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The estimation of factors in FAVAR models

Erik Berggren

Supervised by Professor Joakim Westerlund

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Abstract

The use of factor-augmented vector autoregression (FAVAR) models has become increasingly popular in the literature of empirical macroeconomics. This paper sheds light on the different factor estimation methods that are available to researchers. More specifically, this paper examines the widely used principal component method but also the computationally simpler common correlated effects method as well as the more advanced likelihood-based method using the Gibbs sampler. The results indicate very little difference between the principal component method and the common correlated effects method, which can facilitate the estimation of FAVAR models for researchers within the field of macroeconomics.

KEYWORDS: Common correlated effects, principal component analysis, Gibbs sampling, impulse response, factor models

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1. Introduction

Policy makers at central banks today have more than a hundred of economic indicators to monitor when conducting monetary policy. To gain insight from these variables is therefore essential for the understanding of how monetary policy affects the price level and the economy as a whole. Sims (1980) developed a tool for analysing economic time series when he introduced the vector autoregression (VAR) model as an alternative to the simultaneous equation models that had previously dominated the field of empirical macroeconomics. VAR models have become a popular choice of researchers aiming to measure the effects of monetary policy on macroeconomic variables. Bernanke and Blinder (1992) use VAR models to show that the Federal funds rate is very informative about future movements of real macroeconomic variables and Sims (1992) find that patterns in the data consistent with effective monetary policy are strikingly similar across countries.

However, VAR models often require the researcher to identify only a small amount of variables that should enter the model, to avoid the curse of dimensionality. Standard VAR models do not often include more than six to eight variables in order to minimise the loss of degrees of freedom, which can have a substantial effect if the time dimension of the dataset already is low to start with. The sparse information sets in the VAR analysis is one of the reasons for the so-called “price puzzle” that Sims (1992) noted. According to economic theory, an increase in the policy interest rate ought to lead to a decrease in the price level, but a conventional finding of studies using low-dimensional VAR models is that the price level tends to increase following a contractionary monetary policy shock. Sims argues that the price puzzle is a result of imperfectly controlling for information that policy makers may have about future inflation. The conventional solution for this puzzle is to include a commodity price index in the model, but as Hanson (2004) argues, the inclusion of any “information variable” in a monetary VAR is often fairly *ad hoc* and lacks theoretical justification.

The missing information in VAR models that policy makers may have at their disposal can probably not even be summarised by a single economic time series. Observable variables, such as industrial production or GDP, are imperfect measures of overall economic activity and are likely to suffer from measurement

errors. These insights motivated the use of factor analysis in macroeconomics as it lets the researcher use information from a large cross-section of time series without including all variables in the model. The use of factor models in time series was introduced by Sargent and Sims (1977) and Geweke (1977) and have since then been popularised by Stock and Watson (1999), who used factor models based on over a hundred series to forecast inflation. Bernanke, Boivin and Eliasziw (2005) developed the factor-augmented vector autoregression (FAVAR) model that builds on earlier factor literature. Their FAVAR approach introduces two changes to the standard factor model as it allows for additional observables (in their paper it is the Federal funds rate) as well they let the unobservable factors and the observable variables jointly follow a VAR process.

The use of FAVAR models in empirical macroeconomics has become increasingly popular as the availability of larger datasets increases. Belviso and Milani (2006) estimate a structural FAVAR to study shocks in the U.S. economy and Ludvigson and Ng (2009) take the FAVAR approach to study bond risk premia. In another study of monetary policy shocks, Laganá and Mountford (2005) use a U.K. dataset and conclude that FAVAR models improve results compared to VAR models without factors. The methodology by Bernanke et al. (2005) has furthermore been applied in forecasting settings and the results of Gavin and Kliesen (2008) suggest that factor-based models performed best at longer horizons, such as 12 to 24 months ahead. Matheson (2006) found that using one or two factors in the model improve results when using data from New Zealand.

