Can FAVAR improve Swedish inflation forecasting?

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Abstract

The purpose of this thesis is to investigate whether factor augmented vectorautoregression (FAVAR) models estimated using principal component analysis are able to improve monthly inflation rate forecasts for Sweden. We produce 42 forecasts for the period January 2012 to June 2015 and evaluate the forecasts by their root mean square errors as well as their ability to correctly predict the sign of the inflation rate. The models forecasting performances are compared using the Diebold-Mariano test of equal predictive accuracy. Our results show that the investigated FAVAR models cannot significantly improve forecasts relative to a univariate model and that the FAVAR models perform worse with twelve lags than with only one lag.

KEYWORDS: Forecasting, factor models, principal component analysis, Phillips curve, Taylor rule

1 Introduction

Forecasting how the price level in the economy is evolving is a difficult yet important task for both the private and public sectors. The Swedish central bank, the Riksbank, like many central banks has an explicit target to keep inflation at two percent. To reach the inflation target it is of great importance for a central bank using the New Keynesian model to base decisions on optimal inflation forecasts, (Svensson, 2005). Reliable forecasts are also imperative for a central bank in order for it to maintain its credibility which is at risk of suffering if inflation forecasts are too far off the actual outcome.

Researchers in the field of empirical macroeconomics received a sophisticated upgrade to their toolbox in 1980 when Christopher A. Sims proposed that the observations of macroeconomic variables could be analysed using the statistical tool that is the vector autoregression (VAR). The VAR model is constructed as a multivariate autoregressive model in which the stochastic process is generated by a vector of variables and helps a researcher understand what causes what in the macro economy – a contribution for which Sims later received The Nobel Memorial Prize in Economic Science. Stock and Watson (1999) undertook one of the most thorough studies of inflation forecasting using VAR models, testing the utility of the Phillips curve for forecasting.

Today, forecasters are presented with a wide range of statistical tools and models when attempting to predict future inflation. By looking at inflation-protected bonds one can infer the market participant's expectations of future inflation, although Faust & Wright (2011) state that this way of forecasting will lead policy makers into believing that inflation expectations are in a constant state of turmoil. Instead, many central banks are today using Stochastic General Equilibrium (DSGE) and Bayesian VAR models to complement their subjective forecasts. This is also how the Swedish central bank, the Riksbank, produce their forecasts as discussed in Hallsten and Tägström (2009).

The use of dynamic factor models in time series was introduced by Geweke (1977) and later popularised by Stock and Watson (2002). The practice of principal component analysis (PCA) nonetheless stretches back to 1901 when Karl Pearson discovered the statistical procedure of forming orthogonal transformations of

potentially correlated observations into uncorrelated linear combinations called principal components. Bernanke et al. (2005) published a ground breaking article using *factor augmented* vectorautoregressions (FAVAR) to measure the effects of monetary policy and their article was a result of some of the critique against traditional VAR models.

The critique involves the difficulty to find a suitable measure for the unobservable concept of economic activity. Rather than having to select proxies such as industrial production, the FAVAR framework allows a researcher to create a factor (or factors) containing up to several hundred time series. FAVAR models also help solving degrees of freedom problems associated with modelling many different variables in one VAR model since a factor is considered as only one variable that contains information from many other variables. Perhaps most importantly, FAVAR models mitigate the risk of omitting important variables since it does not require the practitioner to select the most important variables as it is now possible to include variables that are not intuitively certain to have an influence on the dependent variable of interest. The study laid the groundwork for new ways to analyse the effects of monetary policy and the use of dynamic factor models has become increasingly popular in time series econometrics.

Laganà and Mountford (2005) used factor models in an impulse response analysis of the British monetary policy and concluded that adding factors to VAR models result in superior predictions compared to simple VAR and AR models. Gavin and Kliesen (2008) compared dynamic factor models with simpler univariate models and concluded that data-rich models performed best at longer horizons, in their case 12 months and 24 months ahead. However, forecasts with longer horizons are difficult to model with monthly stationary time series by construction of the models and thus not considered in this thesis.

Whilst the forecasting literature on dynamic factor models is rapidly increasing in line with the support of their effectiveness, there are to our best knowledge currently no studies applying these models to a Swedish data set. Hence, the purpose of this study is to investigate whether FAVAR models can improve monthly inflation forecasts for Sweden?

