Implementing Monetary Policy:

Was the Swiss National Bank Correct in Abandoning the Monetary Aggregates?

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Abstract

We examine recent monetary policy in Switzerland and investigate the performance of the Divisia monetary aggregate vis a vis its simple sum counterpart in a inflation forecasting experiment. We return to the basic question: Is the Swiss inflation rate still linked closely with variations in money growth? More precisely, we ask whether Swiss Divisia aggregates could be employed productively in forecasting the Swiss inflation rate out-of-sample. To this end, the results are somewhat mixed. Using non-linear, recurrent neural networks in our forecasting experiment, we found that Divisia M2 now seems to be the aggregate most closely linked with the Swiss inflation rate over longer forecasting horizons beyond 30 months, and, by one criterion, a model containing it and lags of inflation produce the best forecasting results. By a different criterion, however, a model based on inflation's own past could be judged to be the best model and that lags of the growth rate of Divisia M3 add no significant information. We conclude that further improvements in the construction of the money supply to take into account recent financial innovations in the way we hold and use money are recommended in future research.

Monetary Policy in Switzerland

Few central banks have a stronger perceived commitment to price stability than the Swiss National Bank (SNB). Long before the inflationary episode of the 1970s and early 1980s led other countries to re-write their constitutions or pass laws that would direct their central banks to pursue the single goal of price stability, the Swiss National Bank already was committed to an objective of keeping inflation low, stable and predictable. Directed to pursuit of this objective by Article 5 of the National Bank Act, the SNB also had established a long record of success in achieving its policy goal: Between 1976 and 2008, the Swiss inflation rate ranged between -0.17 and 7.48 percent, the largest policy error occurring during the late 1980s when, apparently under pressure from exporters, the SNB seemed to allow money growth to accelerate in an effort to reduce the Swiss Franc/Deutsche Mark exchange rate. [1] Once off target, however, the SNB wasted little time in renewing its commitment to price stability and, by 1994, the Swiss inflation rate again was less than two percent. In word and deed, the SNB can offer abundant evidence that it has been fully committed to pursuing a goal of price stability.

The SNB also demonstrated its commitment to price stability in the post-financial innovations era in a manner followed by few other central banks: It continued to implement monetary policy by setting targets for the monetary aggregates. Although most central banks had acknowledged that excessive money growth had been the root cause of the high inflation of the 1970s and early 1980s and that reducing the rate of money growth had been responsible for the disinflation that followed, the subsequent era of financial innovations had made a continuation of monetary targeting problematic. With the payment of interest on checkable deposits, the introduction of new checkable deposits by non-bank firms and the elimination of interest rate ceilings on deposit accounts, the traditional aggregates began to behave in erratic ways that made their use in policy analysis open to wide, and sometimes highly misleading, interpretation. The SNB, however, stuck to its monetarist principles and, in a commitment to "policy transparency," continued to publish data on the behavior of money growth relative to the Bank's objectives for price stability long after other central banks had abandoned this practice. In fairness, the SNB may have been able to do this because a more limited variety of financial assets had smaller impacts on the aggregates than they did in other countries or the SNB may have had a greater commitment to monetarist principles than did other central banks. But, no matter what the reason, the SNB continued with the practice of monetary targeting far longer than other central banks.

Eventually, however, the SNB discovered that it, too, could no longer rely on the traditional monetary aggregates as the best guide for the implementation of monetary policy. After considerable deliberation, the SNB implemented a practice of interest rate targeting for its conduct of monetary policy at the end of 1999. While consistent with much of mainstream academic thought and offering an alternative to problems caused by increasingly erratic behavior in the monetary aggregates, this switch caused at least two problems for the SNB. The first was one of public relations, convincing a public used to hearing discussions of Swiss monetary policy in terms of the aggregates that this switch to interest rate targeting did nothing to erode the SNB's commitment to the maintenance of price stability. The second problem was an issue of policy transparency. Under a practice of monetary targeting, because the public understands there is a one-to-one long run relationship between money growth and the inflation rate, publishing data on the behavior of the aggregates allows the public to monitor central bank actions. Under interest rate targeting, however, there is no clear connection between a target value for an interest rate and the Bank's goal for price stability. The severity of both issues was understood but the increasing unreliability of the traditional monetary aggregates was seen as the greater problem so, in this context, the SNB abandoned monetary targeting in 2000.

Whether the Swiss National Bank's decision to adopt the practice of interest rate targeting was good, bad or indifferent is not at issue in this paper. Instead, this paper investigates whether the decision was made with the best information available. Because the SNB used traditional simple sum monetary aggregates as the basis for its decision, we examine whether Divisia aggregates exhibited erratic behavior in a manner that was comparable to that demonstrated by the official simple sum aggregates. If so, abandoning the aggregates as a vehicle for the implementation of monetary policy may have been a proper course of action. On the other hand, if erratic behavior in the official aggregates is simply an artifact of the known flaws in simple sum index numbers, the SNB may have made a change in operating procedures on the basis of inferior information and, looking forward, may be missing an opportunity to monitor one or more Divisia monetary aggregates as, at minimum, an indicator variable, for use in its decision making, if not an intermediate target variable for the implementation of policy. [2]

The importance of measurement has been revealed in studies which have shown inference to be sensitive to how the aggregate quantity of money is constructed. In the case of the United States, for example, both Belongia (1996) and Hendrickson (2011) have replicated studies that found no association between money and aggregate economic activity or instability in the demand for money function when data from the financial innovations era dominated the sample period. Their replications, which merely replaced the Federal Reserve's official simple sum monetary aggregates with Divisia monetary aggregates, reversed the qualitative conclusions of the original studies. Thus, in contrast to a modern conventional wisdom which appears to hold that variations in money are no longer relevant for economic fluctuations, these replications found that the robustness of money's influence on economic activity and the stability of the demand for money typical of pre-1980 data still were present in post-1970s ***if*** the aggregate quantity of money is measured on a basis consistent with modern aggregation theory. If this same basic measurement issue exists in Swiss data, it may be the case that the Swiss monetary aggregates – when measured properly -- were not "misbehaving" in any way that would have disqualified them for use as an intermediate target for the conduct of monetary policy and the SNB could have maintained its historical practice of monetary targeting if only it had altered the manner in which it measured the aggregate quantity of money.

In what follows below, we first discuss the basic issues related to the data and measuring the aggregate quantity of money. After this overview, we employ a neural network technology to examine whether Divisia monetary aggregates can be useful in forecasting Swiss inflation out-of-sample. We end with some concluding remarks and suggestions for future research.

Background

Initial work on Divisia monetary aggregates for Switzerland was reported in Yue and Fluri (1991). In that paper, the authors focused solely on the question of whether monetary aggregates could be used in a traditional intermediate targeting strategy in which the monetary base was used as the central bank's policy instrument and a path for a monetary aggregate was its intermediate target; in this framework, a desired rate of inflation was the ultimate goal of monetary policy. Yue and Fluri found that, while the simple sum aggregates (except for sum M1) demonstrated the same instability that had been typical in the United States and elsewhere since the early 1980s, both Divisia M1 and Divisia M2 continued to exhibit close relationships with the Swiss inflation rate. For a strategy of monetary targeting, however, Divisia M1 would have been the preferred measure because its path was more closely linked to the monetary base and this gave the Swiss National Bank a greater degree of control over its behavior in setting a course as an intermediate target variable. Updates to these data and more extensive analysis of them – examining the relationships between money and output as well as inflation -- were reported in Fluri and Spoerndli (2000). This latter study again found that Divisia aggregates exhibited superior performance to their sum counterparts, but did find that the marginal information content of money in predicting inflation was limited when other information, such as lagged inflation, was added to their regressions. Although never reported formally as an official series by the Swiss National Bank, the Divisia data were maintained and updated by Fluri until his retirement in 2008.

