A Note on the Efficient Estimation of Inflation in Brazil

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I. Introduction

On June 21, 1999, the President of Brazil directed the Bank of Brazil to adopt multiyear inflation targets. Specifically, the Bank was asked to set explicit numerical targets for the 12-month inflation rate for the years 1999 through 2001, and to extend that target outwards annually two years in advance beginning in the year 2000.[1]

A renewed interest in the measurement of inflation has accompanied the rise in the number of the world's central banks that set specific inflation targets. In this paper, we investigate the use of trimmed-mean estimators as a method to improve the ability of the central bank to hit it's inflation target by increasing the signal-to-noise ratio between the incoming, high-frequency, price data and the longer-term inflation trend. We show that such estimators greatly improve the accuracy of the measurement of the IPCA growth trend. Indeed, we find that asymmetrically trimming 24 percent from the tails of the price-change distribution reduces the RMSE of the monthly inflation statistic as a measure of the inflation trend by 23 percent—making it as accurate as the three-month average growth rate for the ordinary mean IPCA. Further, we demonstrate that a 3-month lagged moving average of the optimal (asymmetrically) trimmed mean is as efficient an estimator of the 24-month centered IPCA trend as the IPCA mean inflation rate averaged over *any* horizon.

We believe these results are important, as they suggest that trimmed-mean estimators substantially reduce the time required to identify changes in the inflation trend

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[1] Among the other requirements of this action, the National Monetary Council (in conjunction with the Minister of Finance) is assigned the responsibility of setting the inflation targets and tolerance ranges. Moreover, the central bank is given full responsibility for the implementation of the policies need to achieve the targets and is expected to show accountability for the achievement of the targets, and to make transparent the central bank's policies, including the issuance of a quarterly *Inflation Report*. For a more complete discussion of this program, see Mishkin and Savastano (2000).

and thus significantly improve the central bank's chances of successfully hitting their IPCA target.

Section II provides a brief description of the Brazilian retail price data. In section III, we discus the sampling noise inherent in the calculation of aggregate price statistics and the use of trimmed mean estimators as a method for reducing that noise. In section IV, we combine the use of trimmed mean estimators with another popular noise-reduction technique, time series averaging, to produce the optimal inflation trend estimators for the Bank of Brazil over monthly horizons from 1 to 12 months. We make some concluding observations in section V.

II. Inflation in Brazil: A Preliminary Look

The inflation statistic chosen as the target for the Bank of Brazil's is a broad measure of retail prices, called the Consumer Price Index Amplified, or IPCA, similar in construction to the Consumer Price Index produced by the U.S. Department of Labor. The IPCA, calculated by the Brazilian Institute of Geography and Statistics (IBGE), is a comprehensive price statistic measuring price changes in eleven metropolitan areas. It is available beginning in 1979. The IPCA target was 8% in 1999, falling to 6%, 4%, and 3½% in 2000, 2001, and 2002, respectively. The Bank has been given a tolerance range of +/- 2 percentage points around these targets.

In this study, we explore between forty-eight and fifty-three components of the Brazilian retail price index (sample size varies due to data availability over the full sample period, 1994 to 2000). Table 1 reports the average expenditure weight for each component and its time-series variance. Note that food and energy represent a disproportion share of the commodities that demonstrate above-average variance. This is a common finding and the rationale behind the exclusion of these goods in the calculation of a central bank's "core" inflation statistic. We think the procedure of ex-ante exclusion of certain items from the retail marketbasket is problematic for several reasons. Clearly, once we systematically alter the market basket in such a way, we no longer pretend to be measuring a representative expenditure-weighted cost-of-living statistic. Indeed, given the underlying price-change distribution, it is probable that such an altering of the weights will systematically introduce a bias in the re-weighted price aggregate that it will no longer track the IPCA over time. Moreover, we have altered the price statistic's weights such that the resulting aggregate price change answers a fundamentally different question than the more traditional measures were designed to answer. And what question the modified price index answers is not always clear.

Second, there is no reason to believe that this broad exclusionary technique is justified for all commodities. For example, in the case of the Brazilian data, some food items show less-than-average volatility, such as canned foods, beverages, flour and prepared flour mixes, spices, and processed meats and fish. On the other hand, several commodities exhibit excessive volatility from month to month that will not be accounted for by the excluding food and energy technique, such as communications, domestic services, rent, and public transportation.