Our results indicate some support for FAVAR models in the use for forecasting although the models are not significantly better than a simple univariate model.

The thesis is structured as following. Section 2 presents the econometric approach, Section 3 presents the data that has been used, Section 4 presents the results and Section 5 concludes. The time series and their transformations are displayed in the Appendix.

1.1 Earlier Research

Dynamic factor models constitute a relatively new field within time series econometrics and there is no definite answer to which settings that yield the best results for inflation forecasting. Specifically, there is no prominent earlier research on Swedish inflation forecasting using dynamic factor models. The most recognised studies of dynamic factor models in forecasting include Stock and Watson (2002a, 2002b, 2005) and Bernanke et al. (2005) who found support in favour of factor models when using data from the United States.

Out of the growing literature on dynamic factor models used for forecasting, the following studies are investigating countries that are somewhat similar to the Swedish economy. Hence, they ought to give an indication of the view on dynamic factor models used for small, industrialised and open economies similar to Sweden.

Pang (2010) investigated the predictive ability of dynamic factor models on inflation for the Hong Kong economy. The study tested a large amount of different settings using both different amounts of factors and had the number of lags vary between one and thirteen as a min-max setting. The findings give support for dynamic factor models in inflation forecasting for both short and long horizons.

Matheson (2006) tested a dynamic factor model for inflation forecasting with time series data from New Zealand. The results indicate that factor models with one or two factors improve forecasts relative to forecasts from the New Zealand Reserve Bank, which were used as benchmark forecasts.

Brisson et al. (2001) found that dynamic factor models can improve forecasts and especially for forecasts on shorter horizons. The researchers concluded that

dynamic factor models are especially good at exploiting very recent information in macroeconomic series, which gives the forecaster an edge towards simpler models particularly for shorter horizons.

Arratibel et al. (2009) used data for a selection of new EU member states and found that univariate models are difficult to beat in short-term forecasting albeit factor-based models that include proxies for monetary activity could improve forecasts for longer horizons. Moreover, the researchers noted that the model performances varied substantially among the countries and this was a pattern occurring for all forecasting horizons.

2 Econometric approach

The economic term inflation is defined as the rate at which the general price level of goods and services increases in an economy over time. It is commonly measured through various indices created by national statistics agencies. In this thesis, the *1*-period (monthly) inflation will from here on be defined as

$$\pi_t = ln\left(\frac{P_t}{P_{t-1}}\right) = \ln P_t - \ln P_{t-1} \tag{1}$$

where π_t is monthly inflation at time t expressed as the logarithmic first difference of P_t, the Consumer Price Index (CPI).

The FAVAR framework used by Bernanke et al. (2005) is given as

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \upsilon_t \tag{2}$$

where $\Phi(L)$ is a conformable lag polynomial of finite order d, which in this thesis is constrained to be equal to either one or twelve in order to obtain a min-max lag setting. The error term, υ_t, is mean zero with covariance matrix Σ. In this thesis, should the terms in $\Phi(L)$ that relate F_{t-1} to Y_t be zero, the equation above would be reduced to a univariate *AR(p)* model since the variation in the factors do not contribute to explaining any of the variation in inflation. If, Y_t and F_{t-1} in fact are related, this equation will be referred to as a *factor-augmented vector autoregression*, or FAVAR.

This thesis follows the two-step principal component (PC) method used by Stock and Watson (2002b) as well as Bernanke et al. (2005) to estimate the FAVAR models. Let, F_t be a $K \times 1$ vector of unobservable factors that is supposed to function as a proxy for the dynamics of the economy and summarise the information of X_t which is a $N \times 1$ vector of stationary time series observed for $t = 1, \dots, T$. The factors, F_t, are supposed to be "small" in comparison to the number of informational time series, N. In fact, N may be larger than T. Let Y_t be a $M \times 1$ vector of observable macroeconomic time series which is a subset of X_t, (for this thesis Y_t contains only the time series for inflation which is the series of forecasting interest). The joint dynamics of X_t, Y_t and F_t is then given by Stock and Watson (2002) as

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + \varepsilon_t' \tag{3}$$

where Λ^f is a $N \times K$ matrix of factor loadings, Λ^y is $N \times M$ and ε_t is a $N \times 1$ vector of error terms that are assumed to be mean zero but may display some small degree of cross-autocorrelation. Hence, equation 3 above states that the informational time series in X_t are explained by the estimated factors in F_t and the time series of interest in Y_t plus a mean zero error term, ε_t.

