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How Useful is Core Inflation for Forecasting Headline Inflation?

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Abstract

The paper constructs various core inflation measures. These include various trimmed means using highly disaggregated data and a structural VAR estimate of core inflation for Ireland. The ability of these core inflation measures to forecast future headline inflation is compared using a simple regression model. An ARIMA model fitted to the headline inflation rate is used to construct the benchmark forecast. The forecasts from the ARIMA model are most accurate over short time horizons for monthly data. The structural VAR based estimate is most accurate over longer time horizons. For quarterly data, the structural VAR provides the optimal forecast over all time horizons considered.

1 Introduction

During the past decade, there has been a revival of interest in the topic of core inflation as more central banks engage in inflation targeting. Specific inflation targets have been adopted by central banks in several countries including Australia, Canada, Finland, New Zealand, Spain, Sweden and the United Kingdom. The European Central Bank has also committed to maintaining the inflation rate in the euro area below two per cent. Core inflation can be used as an indicator of future trends in headline inflation. Consequently, it provides a tool in the formulation of monetary policy, particularly for central banks that engage in inflation targeting.

Core inflation, like potential output, is abstract in nature. It is not measured directly but is constructed based on a concept or a definition. Consequently, any measure will depend on how core inflation is defined. Similarly, the optimal measure will depend on the criterion used to assess competing measures of core inflation. In the literature, there are a variety of definitions and criteria used in relation to core inflation.

From the perspective of a central bank, the most useful definition of core inflation is that it represents monetary inflation, which is distinct from headline inflation. Monetary inflation is inflation that is directly influenced by monetary policy. It is conceived as affecting all prices uniformly and represents a common element to all price changes. Headline inflation, as measured the national consumer price index, is generally used as an indicator of changes in the cost of living as its weights are derived on the basis of expenditure shares on a representative basket of goods. The distinction between headline inflation and monetary inflation is made on the basis that monetary inflation determines the price level in the long-run but non-monetary, short-run factors can influence the headline inflation rate in the short-run. The challenge empirically is to distil monetary or core inflation from the headline inflation rate.

Given this definition of core inflation as monetary inflation, its usefulness as a forecasting tool is obvious. The aim of this paper is to find a measure of core inflation consistent with this concept and test its ability to forecast headline inflation against purely statistical alternatives. The first structural VAR measure of core inflation for Ireland is estimated using long-run restrictions. An Autoregressive Integrated Moving Average (ARIMA) model fitted to the headline inflation rate is used to construct the benchmark forecast. The

ARIMA forecast is found to be the best way of forecasting headline inflation over very short time horizons using monthly data. For forecasts over longer horizons, a forecast using a structural VAR measure of core inflation out-performs statistical measures of core inflation put in the same forecasting model. It also out-performs forecasts from the ARIMA benchmark. For quarterly data, the structural VAR forecast is optimal over all horizons.

2 Literature Review

There are two basic approaches to measuring core inflation. Hogan et al (2001) label one the statistical approach and the other the modelling approach. The statistical approach is a practical, data-driven approach. The problem is to find a measure of core inflation from the data on price indices and inflation rates. The most simple of these approaches is to exclude some component of the consumer price index that is the most volatile. For instance, a common euro area measure of core inflation is the Harmonised Index of Consumer Prices (HICP) excluding energy. In essence, this represents a re-weighting of the HICP with the energy component given a zero weighting. However, energy may not be the most volatile component in every period. Despite this drawback, I include the HICP excluding energy as one of the measures of core inflation because it is very widely reported and because there is no computational cost.

Macklem (2001) suggests a measure of core inflation that excludes the eight most volatile components of the CPI (out of a total of fifty-four) on the basis of measured average volatility over a number of preceding time periods. This approach is also open to the criticism that the most volatile components in each period may not be excluded. A more dynamic method is to measure the volatility of all components in each period and then exclude a certain number. A problem with these approaches is that the excluded items, although volatile, may contain information regarding the core inflation signal. Dow (1994) re-weights the CPI so that the weight of each component is inversely proportional to its variance. In this way, no component with potentially valuable information regarding core inflation is totally excluded. Blinder (1997) also suggests an inclusive measure in which each component is weighted according to its ability to forecast future inflation.

It is also possible to apply a simple statistical smoothing or filtering technique to arrive at a measure of core inflation. A statistical filter generally works on the premise that the inflation rate being examined contains both a trend and a cyclical component. The aim is to "filter" out the cyclical component, leaving only the underlying trend in inflation. Basic techniques, such as standard or centred moving averages, can also be used. The statistical filter used in this study is the Hodrick-Prescott (HP) filter. The main advantage of using a HP filter is that it is well understood in the profession. However, the end-point problem with the HP filter will hinder forecasts to a certain extent.

Another strand of literature in the statistical approach considers the distribution of individual price changes that constitutes the CPI. The key insight in this approach is that the observed price changes are a sample drawn from an unobserved population distribution of price changes. The aim is to estimate the population mean from the observed sample. If the population is normally distributed, the sample mean will be an unbiased and efficient estimator. However, if the population distribution exhibits excess kurtosis, the sample will contain more extreme values than a normal distribution. In this case, the sample mean will not be an efficient estimator of the population mean. In general, as the kurtosis of the distribution increases, the efficiency of estimators - like the sample mean - that place a high weight on observations in the tails of the distribution decreases relative to estimators that place a low weight on the tails of the distribution (Roger, 1997).

In many countries, it has been found that the distribution of price changes is positively skewed with excess kurtosis. Meyler (1999) demonstrates that this characterisation also holds for Irish price changes. Robust or limited-influence estimators have been proposed as the optimal measure of population central tendency in this case. These estimators ignore a certain proportion of the tails of the distribution. Consequently, they aren't influenced by extreme observations. For example, a 10% trimmed mean ignores 5% of the observations at each end of the distribution and takes the mean of the remaining observations. Trimmed means are the most common limited influence estimator but trimmed medians can also be used. Updating the work of Meyler (1999), trimmed means with various levels of trim are estimated in this paper although a slightly different methodology is employed.

The optimal trim depends on the benchmark used. A desirable characteristic of core inflation is that it should track trend inflation. Cecchetti (1997), Kearns (1998) and Meyler (1999) compare their estimates of core inflation to a centred moving average of headline inflation, which is assumed to mimic trend inflation. Another common benchmark is to compare the error from a forecasting model using core inflation against the same forecasts made using headline inflation. Meyler (1999) and Clark (2001) compare forecast errors from an ARIMA model and a simple regression respectively. Forecasting ability is the benchmark used when assessing the optimal level of trim in this paper.

Statistical approaches are often criticised on the grounds that they don't rely on any economic theory. In contrast, structural models of core inflation are heavily grounded in theory. Quah and Vahey (1995) propose a measure of core inflation based on the concept of a vertical Philips curve. Inflation is assumed to be affected by two different types of shock, distinguished by their effect on output. The core inflation shock is output neutral after some fixed horizon whereas the non-core shock is allowed to influence output in the long-run. Core inflation is defined by Quah and Vahey as "the underlying movement in measured inflation associated only with the first kind of disturbance". The methodology has been widely implemented to measure core inflation internationally but has yet to be applied in Ireland.