The variability of the components in the IPCA are reflected in the extreme month-to-month movements in the price aggregate (figure 1.) Although the disinflation trend over the period is clear, fluctuations around that trend are large, often five percentage points or more above and below the centered 24-month moving average trend growth rate. This high-frequency variable introduces a problem for an inflation-targeting central bank, as it makes it difficult for the Bank to disentangle transitory movements in the price data from the inflation trend it hopes to control. In the section that follows, we discuss the use of trimmed-mean estimators as a technique for reducing some of the month-to-month variation in the aggregate price data.

III. Sampling Noise in Price Statistics

In earlier research (Bryan and Cecchetti [1994, 1999], and Bryan, Cecchetti, and Wiggins [1997]), we have investigated the advantages of trimmed mean estimators as measures of high-frequency inflation. These estimators can be described as

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

The estimators, $\bar{x}_\alpha$, are computed by ordering the component price-change data, the π_{it}, and their associated weights, w_i, as defined by expenditure or value-added criteria. The set of observations to be averaged, I_α, is the set of price changes for which the 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.

In large part, these estimators are motivated by a statistical anomaly in aggregate price-change estimation. Specifically, price-change distributions have a tendency to be exceptionally leptokurtic—that is, they have "fat tails."

To see what we mean, consider the distribution plotted in figure 2, price changes for the IPCA in May 2000. For this particular month, the mean price change was nearly zero, but there is substantial dispersion among the components. Furthermore, this month is not atypical. To show this, figure 3 plots the average distribution of retail price changes for the period since Brazil's monetary reform (July 1994 to May 2000.) For our purposes, the most important point to note is that the price-change distributions have unusually elongated and fat tails compared to a standard normal distribution, which we also plot on the figure for reference.

Such a price change distribution appears to be common across a broad range of countries. In table 2 we report the distributional characteristics of retail price data for eleven countries including Brazil. Indeed, in the set of countries for which we have data, the average kurtosis is 22.5, more extreme than the average for Brazil (16.4).[2]

The reason for such unusually shaped distributions is unknown, but we would note that they could easily occur by mixing together price data with widely differing variances (figure 4). Mixing together normal distributions with different variances is one way to produce a leptokurtic aggregate price-change distribution.

The presence of fat-tailed price-change distributions may have a structural economic explanation. It may be, as Ball and Mankiw (1995) suggest, that such distributions are reflections of price stickiness resulting from menu costs, where the more extreme the market pressures, the more likely a price change will result. Their model was a primary motivation for our early work on the subject. More recently, Balke and Wynne (2000) have demonstrated that these distributions can also be generated by model economies with flexible prices and sectoral technology shocks.

Regardless of the source, the statistical estimation implications are clear—when individual price change data are generated by fat-tailed distributions, measuring aggregate price change using a weighted mean is unlikely to be efficient. The occasional

[2] Data of different frequencies are not directly comparable as underlying price change distributions become less variable and less kurtotic as the data are averaged.

draws from one tail of the distribution is unlikely to be balanced by an equal draw from the opposite tail, resulting in skewed samples and producing unnecessarily large swings in the mean price data. By trimming the tails of the distribution, we improve the statistical efficiency of the aggregate statistic.

While this is usually a straightforward procedure, in the case of Brazil the retail price data suffer from unusually persistent positive skewness, such that a disproportionate number of price changes are on the positive tail of the distribution. Some have given economic meaning to these positive outliers in the data, although in the United States we have seen that a purely statistical explanation, using arithmetic rather than geometric averaging techniques, can be important. Figueiredo (2000) suggests these outliers may result from the existence of intermittent price adjustment by a significant subcomponent of the retail price set. This is similar in spirit at least to the sticky-price explanation of Ball and Mankiw (1995) referred to earlier. The statistical consequence is that the set of trimmed-mean statistics will be biased estimators of the central tendency of price changes. That is, the trimmed estimators will tend to be too small, containing a persistent negative bias. As a result, they will not directly correspond to the central bank's target that is based on the behavior of the mean index.

Our strategy is to consider a generalization to the symmetric trimming procedure, in which we trim asymmetrically thereby preserving the unbiasedness of the estimator. To do this, we begin by finding the percentile of the price change distribution that yields average inflation equal to that of the official (mean) inflation index. We refer to this as the mean percentile, and in the case of Brazil it occurs at slightly above the 60th percentile (see figure 5.) Although the mean percentile of the Brazilian retail price-change distribution is variable from month to month, there appears to be little systematic movement away from the 60th percentile during the post-monetary-reform era (June 1994).

