Do Monetary Aggregates Improve Inflation Forecasting in Switzerland?

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This study examines whether or not Swiss monetary aggregates enhance inflation forecasting in Switzerland during the out-of-sample period, December 2008 to November 2019. We use a state-of-the-art multi-recurrent neural network endowed with a sluggish state-based memory to approximate a non-linear auto-regressive moving average model. Conventional monetary aggregates have been shown to lose dynamic information, potentially explaining why many deem traditional measures of the money supply to have minimal economic relevance. Our findings suggest that when conventional monetary aggregates, Divisia money measures, and a short-term interest rate are combined, forecasts of Swiss inflation over the 12, 24 and 36-month forecasting horizons are significantly improved compared to a model that excludes a measure of the money supply.

Keywords: Divisia monetary aggregates, inflation, recurrent neural networks, Swiss monetary policy

INTRODUCTION

The Swiss National Bank (SNB) is a self-governing central bank that strives to ensure stable prices in different economic circumstances. The SNB characterizes stable prices as an increase in the Swiss Consumer Price Index (CPI) of no more than 2% per year. Sustaining a long-term inflation-targeting regime necessitates dependable forecasting; nonetheless, existing discussions cast doubt on the utility of money as a forecasting tool, fueled by empirical research indicating the instability of the money demand function (Hendrickson, 2014). The perceived ineffectiveness of monetary aggregates may be attributed to the conventional methodology employed in calculating official monetary aggregate data, utilizing a simple sum index number. A plethora of studies assert that appropriately formulated monetary aggregates do indeed encapsulate pertinent information.[1]

Our research shows that incorporating nonlinear models along with using both simple sum monetary aggregates, i.e., the total market price of the monetary portfolio and Divisia monetary aggregates, i.e., the monetary service flow provided by the money stock, can significantly enhance the accuracy of long-term inflation forecasts.

DATA OVERVIEW

We use monthly data from Switzerland including the official M3 monetary aggregate from the Swiss National Bank, Divisia M3 Monetary aggregate, the Swiss consumer price index (CPI), and the Swiss Franc One-year Deposit Rate. Our sample period is from December 1984 through November 2019. All data was sourced from the Swiss National Bank via DataStream.

Monetary Aggregates

M3

Official monetary aggregates reported by most central banks utilize simple sum aggregate, i.e., the simple–unweighted–sum of monetary assets. These aggregates have long been criticized as inaccurate measures of both the monetary serves flow (Barnett, 2000a, 2000b; Diewert, 1976; Binner et al., 2018) and the money stock (Kelly, 2009). However, the official simple sum aggregates do express the market value of the current portfolio of monetary aggregates. We utilize the Swiss M3 monetary aggregate in this study.

Divisia M3

Divisia M3 measures the flow of monetary services from money holdings by weighting each monetary asset based on expenditure shares, (Barnett, 2000a, 2000b; Diewert, 1976). Divisia aggregates, rooted in microeconomic aggregation theory, offer an advanced approach that considers the level of monetary services provided by each asset. See, e.g., Kelly et al. (2011) and Bissoondeeal et al. (2023), among others, for demonstrations of the superiority of Divisa monetary aggregates for various applications.