2.1 Model specifications

The first FAVAR model is a generalised Phillips curve similar to the model used by Stock and Watson (1999) where unemployment is replaced by an aggregate measure of *real economic activity* based on several macroeconomic time series. The Phillips curve is known in macroeconomics as the relationship between the change in inflation and the unemployment gap, i.e. the difference between current unemployment and the so-called *non-accelerating inflation rate of unemployment* (NAIRU). It is however well known that policy makers at central banks take a large amount of time series into account when forecasting inflation. The addition of factors supposed to summarise real economic activity thus ought to resemble the method used by policy makers and therefore improve forecasts relative to a simpler model that only uses unemployment.

This study will consider two different FAVAR models and the first model is the factor augmented Phillips curve, which is given as

$$\pi_t = \phi + \gamma(L)\pi_{t-1} + \varphi(L)F'_{t-1,e} + \varepsilon_t \quad (4)$$

where $F_{t-1,e}$ is a $K \times 1$ vector of factors used as an aggregate measure of real economic activity. ϕ is an intercept, γ and φ are parameters to be estimated whilst ε_t is the forecasting error term.

The second FAVAR model is based on a Taylor rule representation similar to Bernanke et al. (2005) with the slight modification that rather than considering the central bank policy rate as observable, this study replaces the interest rate term by factors that are supposed to summarise *monetary activity.* Correspondingly, the proxy for the output gap is replaced by factors thought to encapsulate the unobservable series of real economic activity. The Taylor rule, (Taylor, 1993), is one of many simple rules for monetary policy and it is said to describe Swedish monetary policy rather well according to a study by Berg et al. (2004). Although monetary policy is partly piloted by discretionary decisions, simple rules can serve as a benchmark for policy making and it is therefore of interest to test the rule in a forecasting exercise.

A problem with dynamic factor models is that the factors are sometimes difficult to give a meaningful economic interpretation. By dividing the macroeconomic time series into different categories before estimating the factors with PCA, we want to investigate whether this improves forecasting. Also, the division into categories could provide the forecaster with an indication of which category of series that has the highest predictive ability by looking at the number of factors from each group. Thus, the factor augmented Taylor rule is given as

$$\pi_t = \phi + \gamma(L)\pi_{t-1} + \beta(L)F'_{t-1,m} + \varphi(L)F'_{t-1,e} + \varepsilon_t \quad (5)$$

where $F_{t-1,m}$ and $F_{t-1,e}$ are $K \times 1$ vectors of monetary activity and real economic activity respectively.

There are several methods available for determining the optimal number of factors in factor models. Bai and Ng (2002, 2008) suggest penalty functions to use when the number of informational time series, N, is large, ($N > 100$). However, more advanced methods are deemed insufficient for the purpose of this study since N is considered small. Instead, the number of factors has been decided after assessing the magnitude of the eigenvalues in the principal component analysis. The Kaiser-

Guttman criterion applied in this study is a simple yet intuitively appealing decision-rule for determining the number of factors as the same amount of eigenvalues that exceeds unity, which is the average size of the eigenvalue of the correlation matrix (Breitung and Choi, 2013). Because the principal components are orthogonal to each other, approximately two thirds of the variation in the informational series is normally captured by the factors after applying the Kaiser-Guttman criterion.

2.2 Forecast exercise

The dataset has been divided into an in-sample period and an out-of-sample period where the in-sample observations were used to estimate the parameters. The out-of-sample period starts in January 2012 leading to a total of 42 monthly forecasts up until June 2015.The forecast horizon is limited to one month as a consequence of time limitation but mostly due to the characteristics of the chosen out-of-sample period. The forecasting period is characterised by very non-volatile inflation and a longer forecast horizon will by construction of the stationary models only forecast inflation close to the conditional mean which is zero.