Following our earlier work, we now proceed to examine the efficiency of the full set of asymmetrically trimmed means. Specifically, we compare the efficiency of the mean IPCA to each of the trimmed-mean estimators centered on the 60th percentile of the price-change distribution. That is, we trim the tails of the price-change distribution such that 60 percent of every percentage point is trimmed off the lower tail of the distribution relative to 40 percent off the upper tail of the distribution. In that way, we assure that the distribution remains centered on the 60th percentile of the data and that our estimators are unbiased. We compare these estimators to the 24-month centered moving average of the IPCA growth rate, a proxy for the central bank's inflation target, measuring efficiency using the root-mean-squared error (RMSE). [3]

Figure 6 plots the RMSE for all of the asymmetrically trimmed means. The decline in the RMSE is a measure of the efficiency gains obtained by trimming. Large efficiency gains are achieved from relatively small trims of the data. The most efficient estimator, the one with the minimum RMSE, is the 24 percent trim. The efficiency gain from using the 24 percent asymmetrically trimmed-mean is about 23% relative to the simple mean IPCA (RMSE of 3.47 versus 4.51 percent.) But all of the estimators with trims between 16 percent and 96 percent produce similar levels of efficiency.

[3] This is a shorter time trend than in our earlier work (typically 36 months.) This change was required due to the relatively short period for which consistent data are available (June 1994 to present).

IV. Reducing Transitory Noise by Time-series Averaging

The sampling problems discussed so far, are only one source of a "noisy" inflation statistic. Other factors, such as transitory shocks to either the demand or the supply-sides of the marketplace, can also obscure the aggregate price change trend that a central bank hopes to measure.[4] Most central banks and government statistical agencies have adopted methods for reducing the influence of these factors on the inflation measure. Seasonal adjustment, for example, is commonly employed to eliminate within-year variations in component prices. Other popular techniques include various moving averages of the data. Indeed, most central banks that currently target "inflation", including Brazil, use 12-month trends.

We investigate two candidate methods for removing this time-series noise. Both are in combination with the asymmetric trimming procedure we have already considered and they involve the use of one to 12-month time-series averages of the data. In the first, we compute the asymmetric trimmed means as before, and then take the time-series average. We refer to this as "post-trim" averaging. We then examine the consequences of reversing these two operations, by computing time-series averages of the components before we trim the price-change distribution. We refer to this as "post-trim" averaging.

The results for post-trim averaging are presented in figure 7. We report is most efficient trimmed mean for each post-trim horizon (the light bar) together with the RMSE

[4] Why such transitory events, insofar as they stem from real events, are not worthy of the central bank's attention is not entirely clear. Certainly they can have important, although impermanent repercussions on a region's cost-of-living, or value-of-production. However, to the extent that the costs of inflation are usually thought to run through the inflationary expectations of the agents operating in an economy and the transitory nature of these shocks is unlikely to affect those expectations, their elimination from the central bank's inflation statistic seems desirable.

of the time-series average of the actual monthly inflation data (the dark bar).[5] Looking tat the results, we first note that the monthly asymmetric 24 percent trimmed-mean of the IPCA is as efficient an estimator of the benchmark as the three-month trend in the mean IPCA. That is, by using the 24 percent trimmed-mean the central bank learns about movements in the inflation trend two months earlier. This would seem to be an important saving for policymakers who hope to identify changes in the inflation trend before its influence becomes imbedded in the economy.

Continuing to look at the table, we also note that the most efficient 3-month estimator (a 96 percent asymmetric trimmed-mean) is as efficient an estimator of the centered IPCA trend as the IPCA averaged over any horizon up to 12 months. The most efficient estimator in the entire set of post-trim averages was found to be the 40 percent trimmed-mean, averaged over a nine-month period. However, the efficiency gains of this estimator compared to other estimators, such as the 34 percent trimmed mean averaged over a 6-month period is small.

Next we move on to study pre-trim averaging. Here we time-average each of the component price changes over monthly horizons from one to 12 months and then compute the asymmetric trimmed means with the lowest RMSE. In all of the experiments reported thus far, we have considered only monthly percent changes in the component price data, or pre-trim averages of length 1. We combine pre-trim averaging of component price data with the post-trim averaging described earlier. For example, estimators with a pre-trim of 6 and a post-trim equal to 12 represent estimators based on component price change data that is computed over the past six months, trimmed, and then averaged over a 12-month period.

[5] Again from a 24-month centered moving average benchmark.

By computing the estimators in this way, we hope to account for two different types of noise in the data generating process. Noise that is component-specific might best be addressed through pre-trim averaging of the component price change data. However, transitory shocks that are offset by price adjustments elsewhere in the price change distribution (and are therefore correlated across components) might more effectively reduced through post-trim averaging of the estimators.