Though the FAVAR literature is vast, little attention has been paid to the estimation of factors in the model. The principal component (PC) approach used by Stock and Watson (2002b) is overwhelmingly favoured by researchers as Bernanke et al. (2005) conclude that the computationally more demanding likelihood-based approach led to qualitatively similar results. However, a simpler method to estimate factors is to use the cross-sectional averages of the series in the dataset, as proposed by Pesaran (2006). This method has been shown to yield consistent factor estimates and eases the estimation when the number of variables is high. The method has been extended by Kapetanios, Pesaran and Yagamata (2011), Pesaran and Tosetti (2011), and Chudnik, Pesaran and Tosetti (2011) to

work in different kinds of settings. To the best of my knowledge, this factor estimation approach has not been applied to FAVAR models before and the purpose of this paper is therefore to evaluate the principal component approach and the factor estimation method proposed by Pesaran (2006), called Common Correlated Effects (CCE). The use of cross-sectional averages in factor estimation for FAVAR models could lead to an even bigger surge in the use of factor models in time series analysis as it becomes even simpler to extract information from a large amount of time series without having to increase the size of the model. For the sake of comparability with Bernanke et al. (2005), this paper will also evaluate the likelihood-based estimation using the Gibbs sampler in order to investigate a more advanced method as well.

The paper is organised into five sections, of which this is the introduction. Section 2 presents the econometric framework and Section 3 describes the data. The empirical results are discussed in Section 4 and Section 5 concludes. In brief, the results indicate a very small difference between the principal component approach and the common correlated effects method. The likelihood-based method is discarded due to the results being qualitatively useless.

2. Econometric framework

This study follows the approach developed by Bernanke et al. (2005). They assume that the joint dynamics of (F_t', Y_t') is given by the following equation:

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

where $\Phi(L)$ is a conformable lag polynomial of finite order d and the error term, v_t , is mean zero with covariance matrix Σ . The vector Y_t contains M observable economic variables and the vector F_t represents K unobserved factors that are supposed to influence the economic variables. The factors can be thought of as unobservable concepts such as *economic activity* or *investment climate*, which cannot be represented by any observable macroeconomic series but instead several series of economic indicators. Subsequently, should the terms of $\Phi(L)$ that relate Y_t to F_{t-1} all be zero, then equation (1) would be reduced to a standard VAR in Y_t . If Y_t in fact is related to the lagged factors then equation (1) will be referred to as a *factor-augmented vector autoregression*, or FAVAR.

The framework described above applies for all factor estimation methods but only the PC approach and the CCE method are based on equation (2) and (3) below. Equation (1) cannot be estimated directly since the factors F_t are unobservable and have to be replaced by \hat{F}_t . The estimated factors, \hat{F}_t , are assumed to be based on a number of time series that collectively are denoted by the $N \times 1$ vector X_t . Any given developed economy involves many different activities that can be described by various time series. The number of time series N in X_t is therefore assumed to be large, and may well be larger than T , the number of time periods. Bernanke et al. (2005) assume that the time series in X_t are related to the unobservable factors F_t and the observable economic variables Y_t by an equation given by

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \quad (2)$$

where Λ^f is a $N \times K$ matrix of factor loadings, Λ^y is $N \times M$ and e_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-correlation depending on the estimation method. Equation (2) express the idea that both Y_t and F_t , which can be correlated, epitomise the common forces that drive the dynamics of the noisy measures of X_t .

As for the estimations of \hat{F}_t , Bernanke et al. (2005) propose two different methods and it is not obvious *a priori* which method that should be preferred. The first method is a two-step principal component estimation and the second method is a joint estimation of equation (1) and (2) using a likelihood-based Gibbs sampling technique. For the two-step estimation, the authors make a distinction between “slow-moving” and “fast-moving” variables in X_t . The difference between a slow-moving and a fast-moving variable is that the former is assumed to not react contemporaneously to shocks, while the latter reacts instantaneously to changes in monetary policy or economic activity. Hence, the first step in the two-step is to use principal component analysis to estimate the common factors C_t from all the variables in X_t and Y_t . In the second step all variables in X_t are divided into either a group of slow-moving variables or fast-moving variables. This step also involves the estimation of the slow-moving factors \hat{F}_t^s as the principal components of the slow-moving variables, X_t^s . Thereafter, the following regression is estimated:

$$\hat{C}_t = b_{Fs}\hat{F}_t^s + b_Y Y_t + e \quad (3)$$

and based on these estimates, the factors \hat{F}_t are constructed from $\hat{C}_t - \hat{b}_Y Y_t$. The second step is then to estimate the FAVAR by replacing F_t with \hat{F}_t .

