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Forecasting Credit Dynamics: VAR, VECM or modern Factor-Augmented VAR approach?*

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Abstract

Following the financial crisis of 2008, central banks started paying more attention to the issue of financial stability and to the amount of credit circulating in the economy. However, the methods used to forecast credit often are underdeveloped and don't make the most out of access to big data. This paper evaluates the performance of various models in forecasting the Dynamics of Credit to the Non-Financial Sector in the United States. It explores three approaches: the reduced form Vector Autoregressive model, Vector Error Correction model and Factor-Augmented Autoregressive model. The paper compares the RMSE of the models and finds that FAVAR approach outperforms traditional VAR and VEC models and produces more accurate forecasts of credit dynamics. .

Keywords: Macroeconometric Forecasting, Big data, Credit
JEL Codes: C53, C55, E47, E51

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1 Introduction

The financial systems are considered stable when a wide range of financial institutions – i.e., banks or financial markets, can provide households and businesses with the financing they need to participate in the economy (Federal Reserve Board, 2023). It is a common idea in the literature that the performance of the real economy is related to the accessibility of credit. Bernanke et al. (1999) discover the idea of a 'financial accelerator' as a response to the 'small shocks, large cycles' puzzle. They argue that exogenous shocks to the economy are exacerbated by developments in the financial markets and the availability of credit. Therefore, credit dynamics is a vital variable that economists and central banks need to consider when evaluating the resilience of financial systems to various risks. Central banks recognise this fact and include credit considerations in their Financial Stability Reports (Federal Reserve Board, 2023).

Therefore central banks should use cutting-edge methodologies to forecast changes in credit and take them into consideration when deciding on their policies. However, the literature on this topic is rather sparse. When developing modern approaches, macroeconomists usually focus on variables like GDP, Industrial Productivity, Interest Rate or Inflation. (Bernanke et al., 2005; Paccagnini, 2017). Alternatively, financial economists and data scientists focus on credit risk for purposes of the financial sector, often using machine learning models. (Belhadi et al., 2021; Montesi et al., 2018). However, the issue with ML models is that they are the 'Black Box', that is, it is virtually impossible to track how changes in input affect output. Central banks need to be able to interpret those changes to inform their policies. There seems to be little literature focusing on forecasting credit dynamics from a macroeconomic perspective. I aim to contribute to this field by adapting an interpretable 'big data' approach of forecasting macroeconomic variables to forecast credit dynamics.

In this dissertation, I focus on answering the question of whether central banks should adopt the Factor-Augemented VAR methodology to create forecasts of credit dynamics. The paper explores three different approaches to forecasting macroeconomic variables: Vector Autoregressive Model (Sims, 1980), its Vector Error Correction transformation, and lastly Factor-Augmented Vector Autoregressive Model as proposed by (Bernanke et al., 2005). VAR inherently suffer from the dimensionality trade-off between its degrees of freedom and the information it contains. The researcher can include only a few variables based on economic theory so as not to lose statistical advantage. Using FAVAR is a way to solve this issue. It is a rather modern approach that makes use of large amounts of data gathered by central banks. It has been shown to increase the forecasting power of models in predicting macroeconomic variables (Paccagnini, 2017). Furthermore, after small modifications, I transform the original VAR into a Vector Error Correction Model. I use it to analyse long-run credit demand factors and treat it as an alternative approach for forecasting purposes.

This paper will show that small VAR can produce relatively accurate forecasts, however, it can be improved upon by factor augmentation. Correctly specified FAVAR produces more accurate forecasts and is especially effective in forecasting horizons shorter than 2 years ahead. The remainder of the work is structured as follows: in the following section I highlight papers, I drew inspiration from. In section 2, I explain the theory behind the econometric models I will be using. In the following section, I present the empirical strategy by presenting the data and explaining how each model was derived empirically. In section 3, I compare the models' performance and present a deeper analysis of interesting results. In the final section, I present the concluding remarks and some limitations and outline potential avenues for further research.

1.1 Related Work

This project draws from two branches of economic literature. First I use literature to build my understanding of the theoretical modelling of macroeconomic determinants of credit in the economy. Hofmann (2001) argues that the standard credit demand factors are GDP and real interest rate, but also discovers that property prices are key in explaining long-run developments of credit. Koju et al. (2020) confirm that those variables are substantial in determining credit risk, and therefore credit dynamics.

More importantly, however, this work attempts to combine and emulate econometric approaches presented in classical literature on forecasting macroeconomic variables. Most notably, Stock and Watson (2002, 2005) discuss data reduction techniques and the development of Dynamics Factor Models (DFM), which allow for summarising of large data sets with a few common factors. Naturally, the paper by Bernanke et al. (2005) was heavily influential on my research. Using DFM, they develop a structural FAVAR to analyse the impulse response functions of different macroeconomic variables and draw causal conclusions about how shocks to one variable affect others. I use an atheoretical version of FAVAR for forecasting purposes instead. Furthermore, I draw inspiration from papers that focus on Vector Error Correction Models to create an alternative approach to FAVAR. VECM, as proposed by Granger (1981), is a restricted form of VAR, where researchers, through analysis of cointegration, can impose a long-run equilibrium that variables converge to. Engle and Yoo (1987) create simulations to compare the performance of unrestricted VAR and VECM. They find that VAR is more accurate in producing short-run forecasts (up to three-step ahead), however, in the longer run VECM outperforms VAR. The technical details of this paper are derived using Kilian and Lütkepohl (2017).