Origins of Gaps Between Divisia and Simple Sum Aggregates

Recall that a Divisia index of money can be expressed as:

$$\Delta \ln M_t = \sum_{i=1}^{n} 0.5 * (s_{it} + s_{i,t-1}) * \Delta \ln q_{it} \quad (1)$$

where s_{it} is the share of total expenditures on monetary assets allocated to asset i and q_{it} is the quantity held of the i^{th} asset. This growth rate index, which is designed to track the unknown sub-utility function for a flow of monetary services from a given stock of monetary assets, differs from a simple sum measure only in the weights attributed to each asset. [3]

The expenditure shares of a Divisia index take the form:

$$s_{it} = (q_{it} * u_{it}) / \sum_{i=1}^{k} q_{it} * u_{it} \quad (2)$$

where q_{it} is the quantity of the i^{th} asset group at time t and u_{it} is that asset's user cost. With demands for individual components of money having downward-sloping demand curves, this expression indicates that expenditure shares will change when changes in user costs induce changes in quantities held; the degree of change in individual expenditure shares therefore also depends upon the individual elasticities of demand. Finally, the real user costs shown in the share equation are defined as:

$$u_{it} = \{(R_t - r_{it})/(1 + R_t)\}, \quad (3)$$

where R_t is the rate of return on a benchmark asset and r_{it} is the rate of return on the i^{th} asset. [4]

In contrast to these relationships, a simple sum monetary aggregate is merely the accounting sum of a particular grouping of bank liabilities. If this type of levels aggregate is composed of three assets (A, B and C), the growth rate of M would be:

$$(A/M)*dlnA + (B/M)*dlnB + (C/M)*dlnC \quad (4)$$

where the simple ratios of individual quantities held relative to the aggregate quantity serve as the "weights." And while these ratios may give the appearance of representing expenditure shares, this occurs only because all quantities are denominated in dollars. In this application, however, the "dollars" unit serves the same role as "ounces" or "feet" in constructing other numerical sums whereas a genuine expenditure share is determined both by quantities and the market prices (user costs) of those goods; no own-prices for individual monetary commodities appears in a simple sum aggregate.

The important economic implication of this distinction between index weights is that the value of a Divisia index will not change unless an income effect is present; pure substitution effects will be internalized and the estimated value of the sub-utility function will remain constant. Conversely, because the weights of a simple sum index depend only on quantity shares irrespective of substitutions induced by changes relative prices, there is no mechanism by which a substitution effect can be internalized. This property allows a simple sum measure to change when no income effect is present. In the specific case of monetary aggregates, this characteristic allows, as in the United States in the early 1980s, periods of rapid M1 growth to occur when, in fact, the public merely was responding to higher own rates of return on new forms of interest-bearing checkable deposits (lower user costs) and making portfolio substitutions that were reflected in much slower growth rates for Divisia M1. The false warnings of renewed inflation that occurred at that time could have been avoided if US monetary statistics had been measured in a way that internalized pure substitution effects. [5]

The Swiss Divisia Aggregates

To examine whether the Swiss monetary aggregates may have been influenced by the same sorts of measurement error influenced by changes in user costs and portfolio re-allocations in the era of financial innovations, we begin with an overview of the data. Swiss monetary aggregates, over a sample of monthly data spanning 1976 – 2008, are shown in Figures 1 – 3. Figure 1, which plots the growth rates of Divisia and simple sum M1, indicates that the two series move closely together with the exception of the period between 1978 – 87. The initial years shown in Figure 1b are important, however, in illustrating how measurement error might mislead a central bank committed to price stability and monetary targeting: Sum M1 consistently shows a growth rate that is two or three percentage points less than the underlying monetary service flow entering the Swiss economy. Whereas the simple sum aggregates in the United States were indicating – incorrectly - an excessively expansionary monetary policy during this same period, the sum M1 aggregate in Switzerland was indicating more monetary restraint than was the case. This gap between the growth rates of Divisia and sum M1 might well explain the unintended acceleration in Swiss inflation of the late 1980s.

Similarly, Figure 2 shows that the Divisia and simple sum measures of M2 share generally common movements with the exception of higher peaks for Divisia M2 growth on at least three distinct occasions: Late 1979, late 1983 and 1994. Apart from these divergences, however, there is little to distinguish the two series. Finally, Figure 3 plots money growth at its highest level of aggregation, M3. Here, the two series reveal that issues of aggregation (combining time deposits and means of payment) and index numbers (simple sum v. Divisia) both are at work in making the two growth rates move apart from each other on numerous occasions and, in several instances, to move in the opposite direction. If one were to be making monetary policy decisions based on the behavior of simple sum M3 or Divisia M3, there clearly would be occasions where the decision would be different based on which aggregate was chosen.

More systematic insights can be gleaned from these data by consideration of some statistical properties of the data. Although the figures suggest that the Divisia and simple sum series may share similar growth rates, a key question for their use in an intermediate targeting strategy is whether they share the same trend because trend money growth ultimately will be linked to the central bank's desired path for inflation. If the trends for the Divisia and sum aggregates diverge, targeting the growth rate for the simple sum aggregate implies that the central bank will be thrown off of its desired path for inflation. Therefore, tests for the presence of unit roots were conducted on a variable X, where X is defined as the growth rate of Divisia aggregate minus the growth rate of a comparable simple sum aggregate. At the M2 and M3 levels of aggregation, ADF statistics of -3.18 and -4.13, respectively, indicate that the null hypothesis of a unit root can be rejected (c.v. = -2.87). At the M1 level of aggregation, however, an ADF statistic of -1.77 indicates that, had the SNB been targeting or monitoring simple sum M1 in its implementation of monetary policy, its efforts to hit a long run path for inflation ultimately would have been undermined by the drift between the sum and Divisia measures of M1.

The top panel of Table 1 reports the results of some simple tests of Granger causality between various measures of money growth and the Swiss inflation rate over the same 1976:1 –

2008:2 sample period. For the most part, the series show no association except at the M3 level of aggregation, where some evidence of bi-directional causation is found. This is at odds with the earlier results reported by Yue and Fluri (1991) and Fluri and Spoerndli (2000), both of which found evidence of significant relationships between Divisia M1 and Divisia M2 growth and Swiss inflation. Whether the diminished explanatory power of the narrow aggregates can be attributed to less variation in the inflation rate in the post-1993 period, the effects that evolving financial innovations had on different levels of aggregation, or still other influences, is unknown. (Note: test of the Fluri-Spoerndli sample and other sub-samples and report).

The bottom portion of Table 1 offers some additional evidence on the issue of measurement by examining whether there is any relationship between inflation and the same variable X used in the ADF tests above. Recall that this variable is the *difference* between the growth rate of, e.g., Divisia M1 and sum M1 and that these growth rates will differ only because the components of the M1 aggregate are weighted differently. Thus, if any significance is found, evidence is offered on a central question of the paper: Do inferences that are drawn about money's influence on economic activity depend upon how money is measured?

To this end, the results indicate that, at both the M2 and M3 levels of aggregation, the difference between the growth rates of Divisia and simple sum measures of money share a causal relationship with the Swiss inflation rate. This implies that, if the central bank was attempting to achieve price stability or forecast inflation using a traditional simple sum aggregate, it would be leaving unexploited information on the table by not using a Divisia aggregate in its place. From the manner that Divisia aggregates are constructed, this result is to be expected but the results from these causality tests offer some confirming evidence of the intuition. In the next section, the usefulness of Divisia aggregates in forecasting Swiss inflation is examined by deploying them within a neural network framework.

Forecasting with a Recurrent Neural Network

The use of artificial neural network technology in the field of economics is growing in popularity, as indicated by the diverse range of applications surveyed in Binner et al (2004) and more recently Andesron et al (2012). Neural networks allow approximation of highly non-linear functions and so offer more promise in the context of econometric modelling than standard linear models, especially since there is no requirement to specify regression parameters and assumptions about data distribution are less rigorous. Where time series such as those in the present study are concerned, neural networks are limited by the shortage of data points on which to train the network. However, promising results in earlier neural network studies have encouraged us to believe that the technique holds great potential and that exploratory studies such as this one are worthwhile; see for example, Binner et al (2002).

Neural networks are constructions made up of many relatively simple, interconnected processors. Establishing the architecture for the neural network is analogous to curve fitting Refenes and Azema-Barac (1994), in that choosing the number of hidden layers and hidden neurons is like choosing the order of a polynomial. Choosing a lower order of polynomial than required leads to a poor fit with the data (the network fails to converge for the training data and prediction for new data is poor). Choosing a higher order than required leads to a good or perfect fit to the data (overfitting to the training data) but poor prediction for new data (poor generalisation).

The advantage of a neural network methodology for this investigation, however, is that neural networks are inductive. Thus, even when there is no exact knowledge of the rules determining the features of a given phenomenon, knowledge of empirical regularities can still allow the phenomenon to be modelled and this is the strength of the neural network. The process of training allows the network, in effect, to ignore excess input variables. The technique seems ideal for economic phenomena where the central task is to model a system of immense complexity without losing predictive power. It seems, however, that the potential of non-traditional techniques such as the neural network has not yet been fully exploited

Recurrent neural networks (RNNs) typically are adaptations of the traditional feed-forward multi-layered perceptron (FF-MLP), trained with gradient-descent learning algorithms (see Pearlmutter, 1995, and Rumelhart et al., 1986). This class of RNN extends the FF-MLP architecture to include recurrent connections that allow network activations to feed back as inputs to units within the same or preceding layer(s). Such internal memories enable the RNN to construct dynamic internal representations of temporal order and dependencies which may exist within the data. Units that receive feedback values often are referred to as *context* or *state* units. Also, assuming non-linear activation functions are used, the universal function approximation properties of FF-MLPs naturally extend to RNNs. These properties have led to wide appeal of RNNs for modeling time-series data; see, for example, Binner et al. (2010); Moshiri, et al. (1999); Tenti (1996); Ulbricht (1994).

