Redefining Risk: Unleashing the Power of PLS-SEM & Ensemble ML at ELCON

Tobias Brammer

February 29, 2024

Aarhus University | Business and Social Sciences

Department of Economics and Business Economics

4873: Project-based Intership

Redefining Risk: Unleashing the Power of PLS-SEM & Ensemble ML at ELCON

Tobias Brammer

Supervisor: Benjamin D. Liengaard

Approx. 72,000 characters including blanks.

February 29, 2024

Tobias Brammer
Student id: 201909514
Redefining Risk: Unleashing the Power of PLS-SEM & Ensemble ML at ELCON
4873: Project-based Intership
Supervisor: Benjamin D. Liengaard

Aarhus University | **Business and Social Sciences**
Department of Economics and Business Economics
Fuglesangs Allé 4
8210, Aarhus V

Abstract

This paper investigates the forecasting capabilities of four models — Random Walk, Vector Autoregressive (VAR), Factor Autoregressive (FAR), and Factor-Augmented Vector Autoregressive (FAVAR) — for predicting the federal funds rate. Utilizing out-of-sample forecast evaluations with fixed, rolling, and expanding window estimation techniques, the study reveals the superior accuracy and adaptability of the factor-based models, especially when employing rolling and expanding window methods. The paper emphasizes the value of factor-augmented approaches, including principal component analysis (PCA), for addressing multicollinearity and overfitting in macroeconomic forecasting. The findings illuminate the capacity of factor-based models to account for intricate interdependencies among macroeconomic variables, thus providing a more nuanced foundation for monetary policy decision-making. The results, while promising, also underscore the need for further robustness tests and exploration of alternative models and methods to ensure a comprehensive understanding of federal funds rate predictions.

Contents

1 Introduction

This paper focuses on the evaluation and comparison of four distinct models for predicting the federal funds rate: the Random Walk, Vector Autoregressive (VAR), Factor Autoregressive (FAR), and Factor-Augmented Vector Autoregressive (FAVAR) models. The central contribution is the identification of the best-performing model in terms of forecasting accuracy, adaptability to changing economic conditions, and relevance for monetary policy decisions, drawing on an extensive literature including Bernanke and Blinder (1992), Stock and Watson (2002), and Bernanke, Boivin, et al. (2005).

The findings reveal that the Factor Autoregressive (FAR) and Factor-Augmented Vector Autoregressive (FAVAR) models consistently outperform their counterparts, resonating with the results reported by Bernanke, Boivin, et al. (2005). Specifically, the results underscore the efficacy of these factor-based models in aptly accounting for intricate interdependencies among macroeconomic variables, a sentiment echoed by Stock and Watson (2002) and Sims (1980). This capability gives rise to superior forecasts of the federal funds rate.

A comparison of Mean Squared Forecast Errors (MSFE) across models highlights the elevated predictive accuracy of both FAR and FAVAR models, as they exhibit lower MSFEs compared to the other models under consideration.

These findings have significant implications for policymakers and researchers. A more accurate understanding of federal funds rate dynamics enables central banks, such as the Federal Reserve, to make more informed monetary policy decisions, as underscored by Bernanke and Blinder (1992) and Bernanke and Gertler (2003). Moreover, the results support the value of incorporating factor-augmented approaches, like the FAVAR model, in macroeconomic forecasting, consistent with the work of Lütkepohl (2005) and Pesaran and Pick (2011).

The remainder of this paper proceeds as follows. It begins by providing an overview of the four forecasting models, discussing their underlying assumptions. Next, the methodology for comparing the models is described, using fixed window, rolling window, and expanding window estimation techniques to assess their relative performance under different economic conditions, drawing on the work of Clark and West (2007) and Rossi and Inoue (2012).

The empirical results are then presented, highlighting the Factor-based model's superior forecasting performance and discussing its implications for monetary policy. The paper concludes with a summary of the main findings and their implications for future research in macroeconomic forecasting.

2 Literature Review

This chapter provides a review of the literature on forecasting methods for predicting the federal funds rate, focusing on the Random Walk, Vector Autoregressive (VAR), Factor Autoregressive (FAR), and Factor-Augmented Vector Autoregressive (FAVAR) models. The literature review is organized as follows: Section 2.1 discusses the Random Walk model; Section 2.2 covers the VAR model; Section 2.3 addresses the FAR model; and Section 2.4 explores the FAVAR model. The chapter concludes with a brief summary of the key findings from the literature.

2.1 Random Walk Model

The Random Walk model is a widely used benchmark in the forecasting literature due to its simplicity and ease of implementation. It posits that future changes in the federal funds rate are unpredictable and determined solely by a random error term. In the context of the federal funds rate, the Random Walk model assumes that the best predictor of the rate at any given point in time is its current level Malkiel (1973). A critical assumption of this model is that changes in the federal funds rate follow a white noise process, implying that changes are uncorrelated and have a constant variance. The model takes the form of:

$$y_{t+1} = y_t + \varepsilon_{t+1}$$

where $\varepsilon_{t+1} \sim N(0, 1)$. Several studies have shown that the Random Walk model can perform surprisingly well when compared to more sophisticated forecasting methods. For example, Meese and Rogoff (1983) found that the Random Walk model outperformed several structural models in predicting exchange rates, while Diebold and Mariano (1995) demonstrated that the Random Walk model provided accurate forecasts of U.S. short-term interest rates.

2.2 Vector Autoregressive (VAR) Model

The VAR model, introduced by Sims (1980), has become a popular tool for forecasting and analyzing the relationships between macroeconomic variables. In a VAR model, each variable is expressed as a linear function of its own lagged values and the lagged values of all other variables in the system. This approach allows for the simultaneous modeling of the dynamic relationships between multiple variables, providing a rich framework for understanding the interactions between the federal funds rate and other macroeconomic variables. An essential assumption in the VAR model is that the relationships between the variables are linear and time-invariant.

A substantial body of literature has investigated the performance of VAR models in forecasting the federal funds rate. For example, Stock and Watson (2003) found that VAR models outperformed univariate time series models in predicting the federal funds rate, while Rudebusch (1998) demonstrated that the VAR model provided more accurate forecasts than the Random Walk model for U.S. short-term interest rates.

2.3 Factor Autoregressive (FAR) Model

Factor Autoregressive (FAR) Models, introduced by Stock and Watson (2002), extend traditional regression models by incorporating latent factors that summarize the information contained in a large number of macroeconomic variables. These factors are typically extracted using principal component analysis (PCA) or other dimensionality reduction techniques. By including these factors as explanatory variables in the regression model, FAR models can effectively capture the complex relationships between the federal funds rate and a wide range of macroeconomic variables. An underlying assumption in the FAR model is that a few latent factors can capture the majority of the information in the data.

A growing body of literature has examined the forecasting performance of FAR models. Bernanke and Gertler (2003) found that FAR models outperformed both traditional regression models and VAR models in predicting the federal funds rate, while Forni et al. (2005) demonstrated that FAR models provided more accurate forecasts than both univariate time series models and VAR models for a variety of macroeconomic variables.

2.4 Factor-Augmented Vector Autoregressive (FAVAR) Model

The Factor-Augmented Vector Autoregressive (FAVAR) model, proposed by Bernanke, Boivin, et al. (2005), combines the strengths of both VAR and FAR models. The FAVAR model extends the VAR framework by incorporating latent factors that summarize the information contained in a large number of macroeconomic variables. This approach allows the FAVAR model to capture the complex dynamics between the federal funds rate and other macroeconomic variables while accounting for the potential influence of unobserved factors. A critical assumption of the FAVAR model is that the unobserved factors can be adequately captured through dimensionality reduction techniques, such as PCA, and that they evolve according to a VAR process.

The forecasting performance of FAVAR models has been studied extensively in the literature. Boivin and Giannoni (2006) found that FAVAR models outperformed both VAR and FAR models in predicting the federal funds rate, while Banbura and Modugno (2014) demonstrated that FAVAR models provided more accurate forecasts than standard VAR models for a range of macroeconomic variables. Moreover, Koop and Korobilis (2010) showed that FAVAR models outperformed both univariate time series models and VAR models in predicting U.S. macroeconomic variables, suggesting that the inclusion of latent factors could improve the accuracy of macroeconomic forecasts.

2.5 Summary

The literature on forecasting methods for predicting the federal funds rate has evolved over time, with more recent models incorporating latent factors to capture the complex relationships between the federal funds rate and other macroeconomic variables. While the Random Walk model serves as a simple benchmark, the VAR, FAR, and FAVAR models offer more sophisticated approaches for understanding and predicting the dynamics of the federal funds rate.

The VAR model, which models the relationships between multiple variables simultaneously, has been shown to outperform univariate time series models in predicting the federal funds rate. The FAR model extends traditional regression models by incorporating latent factors, providing more accurate forecasts than both traditional regression models and VAR models. Finally, the FAVAR model combines the strengths of both VAR and FAR models, offering improved forecasting performance relative to both individual approaches.