The forecasts are performed using a recursive window approach, which means that for each period the in-sample window is expanding ahead of each monthly forecast. This study follows the guidelines of Pesaran and Timmermann (2007) for determining the optimal window size as the in-sample portion starts after the target inflation regime was implemented, although the in-sample period has not been tested for structural break. The parameters are estimated using observations during the financial crisis of 2007-2009 since this period did not cause any alarming concern, however more formal tests for structural break are encouraged in future studies. The models are estimated by OLS and all forecasts are made using Eviews 8. The tests below are performed in MS Excel.

The forecasts are evaluated by their root mean square error (RMSE), which is defined as

$$RMSE = \sqrt{\frac{1}{T_0}\sum_{t=t_0}^{T_0}\left(\hat{\pi}_{t+h} - \pi_{t+h|t}\right)^2} = \sqrt{\frac{1}{T_0}\sum_{t=t_0}^{T_0}\left(\varepsilon_{t+h|t}\right)^2} \qquad (6)$$

where $\hat{\pi}_{t+h}$ is the inflation forecast at time t and $\pi_{t+h|t}$ is the actual inflation at time t. $\varepsilon_{t+h|t}$ is thus the forecasting error and T_0 is the number of forecasts. Clearly, the lower the RMSE, the better is the forecasting performance.

Diebold and Mariano (1995) discovered a double-sided test that examines whether two models have equal forecasting performance. The test is based on the loss differential

$$d_t = L\left(\varepsilon^1_{t+h|t}\right) - L\left(\varepsilon^2_{t+h|t}\right) \tag{7}$$

where $L\left(\varepsilon^i_{t+h|t}\right) = \left(\varepsilon^i_{t+h|t}\right)^2$, i.e. the squared forecasting error of model 1 and model 2 respectively. The null hypothesis of equal predictive accuracy is thereafter tested using the test statistic in equation 8 below.

$$S = \frac{\bar{d}}{\left(\widehat{LRV}_{\bar{d}}/T_0\right)^{1/2}} \tag{8}$$

where $\bar{d} = T_0^{-1}\sum_{t=t_0}^{T} d_t$ and $\widehat{LRV}_{\bar{d}}$ is a consistent estimate of the asymptotic (long-run) variance estimated with the Bartlett kernel in accordance to Newey and West (1987).

Diebold and Mariano (1995) show that asymptotically $S \sim N(0,1)$ under the null hypothesis of equal predictive accuracy.

The models are also evaluated by how often they project the correct sign of the one-step-ahead forecasts and tested whether this ratio is significantly different from the expectation. Ideally, even if the point estimates are inaccurate, a practitioner would benefit if the model would correctly indicate the sign in front of the monthly inflation digit.

The factor augmented Phillips curve will also be compared with its non-factor based equivalent and the similar modifications as Stock and Watson (1999) are adopted when they modelled the Phillips curve as

$$\pi_t = \phi + \gamma(L)\pi_{t-1} + \beta(L)u_{t-1} + \varepsilon_t \tag{9}$$

where inflation is a function of its lagged values and unemployment.

Similarly, factor augmented Taylor rule is compared to its simpler equivalent, which is modelled as

$$\pi_t = \phi + \gamma(L)\pi_{t-1} + \beta(L)r_{t-1} + \varphi(L)y_{t-1}^{ip} + \varepsilon_t \tag{10}$$

where r_{t-1} is the first difference of the change in the short-term interest rate used as a proxy for the policy rate set by the central bank and y_{t-1}^{ip} is the change in the industrial production in the economy which is used as a proxy for the output gap.

Conventionally, the more advanced models are compared to the univariate autoregressive model where inflation is modelled as a function of its own lagged values. The autoregressive model for inflation is given as

$$\pi_t = \phi + \gamma(L)\pi_{t-1} + \varepsilon_t. \tag{11}$$

Finally, the models are compared to a *No change* model that predicts no change in inflation from the previous month. If the No change model performs best it indicates that there is little or no forecastable variation in the inflation series during the selected time period.