We build upon our previous successes with RNNs for direct $t + \tau$ ahead prediction tasks (Binner et al., 2004; 2006; 2010), to model the inflation data described above using the data sets presented in table 3 where the input data will consist of either past inflation values (the auto-regressive term) alone or past inflation values coupled with one of the Divisia measures of money. We extend our RNN models to a subset of RNNs referred to as multi-recurrent networks (MRNs), Ulbricht (1994) and Dorffner (1996). The MRN architecture combines several types of feedback and delay to form a state-based model whose state transitions are modeled as an extended non-linear auto-regressive moving average (ARMA) process, Dorffner (1996). The architecture we use in this research employs four levels of feedback allowing recurrent connections from: i) the output layer back to the input layer, as found in Jordan networks, Jordan (1986); ii) the hidden layer back to the input layer, as found in Simple Recurrent Networks (SRNs), Elman (1990) and iii) the external input nodes back to the context units in the input layer to form input memories and finally iv) from the context units within the input layer back to themselves (self-recurrent links).

As described earlier, the external input vector $\mathbf{x}(t)$ consists of between two to four input variables representing combinations of previous standardized inflation rates with their corresponding standardized log differences together with one of the measures of money in both standardized and standardized log difference form. Unlike Binner et al (2010), we do permit recurrent or self-recurrent connections from external input units. We extend each allowable feedback by additional banks of context units (memory banks) on the input layer. The number of additional memory banks relates directly to the degree of granularity at which past and current information is integrated and stored. Following Ulbricht (1994), we use φ memory banks where $4 \leq \varphi \leq 6$ as past experience has shown that moving beyond this does not lead to enhanced performance. Rather, it is the number of units within each bank that is pivotal to the performance of the network and that is determined on the validation set. The MRN architecture is shown in figure 4 and can be expressed generally as:

$$\hat{y}(t+\tau)=g(f(\mathbf{c}(t),\mathbf{x}(t),\mathbf{W}_f(t)),\mathbf{W}_g(t)) \tag{5}$$

where $\hat{y}(t+\tau)$ denotes the predicted value of inflation (the target for $\hat{y}(t+\tau)$ is $y(t+\tau)$ where τ is equal to inflation either 3, 6, 9, 12, 15, 18, 21, 24, 27, 30, 33 or 36 months ahead as per Dorsey (2000)); $\mathbf{c}(t)$ (the context vector) is the concatenation of the previous external input vector with φ delays of varying strength, the previous hidden state vector with φ delays of varying strength and finally the previous output activation vector with φ delays of varying strength; $\mathbf{x}(t)$ is the external vector of input variables; $\mathbf{W}_f(t)$ is the weight matrix connecting the input layer to the hidden layer, $\mathbf{W}_g(t)$ is the weight matrix connecting the hidden layer to the output layer and, finally, vector function f and function g return the activation vectors from the hidden and output layers, respectively. We apply the hyperbolic tangent function to the inner products performed for f and the identity function to the inner products performed for g.

The context vector, $\mathbf{c}(t)$, represents an internal memory of varying rigidity – that is some context units will represent information from very recent time steps and thus change rapidly whilst others will represent information further back in time and change much more slowly. To achieve this, the unit values fed back from the input, hidden and output layers are combined, to varying degrees, with their respective context units, $\mathbf{c}_i(t)$, in the input layer (as determined by the weighting values applied to their recurrent links). The influence of the previous context unit values are determined by the weighting values applied to the self-recurrent links. When the weighting on the recurrent links are greater than those on the self-recurrent links then more flexible memories are formed storing more recent information at the expense of historical information stored in the context units. Conversely, if the weighting values on the self-recurrent links are greater than those on the recurrent links then more rigid memories are formed since more historical information is preserved in the context units at the expense of the more recent information being fed back from subsequent layers. This can be generally expressed as follows:

$$c_i(t) = f(a_j(t-1)v_j + c_i(t-1)z_i) \tag{6}$$

where $c_i(t)$ refers to context unit i at time t; $a_j(t-1)$ denotes either an internal output target value or a hidden unit activation value at time t-1; v_j refers to the connection strength of the recurrent link from a_j to c_i where $v_j = \frac{1}{\varphi} j$ where $j = 1,2,\ldots,\varphi$; $c_i(t-1)$ refers to context unit i at time t-1; and finally z_i refers to the connection strength of the self-recurrent link for c_i where $z_i = \frac{1}{\varphi} i$ where $i = 1,2,\ldots,\varphi$. The number of hidden units, and thus size of the recurrent layer, is a significant hyper-parameter for this model and is determined by performance on the validation set.

We use back propagation-through-time (Werbos, 1990; Williams and Peng, 1990), an efficient gradient-descent learning algorithm for training RNNs. Input data were scaled to zero mean and unit variance. To facilitate convergent learning, the 'search and converge' learning rate schedule as defined by Darken et al. (1992) was used for all training experiments with an initial learning rate, η_0 of 0.003. This provides an effective time varying learning rate that guarantees convergence of stochastic approximation algorithms and has proven effective for temporal domains, for example see Lawrence et al. (2000). The momentum term is fixed at 0.75 due to the low learning rates. To identify the onset of over-fitting during training we use the decline in performance on the validation set as the basis for terminating the training process. We generate independent training sequences directly from the time-series using a time window, whose lag size is determined by performance on the validation set. The MRN context units are initialized to known values at the beginning of each sequence of data and each element within a sequence is processed sequentially by the network. Although this restricts the MRN to behaving as a finite memory model and also means that the MRN must first learn to ignore the first context values of each sequence, it allows for efficient randomized learning.

Although such RNNs and variants thereof have enjoyed some success for time-series problem domains we tread with cautious optimism. Due to the additional recurrency, such models inherently contain large degrees of freedom (weights) which may require many training cases to constrain. Also, gradient descent-based learning algorithms are notoriously difficult at finding the optimum solution the architecture is theoretically capable of representing: Bengio et al. (1994) and Siegelmann et al (1991).

Results

Before reporting results of individual prediction techniques, we briefly describe performance measures that form the basis of our model evaluation and comparison. The actual and predicted inflation rates at time *t* are denoted $y(t)$ and $\hat{y}(t)$ respectively. Given a sample of T test times $t_1, t_2, ..., t_T$, we calculate the root mean square error (RMSE) of the model predictions

$$RMSE = \sqrt{\frac{1}{T}\sum_{n=1}^{T}(y(t_n) - \hat{y}(t_n))^2} \quad (7)$$

However, it may be difficult to appreciate the value of RMSE for model M on its own. Therefore, we also report the rate (in percent) of improvement in RMSE of the tested model M with respect to the baseline random walk (RW) assumption:

$$IORW(M) = \frac{RMSE(RW) - RMSE(M)}{RMSE(M)} \tag{8}$$

where *RMSE(M)* and *RMSE(RW)* are the RMSE of the model M and RW baseline, respectively. Negative values of *IORW(M)* indicate the case where model predictions are worse than baseline prediction capabilities.

Similar to Dorsey (2000), we assess the MRN's ability to forecast a range of forecast horizons spanning 36 months using each of the different input variable combinations. More specifically, we examine the MRN's ability to perform out-of-sample forecasts for each of the 12 quarters (forecast horizons from 3 to 36 months). The key purpose here is to ascertain the degree to which the MRN models are stable predictors beyond the estimation period and to determine the influence of Divisia monetary measures, DM1, DM2 and DM3 on the prediction task.

To determine the combination of allowable input variables which have the most influence on predicted inflation values, a simple selection scheme was followed. First, experiments with only past inflation rates were performed and then to determine the influence of Divisia monetary measures, both the standardized and standardized log difference forms of a measure of money were also included as additional external input variables. Since preliminary experiments using only Divisia measures of money as the source of external input (i.e. no autoregressive term) resulted in substantially poor predictive performance on a consistent basis, all experiments with Divisia measures reported here included both standardized and log differenced standardized inflation values as mandatory external input variables.