The two-step estimation using PC is the same as the method used in the forecasting exercises of Stock and Watson (2002b) and is widely used as the standard method in the FAVAR literature. A computationally simpler method to estimate \hat{F}_t is to use the cross-section average approach of Pesaran (2006). The CCE-based two-step procedure is very similar to the PC-based one described before, except for the fact that the slow-moving factor \hat{F}_t^s is computed as the cross section average of all slow-moving variables in X_t . Similarly, \hat{C}_t is estimated as the cross section average of all series in X_t . The method is computationally very easy and does not require any statistical software for the estimation of factors. An advantage of the CCE approach is that it does not require any previous knowledge of the number of unobserved factors. The downside is that if there is no division of X_t then there is just one average, which means just one factor. Also, the CCE approach has been proved to yield consistent estimates under variety of situations, as described in Chudnik and Pesaran (2013a).

Bernanke et al. (2005) estimate the factors according to the regression in equation (3) in order to avoid potential collinearity between the policy rate and the fast-moving factors as the information in the fast-moving factors ought to be accounted for in the federal funds rate used in their paper. However, the authors nonetheless propose the use of extracting both slow-moving and fast-moving factors in order to account for the fact that the estimated factors could respond contemporaneously to interest rate shocks. The optimal method is not clear beforehand and since this study is based on a completely different dataset than the one used by Bernanke et al. (2005), \hat{F}_t will be estimated both using the regression in equation (3) and by extracting both a slow-moving and a fast-moving factor.

In contrast to CCE and PC estimation, the likelihood-based method used by Bernanke et al. (2005) is fully parametric and computationally more demanding. It could in principle be possible to assume independent normal errors and estimate equation (1) and (2) jointly by ML, but Bernanke et al. (2005) point out that the very large dimensions of this model and the irregular nature of the likelihood

function makes estimation by ML infeasible in practice. The method they instead propose was developed by Geman and Geman (1984), Gelman and Rubin (1992) and Carter and Kohn (1994), and its application to large dynamic factor models is discussed in Elias (2002). Bernanke et al. (2005) implement a multi-move version of the Gibbs sampler in which factors are sampled conditional on the most recent draws of the factors. This Bayesian approach is undertaken in order to circumvent the high-dimensionality problem of the model by approximating marginal likelihoods by empirical densities. More details about the estimation procedure can be found in the appendix of the working paper version of Bernanke et al. (2005). Kim and Nelson (1999) survey different papers using the Gibbs sampling technique, and the Markov Chain Monte Carlo (MCMC) methodology used in the implementation is thoroughly explained in Del Negro and Schorfheide (2010) and Koop and Korobilis (2010).

3. Data

The following section describes the data used in this paper. All macroeconomic series are collected from OECD, The National Institute of Economic Research (NIER) and St. Louis Federal Reserve database FRED, and ranges from January 1998 to December 2016. The time period is chosen to account for the introduction of the floating exchange rate regime of the Riksbank in 1992 and the adoption of explicit inflation targeting in 1993. Borys et al. (2009) survey several studies of the Czech economy and argue that ignoring regime switches leads to results that exhibit the price puzzle. While studies within the VAR literature often employ quarterly data, this study will use monthly data in order to obtain as many observations as possible given the time period. Consequently, the study is based on 192 observations of each series. Bernanke et al. (2005) employ the same dataset as Stock and Watson (1999, 2002a), which consists of a mix of both monthly and quarterly data that has been merged using an Expectation Maximisation (EM) algorithm as in Bernanke and Boivin (2003). However, due to the availability of data this study will only apply 38 time series in contrast to the 120 macroeconomic series used by Bernanke et al. (2005). On the other hand, fewer series may not necessarily result in poor results as Boivin and Ng (2006)

found that as few as 40 series often lead to better results than using more than hundred series.