3 Methodology

The methodology is identical to that used by Quah and Vahey (1995), using the type of long-run restrictions first proposed by Blanchard and Quah (1989) although the exposition of the model generally mirrors that of Claus (1999). The model is formulated in terms of the first differences of oil prices, output and the inflation rate. In the moving average representation, the series can be expressed as a function of past and present structural shocks:

$$\Delta oil_t = \sum_{k=0}^{\infty} s_{11,k}\ \epsilon_{1t-k} + \sum_{k=0}^{\infty} s_{12,k}\ \epsilon_{2t-k} + \sum_{k=0}^{\infty} s_{13,k}\ \epsilon_{3t-k} \tag{1}$$

$$\Delta y_t = \sum_{k=0}^{\infty} s_{21,k}\ \epsilon_{1t-k} + \sum_{k=0}^{\infty} s_{22,k}\ \epsilon_{2t-k} + \sum_{k=0}^{\infty} s_{13,k}\ \epsilon_{3t-k} \tag{2}$$

$$\Delta \pi_t = \sum_{k=0}^{\infty} s_{31,k}\ \epsilon_{1t-k} + \sum_{k=0}^{\infty} s_{32,k}\ \epsilon_{2t-k} + \sum_{k=0}^{\infty} s_{33,k}\ \epsilon_{3t-k} \tag{3}$$

where oil_t, y_t and π_t denote the logs of oil prices, output and the inflation rate respectively. The three structural shocks ϵ_{1t}, ϵ_{2t} and ϵ_{3t} can be thought of as an oil price shock, a non-core shock and a core shock respectively. These shocks are orthogonal, white noise errors.

This type of model is frequently modelled with a bivariate specification using only output and inflation but the openness of the Irish economy suggests some role for external shocks in the system. For this reason, oil prices were also chosen from a selection of open economy variables. In matrix form, this system can be written:

$$\begin{bmatrix} \Delta oil_t \\ \Delta y_t \\ \Delta \pi_t \end{bmatrix} = \begin{bmatrix} S_{11}(L) & S_{12}(L) & S_{13}(L) \\ S_{21}(L) & S_{22}(L) & S_{23}(L) \\ S_{31}(L) & S_{32}(L) & S_{33}(L) \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} \tag{4}$$

or

$$X_t = S(L)\epsilon_t \tag{5}$$

where $S(L)$ is a polynomial in the lag operator whose individual coefficients are denoted $s_{ij,k}$. The structural shocks are normalized so that their covariance matrix is the identity matrix:

$$E\left(\epsilon_t\ \epsilon_t'\right) = \Sigma_\epsilon = \begin{bmatrix} var\left(\epsilon_{1t}\right) & cov\left(\epsilon_{1t}\ \epsilon_{2t}\right) & cov\left(\epsilon_{1t}\ \epsilon_{3t}\right) \\ cov\left(\epsilon_{2t}\ \epsilon_{1t}\right) & var\left(\epsilon_{2t}\right) & cov\left(\epsilon_{2t}\ \epsilon_{3t}\right) \\ cov\left(\epsilon_{3t}\ \epsilon_{1t}\right) & cov\left(\epsilon_{3t}\ \epsilon_{2t}\right) & var\left(\epsilon_{3t}\right) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_3 \tag{6}$$

It is the behaviour of the structural shocks, which represent the core and non-core inflation shocks, that is really of interest. The problem is that, in the estimation of a standard reduced-form VAR, it is the reduced-form shocks and not the structural shocks that are estimated. Nonetheless, the first step in identifying the structural shocks is the estimation of the reduced-form VAR. Ignoring the intercept for simplicity:

$$\begin{bmatrix} \Delta oil_t \\ \Delta y_t \\ \Delta \pi_t \end{bmatrix} = \begin{bmatrix} \Theta_{11} & \Theta_{12} & \Theta_{13} \\ \Theta_{21} & \Theta_{22} & \Theta_{23} \\ \Theta_{31} & \Theta_{32} & \Theta_{33} \end{bmatrix} \begin{bmatrix} \Delta oil_{t-1} \\ \Delta y_{t-1} \\ \Delta \pi_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{7}$$

or

$$X_t = \Theta X_{t-1} + e_t \tag{8}$$

Assuming that Θ is invertible, the Wold moving average representation can be obtained:

$$\begin{bmatrix} \Delta oil_t \\ \Delta y_t \\ \Delta \pi_t \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) & C_{13}(L) \\ C_{21}(L) & C_{22}(L) & C_{23}(L) \\ C_{31}(L) & C_{32}(L) & C_{33}(L) \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{9}$$

or

$$X_t = C(L)e_t \tag{10}$$

where $C(L)$ is a polynomial in the lag operator. This means X_t can be expressed:

$$X_t = e_t + \Theta e_{t-1} + \Theta^2 e_{t-2} + ... \tag{11}$$

The matrix $C(1)$ is the matrix of long-run effects with respect to the reduced-form shocks.

$$C(1) = \sum_{k=0}^{\infty} C_k L^k, \;\; C_0 = I_3, C_k = \Theta^k \tag{12}$$

$$= (I_3 - \Theta L)^{-1} \tag{13}$$

The reduced-form shocks are a linear combination of the structural shocks:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} = \begin{bmatrix} s_{11}(0) & s_{12}(0) & s_{13}(0) \\ s_{21}(0) & s_{22}(0) & s_{23}(0) \\ s_{31}(0) & s_{32}(0) & s_{33}(0) \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} \tag{14}$$

or

$$e_t = S(0)\epsilon_t \tag{15}$$

Given this relationship between the structural and reduced-form shocks, equation (13) can be re-written in terms of the structural shocks as follows:

$$X_t = S(0)\epsilon_t + \Theta S(0)\epsilon_{t-1} + \Theta^2 S(0)\epsilon_{t-2} + ... \tag{16}$$

The elements of the matrix $S(0)$ are still unknown. The matrix contains nine elements. Thus, nine independent equations are needed in the nine elements. Consider the variance/covariance matrix of the reduced-form residuals:

$$\Sigma = E(e_t {e_t}') = S(0)E(\epsilon_t {\epsilon_t}')S'(0) = S(0)S'(0) \tag{17}$$