3 Data

The time series in this study are collected from OECD, ILO and Statistics Sweden and sum up to 22 monthly macroeconomic series in total. As always in empirical macroeconomics, we are restricted by the availability of data. However, Boivin and Ng (2006) nevertheless found that as few as 40 series often yield satisfactory or even better results than more than hundred series. All series ranges from January 1994 to June 2015, which yields 258 observations for each series. The reason the sample period starts at 1994 is to exclude the potential structural break related to the Riksbank's decision in November 1992 to switch to a floating exchange rate regime and the adoption of explicit target inflation in January 1993. Lucas (1976) argued that econometric models with lagged variables developed under one policy regime cannot be used to forecast behaviour during another policy regime, hence this study only uses data after 1994 despite the fact that earlier observations are available for most series. All series are transformed using the same method as Stock and Watson (2005).

After visually examining the inflation series, a distinguished negative spike in the observations for January was frequently found. The reason for this spike is unknown and beyond the scope of this study albeit a possible reason for these spikes could be the effect of January sales after Christmas. Further research on the presence of this potential anomaly is encouraged but not further discussed in this study. Therefore, in order to avoid bias in the estimated models, this effect has been removed by the use of a dummy variable for the month of January.

However, there are other methods to mitigate bias in the models. Stock and Watson (1999) experimented with different methods of a one-sided Hodrick-Prescott filter in order to enhance trend components of the series rather than the raw series of their own. Harvey and Jaeger (1993) provide further discussions of optimal filtering but conclude that detrending based on the Hodrick-Prescott filter can lead researchers to report spurious cyclical behaviour. Similarly, King and Rebelo (1993) offer examples of how HP filtering dramatically alters measures of persistence, variability, and co-movement. Hence, the series in this study have, apart from the January dummy variable for inflation, not been filtered in order to keep as much variation in the series as possible and to avoid accidentally losing important information.

4 Empirical results

The forecast root mean square errors, the *p*-values and the percentage of times the models predicted the correct sign of the monthly inflation digit are presented and discussed below. Again, the model(s) with the lowest RMSE are considered superior and the Diebold-Mariano test is used in order to investigate whether the forecasting errors are significantly different from each other. For consistency, the factor models are only tested against their simpler versions, i.e. the factor-augmented Phillips curve is compared to its VAR equivalent and vice versa. The sign evaluation is performed in order to assess how often the models manage to forecast whether inflation is accelerating or decelerating and whether this ratio is statistically significant from the expected performance of a coin toss. After estimating the factors with PCA and determining the number of factor with the Kaiser-Guttman criterion, the FAVAR models include a total of eight and seven

factors (two monetary and five economic) respectively, which capture the vast majority of the variation in the series. Table 1 below displays the forecast statistics for the models with one lag.

Table 1: Results for k=1

k=1	RMSE	FAVAR1	FAVAR2	Sign
FAVAR1	0,00301	x	0,299	40%
FAVAR2	0,00309	0,299	x	55%
VAR1	0,00322	0,129	x	29%*
VAR2	0,00323	x	0,241	36%*
AR	0,00325	0,136	0,218	36%*
No change	0,00306	0,385	0,396	x

Column 1 displays RMSE values. Column 2 displays p-values from DM statistics and column 3 displays the sign evaluation where * = p < 0,1, ** = p < 0,05 and *** = p < 0,01

The first column of Table 1 displays the root mean square errors and particularly the FAVAR models appear to stand out with the smallest RMSE values. The factor augmented Phillips curve produced the best forecasts followed by the No change model, which constantly predicted zero inflation. The factor augmented Taylor rule was slightly outdone by the No change model whereas the simpler VAR/AR models produced the highest RMSE values. The fact that the No change model was bettered, albeit only marginally, by the first FAVAR model gives some support to the hypothesis that there is at least some variation in inflation that is forecastable.

The second column of Table 1 presents the *p*-values from the Diebold-Mariano test of equal predictive ability. None of the *p*-values are significant which means that there is no statistically significant difference in the performance of the different models when one lag is used. Rossi and Sekhposyan (2010) find that the predictive ability of inflation models significantly worsened around the time of the Great Moderation[1] and that generally fewer predictors are significant for inflation compared to other macroeconomic variables. The relatively good performance of the No change model in our sample support their findings that inflation is difficult to forecast during times of moderate inflation but further

[1] The Great Moderation is referring to the period of decreased macroeconomic volatility experienced in the United States by the time after the 1980's.

research is needed to investigate whether the performances of the models have worsened for Sweden similarly to the results of Rossi and Sekhposyan (2010).