For each of the above variable combinations, time-lags of 12, 24, 36 and 120 months were examined and it was established that a lag of 12 months provided the most meaningful results with a significant degradation in performance across models when the lag period was extended beyond this. The MRN architecture and training regime described earlier was used in all experiments. The number of allowable free parameters (and thus hidden nodes) was determined empirically and it was noted that for most experiments 30 hidden nodes provided optimum performance. For each data set, the model was estimated five times and the model whose performance on the *validation set* was best was selected as the chosen model.

After training a set of MRNs for each of the different quarterly forecast horizons (each constituting a different direct prediction task), the out-of-sample forecasts shown in Table 2 were obtained. In addition to the RMSE and IORW figure, the mean absolute forecast error (MAE) was also computed to indicate typical magnitude of the forecast error for each model. As expected, the RW forecasts deteriorate substantially as the forecast horizon increases, notably from 24 months to 36 months with the error doubling from 33 to 36 months indicating the lack of relevance of the RW hypothesis. It is clear from our findings, that there is little support for the usefulness of monetary aggregates in forecasting inflation as superior forecast performance appears to be consistently obtained across *all* forecast horizons when using past inflation rates *without* any Divisia measures of money. Such models provided an average improvement over RW of 34.17% across the first six quarterly forecast horizons and an average improvement of 73.19% across the latter six quarterly forecast horizons. This gives a strong positive indication of the predictive capacity of this model class and also suggests that further improvements in the construction of the money supply may be needed to obtain improvements in the inflation forecasting performance of the monetary aggregates.

MRNs trained with Divisia measure M1 (DM1) to forecast inflation on average exhibited poorer predictive performance than other variable combinations with 22.74% **worse** performance than RW over the first six quarterly forecast horizons and an average of 17.85% better performance across the latter six quarterly forecast horizons. Finally, Divisia measure M3 (DM3) provided the stronger predictive performance of the different Divisia measures achieving an average improvement over RW of 7.65% across the first six quarterly forecast horizons and an average improvement of 38.67% over the latter six quarterly forecast horizons.

It is interesting to note that the performance of all models (except for those using DM1) is substantially superior to that of RW between forecast horizons 24 and 36 months likely indicating the impact latency of economic events. In particular, it was striking to note that Divisia measure M2 consistently proved to be the preferred monetary measure over forecast horizons 33 and 36 months. Figure 5 shows the change in RMSE across the 3 year forecast period whilst figures 6a to 6d graphically show the out-of-sample forecast performance for each of the models for horizons of six months and one, two and three years.

Our findings are consistent with our previous work with US inflation rates (Binner et al 2010) in that neither the aggregation method nor level of aggregation appears to have a positive impact on the performance of our models, in contrast to the results reported by Dorsey (2000) who appeared to find some evidence, using traditional feed-forward neural networks, that aggregated monetary measures were useful in the inflation prediction task across a range of forecast horizons (up to 3 years). It should be noted that our results are consistent with Dorsey's in that predictive accuracy remains strong across the longer forecast horizons. Also, we find that inclusion of historical inflation rates alone work quite well for the recurrent neural network model class. We may speculate that the value of money is implicitly represented in the inflation rates and thus their explicit inclusion as input variables does not help; rather, it can actually make things worse because of the under-sampling problems.

Conclusions

Previous work by Yue and Fluri (1991) and Fluri and Spoerndli (2000) reported that Divisia measures of Swiss monetary aggregates could be employed to explain and forecast the Swiss inflation rate. The latter work, however, reported that some of money's explanatory power was diminished when lagged values of inflation were included in the econometric model and that, relative to the initial study, the explanatory power of money seemed to shift from the narrow aggregates to broader levels of aggregation.

Because these studies have not been re-examined for over fifteen years, we returned to the basic question: Is the Swiss inflation rate still linked closely with variations in money growth? More precisely, we asked whether Swiss Divisia aggregates could be employed productively in forecasting the Swiss inflation rate out-of-sample. To this end, the results are somewhat mixed.

In line with the earlier work by Fluri and Spoerndli, (2000, p112), we found that Divisia M2 now seems to be the aggregate most closely linked with the Swiss inflation rate over longer forecasting horizons beyond 30 months, and, by one criterion, a model containing it and lags of inflation produce the best forecasting results. By a different criterion, however, a model based on inflation's own past could be judged to be the best model and that lags of the growth rate of Divisia M3 add no significant information. The market is typically considered efficient in the sense that it is difficult to beat the naïve RW model. The IORW measure is best suited for our purposes, because rather than worrying about the precise RMSE values, we should be concerned about by how much we can beat the rather obvious RW strategy. Generally speaking, in our experiments we found that the longer the prediction horizon, the harder it is to accurately predict the inflation rate although the neural network models significantly outperformed the naïve RW models (with a number of exceptions when using DM1).

At this stage, however, these results should be judged as preliminary, particularly as there are striking differences between our findings and those of other researchers using non-recurrent neural network methods. Dorsey (2000), for example, used a traditional feed-forward neural network algorithm and Divisia measures of money to generate inflation forecasts for the United States, Germany and Japan. In that case, Dorsey produced forecasts for 12 and 24 months out-of-sample and two characteristics of the results were striking: The contribution of Divisia money to the forecasts was important in each country and the quality of the forecasts did not diminish as the length of the forecast horizon was extended. These are matters that need to be examined in greater detail in further experimentation. Work is also ongoing to enhance the construction of Divisia money in line with recent financial innovations, see for example Binner (2009), Binner et al (2004) and Anderson and Jones (2011). Thus the destabilisation of the money demand function may be attributed to the financial innovations and deregulations revealing flaws in the construction of monetary aggregates. It has been suggested that it might be appropriate, given the increased financial innovations in the way money is held and utilized, to include risky assets, e.g. equities, bonds and unit trusts, into the construction of monetary aggregates (see e.g. Barnett and Zhou (1995) and Elger and Binner (2004)). The latter estimated a demand system over both capital certain and risky assets held by the UK personal sector and showed that risky assets are substitutes for more liquid assets. Money velocity appears to depend on the degree of risk in the returns on monetary assets and the level of risk aversion. With continual innovation in financial markets, the impact on the measurement of monetary aggregates will continue to present problems in empirical studies. More sophisticated Divisia monetary aggregates have the potential to make a valuable contribution to future studies, and should ideally focus on finding enhanced methods of capturing the true user cost of money by e.g. finding enhanced ways of incorporating the risk of holding the asset and more thorough theoretical treatment of the modeling of the opportunity costs for Divisia money, including improvements on measuring the benchmark rate of return in the construction along the lines proposed by Binner (2010). The relationship between monetary policy and long term interest rates is currently in hot debate, see e.g. Beckworth et al (2012), and of great concern to proponents of Divisia money where the role of the Divisia price dual is under – researched and neglected, Belongia (2005); and hence a natural topic for further investigation. Future models should also make full use of the relevant theory, as emphasized by Belongia and Ireland (2012). We echo Carlstrom and Fuerst (2004) who state "…we think the current de-emphasis on the role of money may have gone too far. It is important to think seriously about the role of money and how money affects optimal policy." In a similar vein, the former Governor of the Bank of England Mervyn King (2002) stated "My own belief is that the absence of money in the standard models which economists use will cause problems in future, and that there will be profitable developments from future research into the way in which money affects risk premia and economic behavior more generally. Money, I conjecture, will regain an important place in the conversation of economists."

In keeping with Barnett and Chauvet (2011), we conclude that the use of simple sum monetary aggregates is indefensible in a modern economy. These are matters that need to be examined in greater detail in further experimentation. Taken together, our results indicate that future research into improved constructions of monetary aggregates is promising and is a worthwhile route to pursue.

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Table 1. Results of Granger Causality (table entries are F-statistics)

Sample: 1976:1 – 2008:2	n=6 lags	n=12 lags
DM1 causes Inflation	1.13	0.98
Inflation causes DM1	0.72	1.71
DM2 causes Inflation	1.21	1.01
Inflation causes DM2	0.75	1.71
DM3 causes Inflation	2.91*	2.43*
Inflation causes DM3	0.72	2.16*
Sample: 1976:1 – 2008:2		
M1diff causes Inflation	0.87	1.64
Inflation causes M1diff	1.08	0.99
M2 diff causes Inflation	2.62*	1.87
Inflation causes M2diff	2.06	1.41
M3diff causes Inflation	4.94*	2.87*
Inflation causes M3diff	1.69	2.55*

Table 2. MRN out-of-sample forecast errors for each forecast horizon (t-lag for all models was 12 months).

