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A forecasting framework for core domestic banks in Malta

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A forecasting framework for core domestic banks in Malta*

Michele Andreani[†]

WP/05/2024

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The views expressed in this paper are the author's own and do not necessarily reflect the views of the Central Bank of Malta. Correspondence: publicrelations@centralbankmalta.org.

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Abstract

This study develops a framework for forecasting selected balance sheet items of the four largest Maltese core banks, with a particular emphasis on bank profitability. Methodologically, it employs two multivariate time series models, namely a Factor-Augmented VAR (FAVAR) and a Bayesian VAR (BVAR). These models are estimated using macroeconomic series alongside a novel bank-level dataset for selected Maltese core banks compiled by merging data from various sources. Forecasting accuracy is assessed through in-sample forecast evaluation across various data sub-samples. This paper also discusses how these models are used to compute forecasts conditional on a given path for selected macroeconomic variables, providing a comprehensive profitability outlook for the Maltese core banking sector.

Key findings are summarized as follows: (i) neither of the two models exhibits a distinct superiority in forecasting performance, yet both demonstrate relative strengths when compared with a naive forecasting model in-sample, (ii) both models generate similar out-of-sample forecasts for the period 2023Q4 – 2025Q4.

JEL Classification: C32, C53, G17, G21

Keywords: Time-series forecasting, profitability, core banks

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1 Introduction

This paper builds a framework to forecast balance sheet items of Maltese core banks, focusing specifically on bank profitability. The motivation for this investigation arises from the considerable size of these banks, their dominant role in lending and providing core financial services, and their importance in ensuring the functioning of the Maltese economy. To achieve this objective, I employ a Factor-Augmented Vector Autoregression (FAVAR) and a Bayesian Vector Autoregression (BVAR) to produce forecasts for both individual bank-specific and *aggregate* selected core banks' balance sheets. The two models offer valuable insights into the major Maltese banks, and links with the real economy. Furthermore, this study introduces a novel time series dataset for Maltese core banks, obtained through data collection and integration from various internal sources. This process was essential to acquire a longer time sample by merging historical data with more recent observations. This dataset enables a comprehensive review of each institution's performance over the past two decades, encompassing time series for several bank balance sheet items.

The Maltese core banking sector represents the primary local banking entities in the country, holding assets collectively equivalent to 168% of the domestic GDP as of 2022. These institutions coexist with non-core and international banks; the former have domestic links, albeit limited compared to core banks, while the latter predominantly serve foreign individuals and businesses. During the global financial crisis, core banks experienced a decline in profitability, although this was less severe compared to the average decline in bank profits in the euro area ([Central Bank of Malta, 2017](#)). Despite adverse conditions over the last three years,¹ the core banking sector continues to exhibit resilience and sustained recovery, with a 27% profit growth in 2022 compared to the previous year, and an increasing trend in domestic lending. Deposits continue to constitute the primary funding source, financing more than 80% of overall core banks' assets ([Central Bank of Malta, 2023](#)). Figure 1 depicts the four selected core banks' share of loans to residents and total deposits as a fraction of core plus non-core banking sectors.²

Both the FAVAR and BVAR models used in this paper possess numerous shared characteristics, as elaborated below. However, the former generates forecasts that enable the examination of dynamics between banks' balance sheets (that is, bank-level forecasts), whereas the latter forecasts *aggregate* bank time series and provides a cross-check with the output from the FAVAR. Bayesian methods are used here to estimate probabilistic density forecasts, and to overcome short data samples.

A forecast evaluation exercise scrutinizes the prediction accuracy of the two models by comparing their projections with those derived from a Random Walk (RW) model. This comparison is conducted across numerous data subsamples and forecast horizons. Finally, the two proposed models are used to generate out-of-sample forecasts conditional on macroeconomic projections for the period 2024-2025. To ensure comparability between the two models, I also *aggregate* the forecasts from the FAVAR, for direct comparison with those from the BVAR. As a key result,

¹Such as the Covid-19 pandemic, the monetary policy tightening subsequent to the recent surge in inflation, and bank-specific events have profoundly impacted the overall profitability of core banks.

²As it will be described shortly, this study focuses on four domestic core banks.

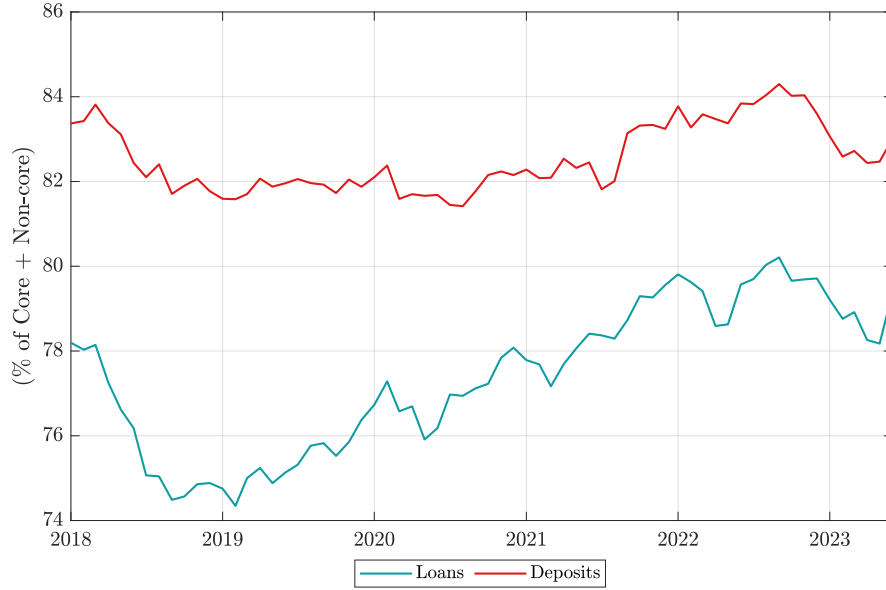


Figure 1: Share of selected core banks' loans to residents and total deposits, as fraction of core plus non-core banking sectors.

Source: Central Bank of Malta, author's calculation.

neither of the two models is superior in terms of forecasting accuracy; nonetheless, both models exhibit promising in-sample results. Finally, the out-of-sample conditional forecasting exercise results in a banking outlook for core banks in Malta for the upcoming two years. Hence, the models developed in this paper are beneficial for informing policy-making regarding financial stability.

The organisation of the paper is as follows: section 2 presents a review of related literature on bank profitability, while section 3 describes the data which is used in the estimation of the models. Section 4 introduces the models and the employed methodology. Section 5 contains results from both forecasts evaluation and out-of-sample conditional forecasting. Section 6 concludes the paper.

2 Brief literature review on bank profitability

The literature review by [Jayasekara et al. \(2020\)](#) highlights the role of profits in determining bank performance, beside other factors such as bank size, equity ratios, and type of loans. Profitable banks are also a symptom of less efficient financial markets, and scarce competition between banks may ensure higher net interest margins ([Demirguc-Kunt and Huizinga, 2000](#)). Other works consolidated the linkage between banking sector profitability and financial stability. [Aspachs et al. \(2006\)](#) associate a decrease in bank profits with a more financially-fragile economy, signalling deteriorating financial conditions. According to [European Central Bank \(2016\)](#), the relationship between profit deterioration and financial fragility has strengthened in more recent

times. [Teng et al. \(2019\)](#) further support the importance of bank profitability in shaping risks in the financial system, with bank profits playing a role in mitigating systemic risk by providing capital buffers and reducing risk-taking.

Although there is consensus that accomodating monetary conditions would stimulate positive banking performance, evidence suggests that these also produce negative *side effects* such as the declining of bank interest margins ([Bank for International Settlements, 2012](#); [Borio et al., 2017](#)). This turns out to be proportional to the operational efficiency of a given bank, that is, less beneficial for banks which incur higher costs ([Altavilla et al., 2018](#)). In a similar manner, monetary tightening would contract bank profits on average, provoking sharp declines in the return on equity (RoE) and the return on assets (RoA), albeit a large amount of deposits can buffer such aftermath by raising interest rate spreads ([Zimmermann, 2019](#); [European Central Bank, 2023](#)).

Other international studies have utilized bank-level data in conjunction with aggregate macro-financial series for macroeconomic analysis. For instance, [Jimborean and Méesonniér \(2010\)](#) estimate a Dynamic Factor Model (DFM) using a comprehensive bank balance sheet dataset for French banks, demonstrating that such variables are valuable in explaining macroeconomic fluctuations and the transmission of monetary policy shocks. Additionally, [Jokipii and Monnin \(2013\)](#) conduct a large panel VAR analysis, illustrating how financial conditions of the banking system contain valuable information for generating output growth forecasts. However, [Guerrieri and Welch \(2012\)](#) questioned the efficiency of banks' performance forecasts, particularly when based on macroeconomic indicators employed in stress testing exercises; results highlight large forecasting uncertainty, suggesting that bank forecasts are not sensitive to macroeconomic scenarios.

Previous research related to the Maltese banking sector has analysed banks' heterogeneity in generating profits ([Camilleri, 2005](#)), and the significance of real activity cycles in determining banking activity performance ([Attard, 2014](#)). Considering the publication dates of these works, it is advisable to conscientiously review the lessons drawn and consider them as a foundation for potential enhancements in future research endeavours.

3 Data

This analysis employs key macroeconomic variables and confidential bank-level time series data to capture the interaction between real macroeconomic aggregates for both Malta and the euro area, along with bank-level information specific to Maltese core banks included in the sample. Table 1 lists all the variables used to estimate the models, together with the transformation applied. Subsequent sections delve into the details of the two datasets employed in the analysis.