2 Econometric Modeling

2.1 Classical Vector Autoregressive Model

The mathematical expression for reduced form VAR is as follows:

$$y_t = \alpha + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t$$

y_t is a $N \times 1$ vector of endogenous variables, A_i $i = 1, ..., p$ are $N \times N$ parameter matrices and ε_t is N-dimensional iid white noise process with contemporaneous covariance matrix $\mathbb{E}(\varepsilon_t \varepsilon_t') = \Sigma$ such that ε_t $(0, \Sigma)$.

In my estimations, I am considering two different models varying the choice of variables. VAR usually is estimated by multivariate least squares, which is equivalent to using OLS for each equation. OLS assumptions requires all endogenous variables used to be stationary.

2.2 Vector Error Correction Model

If the endogenous variables in levels are cointegrated, classical VAR can be transformed into Vector Error Correction Model. The set of integrated variables is cointegrated if they are jointly driven by the same stochastic trend. In this way, their linear combinations can be stationary.

More formally, the components of vector y_t are cointegrated of order d, b, denoted $y_t \sim CI(d, b)$, if all components of Y_t are $I(d)$ and there exists a vector $\beta (\neq 0)$, such that $z_t = \beta' y_t \sim I(d - b), b > 0$. The vector β is called a cointegration vector (Engle and Granger, 1987).

By subtracting y_{t-1} from both sides, the reduced form VAR from above can be rearranged into the following VECM

$$\Delta y_t = \mathbf{\Pi} y_{t-1} + \mathbf{\Gamma_1} \Delta y_{t-1} + ... + \mathbf{\Gamma_{p-1}} \Delta y_{t-p-1} + u_t$$

where

$$\mathbf{\Pi} = -(I_N - A_1 - ... - A_p)$$

and

$$\mathbf{\Gamma_i} = -(A_{i+1} + ... + A_p), \;\; i = 1, ...p - 1.$$

$\mathbf{\Pi}$ is a coefficient matrix for error correction term. If there are r linearly independent cointegrating relationships in the system, $\mathbf{\Pi}$ has a rank r and is called the cointegrating rank of the process y_t. $\mathbf{\Pi}$ can be decomposed as $\mathbf{\Pi} = \alpha\beta'$. Matrix β is called the cointegration matrix and α is referred to as the loading matrix.

2.3 Factor-Augmented Vector Autoregressive Model

Another approach to modelling various economic variables is building Factor-Augmented VAR. The issue with modelling VARs is the trade-off between preserving statistical advantage by including few variables and adding too many variables which decreases degrees of freedom. This means that traditional low-dimensional VAR models are inherently at risk of suffering omitted variable problems as researchers have to pick only a few variables to include in the model.

However, after Stock and Watson (2002) proposed a Dynamic Factor Model it is possible to summarise a large amount of information about an economy with a few factors that explain most of the variance in the data. Following Bernanke et al. (2005) I utilise those factors in estimating VAR containing more information. First, like the VAR above, I assume that there are a number of observable variables that drive credit dynamics, contained in a $N \times 1$ y_t vector. However, there is economic information relevant to credit dynamics not included in this vector. Suppose that the majority of the rest of the economic information can be summarised by the latent Kx1 vector f_t. I assume this information explains some economic conditions relevant to credit dynamics that are not easily explained by one or two variables. Then the joint dynamics of y_t and f_t can be written in the VAR form as:

$$\begin{bmatrix} \mathrm{f}_t \\ \\ \mathrm{y}_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \mathrm{f}_{t-1} \\ \\ \mathrm{y}_{t-1} \end{bmatrix} + \nu_t$$

where ν_t is a $(N + K)$-dimensional white noise process and $\Phi(L)$ is a conformable lag operator of finite order. Typically it may contain structural restrictions, however, I am interpreting this VAR as an atheoretic forecasting model, therefore not imposing structural restrictions.

This equation cannot be estimated directly as f_t is unobservable. However, we can estimate it based on the $M \times 1$ vector of observable economic time series, usually referred to as 'informational' series, denoted by x_t. Informational series x_t are related to unobservable factors f_t and observable variables y_t by the following Dynamic Factor Model:

$$\mathrm{x}_t = \Lambda^f f_t + \Lambda^y y_t + e_t$$

where Λ^f is a $M \times K$ matrix of factor loadings, Λ^y is a $M \times N$ matrix of coefficients, and e_t is vector $M \times 1$ of error terms that are assumed to be mean zero and uncorrelated or cross-correlation between error terms must vanish as M tends to infinity. The number of informational series must be much larger than the number of observed series and latent factors driving the dynamics of the economy, meaning that $M >> N + K$.

The interpretation of this DFM is that f_t and y_t ultimately drive the dynamics of x_t. I have used DFM in static form as I only assume a contemporaneous relationship between x_t, f_t and y_t, however, Bernanke et al. (2005) argue that this condition is not bounding as f_t could include arbitrary lags of fundamental factors.

Following Bernanke et al. (2005) I implemented a two-step principal components approach. Define sample size T=$1, 2 \ldots, T$ and let $F = [f_t]_{t \in T}$ be a $K \times T$ matrix. In the first step I estimate the factors from the equation above by imposing orthogonality restriction, implicit in the principal components analysis, that is $\frac{1}{T}(FF') = I$. PCA aims to find K factors such that the variance along the direction of each factor is maximised, subject to an orthogonality restriction between these factors. Mathematically the solution to this problem is obtained through the eigendecomposition of the sample covariance matrix XX'. Therefore giving us $\hat{F} = \sqrt{T}\hat{Z}$, where $\hat{Z}$ are the eigenvectors corresponding to the K largest eigenvalues of XX' sorted in descending order. This allows me to identify $\hat{f}_t$, that is the space covered by principal components and not covered by y_t. In the second step, FAVAR is estimated as reduced form VAR model, using multivariate least squares, but with f_t replaced by estimated $\hat{f}_t$.