	Hidden Nodes	Memory Banks	Money Measure	MAE	RMSE	% IORW
t+3 (RW Test RMSE = 1.95, RW Test MAE= 1.60E+00)	25	6	-	1.11E+00	1.30	33.46
	30	4	DM1	2.06E+00	2.58	-32.24
	30	4	DM2	1.51E+00	1.75	10.01
	30	4	DM3	1.49E+00	1.73	11.11
t+6 (RW Test RMSE = 2.26, RW Test MAE= 1.95E+00)	30	4	-	1.49E+00	1.71	24.55
	30	4	DM1	2.54E+00	3.12	-38.00
	30	4	DM2	1.62E+00	1.91	15.55
	30	4	DM3	1.64E+00	1.99	11.80
t+9 (RW Test RMSE = 3.24, RW Test MAE= 2.68E+00)	30	4	-	2.01E+00	2.75	15.37
	30	4	DM1	3.29E+00	4.27	-31.64
	30	4	DM2	3.44E+00	4.41	-35.87
	30	4	DM3	3.07E+00	3.75	-15.73
t+12 (RW Test RMSE = 3.39, RW Test MAE= 2.67E+00)	30	4	-	1.83E+00	2.20	34.92
	30	4	DM1	3.30E+00	4.23	-25.00
	30	4	DM2	2.44E+00	3.23	4.68
	30	4	DM3	1.93E+00	2.62	22.71
t+15 (RW Test RMSE = 4.07, RW Test MAE= 3.27E+00)	30	4	-	1.85E+00	2.19	46.07
	30	4	DM1	3.38E+00	4.32	-6.28
	30	4	DM2	2.90E+00	4.01	1.46
	30	4	DM3	2.58E+00	3.57	12.23
t+18 (RW Test RMSE = 4.16, RW Test MAE= 3.54+00)	30	4	-	1.88E+00	2.06	50.62
	30	4	DM1	3.43E+00	4.30	-3.29
	30	4	DM2	3.24E+00	4.11	1.25
	30	4	DM3	3.26E+00	4.00	3.80
t+21 (RW Test RMSE = 4.45,	30	4	-	1.23E+00	1.47	66.91
	30	4	DM1	4.20E+00	4.71	-5.76
	30	4	DM2	2.99E+00	3.95	11.36
	30	4	DM3	3.13E+00	3.81	14.52

RW Test MAE= 3.90E+00)						
t+24 (RW Test RMSE = 4.57, RW Test MAE= 4.32E+00)	30	4	-	1.12E+00	1.28	71.95
	30	4	DM1	2.10E+00	2.85	37.63
	30	4	DM2	2.15E+00	2.98	34.89
	30	4	DM3	1.98E+00	2.59	43.30
t+27 (RW Test RMSE = 5.29, RW Test MAE= 4.91E+00)	30	4	-	1.08E+00	1.42	73.15
	30	4	DM1	4.07E+00	4.76	10.03
	30	4	DM2	3.00E+00	3.94	25.58
	30	4	DM3	2.49E+00	3.25	38.53
t+30 (RW Test RMSE = 5.73, RW Test MAE= 5.5E+00)	30	4	-	1.11E+00	1.51	73.70
	30	4	DM1	5.71E+00	6.36	-10.90
	30	4	DM2	4.37E+00	4.96	13.54
	30	4	DM3	3.52E+00	4.22	26.48
t+33 (RW Test RMSE = 6.46, RW Test MAE= 6.11E+00)	30	4	-	1.48E+00	1.99	69.16
	30	4	DM1	6.10E+00	6.48	-0.44
	30	4	DM2	2.13E+00	2.52	61.04
	30	4	DM3	3.49E+00	3.84	40.53
t+36 (RW Test RMSE = 13.89, RW Test MAE= 6.70E+00)	30	4	-	1.70E+00	2.18	84.29
	30	4	DM1	2.89E+00	3.26	76.53
	30	4	DM2	1.90E+00	2.46	82.28
	30	4	DM3	3.91E+00	4.36	68.63

NOTE: Each row refers to an MRN model and all models included, as a common input, the standardized values and log differenced values of the past inflation rate.