3.1 Macroeconomic block

The macroeconomic block utilized in the models comprises real GDP and real house prices for Malta, real GDP and the Harmonized Index of Consumer Prices (HICP) for the euro area, the monetary policy stance (measured by the Shadow Short Rate, as per [Krippner, 2020](#)), and the

Variable	Transformation
MACROECONOMIC DATA	
Real GDP (MT)	Year-on-year growth rate
Real house prices (MT)	Property Prices Index based on Advertised Prices, deflated by HICP (MT), % change from previous year
Real GDP (EA)	Year-on-year growth rate
HICP (EA)	Index, % change from previous year
Short Shadow Rate (SSR)	Level, quarterly average
Interest rate spread	Level, quarterly average of differential between lending rate and deposit rate (weighted average)
BANK-LEVEL DATA	
Return-on-Assets (ROA)	Ratio between profits before tax (4QMS) and total assets
Interest income	Year-on-year growth rate
Interest expense	Year-on-year growth rate
Total loans to residents	Year-on-year growth rate
Total assets	Year-on-year growth rate
Total deposits	Year-on-year growth rate
Capital plus Reserves	Year-on-year growth rate

Table 1: Macroeconomic and bank-level time series.

Sources: [DBnomics](#), [LJK macro finance analysis](#), Central Bank of Malta, author’s calculations.

Note: each variable within the BANK-LEVEL DATA section corresponds to four core banks’ time series. 4QMS = four quarters moving sum of flows.

Interest Rate Spread.³ The latter is computed as the difference between the average interest rate on loans and deposits, serving as a proxy for the interest rate margin for core banks. The objective is to monitor the dynamics between the real sectors of both the Maltese and euro area economies, in addition to assessing the stance of conventional and unconventional monetary policy, and the differential between core banks’ lending and borrowing rates. All series are in quarterly frequency, with sample ranging from 2006Q4 to 2023Q3.⁴ Figure 2 depicts the macroeconomic *block* of the model.

3.2 Bank-level data

Confidential bank-level data serves as a valuable resource for delineating bank-specific characteristics. This dataset is collected at the individual bank-level for the Maltese core banks and includes key balance sheet variables essential for determining the overall profitability of banks. Only four core banks out of six are considered in this study, as for two of these banks the data are available only for a shorter time period, which is not ideal for the estimation of a model. To rely on a longer time interval, such time series are the result of joining data from two internal data repositories at the Central Bank of Malta, with sample starting on 2006Q4. Banks’ financial statements are provided following the *Guidelines and instructions for the reporting of the*

³An earlier version of this study also incorporated the Harmonized Index of Consumer Prices (HICP) for Malta, which did not significantly enhance the forecasting accuracy of the models.

⁴I consider macroeconomic data starting from 2006Q4, as this aligns with the first observation available for bank-level data, as explained in the next section.

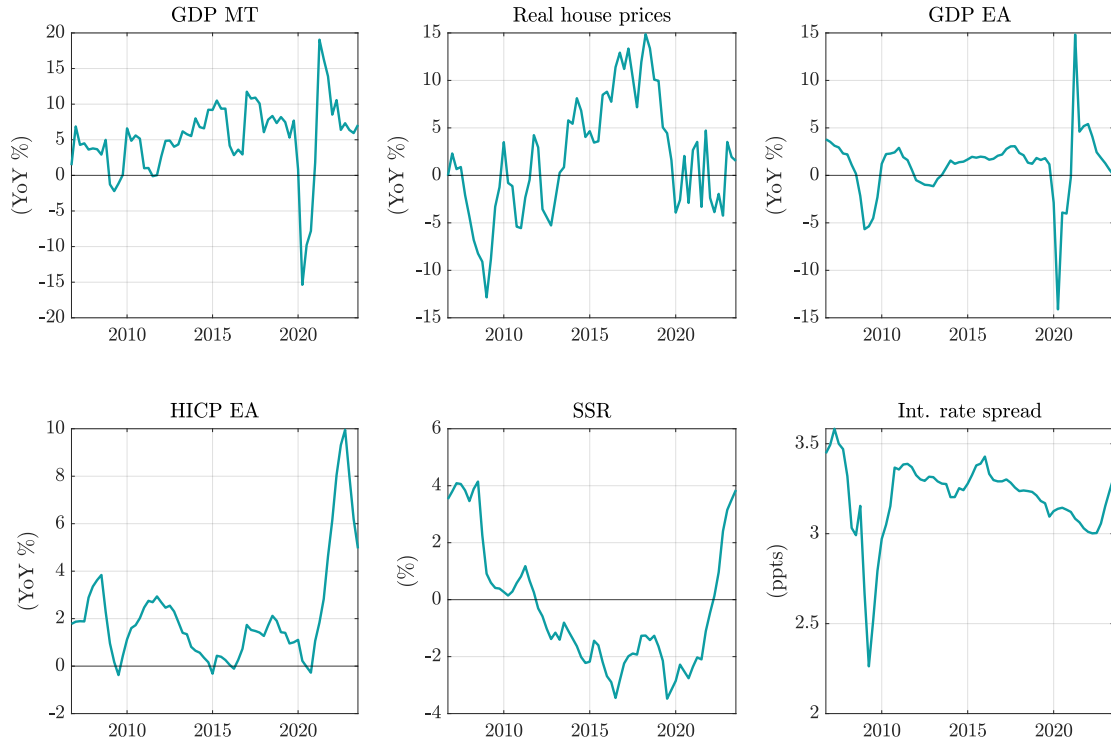


Figure 2: Macroeconomic series used in models' estimation.

Sources: [DBnomics](#), [LJK macro finance analysis](#), [Central Bank of Malta](#), author's calculations.

*Banking Rule No. 6 (BR06) schedules.*⁵

This data block, which will be further treated with data dimensionality reduction, relies on time series for profitability, interest income and expenses, loans, deposits, assets, and capital plus reserves. Bank profitability in this context is calculated as the ratio of profits before tax (computed as a four-quarter moving sum of flows) to total assets, which can be conveniently interpreted as Return-on-Assets (ROA). Additionally, I incorporate time series data for interest income and expenses in this dataset to also monitor the amount of Claims on the Central Bank of Malta (and other Central Banks). As outlined in [Central Bank of Malta \(2023\)](#), placements with the Central Bank remain a substantial component of core banks' assets. Therefore, these have recently emerged as a determinant component driving interest income and, consequently, banks' earnings.

⁵Data collection by the Central Bank of Malta is fulfilled by virtue of Article 23 of the Central Bank of Malta Act (Cap. 204).

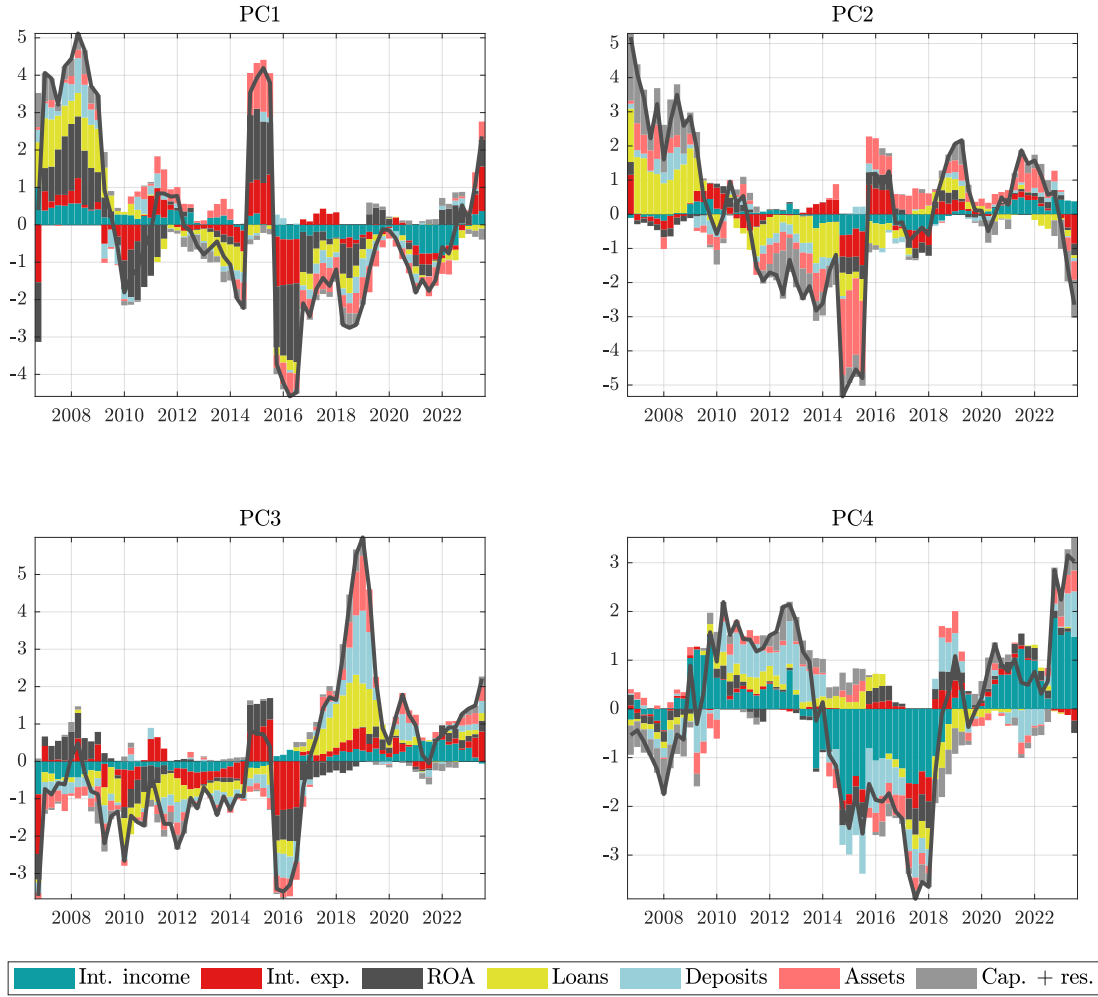


Figure 3: Bank-level factors and balance sheet items' contributions.

Notes: black solid line depicts the bank-level factors, coloured bars depict contributions from selected bank balance sheets. Int. income = Interest income, Int. exp. = interest expense, ROA = Return-on-Assets, Cap. + res. = Capital plus reserves.

3.3 Bank-level factors

Given the large number of bank-level time series to enter into the VAR model, I employ Principal Components Analysis (PCA) to reduce data dimensionality. The extracted factors are subsequently used as regressors in the FAVAR model. This method is frequently employed when researchers seek to condense information from an extensive time series dataset into a few essential indicators. These *factors*, serving as statistical benchmarks for selected core banks' conditions, are pivotal for this econometric modelling purposes. As detailed in section 4.3, such factors will be estimated across a variety of subsamples. Table A.1 and Figure A.1 provide

further details. When estimated over the entire sample, the first four components cumulatively represent 61% of the dataset’s cumulative explained variance.