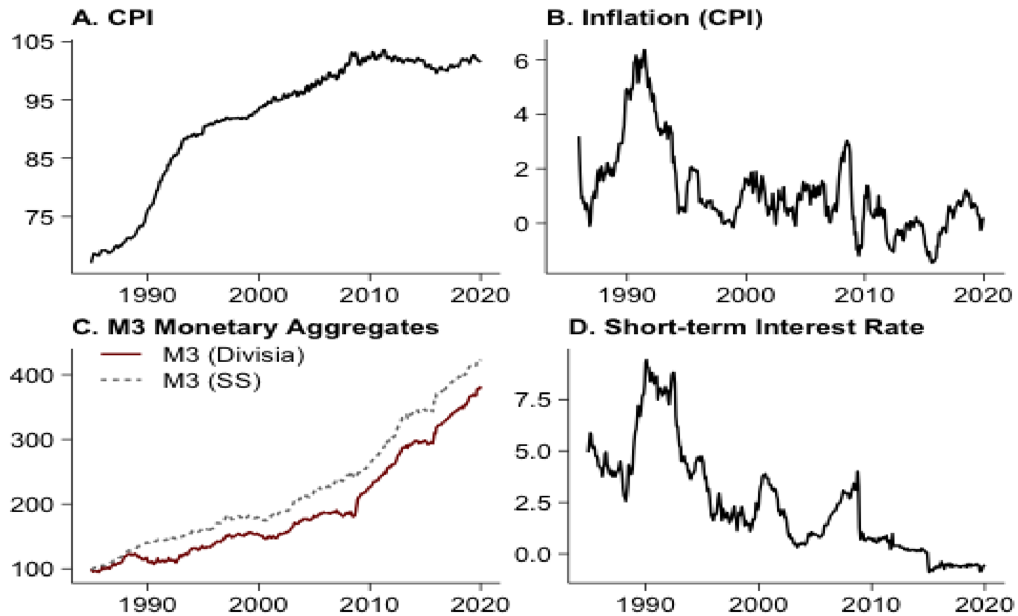
The data from both M3 and Divisia M3 is composed of the assets contained in the Swiss National Bank's definition of M3 (see Swiss National Bank: Monetary Policy Analysis, Zurich, 1 March 2016). We constructed the Divisia M3 monetary aggregate following methodologies applied to the US economy by the Center for Financial Stability (CFS) in New York, as detailed in Barnett et al. (2013).

Other Macroeconomic Data

We also utilize the Swiss consumer price index (CPI) and the Swiss Franc One-year Deposit Rate. The rationale behind selecting this specific interest rate is that it is one of the only short-term rates consistently availability throughout the entire duration of our sample period, making it a reliable and comprehensive choice for our analysis.

Figure 1 presents the levels of Swiss inflation, the Swiss consumer price index (CPI), Swiss inflation, and the Swiss monetary aggregates: M3 (Divisia) and M3 (Simple Sum). These data indicate an apparently close link between Divisia M3 and the price level until the mid-1990s and less of any discernible link from the late 1990s, a change that eventually caused the SNB to abandon its use of monetary targeting. The Swiss Franc One-year Deposit Rate is depicted in figure 1 panel D.

FIGURE 1
MACROECONOMIC DATA USED IN THIS STUDY



Data used in this study: A. Consumer Price Index (CPI), B. Inflation (Annual Growth Rate of CPI), C. M3 Monetary Aggregates (Divisia and Simple Sum), and D. Swiss Franc One Year Deposit Rate. All Data sourced from the Swiss National Bank via DataStream

Unit Root Testing

We test the data for stationarity using the Phillips and Perron unit root tests. We find that all series, i.e., the Swiss consumer price index (CPI) and the Swiss monetary aggregates, and the Swiss franc one-year deposit rate are integrated of order 1. Virili and Freisleben (2000) showed that artificial neural networks have advantages over traditional econometric methods when forecasting nonstationary time series.

FORECASTING FRAMEWORK

Out-of-Sample Setup

The in-sample period of our forecasting experiment is a recursive windowing beginning December 1984 and continuing through to period $t - h$ for each time period t in the out-of-sample period December 2008 through November 2019. The out-of-sample period is selected to avoid the disruption caused by the COVID-19 pandemic.

The Multi-Recurrent Neural Network

This study explores the forecasting relevance of monetary aggregates in the context of a nonlinear predictive model, namely a Multi-recurrent neural network (MRN), see e.g. Orojo et al. (2021) and Orojo et al. (2023). We systematically evaluate various input feature (independent variable) combinations to assess capability for out-of-sample forecasting of inflation. We also provide the corresponding results of a Bayesian VAR benchmark model for comparison purposes. Table 1 presents the definitions of each input feature combination used.