Figure 1. Growth Rates of Divisia and Sum M1

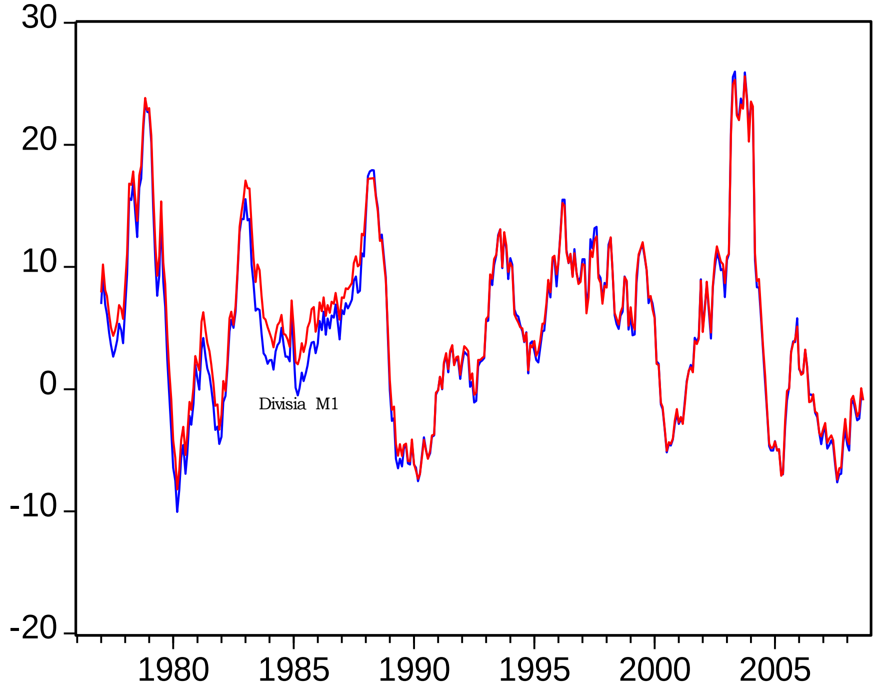


Figure 1b. Difference Between Growth Rates of Divisia and Sum M1

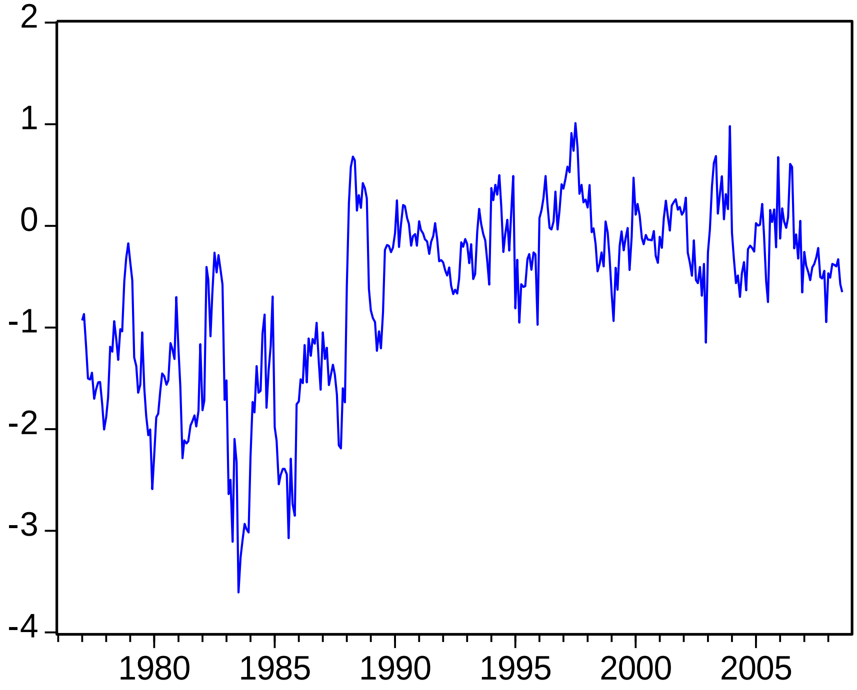


Figure 2b. Difference Between Growth Rates of Divisia and Sum M2

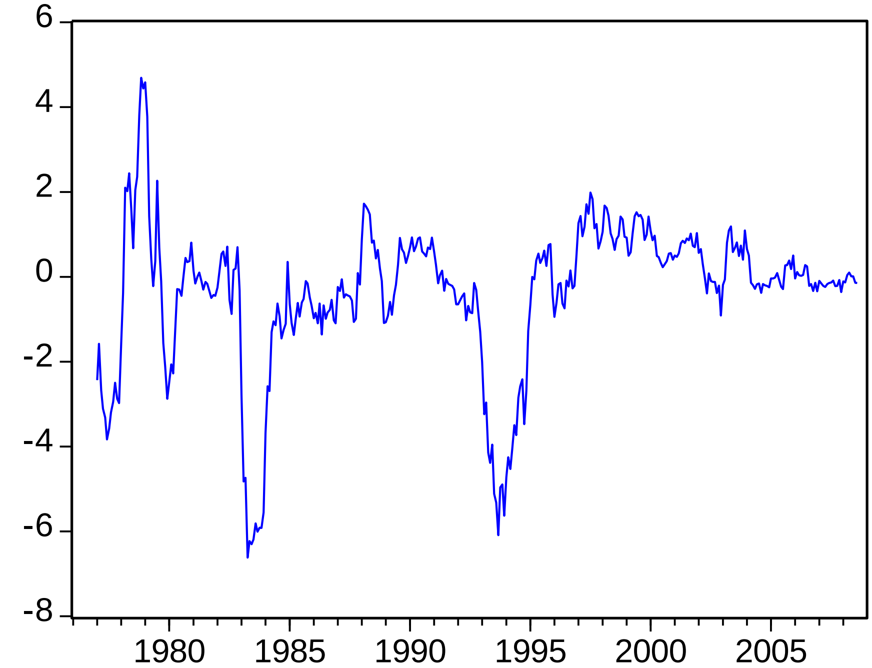


Figure 2a. Growth Rates of Divisia and Sum M2

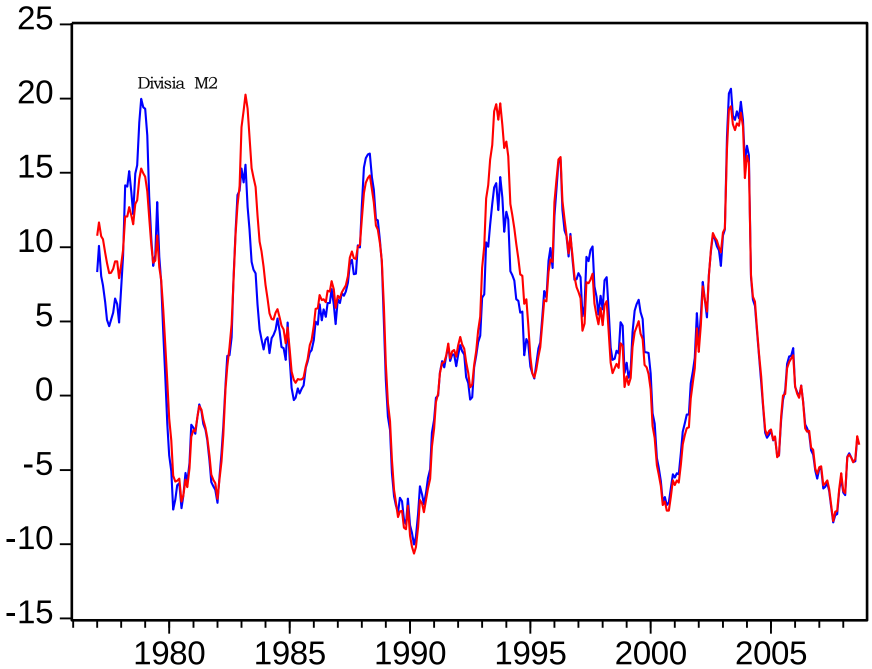


Figure 3a. Growth Rates of Divisia and Sum M3

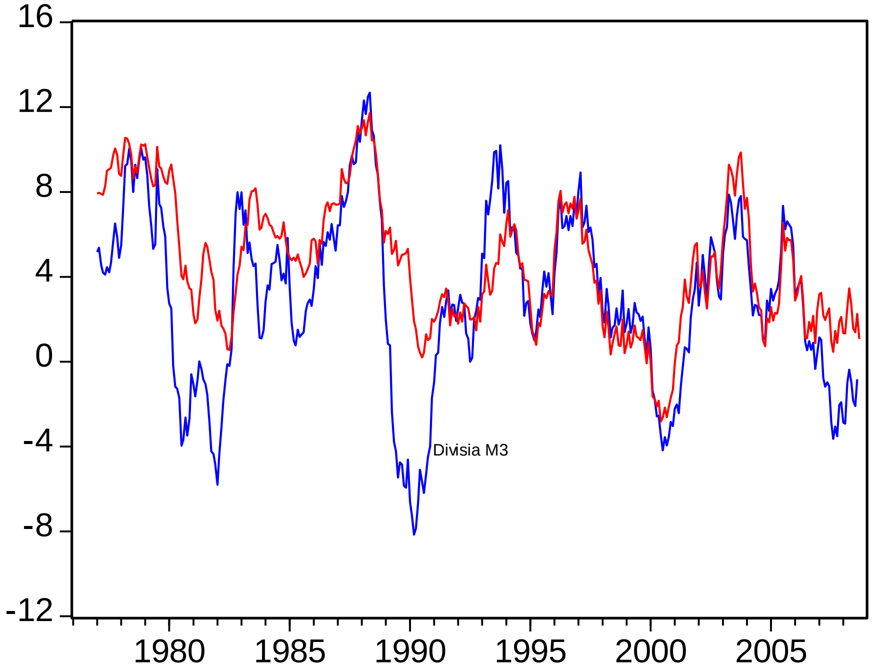


Figure 3b. Difference Between Growth Rates of Divisia and Sum M3

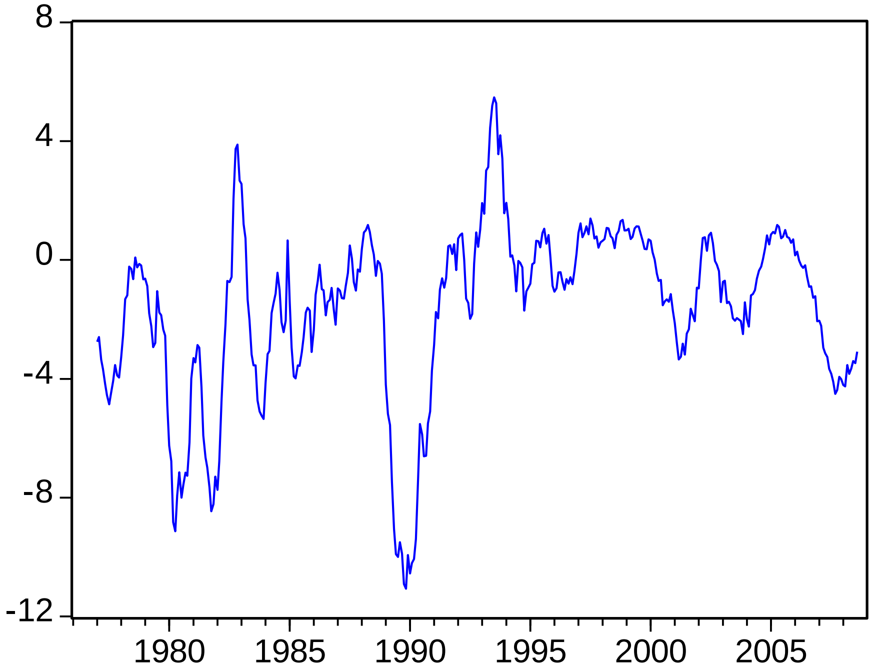


Figure 4. Architecture for the Multi-recurrent Network (for $\varphi = 4$).