The values of Σ are known from the estimation of the reduced-form VAR. This allows us to write six equations in terms of the nine unknowns:

$$\begin{aligned}
var\,(e_{1t}) &= s_{11}(0)^2 + s_{12}(0)^2 + s_{13}(0)^2 && (18)\\
var\,(e_{2t}) &= s_{21}(0)^2 + s_{22}(0)^2 + s_{23}(0)^2 && (19)\\
var\,(e_{3t}) &= s_{31}(0)^2 + s_{32}(0)^2 + s_{33}(0)^2 && (20)\\
cov\,(e_{1t},\ e_{2t}) &= s_{11}(0)s_{21}(0) + s_{12}(0)s_{22}(0) + s_{13}(0)s_{23}(0) && (21)\\
cov\,(e_{1t},\ e_{3t}) &= s_{11}(0)s_{31}(0) + s_{12}(0)s_{32}(0) + s_{13}(0)s_{33}(0) && (22)\\
cov\,(e_{2t},\ e_{3t}) &= s_{21}(0)s_{31}(0) + s_{22}(0)s_{32}(0) + s_{23}(0)s_{33}(0) && (23)
\end{aligned}$$

In order to get the remaining equations, explicit restrictions are placed on the long-run behaviour of the system. The long-run effects of the reduced form shocks were given by the matrix $C(1)$. Equation (14) gives the relationship between the relationship between the reduced form shocks and the structural shocks. This allows the long-run effects of the structural shocks, denoted by the matrix $S(1)$, to be expressed as follows:

$$\begin{bmatrix} S_{11}(1) & S_{12}(1) & S_{13}(1) \\ S_{21}(1) & S_{22}(1) & S_{23}(1) \\ S_{31}(1) & S_{32}(1) & S_{33}(1) \end{bmatrix} = \begin{bmatrix} C_{11}(1) & C_{12}(1) & C_{13}(1) \\ C_{21}(1) & C_{22}(1) & C_{23}(1) \\ C_{31}(1) & C_{32}(1) & C_{33}(1) \end{bmatrix} \begin{bmatrix} s_{11}(0) & s_{12}(0) & s_{13}(0) \\ s_{21}(0) & s_{22}(0) & s_{23}(0) \\ s_{31}(0) & s_{32}(0) & s_{33}(0) \end{bmatrix} \quad (24)$$

or

$$S(1) = C(1)S(0) \quad (25)$$

If the matrix $S(1)$ is lower triangular, the necessary equations for identification can be found from the resulting restrictions. These restrictions impose structure on the economic relationships between the variables in the system. The first restriction is that $S_{23}(1) = 0$ and this amounts to saying that the core shock has no effect on output in the long-run. This is consistent with the idea of a vertical long-run Philips curve and is a traditional identifying assumption in the application of long-run restrictions. The next two restrictions are that $S_{12}(1)$ and $S_{13}(1) = 0$. The implication of these restrictions is that domestic core and non-core shocks have no influence on international oil prices in the long-run. Bjornland (2001) justifies the use of these restrictions in the case of Norway on the basis that it is a small oil producer with limited influence on oil prices. The same restrictions for Ireland are even less contentious given that we are a small oil-importing economy. These three restrictions yield the following equations:

$$C_{11}(1)s_{12}(0) + C_{12}(1)s_{22}(0) + C_{13}(1)s_{23}(0) = 0 \tag{26}$$

$$C_{11}(1)s_{13}(0) + C_{12}(1)s_{23}(0) + C_{13}(1)s_{33}(0) = 0 \tag{27}$$

$$C_{21}(1)s_{13}(0) + C_{22}(1)s_{23}(0) + C_{23}(1)s_{33}(0) = 0 \tag{28}$$

It is now possible to estimate all elements of $S(0)$. Together with $C(1)$, which is calculated from the reduced-form coefficients, this allows the structural shocks to be identified.

4 Data

Both monthly and quarterly data are used to calculate a SVAR measure of core inflation in the paper. The inflation rate considered is the year-on-year change in the Harmonised Index of Consumer Prices (HICP). Output is measured using the seasonally adjusted industrial production index for monthly data and an interpolated measure of real GDP for quarterly data. Oil prices refer to the price of UK Brent. The monthly data are available over the period 1997M1-2006M5. This is a relatively short sample in the context of a SVAR model imposing long-run restrictions but the results from the model appear reasonable. Despite the short sample, it is the results of the monthly analysis that are of most interest because future trends in inflation are most likely to be spotted first from monthly data rather than quarterly data. The inclusion of quarterly data allows the evolution of core inflation to be tracked over a longer period. The monthly data relate to a period when the economy has been in a state of perpetual boom. However, the quarterly data set spans 1980Q1-2005Q4 so it also contains data on a period when the economy was underperforming.

In terms of constructing a trimmed mean, the process is data-intensive. The monthly SVAR data span two inflation base periods. The first base period covers the years 1997-2001 while the second base period covers 2002-present.[1] In the first base period, the HICP has 529 individual price series. This increases to 606 individual series for the second based period. This is a much wider cross section of data that has been available in other comparable studies. The change in the number of individual price series is not solely due to additional

[1] The present base period will run until the end of 2006.

items being included in the representative basket of consumer goods; items are also replaced and deleted.

5 Overview of Core Inflation Measures

5.1 HICP excluding Energy

The first measure of core inflation considered is the HICP excluding energy. This measure of core inflation will only differ from the headline rate to a meaningful degree when there are large changes in energy prices. Figures 1 and 2 graph this measure of core inflation for both monthly and quarterly data. There are few instances of a large sustained divergence between the two series although the effect of high energy prices in the past two years is quite noticeable, particularly from the monthly data. To the extent that the core series is so similar to the HICP, it might not be expected to provide much additional informational content for forecasting headline inflation that is not contained in the headline rate itself.

5.2 Hodrick-Prescott Filter

The Hodrick-Prescott filter is used as the second measure of core inflation. The value of the smoothing parameter, λ, is chosen in order to minimise the errors from a forecasting regression, which is presented later. Figures 3 and 4 graph the headline inflation rate and the HP filtered measure of core inflation for both monthly and quarterly data. The HP measure of core inflation tracks the headline inflation rate in a much smoother fashion than the HICP excluding energy. The difference between the two series alternates from positive to negative quite frequently. The filter is purely mechanical however. It attributes a certain proportion of each shock hitting the series to a change in the trend of the series while the remainder is regarded as temporary noise. As with the HICP excluding energy, there is no structural interpretation to this core measure.

5.3 Trimmed Means

5.3.1 Properties of Price Change Distributions

It was mentioned that the key motivation for the construction of trimmed mean estimates of core inflation is that the sample mean is an inefficient estimator of population central tendency when the sample exhibits excess kurtosis. Table 1 provides a summary of some of the key properties of the sample distribution of price changes. The trimmed means are estimated for the span of the monthly data only. Results are presented for both month-on-month and year-on-year price changes although the year-on-year statistics are of more interest because the year-on-year inflation rate is included in the SVARs. The summary statistics are calculated for both base periods individually and for the sample as a whole. The change from one base period to another presents difficulties when dealing with the year-on-year price changes. At the start of the second base period, new items are introduced, old items are deleted and other items are replaced. This means that some items do not have a comparator from twelve months earlier from which to calculate a year-on-year change. (This problem does not exist with the month-on-month changes because there is a one month overlap in base periods.) Thus the full sample statistics for the year-on-year price changes include a one year gap. When the trimmed means are calculated, year-on-year approximations are estimated from the monthly data for the one year gap.