The observable monetary policy instrument in this study is given by the 3-month STIBOR. Note that this is the interbank rate and not the repo rate, which is the main monetary policy instrument of the Riksbank. This is because the repo rate does not contain any monthly variation as it is fixed between the monetary policy meetings of the Riksbank board. The interbank rate is nonetheless a widely used substitute for the official policy rate and its usefulness has been emphasised after the recent financial crisis when central banks all over Europe used non-standard measures to provide liquidity to the markets. Lenza et al. (2010) describe the non-standard measures used by central banks and argue that the 3-month interbank rate contains both standard and non-standard measures undertaken by a central bank. Therefore, the 3-month STIBOR is assumed to be a good indicator of the monetary policy of Sweden.

As for the observable variables in Y_t , this study will focus on measures of the consumer price index (CPI), industrial production (IP), exports, unemployment and the SEK/USD exchange rate. GDP is traditionally used in VAR studies but this variable is only available on quarterly basis, and is therefore not used in this study. Furthermore, the risk of using ex-post data not available to central banker at the time of the policy decision is avoided by using industrial production as a proxy for GDP. All series have been tested for unit root and been transformed to induce stationarity. A complete list of the variables and their transformations is found in the appendix to this paper.

4. Empirical results

This section presents the results of the different factor estimation methods and the impulse responses the five macroeconomic variables in Y_t . The monetary policy shock is defined as a 15 basis point increase in the 3-month STIBOR. The number of lags in the FAVAR models has been chosen to be 6 in order to fully capture the effect of the shock. Bernanke et al. (2005) used 7 lags and found that the models were rather robust to changes in the number of lags. Information criterions such as BIC and AIC tend to suggest either the lowest number of lags or the highest,

respectively. Instead, the number of lags has been chosen to capture the fact that there are 6 months between the monetary policy meetings of the Swedish central bank. Overall, the results are robust to changes in the number of lags but 6 lags resulted in the most appealing impulse responses. Due to the fact that the FAVAR models involve two types of uncertainty, the uncertainty of the estimated factors and the FAVAR estimates, confidence intervals are normally estimated using bootstrap methods as in Hall (1988) or Kilian (1998). However, since the aim of this paper is to compare factor estimation methods, rather than the impulse responses per se, these bootstrap methods have not been applied. Instead, the impulse responses are displayed with their 95 percent regular confidence intervals. The factor estimation methods will be compared on the basis of the R-square of the FAVAR models and the generated impulse responses of the variables in Y_t .

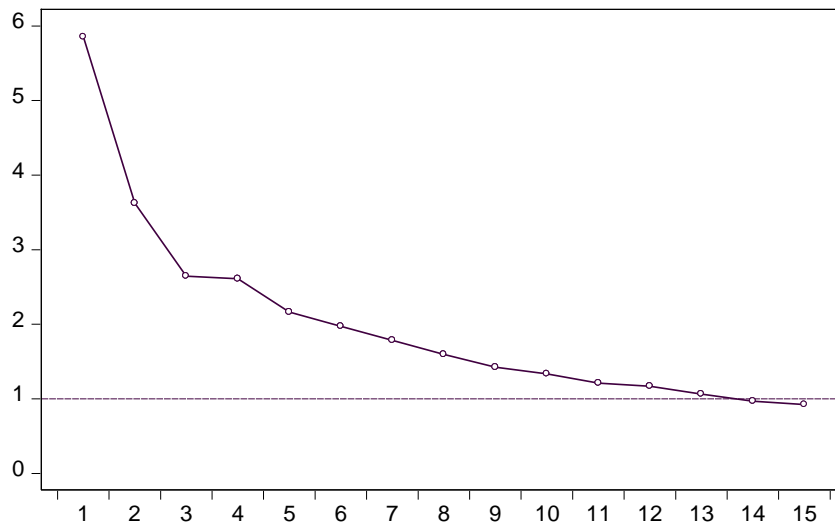


Figure 1 - Scree plot for principal components. The y axis displays the eigenvalue and the x axis shows the factor number.

