SHORT TERM FORECASTING SYSTEM OF PRIVATE DEMAND COMPONENTS IN ARMENIA

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Abstract – This paper describes the system for the short term forecasting of private consumption and private investments in Armenia. The system uses large amount of time series data to produce conditional forecasts, giving analysts the opportunity to use all the available information in real time for the assessment of private demand dynamics before the official estimates 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 forecasts 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 tools for nowcasting and near term analysis of private demand components.
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1. INTRODUCTION

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

Various methods and techniques have been developed to utilize unbalanced panels of available indicators for the estimation of a missing variable which is released with a considerable time lag compared to most of the indicators available in the panel. It is a common practice in Europe to use a single indicator or a combination of few survey-based indicators to track the current state of economic activity. The Bank of England, for

[1]Central Bank of Armenia. The views expressed are those of the author and do not necessarily reflect those of the Central Bank of Armenia. The author is grateful to an anonymous referee for helpful and constructive comments.

example, combines the signals extracted from several global indicators, such as JPMorgan export index, OECD CLI and metal prices, to track large swings in global GDP and trade before the official estimates are available (Stratford, 2013). Another approach for nowcasting is to use factor analysis developed by Stock and Watson (1989) and Bernanke et al. (2005). Finally, the results from various models can be pooled to generate the final estimates of a target economic variable (Matheson, 2010).

This paper describes the system used for near term forecasting and nowcasting of private demand components in the Central Bank of Armenia (CBA). There are several key criteria which are taken into consideration when building the system. First, to make maximum use of the real-time economic information available in the global and local economy, long economic time series must be utilized. Second, the models used in the system should take into consideration the characteristics of the Armenian economy. The ability to utilize relatively short and low quality time series and to apply expert judgment are the key criteria for the selected models. Finally, the system must guarantee flexibility, productivity and safety to be suitable for periodical monetary policy analysis implemented under strict deadlines.

Bayesian VAR and FAVAR models are the key components of the system. Data on 89 time series of both hard and high frequency data are used as input information which are updated on monthly basis. We use an efficient and quickly implementable approach to fill in the missing monthly data before converting monthly indicators into quarterly data. Data are transformed to achieve stationarity before the estimation procedure. We follow Matheson (2010) and use relatively large panel of indicators to filter common trends of the economy using FAVAR model. Additionally, relatively short time series in a narrower panel are modeled in BVAR.

We employ conditional forecasting techniques that use valuable information set available in real time to nowcast and forecast missing private demand components. Expert judgment is used to fine tune the pure model results. Finally, the forecasts 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 illustrates 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 the conditional forecasts outperform the unconditional forecasts for the 3-4 quarter horizon, and pooling the outputs from different models increases the forecast precision even further. All the procedures of data management, estimation, forecasting and historical forecasting experiment are efficiently conducted within the system. We use the functions available in IRIS toolbox and others developed at CBA to operate the system in MatLab environment.[2]

The rest of the paper is organized as follows. Section 2 describes the methodology and estimation techniques used in the short term forecasting system. Section 3 describes the data used in the system 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 VAR models are convenient and widely accepted, they may create problems which must be considered carefully when conducting economic analysis. First, VARs suffer from the loss of degrees 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 is very high because of many variables included. Ciccarelli and Rebucci (2003) give a good description of the overfitting problem. Second, VAR models produce explosive impulse responses as a result of biased coefficient estimates. Both problems become more severe in case of short and low quality time series data used for estimation which is the case for developing countries and Armenia in particular.

[2]See www.iris-toolbox.com for more detailed information on IRIS toolbox.

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

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_p X_{t-p} + \varepsilon_t, \qquad t = 1, \ldots, T \tag{2.1}$$

where the constant term c is a $r \times 1$ vector, $\beta_1 \ldots \beta_p$ 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.

We use Bayesian estimation procedure by Litterman (1980) to estimate the system (2.1). 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, the Bayesian approach sets priors as distributions around a central value summarizing the researcher's uncertainty over the model parameters.

This method of imposing priors allows the data to alter the 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, the Bayesian approach avoids the overfitting problem and produces more accurate forecasts than reduced form classic VARs (Canova, 1995).

The literature proposes various forms of priors for Bayesian estimation depending on the purpose of research. This paper uses Litterman (1986) priors, also known as "Minnesota" priors. These priors take into consideration several well-known statistical regularities in 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.

These regularities are used as prior information to estimate the model. We assign certain probability distributions to the parameters of the model which satisfy 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 coefficient distribution must decline with the lag length, so that for higher lag coefficients the parameter distributions are squeezed towards zero. Third, the variance of the coefficient distribution is larger for the own lags compared to the variance of other variable's lagged coefficients.

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

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

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

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 around 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 increases with the size of the system to avoid overfitting, λ determines the speed at which the variance of the priors declines with the lag length of the variables included in the model, σ_i/σ_j accounts for different scale and variability of the data, and finally, $0 < \vartheta < 1$ is the parameter that determines 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. We use the Bayesian maximum likelihood method by Ciccarelli and Rebucci (2003) to estimate the BVAR.

2.2. **FAVAR model.** Factor-augmented vector autoregressive (FAVAR) models are used widely in modern macroeconomics as a nowcasting and near term forecasting tool. The most important and useful feature of FAVAR models is their ability to use large datasets to forecast a particular macro variable. FAVAR models solve at least two problems which arise 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 forecast values and dynamics for the “target” macro variable. Sims (1992) illustration of the “price puzzle” is a vivid example of this problem. Second, the amount of impulse responses is constrained by 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”, the forecasted path of real GDP only is not enough. The future dynamics of private demand components, capacity utilization, real estate prices, real wages and costs are among the indicators that policy makers must have to check the quality and reliability of the forecasted “economic activity” and deliver it to the public in plain language. Unfortunately, most available models in modern economics cannot use long time series while preserving degrees of freedom. On the contrary, FAVAR models allow 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.

We present the structure of the FAVAR model by Bernanke et al. (2005). Let $X_t' = (X_{1,t}, \ldots X_{N,t})$ denote a vector of stationary observed variables, where $t = 1, \ldots, T$ measures the time dimension and N is large enough number of variables compared to T.