The statistics in Table 1 are all averages. The mean, median, skew and kurtosis of the price change distribution are calculated each month in the sample and the results presented are sample averages. On examination of national price change data, numerous researchers have found price change distributions to be characterised by positive skew. Table 1 indicates that the month-on-month price change distributions are also characterised by positive skew for Ireland. The year-on-year price change distribution for the full sample is broadly symmetric with a small negative skew in the first base period largely offset by a similar positive skew in the second base period.

Excess kurtosis is an obvious feature of all distributions. It is more pronounced in the case of month-on-month price changes but it is still a significant feature of the data in the year-on-year case. The kurtosis of the distribution is more readily apparent from graphical evidence. As an example, Figure 5 graphs the year-on-year price change distribution for January 2003 overlaid with a normal density using the sample mean and variance. A distribution with excess kurtosis relative to the normal distribution has a more acute peak around the mean and more weight in the tails. The peak in Figure 5 is clearly higher than the normal distribution. The mean price change is 1.5% with a standard deviation of 7.2%. A 99% confidence interval for a normal distribution with these moments is approximately -17% to 20%. However, it is clear from the graph that more than 1% of the distribution lies outside this interval, which is further evidence of the kurtosis of the distribution. The median is 1.9%, slightly higher than mean, resulting in a small negative skew. Figure 6 presents a similar graph for November 2005. It indicates that excess kurtosis is also a feature of the data for months characterised by positive skew. The kurtosis of these distributions warrant the use of trimmed means as measures of core inflation.

5.3.2 Constructing the Trimmed Mean Measures

The trimmed mean can be calculated in two different ways. The most common approach is to estimate the inflation rates of all the individual components that comprise the HICP and then rank these inflation rates and their associated expenditure weights. Exclude the items associated with a certain percentage of the largest and smallest inflation rates. Calculate the aggregate inflation rate of the remaining items, rescaling the weights used to calculate the headline inflation rate so that the new weights still sum to 1. Studies of core inflation that report a trimmed mean mostly report the result of this sort of calculation.

The problem with this sort of approach is that the weights are based on expenditure shares on a representative basket of goods, devised by statistical agencies to approximate changes in the cost of living. There is no reason to believe that this weighting system should still be used when constructing a core inflation measure, which aims to capture the underlying trend in inflation rather than the cost of living. In fact, the weighting system will have a large distortionary effect on the underlying inflation signal if price changes due to idiosyncratic shocks occur in items with large expenditure weights. Thus, a second method to calculate trimmed means simply ignores the weights and calculates a simple average of individual inflation rates following the trimming operation. As before, begin by ordering individual inflation rates and excluding a certain percentage but, this time, take a simple average of the remaining inflation rates. I refer to this as a simple trim to distinguish it from the standard trimming method and this is the method I employ.

Figure 7 plots trimmed means with 5% and 10% trims. Both trimmed mean measures of core inflation are substantially lower than the headline rate of inflation for most of the sample. On average, the 5% trimmed mean is 1.9% lower than headline inflation while the 10% trimmed mean is 1.8% lower. Figure 9 plots the average inflation rate without any trim and the median inflation rate. These two series broadly resemble the trimmed mean series. Average inflation is consistently lower than headline inflation. This indicates that the weighting system used to calculate headline inflation has contributed to the relatively high rate of inflation over much of the sample.

5.4 Structural VAR Estimates

The monthly structural VAR is formulated using a trivariate specification with oil prices, industrial production and the inflation rate. The variables enter the model in first difference form as they are all found to be I(1) but not cointegrated. The results of the unit root tests are presented in Table 2 and cointegration tests are in Table 3. The maximum lag length considered was the frequency of the data plus one. The VAR is specified with four lags. The number of lags was chosen to maximise the forecasting ability of the resulting core measure. The core inflation measure is not sensitive to small changes in the number of lags specified in the VAR. Figure 9 graphs the SVAR measure of core inflation using monthly data. This measure of core inflation largely tracks the headline inflation rate for most of the sample.

The quarterly SVAR also uses a trivariate specification but GDP is used as the output variable rather than industrial production. There are also differences in the stochastic properties of the data. Output and energy prices are again found to be I(1) but the year-on-year inflation rate calculated using quarterly data is found to be I(0). Unit root tests for quarterly data are again provided in Table 2. Despite a high rate of inflation in the early eighties, statistical tests find the series to be stationary. This means that the inflation rate enters the VAR in levels rather than in first differences. Again, Table 3 indicates that the variables are not cointegrated.

Figure 10 graphs headline inflation and the quarterly SVAR measure of core inflation. In the early part of the sample, the two series are broadly similar. However, core inflation is higher than headline inflation in the period from 1995-2002. This reflects the fact that economic growth was exceptionally high over this period. Consider a measure of economic growth calculated as the average of the year-on-year growth rate in real GDP for the four most recent quarters. The average value of this growth rate was just over 9 percent between the first quarter of 1995 and the last quarter of 2002. The average growth rate for the remainder of the sample is roughly half that at 4.5 per cent. Core inflation could be expected to be high during this high growth period in the sample. The two series have again been broadly similar over the final three years of the sample.

6 Forecasting Ability of Core Inflation Measures

In this section, competing measures of core inflation are ranked according to their ability to forecast the headline inflation rate. This is accomplished using a simple forecasting regression:

$$\pi_{t+h} - \pi_t = \alpha + \beta\left(\Pi_t - \pi_t\right) + \upsilon_t \tag{29}$$

where π_t is the inflation rate at time t and Π_t is core inflation. The left hand side of the equation is the difference between headline inflation today and headline inflation h periods in the future. On the right hand side, the term in brackets is the difference between core inflation and headline inflation. The basic premise of this forecasting regression is that difference between headline inflation and core inflation today has predictive power for headline inflation tomorrow. In particular, if there is a large divergence between headline inflation and core inflation, you would expect headline inflation to move back towards core inflation because core inflation is a measure of the general trend in inflation.

The regression computes a forecast over a fixed horizon. For example, using monthly data and setting $h = 12$ would yield a forecast of headline inflation twelve months in the future but would not forecast inflation in the intervening periods. There are two ways to get a continuous forecast to the end of the forecasting horizon. Estimate twelve regressions of the type above setting $h = 1...12$. Alternatively, using only the coefficients from the twelve step ahead regression, the forecast for $t + 12$ months ahead can be estimated using the difference between headline inflation and core inflation in period t. Next, the forecast for $t + 11$ months ahead can be estimated using the difference between core inflation and headline inflation in period $t - 1$. Proceeding accordingly, a full set of forecasts can be computed. Forecasts have been computed using both methods and the forecasts calculated using the first approach have the smallest forecast errors for all core measures and over virtually all time horizons. Consequently, the duplicate set forecast errors from the other approach is not reported.