The estimated bank-level principal components are depicted in Figure 3, along with contributions from each aggregate balance sheet item. It is evident that the ROA is a significant factor driving the first principal component, which accounts for 20% of the explained variance in the dataset, in conjunction with Interest Income and Interest Expense. The remaining principal components capture varied contributions from all other bank balance sheets, except for the fourth factor, where Interest Income emerges as a major contributor.⁶

4 Methodology

This study proceeds by describing the adopted methodology. I utilize a Bayesian FAVAR and a BVAR to forecast selected core banks’ profitability and key balance sheet items. These two models offer distinct perspectives on the core banks’ environment: while the BVAR, despite being less computationally intensive, is estimated for and produces forecasts for aggregates, the FAVAR enables the examination of bank-level projections, that is, forecasts for each bank balance sheet included in the dataset. Such models have been extensively employed to generate short-term forecasts for various macroeconomic applications in numerous empirical studies.⁷ Both models are equipped with an identical macroeconomic block, with the main difference in the transformation applied to bank-level data.

4.1 The FAVAR

In this application the raw data matrix \mathbb{Y}_t , as described in Table 1, is divided in two subsets:

$$\mathbb{Y}_t = \begin{bmatrix} \mathbb{Y}_t^M & \mathbb{Y}_t^B \\ (T \times N_Y) & (T \times N_B) \end{bmatrix}$$

where \mathbb{Y}_t^M contains macroeconomic variables (directly included into the VAR models), and \mathbb{Y}_t^B contains bank-level data which is used to extract *factors*. Let the number of observations be denoted by T . The number of macroeconomic and bank-level time series is represented by N_Y and N_B , respectively.⁸ A dynamic factor model is chosen to model bank-level data \mathbb{Y}_t^B ,

$$\mathbb{Y}_t^B = \underset{(T \times N_F)}{\mathbb{F}_t} \times \underset{(N_F \times N_B)}{\Lambda} + \underset{(T \times N_B)}{w_t}, \quad (1)$$

⁶This graphical output aids in determining the main balance sheet components driving the overall dynamics of banking *factors*, although a formal economic interpretation cannot be attached.

⁷Interested readers are directed to [Stock and Watson \(2016\)](#) for a comprehensive review of both methods and seminal empirical applications for FAVARs and DFMs. Additionally, [Koop and Korobilis \(2010\)](#) extensively discuss forecasting with Bayesian VARs.

⁸Note that $N_B > N_Y$, and $N_B + N_Y = N$, which is the total number of time series in the dataset.

where \mathbb{F}_t is the matrix of $N_F = 4$ estimated *bank-level factors*, Λ is the factor loading matrix, and w_t is the matrix of idiosyncratic error terms.

The FAVAR(p) model, then, is as follows:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \quad (2)$$

$$\varepsilon_t \stackrel{N}{\sim} i.i.d.(0, \Sigma_\varepsilon), \quad (3)$$

where $y_t = \begin{bmatrix} \mathbb{Y}_t^M & \mathbb{F}_t \end{bmatrix}$ is the matrix containing endogenous variables, Φ_0 is a vector of constants, Φ_k with $k = 1, \dots, p$ are autoregressive parameters matrices, and ε_t is the matrix of shocks. The model is estimated using Bayesian methods, assuming a Minnesota prior distribution for the VAR coefficients. In this manner, I impose *block exogeneity* on equations concerning euro area variables, under the assumption that domestic variables neither have contemporaneous nor lagged effects on the euro area block. Further details on the prior are in Appendix B. The model is estimated using Gibbs sampling with 30,000 replications, discarding the initial 6,000 draws, and employing a lag order of $p = 4$.⁹ The distributions of estimated coefficients are then utilized to generate one-year (four quarters) forecasts for endogenous variables.

4.2 The BVAR

This work also employs a small scale Bayesian VAR model for forecasting purposes. The model follows the same set of equations as in (2) and (3), and uses the same macroeconomic block. In this case, data used to estimate the BVAR is $y_t = \begin{bmatrix} \mathbb{Y}_t^M & \mathbb{Y}_t^{A.B.} \end{bmatrix}$, where $\mathbb{Y}_t^{A.B.}$ consists in *aggregate* bank-level data for ROA, loans, and deposits. Such data is summarized as follows:

- ROA is the weighted average of bank-level Return-on-Assets, where the weight is the share of total assets for each core bank,
- Loans and deposits are the year-on-year growth rate of the sum of loans and deposits across banks, respectively.

The decision to include only three aggregate bank-level series in the BVAR model is driven by the limited sample length, which is inadequate for estimating a larger model. The prior distribution for the BVAR coefficients, the number of lags, and the forecast horizon are identical to those used in the FAVAR, along with the block exogeneity and Gibbs sampling settings. The main distinction lies in the vector of endogenous variables used in the BVAR.

4.3 Forecasting evaluation

To evaluate the predictive accuracy of the two models, I conduct in-sample unconditional forecasts and subsequently compare them with the observed data,¹⁰ to obtain a metric to quantify forecast errors.

⁹Moreover, only stationary draws are retained throughout the Gibbs sampling algorithm.

¹⁰At this point, unconditional forecasting is conducted due to the challenge of accessing all required data vintages necessary if *conditional* forecasting were to be employed.

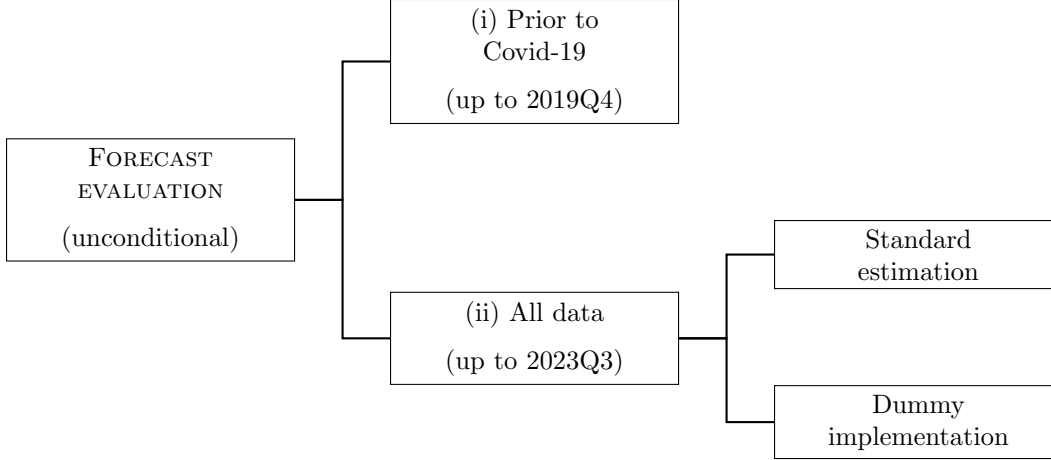


Figure 4: Forecast evaluation procedure.

The forecast evaluation exercise is described by the scheme depicted in Figure 4. In this initial empirical analysis, the models are estimated using data from 2006Q4 to 2017Q4, forecasting for the period from 2018Q1 to 2018Q4. Subsequently, the estimation process iterates, gradually incorporating additional observations into the sample.¹¹ This iterative process continues until reaching the following forecast horizons: (i) up to the year preceding the Covid-19 pandemic (2019Q1 - 2019Q4) and (ii) encompassing all available data (2022Q4 - 2023Q3). This iterative approach serves to evaluate forecasting performance prior to the onset of the Covid-19 pandemic, as subsequent years exhibit significant volatility across most macroeconomic indicators, which can potentially impact the forecasting performance of the two models (Lenza and Primiceri, 2022). A graphical representation of the rolling estimation procedure is provided in Figure 5.

For each rolling estimation, I compute Forecast Errors (F.E.) across the one to four-steps ahead forecasts:

$$\text{F.E.}_{T+h} = y_{T+h}^* - \hat{y}_{T+h}^{\text{VAR}}, \quad h = 1, \dots, 4 \quad (4)$$

where y_{T+h}^* is actual data at forecast horizon h , to further obtain the Root Mean Square Error (RMSE) across forecast horizons and rolling samples,

$$\text{RMSE}_{T+h}^{\text{VAR}} = \sqrt{\frac{1}{n} \sum_{i=1}^n \text{F.E.}_{T+h}^i}, \quad (5)$$

where n is the number of rolling estimations.¹² This metric provides a valuable assessment of

¹¹Given that bank factors are estimated at each iteration, Figure A.1 illustrates the fraction of variance explained by the four factors at each rolling estimation.

¹²Note that n increases as additional observations are incorporated for model estimation. For the full sample rolling estimation, the exercise comprises $n = 20$ rolling samples.

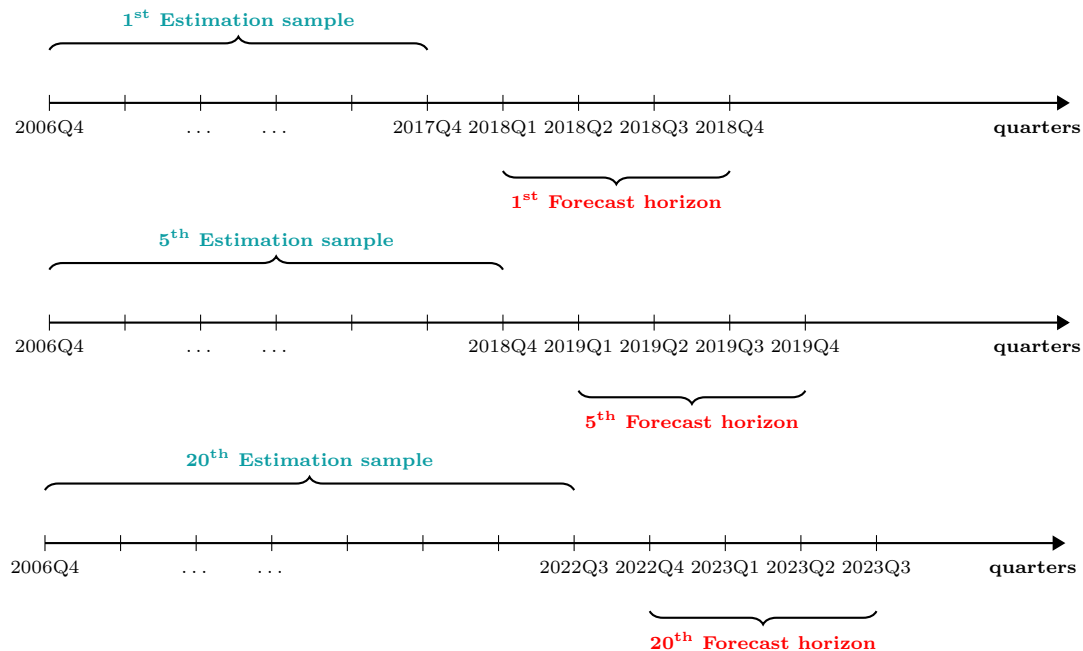


Figure 5: Forecasting evaluation using rolling estimation.