TABLE 1
MODEL ABBREVIATIONS AND DESCRIPTIONS

Mnemonic	Descriptions
AR	Lags of CPI
AR + SFDRTE	Lags of CPI, Short Term Deposit Interest Rate
AR + DM3	Lags of CPI, Divisia M3 Money
AR + SSM3	Lags of CPI, Simple Sum M3 money
All Variables	Lags of CPI, Short Term Deposit Interest Rate, Divisia M3 Money, Simple Sum M3 Money

Building on previous work with MRNs (Ulbricht, 1994; Dorffner, 1996; Elger et al., 2006; Binner et al., 2010; Tepper et al., 2016; Orojo et al., 2019, 2021; Orojo et al., 2023), we utilize an architecture incorporating four levels of feedback and delay, forming a ‘sluggish state-space’ and enabling the representation of varying memory rigidity. This architecture, illustrated in Figure 2, has been shown to outperform more complex models, such as long short-term models (Hochreiter and Schmidhuber, 1997), on volatile time series (Orojo et al., 2019, 2021).

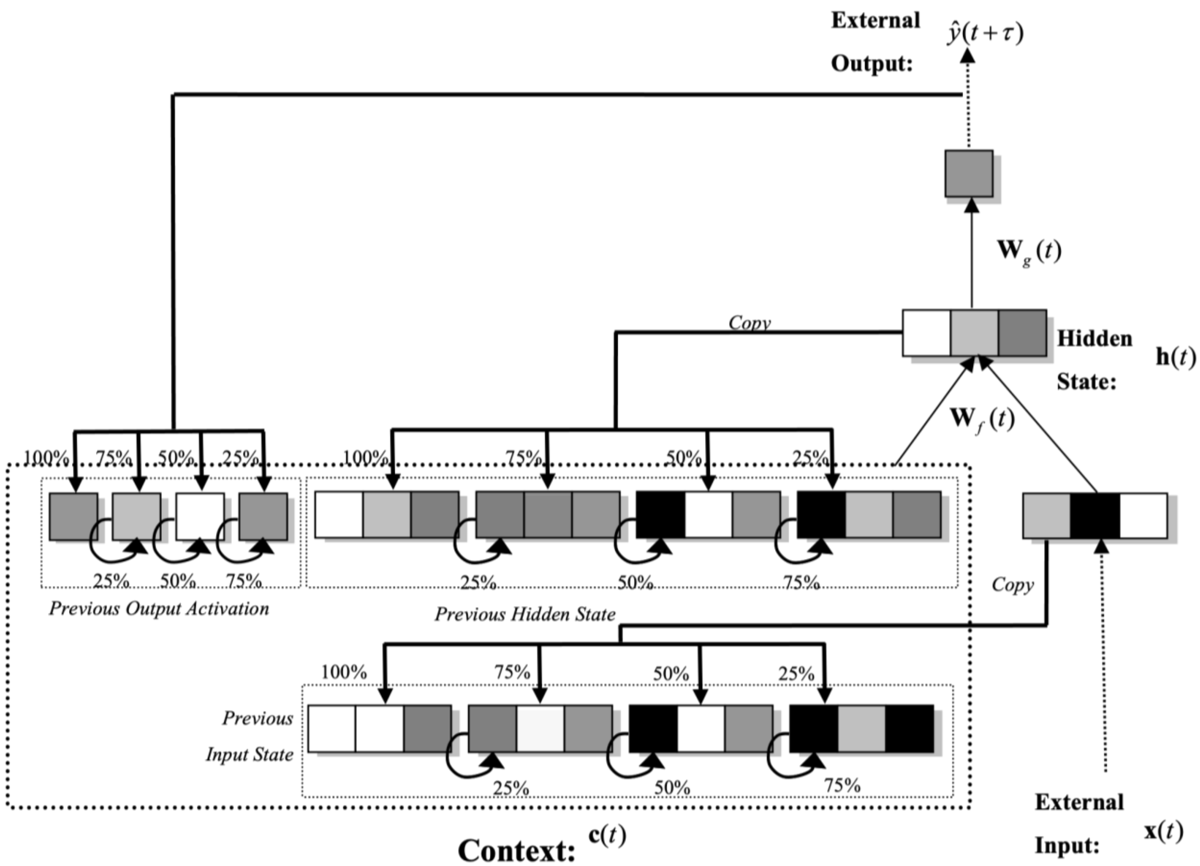
The MRN model can be generalized as:

$$\hat{y}(t+\tau) = g\left(W_g(t) f\left(W_f(t)[c(t), x(t)]\right)\right)$$

where $\hat{y}(t+\tau)$ is the predicted inflation value; $c(t)$ is the context vector; $x(t)$ represents input variables; $W_f(t)$ and $W_g(t)$ are the weight matrices; and f and g are activation vectors. The model employs hyperbolic tangent and identity functions for f and g, respectively, with the number of hidden units determined by validation set performance.

The forecasting power of neural networks is substantiated by several studies (Zhang et al., 1998; Adya and Collopy, 1998; Almosova and Andresen, 2023). Moreover, Orojo et al. (2023) found the model we are using in this study to be simpler and superior to the current state-of-the-art recurrent neural network, such as long short-term memory models for a wide range of forecasting applications.

FIGURE 2
MULTI-RECURRENT NETWORK ARCHITECTURE



RESULTS

The MRN provides superior forecasting performance compared to Bayesian VAR models, especially at longer horizons. The inclusion of short-term interest rate and both simple sum and Divisia monetary measures yield the best results. Table 2 presents forecast model comparison using root mean squared error as a metric, and table 3 presents forecast model comparisons using the direction of change as an evaluation criterion.

TABLE 2
FORECAST MODEL COMPARISON: ROOT MEAN SQUARED ERROR

h	Method	Autoregressive	Short Term Rate	Divisia Money	Simple Sum	All Variables
12	BayesianVAR	1.195	1.071	1.369	1.218	1.199
	Multi Recurrent NN	0.996	1.153	0.918	1.012	0.673
24	BayesianVAR	1.213	1.061	1.426	1.262	1.227
	Multi Recurrent NN	0.92	0.983	1.473	0.897	0.442
36	BayesianVAR	1.267	1.048	1.366	1.329	1.249
	Multi Recurrent NN	1.001	2.337	1.431	0.827	0.49

TABLE 3
FORECAST MODEL COMPARISON: DIRECTION OF CHANGE (PERCENT CORRECT)

h	Method	Autoregressive	Short Term Rate	Divisia Money	Simple Sum	All Variables
12	BayesianVAR	53.788	49.242	46.212	56.818	56.818
	Multi Recurrent NN	55.303	64.394	61.364	56.061	79.545
24	BayesianVAR	36.364	37.879	37.121	36.364	36.364
	Multi Recurrent NN	39.394	54.545	46.212	36.364	85.606
36	BayesianVAR	43.182	42.424	55.303	42.424	46.97
	Multi Recurrent NN	57.576	40.152	38.636	40.909	81.061

The MRN outperforms the Bayesian VAR across different horizons, with errors over 22 times larger in the Bayesian VAR. The addition of Divisia to simple sum always adds value, and MRN predicts the direction of change more accurately. Both Divisia and simple sum measures of money are found to be valuable for forecasting inflation owing to their divergent correlations in different economic phases. Further research into the interaction of inflation and multiple monetary aggregates is warranted, please see Gogas et al. (2013) for further evidence. Figures 3, 4 and 5 present both actual and the forecasted values of inflation at the 12, 24 and 36 month forecasting horizons.

