Central Bank of Armenia

Working Paper 14/3/08

Short Term Forecasting System of Private Demand Components in Armenia

Narek Ghazaryan

June 2014

WP/14/3/08

CBA Working Paper

Monetary Policy Department

Short Term Forecasting System of Private Demand Components in Armenia

Narek Ghazaryan

November 2013

Abstract

In this paper a system for the short term forecasting of private consumption and private investments is introduced used in the CBA. Large amount of time series are used in the system to produce conditional forecasts, giving the analysts the opportunity to use all the available information in real time for the assessment of the private demand dynamics before the official data are published by the statistical office. The main forecasting methods used are BVAR and FAVAR. In sample quasi-real time recursive forecast evaluation shows that pooled forecasts outperform individual model forecast and conditioning improves forecast quality. The analysis of the forecast errors confirms that BVAR and FAVAR models produce reliable forecast for 2-3 quarters and hence are good tool for now casting and near term analysis of private demand components in CBA.

Author’s email address: narek.ghazaryan@cba.am

Contents

1. Introduction

Nowcasting and short term forecasting of certain macroeconomic variables play a vital role in contemporary monetary policy analysis implemented by the central banks all across the globe. It is of particular interest to use the recent releases of high frequency indicators and expert judgments to track the dynamics of hard data in real time and make forecasts for the near term future, before the official values are published.

Various methods and techniques have been developed to utilize unbalanced panel of available indicators for the estimation of a missing variable, which is released with a considerable time lag compared to the most of the indicators available in the panel. It's is a common practice in Europe to use information from a single or a combination of a few survey based indicators for tracking current state of economic activity. Bank of England for example combines signals extracted from separate global indicators such as JPMorgan export index, OECD CLI and metal prices for tracking large swings of global GDP and trade before the official estimates of the data are available (see Stratford 2013). Another approach for nowcasting is to use factor analysis developed by Stock Watson (1989) and Bernanke et al (2005). Finally the results from the various forms of models can be pooled to form the final estimates of a target economic variable (see Matheson 2010)

In this paper we describe the system used for near term forecasting and nowcasting of private demand components in the Central Bank of Armenia. There are several key criteria which were taken into consideration when building the system. First large amount of economic time series must be utilized, to make maximum use of the real-time economic information existing in the contemporary global and local economy. Second models used in the system should be selected taking into consideration the characteristics of Armenian economy. The ability to utilize relatively short and low quality time series and the opportunity for expert judgments application are the key criteria that models used must meet. Finally the system must guarantee flexibility, productivity and safety to be suitable for periodical monetary policy analysis implemented under strict deadlines in the CBA.

Bayesian VAR and FAVAR models are used as the key components of the system. Dataset of 89 time series of both hard and high frequency data is used as input information which is updated on monthly basis. A productive and quickly implementable approach of filling the missing monthly data is used before the conversion of monthly indicators to quarterly data. Data are transformed to reach stationarity, before the estimation procedure. We follow the approach of Matheson (2010) and use relatively large panel of indicators to filter common trends of the economy using FAVAR model. On the other hand relatively short time series in a narrower panel are modeled in BVAR.

Conditional forecasting techniques are used to use the valuable information set available in real time to now-cast and forecast missing private demand components. Expert judgments are used to fine tune the pure model results. Finally forecast of BVAR and FAVAR models are weighted with the inverse of the historical RMSEs of the two, which are calculated within the system.

Historical quasi-real time forecast evaluation experiment is conducted to illustrate that the system provides pretty accurate results in tracking the private demand dynamics in the near term. The analysis of forecast error statistics also shows that conditional forecasts outperform the unconditional forecasts for the 3-4 quarter horizon and pooling the outputs from different models increases the forecast precision even more.

The rest of the paper is organized as follows. Section 2 describes the methodology and estimation techniques used in the STFS. Section 3 describes the data used in the STFS and the data management process. Section 4 explains the concepts of conditional and unconditional forecasting and illustrates the historical forecasting experiment. Section 5 concludes.

2. Methodology

2.1 Bayesian VAR model

VAR models are widely used worldwide as an econometric tool for the analysis of dynamic economic problems and forecasting. Although a convenient and mostly accepted tool VAR models can create problems which must be considered carefully when conducting economic analysis. First VARs suffer from the loss of degree of freedom, which becomes more severe with the number of lags and variables included in the model leading to inefficient estimates, although the general fit of the model to the data will be very high because of many variables included. Ciccarelli and Rebucci (2003) give a good description of the above described *overfitting* problem. Second VAR models produce explosive impulse responses rising from biased coefficient estimates. Both problems become more severe in case of short and low quality sample of data used for estimation, which is the case for developing countries and Armenia is not an exception here.

The Bayesian approach to specification and estimation of the VAR models can make things better. Suppose we have a system of equations

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_p X_{t-p} + \varepsilon_t \quad (1)$$

$$t = 1, \dots, T$$

Where the constant term c is a $r \times 1$ vector, β_1 ... β_p are the $r \times 1$ vectors of coefficients, ε_t is a $r \times 1$ vector of independently, identically and normally distributed error terms with a covariance matrix Ω.

Bayesian estimation procedure developed by Litterman (1980) is used to estimate the system (1). The essence of Bayesian approach is to impose priors on the parameters of the VAR before the estimation. To reduce the strong dependency of the inference on the priors imposed, Bayesian approach sets priors as distributions around a central value summarizing the researcher's uncertainty over the model parameters. This method of imposing priors gives the data the opportunity to alter the priori given information in the final estimates of the parameters depending on the strength of the “signal” rather than “noise” present in time series. As a result Bayesian approach avoids the over fitting problem and thus produces more accurate forecasts than reduced form VARs estimated in the classical way[1].Various forms of priors for Bayesian estimation are proposed in economic literature depending on the purpose of the research. In this paper we use Litterman (1986) priors, also known as “Minnesota” priors. These priors take into consideration several well-known regularities about macroeconomic time series. First macroeconomic time series are trending over time. Second more recent lagged values of macro variables explain the current values better than the values deep in the past. Finally the current values of macroeconomic time series are explained better with own lagged values than with the lagged values of other variables.

The described regularities are used as priori information for the model to be estimated. Certain probability distributions are assigned to the parameters of the model which satisfy to the following conditions. First all the coefficients of the model other than the ones for the first lag must have distributions with zero mean. Second the variance of the distribution of the coefficients must decline with the lag length, so that for longer lag coefficients the parameter distributions are squeezed to zero. Third the variance of the coefficient distribution is bigger for the own lags compared to the variance of other variable’s lagged coefficients.

The upper mentioned priori assumptions for the VAR coefficients β_k^{ij} can be formalized in terms of the moments of the normal probability distributions $\beta_k^{ij}\ N(a_k^{ij}, \sigma_k^{ij})$ as follows:

$$a_k^{ij} = \begin{cases} \mu \quad for\ k = 1\ and\ i = j \\ 0 \qquad\qquad otherwise \end{cases}$$

$$\delta_k^{ij} = \begin{cases} \left(\frac{1}{\theta}\frac{1}{k^{\lambda}}\right)^2 \qquad for\ \ i = j \\ \left(\frac{\vartheta}{\theta}\frac{1}{k^{\lambda}}\frac{\sigma^i}{\sigma^j}\right)^2 \qquad for\ i \neq j \end{cases}$$

[1] See Canova (1995) for more details.

where $k = 1 \ldots . p$ is the lag length of the model, $i = j = 1 \ldots r$ is the number of variables included in the model, $0 < \mu < 1$ is the parameter towards which the first lag prior is centered. The hyper-parameter θ controls the overall tightness of the prior distributions around the a_k^{ij} mean, θ should increase with the size of the system to avoid over fitting, λ decides the speed at which the variance of the priors are declining with the lag length of the variables included in the model, σ_i/σ_j accounts for different scale and variability of the data, finally $0 < \vartheta < 1$ is the parameter which , decides the level of importance of own lags compared to other variables. The priors for the constant vector are flat (diffuse) and the covariance matrix Ω is diagonal.

The Bayesian maximum likelihood method described by Ciccarelli and Rebucci (2003) is used for the estimation of the BVAR.

2.2 FAVAR model

Factor-augmented vector autoregressive (FAVAR) models are used widely in modern macroeconomics as a now casting and near term forecasting tool. The most distinguished and useful characteristics of FAVAR models are their ability to use large data sets for the forecast of a particular macro variable. FAVAR models solve at least two problems which rise when one uses models with limited information set. First the models with limited time series may miss important information present in the economy thus leading to contaminated forecasted values and dynamics for a particular macro variable. Sims (1992) illustration of the “price puzzle” is a vivid example for the latter problem. Second the amount of the impulse responses will be constrained with the limited number of input time series, while for a robust economic analysis policy makers need more detailed picture of the expected dynamics of economic variables. For example to understand the expected path of “economic activity” and form the relevant economic story on it, only the forecasted path of real GDP is not enough. The future dynamics of private demand components, capacity utilization, real estate prices, real wages and costs are among the list of indicators which policy makers must have on their table to check the quality and reliability of the forecasted “economic activity” and form the economic story about its development and deliver it to the public. Unfortunately most of the models available in modern economics can’t use large amount of time series for the preservation of degree of freedom. While FAVAR models give the opportunity to use hundreds of time series, such as hard data, various survey indicators and information from financial markets, to produce detailed and reliable forecasts of numerous economic indicators. Below is presented the structure of the FAVAR model, described by Bernanke *et al*. (2005).

Let $X_t' = (X_{1,t}, \dots X_{N,t})$ denote a vector of stationary observed variables, where $t = 1, \dots, T$ the time dimension and N is large enough number of variables compared to $t = 1, \dots, T$.