Table 3a reports the RMSE and the optimal asymmetric trim, centered at the 60th percentile, for the *most* efficient estimators for all candidate pre-trim and post-trim averages. The RMSE's are in the top panel and the trims in the bottom. For monthly data (pre-trim and post-trim equal to one), the minimum RMSE from the 24-month centered moving average benchmark is 3.47 percent, obtained by trimming 14.4 percent from the lower tail and 9.6 percent from the upper tail of the price change distribution (total trims equal to 0.24).

In general, we find that pre-trim averaging of the Brazilian component price change data offers little net improvement in the efficiency relative to post-trim averaging. Indeed, for all but one and two-month post-trim averages, pre-trim averaging actually reduced the efficiency of the optimal estimators. This is interesting, as it suggests that transitory variations in the component price data are negatively correlated across components. Consider that the RMSE of the most trimmed-mean efficient estimator derived from 12-month changes in component data is 44% less efficient that the most efficient monthly estimator averaged over a 12-month period (2.96 percent vs. 2.06 percent).

The most efficient estimator for this data was found by using asymmetrically trimming 40 percent of *monthly* price-change data, and averaging over a nine-month horizon (RMSE = 1.91), although six to eight-month averages of the monthly data produced very similar results.

IV. Conclusion

In this paper, we have investigated ways in which the central bank can compute a reduced-noise estimator of the Brazilian IPCA, the focal point of the Bank of Brazil's inflation targeting strategy. We demonstrate that the most efficient monthly estimator of the 24-month IPCA trend is the 24 percent asymmetrically trimmed-mean (14.4 percent off the bottom tail of the distribution and 9.6 percent off the upper tail of the distribution.) This produces an efficiency gain of 23 percent over the monthly mean IPCA. In other words, we can significantly improve upon the high-frequency signal the Bank uses to monitor the trend of its chosen inflation statistic.

We extended the analysis of the trimmed-mean estimators to include every combination of pre-trim averaging of the component data and post-trim averaging of the trimmed-mean estimator to gauge the efficiency gains available by time-series smoothing. We find that of the two techniques, post-trim averaging of the estimators provided superior results for the Brazilian inflation data. Moreover, relatively small time-series averages of the optimal trimmed-mean estimators were better measures of the IPCA growth trend, than the monthly IPCA price change over any lagged horizon up to 12 months.

Table 1: Alternative Brazilian Retail Price Weights

(Food and energy commodities in bold type.)

	Expend. Weight	Variance
Communication	1.66	101.4
Vegetables	**0.29**	**85.27126**
Potatoes	**0.74**	**71.43292**
Fruits	**1.12**	**31.04574**
Cereals	**1.26**	**26.17532**
Electricity	**1.74**	**23.74232**
Fish	**0.39**	**20.00356**
Household fuel	**0.68**	**12.50976**
Poultry and eggs	**1.23**	**11.54511**
Meat	**2.96**	**11.42585**
Domestic services	4.95	10.55798
Motor fuel	**4.15**	**9.806089**
Housing rent and taxes	10.81	7.867112
Public transportation	5.42	7.758335
Fats and oils	**0.51**	**6.495086**
Bakery products	**2.14**	**6.489982**
Tobacco products	1.37	5.902025
Health insurance	0.88	5.166534
Women's apparel	2.49	4.861535
Men's apparel	2.28	4.666962
Sugar and sweets	1.20	4.346158
Tuition, other school fees and childcare	2.96	4.330936
Dairy products	**2.71**	**4.287679**
Food away from home	**6.88**	**4.155704**
Processed meat and fish	**0.67**	**4.105394**
Spices, seasoning, condiments and sauces	**0.54**	**3.661431**
Professional services	3.18	3.429157
Flour and prepared flour mixes	**0.77**	**3.403608**
Beverages	**1.56**	**3.351478**
Canned food	**0.24**	**3.136316**
Bedding and bath clothes	0.57	3.127851
Children's apparel	1.23	3.080407
Jewelry	0.53	2.670548
Television, sound equipment and	1.28	2.601744
Reading materials	0.74	2.394319
Drugs	2.60	2.189012
Decorator items	0.39	2.155162
Footwear	2.13	2.154739
Hospital and other medical care services	0.95	1.812336
Furniture	1.66	1.37297
Household appliances	1.56	1.355441
Household cleaning products	0.98	1.300379
Vehicles	8.00	1.264885

Entertainment services	3.76	1.214117
Maintenance and repair commodities	0.81	1.11381
Sewing materials	0.48	1.112764
Eyeglasses	0.45	0.898019
Personal care services	1.82	0.795681
Prepared food	0.07	0.540246
Maintenance and repair services	1.41	0.364143
Photograph and film	0.36	0.399651
Educational supplies	0.45	0.300842