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + \xi_t \tag{2.2}$$

From equation (2.2), the vector of variables X_t' is a linear combination of unobservable factors $F_t' = (F_{1,t}, \ldots F_{P,t})$ and some observable variables $Y_t' = (Y_{1,t}, \ldots Y_{R,t})$ 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 $N \times R$ matrix of coefficients of “important” variables and ξ_t is a $N \times 1$ vector of white noise disturbances. The number of factors is “small”, so that $P + R + T < N$. Equation (2.2) captures the idea that factors F_t' and variables in Y_t' are the main forces which define the dynamics of the large set of macro variables. The common shocks in 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' is further defined by the VAR process:

$$\begin{pmatrix} F_t' \\ Y_t' \end{pmatrix} = A_1 \begin{pmatrix} F_{t-1}' \\ Y_{t-1}' \end{pmatrix} + \ldots + A_l \begin{pmatrix} F_{t-l}' \\ Y_{t-l}' \end{pmatrix} + \vartheta_t \tag{2.3}$$

where $A_1 \ldots A_l$ are the coefficient matrices of the lagged variables and ϑ_t is the mean zero error term with a diagonal covariance matrix Θ. The system (2.3) is called factor-augmented vector autoregression which enriches the dynamics of "important" variables Y_t' 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 more robust and economically intuitive if it is analyzed in the framework of equation (2.3), compared to the results produced with simple VAR. However, FAVAR is not used for investigating the structural relationship between "key" macroeconomic variables in the system for short term forecasting described in this paper, but rather as an efficient tool for nowcasting and short-term forecasting of private demand. In this sense we do not use any pervasive macroeconomic variable in the model (2.3) 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'. Since the factors F_t' are unobservable, equation (2.3) cannot be estimated directly. We apply a two-step principal component estimation procedure to estimate equations (2.2)-(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 $\hat{F}_t'$are used as observables to estimate the equation (2.3) with standard techniques.[3]

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

3. DATA

Two important characteristics of the Armenian economy need to be taken into account. First, the time span of Armenian data is relatively short as it is a relatively young post-soviet economy in transition. The longest time series start in early 1990s and cover some indicators of real sector, financial sector and prices, such as GDP, exchange rate and CPI. A broader range of indicators related to the sectors of the economy such as demand components, retail sales, wages and real estate prices start in late 1990s and early 2000s. Thus, a "useful" quarterly panel of data covering broad cross section of the economy is available since 2000. High frequency survey based indicators such as Consumers Confidence Index, Business Climate Indicator and Economic Activity Indicator have been constructed since mid-2000s, leaving the researchers with even shorter panel of data available for real-time monitoring of economic developments.

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

To reach the maximum efficiency in near-term monitoring and economic analysis, the chosen models 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. On the other hand, Bayesian VAR model is an appropriate tool to deal with short time series and contaminated estimates. Having this in mind, we divide the data into two groups based on the length of available time series.

The first (relatively large) panel of data starts in 2000Q1 and includes indicators from the following groups of data:

- National Accounts - 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.

This panel is used in FAVAR model which extracts the common trends from a large number of variables and ignores the noise prevalent in the data.

The second (relatively small) panel starts in 2005Q1 and includes survey measures and remittances via the banking system, which are extremely useful for tracking movements of private consumption and investment especially in times of high turbulence. The survey indicators are of great importance because they become 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 also included here. In particular, the second panel 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.

The length of the second panel is constrained by the availability of survey measures which are being constructed since 2005Q1. To avoid the curse of dimensionality and contaminated estimates, Bayesian VAR is applied on this 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 provide 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. Since the "target" variables – private investment and consumption – are published quarterly, all monthly indicators are converted into quarterly data following the procedure explained in the next section.

3.1. **Frequency Conversion.** An important step in the process of near term analysis of private demand components is the conversion of monthly indicators into quarterly data. The main challenge that researchers and analysts face here is that in real time the data for all three months of a quarter are not available within a quarter. Instead, the data for only 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 1 below illustrates the availability of three indicators in early April 2014 when the second quarter monetary policy analysis started according to CBA's calendar.

From Table 1, we can see that only exchange rate data are available for all three months and hence could be averaged to form the 2014Q1 average USD/AMD exchange rate. However, the data on retail trade turnover and average monthly nominal wage are not available for March and February-March, respectively. To get the quarterly estimates, we need to develop a method for filling these empty cells that makes use of valuable monthly information published within a typical quarter. 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, as is the case for the private demand forecasting system used at the CBA. Instead, we adopt a simpler and faster approach which can raise the flexibility and efficiency of monetary policy analysis under time constraints. Using the historical values of the indicators in Table 1 we calculate the actual 12 month growth rates for the available monthly indicators which are shown in Table 2.

Based on the well-known persistence of growth rates exhibited by macro series, we proxy the quarterly average year-on-year growth of an indicator with the first month's

TABLE 1. The availability of certain macro indicators in Armenia in 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

TABLE 2. 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%

TABLE 3. 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

12 month growth rate if only the first month data are 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. Figures 1 and 2 in the appendix illustrate the high precision of the approximation of quarterly growth rates with using this methodology. The proxies of quarterly growth rates then are used to calculate the levels of quarterly data, using historical quarterly levels of originally monthly indicators. If all three months of the data are available within a quarter the simple average of the three is taken to form the quarterly value. Table 3 illustrates the quarterly levels of the indicators estimated with the above approach. This approach is applied to all 44 monthly indicators used in the system to convert them into quarterly data.

3.2. **Data Transformation.** After filling the missing monthly data and converting monthly series to quarterly we merge the converted dataset to the panel of originally quarterly series, such as GDP and demand components, ending up with a panel of 89 quarterly series. Before using the series for final estimation the following adjustments are made.

(1) Nominal series are deflated with CPI index.
(2) We take the log of trending series multiplied by 100, except those that are measured in percentages or take negative values.
(3) The seasonal series are adjusted using X11.
(4) We compute quarter-on-quarter differences of the logged and seasonally adjusted series $(100 \times ln(X_{it})\_sa - 100 \times ln(X_{it-1})\_sa)$.
(5) Series measured in percentages or 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 and later used to retrieve the forecasted series back to the original format.

Figures 3 and 4 in the appendix show the low frequency components of actual series and the high frequency component for a number of indicators. Some of the series display trend in their growth rates; 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 private demand components forecasting system.

4. Specification and estimation

As described in Section 2, the first longer panel of low frequency component of quarterly differenced series is used for the estimation of FAVAR model and the second shorter panel is used for Bayesian VAR model estimation. Separate FAVAR and BVAR models are

[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.

estimated for private consumption and private investment. The approach for choosing the long and short 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 includes 68 and 62 time series, respectively, starting in 2000Q2, while BVAR model of consumption and investment includes 10 and 9 series, respectively, starting in 2005Q2. All the panels are balanced. To avoid the problem of "over-fitting" in FAVAR models, we follow 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".

Figures 5 and 6 in the appendix show that six and five 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 shown in Table 1 in the appendix.

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 rule 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 $\lambda = 1$. 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 shows the defined values of the hyper-parameters for private consumption and investments models. As the parameters suggest, both models 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 N is the sample size and T is the number of variables included in the BVAR models.

