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**A Neural Network-VAR for  
Long-Term Forecasting:  
An Application to Monetary  
Policy Effects in the Euro  
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### Abstract

We propose a hybrid approach that combines Neural Networks with a Vector Autoregression (VAR) model to generate long-term forecasts of time series. We apply this methodology to forecast the impact of shifts in monetary policies within the Euro area on a comprehensive set of macroeconomic variables. Our analysis begins with a standard (linear) VAR model, which is then enhanced by incorporating Neural Networks to generate long-term forecasts for key variables such as the interest rate, inflation, real output, narrow money, exchange rate, and corporate bond spread. The results suggest that a Neural Network-VAR model offers improvements over the traditional linear VAR for forecasting certain macroeconomic variables in the long run. However, due to the limited sample size, the nonlinear model does not consistently outperform the linear VAR.

### Keywords

Forecasting; VAR; Neural Networks; Monetary policies; Euro area

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# A Neural Network-VAR for Long-Term Forecasting: An Application to Monetary Policy Effects in the Euro Area

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## Abstract

We propose a hybrid approach that combines Neural Networks with a Vector Autoregression (VAR) model to generate long-term forecasts of time series. We apply this methodology to forecast the impact of shifts in monetary policies within the Euro area on a comprehensive set of macroeconomic variables. Our analysis begins with a standard (linear) VAR model, which is then enhanced by incorporating Neural Networks to generate long-term forecasts for key variables such as the interest rate, inflation, real output, narrow money, exchange rate, and corporate bond spread. The results suggest that a Neural Network-VAR model offers improvements over the traditional linear VAR for forecasting certain macroeconomic variables in the long run. However, due to the limited sample size, the nonlinear model does not consistently outperform the linear VAR.

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# 1 Introduction

Accurately forecasting the long-term evolution of time series is a major challenge due to complex and nonlinear interactions among variables. Machine Learning (ML) models, such as Random Forests (Yoon, 2021), Support Vector Machines (Huang et al., 2005), and Artificial Neural Networks (ANNs) (Bredahl Kock and Teräsvirta, 2016), have been proposed for forecasting macroeconomic and financial variables because they can capture nonlinear patterns and improve predictive accuracy. However, when applied alone, ML models are typically limited to one-step-ahead predictions and are less suited for long-term forecasting. Conversely, Vector Autoregressive (VAR) models can generate multi-step forecasts but are constrained by the assumption of linear relationships among variables.

To obtain long-term forecasts of time series and overcome the linearity limitation of traditional VAR models, we propose a hybrid approach that integrates Machine Learning, specifically Artificial Neural Networks (ANNs), within the VAR framework. This integration allows recursive multi-step predictions, feeding the output of each step back into the system while capturing nonlinear dependencies among variables. Although a few studies have explored this hybrid approach (Agustí et al., 2021), none have applied them specifically for long-term forecasting.

A natural and relevant application of our methodology is forecasting the macroeconomic effects of monetary policies. Understanding the impact of these policies is crucial for economic stability, as central banks use them to control inflation, stabilise employment, and promote growth through adjustments to interest rates and money supply. Accurate forecasting ensures that such policies effectively address challenges like inflation and recession, supporting informed decision-making for sustainable economic development.

Various models have been proposed to assess the effects of monetary policies. Dynamic Stochastic General Equilibrium (DSGE) models are frequently used for this purpose (Christiano et al., 2018). Alternatively, VAR models, particularly in their structural form (SVAR), are often employed, as they allow for the incorporation of restrictions based on economic theory and the structure of the macroeconomic system (see Badinger and

Sciman, 2023; Geoger and Güntner, 2024). These approaches provide valuable tools for policymakers to predict the effects of monetary policy shocks, supporting more informed decision-making. More recently, ML models have emerged as a complementary approach for forecasting financial and macroeconomic variables (Goulet Coulombe, 2022; Joseph et al., 2024). ML models often outperform standard linear models in predictive accuracy and, unlike traditional methodologies, are entirely data-driven, requiring no prior knowledge of the system’s underlying dynamics.