Table 2: Weighted, Cross-Sectional Descriptive Price-change Statistics by Country
(Data annualized, standard deviations in parenthesis)

Country	Mean	Std. Dev.	Skewness	Kurtosis
1. Canada	3.4	19.3	0.41	22.0
	(3.8)	(7.3)	(3.2)	(15.8)
2. Japan	4.5	24.8	0.76	32.9
	(7.1)	(14.6)	(4.3)	(40.8)
3. United Kingdom	8.1	24.7	0.78	20.1
	(9.0)	(14.2)	(3.0)	(21.2)
4. Mexico	42.8	82.4	2.62	46.2
	(37.8)	(42.1)	(3.3)	(38.8)
5. Colombia	23.2	33.5	1.04	10.1
	(11.6)	(15.1)	(2.0)	(7.3)
6. United States	5.2	9.0	0.28	11.6
	(3.7)	(5.1)	(2.2)	(10.1)
7. Australia *	7.6	12.1	0.49	10.8
	(5.1)	(11.2)	(2.1)	(9.5)
8. New Zealand *	7.2	7.8	0.66	6.9
	(6.1)	(4.3)	(1.6)	(7.9)
9. Sweden	6.1	25.8	1.05	19.1
	(7.9)	(16.6)	(2.6)	(18.6)
10. Germany	2.7	15.3	-0.02	26.3
	(3.5)	(7.7)	(4.0)	(14.1)
11. Brazil	**206.2**	**60.0**	**0.58**	**14.64**
	(381.74)	**(44.36)**	**(2.51)**	**(11.76)**
(full sample, January 1991- May 2000)				
11a. Brazil	**10.9**	**29.8**	**1.39**	**16.4**
	(9.5)	**(16.7)**	**(2.42)**	**(13.5)**
(post-monetary reform, July 1994-May 2000)				

* Quarterly data.

Table 3a: Summary of RMSE Minima
24-month centered moving average benchmark

RMSE's

Pre-trim	------------------------	------------------------	------------------------	------------------------	------------------------	------------------------Post-Trim Averaging------------------------	------------------------	------------------------	------------------------	------------------------	------------------------	------------------------
Aver.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	3.47	3.04	2.67	2.46	2.35	2.16	2.03	1.95	1.91	1.93	1.99	2.06
2	3.17	2.90	2.73	2.63	2.51	2.40	2.36	2.37	2.41	2.52	2.63	2.75
3	2.86	2.88	2.91	2.85	2.75	2.70	2.67	2.68	2.74	2.85	2.97	3.06
4	2.75	2.94	3.00	3.01	3.02	3.03	3.05	3.11	3.21	3.35	3.42	3.52
5	2.81	2.99	3.08	3.14	3.18	3.23	3.30	3.40	3.54	3.64	3.75	3.86
6	2.77	2.92	3.04	3.14	3.24	3.36	3.48	3.63	3.78	3.87	3.97	4.07
7	2.72	2.88	3.03	3.18	3.33	3.48	3.62	3.76	3.89	4.01	4.13	4.23
8	2.74	2.91	3.09	3.27	3.45	3.62	3.77	3.92	4.06	4.17	4.26	4.37
9	2.78	2.99	3.19	3.38	3.55	3.71	3.87	4.02	4.14	4.24	4.35	4.48
10	2.82	3.03	3.22	3.42	3.60	3.78	3.95	4.09	4.22	4.34	4.47	4.62
11	2.85	3.07	3.28	3.48	3.68	3.87	4.03	4.17	4.31	4.46	4.61	4.76
12	2.96	3.19	3.41	3.63	3.83	4.00	4.16	4.32	4.47	4.63	4.78	4.92

Table 3b: OPTIMAL ASYMMETRIC TRIM PERCENTAGES
24-month centered moving average benchmark