3 Data and Methodology

In this study, the Federal Reserve Economic Data (FRED-MD) dataset[1] is utilized, a large-scale monthly macroeconomic database maintained by the Federal Reserve Bank of St. Louis. The dataset encompasses a broad array of macroeconomic indicators, including real and nominal variables, interest rates, exchange rates, and various inflation measures, among others. The FRED-MD dataset provides a far-reaching source of information for forecasting the federal funds rate, as it incorporates diverse factors that may impact monetary policy decisions.

The data is preprocessed according to the transformation codes included in the FRED-MD dataset. The federal funds rate (FEDFUNDS) undergoes first differencing to address potential non-stationarity, resulting in a stationary time series appropriate for forecasting. Additionally, the data is standardized by subtracting the mean and dividing by the standard deviation for each variable. This transformation enhances the comparability of different variables and facilitates the interpretation of results, as it places all variables on the same scale. The standardization process also improves the numerical stability of the estimation techniques employed in the paper, contributing to more accurate and reliable findings. The entire set of variables along with their respective transformation codes is available in Appendix C.

Figure A.3 reveals a strong correlation at 1 lag, thus three autocorrelated econometric models are employed to forecast the federal funds rate: Vector Autoregression (VAR), Factor Autoregression (FAR), and Factor-Augmented Vector Autoregression (FAVAR). Each model is estimated using a combination of rolling and expanding window techniques to evaluate their relative performance under varying economic conditions.

The Random Walk model is used as the benchmark, which assumes the future value of the differenced federal funds rate equals its current value (Figure A.2). While simple, it may not capture complex dynamics. Its out-of-sample forecast performance serves as a benchmark for other models.

The optimal number of factors for each model is selected following the most parsimonious model specification by Alessi et al. (2010). This method ensures that the model captures relevant information from the dataset while maintaining a reasonable level of complexity. The number of lags is chosen based on the Akaike

[1]The data is gathered and managed through the R-package by Yankang et al. (2023).

Information Criterion (AIC), implemented in the R-package by Pfaff (2023), which selects the model with the lowest AIC value, balancing model fit and parsimony.

3.1 Vector Autoregressive (VAR) Model

The VAR model, a widely-used multivariate time series model, allows for the simultaneous analysis of multiple macroeconomic variables and their interdependencies. It captures dynamic relationships among variables without imposing strong assumptions about the underlying economic structure.

Macroeconomic variables for the VAR model are selected based on their relevance for understanding federal funds rate dynamics and monetary policy decisions. These variables include the effective federal funds rate (FEDFUNDS), Industrial Production Index (INDPRO), Consumer Price Index for All Urban Consumers (CPIAUCSL), and the unemployment rate (UNRATE), essentially encompassing the Taylor rule.

Following the work of Stock and Watson (2003), a VAR model using lagged values of macroeconomic variables to forecast the differenced federal funds rate is implemented. This model accounts for interdependencies between variables but may struggle with high-dimensional datasets. Lag length is optimized using information criteria and out-of-sample forecasts are performed for different horizons. The VAR(p) model takes the form of:

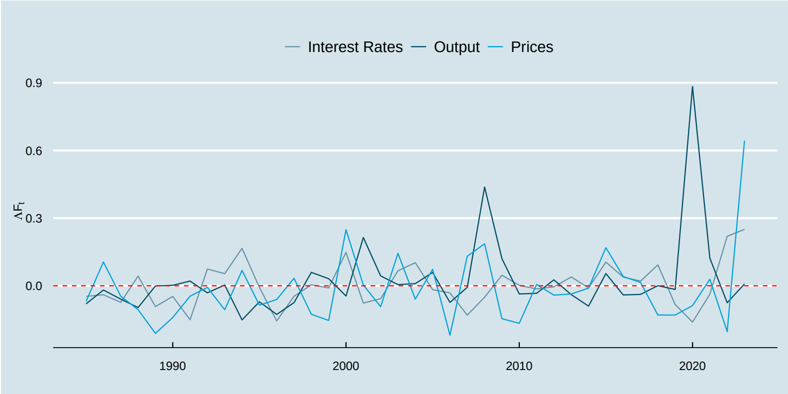
$$y_{t+1} = c + \sum_{i=1}^{p} A_i y_{t+1-i} + u_{t+1}$$

where $u_{t+1} \sim N(0, 1)$. Three out-of-sample estimation methods are employed: fixed window, rolling window, and expanding window, with the initial window size equal to the fixed window. The resulting VAR forecasts can be seen in Figures A.4-A.6.

3.2 Factor Based Forecasts

To provide a better understanding of the factors extracted using principal component analysis (PCA) and employed in the Factor Autoregressive (FAR) and Factor-Augmented Vector Autoregressive (FAVAR) models, a brief analysis of these factors and their economic interpretation is presented. The dynamic factor model is given by:

Fig. 3.1.: Factor Time Series



$$x_t = \Lambda' F_t + \epsilon_t$$

The selection criterion for the number of factors is based on Alessi et al. (2010). Across out-of-sample methods, the model selected three factors, which primarily describe Output, Prices, and Interest Rates. The scree plot can be seen in Figure A.7, which shows the first three principal components explain 32.6% of total variance. The resulting time series for $\Lambda' F_t$ can be seen in Figure 3.1.

Output Factor

The first principal component represents the Output factor[2], which captures the variation in economic activity and growth. This factor includes variables such as real GDP growth, industrial production, and capacity utilization, which are directly related to the overall performance of the economy. The Output factor is important for understanding the response of the federal funds rate to changes in economic conditions, as the Federal Reserve adjusts its monetary policy stance in response to fluctuations in output and employment to fulfill its dual mandate of promoting price stability and maximum sustainable employment.

Prices Factor

The second principal component can be interpreted as the Prices factor[3], which represents the variation in inflation and other price-related variables. This factor

[2] The mR^2 of the FRED-MD groups on PC1 can be seen in Figure A.8.
[3] The mR^2 of the FRED-MD groups on PC2 can be seen in Figure A.9.

includes measures such as the Consumer Price Index (CPI), the Producer Price Index (PPI), and the GDP deflator, reflecting the overall price level and inflation dynamics in the economy. The Prices factor is crucial for understanding the Federal Reserve's policy actions, as the central bank aims to maintain price stability by adjusting the federal funds rate in response to changes in inflation expectations and realized inflation.

Interest Rate Factor

The third principal component can be interpreted as the Interest Rate factor[4]. This factor reflects the general level of interest rates in the economy, including the federal funds rate, Treasury yields, exchange rates, and other market interest rates. The Interest Rate factor is expected to play a crucial role in the transmission of monetary policy, as changes in the federal funds rate have direct and indirect effects on a wide range of interest rates that influence the cost of borrowing and investment decisions in the economy.

In summary, the first three principal components extracted using PCA capture the key macroeconomic dimensions of Interest Rate, Output, and Prices, which are essential for understanding the dynamics of the federal funds rate and the Federal Reserve's monetary policy decisions. By incorporating these factors into the FAR and FAVAR models, complex interdependencies between the federal funds rate and other macroeconomic variables can be accounted for, while effectively handling the challenges posed by high-dimensional data. This approach results in improved forecasting performance, as demonstrated by the out-of-sample forecast evaluations.

3.2.1 Factor Autoregressive (FAR) Model

To tackle the challenges associated with high-dimensional data in forecasting, the methodology proposed by Stock and Watson (2002) is adopted by implementing a Factor Autoregressive (FAR) Model. This model employs principal component analysis (PCA) to extract valuable information from a large number of predictors, addressing the dimensionality issue by focusing on the most significant linear combinations of the original predictors. The FAR model effectively mitigates multicollinearity and overfitting issues by reducing the dimensionality of the dataset while still capturing its underlying structure. This model takes the form of:

[4] The mR^2 of the FRED-MD groups on PC3 can be seen in Figure A.10.

$$y_{t+1} = \Lambda' F_t^p + \varepsilon_{y_{t+1}}$$

where F_t^p stacks current and lagged values of the factors, and $\varepsilon_{y_{t+1}} \sim N(0,1)$. In the analysis, a sensitivity analysis is performed to determine the optimal number of principal components to be included in the FAR model. This step is crucial in balancing the trade-off between capturing the underlying structure of the data and avoiding overfitting. Once the optimal number of principal components is identified, they are included as explanatory variables in the autoregressive model, effectively augmenting it with relevant information from the high-dimensional dataset. The resulting forecasts can be seen in Figures A.11-A.13.