Figure 1 displays a scree plot of the principal components based on all macroeconomic series used in this paper. The number of factors is commonly selected by looking at where the line kinks before it planes out, and this criteria suggest that the first 1 or 2 factors contains most of the information in the series. Several methods exists for determining the optimal number of factors in factor models but as Bernanke et al (2005) noted, none of these criteria address the question of how many factors that should be included in the VAR. The criterions of Bai and Ng (2002, 2008) are evaluated on Monte Carlo simulations where N is

large ($N \gg 100$), which is not the case in this paper, and selecting the number of factors according to the number of eigenvalues larger than one would, as shown in Figure 1, lead to a too large number of factors for the data reduction to be meaningful in the first place.

Having estimated the factors both using regression equation (3) and without the regression, this paper found that extracting both a slow-moving and a fast-moving factor was preferred as it increased the variation captured by the factors without introducing multicollinearity to the models. This may well be due to the fact that this paper does not use a similar policy rate as Bernanke et al. (2005) did, but instead the interbank rate, which is not one for one correlated with the policy rate. Hence, the following models are based on two factors each, i.e. one fast-moving factor and one slow-moving factor.

The distinction between fast-moving and slow-moving series is, however, redundant in the one-step Bayesian likelihood method used by Bernanke et al (2005) as the factors are extracted simultaneously as the FAVAR model is estimated. This paper followed the estimation used by the authors and implemented the Gibbs sampling procedure using 10 000 iterations of which the first 2000 were used as burn-in in order to minimise the effects of the initial conditions. Nevertheless, the results of the Gibbs sampling method in this paper yielded results that were qualitatively worthless in the sense that the effect of the shock was impossible to infer due to very large confidence intervals that made the effect indistinguishable. Bernanke et al (2005) conclude that the likelihood-based method produces factors that do not fully capture the information about real activity and prices, and that the PC factors appear to contain more information. This may well be the case also for the results of this paper, but instead of further explaining the poor results of the likelihood-based method the remainder of this section will focus on the comparison between the factors estimated by PC and those by CCE.

Table 1 – R-square of the estimated factors

Variable	PC	CCE
CPI	0,12	0,04
IP	0,79	0,14
EXPORTS	0,29	0,11
UNEMP	0,01	0,34
SEK/USD	0,59	0,05

Table 1 reports the R-square values of the two factor estimation methods for each of the 5 equations in the FAVAR. Notably, the PC factors yield a significantly larger fraction of explained variance than the CCE factors, with the exception of the unemployment rate, where the PC factors yield a very low R-square. The largest difference between the two methods appears for IP. Whereas the PC method yield a R-square similar to Bernanke et al (2005), the CCE factors only explain 14 percent of the variation. The difference between PC and CCE is probably due to the fact that while PC minimises the idiosyncratic variance (maximises R-square in X_t), CCE just takes the average of X_t . Overall, the factors in this study explain a smaller fraction of the variation than the factors in Bernanke et al (2005), although a prominent exception is the SEK/USD, where both the CCE and PC factors result in a higher R-square than in the reference paper.

One reason for the relatively low R-square values when compared to Bernanke et al. (2005) could be that this paper estimated both a slow-moving and fast-moving factor instead of using the regression in equation (3). Another reason for this might be that, unlike this paper, Bernanke et al. (2005) had access to more than 120 macroeconomic series over a very long period. This explanation is supported by Borys et al. (2009) who found that their FAVAR models may have suffered from imprecisely estimated factors due to limitations in the dataset thereby leading to unsatisfactory results.