TABLE 4. The availability of different groups of data at the end of a typical quarter

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

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 nowcasting and forecasting a missing variable before official estimates are published. In particular, timely indicators can be utilized successfully for forecasting private demand components which become available a quarter or two later contrary to a number of macroeconomic and survey indicators. Table 4 shows the availability of different groups of data in Armenia at the end of a typical quarter within a year. "x" means that quarterly data are available for the quarter, "x_{2m}" means the first two months of data are available within the quarter and "-" means that no data are available for the following quarter.

At the end of a typical quarter 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 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 middle of the third month of each quarter including the time needed for adjusting and regrouping these indicators.

Preliminary operative macroeconomic soft data, such as wages, prices and volume of production in different sectors of the economy, are published by the Armenian National Statistical Service with a 20-21-day lag. As a result, at the end of a typical quarter Q_o, the first two months of these data are available. Finally, a number of survey indicators, such as consumer confidence and business activity indicators, are published on a quarterly basis in the second month of each quarter describing current and expected developments for the current Q_o and the upcoming Q_{o+1} quarter, respectively.

Section 2 described the procedure of estimating the quarterly values of a monthly indicator based on the first two months of data. As a result, at the end of each quarter when monetary policy analysis is conducted forecasters are faced with an unbalanced panel of information, including the estimated quarterly data based on partially available information within a quarter. 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.

The system described in this paper uses FAVAR and BVAR models to accomplish the task of conditional nowcast and near term forecast. The coefficients and error matrices of both BVAR and FAVAR models are estimated using a balanced panel. Thus, as Table 4 suggests, in any current quarter Q_o the panel used for the estimation of model parameters 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. We introduce the concept of conditional forecasting on an example of a general VAR model which can be applied to both BVAR and FAVAR models, as these are also represented in VAR forms.

Suppose we have the VAR system (4.1), where $X_t = (x_{1,t}, \dots x_{6,t})$ is a vector containing quarterly data groups described in Table 4 and ε_t is the vector of independently and identically distributed error terms. The vectors of coefficients $\beta_1 \dots \beta_p$ and residual correlation matrix Ω are estimated using a balanced panel.

TABLE 5. Unconditional forecasts using panel of initial conditions for periods $Q_{o-2-n} \ldots Q_{o-2}$

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

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_p X_{t-n} + \varepsilon_t \tag{4.1}$$

Given the data release pattern described in Table 4, in any current quarter Q_o the balanced panel used for the estimation of system (4.1) will end at Q_{o-2}. After the estimation of parameters is complete, the system (4.1) can be used for nowcasting and forecasting. Suppose in a typical current period Q_o we want to produce a forecast for the next f quarters $Q_{o+1} \ldots Q_{o+f}$ and two quarters of a nowcast for periods Q_{o-1} and Q_o.

As Table 5 shows, in the classical forecasting procedure called unconditional forecasting model the system (4.1) uses a panel of actual data $x_{i,o-2-n} \ldots x_{i,o-2}$ as initial conditions to produce $x^{unc}_{i,o-1}, x^{unc}_{i,o} \ldots x^{unc}_{i,o+f}$ vectors of nowcasted and forecasted values including data where nth number of lags is included in the model and $i = 1 \ldots 6$ denotes the different data groups. In this case the vector of disturbances $\varepsilon_{o-1}, \varepsilon_o \ldots \varepsilon_{o+f}$ is equal to zero along the forecasting horizon and the timely actual observations in the periods Q_{o-1}, Q_o, Q_{o+1} are not used at all.

In other words, given the estimated coefficients of the models, the information set from Q_{o-2-n} to Q_{o-2} is used for unconditional forecasting. In this approach the forecast update is possible only 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. Conditional forecasting on the other hand allows to use all

TABLE 6. Conditional forecasts using a panel for the period $Q_{o-2-n} \ldots Q_{o+1}$

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

the unbalanced information available during the time of forecast implementation. Moreover, forecast can be updated each month as new information becomes available giving the central bank analysts the opportunity to closely monitor the economic developments and give efficient policy advice.

Suppose again our goal is to produce a forecast for the next f quarters $Q_{o+1} \ldots Q_{o+f}$ and two quarters of a nowcast for periods Q_{o-1} and Q_o, though this time we want to condition the forecasts on actual information available for some variables in periods $Q_{o-1} \ldots Q_{o+1}$, such as preliminary macro and survey indicators in Table 4. In this case the residuals $\varepsilon_{o-1}, \varepsilon_o \ldots \varepsilon_{o+1}$ of the equations in the VAR system are not equal to zero anymore, but are set so that the forecasted values of variables which become available earlier are equal to the observed actual values. Based on the estimated historical correlation matrix of the system (4.1), the residuals of missing variables' equations are also altered, leading to different forecasted values compared to those obtained from unconditional forecasting. Table 6 shows the results of conditional forecasting in current time Q_o where $x^{cnd}_{i,o+j}$ are the conditional forecasts for variables of group i and time period j and $x_{i,o+j}$ are actual values for variables of group i and time period j, where $i = 1 \ldots 6$ and $j = -1 \ldots f$.

As mentioned earlier, the process is set so that the forecasted values for available data in the forecast horizon $Q_{o+1} \ldots Q_{o+f}$ are exactly equal to the published values. For example, the actual number of GDP $x_{3,o-1}$ is considered as the conditional nowcast of GDP in the quarter Q_{o-1}. It is important to note that the conditional forecasted values differ from the unconditional ones $X^{cnd}_{o-1+i} \neq X^{unc}_{o-1+i}$ because larger information set of actual data, including indicators from periods $Q_{o-1} \ldots Q_{o+1}$, are used for conditional forecasting.

The conditional forecast is *ex ante* expected to be more precise compared to the unconditional one if the estimated models describe correctly the dynamics of the economy. We address this issue in the next section.

4.2. **Forecast Evaluation.** Economic theory suggests that pooling forecasts produced by various models can improve the forecast quality compared to forecasts produced by a single model; 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 check the *ex ante* assumed hypothesis that using the jagged edge panel for forecasting gives better results compared to the balanced panel approach.

We first estimate FAVAR and BVAR models on two respective balanced panels, using up-to-date information. Then, we conduct a quasi-real time forecasting experiment. We construct the historical availability of data using currently existing data release calendar of the main macroeconomic indicators along with the sample used for estimation. Assuming that data publication follows the same pattern as today, we end up with balanced and unbalanced panel of information that was available for analysis during each quarter of the history along with the estimation sample.