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

Equation (2) represents the vector of observable variables X_t' as a linear combination of unobservable $F_t' = (F_{1,t}, \dots F_{P,t})$ factors, and some observable variables $Y_t' = (Y_{1,t}, \dots Y_{R,t})$ which have pervasive effects throughout the economy, such as policy interest rate and inflation, Λ^f is a $N \times P$ matrix of factor loadings , Λ^y is a $N \times R$, ξ_t is $N \times 1$ vector of white noise disturbances. The number of factors is “small”, so that $P + R + T < N$.

Equation (2) captures the idea that factors F_t' together with variables in Y_t' are the main forces which define the dynamics of the large set of macro variables present in X_t'. The conceptual common shocks for the economy summarized in the factors can be interpreted as “economic activity’’, “financial conditions” and “inflationary pressures”.

The joint dynamics of the common factors and economy wide variables Y_t' , in its turn is defined by the VAR process (3):

$$\begin{pmatrix} F_t' \\ Y_t' \end{pmatrix} = A_1 \begin{pmatrix} F_{t-1}' \\ Y_{t-1}' \end{pmatrix} + \cdots + A_l \begin{pmatrix} F_{t-l}' \\ Y_{t-l}' \end{pmatrix} + \vartheta_t \quad (3)$$

where $A_1 \dots A_l$ are the coefficients of the lagged variables and ϑ_t is the mean zero error term with a diagonal covariance matrix Θ.The system (3) is called *factor-augmented vector auto regression*, which enriches the dynamics of Y_t' “important” variables with information contained in the factors. Bernanke et al (2005) use inflation, industrial production and federal funds rate as Y_t' to investigate the structural relationship among these key macroeconomic variables. They show that the relationship between these variables is much robust and more economically intuitive if they are estimated in the framework of equation (3), compared to the results produced with simple VAR analysis. However inside the system for short term forecasting described in this paper, FAVAR is not used for investigation of the structural relationship between "key" macroeconomic variables but rather as an efficient tool for now casting and short–term forecasting of private demand. In this sense we do not use any pervasive macroeconomic variable in the model (3) so that Y_t' is empty in our case. Instead the pervasive variables such as interest rates and GDP are included in the vector of observables X_t' and contribute to the estimation of common factors F_t'. As the factors F_t' are unobservable, equation (3) can't be estimated directly. A two-step principal component estimation procedure is applied for the estimation of equations (2)-(3). In the first step factors are estimated using the first P principal components of the dataset X_t'. In the second step estimated $\widehat{F_t'}$ are used as observables to estimate the equation (3) with standard techniques[2].

3. Data

Two important characteristics should be taken into consideration when dealing with the data on Armenian economy. First the time span of Armenian data is relatively short as it's a young transition post-soviet economy. The longest time series available start in early 1990s and cover some indicators of real sector, financial sector and prices, such as GDP, exchange rate and CPI. While broader range of indicators on the sectors of economy such as demand components, retail sales, wages and real estate prices started to be complied since late 1990s and early 2000s . Thus a "useful" quarterly panel of data covering broad cross section of the economy is available since 2000.

[2] For more detailed description of two-step estimation procedure see Bernanke et al (2005)

High frequency survey based indicators such as Consumers Confidence Index, Business Climate Indicator and Economic Activity Indicator have been initiated since mid-2000s leaving the researchers with even shorter panel of data available for real-time monitoring of economic developments.

The second issue relates to the low quality of available data and high amount of the noise present in time series, which is more pronounced in the earlier periods of the sample. Imperfect markets, low financial intermediation and high amount of idiosyncrasies present in the economy combined with historically poor statistical methods for data compilation are the main causes of the low quality and noisy Armenian data.

To reach the maximum efficiency in the task of near-term monitoring and economic analysis the models selected must mitigate the data weaknesses described above. Factor models in particular can deal with idiosyncrasies and noise in the data, compressing the signals rather than noise from various time series into common forces driving the economy. The common factors then can be used to identify and forecast any macro series in the economy. FAVAR model is a good candidate for this task.

Bayesian VAR model on the other hand is an appropriate tool to deal with short sample size and avoid the contaminated estimates. Having this in our mind we divide the data into two groups taking into consideration the length of time series available.

The first panel of data starts at 2000Q1 and includes indicators from the following groups of data:

- National Accounts Data- *GDP and components, GNI, GNS, BOP items etc.*
- Activity Hard Data - *retail sales, production volume of construction etc*.
- Monetary and Financial Statistics - *interest rates, exchange rates, monetary aggregates, etc.*
- Labor Market - *employment, unemployment rate, wages etc.*
- Prices and Costs - *CPI, oil prices, metal prices, real estate prices etc.*
- External Hard Data – *Trading Partners GDP (Russia, EU, USA) etc.*

The panel described above is used in FAVAR model as the later extracts the common trends from the large amount of variables available in the panel and ignores the noise prevalent in the data.

The second panel starts at 2005Q1 and includes survey measures and remittances via the banking system, which are extremely useful for tracking movements of private consumption and investments especially in times of high turbulence[3]. The importance of survey indicators underlies in the facts that they became available earlier than all other variables and have high correlation with private demand components. To maintain a reasonable dimension for the second panel some indicators from the first panel are included there. In particular panel 2 contains the following groups of time series:

- Survey Measures – *Consumer Confidence Indicator, Business Confidence Indicator etc.*
- Financial Soft Data – *remittances through the banking system into Armenia*
- Other Indicators – *REER, private demand components, stock of the credit etc.*

As already mentioned the survey measures have been initiated since 2005Q1, so we end up with a short sample size after balancing the panel. To avoid the curse of dimensionality and contaminated estimates, Bayesian VAR is applied on the short panel.

The two panels described above have few series in common and mostly contain complementary rather than competing information for economic analysis. Together they contain 89 time series covering various areas of local and global economy, which provides robust information set for tracking the dynamics of private demand components. The main sources of the data are National Statistical Service of the Republic of Armenia, Central Bank of Armenia, Bloomberg and National Banks and Statistical Offices of Armenia's trading partners. All the monthly indicators are converted to quarterly frequency as the target variables private investment and consumption are published in quarterly frequency. The conversion procedure of monthly indicators to quarterly frequency is described in the next section.

[3] See Stratford (2013)

3.1 Frequency Conversion

An important step in the process of near term analysis of private demand components is the conversion of monthly indicators to quarterly frequency. The main challenge that researchers and analysts face here is that in real time the data for all 3 months are not available within a quarter. Instead data up to the first or second month of a quarter are usually available, so the logical question is how to fill the missing months to get the full quarter estimates of originally monthly indicators.

Table A below illustrates the availability of some indicators in early April 2014, when the second quarter monetary policy analysis started according to CBA's calendar. We can see that out of three indicators listed in the table, only exchange rate data were available for all three months and hence could be averaged to form the 2014 Q1 average USD/AMD exchange rate. While for retail trade turnover and average monthly nominal wages data for March and February-March are missing respectively. A method for filling these empty months should be developed to get the quarterly estimates, which will make use of the valuable published information within the quarter.

Table A. The availability of certain macro indicators in Armenia at early April 2014

	January	February	March	April
Exchange Rate USD/AMD	407.4	411.5	414.2	x
Retail Trade Turnover (Million AMD)	80 756	94 570.5	x	x
Average monthly nominal wages (AMD)	155 940	x	x	x

2014 Q1

Matheson (2011) and Stratford (2013) use univariate $AR(p)$ bridge equations to forecast the values for missing months. The main weakness of this approach is that it is computationally costly, especially when the number of missing monthly indicators is large, which is the case for forecasting system used for private demand. Instead we adopt a simpler and faster approach which can raise the flexibility and efficiency of monetary policy analysis under time constraints. Given the indicators in table A and the availability of their historical values we calculate the actual 12 month growth rates for the available monthly indicators, which are illustrated in table B below.

Table B. 12 month growth rates for certain data available in early April 2014

	January	February	March	2014Q1 Estimate
Retail Trade Turnover (Million AMD)	3.3%	4.5%	x	(3.3%+4.5%)/2
Average monthly nominal wages (AMD)	7%	x	x	7%

Based on the "well known" persistence of growth rates that macro series illustrate, we proxy the quarterly average year on year growth of an indicator , with the first month's 12 month growth rate in case the first month is available. If the first two months of growth rates are available, the average of the two is considered as the year on year growth rate for the whole quarter.

Figure 1 and 2 in the appendix I illustrate the high precision of the approximation of quarterly growth rates with the method described. The proxies of quarterly growth rates then are used to calculate the levels of quarterly data, given the availability of historical quarterly levels of originally monthly indicators. If all the three months of the data are available within a quarter the simple average of the three is taken to form the quarterly value. Table C illustrates the quarterly levels of the indicators estimated with the approach described above.

Table C. Monthly and quarterly values for certain indicators available in early April 2014

	January	February	March	2014Q1
Exchange Rate USD/AMD	407.4	411.5	414.2	410*
Retail Trade Turnover (Million AMD)	80 756	94 570.5	x	92 660**
Average nominal wages (AMD)	155 940	x	x	157 976***

* The simple average of the three month data is taken

** The first month's YoY growth rate is multiplied with the 2013Q1 value

*** The average of the first two month's YoY growth rate is multiplied with the 2013Q1 value

The upper described approach is applied to all the 44 monthly indicators used in the two panels to convert them to quarterly frequency.

3.2 Data Transformation

After the procedure of filling the missing monthly variables and converting monthly series to quarterly frequency we merge the converted database to the panel of originally quarterly series such as GDP and demand components ending up with a panel containing 89 quarterly series. Before using the series for final estimation the following adjustments are applied to the data.

1. Nominal series are deflated with CPI index
2. Logs of the trending series are taken multiplied with 100, except those that are measured in percentage or take negative values.
3. The seasonal series are adjusted using X11
4. Quarter on quarter differences are taken of the logged and seasonally adjusted series $(100 * \ln(X_{it})\_sa - 100 * \ln(X_{it-1})\_sa)$.

