0.002
61	0.552	0.401	1.378	0.383	0.169	0.440	0.034
41	0.564	0.366	1.543	0.396	0.169	0.426	0.003
88	0.574	0.360	1.594	0.279	0.295	1.055	0.001
66	0.577	0.371	1.553	0.509	0.068	0.133	0.003
25	0.583	0.375	1.556	0.365	0.218	0.597	0.002
47	0.586	0.379	1.547	0.255	0.331	1.301	0.013
63	0.592	0.393	1.505	0.061	0.531	8.650	0.039
73	0.656	0.369	1.777	0.291	0.365	1.253	0.003
75	0.663	0.380	1.745	0.331	0.331	1.000	0.015
46	0.663	0.389	1.702	0.282	0.380	1.348	0.033
34	0.669	0.368	1.819	0.457	0.212	0.463	0.005
64	0.709	0.372	1.903	0.696	0.012	0.018	0.009
5	0.801	0.380	2.109	0.365	0.436	1.193	0.025
70	0.933	0.371	2.515	0.442	0.491	1.111	0.004
13	0.933	0.385	2.422	0.509	0.423	0.831	0.006
18	0.951	0.378	2.517	0.497	0.454	0.914	0.018
14	0.954	0.378	2.522	0.472	0.482	1.020	0.024

Note: Seasonally adjusted data, optimal trim = 35 percent. (The expected trim frequencies were approximated from a Monte Carlo simulation of 5,000 replications.)
n.a.: Not applicable.

VI. Conclusions

In this paper, we consider the use of trimmed means as monthly estimators of Japanese core inflation. We are motivated by the apparent low signal-to-noise ratio common to monthly retail price statistics and by what we believe to be a related observation—that the inflation estimators are derived from extremely kurtotic price changes, such as we would find from random draws from prices with heteroskedastic variances. We build upon earlier work done in the United States by Bryan and Cecchetti (1994, 1996) and Bryan, Cecchetti, and Wiggins (1997), and for 12-month price changes in Japan by Shiratsuka (1997).

We find that small trims to the monthly Japanese CPI data provide substantially improved estimates of the CPI trend than either the all-items CPI or the more common monthly core inflation estimator, the CPI less fresh foods. Our results are generally supportive of these measures over the CPI less fresh food and energy estimator, but are largely indistinguishable from this estimator at frequencies of 12 months or greater. Further, we find that the range of symmetric trims between 25 percent and 50 percent of the tails of the price change distribution resulted in very similar estimators and that this range appears to be stable over time, although it may have declined and narrowed a bit in the post-1982 period.

While we believe that such indicators can give Japanese monetary policymakers more timely information than the standard estimators, the noise inherent in these statistics is still considerable. That is, while we can substantially improve the signal-to-noise ratio for the inflation statistic, in this case by as much as two-thirds relative to the standard CPI, a great deal of high-frequency volatility remains to be addressed. This suggests the need to consider additional noise-reduction techniques, including longer-run averages of the price data and other statistical signal-extraction techniques, to provide policymakers with sufficient information to accurately gauge the inflationary environment in which they operate.

APPENDIX: JAPANESE CPI COMPONENTS

Item	Component description	Average weight	Item	Component description	Average weight
1	Rice	0.0267	45	Japanese clothing	0.0078
2	Bread	0.0072	46	Clothing	0.0328
3	Noodles	0.0056	47	Shirts and sweaters	0.0126
4	Flour and other cereals	0.0015	48	Underwear	0.0078
5	Fresh fish and shellfish	0.0249	49	Footwear	0.0087
6	Salted and dried fish	0.0090	50	Cloth	0.0050
7	Fish-paste products	0.0044	51	Thread	0.0009
8	Other processed fish	0.0043	52	Socks and stockings	0.0032
9	Fresh meat	0.0256	53	Other clothing	0.0026
10	Meat products	0.0063	54	Services related to clothing	0.0072
11	Fresh milk	0.0088	55	Medicines	0.0074
12	Dairy products	0.0027	56	Medical supplies and appliances	0.0044
13	Eggs	0.0058	57	Medical services	0.0177
14	Fresh vegetables	0.0244	58	Public transportation	0.0311
15	Dried vegetables and seaweeds	0.0048	59	Automobiles	0.0153
16	Soybean products	0.0042	60	Bicycles	0.0012
17	Other processed vegetables and seaweeds	0.0054	61	Automotive maintenance	0.0336
18	Fresh fruits	0.0182	62	Communication	0.0198
19	Preserved fruits	0.0007	63	Education	0.0390
20	Oils and fats	0.0022	64	TV sets and audio devices	0.0091
21	Seasonings	0.0115	65	Musical instruments	0.0025
22	Cakes and candies	0.0262	66	Other recreational durables	0.0032
23	Cooked food	0.0162	67	Stationary	0.0037
24	Tea	0.0033	68	Sporting goods	0.0070
25	Coffee and cocoa	0.0022	69	Toys	0.0043
26	Other beverages	0.0085	70	Cut flowers	0.0039
27	Alcoholic beverages	0.0169	71	Other recreational goods	0.0046
28	Eating out	0.0685	72	Newspapers	0.0108
29	Rent	0.1130	73	Magazines	0.0028
30	Materials for repairs and maintenance	0.0042	74	Books	0.0055
31	Service charges for repairs and maintenance	0.0180	75	Hotel charges	0.0147
32	Fuel, light, and water charges	0.0539	76	Lesson fees	0.0154
33	Domestic durables	0.0091	77	TV license fees	0.0036
34	Heating and cooling appliances	0.0049	78	Admission and game fees	0.0162
35	General furniture	0.0045	79	Other recreational services	0.0029
36	Interior furnishings	0.0048	80	Personal care services	0.0127
37	Bedding	0.0056	81	Toilet utensils	0.0006
38	Tableware	0.0026	82	Soap and others	0.0023
39	Kitchen utensils	0.0027	83	Cosmetics	0.0086
40	Other domestic utensils	0.0035	84	Bags	0.0047
41	Facial tissue and rolled toilet paper	0.0026	85	Watches and rings	0.0038
42	Detergent	0.0033	86	Other personal effects	0.0012
43	Other nondurables	0.0020	87	Cigarettes	0.0133
44	Domestic services	0.0028	88	Other	0.0006

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