3 Empirical Strategy

3.1 Data

I use a dataset from the US designed for empirical analysis of 'big data' created by McCracken and Ng (2020). Historically, datasets put forward by Stock and Watson starting in 2002 were commonly used by researchers to conduct 'big data' analysis. This dataset emulates the popular dataset by Stock and Watson (2012), and builds on it by adding additional variables. The data set contains 248 quarterly variables, spreading from 1959q1 until 2022q3, divided into 14 main groups. I enhanced the data by adding 'Real interest rate' (Federal Reserve Bank of Cleveland, 2023) and 'Total Credit to Non-Financial Sector', referred to as 'credit' – the forecasted variable. Credit is provided by domestic banks, all other sectors of the economy and non-residents. The "private non-financial sector" includes non-financial corporations, households and non-profit institutions. (Bank for International Settlements, 2023). I removed 20 variables from space x_t as they have significantly fewer observations and restricted the dataset. All the variables have been transformed to induce stationarity. Transformations have been suggested by McCracken and Ng (2020) (Table 1). For the variables contained in the vectors y_t more detailed analysis has been conducted. I use log transformations for most economic variables, including credit and GDP to induce linearity. I then conduct Augmented Dickey-Fuller tests (Tables 3, 5) and difference variables where appropriate, to ensure stationarity of variables in VARs. Before conducting the ADF test I analyse the graphs of each variable to correctly specify deterministic terms (trend and constant) of the test. To choose the appropriate number of lags I start with $p_{max} = 8$, and delete insignificant lags. Therefore, when referring to the value of credit I refer to a change in the log transformation of Total Credit, which can be interpreted as a percentage change of total credit.

3.2 Empirical Implementation

In this section, I argue for the choice of variables used in the models and conduct necessary tests to ensure that models are well-behaved and to maximise models' forecasting power. I consider six different models: NBP VAR (VAR 1), VAR with Property Prices (VAR 2) and its VEC representation, and three different FAVAR specifications defined in section 3.2.3.

3.2.1 Vector Autoregressive Model

I use the model set-up as described above in section 2.1. I consider two alternative choices of endogenous variables included in the vector y_t. The first is inspired by the methodology used by Polish Central Bank to forecast credit dynamics. The second is inspired by the literature on the macroeconomic determinants of credit. Importantly, as I will show in section 3.2.2, the second choice of variables cointegrates and therefore, allow for the Vector Error Correction transformation.

NBP VAR I focus on three variables: Credit, GDP and Fed Funds interest rate. The argument for this choice of variables is as follows. The amount of credit in the economy is determined by two economic factors. First, by the state of the economy; if the economy is in recession households are more inclined to limit spending and save money. Furthermore, recessions tend to be accompanied by a rise in uncertainty, leading companies to limit their investments. GDP is often used as a proxy for the aggregate performance of the economy. The second factor is the cost of borrowing. Economic theory suggests that households and companies are more likely to invest if the cost of borrowing, that is interest rate, is relatively low and the opportunity cost of holding money is high, ie. they are being paid less interest on their savings. There are many ways to measure interest rates but I have chosen the most general one, which is the Fed Funds Effective Rate. Following the ADF test (table 3), I conclude that variables are $I(1)$, so I estimate VAR in differences, ensuring that variables are stationary. Therefore, vector y_t in VAR 1 is defined as follows:

$$y_t = \begin{bmatrix} \Delta ln(credit_t) \\ \Delta ln(GDP_t) \\ \Delta FF_t \end{bmatrix} \tag{3.1}$$

To correctly specify the lag length I consider two alternative Information Criteria, AIC and HQIC. Using 11 lags suggested Akaike Information Criterion allows for modelling VAR free of autocorrelation in residuals. However, Kilian and Lütkepohl (2017) argue that in forecasting exercises the optimal lag length minimises MSPE, even if it allows for a degree of autocorrelation in residuals. Therefore, using Hannan-Quinn IC I choose 5 lags, where VAR suffers from serial correlation to some degree(table 4), but produces more accurate forecasts.

VAR with Property Prices The alternative choice of variables that drive credit dynamics are inspired by Hofmann (2001). He analyses the determinants of credit in the private non-banking sector in various developed countries. He divides system dynamics into: 'standard credit demand factors' and 'real property prices'. To describe credit demand he makes a similar argument to one in the section above and uses Real GDP and Real Interest Rate. Moreover, he argues that Property Prices are relevant for the long-run development of credit. Therefore, after analysing their order of integration (5), in VAR 2, I use differenced log transformation of Credit and GDP, differenced RIR, and twice differenced log transformation of PP, ensuring that variables are stationary. Therefore, the vector of endogenous variables, y_t in VAR 2 is defined as:

$$y_t = \begin{bmatrix} \Delta ln(credit_t) \\ \Delta ln(GDP_t) \\ \Delta RIR_t \\ \Delta^2 ln(PP_t) \end{bmatrix} \tag{3.2}$$

I apply a similar lag length specification process as above(3.2.1), and choose 4 lags, as suggested by AIC, removing serial autocorrelation from residuals (Table 6) and maximising the model's predictive power.

3.2.2 Vector Error Correction Model

An important result of Hofmann (2001) is his analysis of the long-run development of credit. He conducts various cointegration tests and fails to identify cointegrating equations in standard credit demand variables. However, after including property prices in the system he identifies the long-run relationship linking credit positively to GDP and property prices and negatively to the real interest rate. He interprets those relationships as representing long-run credit demand but also allows them to capture effects on credit supply.

In this section, I replicate Hoffmann's result and estimate the Vector Error Correction model.