We apply the ANN-VAR methodology to forecast macroeconomic outcomes in response to monetary policy shocks in the Euro Area. Specifically, we evaluate its performance in the context of the European Central Bank’s (ECB) Quantitative Easing programme in March 2015 and the Pandemic Emergency Purchase Programme in March 2020. Our study contributes to the literature by implementing the ANN-VAR model and comparing its accuracy with that of the standard linear VAR. To date, no research has explored the integration of Neural Networks with a VAR model for predicting the macroeconomic effects of monetary policy in the Euro area. The results provide valuable insights for policymakers, practitioners, and researchers, highlighting the potential advantages of incorporating advanced tools into long-term macroeconomic forecasting frameworks.

The paper is structured as follows. Section 2 describes the methodology and the data. Section 3 reports the empirical results. Section 4 concludes.

## 2 Data and methodology

Our baseline VAR model, used to forecast the impact of monetary policies in the Euro area, is based on the approach outlined in Badinger and Sciman (2023). The model includes six variables: short-term interest rate (EONIA), consumer prices (Harmonised CPI), real output (measured by the Industrial Production Index), narrow money (M1), exchange rate (Euro to USD), and corporate bond spread (ICE BofA Euro High Yield Index Spread). All the variables are obtained from the ECB website, except for the corporate bond spread, retrieved from Ice Data Indices LLC. The  $6 \times 1$  vector of endogenous

variables is:

$$\mathbf{y}_t \equiv (EONIA_t, HCPI_t, IP_t, M1_t, EUR/USD_t, CBS_t) \quad (1)$$

The corporate bond spread, interest rate, and inflation are expressed in percentage terms, while the remaining variables are presented in natural logarithms. The dataset covers monthly observations from January 1999 to December 2021 (276 observations).

We assume that  $\mathbf{y}_t$  follows an autoregressive process of order  $p$ , expressed as follows:

$$\mathbf{y}_t = f(\mathbf{y}_{t-1}, \dots, \mathbf{y}_{t-p}) \quad (2)$$

where  $f(\cdot)$  is an unknown function. In the case of a linear VAR, equation (2) can be written in the following way:

$$\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^p \mathbf{A}_i \mathbf{y}_{t-i} + \boldsymbol{\varepsilon}_t \quad (3)$$

where  $\mathbf{c}$  is a vector of constants,  $\mathbf{A}_i$  is a matrix of autoregressive coefficients for lag  $i$ , and  $\boldsymbol{\varepsilon}_t$  is a vector of residuals. Equation (3) posits that the autoregressive relationship is linear. However, we aim to improve on this limiting assumption by implementing Neural Networks, in particular the Multi Layer Perceptron (MLP) (see [Bishop, 1995](#)), which has been shown to offer superior performance to standard linear models in terms of forecasting. For this reason, we fit a different Neural Network for each equation included in equation (2), which we can rewrite as follows:

$$\mathbf{y}_t = \mathbf{f}_{MLP}(\mathbf{y}_{t-1}, \dots, \mathbf{y}_{t-p}) \quad (4)$$

where  $\mathbf{f}_{MLP} = [f_{MLP_1}(\cdot), \dots, f_{MLP_6}(\cdot)]$  denotes a vector of 6 different nonlinear functions fit with Neural Networks. This makes our strategy highly flexible, on the one hand, and allows us to obtain long-run predictions for our six macroeconomic variables, on the other hand. Note that estimating six separate Neural Networks rather than a single multi-output model offers several advantages. First, the fitting is better tailored to each forecast variable, as it does not impose the constraint that the Neural Network weights must be

identical across all output variables – a restriction inherent in a single multi-output ANN<sup>1</sup>. Second, this approach requires fewer parameters, which is particularly advantageous in our context given the limited amount of available data. Third, it preserves the structure of a VAR – one equation per variable – thereby keeping our methodology closely aligned with the original benchmark, while still allowing for nonlinear relationships within each equation<sup>2</sup>. In Figure 1, we present an example of ANN-VAR architecture for variable  $y_1$  (*EONIA*).