The monthly forecasts are performed up to twelve months in the future whereas the quarterly forecasts are performed up to two years in the future. The forecasts are performed on a recursive basis, with one observation added to the sample each time. The first sample for the monthly estimates is 1998M1-2003M6. The core inflation measures are calculated over this sample and forecasts are performed for the twelve months up to 2004M6. The process is repeated adding one observation each time so by the end of the final estimation period of 2005M5, there are 24 sets of forecasts for each estimation method. An analogous process is used with the quarterly data. The first estimation sample spans 1981Q1-1999Q4 and 16 sets of forecasts are calculated by again adding one observation to the sample at each step.

The forecasts are evaluated using the Root Mean Square Error (RMSE) from pseudo out-of-sample forecasts as the loss function. An ARIMA model is fitted to the headline rate and this is used to construct the benchmark forecast. Table 4 presents the RMSE from the different forecasting regressions over a twelve month forecast horizon while Figure 11 plots the same data. The unbroken line in Figure 11 shows the forecast errors from the ARIMA model. Over the first two months, the forecast errors from the ARIMA model are lower than those from the core inflation measures. The ARIMA model provides a good short-term forecast. Beyond six months, however, the ARIMA models result in the largest forecast errors. Poor forecast performance over longer horizons is a typical feature of univariate forecasting.

With the exception of the first two months, the SVAR measure of core inflation results in the lowest forecast errors. The HP filter and the HICP excluding energy forecasts perform better than the ARIMA forecast beyond a six month horizon but still not as well as the SVAR. It appears that the informational content in the structural model allows it to out-perform the univariate forecast and the purely statistical measures of core inflation over most horizons.

Table 5 presents the RMSE of the quarterly forecasts over the two year forecast horizon and the corresponding series are graphed in Figure 12. Again, the solid line represents the graph from the ARIMA benchmark. In the case of quarterly data, the ARIMA benchmark forecast performs well. It has lower forecast errors that both the HICP excluding energy and the HP filter forecasts over the entire forecast horizon. The forecast errors from the SVAR measure are lower than the benchmark but the improvement in forecast accuracy is small. The results of the quarterly forecast exercises reinforce the usefulness of the SVAR measure of core inflation in forecasting the headline rate but the evidence is less compelling than with the monthly results.

7 Summary and Conclusions

The paper set out to evaluate the ability of different core inflation measures to forecast the headline inflation rate. The four measures included are the HICP excluding energy, the HICP filtered using the Hodrick-Prescott filter, trimmed mean measures of core inflation (which also considered average inflation) and a structural VAR model of core inflation estimated using long-run restrictions. An ARIMA model was used to construct the benchmark forecast. The results from models constructed using both monthly and quarterly data indicate that the SVAR measure of core inflation used in the forecasting regression provide the best forecasts. However, the SVAR model is slightly out-performed by the ARIMA forecast over short time horizons using the monthly data, implying a role for the ARIMA models in short-term forecasting.

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Table 1: Properties of Price Change Distributions

Period	**Mean**	**Median**	**Skew**	**Excess Kurtosis**
Month-on-Month				
1997-2002	0.00205	0.00163	1.21013	49.43845
2002-2005	0.00076	0.00071	1.10814	27.71529
1997-2005	0.00148	0.00122	1.11435	31.91969
Year-on-Year				
1998-2002	0.02024	0.02469	-0.44942	7.87065
2003-2005	0.00293	0.00409	0.47883	5.60401
1998-2005	0.01294	0.01600	-0.05799	9.59957

Table 2: Unit Root Tests

Variable	Frequency	ADF Test Setup+	ADF Test Statistic	5 Percent Critical Value	Decision
π_t	Monthly++	c,3	-1.99	-2.89	I(1)
$\Delta\pi_t$	Monthly	c,1	-6.66	-2.89	I(0)
Y_t	Monthly	c,t,2	-1.68	-3.43	I(1)
ΔY_t	Monthly	c,1	-11.41	-2.88	I(0)
$ *oil*	Monthly	c,t,0	-2.73	-3.43	I(1)
Δ $ *oil*	Monthly	c,0	-10.00	-2.88	I(0)
$log(HICP)$	Quarterly+++	c,4	-1.05	-2.89	I(1)
π_t	Quarterly	c,4	-3.43	-2.89	I(0)
Y_t	Quarterly	c,t,4	-2.70	-3.45	I(1)
ΔY_t	Quarterly	c,0	-14.97	-2.88	I(0)
$ *oil*	Quarterly	c,0	-1.42	-2.88	I(1)
Δ $ *oil*	Quarterly	c,1	-8.20	-2.88	I(0)

+ c = constant, t = trend, integer = number of lags used in unit root test

++ monthly sample period: 1998(2) - 2005(11)

+++ quarterly sample period 1980(2) - 2005(4)

Table 3: Engle-Granger Cointegration Test

Frequency	Statistic	Critical Value	Decision
Monthly+	-3.42	-3.83	Not Cointegrated
Quarterly++	-1.60	-3.83	Not Cointegrated

+ Cointegrating vector: $(Y_t, \pi_t, \$\ oil_t)$

++ Cointegrating vector: $(Y_t, \log(HICP_t), \$\ oil_t)$

Table 4: RMSE from Monthly Inflation Forecasts

Forecast Horizon	Forecast Method				
Months	ARIMA	SVAR	Exc. Energy	HP Filter	Median
1	0.26604	0.28655	0.29661	0.30256	0.28987
2	0.44016	0.46988	0.50140	0.53139	0.48863
3	0.60978	0.59405	0.65738	0.64045	0.63319
4	0.79296	0.73949	0.82787	0.78211	0.81187
5	0.94063	0.85301	0.95916	0.91707	0.95926
6	1.08941	0.94338	1.06291	1.02833	1.09170
7	1.20568	0.99713	1.15083	1.09903	1.18524
8	1.30520	0.99130	1.16362	1.10268	1.21926
9	1.36899	0.96241	1.14462	1.06885	1.24982
10	1.41873	0.88954	1.08209	0.99439	1.26472
11	1.48252	0.82169	1.05068	0.95102	1.31448
12	1.58602	0.85291	1.10732	1.02767	1.45748

Table 5: RMSE from Quarterly Inflation Forecasts

Forecast Horizon	Forecast Method			
Quarters	ARIMA	SVAR	Exc. Energy	HP Filter
1	0.76486	0.75387	0.86515	1.04741
2	1.00738	0.96567	1.24697	1.52917
3	1.06082	1.04412	1.31298	1.77865
4	1.24603	1.17273	1.37202	2.53731
5	1.18470	1.18082	1.35069	2.21109
6	1.11587	1.06581	1.22376	1.98449
7	1.16834	1.13831	1.34807	1.79800
8	1.33649	1.28726	1.46028	1.50892