I start by conducting Johansen tests for cointegration for variables in levels, used in VAR 1 and VAR 2. In both tests, I specify the lag length $p = 12$ as suggested by AIC and allow for the presence of a restricted trend. I achieved the following result

Figure 1: Johansen tests for cointegration for variables in VAR 1

Maximum Rank	**Trace Statistic**	**5% Critical Value**
0	39.8146*	42.44
1	23.1099	25.32
2	9.4191	12.25
3		

Figure 2: Johansen tests for cointegration for variables in VAR 2

Maximum Rank	**Trace Statistic**	**5% Critical Value**
0	106.4302	62.99
1	54.8389	42.44
2	20.1026*	25.32
3	4.8316	12.25
4		

In the first test, I do not reject the first H_0 of no cointegration equation present, implying that all variables are I(1) and do not cointegrate, thus there is no long-run equilibrium. However, after adding property prices, I rejected the first two null hypotheses, implying $r = 2$ of cointegration matrix $\mathbf{\Pi}$. Therefore, I identify two cointegrating equations in the system, allowing for the estimation of the VEC form of VAR 2. The y_t vector of endogenous variables in levels is defined as follows:

$$y_t = \begin{bmatrix} ln(credit_t) \\ ln(GDP_t) \\ RIR_t \\ \Delta ln(PP_t) \end{bmatrix} \tag{3.3}$$

Because there are two cointegrating equations I need to impose $r = 2$ restrictions per cointegrating vector. As my goal is to forecast credit I normalise the coefficient on credit $\beta_{11} = \beta_{21} = 1$ in the estimation of both cointegrating equations. To just-identify the equation I need to introduce two more restrictions. Hofmann (2001) does not suggest any one-to-one long-run relationship so I cannot restrict any coefficient to -1. In the first cointegrating equation, I set the coefficient on GDP $\beta_{12} = 0$, and in the second cointegrating equation, I set the coefficient on PP $\beta_{24} = 0$. To estimate the model I use $p = 8$ lags as this is the lowest number of lags that reduces autocorrelation in residuals (Table 7) and maximised models' prediction power. Estimating VECM with those restrictions yields the following cointegrating equations.

Figure 3: Estimated Cointegrating Equations

	beta	**Coefficient**	**Std. Err.**	**z**	**P>z**	**[95% Conf. Int]**
_ce1						
β_{11}	$ln(credit)$	1	.	.	.	.
β_{12}	$ln(GDP)$	0	(omitted)			
β_{13}	RIR	1.026982	0.2017191	5.09	0	0.6316198 1.422344
β_{14}	$\Delta ln(PP)$	-90.16929	18.94663	-4.76	0	-127.304 -53.03458
	_cons	-9.036997	.	.	.	.
_ce2						
β_{21}	$ln(credit)$	1	.	.	.	.
β_{22}	$ln(GDP)$	-11.15533	0.49962	-22.33	0	-12.13456 -10.17609
β_{23}	RIR	0.4638902	0.0845432	5.49	0	0.2981885 0.6295918
β_{24}	$\Delta ln(PP)$	0	(omitted)			
	_cons	15.75254	.	.	.	.

All the coefficients are significant at any reasonable significance level. Both cointegrating equations allow me to draw the same conclusion as Hofmann (2001) about long-run relationships between credit and other variables. As per the second cointegrating equation, there is a strong positive relationship between credit and GDP. Both equations indicate that there is a negative long-run relationship between credit and real interest rate, even though equations point to different magnitudes of effect. Lastly, the first equation suggests a strong positive long-run relationship between credit and change in the prices of properties.

Alternatively, I could have chosen those restrictions by Maximum Likelihood Estimation, however, it leads to the exclusion of credit from one of the equations and later leads to worse forecast accuracy.

3.2.3 Factor-Augmented Vector Autoregressive Model

As described in the theoretical section, I adopt a two-step approach to estimating FAVAR. I start by estimating factors by principal components analysis. I will argue for the choice of the number of retained factors and analyse the pattern matrix. I follow by estimating 3 different FAVAR models using those factors.

Estimating Factors I apply Principal Components for factor extraction analysis on the space covered by the informational series to extract the unobservable factors. The resulting pattern matrix is hard to interpret as it is densely populated with small non-zero factor loadings. To make it easier to interpret I apply orthogonal varimax rotation. This rotation aims to sparsify the factor loading matrix, by maximising the variable's correlation with one factor while minimising it with other factors, resulting in a higher sparsity of factor loadings. It helps to identify which variables are most important for each factor (Kaiser, 1958). Principal components procedure by design creates uncorrelated factors, applying orthogonal varimax rotation should not change this feature.

Figure 4: Explanatory Power By Extracted Factors

Factor	**Eigenvalue**	**Proportion**	**Cumulative**
Factor1	53.54395	0.2391	0.2391
Factor2	17.85376	0.0797	0.3188
Factor3	14.8165	0.0662	0.3849
Factor4	12.4897	0.0558	0.4407
Factor5	7.69693	0.0344	0.4751
Factor6	6.5941	0.0294	0.5045
Factor7	5.65328	0.0252	0.5297
Factor8	5.3281	0.0238	0.5535
Factor9	4.78604	0.0214	0.5749
Factor10	4.46584	0.0199	0.5948

'Proportion' is what proportion of information is explained by an individual factor
'Cumulative' is what proportion of information is jointly explained by first K factors

Traditional Kaiser Criterion suggests retaining all factors with eigenvalues larger than one, however, in this case, it is too many to use in FAVAR. Information Criteria by Bai and Ng (2002) (table 8) suggest that I can use up to 12 factors, which again seems high. However, IC related to characteristics of eigenvalues (Ahn and Horenstein, 2013) suggest that I should use only one or two factors. Based on the VAR dimensionality trade-off, I do not want to include too many variables in FAVAR. Therefore, I start by retaining four factors, which cumulatively explain over 44% of the variation within the data.