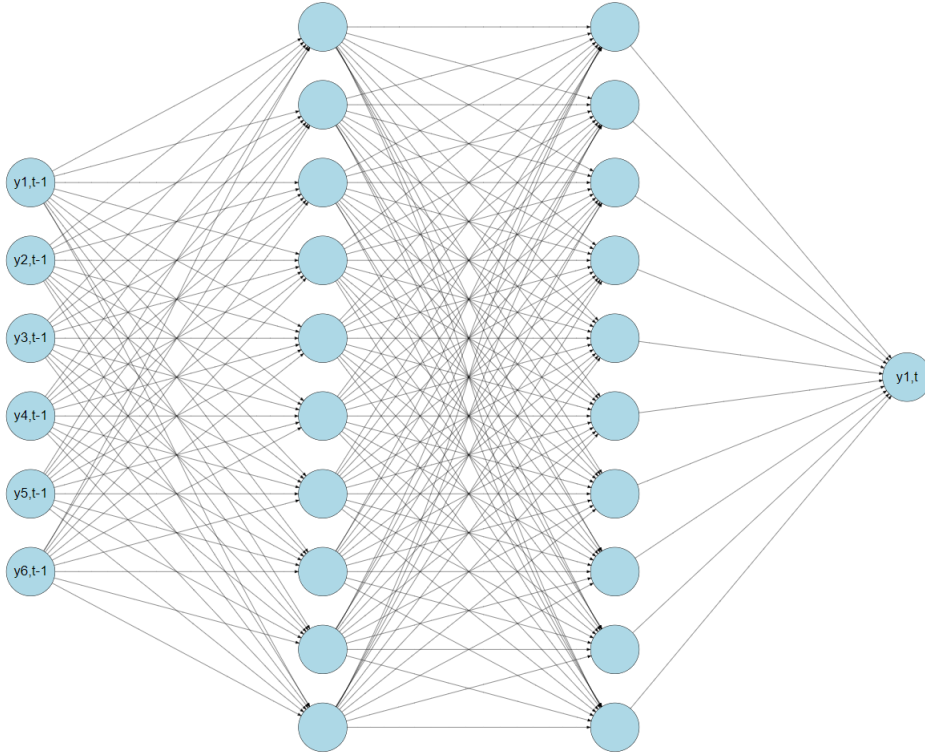


Figure 1: Example of ANN-VAR architecture for variable  $y_1$  (*EONIA*)

Table 1 reports the descriptive statistics for the six variables and Table 2 displays the correlation matrix. Notably, there is a strong negative correlation between *EONIA* and *M1* (-0.855), which is consistent with the expectation that higher interest rates generally reduce the demand for money and may lead to tighter liquidity conditions.

<sup>1</sup>This explains why, in our case, the multi-output Neural Network yields poorer results, i.e., higher RMSE values. Numerical results are omitted for brevity.

<sup>2</sup>Notice that Agustí et al. (2021) also apply an architecture with a single output, modeling each equation individually.

Table 1: Descriptive statistics

	EONIA	HCPI	IP	M1	EUR/USD	CBS
Mean	1.370	1.673	4.547	15.305	0.172	5.990
Median	0.643	1.900	4.543	15.358	0.180	4.795
St. dev.	1.712	0.994	0.054	0.510	0.136	3.702
Min	-0.492	-0.600	4.267	14.395	-0.159	1.910
Max	5.064	5.000	4.657	16.239	0.455	22.780

Table 2: Correlation matrix

	EONIA	HCPI	IP	M1	EUR/USD	CBS
EONIA	1					
HCPI	0.492	1				
IP	-0.129	0.275	1			
M1	-0.855	-0.314	0.478	1		
EUR/USD	-0.246	0.044	0.260	0.300	1	
CBS	0.359	0.088	-0.527	-0.399	-0.210	1

### 3 Results

Before estimating the VAR and the ANN-VAR, we check the stationarity of the six times series. To this purpose, we employ the Augmented Dickey-Fuller (ADF) test. The results of the ADF test (not reported) show that *EONIA*, *EUR/USD*, *HCPI*, and *M1* are not stationary at the 5% significance level, so we take their first difference.