In each historical quarter FAVAR and BVAR models produce conditional and unconditional forecasts for the next four quarters. During each forecasting loop the factors are filtered using the panel of data available up to the point when the forecast is made, whereas the coefficients of two models are fixed to the ones estimated earlier using the full sample of information.

Figures 7-10 in the appendix show the results of a historical in-sample forecasting experiment for private investment and consumption. Forecast exercises for BVAR and FAVAR models start in 2006Q1 and 2001Q2, respectively. For both consumption and investment models conditional forecasts follow the dotted line of actual data more closely than unconditional forecasts, signaling the fact that using all the available information in each particular date of history improves the forecasts.

Furthermore, we compute and analyze the historical forecast errors which are reported in Tables 3 and 4 in the appendix for FAVAR and BVAR models of private demand components. All the error statistics are divided to the historical standard deviation of the forecasted series. The results suggest that both FAVAR and BVAR models produce much better forecasts if the conditioning technique is used, 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 falls from 065 to 0.32, suggesting that the nowcast of private investment is on average 50% more precise if the conditional rather than unconditional approach is used. The mean forecast errors for both models are statistically equal to zero suggesting that the models are estimated efficiently.

We find strong evidence that conditional forecasting is more efficient than the classical method of forecasting. Thus, central banks should closely monitor all the new data releases since the last projection and assess the effects of the newly available information on the path of projected private demand. As a result, the CBA analysts have the opportunity to check whether the economic developments are in line with the previous baseline projection scenario and suggest policy corrections to the board if needed to avoid the negative consequences of the delayed policy response.

Next 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 forecasts 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 using the weights equal to the inverse of the RMSE of each model. We then calculate the forecast errors of the new pooled forecast and compare the error statistics to those produced by FAVAR and BVAR models individually.

Tables 5 and 6 in the appendix show the error statistics of separate and pooled conditional forecasts of private consumption and investments. The results indicate that the averaged forecasts of private investment for the next up to three quarters are more precise than the best forecast of the two models. For example, the mean absolute error of next quarter forecast 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 is 0.20. The pooled forecasts of private consumption are also seem to be more efficient than separate forecasts although to a somewhat weaker extent than in the case of private investment. To sum up, the experiment confirms the hypothesis that using weighted average of various models forecasts is a better idea than relying on a single "best" model for short term economic analysis.

It should be noted that all the presented forecast errors are purely model-based, while in contemporary monetary policy analysis expert judgment is used for fine tuning the forecasts. So "smart" interventions can lead to even further improvements of the forecasts presented in this paper. This creates quality and up to date material for decision making and timely policy response of the CBA to economic shocks to achieve price stability in the medium term.

5. Conclusion

This paper describes a near term forecasting system of private demand components. The system uses 89 monthly and quarterly time series covering various dimensions of local Armenian and global economies. We develop a productive and efficient way for filling in the missing monthly indicators to form quarterly estimates of a macro variable using all the available monthly information in real time. Bayesian VAR and FAVAR models are estimated with carefully managed stationary data. These models are selected for the system taking into consideration the short time series and high amount of noise prevalent in Armenian data.

In today's fast changing global economy it is highly important to monitor and identify the current dynamics of a local economy and make accurate economic projections in order to conduct a relevant monetary policy. For this task it is essential to use all the available timely information in real time and assess their impact on the missing economic variables before the official numbers are published. We introduce the concept of conditional forecasting for BVAR and FAVAR models and show that conditional forecast is more accurate than unconditional one and therefore can be used to increase the efficiency of evaluating the state of the economy in the near term.

The historical real time forecasting experiment suggests that forecast precision indeed increases significantly when all the available monthly and quarterly information is used. Moreover, the results of the experiment suggest that the weighted average of BVAR and FAVAR models should be used for near term forecasting of private demand and consumption expenditures. 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 A.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 A.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 A.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 A.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 A.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 A.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 2 Comparison of Actual and Approximated Growth Rates With Two Months