Even after rotation, the factor loading matrix [1]is difficult to interpret as it contains over 200 variables. I select 13 main macroeconomic variables(Table 1), one from each group suggested by McCracken and Ng (2020), and build a correlation matrix between the variables and factors, representing factor loadings on chosen variables.

[1]It is a 224×4 matrix presenting a correlation between retained factors and each variable. Due to limitations put on the size of the appendix, I cannot include it in this paper.

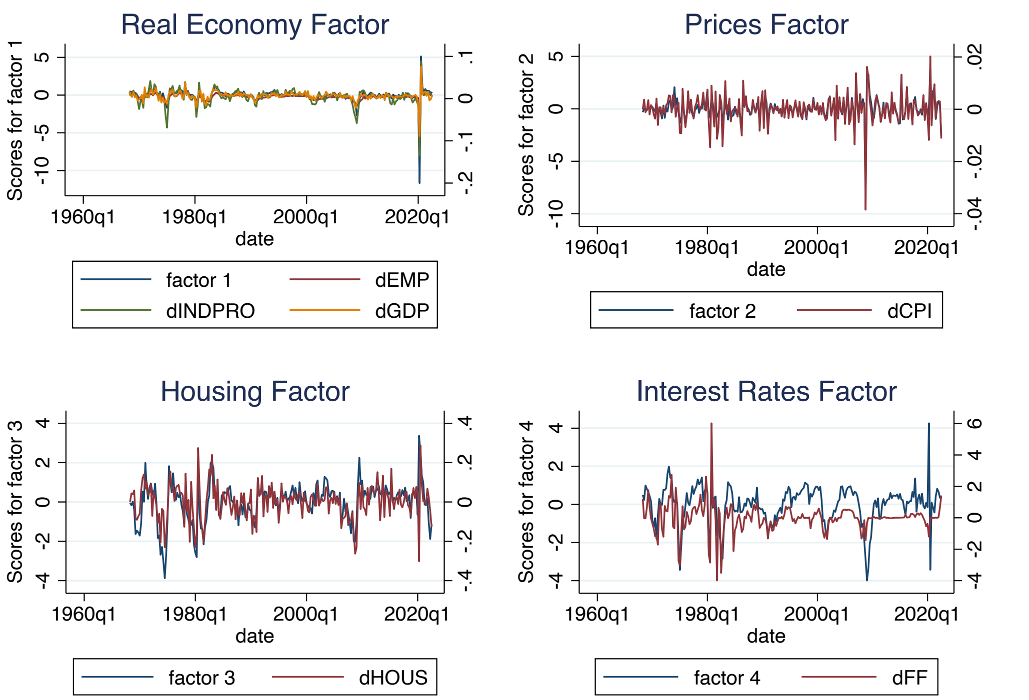
Figure 5: Factor Loadings on chosen variables

	f1	f2	f3	f4
dGDP	0.8647			
dINDPRO	0.868			
dEMP	0.971			
dHOUS	0.4177		0.6425	
dCMRMTSPLx	0.7375		0.4118	
dCPI		0.8932		
dAHETPIx	-0.5983			0.4191
dFEDFUNDS				0.5158
dBOGMBASEREALx	-0.4699	-0.3253		
dTABSHNOx			0.5425	
dTWEXAFEGSMTHx				
dSP500			0.5515	
dGFDEGDQ188S	-0.8492			

Values $< |0.3|$ blanked for clarity
d indicates that appropriate transformation has been applied

I assign variables to each factor based on the level of correlation. Therefore, I can interpret factors and assign an underlying wider economic concept that they represent. The first factor is highly correlated with GDP, Industrial Production and Employment Level, therefore it represents the real side of the economy. The second factor is highly correlated with Consumer Price Index, therefore it represents prices. Third is highly correlated with New Housing, so it represents the state of housing in the US. The last factor is not as easy to interpret, but it is most highly correlated with the Fed Fund interest rate.

Figure 6: Factors



Each factor is stationary (table 9); I can proceed to the second step and estimate FAVAR models.

Estimating FAVAR As a benchmark, I use a three-variable VAR 1 estimated in 3.2.1. I consider three different FAVAR specifications: 1) where I add all four retained factors to three variables used in VAR 1; 2) where I add only the first "Real Economy" factor to original set of variables, 3) FAVAR where only credit is assumed to be observable, meaning I am not including GDP and FF in y_t vector, and instead I add all four retained factors. The first two specifications nest the original VAR allowing for isolating the marginal contribution of adding one or four factors.

For each model, the lag length was chosen to minimise serial autocorrelation within residuals(Tables 10,11,12) and maximise the forecasting power of the model.

3.3 Forecast Evaluation

To evaluate the models' performance I conduct out-of-sample forecasting and compare the Root Mean Squared Prediction Error(RMSE). RMSE represents how close forecasted values are to observed values. I start by splitting the observation sample $T = n + m$ of all observations into the estimation period with n observations and the forecasting period with m observations. I limited sample T to contain observations from 1959q1 to 2019q4, removing observations starting with 2020q1 as outliers. Covid19 represents a structural break in the dynamics of the credit system and due to the heavy influence of non-economic factors, it is almost impossible to forecast credit dynamics in periods following the pandemic. The estimation period n intends to run from the beginning of the observation sample until 2010q1. However, due to differences in data availability, it varies across different models. Models containing RIR variable, that is VAR 2 and VECM, start their estimation period in 1982q1, as this is the first observation for this variable. VAR 1 starts its estimation period in 1959q2. FAVAR models are limited by the shortest observation period of estimated factors, and their estimated period starts in 1968q2. The forecasting period for all models is the same, 2010q1 - 2019q4.

