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PREDICTABILITY OF COMPETING MEASURES OF CORE INFLATION: AN APPLICATION FOR PERU*

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Abstract

A central element of an inflation targeting approach to monetary policy is a proper measure of inflation. The international evidence suggests the use of core inflation measures. In this paper we claim that core inflation should be measured as the underlying trend of inflation that comes from nominal shocks that have no real effect in the long term. However, most of the time core inflation is computed by zero weighting observations at the tail of the inflation distribution. Quah and Vahey (1996) proposed a method of computing core inflation imposing theory restrictions to a SVAR specification. In this paper we present estimation for Peruvian data and compare the predictability properties of competing measures of inflation following an idea of Diebold and Killian (1997).

I. Introduction

Economies worldwide are searching for a more reliable and flexible nominal anchor to achieve permanent price stability. Latin America has not been an exception of this trend. Chile (1990), Colombia (1994), Peru (1994), Mexico (1998) and Brazil (1999) have established inflation target mechanisms recently.[1] This

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sudden change has taken two different formats in Latin America. Brazil, Chile and Colombia are in what we know as an explicit inflation target, while Peru and Mexico are in what we might call an implicit inflation target. The difference, we believe, is important as far as the local monetary authorities have not discussed this reform at all and they are not being held accountable for any lack of compliance of the targets. Furthermore, the Central Bank has lost the opportunity to enhance its credibility in the midst of a disinflationary effort committing to explicit inflation targets.

A central element of an inflation targeting approach to monetary policy is a proper measure of inflation. The basic idea of an inflation target mechanism is to guide monetary policy. The Central Bank will pursue an expansionary (contractionary) monetary policy if the forecast inflation is under (above) the target. Therefore, a key ingredient for this mechanism is not only a measure of inflation that really captures the common growth rate of prices but also a measure of inflation that is forecastable. If the Central Bank forecasts are misguided, this policy framework will increase the volatility of nominal aggregates and probably real aggregates in the short run.

The international evidence suggests the use of core inflation measures instead of headline CPI inflation as an intermediate objective. However, most of the time core inflation is computed by zero weighting observations at the tail of the inflation distribution. In this paper, we claim that core inflation should be measured as the underlying trend of inflation that comes from nominal shocks that have no real effect in the long term. Quah and Vahey (1996) proposed a method of computing core inflation imposing theory restrictions to a SVAR specification. We present estimation for Peruvian data (1991-1998) and compare the predictability properties of competing measures of inflation following a method proposed by Diebold and Killian (1997).

In Section II, we explain how to compute alternative indicators of core inflation. We show the results for Peru and compare the basic features of those alternative measures of inflation. In Section III, we explain the predictability measure proposed by Diebold and Killian (1997); and in Section IV we explore the predictability properties of those core inflation measures. We conclude the paper with some policy recommendations for the Peruvian case and comments on further research.

II. Alternative Measures of Core Inflation for Peru: 1991-1998

The inflation rate in an economy is typically measured as the change in a consumer price index. However, this seemingly very simple calculation could be affected by two sources of distortion: monetary and real shocks. As Cecchetti (1996) points out, the inflation rate is a noisy and biased indicator. These characteristics make the CPI inflation rate a poor indicator for monetary policy design. In particular, if the Central Bank guides its monetary policy using the headline CPI inflation it may react to temporal shocks in relative prices. These

shocks affect the CPI inflation but should not be understood as "monetary" inflation.

This type of noise could be important in a less-developed economy in which the food component in the CPI is sizeable. For instance, in Peru the food component represent 42% of the CPI basket. Along with this relative price shocks we should include possible variations in the exchange rate. Again, if we think of economies with a high proportion of tradable goods the noise-to-signal ratio could be significant.

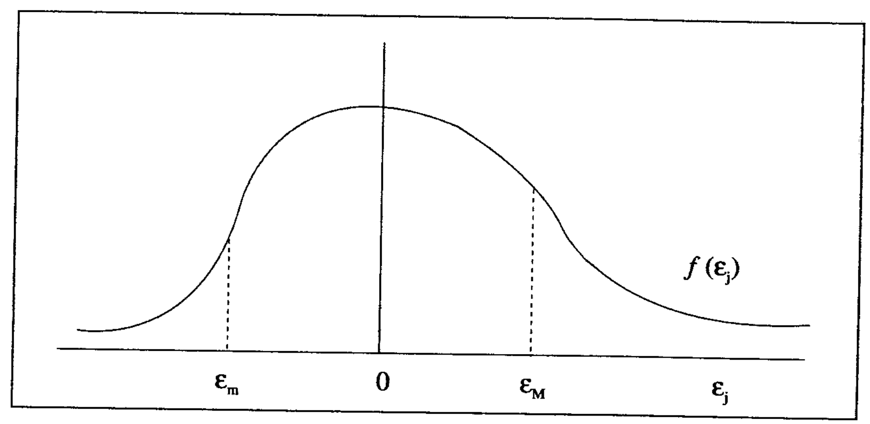
Another source of distortions is the measurement bias computing the CPI inflation. We did not deal with this problem in this paper but the preliminary results of Cabredo and Valdivia (1998) for the Peruvian CPI showed a 5% substitution bias.

The problem from the Central Bank point of view is how to extract the correct information from the CPI inflation. There are shocks that should not worry the authorities while there are other shocks that represent red lights in future monetary policy decisions. This signal extraction problem is tackled from both a parametric and a non parametric approach on how to measure properly core inflation.

Let us define the core inflation of product j at period t, $\pi^c_{j,t}$, as the percentage change in the price of product j caused by a monetary shock. As we said, each product might be influenced by relative price shocks maybe due to seasonal changes, international price swings or factors not directly related to domestic monetary policy. We will need to define ε_j as the relative price shock in the j-market and $f(\varepsilon_{j,t})$ as the probability density function of these shocks (see Graph 1) with the special feature that $E(\varepsilon_{j,t}) = 0$.