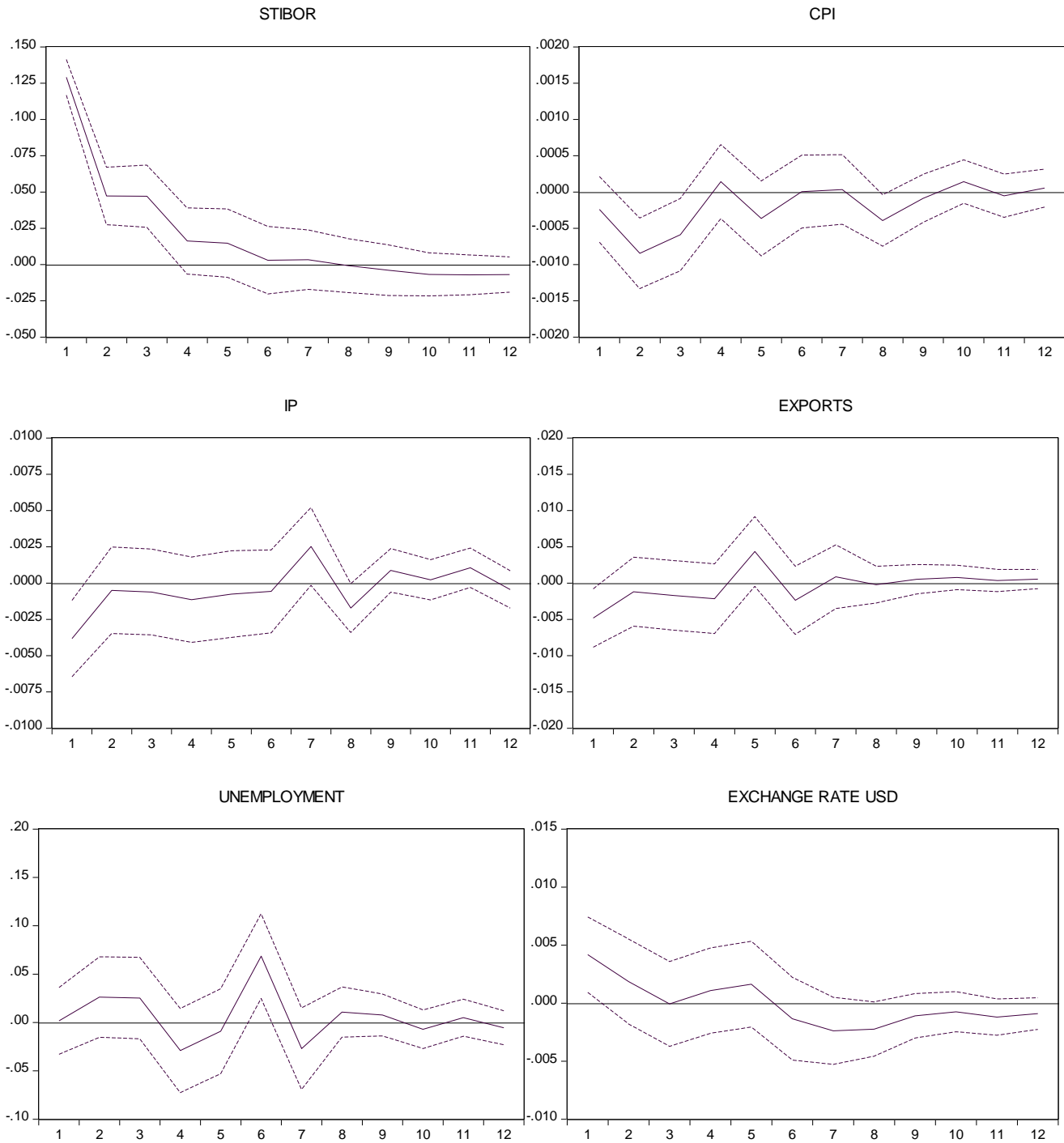


Figure 2 – FAVAR results with PC factors. Note: Impulse responses with 95 % confidence intervals are presented.

Figure 1 display the impulse responses of the 15 basis point interest rate shock in the FAVAR model with two factors estimated by PC. The responses are in line with expected reactions according to macroeconomic theory. Notably, the FAVAR model eliminates the price puzzle as CPI increases following the positive interest shock. Industrial production decreases as well as exports, whereas

unemployment temporarily increases along with the appreciation of the Swedish Krona. The effect is most prominent for CPI with the other variables initially exhibiting an effect that slowly dies out. These results are in line with those of Borys et al. (2009), who used roughly the same amount of series for an almost equally short period in time.