Note: the first two horizontal time lines represent rolling estimations prior to Covid-19, while the third one depicts the 20th rolling estimation, which includes the entire dataset.

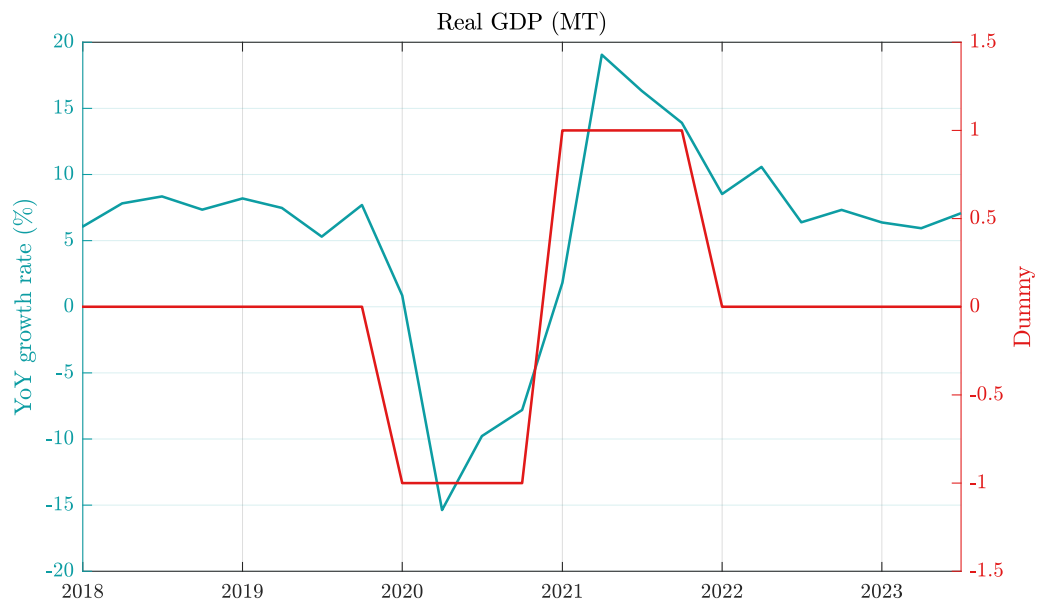


Figure 6: Dummy variable d_t implementation.

average forecasting accuracy at forecast horizon h across all estimation iterations. However, to enhance the validation of this measure, I conduct a comparison between the forecasting accuracy of the VAR models and a naive benchmark model, namely the Random Walk (RW). Consequently, I compute both Forecast Errors (F.E. $_{T+h}$) and Root Mean Square Errors (RMSEs), as outlined in equations (4) and (5), respectively, for the RW model.

Finally, the Relative RMSE is defined as the ratio between the RMSEs obtained from the VAR and the RW, respectively:

$$\text{Relative RMSE} = \frac{\text{RMSE}_{\text{VAR}}}{\text{RMSE}_{\text{RW}}}, \quad (6)$$

where, according to this formula, a value smaller than one suggests the proposed model is able to predict better than the RW, *on average*.

This procedure is valuable for assessing how the forecasting accuracy is impacted by the Covid-19 pandemic. To further investigate this assessment, I also estimate the two models incorporating a dummy variable d_t , primarily to account for the contraction and subsequent recovery from the Covid-19 pandemic.¹³ Note that d_t takes on the following values:

$$d_t = \begin{cases} -1, & \text{if } t \in (2020\text{Q1}, 2020\text{Q4}) \\ +1, & \text{if } t \in (2021\text{Q1}, 2021\text{Q4}) \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

More precisely, the dummy variable takes on a negative value during the contractionary phase of the pandemic and a positive value during the recovery period. When the dummy variable equals zero, it indicates that there is no discernible impact from the Covid-19 pandemic. Figure 6 depicts the shape of d_t .

4.4 Conditional out-of-sample forecasting

Building on the foundational study by Waggoner and Zha (1999), this section describes how the models outlined in Section 4 can forecast banking sector scenarios conditional on the future values of certain macroeconomic indicators or instruments such as the policy rates. Thus far, both the FAVAR and the BVAR have generated in-sample unconditional forecasts. With this additional setup, the models are equipped to provide out-of-sample predictions of selected core banks' balance sheet items, contingent upon the projected macroeconomic scenario and the monetary policy stance.

Macroeconomic projections, at both national and international level, serve as a suitable source of conditioning paths and can be utilized as valuable inputs for multivariate time series models (Robertson and Tallman, 1999). Specifically, I incorporate macroeconomic projections for Malta (real GDP, real house prices), the euro area (real GDP, HICP inflation), and the monetary policy stance (SSR), to estimate the outlook for the core banks included in the sample.

¹³The implementation of the dummy variable is expected to enhance forecasting accuracy for variables characterized by exceptional volatility during the onset of the Covid-19 pandemic, such as real GDP for both Malta and the euro area.

Variable	Source
Real GDP (MT)	CBM projections
Real house prices (MT)	CBM projections
Real GDP (EA)	ECB projections, Dec 2023
HICP inflation (EA)	ECB projections, Dec 2023
Short Shadow Rate (SSR)	Capital market, short-term forecasts

Table 2: Macroeconomic conditioning paths, projection horizon 2023Q4 – 2025Q4

Sources: Central Bank of Malta, Economic Analysis Department; [ECB Macroeconomic projections](#); [LJK macro finance analysis](#); ECB Data Portal.

Note: all conditioning paths are in quarterly frequency.

Such projections extend from 2023Q4 to 2025Q4, consisting in a two-year macroeconomic outlook. Table 2 describes the conditioning paths used to estimate conditional forecasts, alongside with data sources; more details on the conditioning paths are attached in section 5.2.

F. hor	GDP MT	House prices	GDP EA	HICP EA	SSR
1	0.79	1.14	1.29	1.10	1.13
2	0.67	0.84	1.47	1.29	1.35
3	0.81	0.53	1.58	1.27	1.29
4	0.83	0.39	1.79	1.08	1.30
	Spread	PC1	PC2	PC3	PC4
1	2.19	1.09	1.16	1.71	1.41
2	1.28	0.73	0.95	1.54	1.23
3	1.09	0.54	0.86	1.53	1.11
4	0.70	0.53	0.78	1.53	0.96

Table 3: Relative RMSE, FAVAR, in-sample unconditional forecasts, pre-pandemic sample.

Notes: every entry represents an average over $n = 5$ forecast paths.

5 Results

In this section, I present the primary estimation results of the models. These include in-sample forecasting evaluation and out-of-sample conditional forecasts from both the FAVAR and the BVAR. Empirical findings are summarized as follows: section 5.1 encompasses the results of the forecast evaluation, while section 5.2 outlines the banking outlook for the core banks included in the sample.

5.1 Forecast evaluation

For practical purposes, the output presented in this section is divided into two parts: (i) using data that excludes the Covid-19 pandemic, and (ii) up to the most recent available observation (2023Q3). From this point onward, the results consist of figures illustrating forecast distributions and tables containing Relative RMSEs, where values smaller than one are highlighted in red. Each figure showcases the actual series, the median forecast (alongside the 68% forecast credible set), and the RW forecast. Moreover, a vertical dotted black line is utilized to denote the end of the estimation sample.

5.1.1 Estimation prior to Covid-19 pandemic

Table 3 presents the Relative RMSEs statistics derived from the FAVAR model pertaining to the first stage of the forecast evaluation exercise.¹⁴ The model’s predictions exhibit relative accuracy for Maltese GDP and real house prices, as well as for the first two bank factors. Additionally, forecasts for the interest rate spread and the last principal component tend to be more accurate in the longer run, that is, four steps ahead. However, for euro area real GDP, HICP and the SSR, the RW model provides more accurate forecasts.

The primary advantage of adopting a FAVAR model is the ability to obtain projections for all the variables employed in estimating banking factors, thereby providing forecasts at bank-level. It can be seen by examining Table 4, which contains Relative RMSEs for bank balance sheet

¹⁴Rolling estimation is conducted $n = 5$ times using data that excludes observations from the Covid-19 pandemic.