5. Series measured in percentage and taking negative values are differenced after seasonal adjustment $(X_{it})\_sa - (X_{it-1})\_sa$
6. Local level filter is applied to the panel of quarter on quarter differences to make the series stationary[4]. The high frequency (stationary cyclical) component of the series is used as an input for the models. The low frequency (trend) component of the series is interpolated 3-4 quarters ahead, which later is used to retrieve the forecasted series back to the original format.

Figure 3 and 4 in the appendix display the low frequency components of actual series and the high frequency component for a number of indicators. With an unarmed eye it can be seen that some of the series display trend in the growth rates, while after the LLF adjustment the trend is removed and we are left with high frequency stationary component of the time series which are used as inputs for the models of the private demand components' forecasting system.

4. Specification and estimation

As described in section 2 the first large panel of low frequency component of quarterly differenced series is used for the estimation of FAVAR model and the second smaller panel containing shorter time series is used for Bayesian VAR model estimation. Separate FAVAR and BVAR models are estimated for private consumption and private investment. The approach for choosing the large and small panels is the same for both indicators, but the number of variables included slightly differs in each model. In particular FAVAR model of consumption and investment include 68 and 62 series respectively starting at 2000Q2. While BVAR model of consumption and investment include 10 and 9 series respectively starting at 2005Q2. All the panels used are balanced from both sides.

[4] Koopman *et al* (2011) describe the local level filter, which can be stated as an HP filter for time series in growth rates rather than in levels.

To avoid the problem of "over-fitting" in FAVAR models, we use the approach used by Matheson (2010) and Giannone *et al* (2005) and choose the number of factors so that they explain at most 65% of the variance of the "Key Macroeconomic Series".

Figure 5 and 6 in the appendix show that 6 and 5 factors jointly explain the target share of the variance for consumption and investment models respectively. The number of lags for factor's VAR is determined based on AIC and SBC and is equal to 4 for both private consumption and investment models as the table 1 in the appendix illustrates.

Following Ciccarreli and Rebucci (2003) we avoid the computational complexity and costs of *Fully Bayesian Estimation* and use *Empirical Bayesian Estimation*, defining the hyper-parameters of the BVAR priors based on certain criteria and rules of thumb rather than specifying prior distributions for these parameters and estimating them before the main estimation procedure of the BVAR system.

The sample size and the number of variables are used to determine the hyper-parameter θ defining the overall tightness of the prior distributions[5]. To avoid too weak signals from the lagged values of data, we set λ=1. Relative standard deviations σ_i/σ_j are calculated using the relevant historical time series. Finally the first lag prior's mean together with lag length of the BVAR are determined minimizing AIC and SBC. Table 2 in the appendix displays the defined values of the hyper-parameters for private consumption and investments models separately. As the parameters suggest both models priori treat the series as $AR(1)$ processes rather than pure random walk or white noise.

[5] The hyper-parameter is defined using the following formula $\theta = \sqrt{N/T}$, where T is the sample size and T is the number of variables included in the BVAR models.

4.1 Conditional and Unconditional Forecasts

In contemporaneous macroeconomic analysis it is of paramount importance to use all available information in real time to make the forecast of a particular macro variable. In this regard it is very useful to investigate the pattern of different data releases and develop ways to use the timely indicators for the now cast and forecast of missing variables before official estimates are published. In particular timely indicators can be utilized successfully for the forecast of private demand components, which become available a quarter or two later compared to a number of macroeconomic and survey indicators. Table D. shows the availability of different groups of data in Armenia at the end of a typical quarter within a year.

Table D. The availability of different groups of data at the end of each quarter of the year

	Q_{o-2}	Q_{o-1}	Q_o	Q_{o+1}	Q_{o+2}
Private Investments Consumption	$\boldsymbol{x}$	-	-	-	-
National Accounts Data	$\boldsymbol{x}$	-	-	-	-
GDP	$\boldsymbol{x}$	$\boldsymbol{x}$	-	-	-
Preliminary macro-economic indicators	$\boldsymbol{x}$	$\boldsymbol{x}$	$\boldsymbol{x_{2m}}$	-	-
Monetary and Financial indicators	$\boldsymbol{x}$	$\boldsymbol{x}$	$\boldsymbol{x_{2m}}$	-	-
Survey Indicators	$\boldsymbol{x}$	$\boldsymbol{x}$	$\boldsymbol{x}$	$\boldsymbol{x}$	-

In table D “*x*” means that quarterly data are available for the quarter, “x_{2m}” means the first two month of data are available and “-” means data are missing for the following quarter.

According to the table at the end of each quarter of a typical year private investment and consumption data are missing for the same Q_o and previous Q_{o-1}

quarters. The same pattern of data releases is true for all the national accounts indicators, except GDP, for which the previous quarter's value is published at the end of the second month of every quarter.

The picture is different for the other groups of data used for the monetary policy analysis in CBA conducted in the first and last months of each quarter. Financial and monetary indicators such as exchange rate, interest rates and monetary aggregates are well known for their timeliness. The first two months of these data denoted x_{2m} are always available at the mid of the third month of each quarter including the time needed for adjusting and regrouping these indicators.

Preliminary operative macro-economic soft data such as wages, prices and volume of the production in different sectors of the economy are published by the Armenian National Statistical Service with a 20 days lag. As a result at the end of any quarter Q_o, the first two months of data are available. Finally a number of survey indicators such as consumer confidence and business activity indicators are published on quarterly frequency within the second month of each quarter indicating current and expected developments respectively for the current Q_o and the upcoming Q_{o+1} quarter.

In section 2 the procedure of estimating the quarterly values of a monthly indicator based on the availability of first two months data was described. As a result at the end of each quarter when monetary policy analysis is conducted forecasters are faced with an unbalanced panel of information. Thus their task is to make maximum use of the extra edge of the panel to estimate the current Q_o and previous Q_{o-1} missing values of private consumption and investment, which is called conditional "nowcast" in economic literature.

In the system described in this paper FAVAR and BVAR models are used to accomplish the task of conditional "nowcast" and further projection over the forecast horizon in near term. As already mentioned balanced panel is used for the estimation of the coefficients vector and error matrices of both BVAR and FAVAR models. Thus as table D. suggests in any current quarter Q_o the panel used for the estimation of private demand components models ends at the period Q_{o-2}. After the estimation and factor identification is complete both BVAR and FAVAR models are represented as estimated VARs in the forms (1) and (2) respectively as described in the section 2. Thus we introduce the concept of conditional forecasting on an example of a general VAR model, which is invariant on the algorithm of the coefficient estimation and type of variables included in a VAR and hence can be applied to both FAVAR and BVAR models.

Suppose we have the VAR system (4), where $X_t = (x_{1,t} \dots x_{5,t})$ is a vector containing data groups described in table D. The vectors of coefficients $\beta_1 \dots \beta_p$ and residual correlation matrix $\boldsymbol{\Omega}$ are estimated using the balanced panel.

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_p X_{t-n} + \varepsilon_t \quad (4)$$

Having the estimated model suppose we want to produce $f + 2$ quarters ahead forecast in any current quarter denoted Q_o. As table E displays in the classical forecasting procedure called unconditional forecasting model (4) will use the panel of actual data $X_{o-2-n} \dots . X_{o-2}$ as initial conditions, to produce $X_{o-1}^{unc}, X_o^{unc} \dots X_{o+f}^{unc}$ vectors of nowcasted and forecasted values, where n is the number of lags included in the model. In this case the vector of disturbances ε_{o-1}, $\varepsilon_o \dots \varepsilon_{o+f}$ is equal to zero along the forecasting horizon and the timely observations available in the vectors X_{o-1}, X_o , X_{o+1} are not used at all.

Table E Unconditional forecasts using panel for period $Q_{o-2-n} \dots Q_{o-2}$

	Q_{o-2-n}	…	Q_{o-2}	Q_{o-1}	…	Q_{o+f}
Private Investments Consumption	$\boldsymbol{x_{1,o-2-n}}$	…	$\boldsymbol{x_{1,o-2}}$	$x_{1,o-1}^{unc}$	…	$x_{1,o+f}^{unc}$
National Accounts Data	$\boldsymbol{x_{2,o-2-n}}$	…	$\boldsymbol{x_{2,o-2}}$	$x_{2,o-1}^{unc}$	…	$x_{2,o+f}^{unc}$
GDP	$\boldsymbol{x_{3,o-2-n}}$	…	$\boldsymbol{x_{3,o-2}}$	$x_{3,o-1}^{unc}$	…	$x_{3,o+f}^{unc}$
Preliminary macro-economic indicators	$\boldsymbol{x_{4,o-2-n}}$	…	$\boldsymbol{x_{4,o-2}}$	$x_{4,o-1}^{unc}$	…	$x_{4,o+f}^{unc}$
Monetary and Financial indicators	$\boldsymbol{x_{5,o-2-n}}$	…	$\boldsymbol{x_{5,o-2}}$	$x_{5,o-1}^{unc}$	…	$x_{5,o+f}^{unc}$
Survey Indicators	$\boldsymbol{x_{6,o-2-n}}$	…	$\boldsymbol{x_{6,o-2}}$	$x_{6,o-1}^{unc}$	…	$x_{6,o+f}^{unc}$

Putting in other way given the estimated coefficients of the models, the information set from Q_{o-2-n} to Q_{o-2} is used for unconditional forecasting as table E displays. This approach will lead to the change in forecast after the national accounts data are released and the balanced panel is prolonged with one more quarter, which makes it impossible to conduct the necessary monthly monitoring of the economy and leads to delayed policy response and loss of credibility of the central bank.

The concept of the conditional forecasting on the other hand gives the opportunity to use all the new information available during the time of forecast implementation.