Forecasts are calculated on four different forecasting horizons, $h = 1, 2, 4, 8$. Forecasts for horizons longer than 1-step-ahead are calculated recursively. Forecasting power refers to models' ability to minimise RMSE for a given forecast horizon h defined as follows:

$$RMSE = \sqrt{\frac{1}{m-h} \sum_{j=0}^{m-h} (y_{n+j+h} - \hat{y}_{n+j+h})^2}$$

where $\hat{y}_{n+h} = \mathbb{E}[y_{n+h}|y_n]$, is a forecasted value of credit.

4 Results

4.1 Forecast Accuracy Comparision

The following table shows the RMSE of the considered model for given forecast horizons.

Figure 7: Reported RMSE for all models

	VAR 1	**VAR 2**	**VECM**	**FAVAR 1**	**FAVAR 2**	**FAVAR 3**
h=1	0.00360068	0.0040509	0.00470657	0.00467979	0.00314729	0.00330159
h=2	0.00333386	0.00419547	0.0078826	0.00426505	0.00291715	0.00308029
h=4	0.0037304	0.00463852	0.01764729	0.00407336	0.00355525	0.00354861
h=8	0.00427054	0.00646352	0.05250883	0.00420412	0.00461149	0.00375016

For easier interpretation, I normalise the RMSE of VAR 1 to one. This allows me to compare other models to the standard VAR. After normalisation, if the reported value is higher than one, then this model produces a higher RMSE and therefore a less accurate forecast than VAR 1. If the value is below one, the model produces a more accurate forecast.

Figure 8: Normalised RMSE

	VAR 1	**VAR 2**	**VECM**	**FAVAR 1**	**FAVAR 2**	**FAVAR 3**
h=1	1	1.125	1.307	1.300	0.874	0.917
h=2	1	1.258	2.364	1.279	0.875	0.924
h=4	1	1.243	4.731	1.092	0.953	0.951
h=8	1	1.514	12.296	0.984	1.080	0.878

Values reported to the third decimal point

Comparing the results of the first two VARs suggest that ”standard credit demand” is enough to accurately forecast credit and adding property prices does not improve the performance of the model. I will further inspect this result in section 4.2. The VECM performs worse than the same VAR model without imposed cointegration, which contradicts simulated results by Engle and Yoo (1987). Interestingly, the relative performance of VECM worsens as the forecasting horizon increases. This suggests that the reason for the worsening performance of VECM is that the long-run relationship in the estimation period breaks down in the forecasting period, and variables converge to the wrong long-run equilibrium.

The most important result of my paper, however, concerns the performance of Factor-Augmented VARs. I can show that FAVAR can outperform standard VAR. FAVAR with original variables and one retained factor outperforms benchmark VAR. Especially in the shorter horizons, up to one year ahead, is the best-performing model. Interestingly, similar FAVAR but with four factors, performs worse than standard VAR in the short-run, however, in the long-run it matches VAR's performance and outperforms FAVAR 2. Lastly, FAVAR with only credit and four factors, consistently outperforms standard VAR, regardless of the forecasting horizon.

4.2 Granger Causality Analysis

Finally, to deeper understand the performance of different models I analyse if additional variables and factors Granger Cause credit. I will compare the original VAR 1, the alternative VAR 2 with Property Prices and the first FAVAR specification. Granger Causality procedure (Granger, 1969) shows whether lags of one endogenous variable help predict another variable. In this case, I will analyse if the lags of different variables are effective in forecasting credit.

Figure 9: Test for Granger Causality for chosen models

VAR 1			**VAR 2**			**FAVAR 1**		
variable	χ^2	**p-val**	**variable**	χ^2	**p-val**	**variable**	χ^2	**p-val**
$\Delta ln(GDP)$	30.283	0***	$\Delta ln(GDP)$	36.936	0***	$\Delta ln(GDP)$	9.6753	0.085*
ΔFF	4.7766	0.444	ΔRIR	6.0061	0.199	ΔFF	9.766	0.082*
ALL	34.061	0.006***	$\Delta^2 ln(PP)$	15.318	0.004***	f1	15.778	0.008***
			ALL	60.437	0***	f2	11.567	0.041**
						f3	27.435	0***
						f4	11.08	0.05**
						ALL	119.73	0***

H0: variable does not Granger Cause credit
$*p < 0.1, **p < 0.05, ***p < 0.01.$

The p-value tests the Null hypothesis that lags of a given variable do not help forecast credit. Therefore if p-value < 0.05 I conclude that the variable does help forecast credit.

First I focus on a comparison between VAR 1 and VAR 2. The p-value on Property Prices is below 0.05 therefore it helps forecast credit dynamics. This result is surprising given the previous result of VAR 1 outperforming VAR 2. A possible explanation is that the Real Interest Rate is significantly worse than Fed Funds Interest Rate in forecasting credit, even though they aim to represent the same concept. However, it seems that the χ^2 value is higher for RIR than FF, so this theory does not seem to explain this contradiction.

More important for this paper is the comparison between VAR 1 and FAVAR 1. It seems that all p-values on all factors are lower or equal to 0.05, implying that lags of retained factors are effective in forecasting credit at a 5% significance level. However, this again contradicts the result from above that VAR 1 produces better forecasts than FAVAR 1. I believe this can be explained by the decrease in forecasting power produced by lags of GDP. In VAR 1, GDP is the most significant variable in forecasting credit, however, the χ^2 value associated with GDP decreased significantly in FAVAR 1 and at 5% significance level Granger Causality test suggests that GDP does not help in forecasting credit. This is likely due to the fact that the first factor contains the same information as GDP and dilutes the forecasting power that GDP would otherwise have.