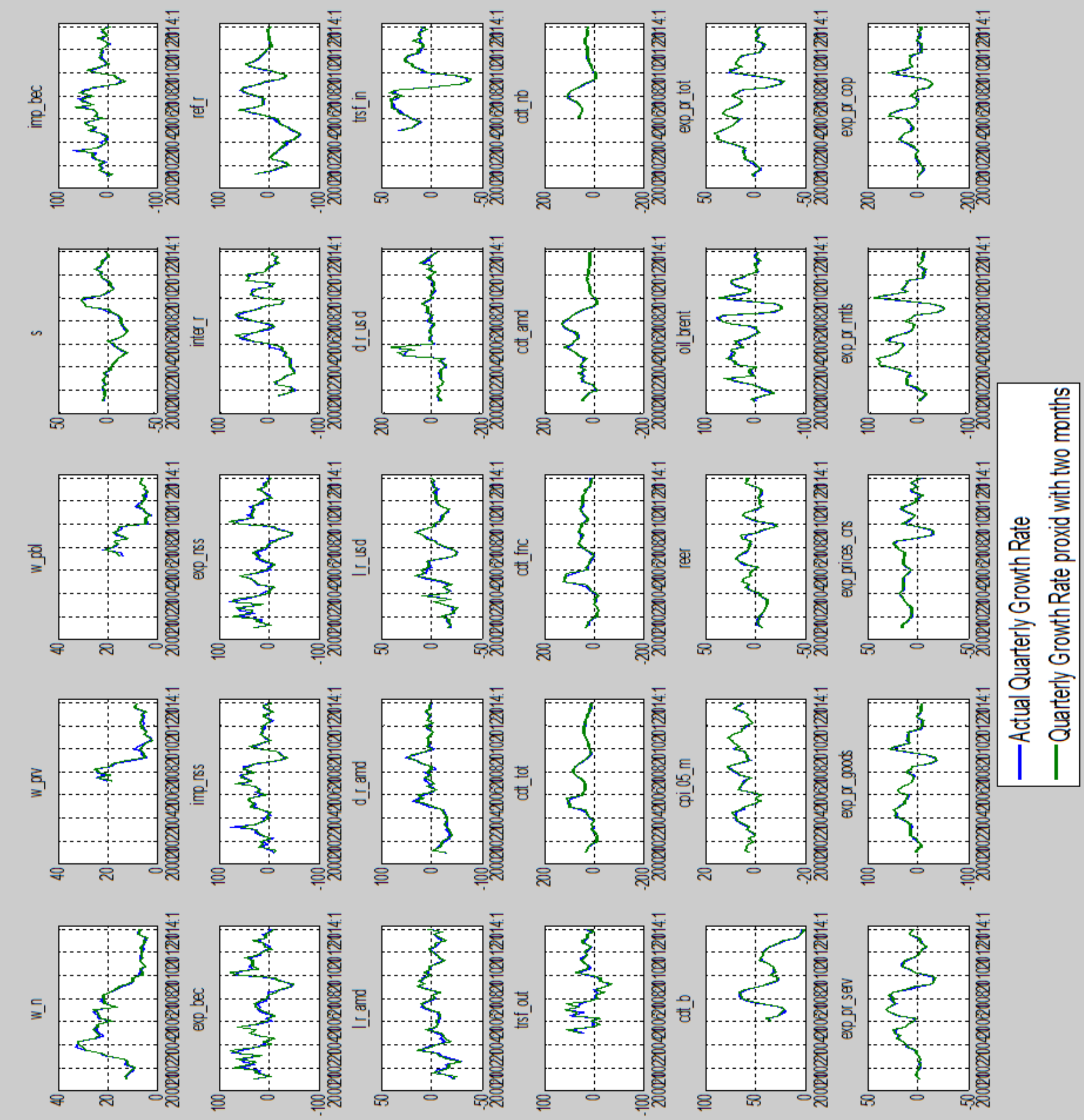
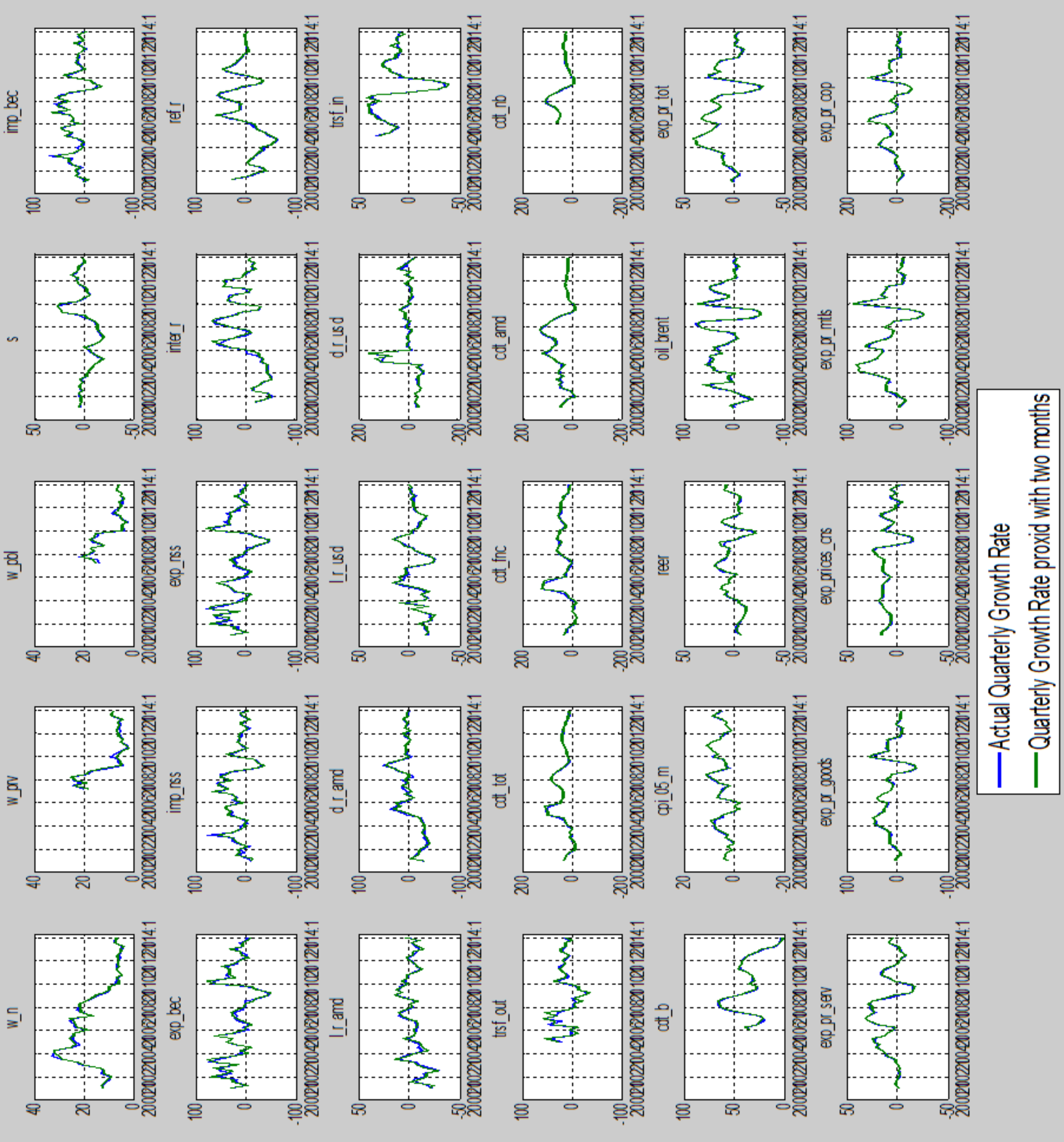