	Q_{o-2}	Q_{o-1}	Q_o	Q_{o+1}	...	Q_{o+f}
Private Investments Consumption	$\boldsymbol{x_{1,o-2}}$	$x_{1,o-1}^{cnd}$	$x_{1,o}^{cnd}$	$x_{1,o+1}^{cnd}$	...	$x_{1,o+f}^{cnd}$
National Accounts Data	$\boldsymbol{x_{2,o-2}}$	$x_{2,o-1}^{cnd}$	$x_{2,o}^{cnd}$	$x_{2,o+1}^{cnd}$	...	$x_{2,o+f}^{cnd}$
GDP	$\boldsymbol{x_{3,o-2}}$	$\boldsymbol{x_{3,o-1}}$	$x_{3,o}^{cnd}$	$x_{3,o+1}^{cnd}$	...	$x_{3,o+f}^{cnd}$
Preliminary macro-economic indicators	$\boldsymbol{x_{4,o-2}}$	$\boldsymbol{x_{4,o-1}}$	$\boldsymbol{x_{4,o}}$	$x_{4,o+1}^{cnd}$	...	$x_{4,o+f}^{cnd}$
Monetary and Financial indicators	$\boldsymbol{x_{5,o-2}}$	$\boldsymbol{x_{5,o-1}}$	$\boldsymbol{x_{5,o}}$	$x_{5,o+1}^{cnd}$	...	$x_{5,o+f}^{cnd}$
Survey Indicators	$\boldsymbol{x_{6,o-2}}$	$\boldsymbol{x_{6,o-1}}$	$\boldsymbol{x_{6,o}}$	$\boldsymbol{x_{6,o+1}}$	...	$x_{6,o+f}^{cnd}$

Table F Conditional forecasts using panel for the period Q_{o-n-2} …. Q_{o+1}

Suppose the conditional forecast is again carried at the current quarter Q_o. In this case the residuals ε_{o-1}, ε_o ... ε_{o+f} of the equations in the system are not equal to zero any more, but are set so that the forecasted values of variables which became available earlier are equal to the observed available values. Based on the estimated historical correlation matrix of the system (4) the residuals of missing variable's equations are altered also thus leading to different forecasted values compared to the results one would get using unconditional forecasting. Table F displays the results of conditional forecasting conducted in current time Q_o. In this case all the available information spanning from Q_{o-2-n} to Q_{o+1} is used.

As described the process is set so that in the forecast horizon $Q_{o-1} \dots Q_{o+f}$ the forecasted values for the available data are exactly equal to the values published. For example $x_{3,o-1}$ actual number of GDP is considered as the conditional forecast of GDP in the quarter Q_{o-1}. For the missing values the conditional forecasts are denoted X_{o-i}^{cnd}. It is important to note that conditional forecasted values differ from the unconditional ones $X_{o-1+i}^{cnd} \neq X_{o-1+i}^{unc}$ $(i = 0 \dots f)$. The precision of the conditional forecast is ex-ante expected to be higher compared to the unconditional if the estimated models describe correctly the dynamics of the economy, this issue is analyzed in the next section.

4.2 Forecast Evaluation

In this section historical forecasting experiments are conducted to check the ex-ante assumed hypotheses that using jagged edge panel for forecasting gives better results compared to the balanced panel approach. Economic theory suggests that pooling forecast produced by various models can improve the forecast quality over the separate model results see for example Clements and Hendry (2004) for theoretical results and Assenmacher-Wesche and Pesaran (2008) for recent empirical applications. We conduct a historical forecasting exercise to answer this question also.

First FAVAR and BVAR models are estimated on two respective balanced panels, using the up to date information. After the model coefficients are estimated a quasi-real time forecasting experiment is conducted. The currently existing data release calendar of the main macroeconomic indicators described in the Table D is used to construct the historical availability of the data along the sample used for estimation. So that we end up with balanced and unbalanced panel of information that was available for analysis during each quarter of the history, assuming that data were published on the same pattern as they do today.

FAVAR and BVAR models produce 4 quarters ahead conditional and unconditional historical forecasts. During each forecasting loop the factors are filtered using the panel of data available up to the point of time in the history where the forecast was supposed to be made. While the coefficients of the two models are fixed to the ones estimated before the exercise using the full sample of information.

Figures 7-10 show the results of historical in-sample forecasting experiment, for private investment and consumption. BVAR model forecast exercise starts in 2006 Q1, while for the FAVAR model the experiment have been conducted since 2001Q2. For both consumption and investment models conditional forecasts follow the dotted line of actual data more closely than unconditional forecast signaling the fact that using all the available information in each particular date of the history improves the forecasts.

To be more precise on this issue the historical forecasts errors of the upper mentioned experiment are calculated and analyzed. Tables 3 and 4 in the appendix display the forecast error statistics for FAVAR and BVAR models of private demand components. To avoid scale illusions all the error statistics are divided to the historical standard deviation of the series to be forecasted.

The results suggest that both FAVAR and BVAR models produce much better forecasts if the conditioning technique is applied, especially over the first two quarters of the forecast horizon. For example the Root Mean Square Error of the private investments forecast decreases to 0.35 from 0.72 for the first quarter of the forecast if extra data releases are used for the forecast as useful information. The mean forecast error of the FAVAR model shrinks from 065 to 0.32, suggesting that on average one could be 50% more precise in the task of private investment now cast if the conditional rather than unconditional approach was historically used.

The mean forecast errors for both models are statistically equal to zero suggesting that the models were estimated efficiently.

In short strong evidence is achieved suggesting that conditional forecasting is more efficient than the classical method of forecasting. Thus central bank should closely monitor all the new data releases since the end of the last projection and asses the effects of the newly available information on the path of projected private demand. The analysts of the CBA thus have the opportunity to check whether the economic developments are on line with the previous baseline projection scenario or not and suggest policy corrections to the board if needed avoiding the negative consequences of the delayed policy response.

Finally we want to answer the question whether to average the forecasts of different models or use the results of the "best" model. Economic theory suggests that forecast accuracy can improve if the forecast from different models are pooled. To check this hypothesis on Armenian data, we conduct an experiment where the historical forecasts of BVAR and FAVAR models are averaged. The weights are equal to the inverse of the RMSE of each model. After the weighted average of the two model's forecast is available, we calculate the forecast errors of the new pooled forecast and compare the error statistics to the error statistics of the FAVAR and BVAR models separately.

Tables 5 and 6 in the appendix show the error statistics of separate and pooled conditional forecasts of private consumption and investments. The results suggest that up to 3 quarter ahead averaged forecasts of private investment are more precise than the best forecast of the two models. For example the mean absolute error of 1 quarter ahead forecasts of private investments produced by the BVAR and FAVAR models are 0.30 and 0.27 respectively, while the mean absolute error of the weighted average of the two declines to 0.20.

The pooled forecasts of private consumption are also proved to be more efficient than separate forecasts although to somewhat weaker extent then in the case of private investment. To sum up the experiment confirms the hypothesis of using weighted average of various model forecast is a better idea than to rely on a single "best" model for short term economic analysis.

Finally it should be noted that all the forecast errors presented are purely model based, while in contemporary monetary policy analysis expert judgments must be used for fine tuning the forecasts. So the "smart" intervention to the pure model results can lead to even further improvements of the forecasts presented in this paper. This will create quality and up to date material for decision making and timely policy response of the CBA to economic shocks for the fulfillment of its primary goal of price stability in the medium term.

Summary

This paper describes the near term forecasting system of private demand components used in the CBA. The system uses 89 monthly and quarterly time series covering wide dimensions of local and global economies. A productive and efficient way is developed for filling the missing monthly indicators to form the quarterly estimates of a macro-variable at the same time using all the available monthly information in real time. Carefully managed stationary data are used for the estimation of Bayesian VAR and FAVAR models. The models are selected for the system taking into consideration, the short sampled and noisy Armenian data.

In today's fast changing global economy it is highly important to monitor and identify the current dynamics of the local economy and correct economic projections respectively responding with relevant monetary policy if needed. For this task it is highly useful to use all the available timely information in real time and assess their impact on the missing economic variables. Having this in mind we introduce the concept of conditional forecasting for BVAR and FAVAR models and argue that conditional forecast must be more accurate then unconditional.

The historical real time forecasting experiment results suggest that forecast efficiency increases significantly if the analysts use all the available monthly and quarterly information, rather than balancing the panel with the end values of private demand components and using this information only for forecast. Moreover

the results of the experiment suggest that the weighted average of BVAR and FAVAR models should be used for the task of near term forecasting of private demand and consumption expenditures in CBA.

All the steps of data management, model estimation and historical forecast experiments are implemented inside the forecasting system of demand components. The utilization of the system raises the productivity and efficiency of the monetary policy analysis making significant contribution to the achievement of CBA's primary goal of maintaining price stability in the medium term.

Appendix

Table 1 The structure and information criterion of FAVAR models

	Lag length	Number of factors	AIC	SBC
Consumption FAVAR	4	6	8.3	8.2
Investment FAVAR	4	5	6.8	6.7

Table 2 Hyper-Parameters and information criterion of BVAR models

	μ	θ	λ	k	υ	AIC	SBC
Consumption BVAR	0.65	0.54	1	3	1	28.3	42.9
Investment BVAR	0.2	0.51	1	3	1	32.9	43.9

Table 3 In-sample conditional and unconditional forecast error statistics for private investment models.