3.2.2 Factor-Augmented Vector Autoregressive (FAVAR) Model

The Factor-Augmented Vector Autoregressive (FAVAR) model is employed, which synergistically combines the strengths of both the VAR and FAR models. The FAVAR model integrates the principal components derived from the FAR model into the VAR framework, providing a more comprehensive representation of the relationships between the federal funds rate and other macroeconomic variables. At the same time, it addresses the challenges associated with high-dimensional data by leveraging the dimensionality reduction provided by PCA.

The FAVAR model is based on the idea that the latent factors extracted from the high-dimensional dataset, represented by the principal components, capture the essential information driving the dynamics of the macroeconomic variables. By incorporating these factors into the VAR framework, the FAVAR model accounts for the complex interdependencies among the variables without being hindered by the issues that typically arise in high-dimensional settings, such as multicollinearity and overfitting. The model takes the form of:

$$y_{t+1} = \Lambda' F_t^p + \Gamma' w_t + \varepsilon_{y_{t+1}},$$

where w_t contains observable predictor variables and lagged values of y, and $\varepsilon_{y_{t+1}} \sim N(0,1)$. To fine-tune the FAVAR model, both the lag length and the number of principal components are optimized. The optimal lag length is determined using information criteria[5], ensuring that the model captures the relevant dynamics of the data without overfitting. The optimal number of principal components is chosen

[5] AIC from Pfaff (2023).

through a sensitivity analysis, balancing the need to capture the underlying structure of the data while avoiding overfitting and excessive complexity. The resulting forecasts can be seen in Figures A.14-A.16.

To compare the forecasting performance of these models, the Mean Squared Forecast Errors (MSFE) are calculated and the Clark-West test is performed to assess the statistical significance of the differences in MSFE between the models.

Each model is estimated using a combination of fixed, rolling and expanding window techniques to assess their relative performance under different economic conditions. These estimation techniques allow for the assessment of the models' performance under various sample periods and investigation of their robustness to changing economic conditions.

While it is crucial to reverse the transformations to obtain actual federal funds rate forecasts for policy analysis and decision-making, it is appropriate to maintain the first differenced and standardized form of the forecasts when analyzing and comparing the forecast models. This approach facilitates a fair and informative comparison of the models' performance and allows researchers to determine which model performs best in predicting changes in the federal funds rate.

4 Comparison of Forecasting Methods

This chapter compares four forecasting methods for predicting the federal funds rate, including Random Walk, Vector Autoregressive (VAR), Factor-Augmented Regression (FAR), and Factor-Augmented Vector Autoregressive (FAVAR) models, drawing on insights from the literature, such as Stock and Watson (2002). The data is standardized and transformation is applied to ensure stationarity and facilitate comparability across models. The variables and corresponding transformations are listed in Appendix C.

4.1 Out-of-Sample Forecast Evaluation

To rigorously compare the forecasting performance of the Random Walk, VAR, FAR, and FAVAR models, three different out-of-sample estimation techniques are employed: fixed window, rolling window, and expanding window. These methods enable the assessment of the stability and robustness of the forecasts across different sample sizes and time periods. The initial window size is set equal to the fixed window size, ensuring a consistent starting point for each of the out-of-sample estimation techniques[1].

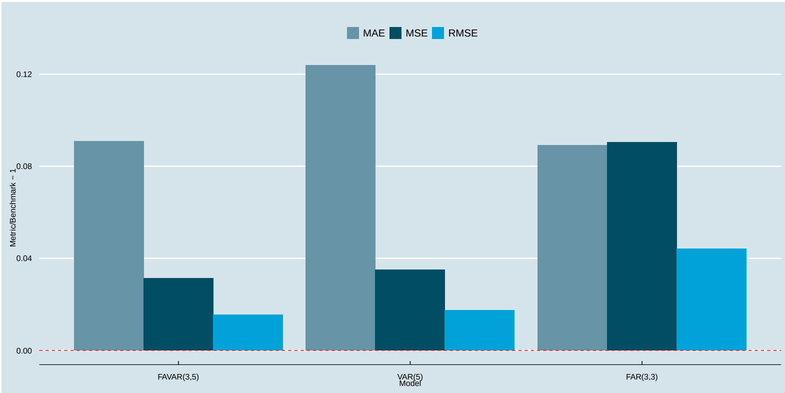
4.1.1 Fixed Window Estimation

In the fixed window estimation approach, the size of the estimation sample remains constant, with the parameters estimated once using a specific set of observations. The starting and ending points of the sample do not move forward in time, and new data does not influence the estimates. This method allows for the assessment of the forecasting performance of each model in a stable, fixed-sample setting. By comparing the forecasts generated by the fixed window estimation to the actual observed values, the accuracy and reliability of each model's predictions can be evaluated.

[1]The evaluation metrics are also reported in Table 4.1 along with the R^2_{oos}.

As evident in figure 4.1, none of the models are able to beat the benchmark model in terms of MAE, MSE, and RMSE. Of the three models, FAVAR performs best with a 1.6% increase in RMSE over the benchmark, whereas FAR performs worst with an increase of 4.4%.

Fig. 4.1.: Fixed Window Evaluation Metrics Compared to Benchmark



4.1.2 Rolling Window Estimation

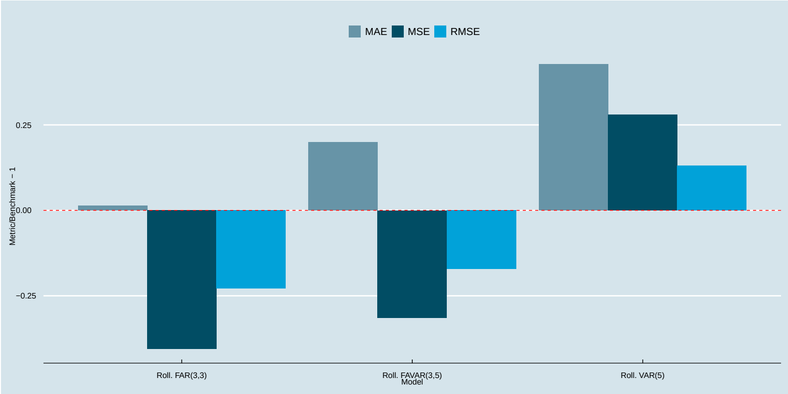
The rolling window estimation method involves moving the starting and ending points of the estimation sample forward by one period at a time, keeping the window size constant. This approach provides a more dynamic assessment of the models' forecasting performance, as it allows for the observation of how their predictions evolve over time in response to changes in the underlying data. By comparing the rolling window forecasts to the actual observed values, the adaptability and responsiveness of each model to changing economic conditions can be assessed.

From figure 4.2, there is a shift in the performance of the models, where each factor-based model performs better than the benchmark. The best model in the rolling window estimation is the FAR, with a 22.9% decrease in RMSE. FAVAR outperforms the benchmark with a decrease in RMSE of 17.2%. VAR, however, performs worse still, with an increase in RMSE of 13.1%.

4.1.3 Expanding Window Estimation

In the expanding window estimation technique, the ending point of the estimation sample is moved forward by one period at a time, while keeping the starting point fixed. This results in an increasing sample size for each successive estimation. The

Fig. 4.2.: Rolling Window Evaluation Metrics Compared to Benchmark



expanding window method enables the evaluation of the forecasting performance of the models as more information becomes available, providing insights into their ability to incorporate new data and improve their predictions over time. By comparing the expanding window forecasts to the actual observed values, the models' capacity to learn from new information and refine their forecasts accordingly can be assessed.

Figure 4.3 shows that, once again, the models outperform the benchmark. As in the test with a rolling window, the FAR model performs best with a 16.5% decrease in RMSE. In this case, FAVAR shows a decrease in RMSE of 5.4%, whereas VAR yet again results in an increase of 12.4%.