GRAPH 1

PROBABILITY DISTRIBUTION OF RELATIVE PRICE SHOCKS

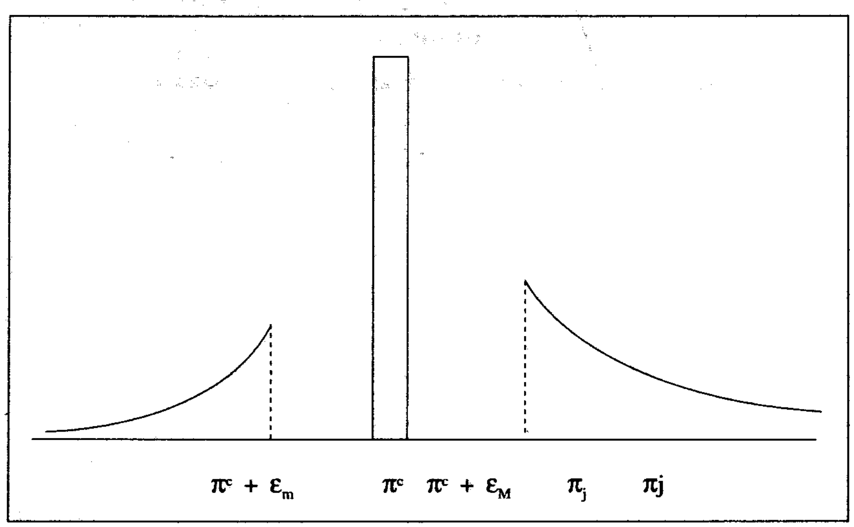


At least two different stories might be used to justify that small relative-price shocks $\varepsilon_j \in (\varepsilon_m, \varepsilon_M)$ do not get any response. One is a standard new-keynesian menu cost approach in which firms face a costly decision to update prices. Therefore, they will only respond optimally to sizeable changes in the relative prices. Another explanation goes along the lines of Lucas' signal extraction problem. If the firms of these markets are unable of perfectly discriminate between a nominal and a real shock they might choose to react only to big changes. Either way we will end up with a probability distribution function of j-good inflation as in Graph 2. What really matters is not if there are discontinuities but if the distribution is asymmetric and if it shows high kurtosis. If the distribution is skewed the mean and the median will not coincide. More precisely, the mean will not be a good measure of core inflation. If the kurtosis is high, extreme values will have a significant impact on the mean. We might think of extreme values as non-representatives of the core inflation.

If the skewness is positive, the core inflation will be below the CPI inflation. To check this as well as the kurtosis behavior of the cross sectional distribution of prices we use the price database collected by the National Institute of Statistics (INEI). We compute the skewness and kurtosis of the cross sectional distribution of inflation. The data covers 1991:01 through 1997:12 for the 44 components of the CPI.

GRAPH 2

PROBABILITY DISTRIBUTION FUNCTION OF INFLATION



Given the fact that we can represent the inflation in the j–th component of the CPI as the sum of average inflation plus a relative price shock, we will have:

$$\pi_{j,t} = \pi_t + \varepsilon_{j,t} \tag{1}$$

If we define $\pi^k_{j,t}$ as the average inflation rate of the j–th component at period t for the following k periods we will have:

$$\pi^K_{j,t} = \pi^K_t + \frac{1}{K}\sum_{i=1}^{K} \varepsilon_{j,t+i} \tag{2}$$

What we compute is the skewness and kurtosis for different time horizons (K = 1, 2, 3, 6, 9, 12, 24 months). The results are in Table 1. As expected both moments decrease as we extend the horizon. It is also interesting to note how does Peru compare to other country studies. Bryan and Cecchetti (1996) report for the US a skewness of 0.23 and a kurtosis of 8.07. Roger (1997) in a study for New Zealand reports a skewness of 0.79 and a kurtosis of 7.65. In both studies they have access to longer series.

Our results for Peru show a smaller kurtosis (5.91). The skewness that we found (0.82) is very high compared to the US but about the same as in New Zealand. Therefore the cross sectional distribution of prices is highly skewed and leptokurtic. As mentioned before, the mean will not be a good estimator of the core inflation.

TABLE 1

SKEWNESS AND KURTOSIS OF INFLATION RATE (1991:01-1997:12)
(Computed using overlapping observations of K months)

K	Average of Skewness	Average of Kurtosis
1	0,8213	5,9131
2	0,6867	6,0327
3	0,5659	6,2815
6	0,5226	6,0500
9	0,5811	5,5562
12	0,4399	5,4058
24	0,6835	2,6485

The table shows weighted statistics.

We calculate three measures of inflation that might be more informative from the point of view of the Central Bank. The first one is the **adjusted mean**. This method follows the idea of zero-weighting some components of the consumer basket that are too volatile. In practice, several central banks in the world use this "excluding food and energy" inflation indicator.[2] In our study we could not follow the same strategy, as the food component is almost half of the index (see Appendix I). Instead, we computed the variance of each component of the CPI and exclude those with higher variance. The problems with these calculations are: (i) there is no clear-cut limit to up to which point we should exclude volatile components; and (ii) the measure is non-invariant with more disaggregated data on prices.

The Peruvian Central Bank (1998) measures core inflation in a slightly different manner. They exclude those components whose weighted-contribution to the inflation rate is too volatile. The excluded components are similar to the ones that we exclude. However, they use more disaggregated information. For the sake of comparison with other alternatives we decide to use the official measure of core inflation of the Central Bank.[3]

A second alternative is the **weighted-median inflation** proposed by Bryan and Cecchetti (1993a, 1993b). The evidence of positive skewness (0.82) and high kurtosis (5.91) in the cross sectional distribution of prices for the Peruvian case suggests the need to use a different central tendency moment instead of the mean of the inflation rate. The median inflation will not be influenced by sector-specific volatility in the inflation rate and therefore will be a much better indicator of monetary inflation.