Pre-trim	------------------------	------------------------	------------------------	------------------------	------------------------	------------------------Post-Trim Averaging------------------------	------------------------	------------------------	------------------------	------------------------	------------------------	------------------------
Avg.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0.24	0.80	0.96	0.94	0.32	0.34	0.36	0.38	0.40	0.46	0.46	0.48
2	0.82	0.80	0.78	0.76	0.76	0.74	0.72	0.70	0.68	0.58	0.56	0.56
3	0.78	0.78	0.78	0.76	0.76	0.76	0.56	0.58	0.58	0.58	0.56	0.56
4	0.28	0.82	0.82	0.80	0.80	0.78	0.70	0.66	0.64	0.56	0.56	0.60
5	0.26	0.84	0.82	0.82	0.00	0.82	0.82	0.82	0.82	0.82	0.70	0.70
6	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.82	0.60	0.60	0.58
7	0.00	0.00	0.00	0.00	0.00	0.86	0.88	0.88	0.88	0.88	0.88	0.56
8	0.00	0.00	0.00	0.00	0.00	0.92	0.92	0.92	0.92	0.56	0.56	0.56
9	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
10	0.48	0.48	0.48	0.48	0.52	0.52	0.58	0.58	0.58	0.58	0.58	0.58
11	0.48	0.48	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
12	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.44	0.44	0.44	0.44

Figure 1: Brazilian Inflation Estimates
(monthly percent changes, August 1994 to May 2000)

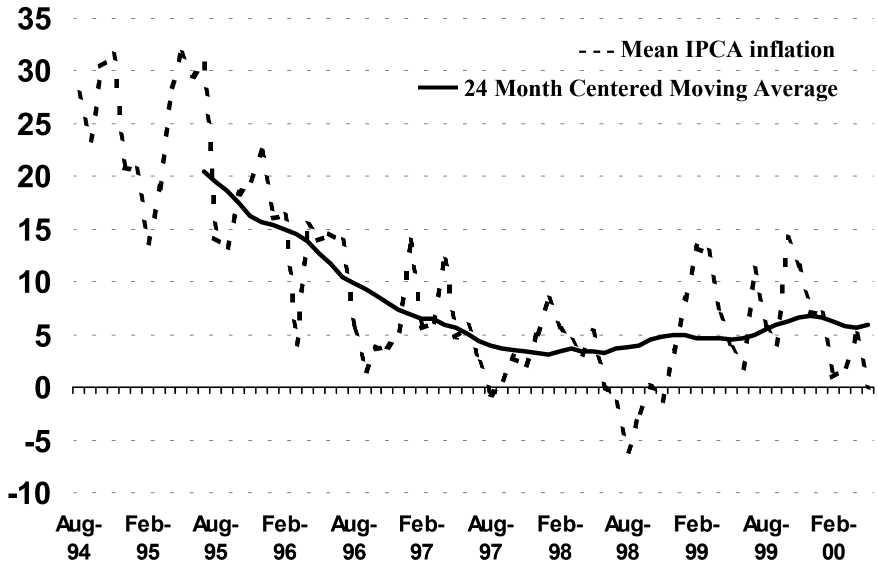


Figure 2: Brazilian Price Changes
(retail prices, May 2000)

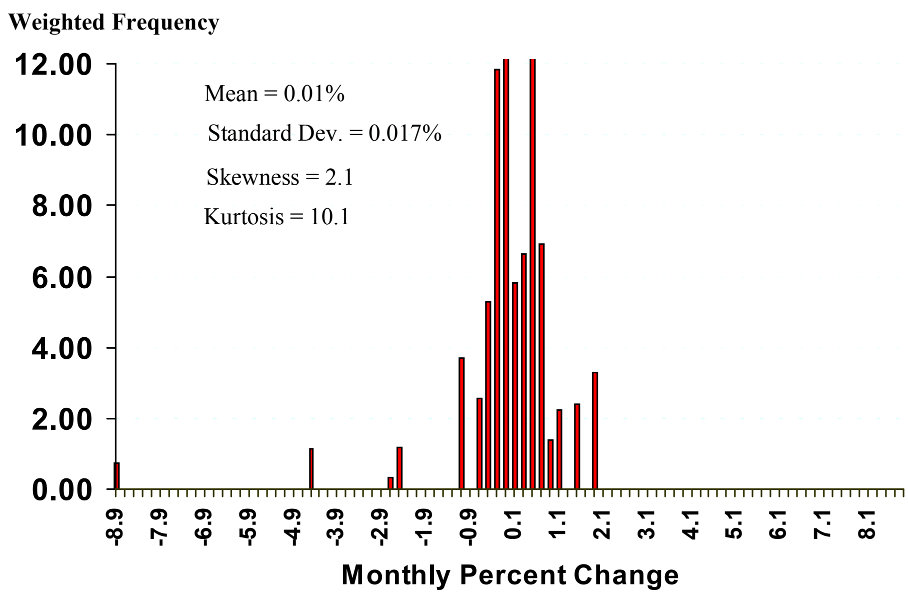


Figure 3: The Distribution of Brazilian Price Changes
(Retail prices, July 1994 - May 2000)