Figure 1: Inflation and Inflation excluding Energy

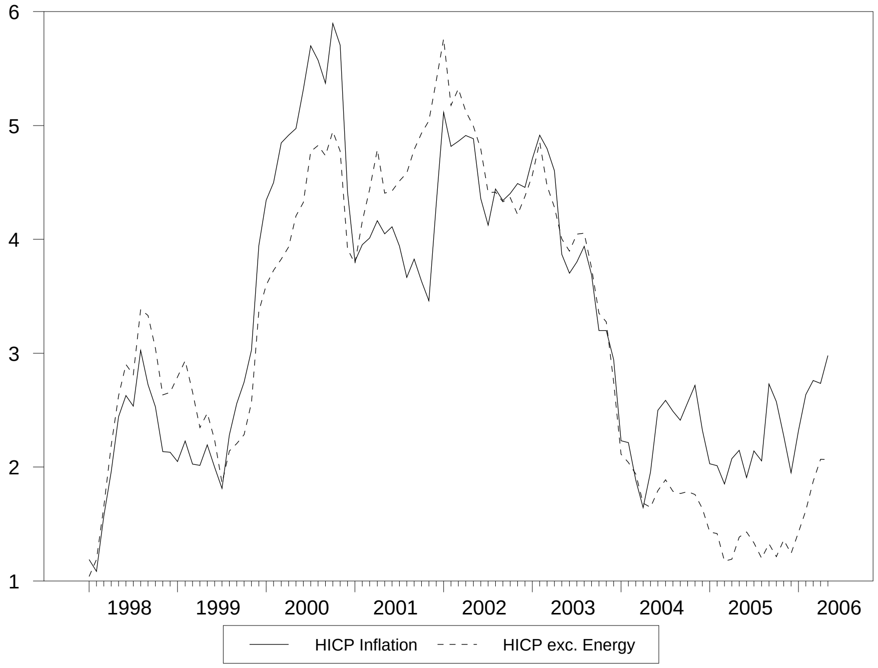

Figure 2: Inflation and Inflation excluding Energy

Quarterly Data

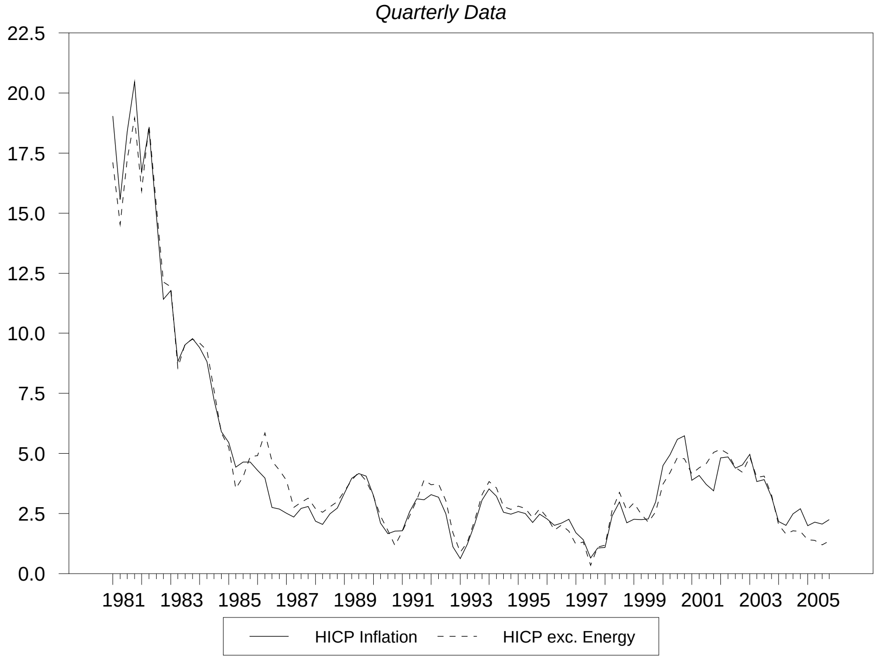

Figure 3: Headline Inflation and HP Filter

Monthly Data

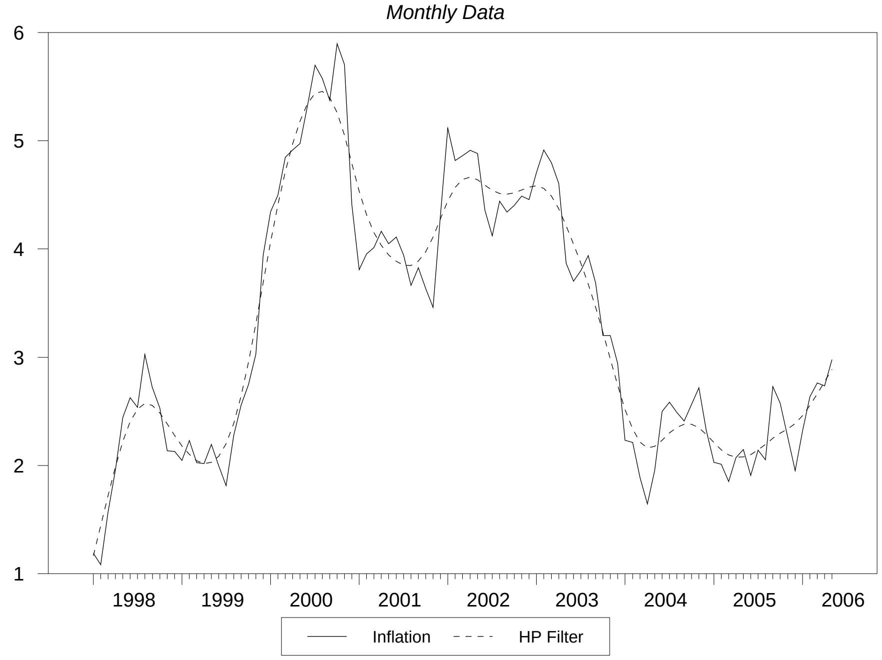

Figure 4: Headline Inflation and HP Filter

Quarterly Data