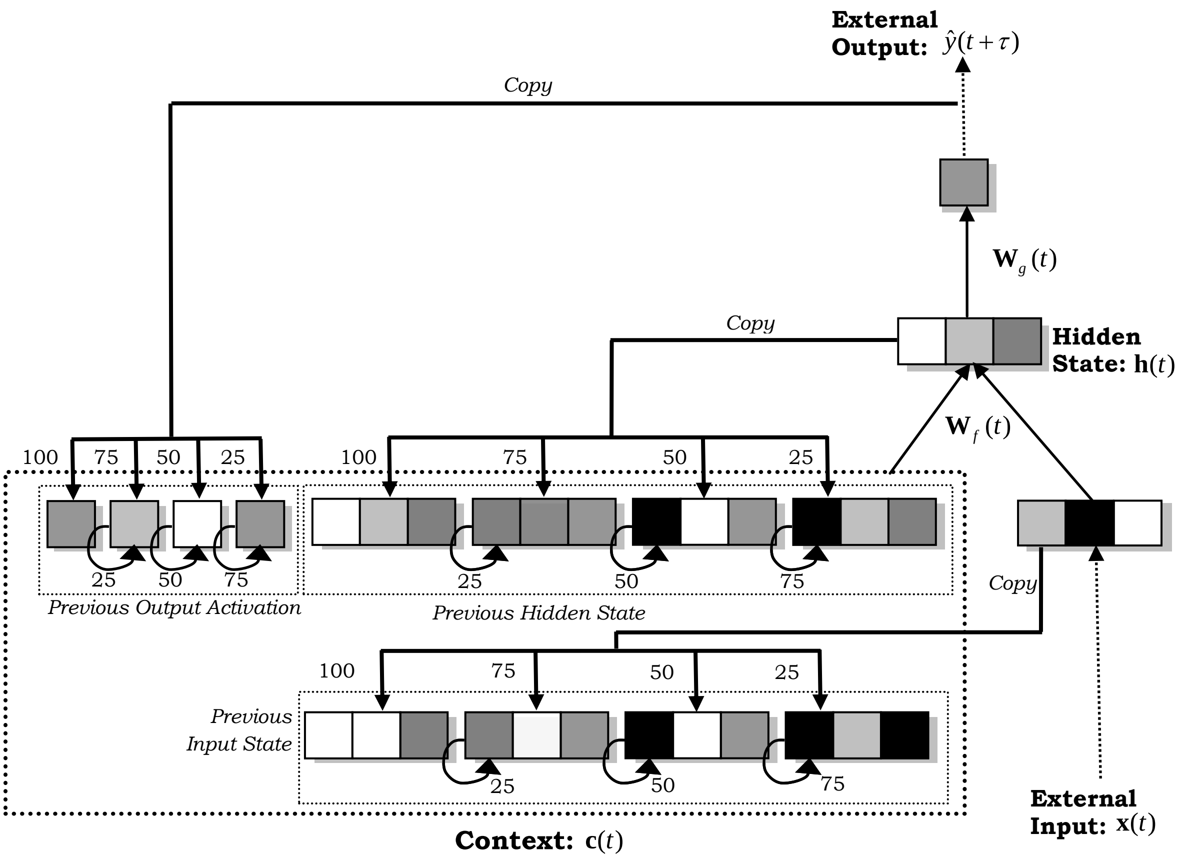


Figure 5: MRN out-of-sample RMSE for each forecast horizon.

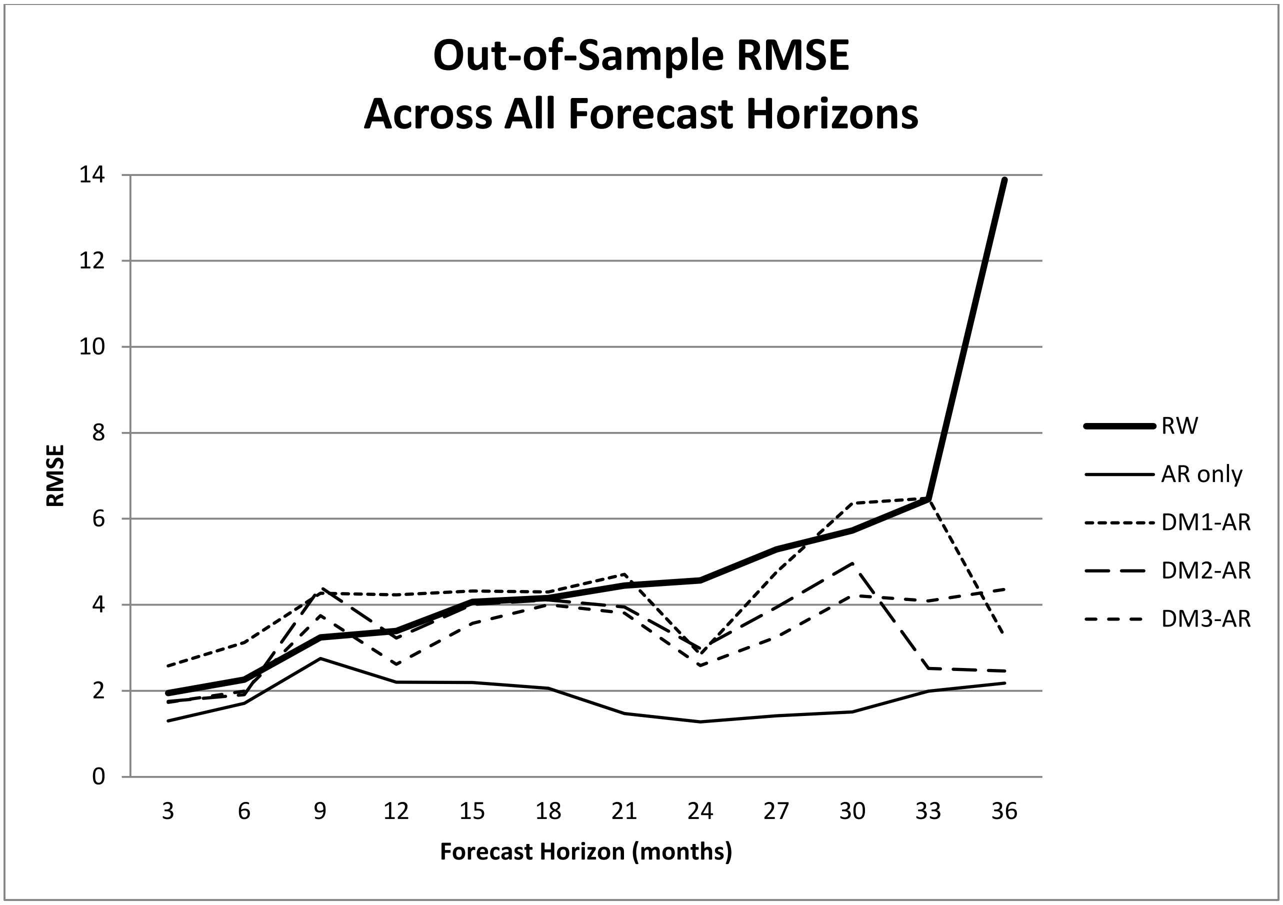


Figure 6a: MRN out-of-sample forecasts for forecast horizon *t+6*.

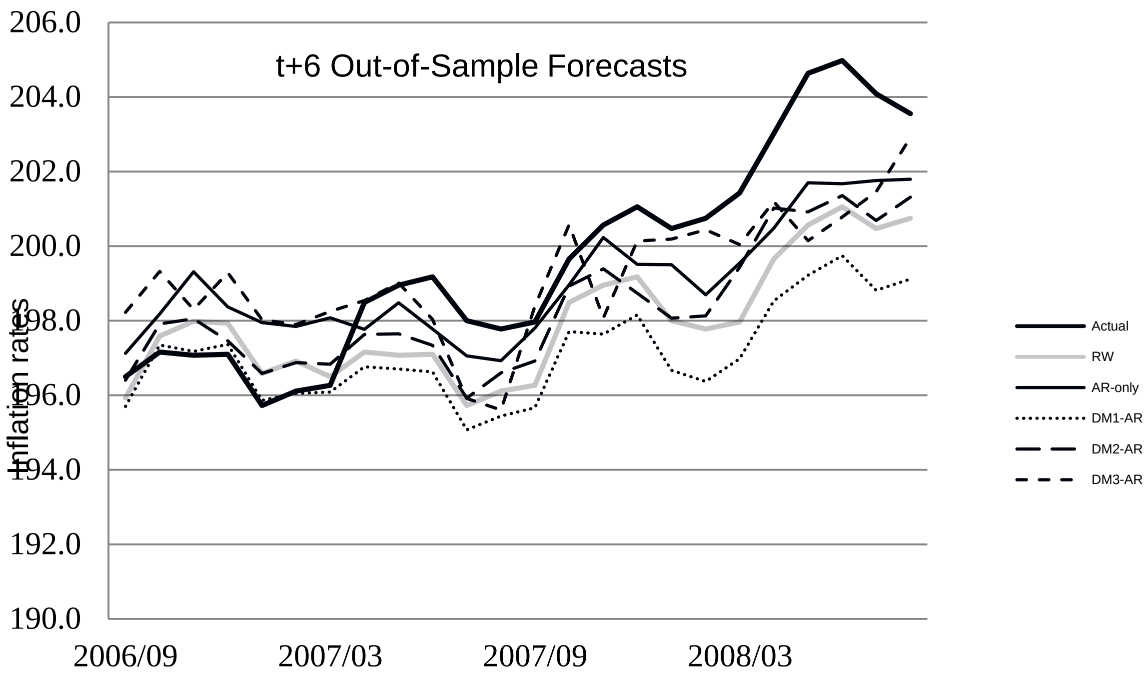


Figure 6b: MRN out-of-sample forecasts for forecast horizon *t+12*.