Figure 2 Comparison of Actual and Approximated Growth Rates With Two Months



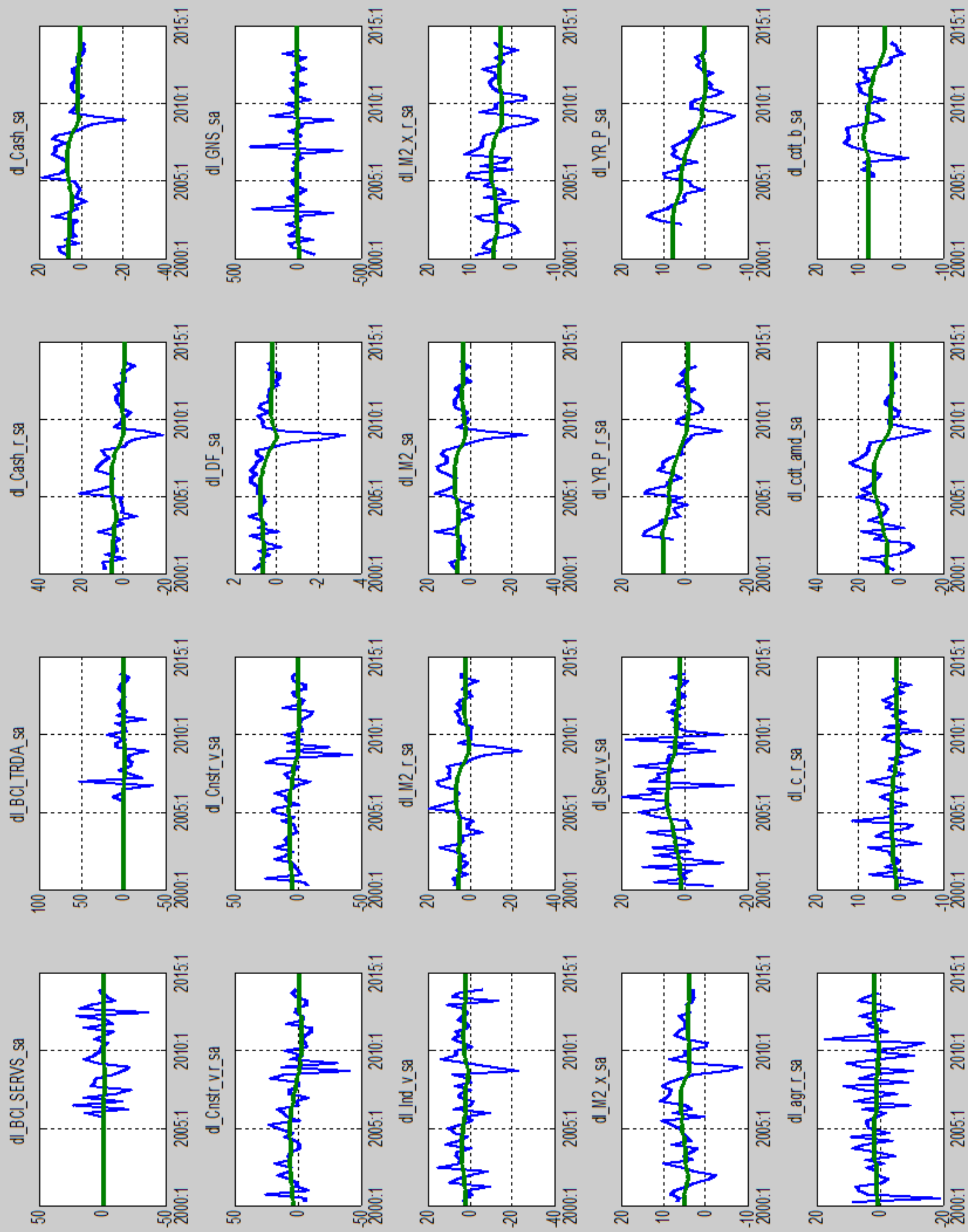


Figure 3. LLF Trend and Actual Differenced Series

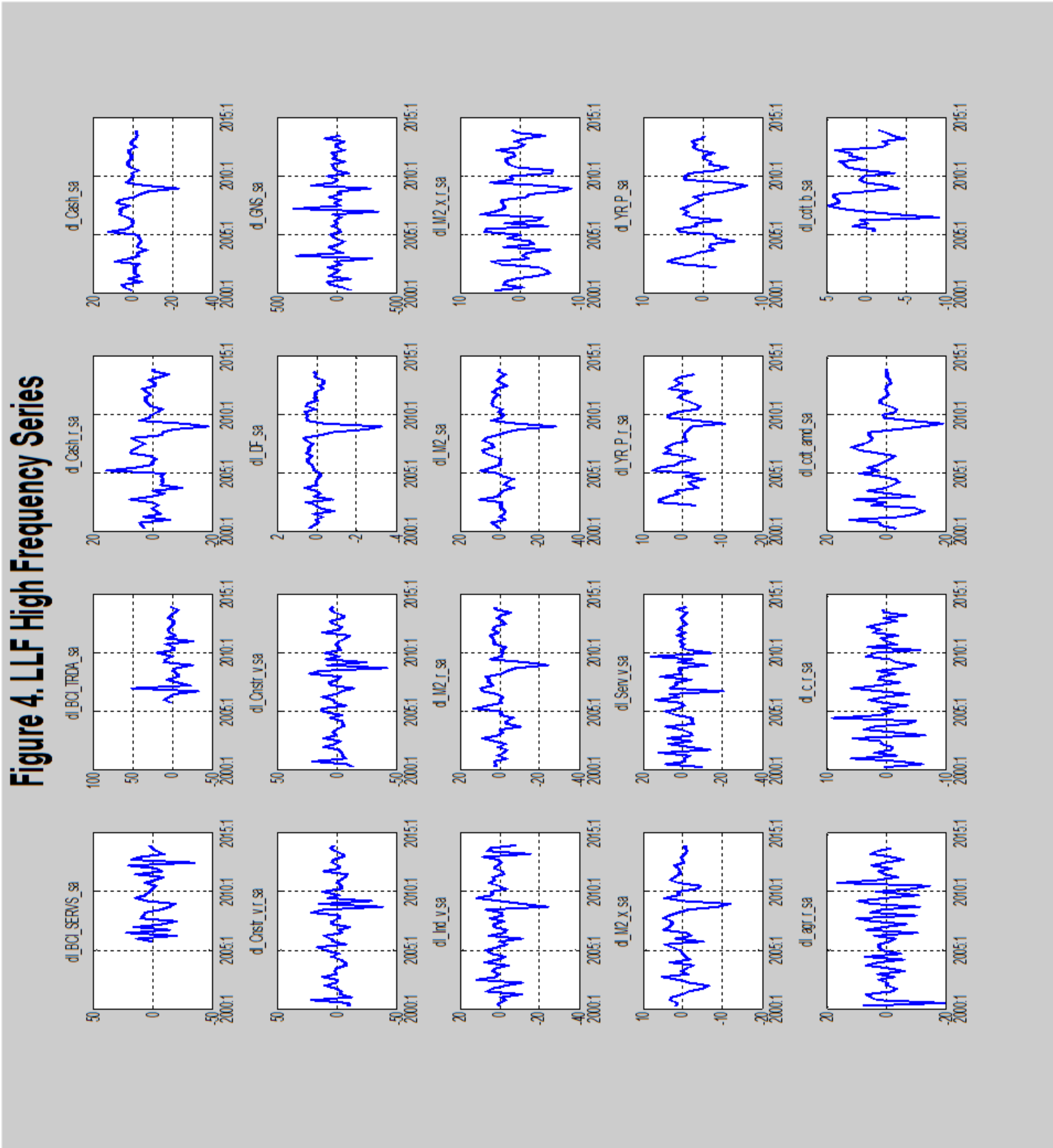


Figure 4. LLF High Frequency Series

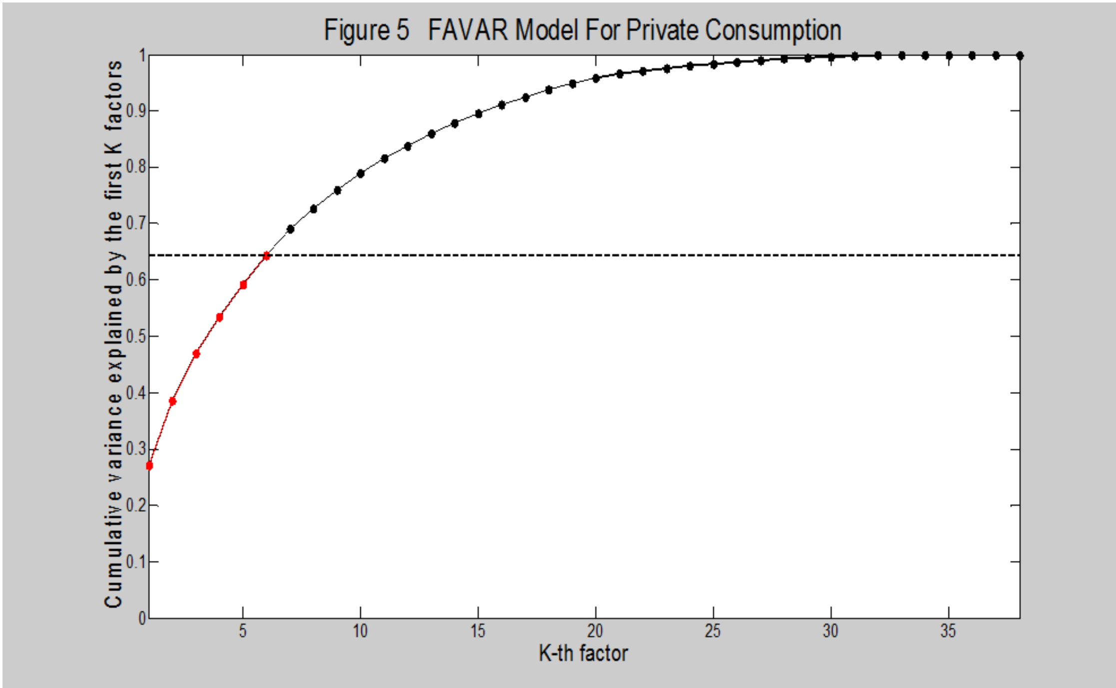