A third measure of core inflation is a generalization of the idea of the two previous methods called **trimmed-mean inflation**. For each month, we compute the empirical cross-sectional distribution of inflation rates. Once we have that, we can exclude from the inflation rate those components that showed too much or too little inflation. We trim the inflation rates that are at the 7.5% of each tail of the distribution. Actually, we can trim the distribution up to 50% and leave just the median inflation.

However, all these non parametric measures lack from a theoretical support. Quah and Vahey (1996) argue that the notion of core inflation should be understood as the permanent component of the CPI inflation in the sense of Beveridge and Nelson (1981) rather than just excluding some components of the CPI. The idea of the methodology is the following. We estimate a Structural Vector Autoregresive SVAR model imposing a theoretical restriction: money is neutral in the long run. Therefore, the core inflation has no impact over the medium and long term behavior of the real product.[4] In the remainder sections of the paper, we will refer to this alternative measure as **latent inflation** or **Quah-style inflation**.

In Table 2 we present some descriptive statistics of all measures of core inflation. In Graph 3 we present the time series.

TABLE 2

COMPARISON OF ALTERNATIVE MEASURES OF CORE INFLATION, PERU: 1992:01-1998:07
(Computed with 12-month inflation data)

	All Items CPI (1)	Adjusted Mean (BCRP) (2)	Weighted-Median (3)	15% Trimmed Mean (4)	Latent (Quah-Vahey) (5)
μ	10.07463	10.18210	7.891666	9.033643	11.49147
σ	1.776787	2.254899	1.953378	1.705107	4.160953

	Correlation Matrix				
	(1)	(2)	(3)	(4)	(5)
(1)	1.000000	0.785104	0.848691	0.951720	0.559413
(2)	0.785104	1.000000	0.917420	0.866679	0.893370
(3)	0.848691	0.917420	1.000000	0.915741	0.852673
(4)	0.951720	0.866679	0.915741	1.000000	0.668437
(5)	0.559413	0.893370	0.852673	0.668437	1.000000

From the Central Bank perspective, choosing among these alternatives should be based on the information content of the indicator and, of course, on the possibility of forecast the future behavior of inflation. It is important to emphasize that the whole idea of inflation targeting is based on the assumption that the Central Bank would be able to forecast future inflation timely and accurately. In the following section we explore this issue.

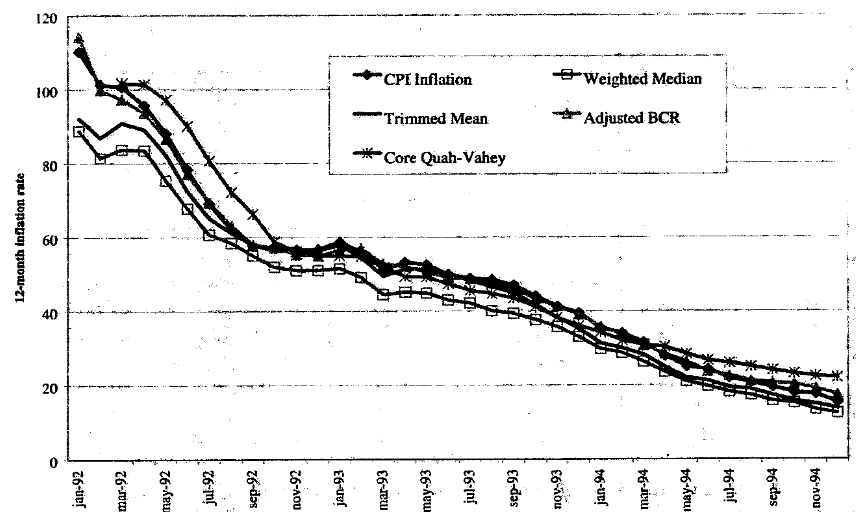
III. An Exercise on Predictability

In this section we conduct a simple exercise on predictability. From the Central Bank perspective, they would like to have not only a meaningful but also a forecastable measure of inflation in order to guide the monetary policy decisions in the short run. One natural way to think about how to select among different indicators of inflation could be check the predictability of each series. As Diebold and Killian (1997) point out, there are three issues at hand. First, the issue is how to measure the degree of the predictability of the series. Second, the series are not just more or less predictable. The predictability of a series depends on which metric we use, the loss function and the forecast horizon. Some series have complicated dynamics in the short run but very simple ones in the long run. Third, we need a common base of comparison. After all, predictability is a relative concept.

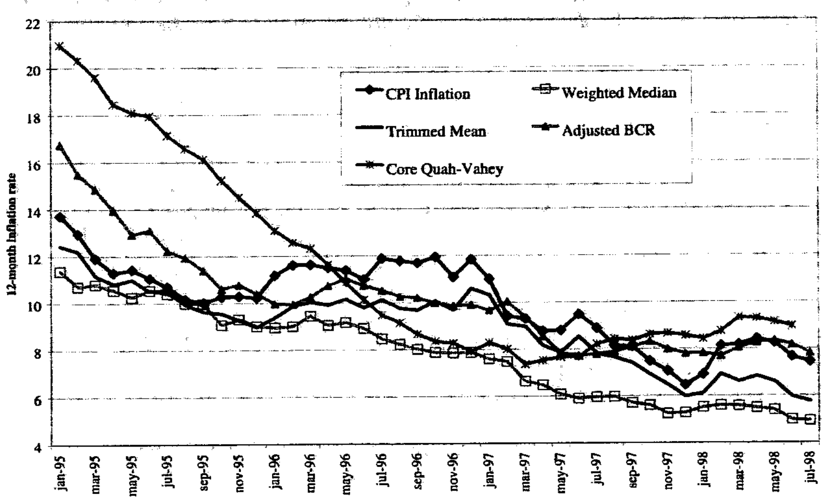
GRAPH 3

ALTERNATIVE MEASURES OF CORE INFLATION

PANEL A: PERU: 1992-1994



PANEL B: PERU: 1995-1998



Granger and Newbold (1986) suggest an R^2-type measure of predictability of a covariance stationary series under the assumption of a symmetric loss function:

$$G = \frac{\mathrm{var}(\hat{y}_{t+j,t})}{\mathrm{var}(y_{t+j})} = 1 - \frac{\mathrm{var}(e_{t+j,t})}{\mathrm{var}(y_{t+j})}$$

where G represents the proportion of the unconditional forecast variance that is explained by the model conditioned on the information up to date t. Therefore, $\hat{y}_{t+j,t}$ is the conditional mean forecast of y_{t+j} given all the information at t. This forecast is optimal under the assumption of a quadratic (and symmetric) loss function.

Diebold and Killian (1997) generalize the idea and suggest the following indicator as a better measure of predictability:

$$P(L,\Omega,j,k) = 1 - \frac{E\left[L\left(e_{t+j,t}\right)\right]}{E\left[L\left(e_{t+k,t}\right)\right]}$$

Given an information set Ω, a loss function L(.), and assuming $j << k$, we compare the optimal short-run forecast $E[L(e_{t+j,t})]$ with the optimal long-run $E[L(e_{t+k,t})]$. If both forecasts are more or less the same, we should say that we have no way to predict accurately the time series. More accurately, the series is almost unpredictable at horizon j relative to k. Therefore, we are interested up to which date j* the optimal short-run forecast is significantly different from the long-run forecast.[5]

The methodology is quite general and could be applied in a variety of cases. First, it does not matter if we are dealing with stationary or non-stationary data. But we need to use a $k < \infty$. Second, the loss function could be asymmetric. The only restrictions are that $L(0)=0$ and that L(.) is strictly monotonic. Third, the information set is not restricted for univariate processes. Fourth, the researcher may choose j and k according the relevant forecast horizon. We will discuss this later.

What we report is not the P estimates but a bootstrap approximation to the sampling distribution of the P estimates.[6] Our procedure is to select the best model for each inflation series correcting for GARCH errors. This allows us to resample with replacement from the residuals as if they were the population ones.

One of the problems with this resampling technique is that uses the residuals from an initial OLS estimation of the autoregressive processes. Those coefficients have a small-sample bias that can be removed partially through first-order bias corrections developed by Pope (1990) and Killian (1998). We report the distribution of the P estimates with and without small-sample bias correction. Brännström (1995) proposed to add second-order bias corrections, but we defer that to further research. Furthermore, we followed Killian (1998) suggestion and correct for bias in the bootstrap estimates.

Even though one would be inclined to do inference through t-tests of the estimates of P, this is not feasible as the asymptotic normality of $\hat{P}$. Our preliminary results confirmed the expectation of Diebold and Killian (1997) that the distribution of $\hat{P}$ is skewed in small samples.

IV. Predictability of Core Inflation Measures

But let us see the results of our experiment for alternative measures of core inflation for a period between 1992:01 and 1998:07. We use 12-month inflation rates in all cases and treat each series individually. We estimate our baseline models evaluating the presence of a single break through Andrews (1993) sup-F test. After that, we model the series as ARMA(p,q) processes testing for ARCH-type errors. In all the results that we present below, we use a quadratic loss function and 1000 bootstrap replications.[7] Instead of plotting the point estimates of P, we present the 90% confidence intervals based on the 5% and 95% points of the bootstrap distribution. In Figure 1 we plot interval estimates of P assuming $k = 24$ months against near-term forecast horizons $j = 1, 2, ..., 24$. As suggested by Killian (1996), we endogenize the lag order choice by reestimating the lag order for each of the bootstrap replications. We used the Akaike information criterion.

In Figure 1 we show that all measures of core inflation have very similar patterns. The only exception is the Quah-style measure of core inflation. The P-intervals for this measure dominate clearly all the alternatives. CPI inflation is the least forecastable of all alternatives. Another characteristic to note is the width of the interval of the Quah-style inflation. To check for possible asymmetries in the distribution of the intervals, we compute the sample skewness of each cross-sectional bootstrap distribution. Our estimates ..e in Figure 2. What we can observe is that the Quah-style inflation is the one less skewed while the others have a significant positive skewness. Therefore, the confidence intervals are denser in their lower limits implying less predictability.

The inflation measure used by the Central Bank is more predictable than the CPI inflation but still the difference is not really significant. However, it is the second in the predictability ranking.

These results are robust to several changes. First, we modify the long-term horizon of comparison. Second, we correct the small sample bias explained by Killian (1998). Third, we choose a different lag selection rule to model each measure of inflation.

In Figure 3, we change the long-term forecast horizon to $k = 12$ months. We plot the interval estimates for $j = 1, ..., 12$ and the results are similar. As we mentioned before the bootstrap distribution for each $j = 1, ..., 24$ are highly skewed as we show in Figure 4. Among the different setups the p-estimates of the latent inflation were always the more left-skewed.[8]

FIGURE 1

PREDICTABILITY OF ALTERNATIVE MEASURES OF CORE INFLATION (k = 24)