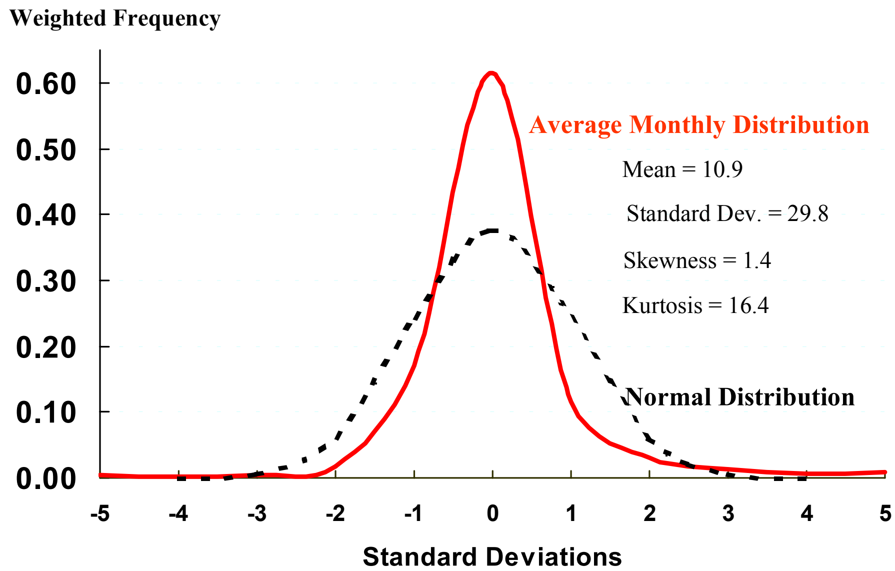


Figure 4: Hypothetical Mixed Normal Distribution

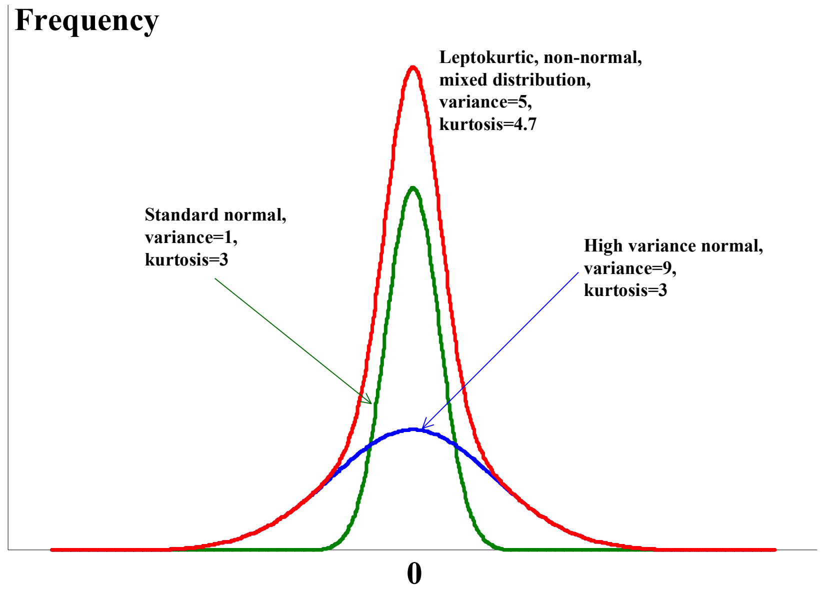


Figure 5: Brazilian Price Asymmetry
(Mean percentile of the price-change distribution)
August 1994 to May 2000