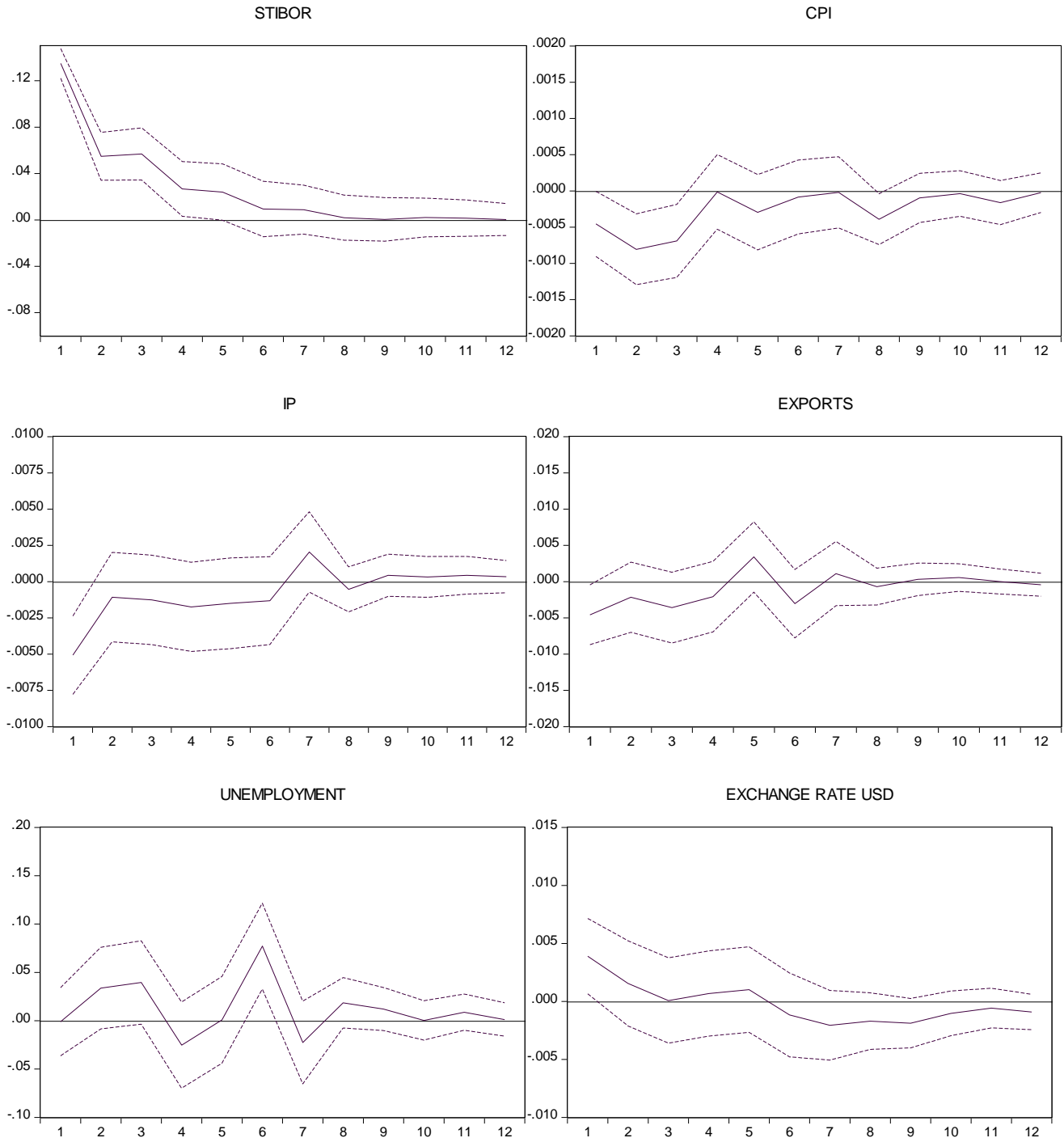


Figure 2 - FAVAR results with CCE factors. Note: Impulse responses with 95 % confidence intervals are presented.