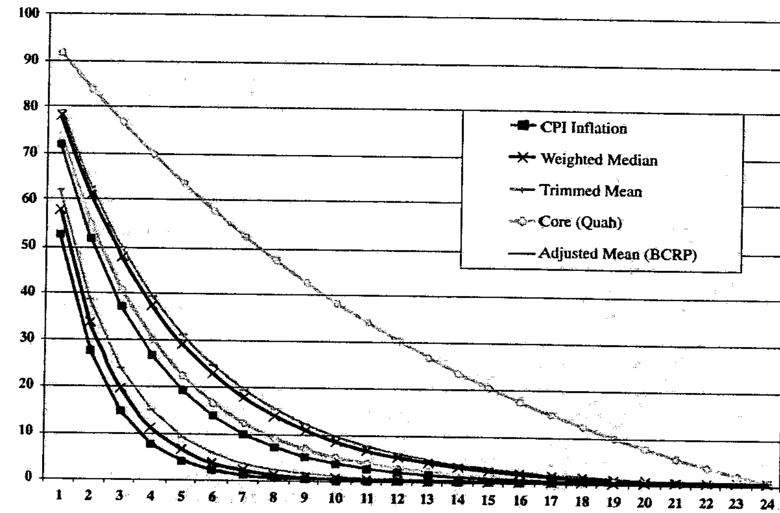


FIGURE 2

SAMPLE SKEWNESS OF BOOTSTRAP DISTRIBUTION OF P (k = 24)

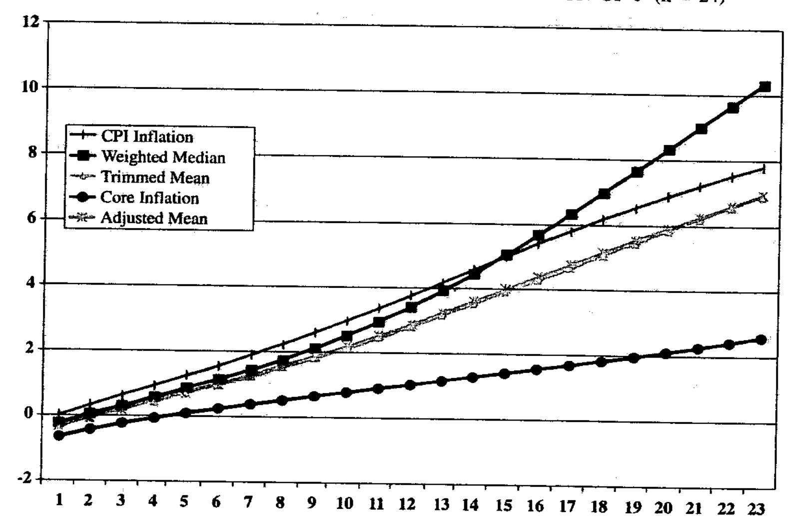


FIGURE 3

PREDICTABILITY OF COMPETING MEASURES OF CORE INFLATION (k = 12)

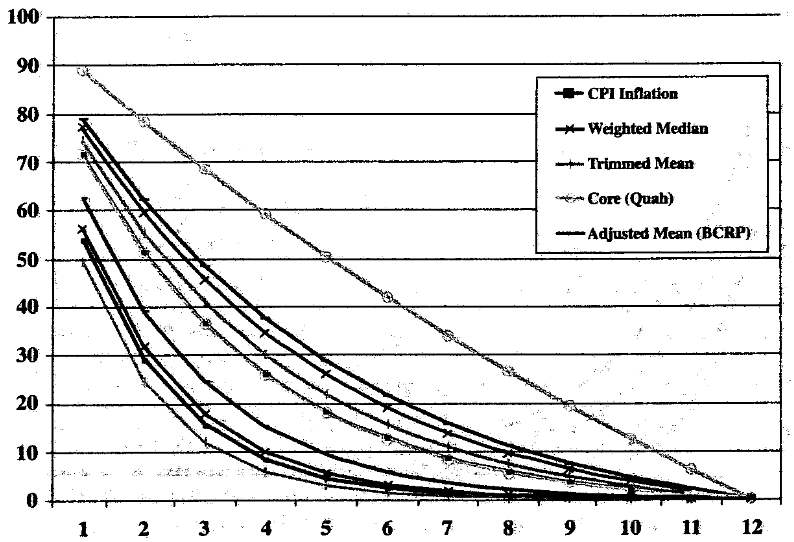
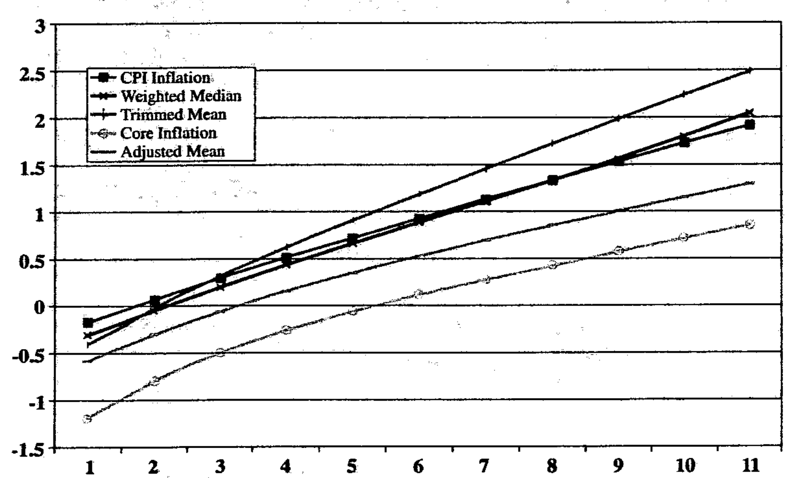


FIGURE 4

SAMPLE SKEWNESS OF BOOTSTRAP DISTRIBUTION OF P (k = 12)



In Figures 5 and 6, we corrected the small sample bias[9]. The difference between the two is that in Figure 5, the maximum lag order allowed was 4 while in Figure 6 the maximum lag was 12. In both cases, we used the Akaike criterion as the selection rule.[10] The only change was in the ranking. The latent inflation was still the more predictable series followed in all cases by the weighted median. Adjusted mean and trimmed mean share the third and fourth places. However, in all cases the latent (Quah) inflation was far more predictable than any other inflation measure. The results were robust to changes in the long-term forecast horizon from 24 to 12 months. In particular, the core inflation measured by the Quah and Vahey procedure is always more predictable than the Peruvian Central Bank choice (adjusted mean).[11]

However, these results should be taken with caution, as the P statistic does not indicate the size of the forecast errors of each model. If we take the Central Bank view, we are interested in a particular model that gives an accurate forecast. Using real data for the period September 1998 - October 1999 we computed the forecast error for each of the alternative measures of inflation. The result (see Figure 7) is clear, the lower forecast errors are for the weighted median while the CPI inflation has the biggest. The explanation of this result lies on the fact that during this period the Peruvian economy suffered the El Niño temporary shock. This massive supply shock experienced is filtered out in the weighted median.