Fig. 4.3.: Expanding Window Evaluation Metrics Compared to Benchmark

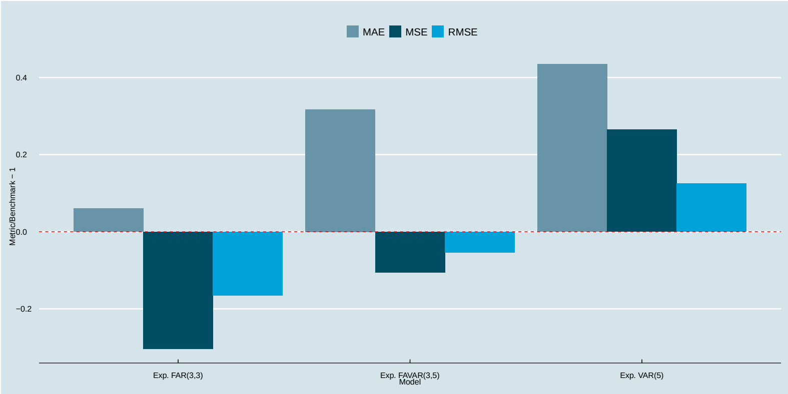


Table **??** compares evaluation metrics of the FAR(3,3) and Expanding FAR(3,3) models as percentage differences from a random walk. The Expanding FAR(3,3) consistently surpasses the benchmark at 3-month, 6-month, and 1-year horizons. Meanwhile, the FAR(3,3) shows varied results, performing better at 1-year and

Tab. 4.1.: Evaluation Metrics

	MAE	MSE	RMSE	R^2_{oos}
RW	0.897	2.081	1.443	0.000
Roll. RW	0.436	0.606	0.778	0.000
Exp. RW	0.436	0.606	0.778	0.000
VAR(5)	1.008	2.154	1.468	-0.035
Roll. VAR(5)	0.623	0.775	0.881	-0.280
Exp. VAR(5)	0.625	0.766	0.875	-0.264
FAR(3,3)	0.976	2.269	1.506	-0.090
Roll. FAR(3,3)	0.442	0.360	0.600	0.405
Exp. FAR(3,3)	0.462	0.422	0.650	0.304
FAVAR(3,5)	0.978	2.146	1.465	-0.031
Roll. FAVAR(3,5)	0.523	0.416	0.645	0.314
Exp. FAVAR(3,5)	0.574	0.542	0.736	0.105

The R^2_{oss} is calculated by $1 - MSE_m/MSE_{bmk}$, where MSE_m is the MSE of the model, and MSE_{bmk} is the MSE of the RW-model using the corresponding estimation window.

3-year horizons but not at others. This underlines the superior forecasting accuracy of the Expanding FAR(3,3) model.

4.1.4 Diebold-Mariano Test Results

The Diebold-Mariano test is employed to assess the performance of different forecasting models against the Random Walk model and to compare their performance against each other. Table **??** presents the p-values obtained from the Diebold-Mariano test.

It is evident that the factor-based models outperform the Random Walk model, with lower p-values indicating superior forecasting performance.

However, it is crucial to acknowledge the limitations of the Diebold-Mariano test. One of the primary limitations is its sensitivity to the choice of loss function. Different loss functions can yield different results, potentially leading to conflicting conclusions about the models' comparative performance. Additionally, the test assumes that the forecast errors are uncorrelated, which may not always hold in practice.

Despite these limitations, the Diebold-Mariano test results provide valuable insights into the relative forecasting performance of the models. They suggest that the Factor-based models, in particular, are more effective in forecasting key macroeconomic variables than their VAR and Random Walk counterparts.

Tab. 4.2.: P-values from Clark West Test against Random Walk

	p-value
VAR(5)	0.099
Roll. VAR(5)	0.352
Exp. VAR(5)	0.349
FAR(3,3)	0.001
Roll. FAR(3,3)	0.090
Exp. FAR(3,3)	0.108
FAVAR(3,5)	0.019
Roll. FAVAR(3,5)	0.058
Exp. FAVAR(3,5)	0.082

4.1.5 Clark-West Test Results

The Clark-West test is used alongside the Diebold-Mariano test to assess forecasting performance because it addresses key limitations. The Clark-West test accounts for correlated forecast errors and emphasizes the statistical significance of differences in model performance. Additionally, it is less sensitive to the choice of loss function.

The Clark-West test results in Table 4.2 provide p-values for each model against the corresponding Random Walk model. Lower p-values indicate that the model significantly outperforms the Random Walk counterpart. In the case of fixed window estimations, both the FAR(3,3) and FAVAR(3,5) models significantly outperform the Random Walk counterpart, as evidenced by p-values below 0.05. The VAR(5) model also surpasses the Random Walk model, albeit with less statistical significance, reflected in a p-value of 0.099. It is worth noting that this superior performance is not as pronounced in the rolling and expanding window versions of these models.

The results in Table **??** provide p-values for each model comparison using the Clark-West test. Lower p-values indicate that the model in the "Large Model" column significantly outperforms the model in the "Small Model" column. In this case, the focus is on the comparisons between the VAR, FAR, and FAVAR models, as well as their rolling and expanding window estimations. Notably, the FAVAR model significantly outperforms the FAR model with a p-value of 0.00. The rolling and expanding window estimations for all the models also show significant improvements in forecasting performance compared to their respective fixed window estimations, with p-values lower than 0.01.

When comparing the VAR model with the FAR model, the p-value is 0.602, suggesting no significant difference in their forecasting performance. However, the comparisons between the rolling and expanding window estimations of the fixed VAR, FAR, and FAVAR models demonstrate considerable improvements in forecasting performance, with p-values ranging between 0.002 and 0.005. This further supports the idea that the rolling and expanding window estimation methods can effectively capture the changing dynamics in the data, leading to more accurate forecasts.

In summary, the results showed that no model significantly outperformed the benchmark Random Walk model in a fixed window estimation. However, in rolling and expanding window estimations, the factor-based models FAR and FAVAR outperformed the benchmark. In particular, the FAR model showed a significant decrease in Root Mean Squared Error (RMSE), an indicator of forecasting accuracy.

The Diebold-Mariano and Clark-West tests confirmed the superior performance of factor-based models over the Random Walk and VAR models. However, they highlighted potential limitations, including sensitivity to the choice of loss function and the assumption of uncorrelated forecast errors.

The Model Confidence Set (MCS) procedure was employed to identify superior forecasting models, revealing interesting insights[2]. The rolling and expanding versions of the FAR and FAVAR models were included in the superior set, indicating their robust forecasting performance. However, the VAR model was notably rejected by the MCS procedure, suggesting its inferior performance relative to other models, even the simple Random Walk.

These findings underscore the effectiveness of factor-based models, particularly when applied with rolling and expanding window estimation techniques, in the context of federal funds rate forecasting, but also show the power of the simple Random Walk, when using a rolling or expanding window.

[2]The results are posted in Table **??**.

5 Concluding Remarks

In this paper, the forecasting performance of four distinct models for predicting the federal funds rate has been analyzed: the Random Walk, Vector Autoregressive (VAR) Model, Factor Autoregressive (FAR) Model, and Factor-Augmented Vector Autoregressive (FAVAR) Model. The findings highlight the superior forecasting accuracy of the FAR and FAVAR models, especially when utilizing rolling and expanding window estimation techniques.

These results carry significant implications for both policymakers and researchers. For one, the superior performance of factor-based models, which account for complex interdependencies among macroeconomic variables, can provide a more nuanced understanding of the federal funds rate. This insight is valuable to institutions like the Federal Reserve, aiding more informed decision-making on monetary policy.

Moreover, this study underscores the utility of factor-augmented approaches in macroeconomic forecasting. By employing principal component analysis (PCA) to distill latent factors from high-dimensional datasets, potential issues like multicollinearity and overfitting can be managed, leading to more accurate and robust forecasting models.

Though the FAR and FAVAR models performed well in this analysis, it's crucial to note that results might be sensitive to model choices, estimation techniques, and sample periods. Future research should address this potential limitation by conducting robustness tests and exploring alternative models and methods, providing a more reliable understanding of variable relationships and their implications for federal funds rate predictions.

In conclusion, the study validates the use of sophisticated econometric techniques like the FAVAR model to better comprehend the federal funds rate and its monetary policy implications. By harnessing these tools, policymakers and researchers can more accurately anticipate economic shifts and make informed decisions promoting stability and growth.

Bibliography

Alessi, Lucia, Matteo Barigozzi, and Marco Capasso (2010). "Improved penalization for determining the number of factors in approximate factor models". In: *Statistics & Probability Letters* 80(23-24), pp. 1806–1813 (cit. on pp. 7, 9).

Banbura, Marta and Michele Modugno (2014). "Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data". In: *Journal of Applied Econometrics* 29(1), pp. 133–160 (cit. on p. 5).

Bernanke, Ben and Alan Blinder (1992). "The federal funds rate and the channels of monetary transmission". In: *The American Economic Review*, pp. 901–921 (cit. on p. 1).

Bernanke, Ben, Jean Boivin, and Piotr Eliasz (2005). "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach". In: *The Quarterly Journal of Economics* 120(1), pp. 387–422 (cit. on pp. 1, 5).

Bernanke, Ben and Mark Gertler (2003). "Monetary policy and asset price volatility". In: *Economic Review* 84(4), pp. 17–51 (cit. on pp. 1, 4).

Boivin, Jean and Marc P Giannoni (2006). "DSGE models in a data-rich environment". In: *Technical report, Columbia University* (cit. on p. 5).

Clark, Todd and Kenneth West (2007). "A comparison of some methods for constructing confidence intervals for policy-relevant functions of regression parameters". In: *Journal of Business & Economic Statistics* 25(3), pp. 314–324 (cit. on p. 1).

Diebold, Francis X and Roberto S Mariano (1995). "Comparing predictive accuracy". In: *Journal of Business & Economic Statistics* 13(3), pp. 253–263 (cit. on p. 3).