Figure 5 FAVAR Model For Private Consumption
Cumulative variance explained by the first K factors
K-th factor

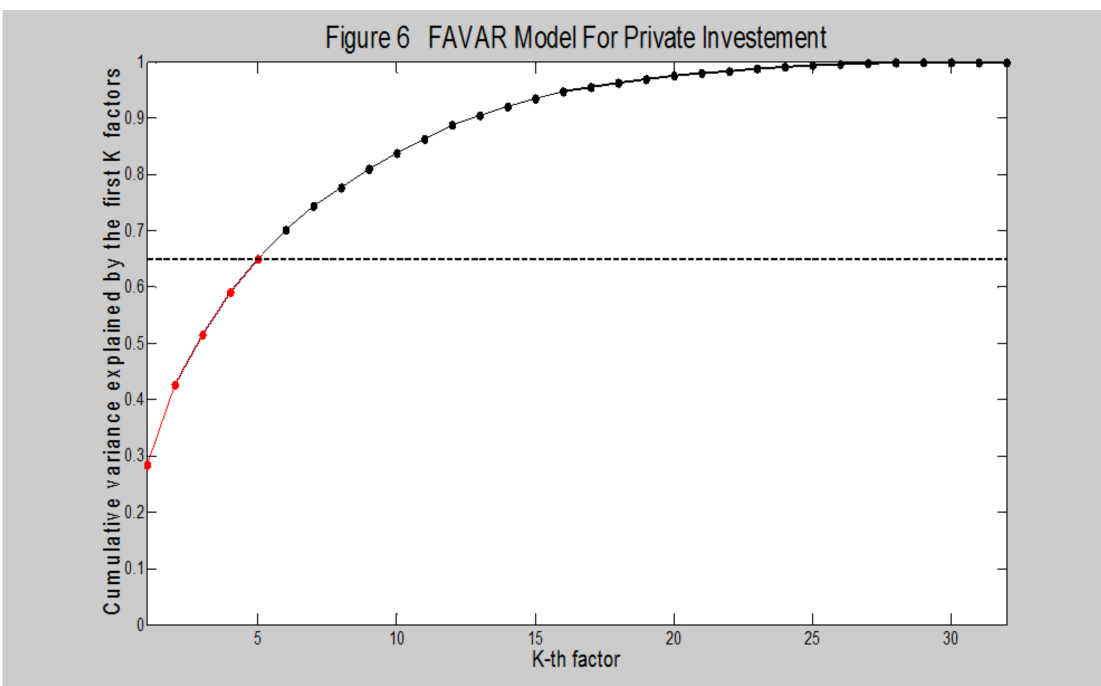


Figure 6 FAVAR Model For Private Investement
Cumulative variance explained by the first K factors
K-th factor