Forecast Horizon	*1*	*2*	*3*	*4*	*Total*
RMSE					
BVAR Conditional	**0.37**	**0.57**	**0.74**	**0.81**	**0.65**
BVAR Unconditional	**0.59**	**0.73**	**0.81**	**0.95**	**0.78**
FAVAR Conditional	**0.35**	**0.40**	**0.76**	**0.84**	**0.63**
FAVAR Unconditional	**0.75**	**0.82**	**0.84**	**0.89**	**0.82**
Mean of Absolute Errors					
BVAR Conditional	**0.30**	**0.46**	**0.57**	**0.60**	**0.48**
BVAR Unconditional	**0.48**	**0.57**	**0.60**	**0.72**	**0.59**
FAVAR Conditional	**0.27**	**0.32**	**0.60**	**0.67**	**0.47**
FAVAR Unconditional	**0.58**	**0.65**	**0.66**	**0.68**	**0.64**
Mean of Errors					
BVAR Conditional	**0.00**	**0.01**	**-0.03**	**-0.03**	**-0.01**
BVAR Unconditional	**0.00**	**-0.01**	**-0.04**	**-0.02**	**-0.02**
FAVAR Conditional	**0.02**	**0.02**	**-0.00**	**-0.05**	**-0.00**
FAVAR Unconditional	**-0.01**	**-0.04**	**-0.08**	**-0.05**	**-0.05**

Table 4 In sample conditional and unconditional forecast error statistics for private consumption models.

Forecast Horizon	*1*	*2*	*3*	*4*	*Total*
RMSE					
BVAR Conditional	**0.35**	**0.46**	**0.52**	**0.59**	**0.49**
BVAR Unconditional	**0.46**	**0.54**	**0.59**	**0.61**	**0.55**
FAVAR Conditional	**0.42**	**0.47**	**0.87**	**0.91**	**0.71**
FAVAR Unconditional	**0.86**	**0.91**	**0.95**	**0.95**	**0.92**
Mean of Absolute Errors					
BVAR Conditional	**0.28**	**0.38**	**0.38**	**0.45**	**0.37**
BVAR Unconditional	**0.34**	**0.40**	**0.45**	**0.47**	**0.41**
FAVAR Conditional	**0.33**	**0.38**	**0.68**	**0.71**	**0.53**
FAVAR Unconditional	**0.67**	**0.70**	**0.72**	**0.70**	**0.70**
Mean of Errors					
BVAR Conditional	**0.00**	**0.02**	**0.05**	**0.03**	**0.03**
BVAR Unconditional	**0.00**	**0.02**	**0.05**	**0.05**	**0.03**
FAVAR Conditional	**-0.03**	**-0.03**	**-0.01**	**-0.02**	**-0.02**
FAVAR Unconditional	**-0.04**	**-0.04**	**-0.05**	**-0.05**	**-0.04**

Table 5 Error statistics of separate and pooled conditional forecasts of private investment

Forecast Horizon	*1*	*2*	*3*	*4*	*Total*
RMSE					
BVAR Model	**0.37**	**0.57**	**0.74**	**0.81**	**0.65**
FAVAR Model	**0.35**	**0.40**	**0.76**	**0.84**	**0.63**
Weighted Average	**0.27**	**0.36**	**0.71**	**0.80**	**0.58**
Mean of Absolute Errors					
BVAR Model	**0.30**	**0.46**	**0.57**	**0.60**	**0.48**
FAVAR Model	**0.27**	**0.32**	**0.60**	**0.67**	**0.47**
Weighted Average	**0.20**	**0.28**	**0.56**	**0.61**	**0.41**

Table 6 Error statistics of separate and pooled conditional forecasts of private consumption

Forecast Horizon	*1*	*2*	*3*	*4*	*Total*
RMSE					
BVAR Model	**0.35**	**0.46**	**0.52**	**0.59**	**0.49**
FAVAR Model	**0.42**	**0.47**	**0.87**	**0.91**	**0.71**
Weighted Average	**0.33**	**0.41**	**0.56**	**0.62**	**0.49**
Mean of Absolute Errors					
BVAR Model	**0.28**	**0.38**	**0.38**	**0.45**	**0.37**
FAVAR Model	**0.33**	**0.33**	**0.68**	**0.71**	**0.53**
Weighted Average	**0.26**	**0.32**	**0.44**	**0.49**	**0.38**