FIGURE 5

SMALL SAMPLE BIAS CORRECTION
k = 24, AIC SELECTION RULE, MAX. LAGS = 4

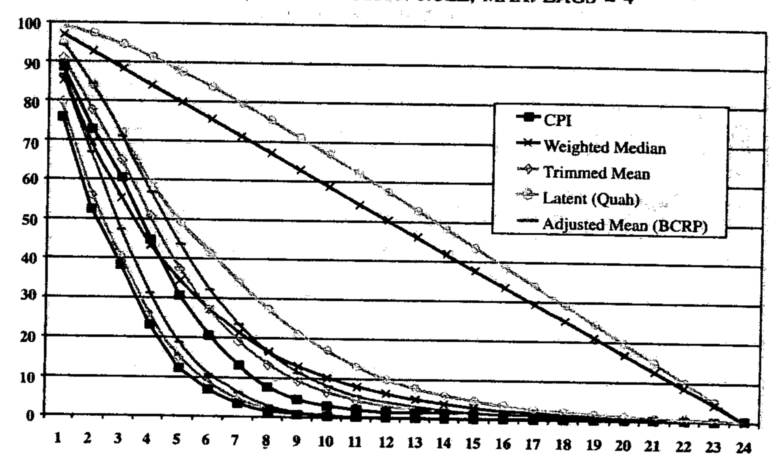


FIGURE 6

SMALL SAMPLE BIAS CORRECTION
k = 24, AIC SELECTION RULE, MAX. LAGS = 12

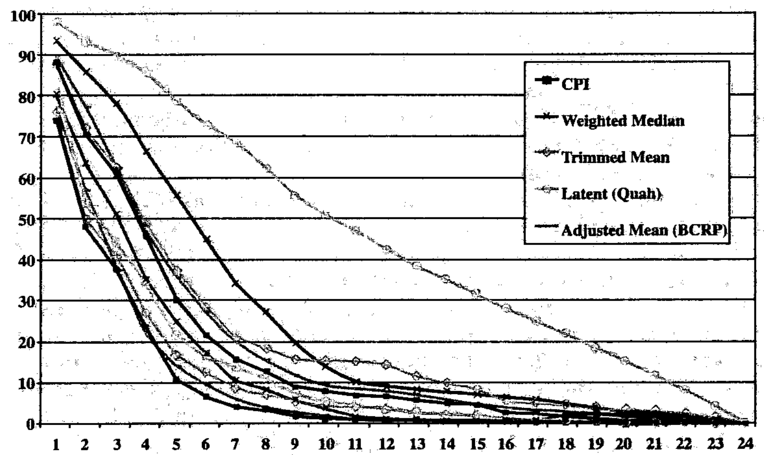
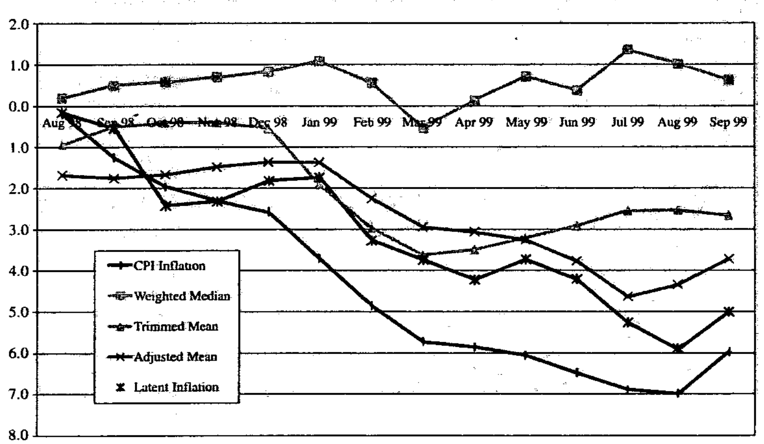


FIGURE 7

FORECAST ERRORS OF ALTERNATIVE INFLATION INDICATORS
UNDER A TEMPORARY SHOCK



V. Conclusions

The results are rather conclusive. The best measure of core inflation is the one suggested by Quah and Vahey (1996). We claim that this result is robust to different choices of long-term forecast comparison, lag selection rules, and to the correction of small sample bias. This result should be qualified in terms of policy recommendations. The most adequate measure of core inflation is the suggested by our exercise on predictability. However, this measure is the most difficult to understand for the public and might not render the lowest forecast errors in the presence of temporary shocks.

An inflation-targeting regime involves the use of inflation indicators at several but different stages. The first stage is to set a target and check how feasible is going to be. The target could be a political decision but the feasibility should be checked using either the weighted median or the trimmed mean indicators to establish which is the most likely inflation rate in the future. We recommend the use of these indicators to avoid the impact of temporary shocks in the other measures of inflation. Once this decision is made is much more accountable if the authorities choose the CPI inflation as the targeted indicator. Is very hard to convince the public (or gain credibility for that matter) that they have to compute a highly sophisticated model to check if the Central Bank is doing its job or not.