FIGURE 3
TWELVE-MONTH AHEAD FORECAST OF INFLATION BY MODEL AND VARIABLE SELECTION

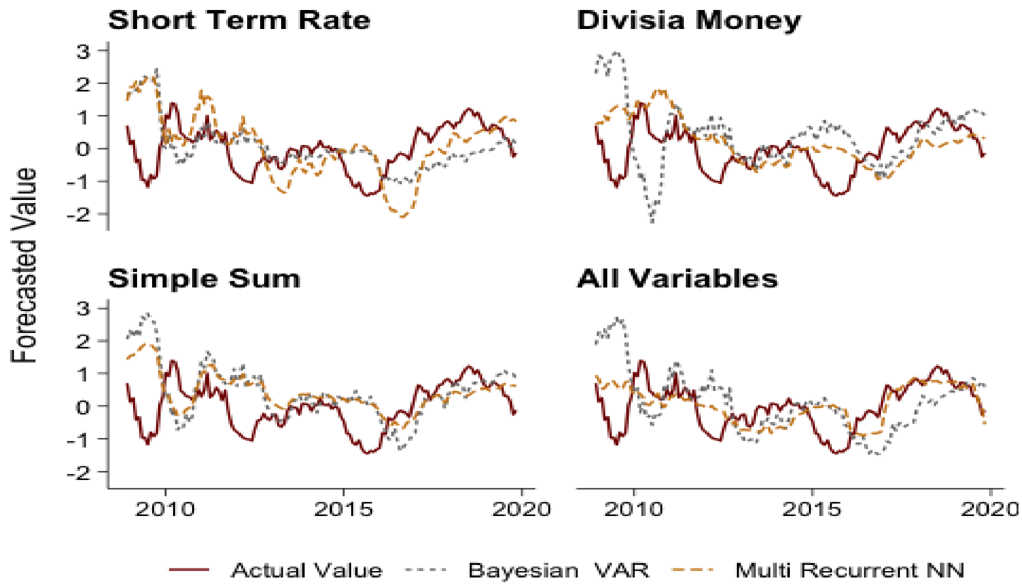


FIGURE 4
TWENTY-FOUR-MONTH AHEAD FORECAST OF INFLATION BY MODEL AND VARIABLE SELECTION

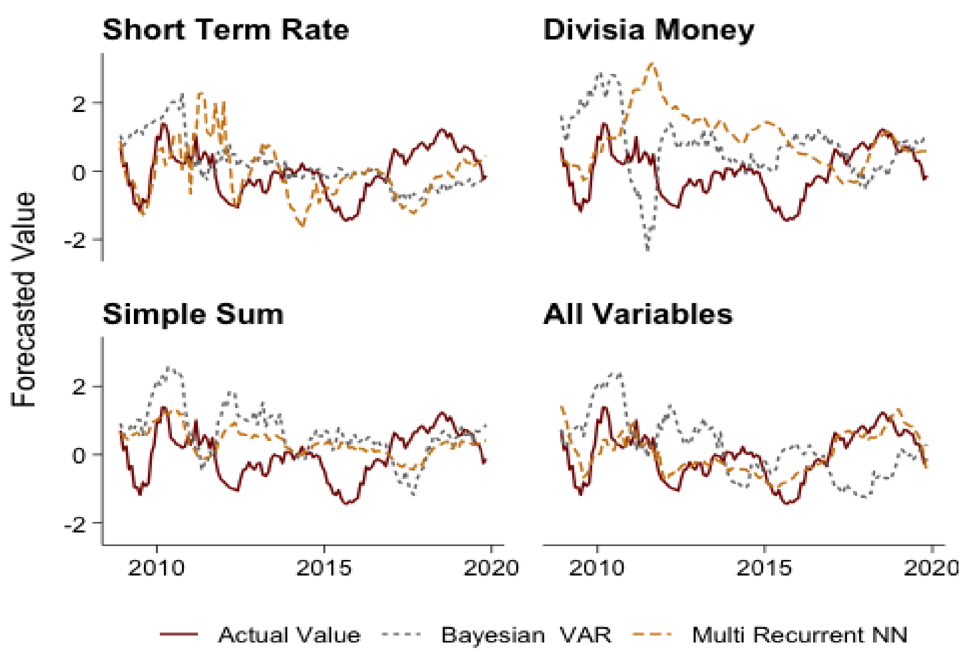
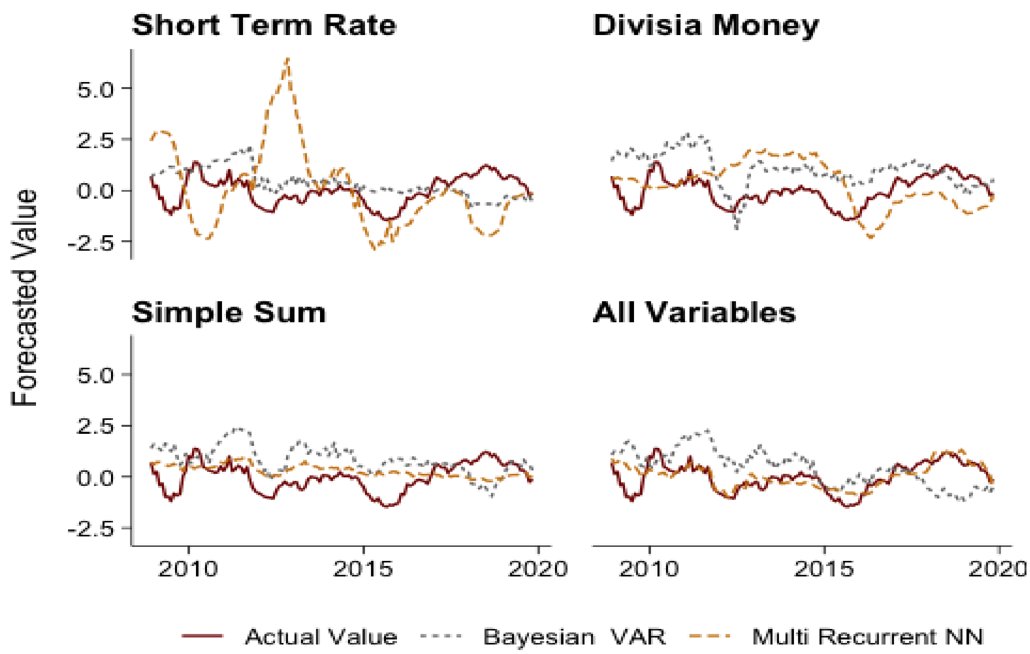


FIGURE 5
THIRTY-SIX-MONTH AHEAD FORECAST OF INFLATION BY MODEL AND VARIABLE SELECTION



CONCLUSION

In this study, we discover that incorporating both traditional simple sum monetary aggregates and their more sophisticated Divisia monetary aggregate counterpart, significantly enhances the accuracy of MRN and traditional Bayesian VAR forecasts, particularly in long-run MRN forecasts. The MRN models consistently outperform Bayesian VAR models owing to their non-linear nature and their ability to use non-stationary series data directly. The best-performing models included CPI, the short-term interest rate, and both measures of the monetary aggregates, reflecting the divergent correlation of each monetary aggregate with inflation across business cycles, as demonstrated by the behavior of the traditional simple sum M3 and more sophisticated Divisia M3 aggregates.

Given that long-term inflation forecasts are crucial for determining monetary policy, our research suggests that using non-linear inflation forecasting models that include interest rates, as well as measures of the simple stock of monetary assets and also measures of the monetary service flow may be useful in determining monetary policy. Our simple experiment, which adds each measure of monetary services plus the relevant interest rate to the inflation forecasting model in an incremental way, clearly demonstrates that monetary measures, however defined, are important measures of monetary conditions in an economy and, should be taken seriously by monetary authorities.

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ENDNOTE

1. See e.g., Binner et al. (2018), Binner and Kelly (2017), Binner et al. (2010), Belongia and Ireland (2022), Belongia and Ireland (2016), Belongia and Ireland (2015), Liu and Kool (2018), and Bissoondeeal et al. (2019).

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