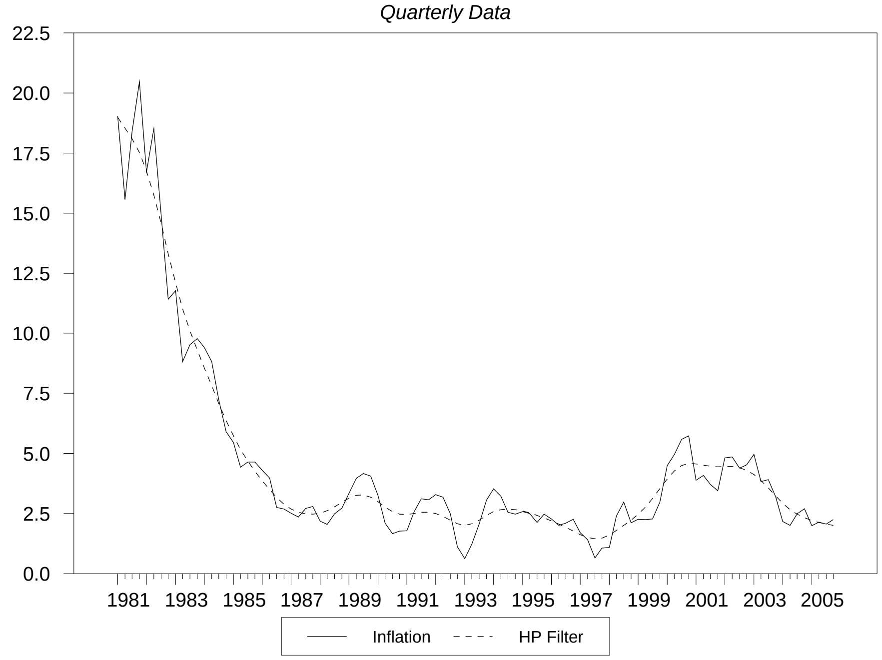

Figure 5: Distrubution of Year-on-Year Price Changes

Period: January 2003

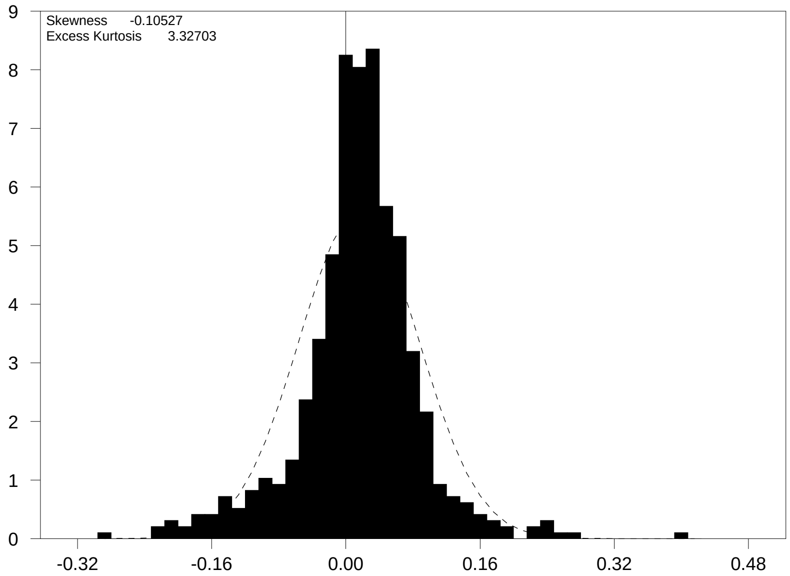

Figure 6: Distrubution of Year-on-Year Price Changes

Period: November 2005

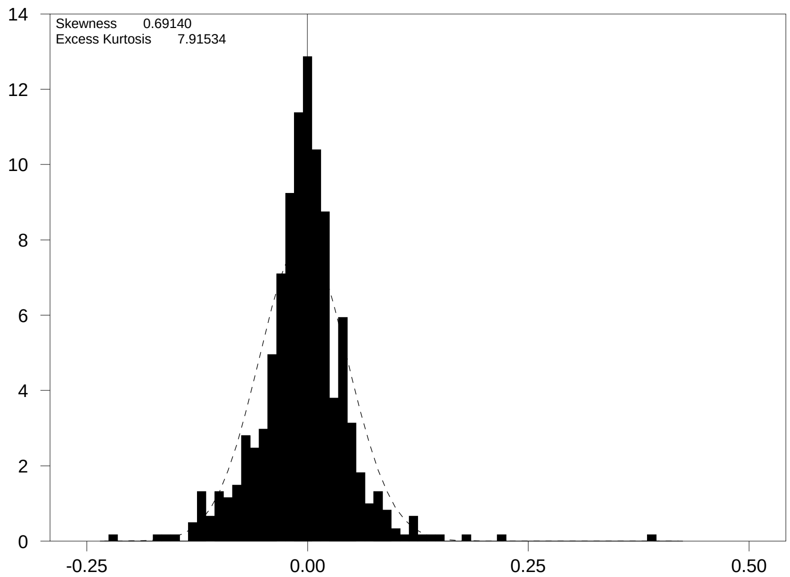

Figure 7: Headline Inflation, 5% and 10% Simple Trim

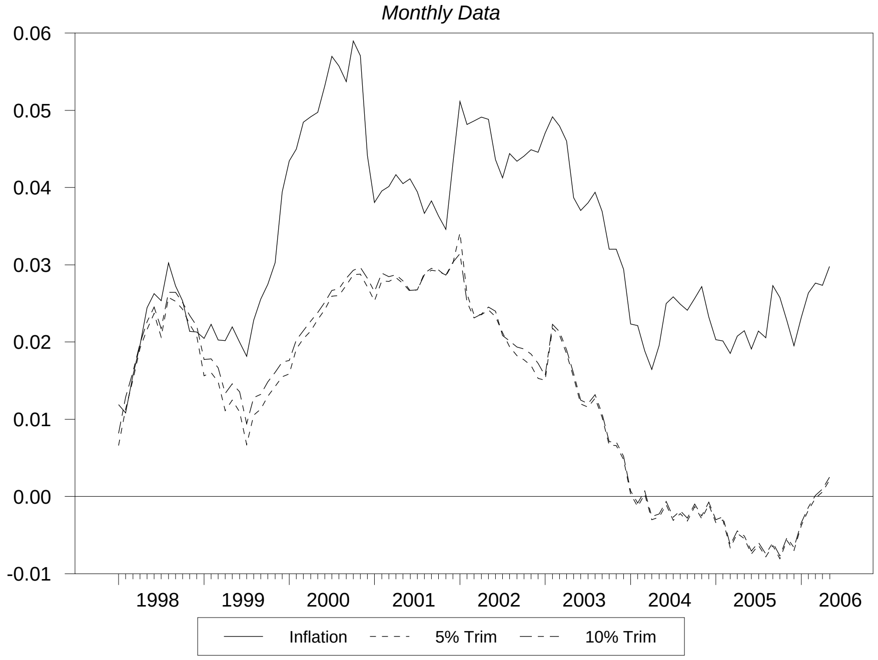

Figure 8: Headline, Median and Average Inflation Rates