F. hor	ROA Bank 1	ROA Bank 2	ROA Bank 3	ROA Bank 4
1	2.23	0.96	4.38	1.48
2	2.09	1.03	2.12	1.49
3	1.91	0.89	1.74	1.50
4	1.72	0.82	1.53	1.43
	Int. income Bank 1	Int. income Bank 2	Int. income Bank 3	Int. income Bank 4
1	1.84	1.01	1.98	0.85
2	1.71	0.86	2.68	0.91
3	1.64	0.73	2.60	1.11
4	1.59	0.57	1.05	1.16
	Int. exp. Bank 1	Int. exp. Bank 2	Int. exp. Bank 3	Int. exp. Bank 4
1	1.03	0.98	1.19	3.54
2	0.57	0.89	0.57	2.84
3	0.50	0.76	0.57	1.90
4	0.56	0.60	0.63	1.02
	Loans Bank 1	Loans Bank 2	Loans Bank 3	Loans Bank 4
1	1.41	1.68	2.33	1.42
2	1.46	2.33	1.82	2.04
3	1.36	3.02	1.41	1.44
4	1.18	1.30	1.25	1.35
	Deposits Bank 1	Deposits Bank 2	Deposits Bank 3	Deposits Bank 4
1	0.53	1.52	1.91	2.52
2	0.72	1.23	1.76	1.91
3	0.85	1.07	1.88	1.43
4	0.93	0.94	1.78	0.98
	Assets Bank 1	Assets Bank 2	Assets Bank 3	Assets Bank 4
1	0.59	0.68	1.84	1.71
2	0.75	0.62	2.45	1.51
3	0.85	0.71	3.46	1.11
4	0.92	0.75	2.68	0.89
	Cap. + res. Bank 1	Cap. + res. Bank 2	Cap. + res. Bank 3	Cap. + res. Bank 4
1	1.60	1.04	0.88	1.19
2	1.41	0.91	0.85	1.07
3	0.72	0.76	1.03	1.16
4	0.71	0.62	1.00	1.06

Table 4: Bank-level Relative RMSE, in-sample unconditional forecasts, pre-pandemic sample.

Note: every entry represents an average over $n = 5$ forecast paths. ROA = Return-on-Assets, Int. income = Interest income, Int. exp. = interest expense, Cap. + res. = Capital plus reserves.

F. hor.	GDP MT	House prices	GDP EA	HICP EA	SSR	Spread	ROA	Loans	Deposits
1	0.60	1.11	0.85	0.90	0.94	3.21	1.01	0.74	1.09
2	0.71	0.93	0.85	0.80	0.92	2.06	1.12	0.91	1.00
3	1.02	0.68	0.82	0.73	0.96	1.08	1.18	1.13	0.77
4	0.76	0.50	0.76	0.62	0.95	0.73	1.06	1.18	0.88

Table 5: Relative RMSE, BVAR, in-sample unconditional forecasts, pre-pandemic sample.

Notes: every entry represents an average over $n = 5$ forecast paths.

F. hor	GDP MT	House prices	GDP EA	HICP EA	SSR
1	0.93	1.01	1.06	1.17	1.01
2	0.86	1.19	0.99	1.27	1.05
3	0.79	1.17	0.95	1.26	1.08
4	0.72	1.02	0.97	1.17	1.09
	Int. rate spread	PC1	PC2	PC3	PC4
1	2.57	1.03	1.11	1.35	1.30
2	1.90	0.88	1.03	1.29	1.18
3	1.86	0.85	0.96	1.32	1.09
4	1.66	0.90	0.87	1.31	1.05

Table 6: Relative RMSE, FAVAR, in-sample unconditional forecasts, full sample.

Notes: every entry represents an average over $n = 20$ forecast paths.

items projections prior to the Covid-19 pandemic, which have been anonymised into Bank 1, Bank 2, etc. As indicated by the red entries in the table, the forecasting outcomes are promising for many bank balance sheet items. The FAVAR is able to predict on average better than the Random Walk balance sheets for the first two banks, especially interest expense, deposits, and assets.

Table 5 depicts the output from the BVAR model. Relative RMSEs are frequently lower than one, indicating that the BVAR model outperforms the RW for several variables and across various forecast horizons. Specifically, the model generates relatively accurate forecasts for the entire macroeconomic block, with exceptions noted for the interest rate spread, and occasionally for loans and deposits from the core banks' perspective.

5.1.2 Full sample estimation

Incorporating all available data into the rolling estimation procedure augments the number of rolling estimations, leading to Relative RMSEs that reflect average values across $n = 20$ models. The additional observations correspond to the Covid-19 pandemic and the recent upsurge in inflation in the euro area, inevitably encompassing *extreme* values for real GDP growth for both Malta and the euro area, as well as inflation. Consequently, such data points have the potential to adversely impact the forecasting accuracy of the model (Lenza and Primiceri, 2022). Figures 7 and 8 depict the last rolling estimation for the FAVAR and the BVAR models, respectively, forecasting from 2022Q4 to 2023Q3.

As shown in Table 6, the average forecasting performance of the FAVAR diminished compared to the results presented in the previous section. Specifically, the accuracy in forecasting Maltese GDP growth is confirmed by values smaller than one at each forecast horizon, while

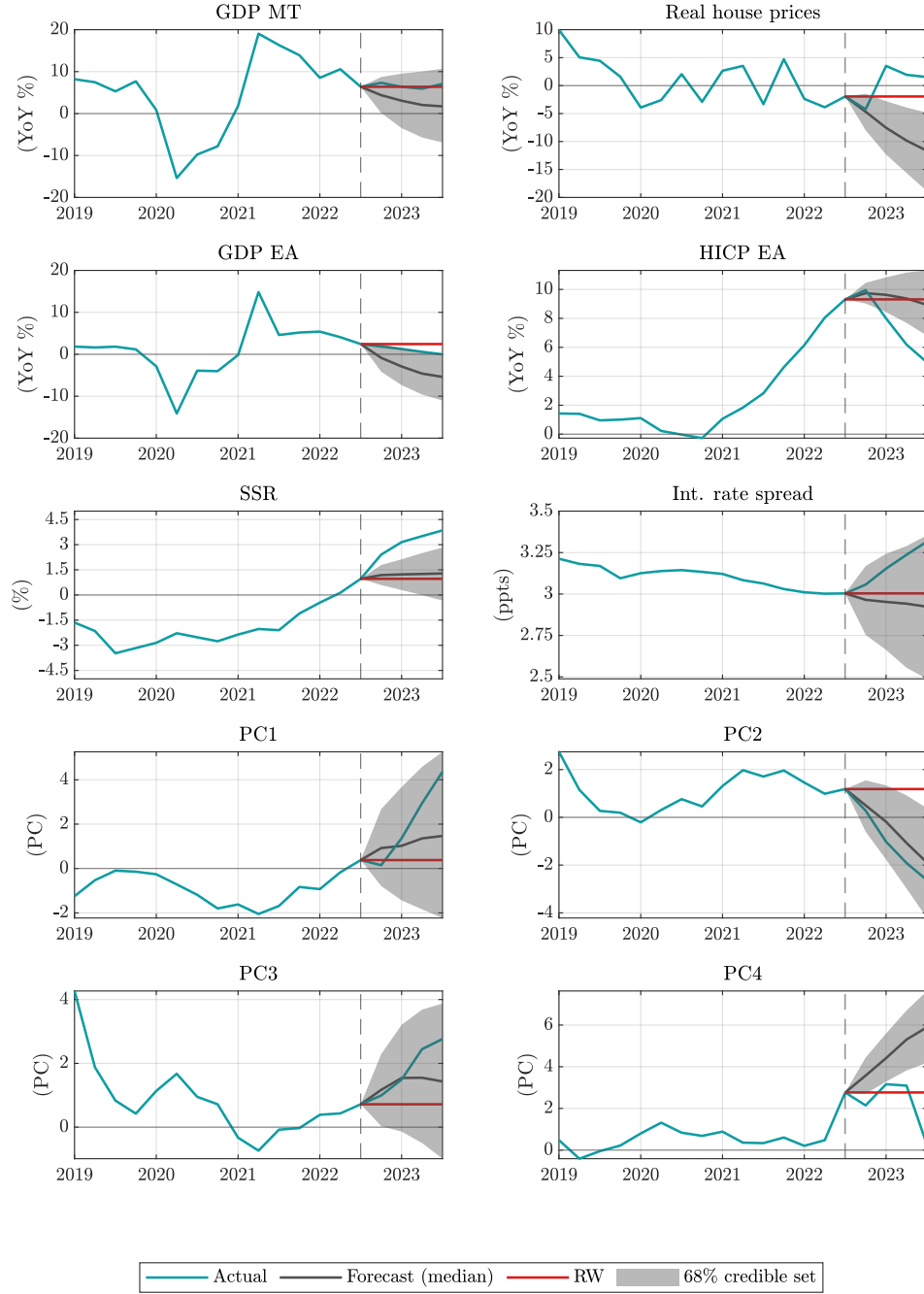


Figure 7: In-sample unconditional forecasts, FAVAR, forecast horizon 2022Q4 – 2023Q3.

F. hor	ROA Bank 1	ROA Bank 2	ROA Bank 3	ROA Bank 4
1	1.91	1.83	4.06	1.10
2	1.48	1.46	2.86	0.95
3	1.29	1.37	2.00	0.84
4	1.16	1.29	1.49	0.84
	Int. income Bank 1	Int. income Bank 2	Int. income Bank 3	Int. income Bank 4
1	1.92	1.06	2.30	1.12
2	1.61	0.93	1.02	0.96
3	1.51	0.85	0.65	0.96
4	1.28	0.79	0.70	0.91
	Int. exp. Bank 1	Int. exp. Bank 2	Int. exp. Bank 3	Int. exp. Bank 4
1	1.75	1.00	1.84	2.42
2	0.80	0.92	1.05	1.83
3	0.53	0.86	0.86	1.49
4	0.61	0.85	0.75	1.28
	Loans Bank 1	Loans Bank 2	Loans Bank 3	Loans Bank 4
1	1.36	1.30	2.35	1.17
2	1.25	0.87	1.55	0.99
3	1.20	0.86	1.17	0.97
4	1.04	1.02	1.06	0.99
	Deposits Bank 1	Deposits Bank 2	Deposits Bank 3	Deposits Bank 4
1	0.62	1.44	1.41	1.59
2	0.70	1.08	1.40	1.58
3	0.80	0.91	1.54	1.48
4	0.88	0.76	1.33	0.99
	Assets Bank 1	Assets Bank 2	Assets Bank 3	Assets Bank 4
1	0.67	0.78	1.41	1.50
2	0.75	0.60	1.58	1.55
3	0.82	0.67	1.93	1.41
4	0.88	0.69	1.75	1.08
	Cap. + res. Bank 1	Cap. + res. Bank 2	Cap. + res. Bank 3	Cap. + res. Bank 4
1	0.98	1.37	1.47	1.47
2	0.76	1.13	1.25	1.12
3	0.66	0.97	1.19	0.92
4	0.65	0.83	1.02	0.79

Table 7: Bank-level Relative RMSE, In-sample unconditional forecasts, full sample.