The third column of Table 1 displays the ability of the models to correctly predict whether inflation is accelerating or decelerating. Notably, only the FAVAR models could correctly predict the sign approximately half of the times. All other models (except for the No change model which was not tested due to the construction of the model) failed to predict the correct sign half of the time and their performances were significantly worse than a coin toss. These results give support for the FAVAR models ability to more effectively capture information in macroeconomic series and give useful predictions for future inflation.

The performances of the same models but with twelve lags are presented in Table 2 below.

Table 2: Results for k=12

k=12	RMSE	FAVAR1	FAVAR2	Sign
FAVAR1	0,00436	x	0,387	55%
FAVAR2	0,00422	0,387	x	50%
VAR1	0,00282	0,040	x	60%
VAR2	0,00273	x	0,001	64%*
AR	0,00263	0,004	0,008	60%
No change	0,00306	0,020	0,049	x

Column 1 displays RMSE values. Column 2 displays p-values from DM statistics and column 3 displays the sign evaluation where * = p < 0,1, ** = p < 0,05 and *** = p < 0,01

The RMSE for the models with twelve lags displays another ranking of the models in contrast to the models with only one lag. The two FAVAR models perform much worse than all other models and their RMSE values are much higher compared to when modelled with one lag. As shown in Table 2, no model could beat the univariate AR model, which obtained the smallest RMSE of all the models. The FAVAR models are no longer better than their simpler VAR equivalents although the reason appear to be a very good performance by the inflation driven AR part of the VAR models since the AR obtained the smallest RMSE. Hence, for twelve lags there appear to be no gain from including measures of economic or monetary activity for this sample period.

The second column of Table 2 displays the *p*-values for the Diebold-Mariano test and even though there is not significant difference in the forecasting performance of the two FAVAR models, they are both significantly outperformed by all other models including the No change model. The AR model outperforms the FAVAR models on the one percent significance level, which leads us into believing that FAVAR models perform worse with more lags than with fewer lags. This result could be caused by redundant information in lagged values of the series that laid ground for the constructed factors. Since the factors are constructed using both fast and slow moving series and no distinction is made between them, it could well be the case that some lagged values of the informational series are uncorrelated with current inflation and should thus not be included. This finding is in line with Brisson et al. (2001) who found that factor models are very efficient at using recent information but that past information remain no more informative than the conditional mean.

The third column of Table 2 displays the sign evaluation of the models and notably the simpler AR/VAR models perform much better than they did with one lag. The FAVAR models are approximately equally good with twelve lags as with one lag when it comes to predicting the sign of the monthly inflation rate. Overall, all models are equally good or better than what one can expect from a coin toss and the Taylor rule VAR is on the ten percent level significantly better than a coin toss, which indicate that lagged values of the short-term interest are more useful than other variables when predicting whether inflation is accelerating or decelerating.

For the Phillips curve VAR model, the unemployment as a measure for economic activity can be questioned. The fact that the Phillips curve VAR performed slightly worse than the AR model when twelve lags where included and roughly the same for one lag indicates that unemployment has poor predictive ability for inflation in this sample period. This statement can also be supported by the fact that the factor augmented Phillips curve model performed better than the Phillips curve VAR with one lag. Hence, when modelling economic activity, using only unemployment as a measure does not seem to be a sufficiently good proxy. At least not when forecasting one period ahead with these time series. These findings are also in line with the results from Stock and Watson (1999) who used United

States data. Although for the US it is possible that unemployment plays a more important role when forecasting inflation since the Federal Reserve in addition to stable inflation also target unemployment, whereas the Riksbank has no unemployment target as it instead only targets stable inflation.

Overall, the results indicate that inflation during this time period has been very difficult to forecast and that the simple No change model has performed rather well compared to more advanced FAVAR models. However, the factor augmented Phillips curve with one lag was slightly better than the No change model, which indicates some forecastability in the series. Stock and Watson (2008) survey different studies investigating the performance of the Phillips curve as a predictor for inflation. They find that the relative performance of the Phillips curve varies over time and performs best when inflation is volatile. The out-of-sample period in this study however is characterised by both rather stable macroeconomic series and non-volatile inflation, which may explain the poor performance of the Phillips curve and other stationary time series models too. It appears that it difficult to beat univariate models when times are quite.