Figure 1 Comparison of Actual and Approximated Growth Rates With One Month

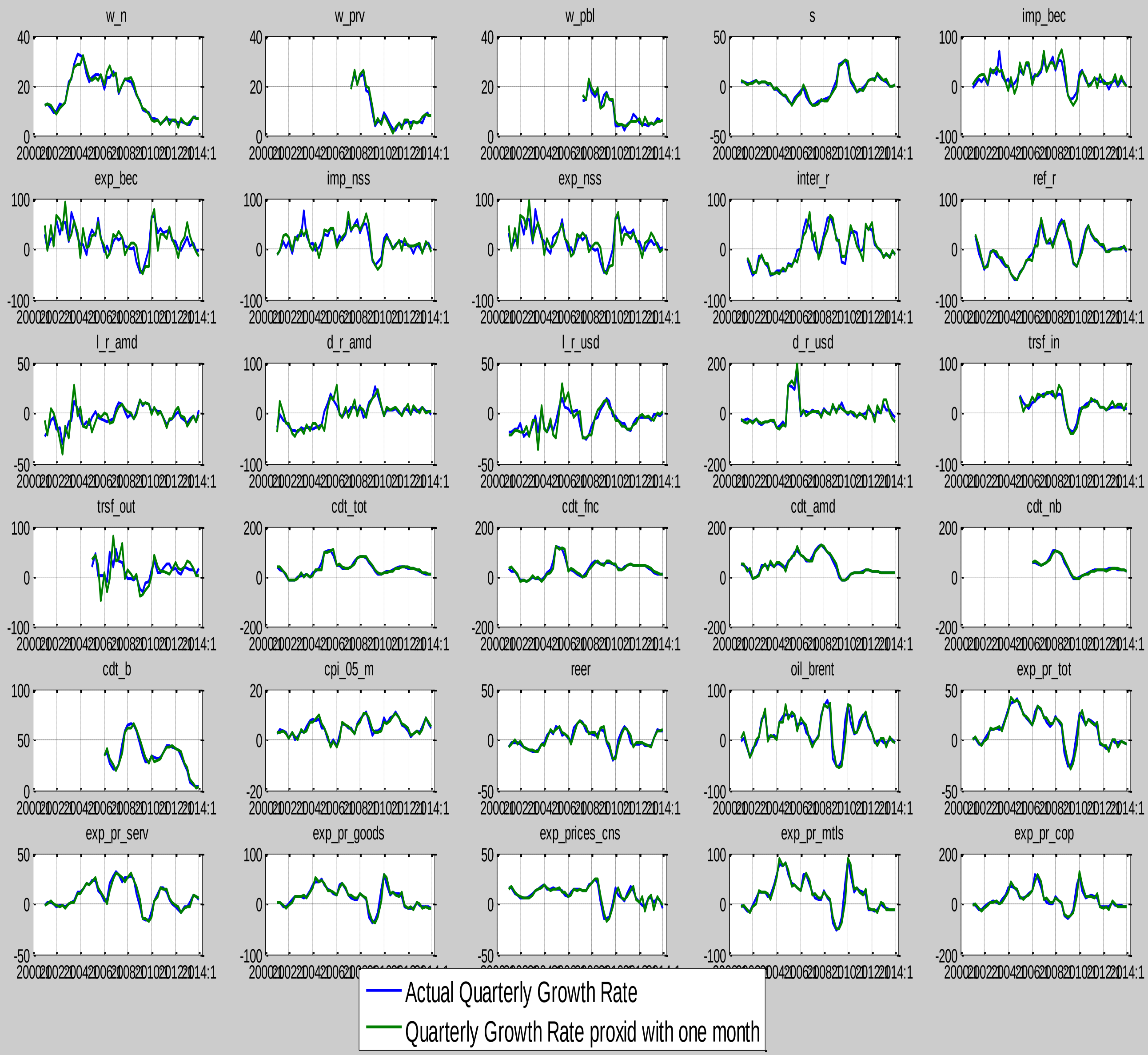


Figure 2 Comparison of Actual and Approximated Growth Rates With Two Months

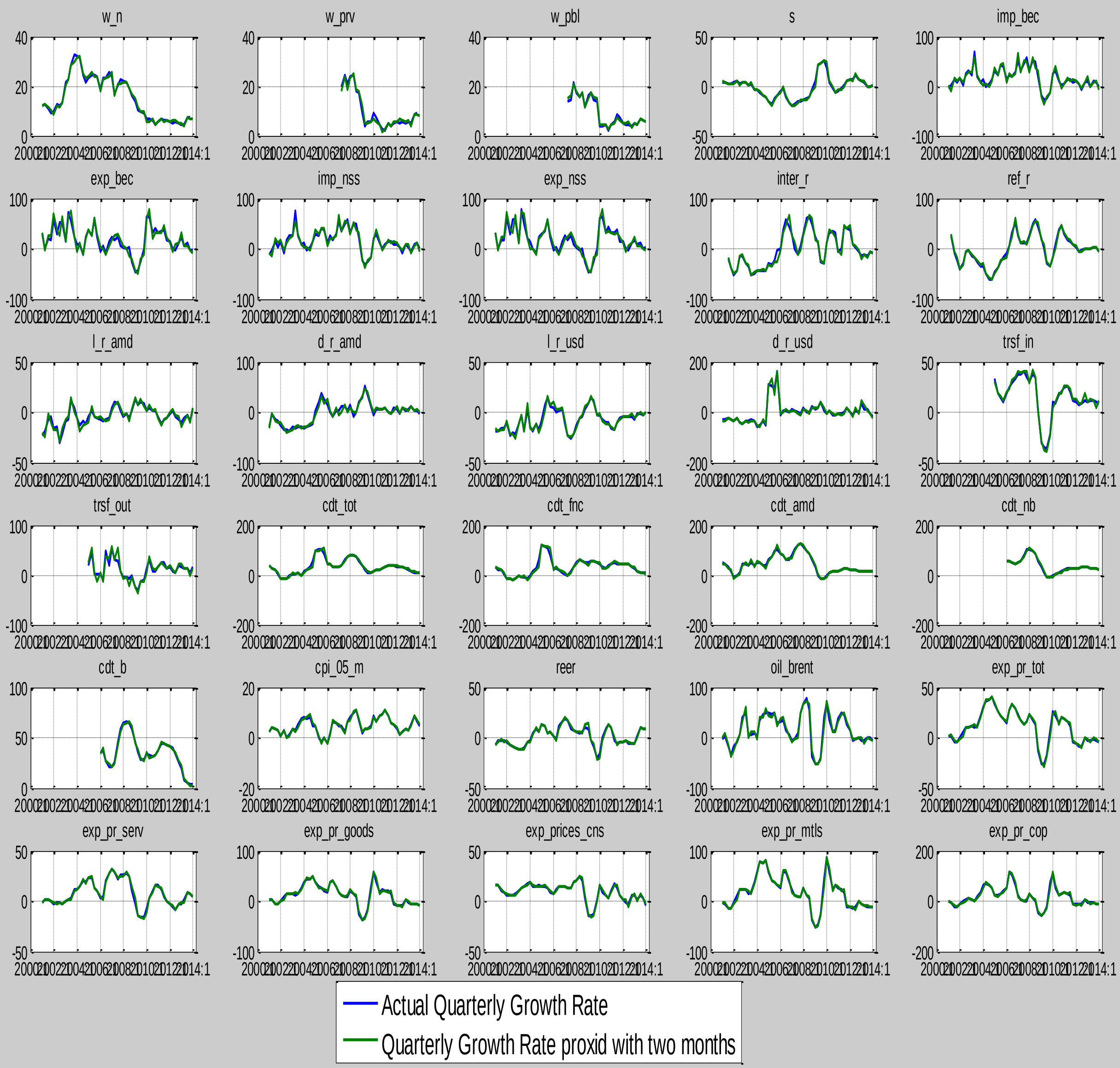


Figure 3. LLF Trend and Actual Differenced Series

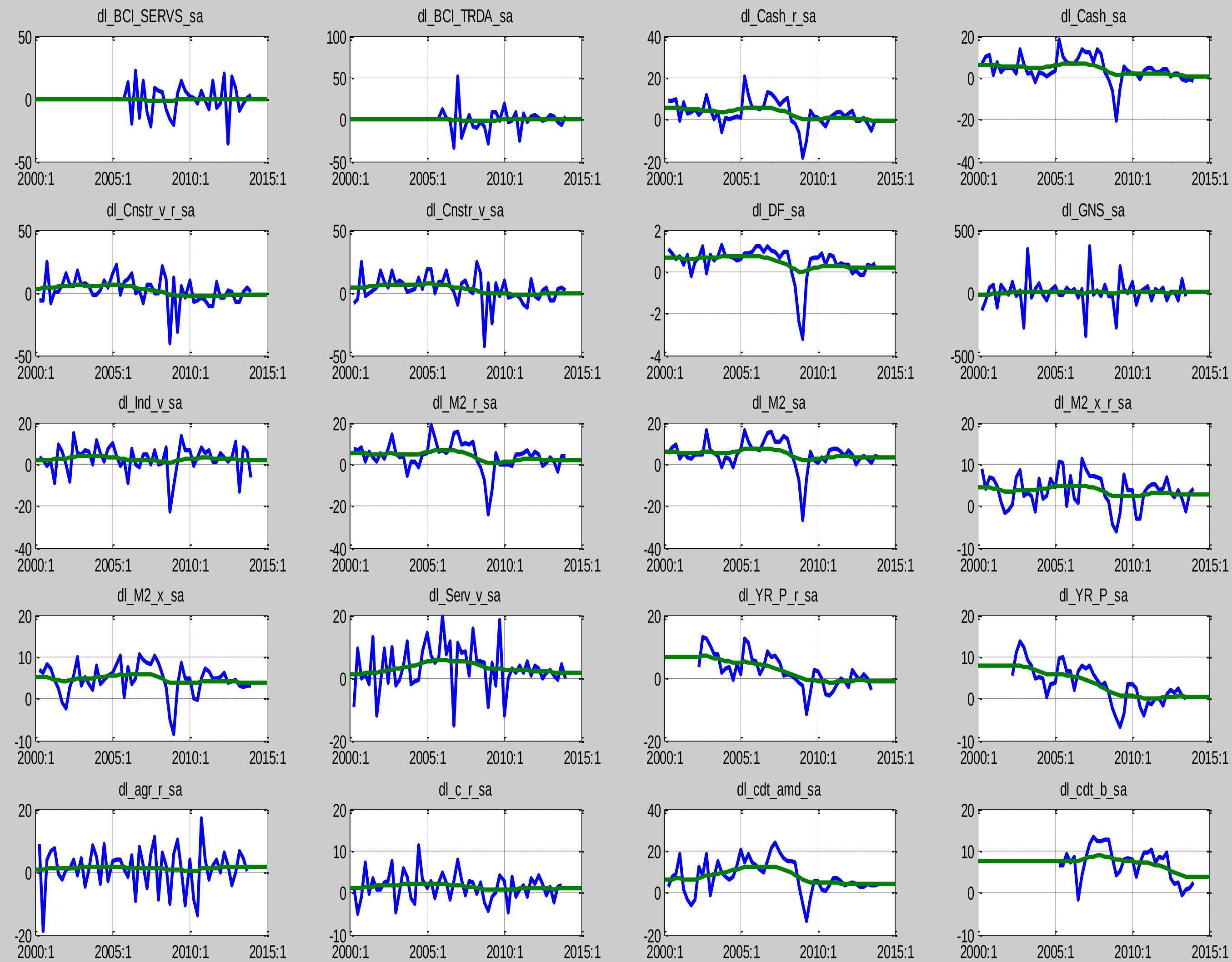
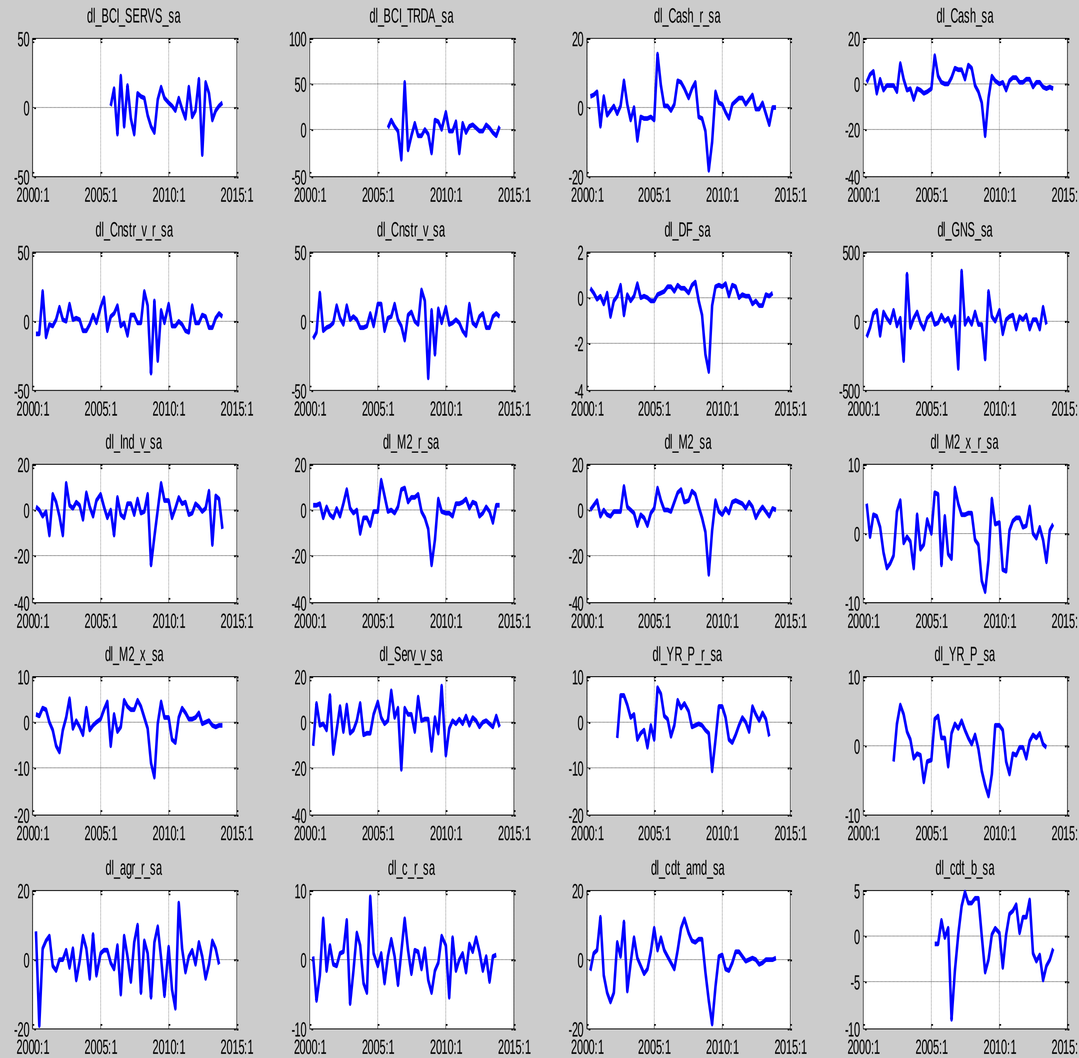