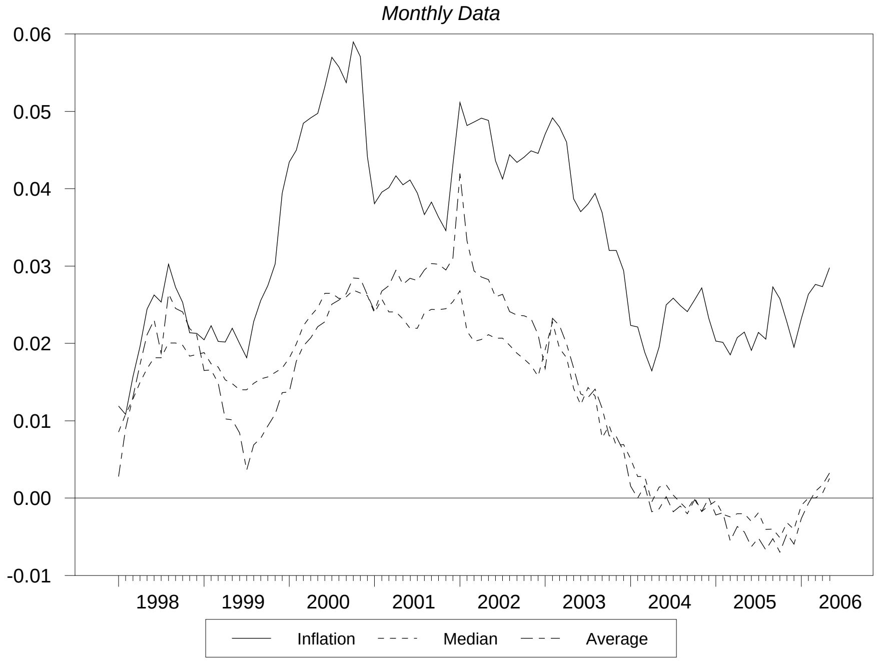

Figure 9: Headline Inflation and SVAR Core Inflation

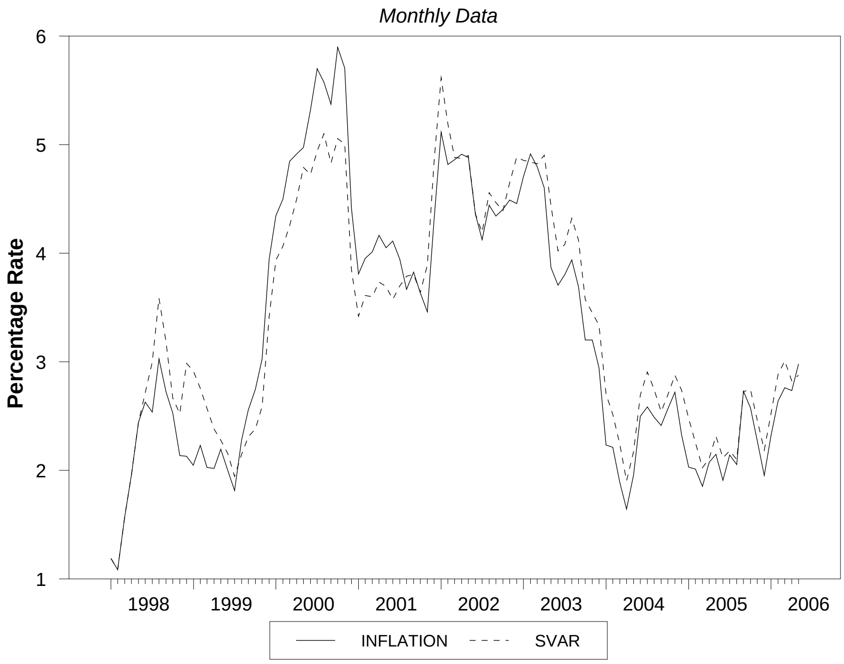

Figure 10: Headline Inflation and SVAR Core Inflation

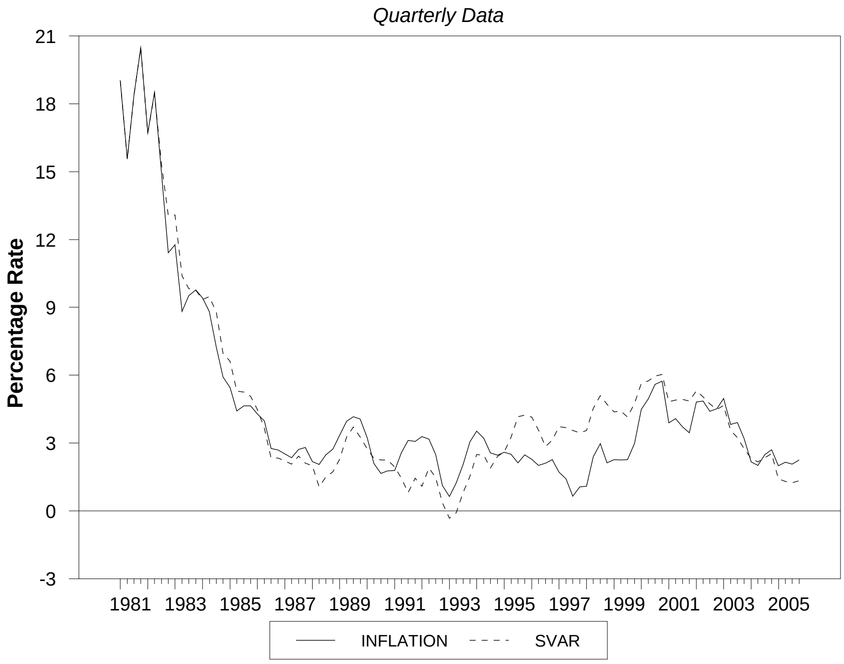

Figure 11: RMSE from Monthly Forecasts

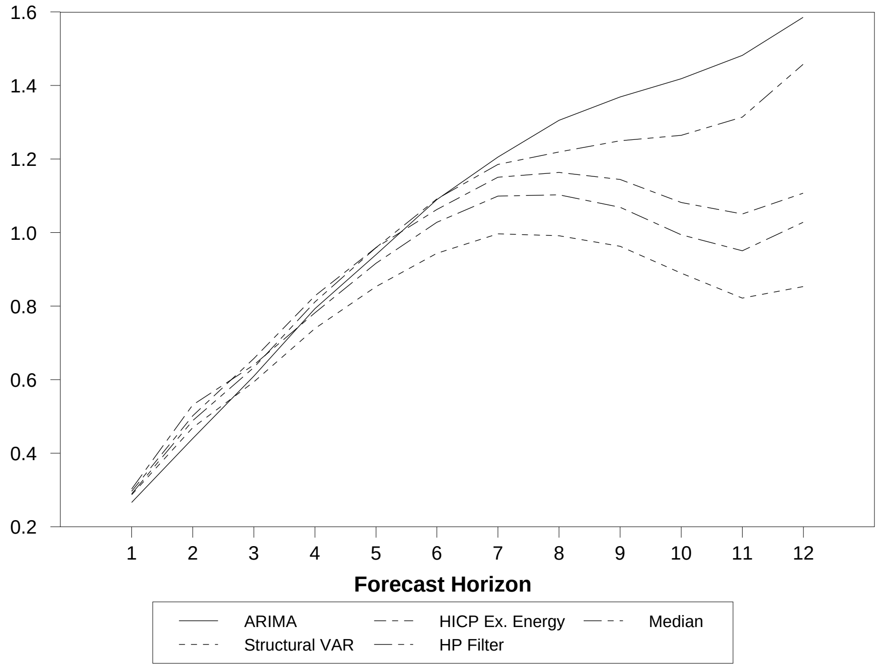

Figure 12: RMSE from Quarterly Forecasts