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin (2005). "Generalized dynamic factor models and volatilities: estimation and forecasting". In: *Journal of the American Statistical Association* 100(472), pp. 830–840 (cit. on p. 4).

Koop, Gary and Dimitris Korobilis (2010). "Forecasting with medium and large Bayesian VARs". In: *Journal of Applied Econometrics* 25(1), pp. 71–92 (cit. on p. 5).

Lütkepohl, Helmut (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media (cit. on p. 1).

Malkiel, Burton G (1973). *A random walk down Wall Street: The time-tested strategy for successful investing*. WW Norton & Company (cit. on p. 3).

Meese, Richard A and Kenneth Rogoff (1983). "Empirical exchange rate models of the seventies: Do they fit out of sample?" In: *Journal of International Economics* 14(1-2), pp. 3–24 (cit. on p. 3).

Pesaran, M. Hashem and Andreas Pick (2011). "Forecast averaging in models with a large number of predictors". In: *Journal of Applied Econometrics* 26(4), pp. 646–685 (cit. on p. 1).

Pfaff, Bernhard (2023). *R Package 'vars'*. URL: `https://github.com/bpfaff/vars` (cit. on pp. 8, 11).

Rossi, Barbara and Atsushi Inoue (2012). "Out-of-Sample Forecast Tests Robust to the Choice of Window Size". In: *Journal of Business & Economic Statistics* 30(3), pp. 432–453 (cit. on p. 1).

Rudebusch, Glenn D (1998). "Testing the random walk hypothesis: A time-series approach". In: *Federal Reserve Bank of San Francisco Economic Review* 2, pp. 21–35 (cit. on p. 4).

Sims, Christopher A (1980). "Macroeconomics and reality". In: *Econometrica: Journal of the Econometric Society*, pp. 1–48 (cit. on pp. 1, 4).

Stock, James and Mark Watson (Sept. 2003). "Forecasting Output and Inflation: The Role of Asset Prices". In: *Journal of Economic Literature* 41(3), pp. 788–829 (cit. on pp. 4, 8).

Stock, James and Mark Watson (2002). "Forecasting using principal components from a large number of predictors". In: *Journal of the American Statistical Association* 97(460), pp. 1167–1179 (cit. on pp. 1, 4, 10, 13).

Yankang, (Bennie) Chen, Serena Ng, and Jushan Bai (2023). *Factor-Based Imputation and FRED-MD/QD Data Set*. URL: `https://github.com/cykbennie/fbi` (cit. on p. 7).