5 Conclusion

This paper studied the performance of three different theoretical econometric models in forecasting credit dynamics by comparing RMSE for time horizons varying from a quarter to two years ahead. I have shown that FAVAR with original variables and one additional factor outperforms the benchmark VAR when the forecasting horizon is shorter than eight steps ahead. Furthermore, I have shown that modified FAVAR, with only credit and four retained factors, consistently outperforms original VAR. Crucially my results show that imposing long-run equilibrium by estimating the VECM does not produce more accurate forecasts.

I conclude that central banks that use traditional methodology should consider adopting techniques that use 'big data' and develop FAVAR models to forecast credit dynamics. However, it must be highlighted that economic conditions vary across countries, and it is possible that the models I considered in the US context will also perform differently. Further research needs to be conducted to identify if these results can be replicated in different countries.

Another avenue for further research would include comparing FAVAR with other VAR-based models used for forecasting purposes such as Bayesian VAR. Furthermore, it would be interesting to see how FAVAR fairs in comparison with machine learning techniques such as Long Short Term Memory (LSTM) structure used in neural networks.

Lastly, the key limitation of this paper is the forecasting period I choose. I decided to exclude the period following the Covid-19 pandemic as an outlier. However, central banks need to take into account this structural break and adapt their models to this paradigm shift. Crucially, however, my research shows that FAVAR can outperform traditional econometric techniques and should be considered when updating forecasting methodologies.

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A Appendix

A.1 Descriptions of chosen variables

Table 1: Descriptions of chosen variables

Variable	Abbreviation	Transformation	Description
Total Credit	credit	5	Long series on credit to private non-financial sectors
GDP	GDP	5	Real Gross Domestic Product, 3 Decimal (Billions of Chained 2012 Dollars)
Fed Funds Interest Rate	FF	2	Effective Federal Funds Rate (Percent)
Real Interest Rate	RIR	2	1-Year Real Interest Rate, Percent, Quarterly, Not Seasonally Adjusted
Property Index	PP	6	All-Transactions House Price Index for the United States (Index 1980 Q1=100)
Industrial Production	INDPRO	5	Industrial Production Index (Index 2012=100)
All Employees	EMP	5	All Employees: Total nonfarm (Thousands of Persons)
Housing Starts	HOUS	5	Housing Starts: Total: New Privately Owned Housing Units Started (Thousands of Units)
Manufacturing	CMRMTSPLx	5	Real Manufacturing and Trade Industries Sales (Millions of Chained 2012 Dollars)
CPI Index	CPI	6	Consumer Price Index for All Urban Consumers: All Items (Index 1982-84=100)
Earnings	AHETPIx	5	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private (2012 Dollars per Hour), deflated by Core PCE
Monetary Base	BOGMBASEREALx	5	Monetary Base (Millions of 1982-84 Dollars), deflated by CPI
Total Assets	TABSHNOx	5	Real Total Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE
U.S. Dollar Index	TWEXAFEGSMTHx	5	Trade Weighted U.S. Dollar Index: Advanced Foreign Currencies (Index Jan 2006=100)
S&P500 Index	SP500	5	S&P's Common Stock Price Index: Composite
Federal Debt	GFDEGDQ188S	2	Federal Debt: Total Public Debt as Percent of GDP (Percent)

For description of all variables refer to McCracken and Ng (2020)
Transformations applied are defined as: (2)Δx_t; (5) $\Delta \ln(x_t)$ (6) $\Delta^2 \ln(x_t)$

A.2 Summary Statistics

Table 2: Summary Statistics of chosen variables

Variable	Observations	Mean	Std. Dev.	Min	Max
credit	254	11159.13	10900.98	357.062	37955.12
GDP	255	9.104036	0.541526	8.046862	9.906217
FF	255	4.771504	3.664833	0.06	17.78
RIR	164	1.369222	2.392142	-3.966425	9.286022
PP	191	5.68588	0.2142423	5.342095	6.228846
INDPRO	255	4.105008	0.4530346	3.100263	4.649861
EMP	255	11.51982	0.3162709	10.87288	11.93639
HOUS	255	7.227162	0.3012339	6.264667	7.793174
CMRMTSPLx	255	13.5295	0.5076374	12.56076	14.26712
CPI	255	4.652802	0.7501998	3.367065	5.689967
AHETPIx	235	2.846759	0.1147827	2.631015	3.105389
BOGMBASEREALx	255	12.75689	0.7895974	12.00138	14.64835
TABSHNOx	227	60.96866	27.12808	30.60333	134.8353
TWEXAFEGSMTHx	255	10.62342	0.6883275	9.452539	11.85597
SP500	199	4.703952	0.1379569	4.42156	5.125183
GFDEGDQ188S	255	5.929721	1.329713	4.013375	8.43402

A.3 ADF Test 1

Table 3: Augmented Dickey-Fuller test for unit root

Variable	**Model**	**Lags**	**Test Statistic**	**5% Critical Value**	**Stationary**
$ln(credit)$	C	8	-1.04	-3.431	No
$\Delta ln(credit)$	B	4	-2.942	-2.88	Yes
$ln(GDP)$	C	4	-1.497	-3.43	No
$\Delta ln(GDP)$	B	4	-6.248	-2.88	Yes
FF	B	8	-2.107	-2.88	No
ΔFF	B	8	-6.136	-2.88	Yes

Model represents deterministic values used:
(B) - unrestricted intercept and no trend; (C) - unrestricted intercept, restricted trend
if Test Statistic < 5% Critical Value I conclude that variable is Stationary

A.4 LM test for autocorrelation for VAR 1

Table 4: Lagrange-multiplier test for autocorrelation in residuals for VAR(5)

lag	**chi2**	**Prob >chi2**
1	16.855	0.05104*
2	17.6886	0.03896**
3	23.0421	0.0061***
4	9.1493	0.42361
5	21.8798	0.00927***
6	6.0369	0.73622
7	7.9871	0.53545
8	23.5659	0.00504***
9	18.6176	0.02865**

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01$.