Notes: every entry represents an average over $n = 20$ forecast paths. ROA = Return-on-Assets, Int. income = Interest income, Int. exp. = interest expense, Cap. + res. = Capital plus reserves.

F. hor.	GDP MT	House prices	GDP EA	HICP EA	SSR	Spread	ROA	Loans	Deposits
1	0.94	1.03	0.93	1.00	0.94	2.91	1.17	1.46	1.65
2	0.88	1.23	0.87	1.05	0.93	2.42	1.25	1.41	1.54
3	0.81	1.22	0.82	1.08	0.94	2.24	1.33	1.44	1.29
4	0.71	1.12	0.80	1.07	0.96	2.10	1.32	1.81	1.03

Table 8: Relative RMSE, BVAR, in-sample unconditional forecasts, full sample.

Notes: every entry represents an average over $n = 20$ forecast paths.

the forecasting precision of the first two banking factors exhibits a decline compared to the RW. Furthermore, incorporating all available data improves forecasts for euro area GDP growth but worsens the forecasting accuracy for Maltese house prices. From a bank-level perspective, the model still produces positive outcomes pertaining to several bank balance sheets, as described in Table 7.

In particular, the FAVAR outperforms the RW for two specific banks' assets, deposits, and capital plus reserves; the most encouraging results come from both interest income and expense, which have the potential to explain bank earnings' dynamics.¹⁵ Regarding ROA, the FAVAR outperforms the RW just for a single bank; this result may be attributed to the inclusion of more recent data, which is characterized by increasing profit volatility across banks. As indicated in Table 8, it is evident that the average forecasting performance of the BVAR has diminished, although Relative RMSEs for real GDP (both Maltese and for the euro area) and the SSR maintained a value smaller than one at every forecast horizon. Moreover, Figure 8 provides forecasts for loans and deposits closely aligned with actual data, demonstrating reasonable forecasting accuracy.

5.1.3 Dummy implementation

In the last section, the rolling estimation encompassed all available data. The years involved in this analysis have been characterized by exceptional macroeconomic fluctuations and the implementation of restrictive monetary policy responses to the recent surge of inflation in the euro area. Specifically, attention is drawn to the significant contraction in GDP following the onset of the Covid-19 pandemic in 2020, followed by the subsequent recovery phase in 2021. It is reasonable to hypothesize that such observations may have influenced the forecasting performance of the models.

Therefore, in this section, I estimate both the FAVAR and the BVAR models incorporating a dummy variable d_t , as per equation (7) and Figure 6, to account for the pronounced volatility in real GDP growth resulting from the Covid-19 pandemic. The rolling forecasting procedure now commences in 2020Q1 and utilizes all available observations.

Tables displaying Relative RMSEs and Figures containing in-sample forecasts are appended in Appendix C. Here it is observed that the introduction of a dummy variable positively influenced the forecasting accuracy of real GDP for both Malta and the euro area, while no improvement is observed for the other endogenous variables. Furthermore, a similar outcome is

¹⁵As presented in Central Bank of Malta (2023), placements with the Central Bank still continue to represent a non-negligible portion of core banks' assets, thereby generating interest income.

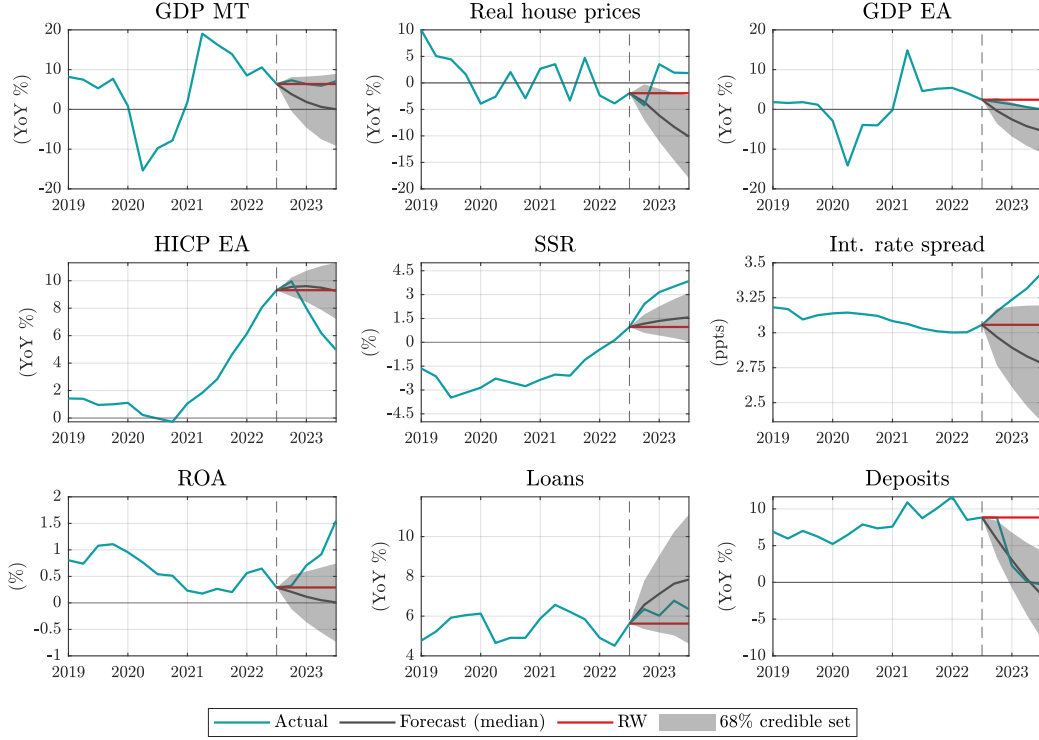


Figure 8: In-sample unconditional forecasts, BVAR, forecast horizon 2022Q4 – 2023Q3.

noted in bank-level forecasts, where predictive accuracy decreased across various balance sheet components and forecast horizons. This outcome aligns with the expectation that incorporating a dummy variable that mimics the dynamics of the business cycle during the pandemic may not capture other variables' dynamics. Hence, these findings confirm that Maltese real GDP is not particularly informative for forecasting bank-level variables, a result consistent with [Guerrieri and Welch \(2012\)](#).

5.2 Banking sector outlook

The final piece of empirical results entails the banking outlook for selected core banks in Malta, given the projected development of the overall macroeconomic scenario, presented in Figure 9. The banking outlook is forecasted based on a macroeconomic scenario in which HICP inflation for the euro area is projected to reach the target level of 2% by mid-2025. Moreover, the real estate market in Malta is expected to maintain its robust growth trajectory, resulting in a positive real house price growth. Additionally, it is assumed that the monetary policy stance will remain unchanged throughout 2024, with a potential easing anticipated in 2025.¹⁶ Thus,

¹⁶A common assumption made in conducting forecasting exercises for policy purposes is to presume that the policy rate will remain unchanged throughout the entire forecasting horizon. Here, I incorporate into the SSR the forecasts derived from the ECB Capital markets - short term interest rates - Winter, published in March

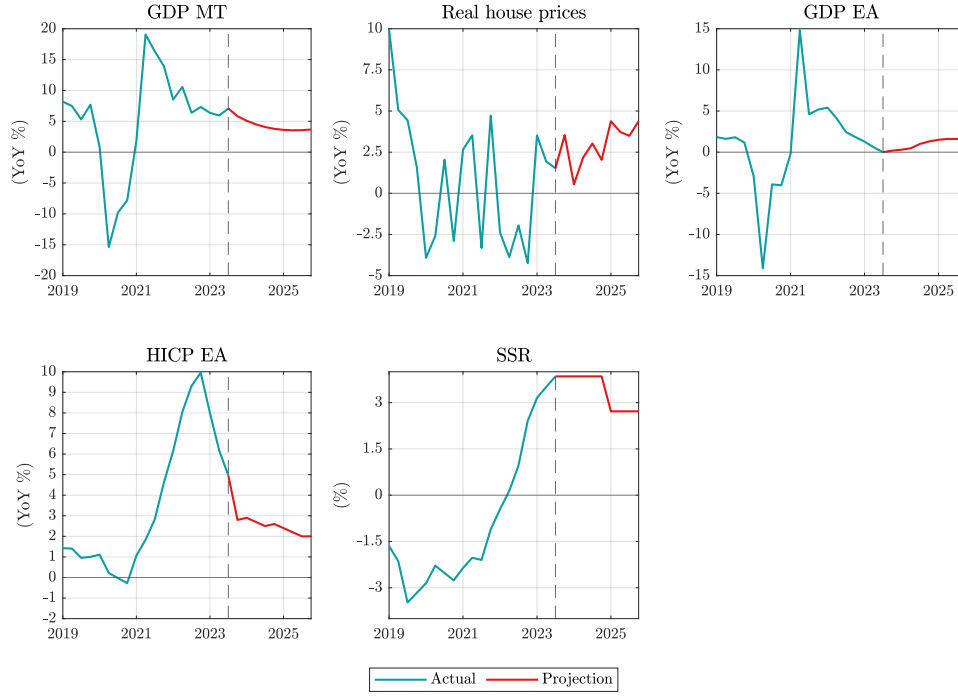


Figure 9: Macroeconomic projections, 2023Q4 – 2025Q4.

Note: lines in teal represent actual observations, macroeconomic projections as described in Table 2 are in red.

from 2024 onwards, Malta's GDP is forecasted to grow at a rate below 5%, indicating that the Maltese economy will continue to expand, albeit at a slower pace compared to the last two years.

Figure 10 illustrates the conditional forecasts from the two models, specifically comparing the outlooks for the sampled core banks provided by the FAVAR and the BVAR. Again, forecasts are presented only for explanatory purpose. The comparison between the two models' output aims to evaluate the extent to which they offer similar outlooks. To directly compare the bank-level forecasts with those obtained from the BVAR, I compute *aggregated* forecasts for the FAVAR, according to the procedure outlined in Section 4.2.