List of Figures

List of Tables

A Figures

Fig. A.1.: Transformed Fed Funds Rate

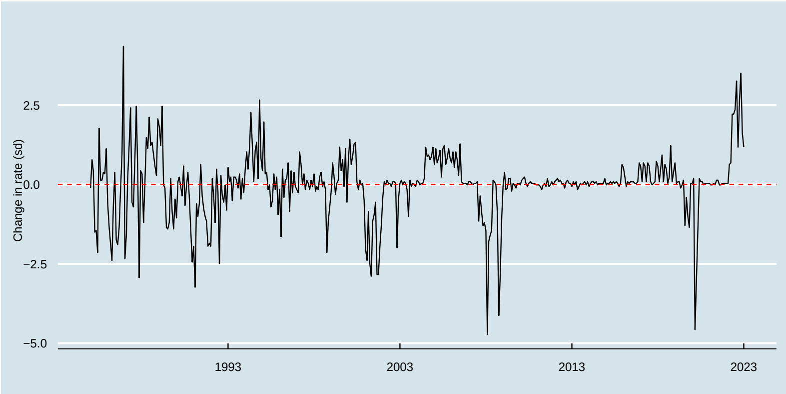


Fig. A.2.: Random Walk Forecast

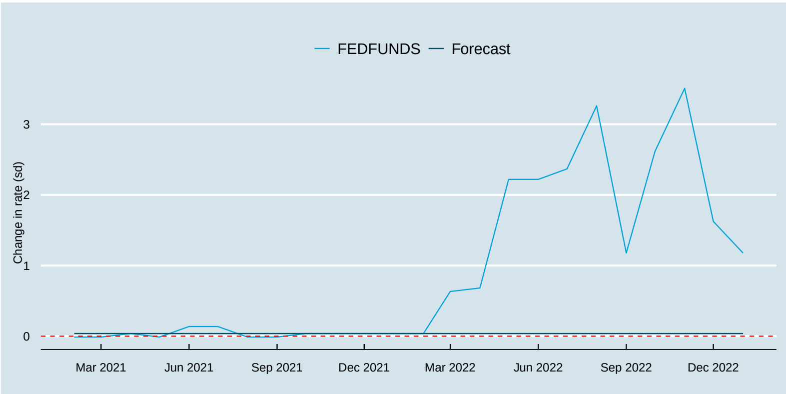


Fig. A.3.: Fed Funds Rate PACF

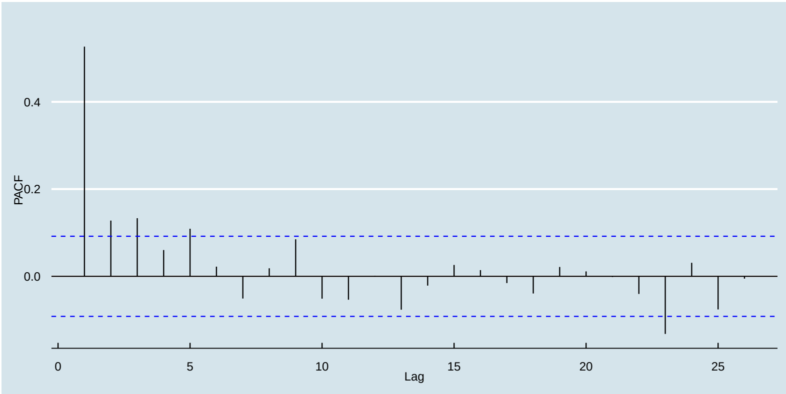


Fig. A.4.: VAR(5) Forecast

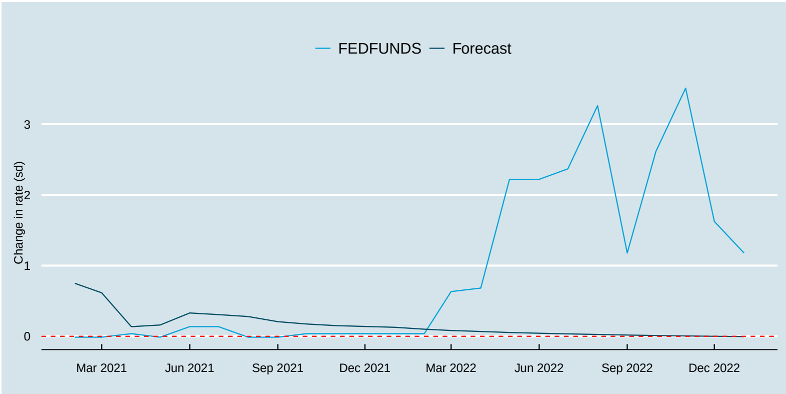


Fig. A.5.: VAR(5) Rolling Forecast

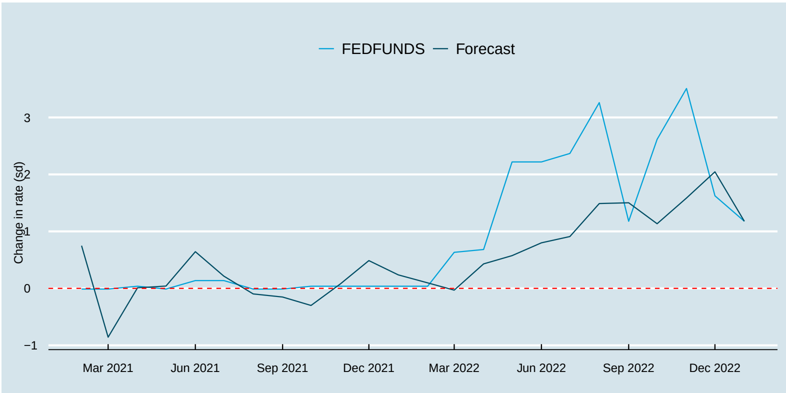


Fig. A.6.: VAR(5) Expanding Forecast

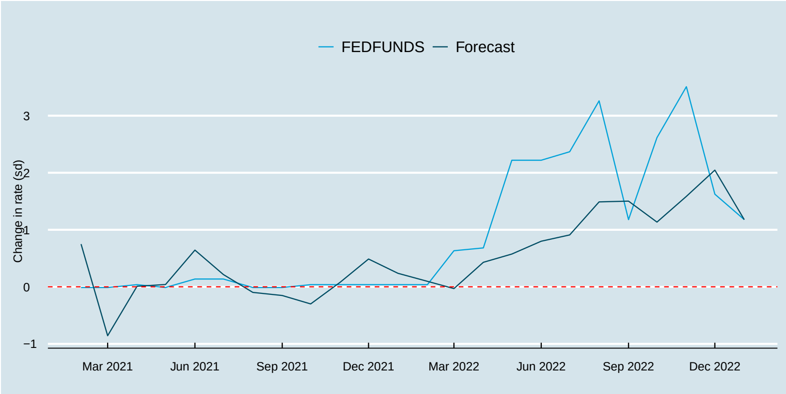


Fig. A.7.: Scree Plot

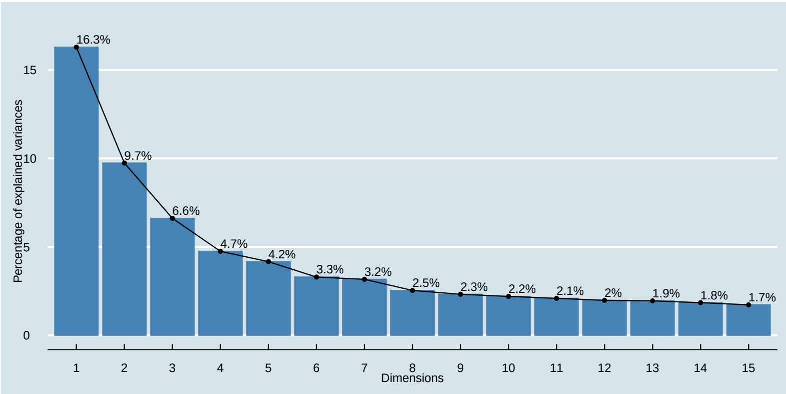


Fig. A.8.: Mean R^2 of Principal Component 1

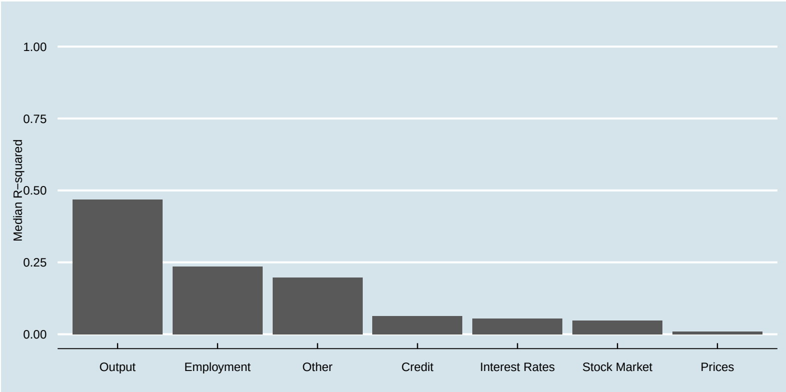


Fig. A.9.: Mean R^2 of Principal Component 2

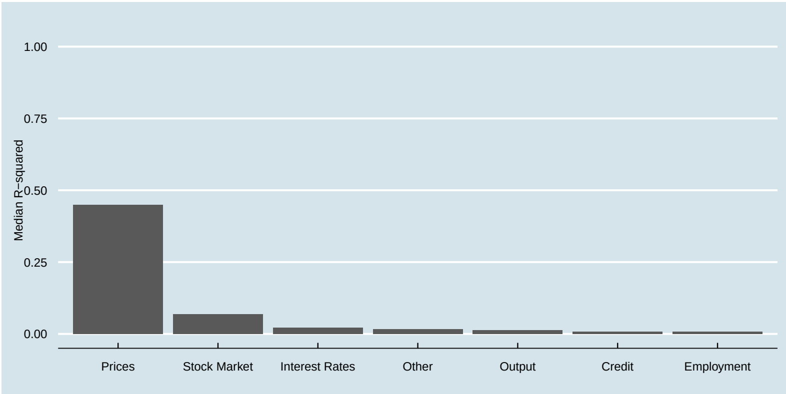


Fig. A.10.: Mean R^2 of Principal Component 3

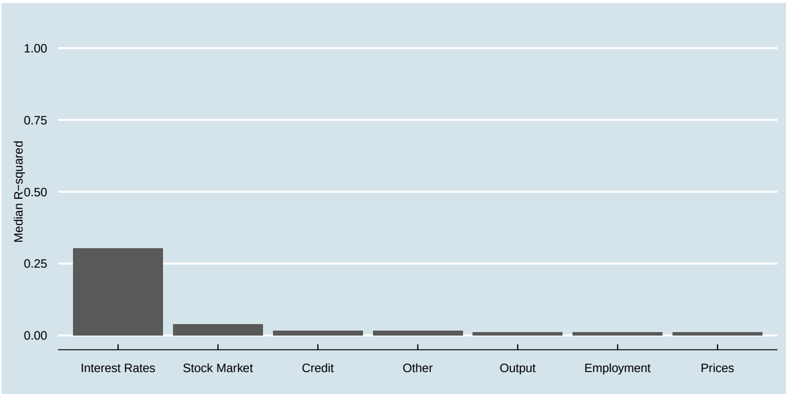


Fig. A.11.: FAR(3,3) Forecast

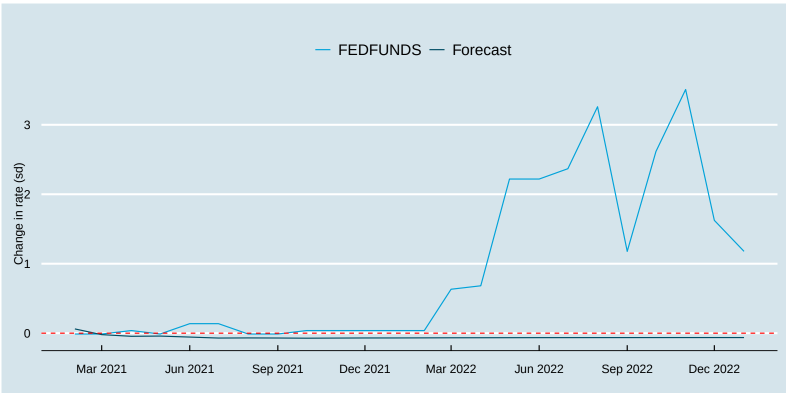


Fig. A.12.: FAR(3,5) Rolling Forecast

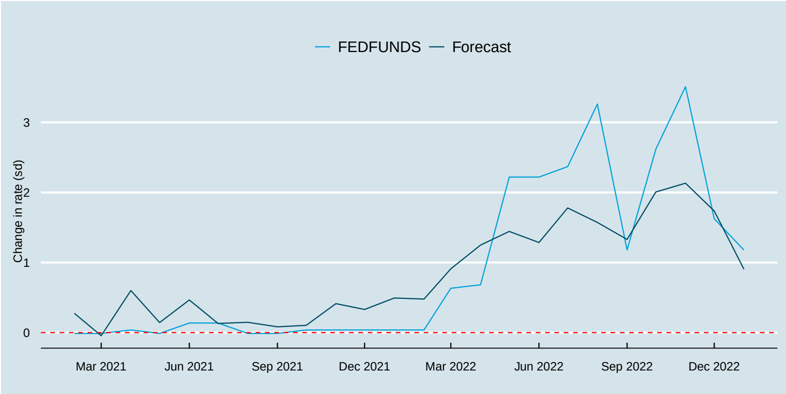


Fig. A.13.: FAR(3,5) Expanding Forecast

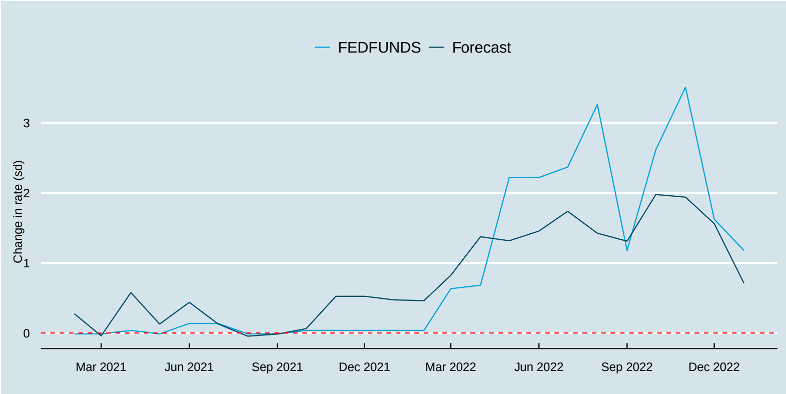


Fig. A.14.: FAVAR(3,3) Forecast

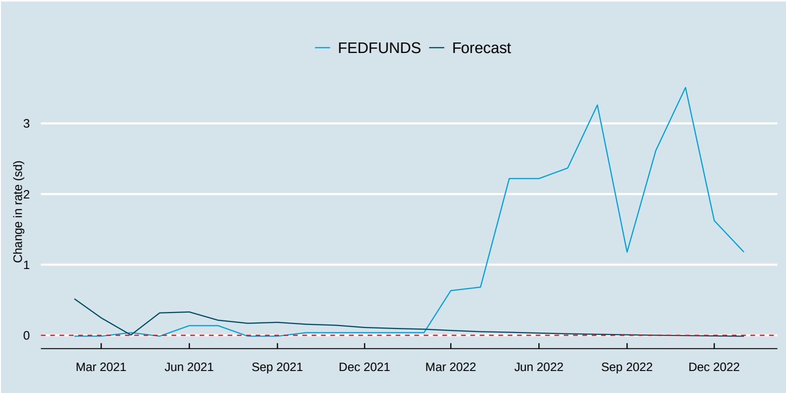


Fig. A.15.: FAVAR(3,8) Rolling Forecast

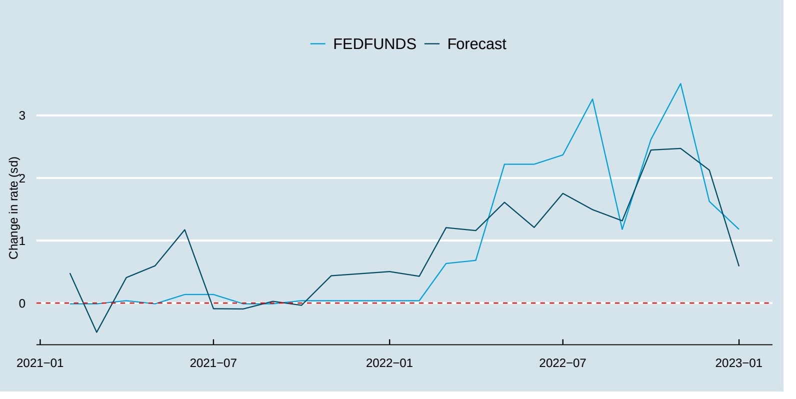


Fig. A.16.: FAVAR(3,6) Expanding Forecast

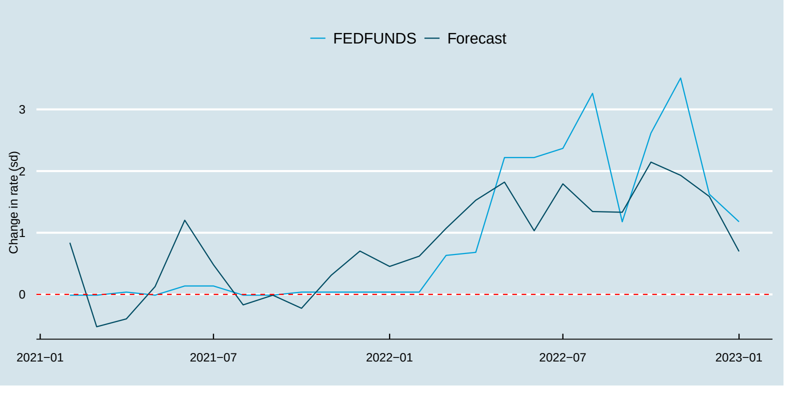


Fig. A.17.: Evaluation Metrics Compared to Benchmark

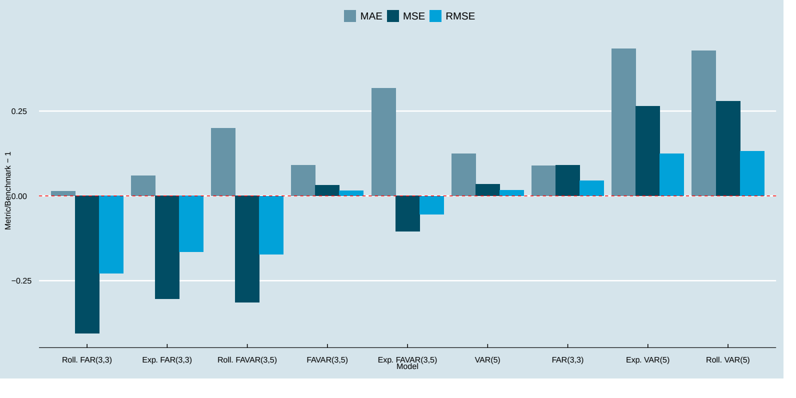
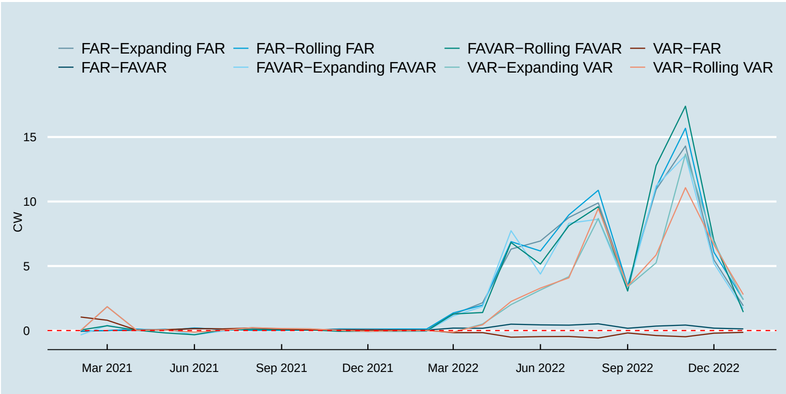


Fig. A.18.: Clark West test statistics



B Tables

Tab. B.1.: Summary of Dataset

	Descriptions	Value
1	Sample size (nrow)	3725
2	No. of variables (ncol)	25
3	No. of numeric/interger variables	11
4	No. of factor variables	0
5	No. of text variables	12
6	No. of logical variables	0
7	No. of identifier variables	0
8	No. of date variables	2
9	No. of zero variance variables (uniform)	0
10	%. of variables having complete cases	96% (24)
11	%. of variables having >0% and <50% missing cases	4% (1)
12	%. of variables having >=50% and <90% missing cases	0% (0)
13	%. of variables having >=90% missing cases	0% (0)

Tab. B.2.: Summary of Variables

	Variable_Name	Variable_Type	Sample_n	Missing_Count	Per_of_Missing	No_of_distinct_values