We begin our analysis with the linear VAR. In contrast to [Badinger and Sciman \(2023\)](#), our focus is on forecasting and data-driven approaches, meaning we do not impose any restrictions on the system. We employ a VAR(1) for two reasons. First, we want a model with a number of lags as parsimonious as possible, so that the comparison between the results of the standard VAR and the ANN-VAR is straightforward; second, the majority of the lag selection criteria (AIC, BIC, HQIC) indicate that 1 lag is sufficient.

Our analysis focuses on the effects of monetary policy shocks on the Euro area macroeconomy, for which we estimate two separate VAR models. The first model spans from January 1999 to March 2015, covering the period leading up to the ECB’s implementation of Quantitative Easing. The second model extends from January 1999 to March 2020, encompassing the period when the Pandemic Emergency Purchase Programme was initiated. Both events represent instances of non-standard monetary policy. We use these

models to forecast the six key macroeconomic variables over the out-of-sample period, extending to December 2021. The performance of these models is evaluated using the Root Mean Square Error (RMSE). Subsequently, we repeat the analysis with the ANN-VAR model, optimising the hyperparameters (number of neurons, hidden layers, activation function) through cross-validation (see Table 3 for the hyperparameter values).

Table 3: Hyperparameter values for the Neural Network models

Model	Dependent variable	No. Hidden layers	No. Neurons	Activation function
$MLP_1$	EONIA	1	20	Logistic
$MLP_2$	HCPI	1	10	Identity
$MLP_3$	IP	2	15	Tanh
$MLP_4$	M1	1	15	Logistic
$MLP_5$	EUR/USD	1	10	Logistic
$MLP_6$	CBS	2	20	ReLU

For both the standard VAR and the ANN-VAR, we present the RMSE values, computed over the 12-month period and the entire out-of-sample period for April 2015 - December 2021 (Table 4) and April 2020 - December 2021 (Table 5), respectively. The results indicate that the ANN-VAR outperforms the standard VAR in forecasting certain time series, such as *EONIA* and the corporate bond spread (*CBS*) in the period 2015-2021, and industrial production (*IP*) between 2020 and 2021. However, it is important to note that the standard VAR generally already delivers strong performance. In some cases, the ANN-VAR even produces less accurate predictions compared to the basic VAR model, particularly for variables such as *IP* and *M1* over the period 2015-2021, likely due to the limited sample size. A larger sample may help to further improve the performance of ML models integrated with a VAR.

Table 4: RMSE values (2015-2021). In bold the best value

Variable	VAR	ANN-VAR	VAR	ANN-VAR
	12-months		Whole period	
EONIA	0.033	<b>0.028</b>	0.032	<b>0.017</b>
HCPI	<b>0.225</b>	0.314	<b>0.338</b>	0.367
IP	<b>0.007</b>	0.275	<b>0.068</b>	0.844
M1	<b>0.003</b>	0.100	<b>0.004</b>	0.084
EUR/USD	<b>0.020</b>	0.031	<b>0.015</b>	0.023
CBS	1.184	<b>0.296</b>	3.573	<b>1.090</b>

Table 5: RMSE values (2020-2021). In bold the best value

Variable	VAR	ANN-VAR	VAR	ANN-VAR
	12-months		Whole period	
EONIA	0.041	<b>0.018</b>	0.041	<b>0.017</b>
HCPI	0.444	<b>0.425</b>	<b>0.419</b>	0.459
IP	<b>0.072</b>	0.076	0.083	<b>0.062</b>
M1	<b>0.003</b>	0.011	<b>0.003</b>	0.009
EUR/USD	<b>0.016</b>	0.018	0.019	<b>0.016</b>
CBS	<b>0.477</b>	1.040	<b>0.385</b>	0.969

Further insights can be gained by examining the forecast time series (Figure 2), which focus on the April 2020 - December 2021 out-of-sample period. Notably, for the variable *EONIA*, the linear VAR predicts overly large changes, whereas the forecast values obtained with the ANN-VAR are closer to the observed values. Additionally, it is interesting to observe that the two models generally show similar responses to monetary policy shocks (e.g., for *HCPI* and *IP*). Finally, for *CBS*, while the VAR model tracks the observed values more closely overall, the ANN-VAR provides a final forecast for December 2021 that is closer to the actual observed value than the VAR forecast. This suggests that, although its average error may be higher, the ANN-VAR can still deliver more accurate forecasts at longer horizons.