Figure 2 display the impulse responses of the FAVAR model with two factors estimated by CCE. Notably, the responses are close to identical to the responses from the model with PC factors. The impact of the shock appears to be somewhat smaller in the CCE model compared to the PC model, but the difference is not statistically significant. Overall, the two factor estimation methods yield very similar results, and based on this it is not clear which of the methods that should be favoured. The fact that the CCE-based estimation method yield similar results as the PC-based method is good news for researchers as it eases the estimation of factors in FAVAR models. However, an advantage with PC is naturally the option to easily extract more factors without having to impose sample restrictions. Extracting more factors using CCE would require the researcher to divide the dataset into subgroups, which of course is easily done if the researcher has prior knowledge or beliefs about correlations between certain series. On the other hand, more factors do not necessarily result in better results and most studies using FAVAR models tend to favour parsimonious models with two or three factors as more factors do not drastically alter the results. Furthermore, the CCE method is much simpler and can easily be extended to estimate factors using a weighted average of all series where the researcher attaches larger weights to series that are believed to be more important for the economic activity as a whole.

5. Concluding remarks

The purpose of this paper has been to evaluate different factor estimation methods for FAVAR models. This paper examines the widely used principal component method, the common correlated effects estimation method as well as a more advanced likelihood-based method. All estimations are based on Swedish data for the period 1998 to 2016 and evaluated by comparing the variation explained by the factors and the impulse responses of the different models. The results indicate that the likelihood-based method leads to implausible results for this dataset and that there appear to be very little difference between the PC-based and the computationally simple CCE-based factor estimation methods.

5.1 Recommendations for further research

Further research on the differences between the three estimation methods is encouraged and it would be interesting to see if the similarities are robust to different datasets. This paper used the FAVAR framework by Bernanke et al. (2005), but the framework has been extended by Boivin and Giannoni (2008) to an open economy case, which perhaps should work better for a small open economy like Sweden. Furthermore, extensions of the CCE method should be explored and especially the mean group estimator that in Chudnik and Pesaran (2013b) is found to be consistent for small time periods such as $T > 50$. Developments in the area of Bayesian econometrics also leads to improvements of more advanced estimation methods, and it would be interesting to evaluate the likelihood-based two-step method by Bai et al. (2016). This method estimates the FAVAR model and explicitly accounts for factors being partially observed.

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Appendix

VAR	Description	Transformation	Source
201	CPI	3	OECD
202	CPI excluding food and energy	3	OECD
203	CPI energy prices	3	OECD
204	CPI food prices	3	OECD
205	CPI services	3	OECD
206	CPI housing	3	OECD
207	Earnings in manufacturing	3	OECD
208	Industrial production	3	OECD
209	Orders in manufacturing	3	OECD
210	Orders in construction	3	OECD
211	Production prices investment	3	OECD
212	Production prices manufacturing	3	OECD
213	Production index manufacturing	3	OECD
214	Production index industrial sector	3	OECD
215	Production index construction	3	OECD
216	Sales value in manufacturing	3	OECD
217	Sales retail volume	3	OECD
218	Sales retail value	3	OECD
219	Sales car registrations	3	OECD
220	Exports	3	OECD
221	Imports	3	OECD
222	Unemployment	3	OECD
223	Labour registered unemployed	3	OECD
224	Labour vacancies	3	OECD
101	SEK/EUR exchange rate	3	NIER
102	SEK/GBP exchange rate	3	NIER
103	SEK/YEN exchange rate	3	NIER
104	SEK/USD exchange rate	3	OECD
105	KIX trade weighted currency index	3	OECD
106	Leading indicator index	3	OECD
107	Share price index	3	OECD
108	M1	3	OECD
109	M3	3	OECD
110	STIBOR 3-month	2	OECD
111	Bonds 2 - 9 years maturity	2	OECD
112	Bonds long maturities	2	OECD
113	Commodity index	3	FRED
114	WTI oil prices	3	FRED

The "slow-moving" variables are numbered in 200 and the "fast-moving" variables are numbered in 100. All series are seasonally adjusted and indices have 2010 = 100. The transformation codes are: 1 - no transformation, 2 - first difference and 3 - first difference of logarithm