Figure 4. LLF High Frequency Series



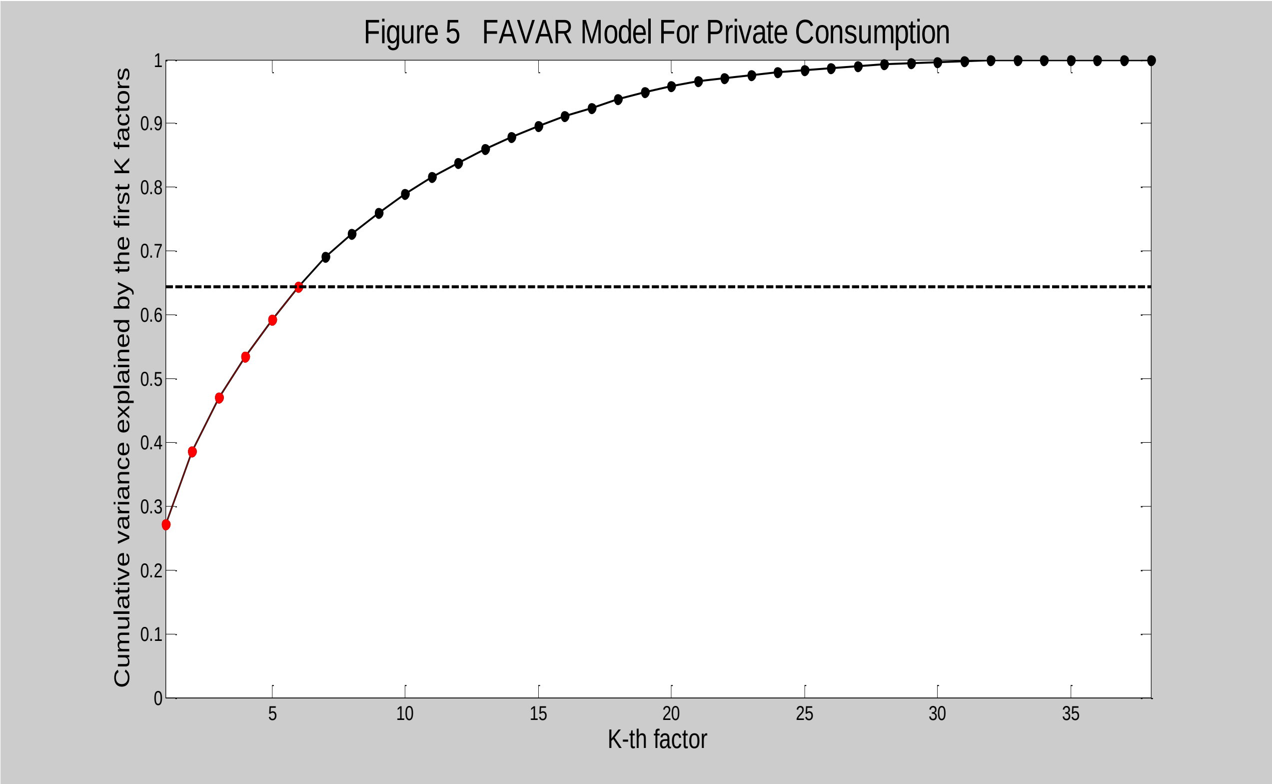


Figure 5 FAVAR Model For Private Consumption
Cumulative variance explained by the first K factors
K-th factor
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
5
10
15
20
25
30
35

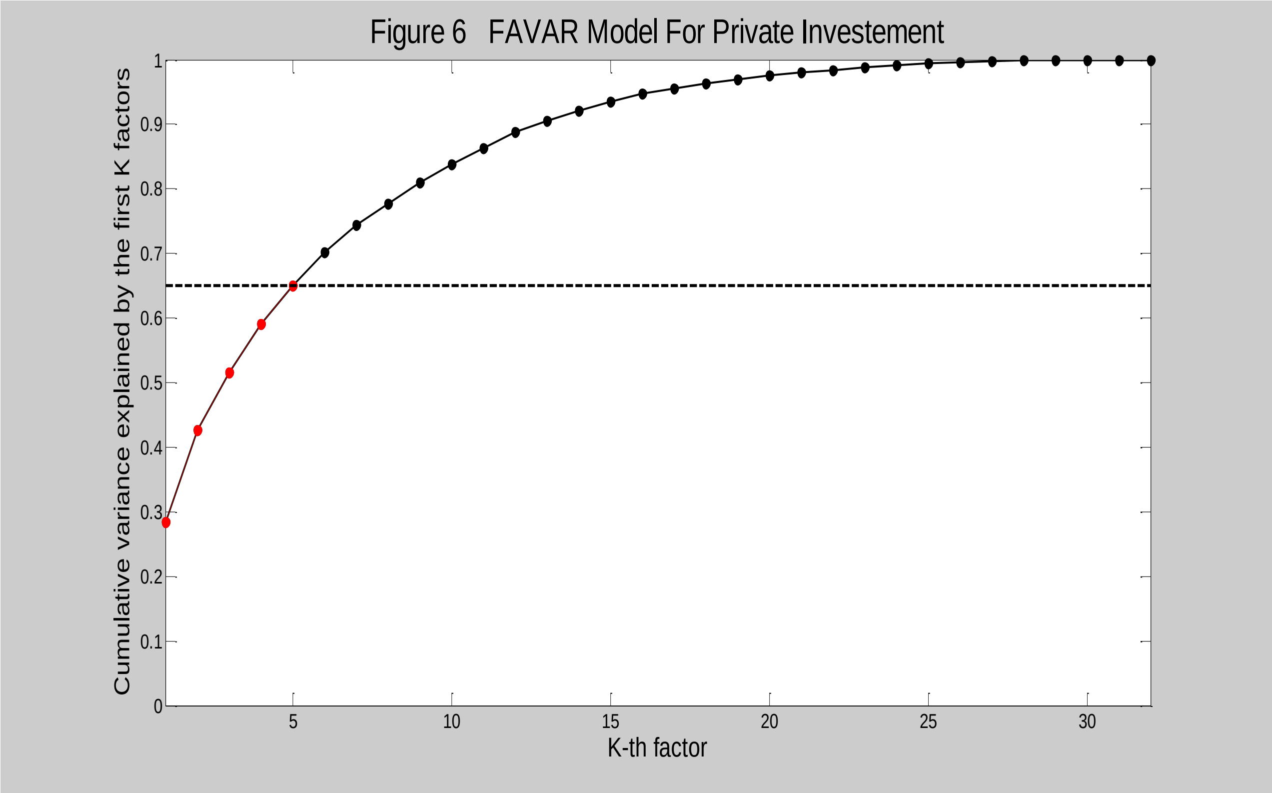
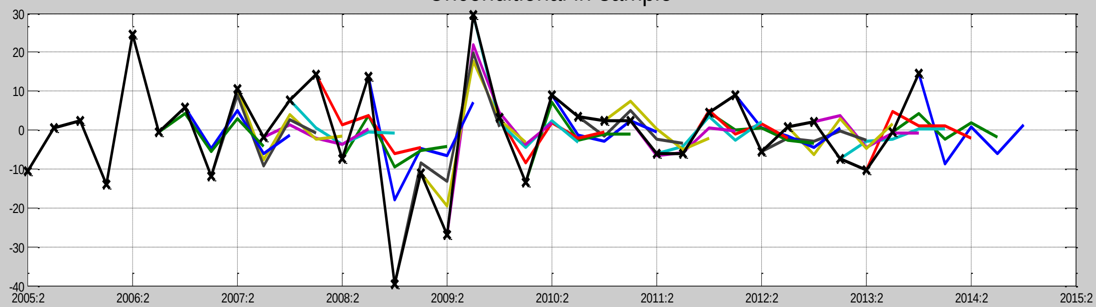


Figure 6 FAVAR Model For Private Investement
Cumulative variance explained by the first K factors
K-th factor
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
5
10
15
20
25
30

Figure 7 BVAR Real Private Investments historical forecasts

Unconditional in-sample



Conditional in-sample

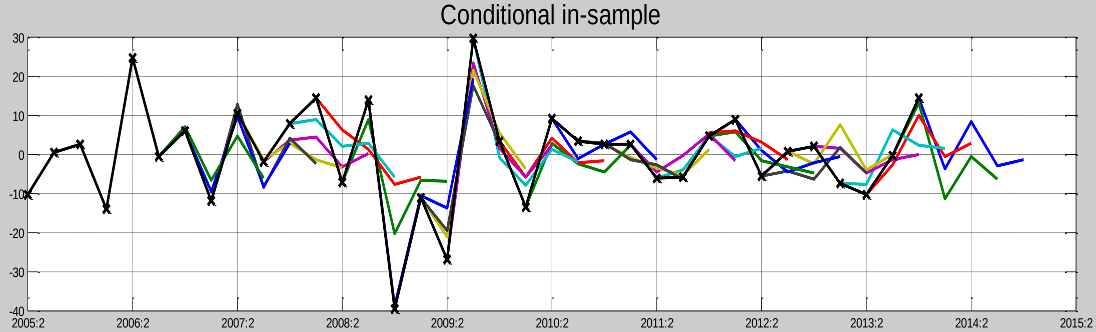
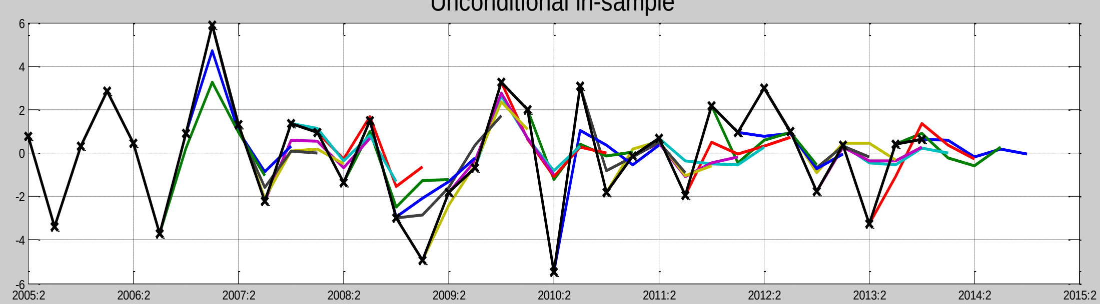