## 4 Conclusions

In this paper, we have applied a method for generating long-term forecasts of time series by combining Neural Networks with the VAR model. We have applied this method to forecast macroeconomic variables following monetary policy shocks in the Euro area. Our results indicate that this approach can outperform the standard (linear) VAR in some cases, by leveraging the nonlinearity of Neural Networks. However, it does not consistently surpass the performance of the standard VAR and, in some instances, can lead to worse predictions. This discrepancy is likely due to the limited sample size. We suggest that further research is needed to explore the full potential of the ANN-VAR model for long-term macroeconomic forecasting. For instance, possible extensions include experimenting with alternative Neural Network architectures beyond the Multi

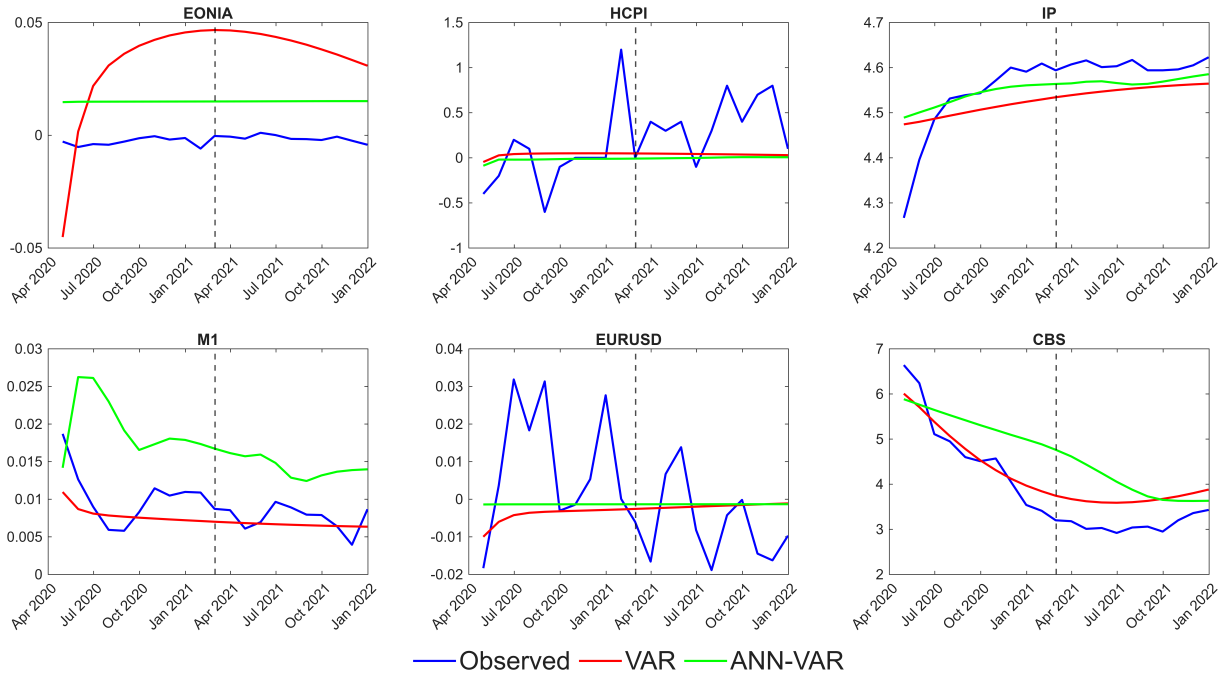


Figure 2: Macroeconomic time series. The forecast values correspond to the period following March 2020. The dotted vertical line represents the 12th month following the first forecast value

Layer Perceptron, such as recurrent networks. We encourage scholars, practitioners, and policymakers to consider integrating Neural Networks, and ML methods more broadly, into VAR models for long-term forecasting of macroeconomic variables. This recommendation stems from the fact that the ANN-VAR has demonstrated improvements over the basic VAR model in certain cases, thereby laying the groundwork for its future application in macroeconomic forecasting.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT for proofreading and to improve the flow of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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