A second stage is the monitoring of inflation and the design of contingent monetary policy on the future state of the intermediate target: forecast of the core inflation. If we use the CPI inflation we will encounter several weaknesses. This is the bottom line of this paper, the Central Bank should monitor inflationary pressures looking at core inflation measures rather than looking at the behavior of the headline inflation.

With respect to the Peruvian case, we believe that the Central Bank choice of using the adjusted mean as the measure of core inflation should be understood as a simple (and imperfect) way to look at the trend inflation. We hope that if the Peruvian Central Bank decides to go for a more formal inflation-targeting regime they will not use this indicator as the explicit target.

There are several lines of further research. One that should be pursued is the estimation of different monetary policy reaction function using these alternative measures of inflation. Not only is important to know which is the best measure of core inflation, but also evaluating the monetary rules that follow from that choice.

APPENDIX I

SECTOR SPECIFIC SHOCK INDICATORS

One way to check if excluding some groups is adequate is to compare the weight of each component of the CPI with how frequently the inflation in that component is similar to the median good. The results are reported in the following table. One typical way to construct core inflation measures consists of zero-weighting some components of the CPI. The two components usually censored are food and energy. If we sum the weights of those components they add up to 47.45% while they represent the median good only 18.83% of the time. That is a clear indication of why is justified to do this arbitrary exclusion. In those sectors not affected by seasonal shocks the weight should be less than the sample frequency.

We also include the relative frequency that each component of the CPI is at the 15% tail of the distribution (7.5% for each side). This will point out items in which is more likely to find extreme observations. The list is not surprising at all: vegetables, tubers, meats, fish and seafood, and fruits are in the most extreme group. Other goods that also have fat tails are electricity, legumes, dairy products and eggs, non-alcoholic beverages and transportation services. The Peruvian Central Bank measure of core inflation excludes the following goods: chicken, potato, onion, bread, urban transport, eggs, fish, citric, and other vegetables.

Another interesting result from this table comes from the total weight of those components that are at least twice as much volatile than expected. We obtain a 25.24% of the total CPI basket corresponds to these volatile components. This is fundamental evidence in favor of a measure of inflation that does not take into account relative price shocks. One conclusion should emerge from these calculations: the Peruvian Central Bank should use a core inflation measure instead of the headline CPI inflation as more than 25% of the CPI basket is composed by highly volatile goods.

COMPONENTS OF THE CPI AND THEIR WEIGHTS

Description	1994 CPI Weight	Frequency at the Median	Frequency at the Tails
Total Food and Beverages	**58.05**	**48.24**	**31.5**
Total Food at Home	**42.67**	**17.65**	**31.5**
Cereals and Bakery products	9.31	5.88	10.7
Meats	9.69	0.00	52.4
Fish and Seafood	2.03	0.00	48.8
Dairy products and eggs	4.21	1.18	26.2
Household fuels	1.62	1.18	8.3
Vegetables	3.46	1.18	67.9
Fruits	2.95	1.18	42.9
Legumes	0.65	0.00	33.3
Tubers and roots	2.29	1.18	66.7
Sugar	1.61	1.18	25.0
Coffee. tea and cocoa	0.84	1.18	14.3
Other Food at home	1.38	1.18	6.0
Non-Alcoholic Beverages	1.22	0.00	27.4
Alcoholic Beverages	1.42	2.35	10.7
Food away from home	**15.38**	**30.59**	0.0
Apparel and Footwear	**6.54**	**10.59**	1.2
Apparel	4.53	8.24	2.4
Footwear	2.00	2.35	0.0
Energy Services and House Rental Services	**9.34**	**8.24**	23.5
House maintenance and Rents	3.54	7.06	7.1
Water and sewage utilities	1.02	0.00	32.1
Electricity	2.18	0.00	38.1
Fuel Oil	2.60	1.18	16.7
Furniture and House Maintenance	**3.85**	**9.41**	3.0
Furniture and maintenance	0.26	2.35	0.0
Bed and Bath furnishings	0.33	0.00	1.2
Home appliances and repairs	0.28	1.18	2.4
House furnishings	0.18	0.00	0.0
Housekeeping supplies	2.30	4.71	2.4
Maid services	0.49	1.18	11.9
Total Medical Care	**2.11**	**1.18**	12.6
Medical Care goods	1.13	0.00	3.6
Therapeutic Equipment	0.06	0.00	6.0
Medical Care services	0.67	1.18	3.6
Hospital expenses	0.14	0.00	23.8
Injury and health insurance	0.12	0.00	26.2
Communications and Transportation	**8.48**	**2.35**	18.2
Personal Transportation	0.03	0.00	15.5
Use of Vehicles expenses	0.87	0.00	6.0
Transportation Services	6.67	2.35	26.2
Communications	0.91	0.00	25.0
Entertainment commodities	**5.79**	**8.24**	9.5
Entertainment goods	0.86	0.00	3.6
Entertainment services	0.29	1.18	7.1
Books. newspapers. magazines	0.78	2.35	11.9
Education services	3.87	4.71	15.5
Other goods and services	**5.85**	**11.76**	4.8
Personal care goods and services	4.81	9.41	0.0
Other goods non-specified	0.15	0.00	2.4
Housing services	0.08	0.00	4.8
Other services non specified	0.61	1.18	6.0
Tobacco	0.19	1.18	10.7

Note: Calculations use 45 components of the CPI, monthly from 1991:01 to 1998:01. "Frequency at the Median" counts the number of months a particular good is the median good, and divides by the total number of months (85).