Both models forecast that profitability for the selected core banks will surpass the level recorded prior to the Covid-19 pandemic. Additionally, both loans and deposits are expected to experience growth over the forecast horizon, while the interest rate spread is projected to remain stable, although the FAVAR model predicts the spread to peak in 2025Q1. The credible sets largely overlap, except for deposits in the very short-term forecast horizon, indicating similar forecast uncertainty between the two models.

Both models predict a stable outlook for selected Maltese core banks for the next two years. Profitability is expected to exceed 2019 levels, while the interest rate margin is forecasted to remain stable, accompanied by an increase in the growth of loans and deposits. Furthermore,

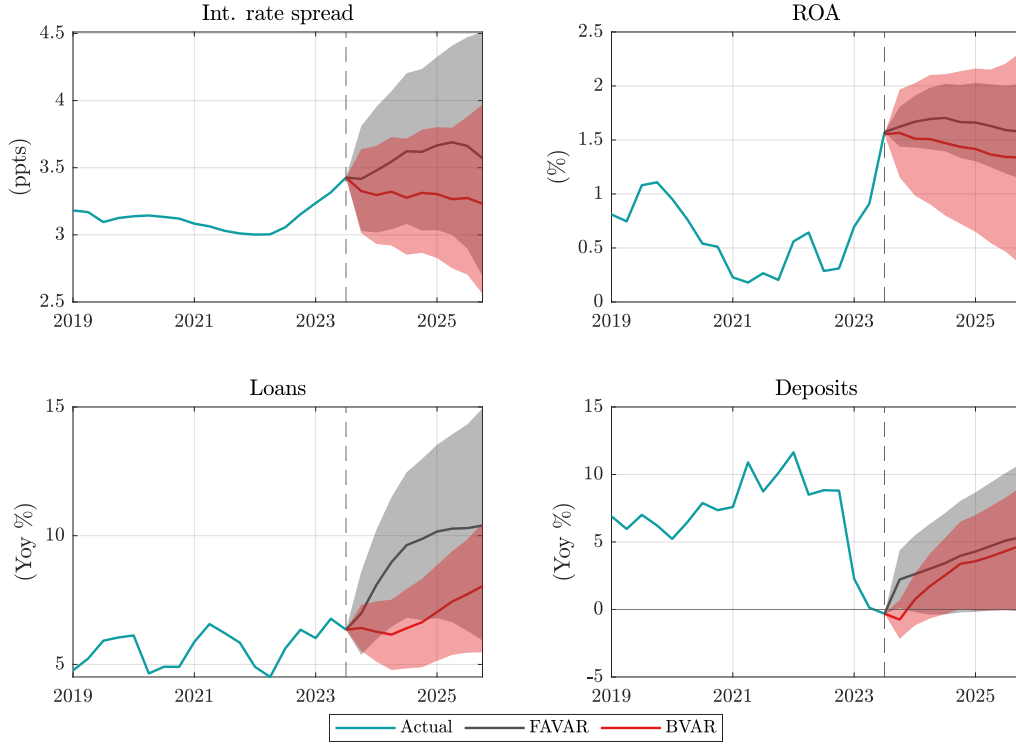


Figure 10: FAVAR and BVAR forecasts comparison, forecast horizon 2023Q4 – 2025Q4.

Note: shaded areas in red and grey depict forecasts' 68% credible sets.

these projections align with the assumption that the monetary policy stance will ease after 2025Q1, facilitating the issuance of new loans in the local economy while maintaining a stable interest rate margin. Such an environment would also be bolstered by an increase in deposits, which continue to constitute the primary funding source for core banks, financing more than 80% of overall banks' assets (Central Bank of Malta, 2023, p. 29).

6 Conclusion

This study aimed to establish a framework for forecasting selected balance sheet items of sampled Maltese core banks, in particular, bank profitability. Methodologically, this work employed two multivariate time series models, namely a FAVAR and a BVAR, both estimated using Bayesian methods. These models utilize macroeconomic time series alongside bank-level data introduced with a novel dataset: the FAVAR provides forecasts at the individual bank-level, whereas the BVAR generates projections for aggregate banking indicators. To evaluate forecasting accuracy, I compared the forecasts from the selected models with those obtained from a conventional Random Walk approach. This assessment was conducted by: (i) considering data before the Covid-19 pandemic, (ii) utilizing the entire available sample, and (iii) incorporating a dummy

variable to account for the most volatile phases of the Covid-19 pandemic.

Empirical findings indicate that neither of the two models demonstrates superior performance over the other. While they may yield comparable outcomes from an *aggregate* perspective, it is noteworthy that only one of the two models, namely the FAVAR, possesses the capability to forecast at bank-level. In this instance, the model generates interesting outcomes, demonstrating its capacity to provide reasonably accurate forecasts for selected Maltese banks' balance sheets items. However, results are heterogeneous across banks. Moreover, the implementation of a dummy variable does not result in any improvement in forecasting accuracy for either of the models. Finally, conditional forecasting leveraging various macroeconomic projections was employed to generate out-of-sample forecasts for the core banks included in the sample. The direct comparison of forecasts between the two models yields analogous results, portraying a healthy core banking system characterized by stable profitability and a rising trend in loan issuance and deposit collection.

The models presented in this paper allow for the formation of an outlook for the core banking system in Malta, which is useful as part of the Central Bank of Malta's task to monitor and maintain financial stability. These models can be utilized to provide an aggregate banking outlook or to focus on a specific bank of interest. The estimated conditional density forecasts, being driven by official macroeconomic projections, can offer a range of plausible trajectories for the banking system. To conclude, these models are sufficiently flexible to accommodate further developments in both local and euro area macroeconomic conditions, as well as future changes in monetary policy decisions.

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Appendix A Principal components estimation details

	PC1	PC2	PC3	PC4	PC5
Standard deviation	2.38	2.13	1.96	1.68	1.54
Proportion of Variance	20%	16%	14%	10%	9%
Cumulative Proportion	20%	37%	51%	61%	70%
	PC6	PC7	PC8	PC9	PC10
Standard deviation	1.26	1.19	0.95	0.86	0.85
Proportion of Variance	6%	5%	3%	3%	3%
Cumulative Proportion	75%	80%	84%	86%	89%

Table A.1: Principal components estimation details, full sample.

Note: the first four principal components are utilized as regressors in the FAVAR model.

Only ten principal components are presented here.

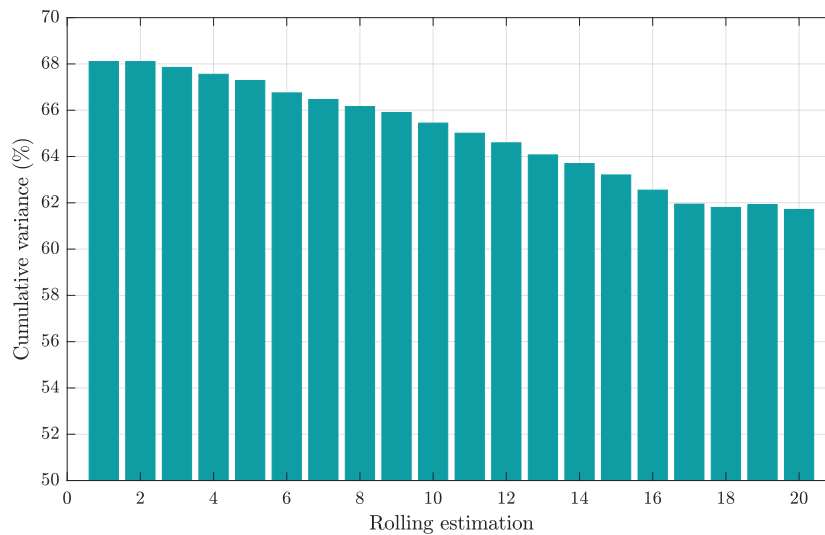


Figure A.1: Cumulative variance explained by $N_F = 4$ principal components across rolling estimation samples.

Appendix B VAR models

This section describes the main models' equations and prior selection, which are valid for both the FAVAR and the BVAR. The basic equations are presented as follows:

$$\begin{aligned} y_t &= \Phi_0 + \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t \\ &= \Phi_0 + \sum_{k=1}^p \Phi_k y_{t-k} + \varepsilon_t \\ \varepsilon_t &\overset{N}{\sim} i.i.d.(0, \Sigma_\varepsilon), \end{aligned}$$

where y_t is $T \times N$ matrix of endogenous variables, Φ_0 is $N \times 1$ vector of constants, Φ_k with $k = 1, \dots, p$ are $N \times N$ matrices containing autoregressive parameters, and ε_t is the $T \times N$ matrix of shocks. The two models are estimated using Bayesian methods, assuming a Minnesota prior. The coefficients $\beta = \text{vec}(\Phi_0, \Phi_1, \dots, \Phi_p)$ follow a Normal prior distribution:

$$p(\beta) \sim N(\beta_0, H),$$

while Σ_ε is assumed to have an Inverse-Wishart prior distribution,

$$p(\Sigma_\varepsilon) \sim IW(\bar{S}, \alpha),$$

with scale matrix \bar{S} and $\alpha = N + 1$ degrees of freedom. The Minnesota prior incorporates the belief that endogenous variables follow an AR(1) process. To do that, I set the coefficient for own variables' lag equal to $\rho = 0.8$. Standard hyperparameters for the model prior variance matrix are imposed following [Canova \(2007\)](#), p. 380:

$$\begin{aligned} \lambda_1 &= 0.2 \\ \lambda_2 &= 0.5 \\ \lambda_3 &= 1 \\ \lambda_4 &= 1000. \end{aligned}$$

For a detailed description of Gibbs sampling and Bayesian model estimation, the reader should refer to [Blake and Mumtaz \(2015\)](#). Moreover, I incorporate *block exogeneity* in the two models, i.e. the prior belief that Maltese variables do not have an impact on euro area ones. Then, in the equations for real GDP (EA), HICP (EA), and Short Shadow Rate (SSR), I impose a tight prior for all coefficients linked to Maltese variables,¹⁷ with zero mean and variance equal to 0.005.

¹⁷Which are real GDP (MT), real house prices (MT), the interest rate spread, and bank-related endogenous variables.