1	date	Date	3725	0	0.00	69
2	month	character	3725	0	0.00	12
3	year	character	3725	0	0.00	6
4	job_posting_group	character	3725	0	0.00	2
5	department	character	3725	0	0.00	2
6	job_no	character	3725	0	0.00	330
7	status	character	3725	0	0.00	2
8	description	character	3725	0	0.00	327
9	customer	character	3725	0	0.00	147
10	customer_zip	character	3725	0	0.00	80
11	address	character	3725	0	0.00	218
12	zip	character	3341	384	0.10	92
13	responsible	character	3725	0	0.00	48
14	end_date	Date	3725	0	0.00	247
15	budget_revenue	numeric	3725	0	0.00	285
16	budget_costs	numeric	3725	0	0.00	276
17	budget_contribution	numeric	3725	0	0.00	281
18	revenue	numeric	3725	0	0.00	2213
19	costs	numeric	3725	0	0.00	3476
20	costs_of_labor	numeric	3725	0	0.00	2666
21	costs_of_materials	numeric	3725	0	0.00	3206
22	other_costs	numeric	3725	0	0.00	1798
23	contribution	numeric	3725	0	0.00	3577
24	estimated_revenue	numeric	3725	0	0.00	3401
25	estimated_contribution	numeric	3725	0	0.00	3524

Tab. B.3.: Summary of Categorical Variables by Deparment

	VARIABLE	CATEGORY	Number	department:505	department:515	TOTAL
1	year	2018	nn	358.00	194.00	552.00
2	year	2019	nn	483.00	154.00	637.00
3	year	2020	nn	407.00	136.00	543.00
4	year	2021	nn	356.00	353.00	709.00
5	year	2022	nn	372.00	425.00	797.00
6	year	2023	nn	254.00	233.00	487.00
7	year	TOTAL	nn	2230.00	1495.00	3725.00
8	year	2018	%	16.05	12.98	14.82
9	year	2019	%	21.66	10.30	17.10
10	year	2020	%	18.25	9.10	14.58
11	year	2021	%	15.96	23.61	19.03
12	year	2022	%	16.68	28.43	21.40
13	year	2023	%	11.39	15.59	13.07
14	year	TOTAL	%	100.00	100.00	100.00
15	job_posting_group	FASTPRIS	nn	1888.00	1254.00	3142.00
16	job_posting_group	PROJEKT	nn	342.00	241.00	583.00
17	job_posting_group	TOTAL	nn	2230.00	1495.00	3725.00
18	job_posting_group	FASTPRIS	%	84.66	83.88	84.35
19	job_posting_group	PROJEKT	%	15.34	16.12	15.65
20	job_posting_group	TOTAL	%	100.00	100.00	100.00
21	status	finished	nn	1778.00	830.00	2608.00
22	status	wip	nn	452.00	665.00	1117.00
23	status	TOTAL	nn	2230.00	1495.00	3725.00
24	status	finished	%	79.73	55.52	70.01
25	status	wip	%	20.27	44.48	29.99
26	status	TOTAL	%	100.00	100.00	100.00