Notes

1. See Svensson (1998) for an updated survey of the inflation targeting literature.
2. For a complete review of the inflation targeting experiences see Mishkin and Posen (1997).
3. The Peruvian Central Bank calculation excludes 21.2% of the total CPI basket. The goods excluded are chicken, potatoes, urban transportation, onion, bread, eggs, fish, citric fruits, and other vegetables.
4. This technique has been used for UK by Quah and Vahey (1996), for the US by Claus (1997), for Sweden by Blix (1995); for Colombia by Melo and Hamann (1998); and for México by Mateos and Gaytán (1998).
5. The Granger-Newbold case happens when $L(x) = x^2$ and $k = \infty$.
6. See Efron and Tibshirani (1993) for a comprehensive explanation on the bootstrap technique.
7. We explore the asymmetric loss function case with Brazilian data but the results stayed the same compared to the symmetric case. See Morón *et al.* (1999).
8. This is an important piece of evidence as we are just showing the confidence intervals instead of the density plots.
9. The following results were obtained using AR(p) specification instead of ARMA models. We did this to simplify the calculations.
10. The weighted median series was the only one in which the Akaike criterion choose an AR(2) specification. In the rest of cases it always choose the maximum lag allowed. The Schwarz information criterion favored more parsimonious models for the weighted median (7 lags) and for the adjusted mean (5 lags).
11. We have obtained similar results using Guatemalan data, see Morón and Zegarra (1999).

References

ANDREWS, D. (1993). "Tests for Parameter Instability and Structural Change with Unknown Change Point", *Econometrica*, Vol. 61, pp. 821-856.

BANCO CENTRAL DE RESERVA DEL PERU (1998), "La Inflación Subyacente en el Perú", *Notas de Estudios* Nº 5.

BEVERIDGE, S. and Ch. NELSON (1981). "A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the Business Cycle", *Journal of Monetary Economics*, Nº 7, pp. 151-74.

BLIX, M. (1995). "Underlying Inflation -A Common Trends Approach", Bank of Sweden. *Working Paper* Nº 23.

BLANCHARD, O. and D. QUAH (1989). "The Dynamic Effects of Aggregate Demand and Supply Disturbances", *American Economic Review*, Vol. 79, Nº 4, September, pp. 655-73.

BRÄNNSTRÖM, T. (1995). "A Second-Order Approximation to the Bias of OLS Estimates in Bivariate VAR Models", Stockholm School of Economics, *Working Paper* Nº 81.

BRYAN, M. and S. CECCHETTI (1993a). "Measuring Core Inflation", *NBER Working Paper* Nº 4303.

BRYAN, M. and S. CECCHETTI (1993b). "The Consumer Price Index as a Measure of Inflation", *NBER Working Paper* Nº 4505.

BRYAN, M., S. CECCHETTI and R. WIGGINS II (1997). "Efficient Inflation Estimation", *NBER Working Paper* Nº 6183.

CABREDO, P. and L. VALDIVIA (1998). "Problemas en la Medición de la Inflación", *Estudios Económicos*, Banco Central de Reserva del Perú, August, pp. 117-129.

CECCHETTI, S. (1996). "Measuring Short-Run Inflation for Central Bankers", *NBER Working Paper* Nº 5786.

CLAUS, I. (1997). "A Measure of Underlying Inflation in the United States", Bank of Canada Working Paper 97-2.

DIEBOLD, F. and L. KILLIAN (1997). "Measuring Predictability: Theory and Macroeconomic Applications", *mimeo*.

EFRON, B. and R.J. TIBSHIRANI (1993). *An Introduction to the Bootstrap*, Chapman and Hall.

FERREYROS, J. and E. MORON (1998). "An Alternative Measure of Core Inflation Imposing Theory Constraints", Universidad del Pacífico, *unpublished Working Paper*.

GRANGER, C. and P. NEWBOLD (1986). *Forecasting Economic Time Series*, 2nd Edition, Academic Press.

HAMILTON, J. (1994). *Time Series Analysis*, Princeton University Press.

KILLIAN, L. (1996). "An Endogenous Lag Order Bootstrap Algorithm with an Application to Impulse Response Analysis", Department of Economics, University of Pennsylvania, *mimeo*.

KILLIAN, L. (1998). "Small-Sample Confidence Intervals for Impulse Response Functions", *The Review of Economics and Statistics*, Vol. 80, Nº 2, May, pp. 218-230.

MATEOS, C. and A. GAYTAN (1998). "Medidas Alternativas de Inflación", Banco de México, *Working Paper* 9802.

MELO, L. F. and F. HAMANN (1998). "Inflación Básica. Una Estimación Basada en Modelos VAR Estructurales", *Working Paper*, Nº 3, June, Banco de la República.

MELO, L. F., F. HAMANN and J. D. URIBE (1998). "Un Análisis de las Medidas de Inflación Básica para Colombia", Banco de la República, *unpublished Working Paper*.

MISHKIN, F. and A. POSEN (1997). "Inflation Targeting: Lessons from Four Countries", *Economic Policy Review*, Federal Reserve Bank of New York, Vol. 3 (3).

MORANDE, F. and K. SCHMIDT-HEBBEL (1997). "Inflation Targets and Indexation in Chile", Central Bank of Chile, *unpublished Working Paper*.

MORON, E. and L. F. ZEGARRA (1998). "Measuring and Targeting Core Inflation in a Small, Open and Dollarized Economy: The Peruvian Case", *unpublished Working Paper*.

MORON, E. and L. F. ZEGARRA (1999). "Predecibilidad de la Inflación: Lecciones para Guatemala y Perú", Universidad del Pacífico, *Working Paper*.

MORON, E., E. OCHOA, F. ORREGO and L. F. ZEGARRA (1999). "How to Choose Among 12 Inflation Indicators? An Application for the Brazilian Inflation Targeting Regime", Universidad del Pacífico, *unpublished Working Paper*.

POPE, A.L. (1990). "Bias in the Estimation of Multivariate Autoregressions", *Australian Journal of Statistics*, 30A, pp. 296-309.

QUAY, D. and S. VAHEY (1996). "Measuring Core Inflation", *Economic Journal* 105, pp. 1130-1144.

SVENSSON, L. (1998). "Inflation Targeting as a Monetary Policy Rule", *mimeo*.