Appendix C Dummy implementation

F. hor	GDP MT	House prices	GDP EA	HICP EA	SSR
1	0.92	1.02	1.05	0.96	1.05
2	0.72	1.41	0.91	1.14	1.10
3	0.56	1.73	0.82	1.23	1.14
4	0.39	1.37	0.75	1.25	1.17
	Int. rate spread	PC1	PC2	PC3	PC4
1	5.29	0.96	2.95	1.33	1.08
2	3.11	1.34	2.74	1.20	0.80
3	2.65	1.43	2.43	1.21	0.88
4	2.17	1.52	2.03	1.07	1.28

Table C.2: Relative RMSE, FAVAR, in-sample unconditional forecasts, *dummy implementation*.

Notes: every entry represents an average over $n = 11$ forecast paths.

F. hor	ROA Bank 1	ROA Bank 2	ROA Bank 3	ROA Bank 4
1	2.22	2.71	5.41	0.99
2	1.81	2.17	3.49	0.71
3	1.61	2.32	2.23	0.60
4	1.45	1.84	1.55	0.71
	Int. income Bank 1	Int. income Bank 2	Int. income Bank 3	Int. income Bank 4
1	2.35	3.91	2.84	1.25
2	1.76	2.68	0.90	0.85
3	1.51	2.00	0.70	0.82
4	1.27	1.69	0.79	0.99
	Int. exp. Bank 1	Int. exp. Bank 2	Int. exp. Bank 3	Int. exp. Bank 4
1	3.02	2.94	2.08	2.43
2	1.85	2.43	1.15	1.95
3	1.36	1.73	0.96	1.81
4	1.19	1.41	0.92	1.79
	Loans Bank 1	Loans Bank 2	Loans Bank 3	Loans Bank 4
1	1.37	1.02	2.94	1.47
2	1.13	1.09	1.63	1.52
3	1.40	1.30	0.86	1.65
4	1.28	1.54	0.74	1.73
	Deposits Bank 1	Deposits Bank 2	Deposits Bank 3	Deposits Bank 4
1	0.92	1.34	1.41	1.17
2	0.98	0.74	1.71	1.18
3	1.09	0.54	2.04	1.35
4	1.03	0.47	1.87	0.99
	Assets Bank 1	Assets Bank 2	Assets Bank 3	Assets Bank 4
1	1.18	0.67	1.64	1.30
2	1.80	0.66	2.11	1.51
3	1.97	0.71	2.61	1.47
4	2.05	0.69	2.34	1.11
	Cap. + res. Bank 1	Cap. + res. Bank 2	Cap. + res. Bank 3	Cap. + res. Bank 4
1	0.85	3.77	2.32	1.61
2	0.68	2.59	2.67	1.17
3	0.64	1.57	2.42	0.90
4	0.65	1.22	1.80	0.98

Table C.3: Bank-level Relative RMSE, in-sample unconditional forecasts, *dummy implementation*.

Notes: every entry represents an average over $n = 11$ forecast paths. ROA = Return-on-Assets, Int. income = Interest income, Int. exp. = interest expense, Cap. + res. = Capital plus reserves.

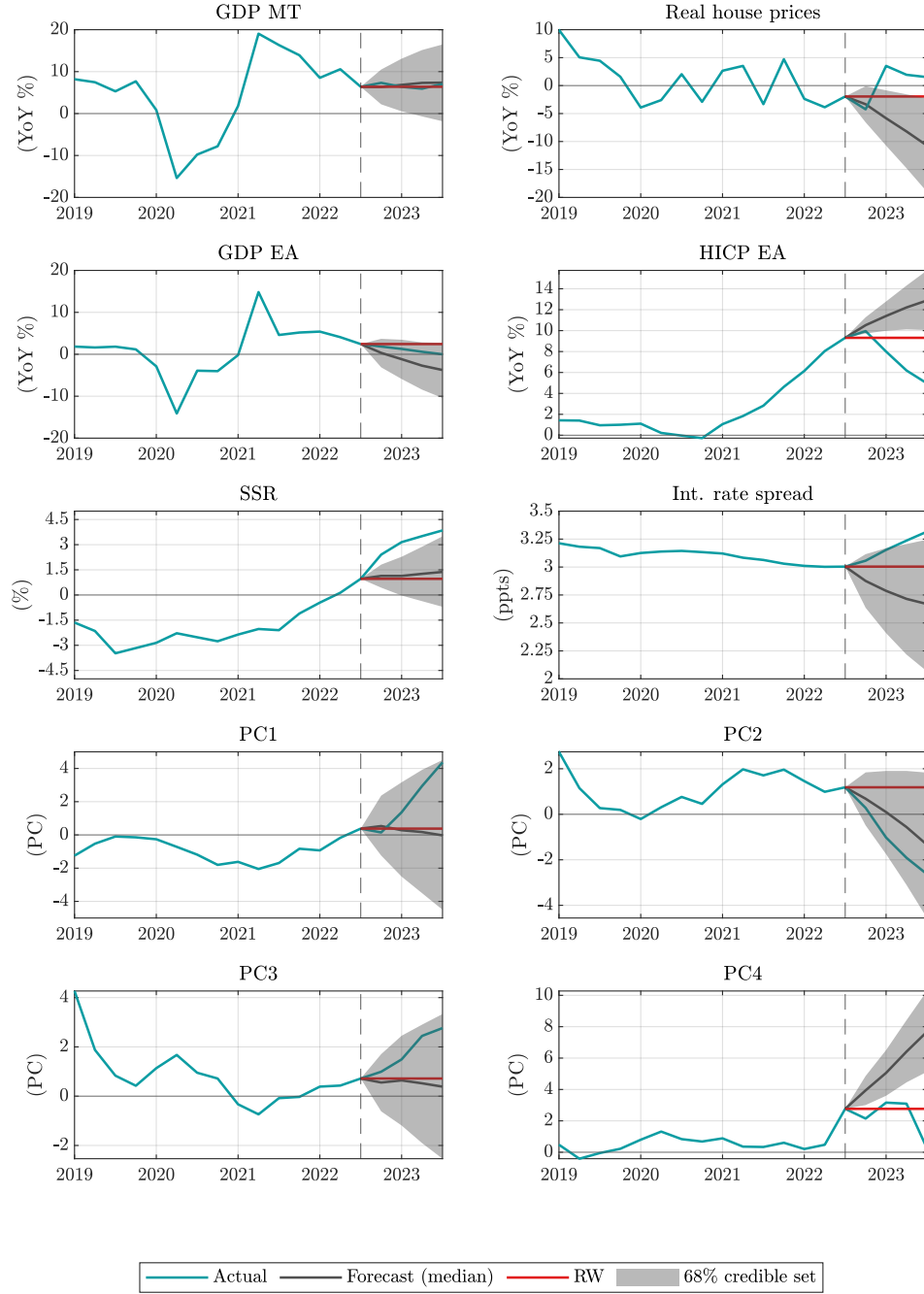


Figure C.1: In-sample unconditional forecasts, FAVAR, *dummy implementation*.

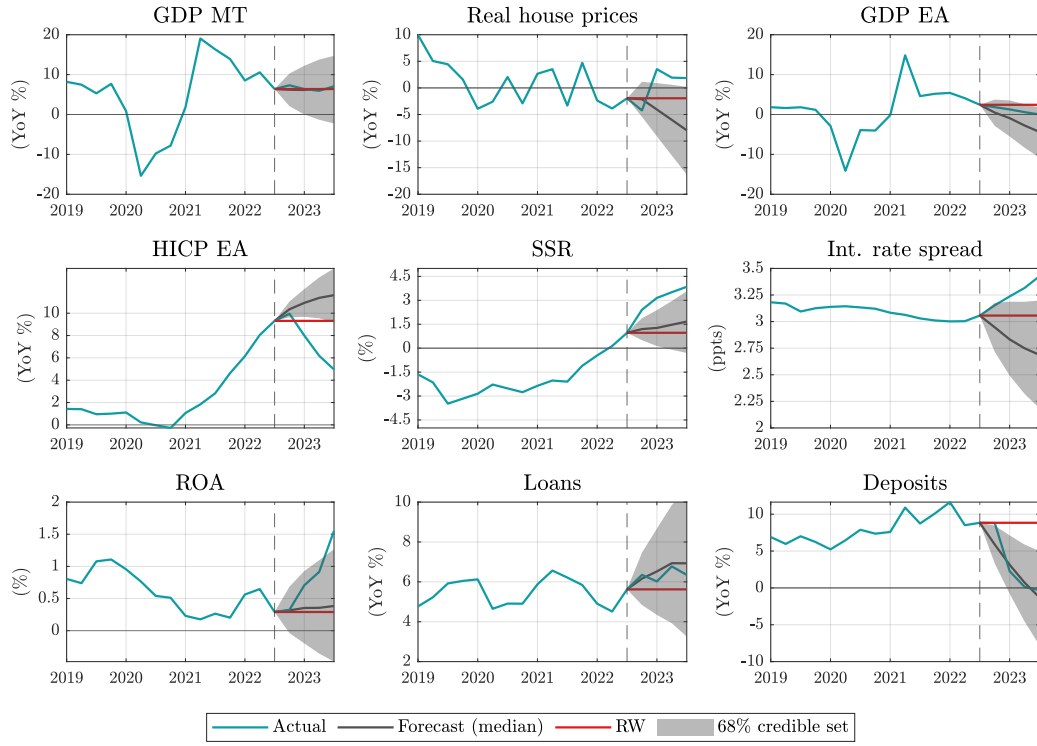


Figure C.2: In-sample unconditional forecasts, BVAR, *dummy implementation*.

F. hor.	GDP MT	House prices	GDP EA	HICP EA	SSR	Spread	ROA	Loans	Deposits
1	0.92	1.06	1.06	0.91	1.06	3.68	2.32	1.86	1.87
2	0.74	1.42	0.87	1.07	1.07	3.39	2.56	2.23	1.69
3	0.59	1.67	0.77	1.14	1.09	3.11	2.80	2.51	1.35
4	0.38	1.36	0.69	1.13	1.10	2.73	2.31	3.24	0.98

Table C.4: Relative RMSE, BVAR, in-sample unconditional forecasts, *dummy implementation*.

Notes: every entry represents an average over $n = 11$ forecast paths.