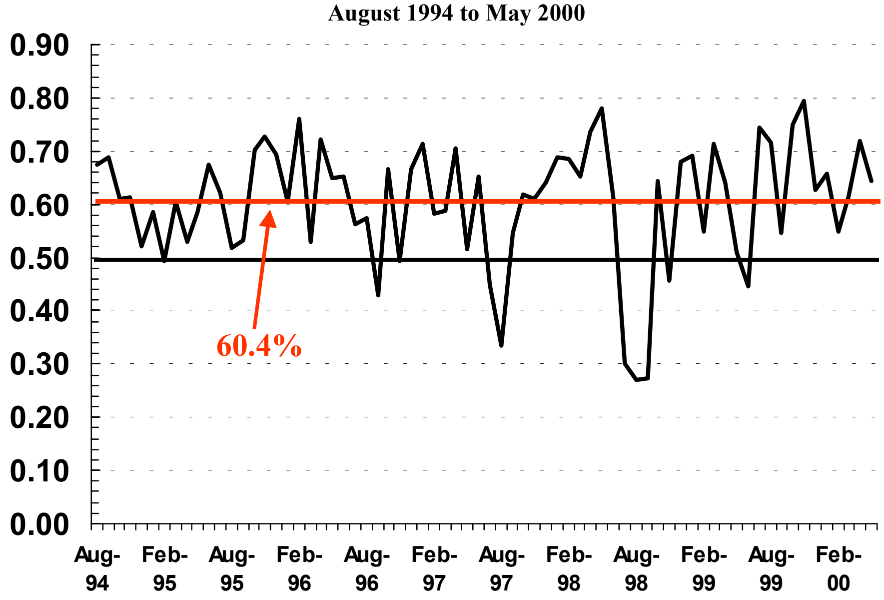


Figure 6: Asymmetric Trimmed Mean Estimators in Brazil
(historical observations, benchmark= 24 mo. centered average)

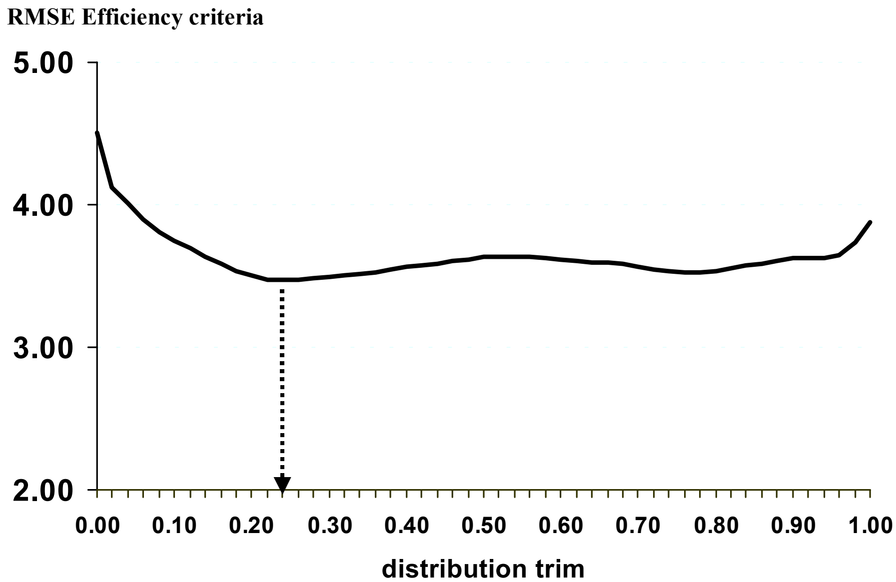
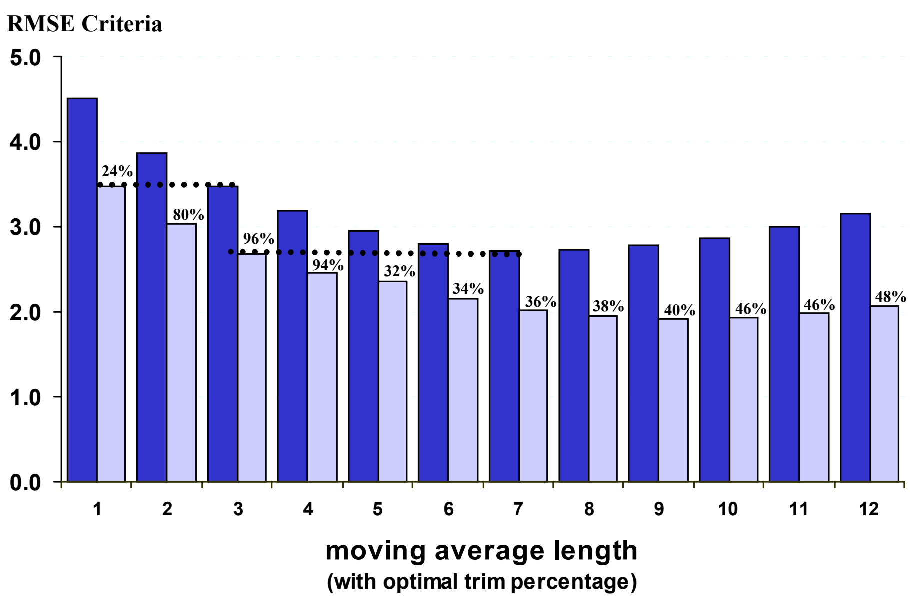


Figure 7: Efficiency Gains Over Mean Brazil Inflation
(August 1994 - May 2000, benchmark = 24 mo. centered average)



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