Figure 8 BVAR Real Private Consumption historical forecasts

Unconditional in-sample



Conditional in-sample

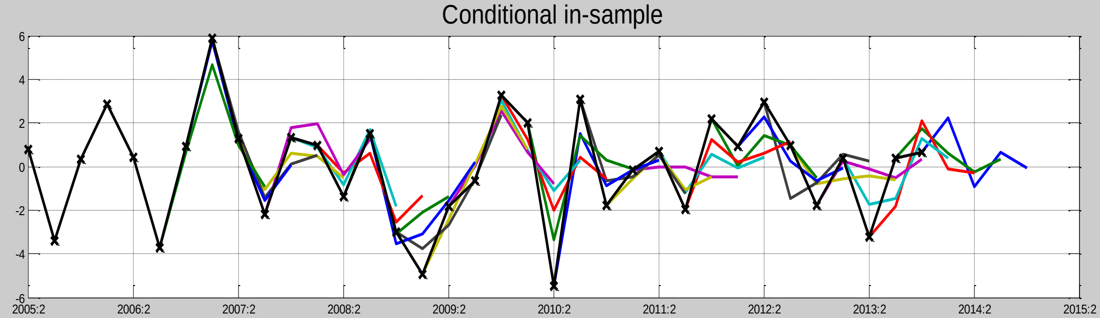


Figure 10 FAVAR Real Private Consumption historical forecasts

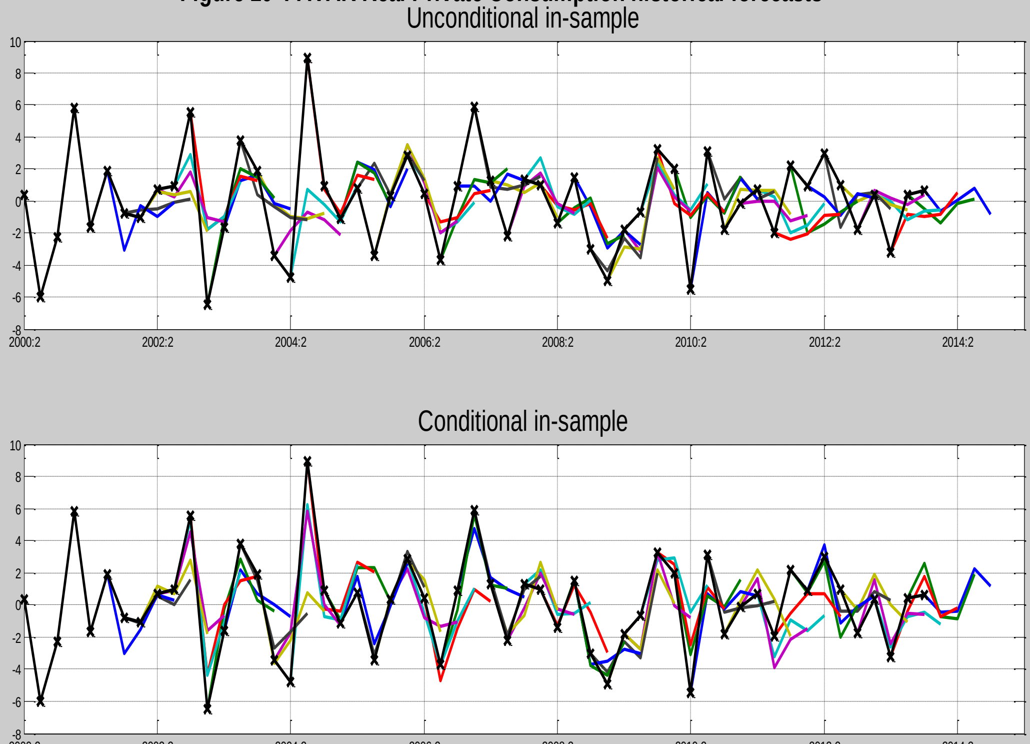
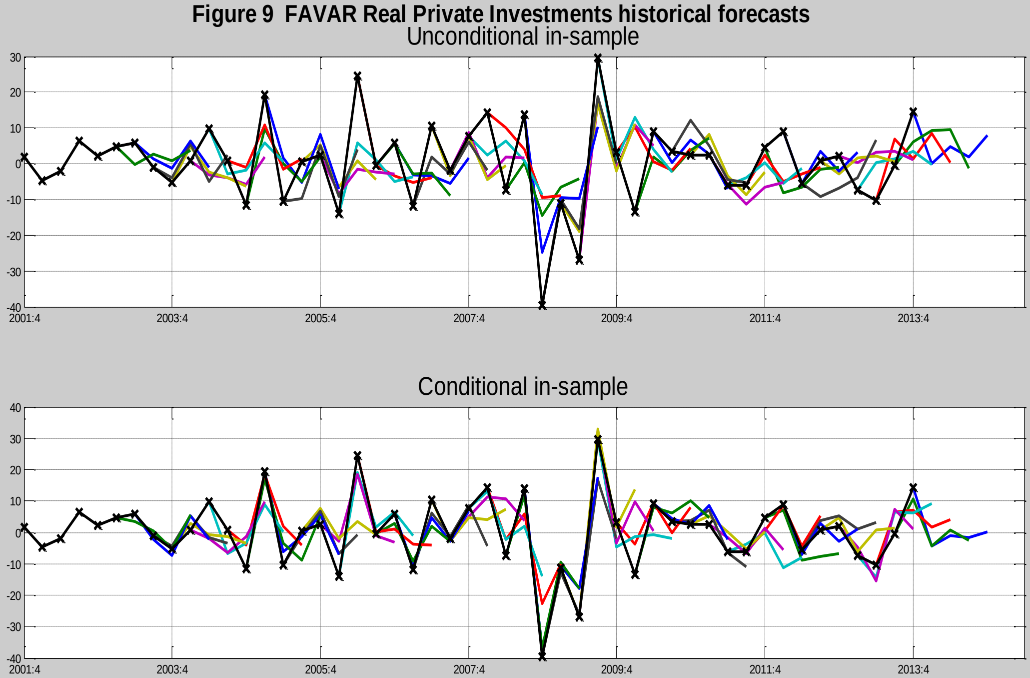


Figure 9 FAVAR Real Private Investments historical forecasts



References

Assenmacher-Wesche, K., H. Pesaran (2008), “Forecasting the Swiss economy using VECX models: an exercise in forecast combination across models and observation windows,” *National Institute Economic Review* 203, 91-108.

Bai, J., S. Ng (2002), “Determining the Number of Factors in Approximate Factor Models,” *Econometrica* 70, 191-221.

Banbura, Marta, Domenico Giannoe, and Lucrezia Reichlin, 2010 “Large Bayesian vector auto regressions,” *Journal of Applied Econometrics,* Vol.25, No.1, pp.71-92

___________, ___________, Michele L. (2014), “Conditional Forecasts and Scenario Analysis with Vector Autoregressions for Large Cross-Sections,” *CEPR Discussion Paper* No. DP9931

Bernanke, Ben, Jean Boivin and Piotr S. Eliasz, 2005, “Measuring the Effects of Monetary Policy: A Factor-augmented Vector Autoregressive (FAVAR) Approach”, *The Quarterly Journal of Economics* 120(1), 387.422.

Clements, M., D. Hendry (2004), “Pooling of Forecasts”, *Econometrics Journal* 7, 1-31.

Doan, T., R. Litterman, and C. A. Sims (1984), “Forecasting and Conditional Projection Using Realistic Prior Distributions,” Econometric Reviews, 3, 1–100.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin, 2007, “A two-step estimator for large approximate dynamic factor models based on Kalman filtering,” Discussion paper 6043, Centre for Economic Policy Research (CEPR)

Giannone, D., L. Reichlin, D. Small 2008, "Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases," *Journal of Monetary Economics* 55, 665-676.

________, _______, and Luca Sala 2005, "Monetary policy in real time," NBER Macroeconomics Annual 2004, (Cambridge, Mass.: MIT Press).

Jarocinski, M. (2010), "Conditional forecasts and uncertainty about forecast revisions in vector autoregressions," *Economics Letters*, 108(3), 257–259.

Koopman Jan, Commander Jacques, Marius Ooms 2011 "Statistical Software for State Space Methods", *Journal of Statistical Software* Vol. 41 Issue 1

Litterman, Richard 1986, "Forecasting with Bayesian Vector Autoregressions-Five Years of Experience," *Journal of Business and Economic Statistics,* Vol. 4, 25-38

Matheson, Troy D., 2010, "An analysis of the informational content of New Zealand data releases: The importance of business opinion surveys," *Economic Modelling,* Vol. 27, 304-314.

________________, **2011** "New Indicators for Tracking Growth in Real Time" *IMF Working Paper* No. 11/43

Matteo Ciccareli, Alessandro Rebucci 2003, "Bayesian VARs: A Survey of the Recent Literature with an Application to the European Monetary System", *IMF Working Paper* WP/03/102

Sims, Christopher 1992, "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy", *European Economic Review* 36, 975-1000

Stock, James, and Mark Watson 1989, "New Indexes of Coincident and Leading Economic Indicators", NBER Macroeconomics Annual (4), Cambridge MA: MIT Press

__________, and ______________, 2002a, "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of the American Statistical Association*, 97, 147–162.

Stratford, K 2013, "Nowcasting world GDP and trade using global Indicators," *Bank of England Quarterly Bulletin*, Vol. 53, No. 3, 233–43.

Venetia Bell, LaiWah Co, Sophie Stone and Gavin Wallis 2014 "Nowcasting UK GDP Growth" *Bank of England Quarterly Bulletin* Vol. 54 No. 1, 58-64