A.5 ADF Test 2

Table 5: Augmented Dickey-Fuller test for unit root

Variable	Model	Lags	Test Statistic	5% Critical Value	Stationary
RIR	B	4	-2.081	-2.886	No
ΔRIR	B	4	-6.35	-2.886	Yes
$ln(PP)$	C	4	-3.275	-3.439	No
$\Delta ln(PP)$	C	3	-2.585	-3.439	No
$\Delta^2 ln(PP)$	B	2	-14.01	-2.884	Yes

Model represents deterministic values used:
(B) - unrestricted intercept and no trend; (C) - unrestricted intercept, restricted trend
if Test Statistic < 5% Critical Value I conclude that variable is Stationary

A.6 LM test for autocorrelation for VAR 2

Table 6: Lagrange-multiplier test for autocorrelation in residuals for VAR(4)

lag	chi2	Prob >chi2
1	26.0025	0.05399*
2	20.3034	0.20687
3	23.7247	0.09569*
4	15.74	0.47125
5	17.2412	0.37016
6	16.9486	0.38893
7	13.9592	0.60175
8	23.2654	0.10682
9	32.8938	0.00763***

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01$.

A.7 LM test for autocorrelation for VECM

Table 7: Lagrange-multiplier test for autocorrelation in residuals for VECM(8)

lag	chi2	Prob >chi2
1	23.6385	0.09770*
2	17.4102	0.35955
3	15.6432	0.47813
4	15.8076	0.46647
5	17.3783	0.36154
6	20.3457	0.20505
7	12.0103	0.74327
8	30.5768	0.01523 **
9	34.0484	0.00535***
10	19.8092	0.22894

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01.$

A.8 Number of Factors

Table 8: Number of Factors Information Criteria

factors	IC_{p1}	ER	GR	GOL
0	19.921	0.185	1.674	4.50E+08
1	9.072	0.00054*	2.439	8272.394
2	4.648	119.962	3.548*	68.89
3	3.43	3.054	0.722	22.509
4	1.727	7.932	1.933	2.778
5	0.865	4.721	2.43	0.534
6	0.534	1.094	0.702	0.482
7	0.046	1.781	1.065	0.241
8	-0.411	1.343	0.762	0.162
9	-1.022	1.619	0.778	0.074
10	-1.818	2.872	1.376	-0.019*
11	-2.386	2.591	1.559	-0.049
12	-2.736*	1.249	0.811	-0.053

IC1: is one of 6 (all give the same result) IC from Bai and Ng(2002) that are based on an adjustment to the sum of squared residuals which corrects for the optimism of the training error.
ER: Information Criterion based on ratio of two subsequent eigenvalues (Ahn and Horenstein (2013))
GR: Information Criterion relies on ratio of growth rates of two subsequent eigenvalues (Ahn and Horenstein (2013))
GOL: Information Criterion considers decreasing sequence of eigenvalues minus a correction term (Gagliardini et al. (2019))

A.9 ADF Test retained factors

Table 9: Augmented Dickey-Fuller test for unit root

Variable	Model	Lags	Test Statistic	5% Critical Value	Stationary
factor 1	B	4	-3.453	-2.889	Yes
factor 2	B	4	-6.469	-2.889	Yes
factor 3	B	4	-4.859	-2.889	Yes
factor 4	B	4	-3.577	-2.889	Yes

Model represents deterministic values used:
(B) - unrestricted intercept and no trend;
if Test Statistic < 5% Critical Value I conclude that variable is Stationary

A.10 LM test for autocorrelation for FAVAR 1

Table 10: Lagrange-multiplier test for autocorrelation in residuals for FAVAR(5)

lag	chi2	Prob >chi2
1	48.9279	0.47603
2	58.2453	0.17174
3	51.5396	0.37473
4	60.7903	0.12037
5	63.5732	0.07881*
6	45.5493	0.61382
7	38.8288	0.85082
8	69.5043	0.02855**
9	61.3522	0.11082

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01$.

A.11 LM test for autocorrelation for FAVAR 2

Table 11: Lagrange-multiplier test for autocorrelation in residuals for FAVAR(4)

lag	chi2	Prob >chi2
1	36.2549	0.00267 ***
2	33.8222	0.00574 ***
3	22.5246	0.12705
4	27.3762	0.03749 **
5	35.7921	0.00309 ***
6	20.1770	0.21236
7	28.2018	0.02991**
8	37.2088	0.00196***
9	21.5785	0.15733

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01$.

A.12 LM test for autocorrelation for FAVAR 3

Table 12: Lagrange-multiplier test for autocorrelation in residuals for FAVAR(4)

lag	**chi2**	**Prob >chi2**
1	25.3516	0.44281
2	24.8296	0.47195
3	27.9548	0.30994
4	24.3280	0.50049
5	26.5523	0.37861
6	30.5969	0.20272
7	26.0550	0.40467
8	41.7870	0.01894**
9	26.5835	0.37700

H0: no autocorrelation at lag order
$*p < 0.1, **p < 0.05, ***p < 0.01.$