Tab. B.4.: Summary of Cross-sectional Dataset

	Descriptions	Value
1	Sample size (nrow)	331
2	No. of variables (ncol)	27
3	No. of numeric/interger variables	13
4	No. of factor variables	0
5	No. of text variables	12
6	No. of logical variables	0
7	No. of identifier variables	0
8	No. of date variables	2
9	No. of zero variance variables (uniform)	0
10	%. of variables having complete cases	92.59% (25)
11	%. of variables having >0% and <50% missing cases	7.41% (2)
12	%. of variables having >=50% and <90% missing cases	0% (0)
13	%. of variables having >=90% missing cases	0% (0)

Tab. B.5.: Summary of Cross-sectional Variables

	Variable_Name	Variable_Type	Sample_n	Missing_Count	Per_of_Missing	No_of_distinct_values
1	date	Date	331	0	0.00	67
2	month	character	331	0	0.00	12
3	year	character	331	0	0.00	6
4	job_posting_group	character	331	0	0.00	2
5	department	character	331	0	0.00	2
6	job_no	character	331	0	0.00	330
7	status	character	331	0	0.00	2
8	description	character	331	0	0.00	327
9	customer	character	331	0	0.00	147
10	customer_zip	character	331	0	0.00	80
11	address	character	331	0	0.00	218
12	zip	character	297	34	0.10	92
13	responsible	character	331	0	0.00	48
14	end_date	Date	331	0	0.00	214
15	budget_revenue	numeric	331	0	0.00	286
16	budget_costs	numeric	331	0	0.00	279
17	budget_contribution	numeric	331	0	0.00	282
18	revenue	numeric	331	0	0.00	281
19	costs	numeric	331	0	0.00	317
20	costs_of_labor	numeric	331	0	0.00	286
21	costs_of_materials	numeric	331	0	0.00	289
22	other_costs	numeric	331	0	0.00	141
23	contribution	numeric	331	0	0.00	327
24	estimated_revenue	numeric	331	0	0.00	284
25	estimated_contribution	numeric	331	0	0.00	316
26	days_until_end	numeric	331	0	0.00	162
27	contribution_margin	numeric	327	4	0.01	274

Tab. B.6.: Summary of Cross-sectional Categorical Variables by Deparment

	VARIABLE	CATEGORY	Number	department:505	department:515	TOTAL
1	year	2018	nn	31.00	21.00	52.00
2	year	2019	nn	51.00	16.00	67.00
3	year	2020	nn	35.00	9.00	44.00
4	year	2021	nn	23.00	9.00	32.00
5	year	2022	nn	21.00	24.00	45.00
6	year	2023	nn	49.00	42.00	91.00
7	year	TOTAL	nn	210.00	121.00	331.00
8	year	2018	%	14.76	17.36	15.71
9	year	2019	%	24.29	13.22	20.24
10	year	2020	%	16.67	7.44	13.29
11	year	2021	%	10.95	7.44	9.67
12	year	2022	%	10.00	19.83	13.60
13	year	2023	%	23.33	34.71	27.49
14	year	TOTAL	%	100.00	100.00	100.00
15	job_posting_group	FASTPRIS	nn	167.00	94.00	261.00
16	job_posting_group	PROJEKT	nn	43.00	27.00	70.00
17	job_posting_group	TOTAL	nn	210.00	121.00	331.00
18	job_posting_group	FASTPRIS	%	79.52	77.69	78.85
19	job_posting_group	PROJEKT	%	20.48	22.31	21.15
20	job_posting_group	TOTAL	%	100.00	100.00	100.00
21	status	finished	nn	175.00	85.00	260.00
22	status	wip	nn	35.00	36.00	71.00
23	status	TOTAL	nn	210.00	121.00	331.00
24	status	finished	%	83.33	70.25	78.55
25	status	wip	%	16.67	29.75	21.45
26	status	TOTAL	%	100.00	100.00	100.00

C Variables

Transformation code denotes the following data transformation for a series x:

1. no transformation
2. Δx_t
3. $\Delta^2 x_t$
4. $\log(x_t)$
5. $\Delta \log(x_t)$
6. $\Delta^2 \log(x_t)$

Variables with **bold** are used in the VAR and FAVAR specifications.

Tab. C.1.: Stationary Variables from FRED-MD

Variable	Group	Transformation code
M1SL	Credit	5
M2SL	Credit	5
M2REAL	Credit	4
TOTRESNS	Credit	5
NONBORRES	Credit	6
BUSLOANS	Credit	5
REALLN	Credit	5
NONREVSL	Credit	5
CONSPI	Credit	2
DTCOLNVHFNM	Credit	5
DTCTHFNM	Credit	5
INVEST	Credit	5
HWI	Employment	2
HWIURATIO	Employment	2
CLF16OV	Employment	4
CE16OV	Employment	4
UNRATE	Employment	2
UEMPMEAN	Employment	2
UEMPLT5	Employment	4
UEMP5TO14	Employment	4

Table C.1 continued from previous page

Variable	Group	Transformation code
UEMP15OV	Employment	4
UEMP15T26	Employment	4
UEMP27OV	Employment	4
CLAIMSx	Employment	4
PAYEMS	Employment	4
USGOOD	Employment	4
CES1021000001	Employment	4
MANEMP	Employment	4
DMANEMP	Employment	4
NDMANEMP	Employment	4
SRVPRD	Employment	4
USTPU	Employment	4
USTRADE	Employment	4
USFIRE	Employment	4
USGOVT	Employment	4
AWOTMAN	Employment	2
CES0600000008	Employment	5
CES2000000008	Employment	5
CES3000000008	Employment	5
FEDFUNDS	Interest Rates	2
CP3Mx	Interest Rates	2
TB3MS	Interest Rates	2
TB6MS	Interest Rates	2
GS1	Interest Rates	2
GS5	Interest Rates	2
GS10	Interest Rates	2
AAA	Interest Rates	2
BAA	Interest Rates	2
COMPAPFFx	Interest Rates	1
TB3SMFFM	Interest Rates	1
TB6SMFFM	Interest Rates	1
T1YFFM	Interest Rates	1
T5YFFM	Interest Rates	1
T10YFFM	Interest Rates	1
BAAFFM	Interest Rates	1
EXSZUSx	Interest Rates	4
EXJPUSx	Interest Rates	4

Table C.1 continued from previous page

Variable	Group	Transformation code
EXUSUKx	Interest Rates	4
EXCAUSx	Interest Rates	4
DPCERA3M086SBEA	Other	4
CMRMTSPLx	Other	4
RETAILx	Other	4
AMDMNOx	Other	4
ANDENOx	Other	4
AMDMUOx	Other	4
BUSINVx	Other	4
ISRATIOx	Other	2
UMCSENTx	Other	2
RPI	Output	4
W875RX1	Output	4
INDPRO	Output	4
IPFPNSS	Output	4
IPFINAL	Output	4
IPCONGD	Output	4
IPDCONGD	Output	4
IPNCONGD	Output	4
IPBUSEQ	Output	4
IPMAT	Output	4
IPDMAT	Output	4
IPNMAT	Output	4
IPMANSICS	Output	4
IPFUELS	Output	4
CUMFNS	Output	2
WPSFD49207	Prices	5
WPSFD49502	Prices	5
WPSID61	Prices	5
WPSID62	Prices	5
OILPRICEx	Prices	5
PPICMM	Prices	5
CPIAUCSL	Prices	5
CPIAPPSL	Prices	5
CPITRNSL	Prices	5
CPIMEDSL	Prices	5
CUSR0000SAC	Prices	5

Table C.1 continued from previous page

Variable	Group	Transformation code
CUSR0000SAD	Prices	5
CUSR0000SAS	Prices	5
CPIULFSL	Prices	5
CUSR0000SA0L2	Prices	5
CUSR0000SA0L5	Prices	5
PCEPI	Prices	5
DDURRG3M086SBEA	Prices	5
DNDGRG3M086SBEA	Prices	5
DSERRG3M086SBEA	Prices	5
S&P 500	Stock Market	4
S&P: indust	Stock Market	4
S&P div yield	Stock Market	2
S&P PE ratio	Stock Market	4

D Reflection on Internship at ELCON

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

D.1 Balancing Internship and Student Work

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

D.2 Presenting Research to Non-technical Peers

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.