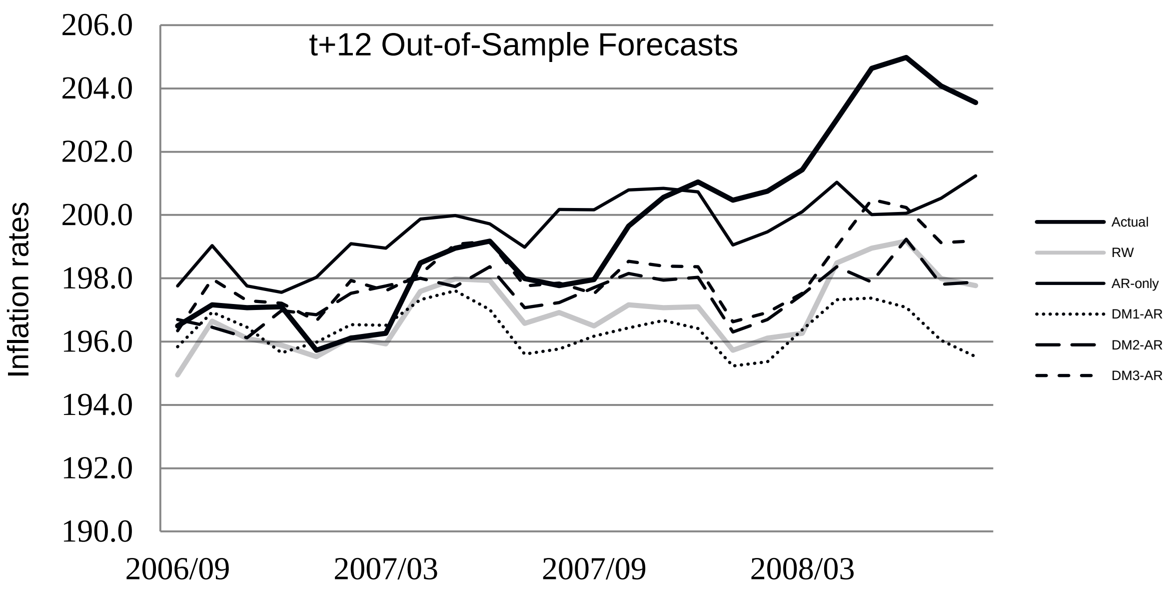


Figure 6c: MRN out-of-sample forecasts for forecast horizon *t+24*.

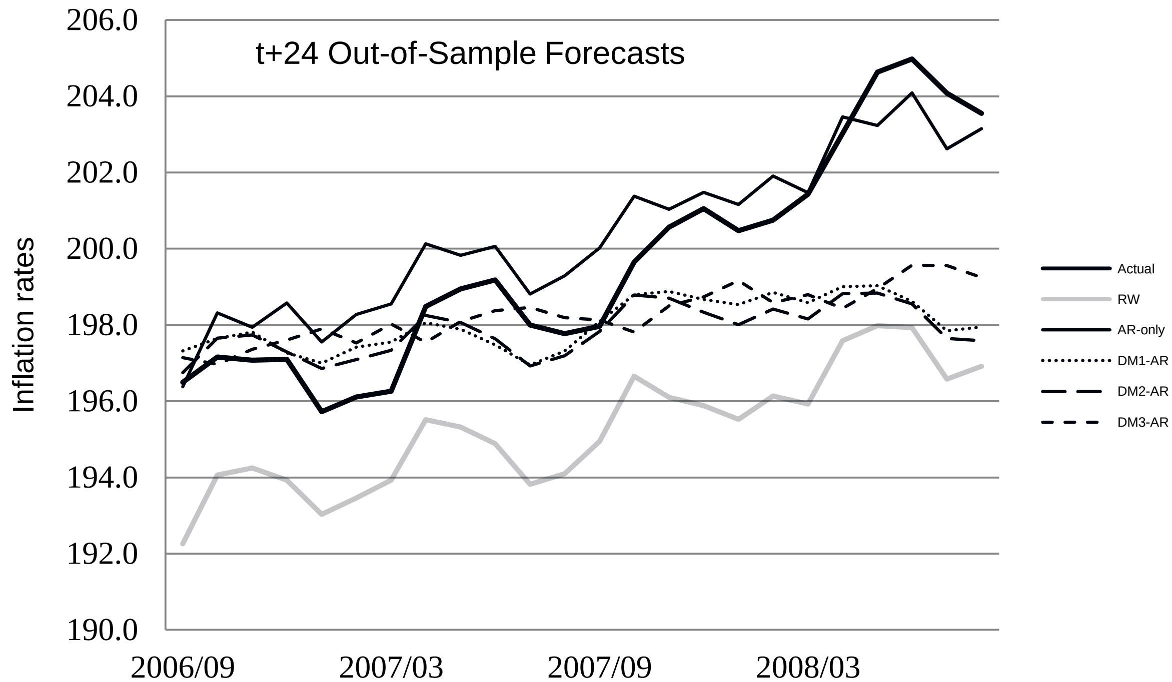
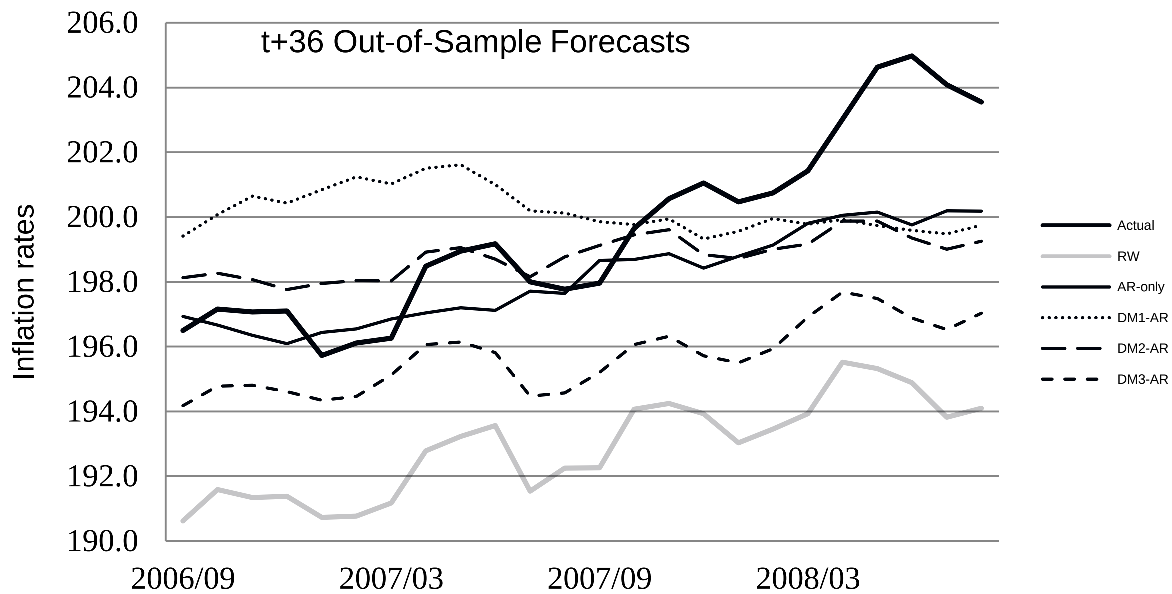


Figure 6d: MRN out-of-sample forecasts for forecast horizon *t+36*.



Endnotes

[1] Switzerland was not the only country involved in a brief flirtation with exchange rate targeting at this time. With European countries joining the Exchange Rate Mechanism (ERM), which linked their currencies to the Deutsche Mark in an arrangement that was a precursor to the Euro, Great Britain remained outside the system. The Chancellor of the Exchequer, however, apparently decided to engage in a "shadow peg" of the Mark at an exchange rate that forced an inflationary monetary policy upon Great Britain. As in Switzerland, recession followed when contractionary policy was implemented to fight the incipient inflation. Details on this episode can be found in Belongia and Chrystal (1990).

[2] See Belongia and Binner (2001 and 2006) for related evidence from around the world on the superior performance of Divisia monetary aggregates and the construction of money.

[3] The classic work on this subject is Barnett (1980).

[4] This expression is due to Barnett (1978).

[5] The most famous episode, which did more than any other to marginalize the use of the aggregates, occurred when Milton Friedman used the growth rate of simple sum M1 to predict a resurgence of inflation in the United States in the middle 1980s. This inflation, of course, never materialized and the use of the aggregates was greatly discredited. See Newsweek (1984).