The performance of the factor augmented Taylor rule give no convincing support that there are gains from separating the factors as measures of monetary and economic activity. Estrella and Mishkin (1997) conclude that monetary aggregates make a poor guide for policy makers and the results of our study does not indicate anything different. Including lagged values of exchange rates and different interest rates appear to worsen the performance of the Taylor rule FAVAR. The redundant information of past values of these variables however is a good thing since it leads to fewer parameters that need to be estimated and thus more parsimonious models.

Finally, even though the FAVAR models aim to mitigate omitted variable bias in the models, there are still variables that may be impossible to include. The degree of competition in the economy clearly affects the prices of goods and services, particularly for longer horizons. In recent years, the degree of competition has increased as a consequence of various price comparing sites emerging on the Internet although the effect on inflation only ought to be limited to the short run as the central bank would have adapted to the new scenario in the long run. Even the

rate of technological growth and innovations has an effect on inflation that is difficult to measure with time series models. As firm's productivity increases as a result of computerisation and the reduced need of input to produce the same amount of output, goods become cheaper to produce and firms can lower prices without it affecting their mark-up. These are variables that ought to impact inflation trends but are difficult to model for econometricians. However, the FAVAR framework could potentially be useful to create proxies for the forces mentioned above in order to better model and forecast inflation in the future.

5 Conclusion

The purpose of this study has been to investigate whether factor augmented vectorautoregression models are able to improve monthly inflation rate forecasts for Sweden during the period 2012 to 2015. The models have either one or twelve lags, and the models forecasting performances are evaluated using RMSE and compared with the Diebold-Mariano test of equal predictive accuracy. Our conclusion is that no FAVAR model could significantly outperform the No change model or the univariate AR model. The FAVAR models in this study performed better with only one lag than with twelve, which indicates there could be economical gains from formally optimising the number of lags used in the models. Even though the out-of-sample was characterised by non-volatile inflation, there has been at least some variation that can be modelled. The use of FAVAR in macroeconomic forecasting and analysis should be explored further as its implications are potentially paramount.

5.1 Recommendations for further studies

Further research is needed to investigate the optimal number of lags for the factors and whether additional time series in the principal component analysis can improve the forecasting accuracy. It would also be of interest to examine whether the models would perform better during another sample period. We have only considered linear relationships between the variables and an interesting idea would be to investigate if non-linear transformations of the variables could improve forecasts. Finally, it would be interesting to assess how the models performs for longer forecasting horizons and to use the models to forecast other macroeconomic series.

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8 Appendix

The transformation codes are as follows: Δ= first difference, lv= level of the data, ln= natural logarithm. 2010 = 100 for all OECD indices.

Time series	Transformation	Source
Inflation series		
Consumer Price Index (1980=100)	Δlv	SCB
Economic Activity series		
Labour force	Δln	ILOSTAT
Industrial Production Index	Δlv	OECD.Stat
Manufactuirng Index	Δlv	OECD.Stat
Production Construction	Δlv	OECD.Stat
Production Total Industry	Δlv	OECD.Stat
Retail trade volume Index	Δlv	OECD.Stat
Share Price Index	Δlv	OECD.Stat
Total Exports	Δln	OECD.Stat
Total Imports	Δln	OECD.Stat
Hourly earnings from Manufacturing	Δlv	OECD.Stat
Harmonised Unemployment	Δlv	OECD.Stat
Composite Leading Indicator Index	Δlv	OECD.Stat
Construction Index	Δlv	OECD.Stat
Monetary series		
SEK / US dollar exchange rate	Δln	OECD.Stat
SEK / British Pound exchange rate	Δln	OECD.Stat
SEK / Euro exchange rate	Δln	OECD.Stat
SEK / Japanese Yen exchange rate	Δln	OECD.Stat
STIBOR Inter bank rate	Δlv	OECD.Stat
Long-term interest rate	Δlv	OECD.Stat
Short-term interest rate	Δlv	OECD.Stat
Swedish M3	Δlv	OECD.Stat