Figure 7 BVAR Real Private Investments historical forecasts

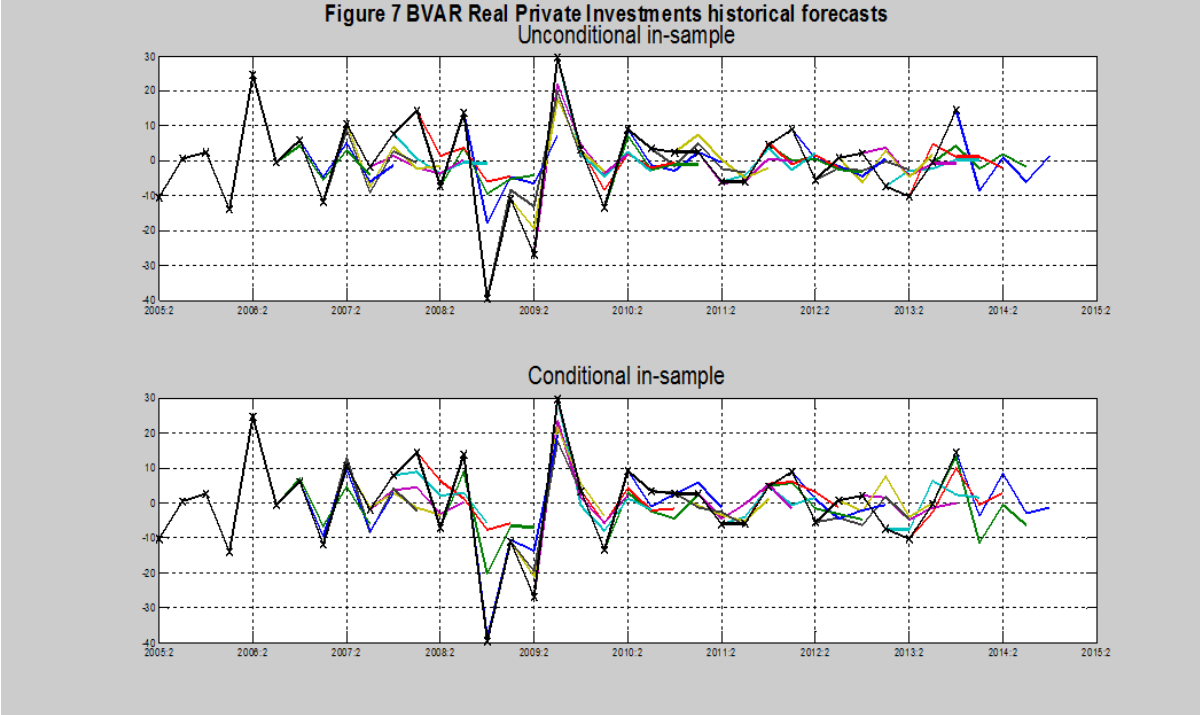


Figure 8 BVAR Real Private Consumption historical forecasts

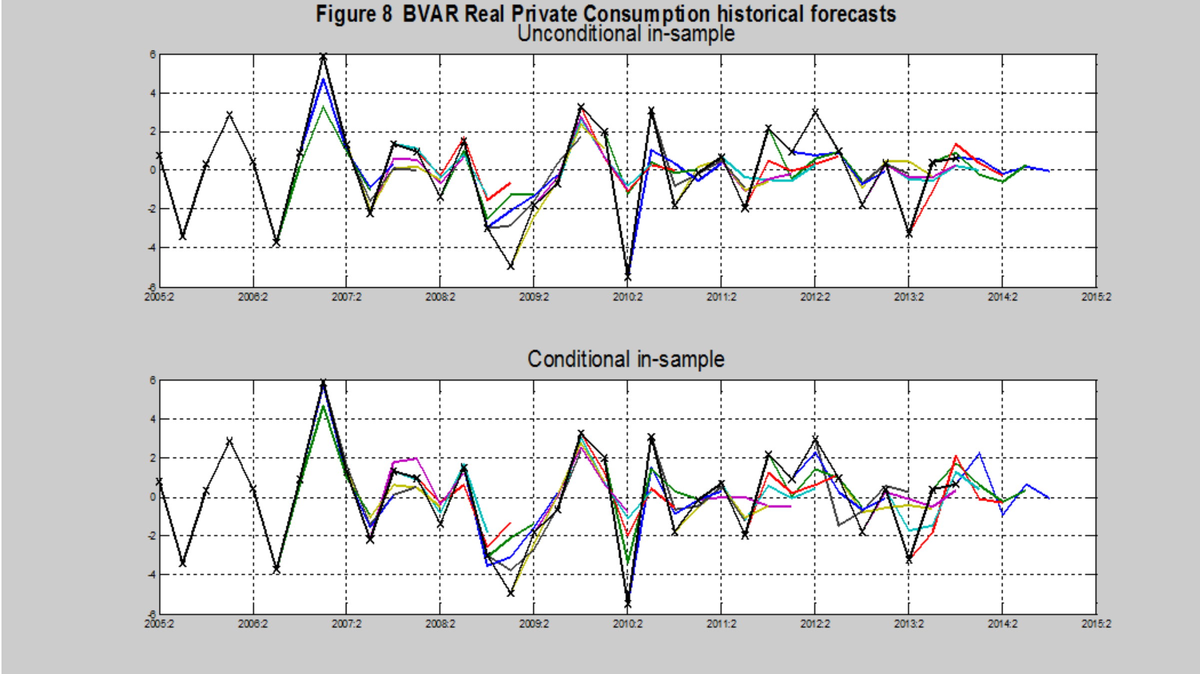


Figure 9 FAVAR Real Private Investments historical forecasts

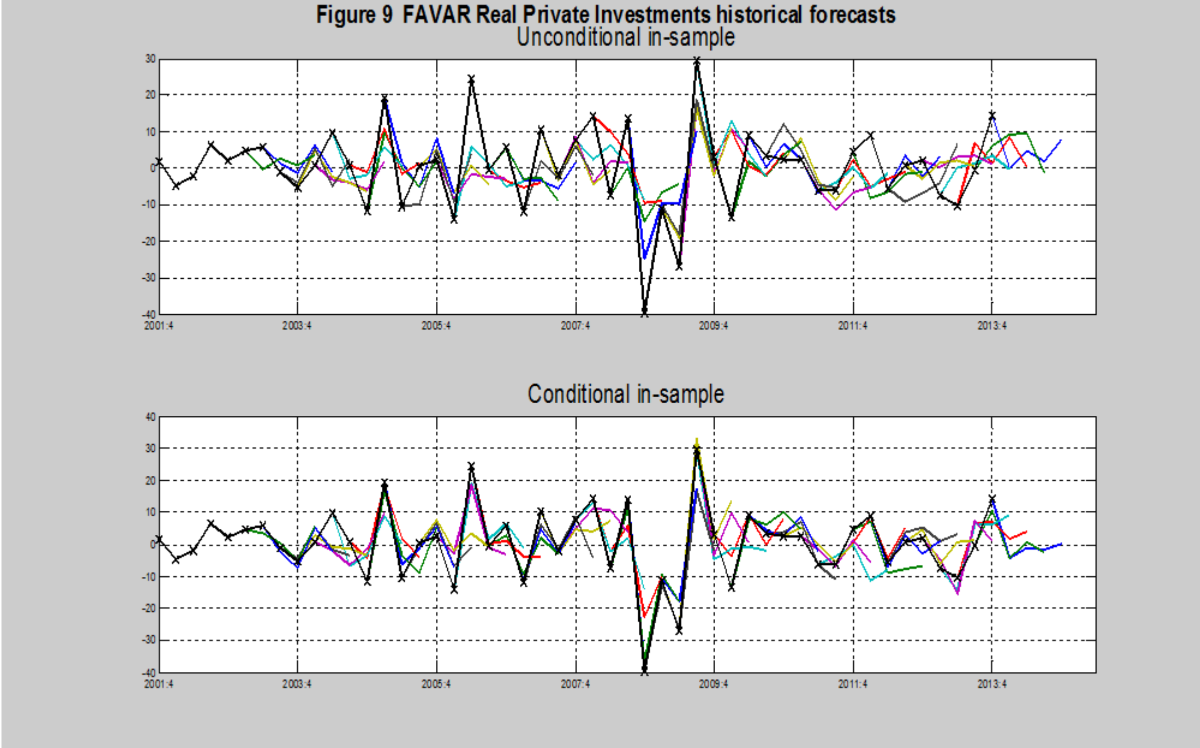
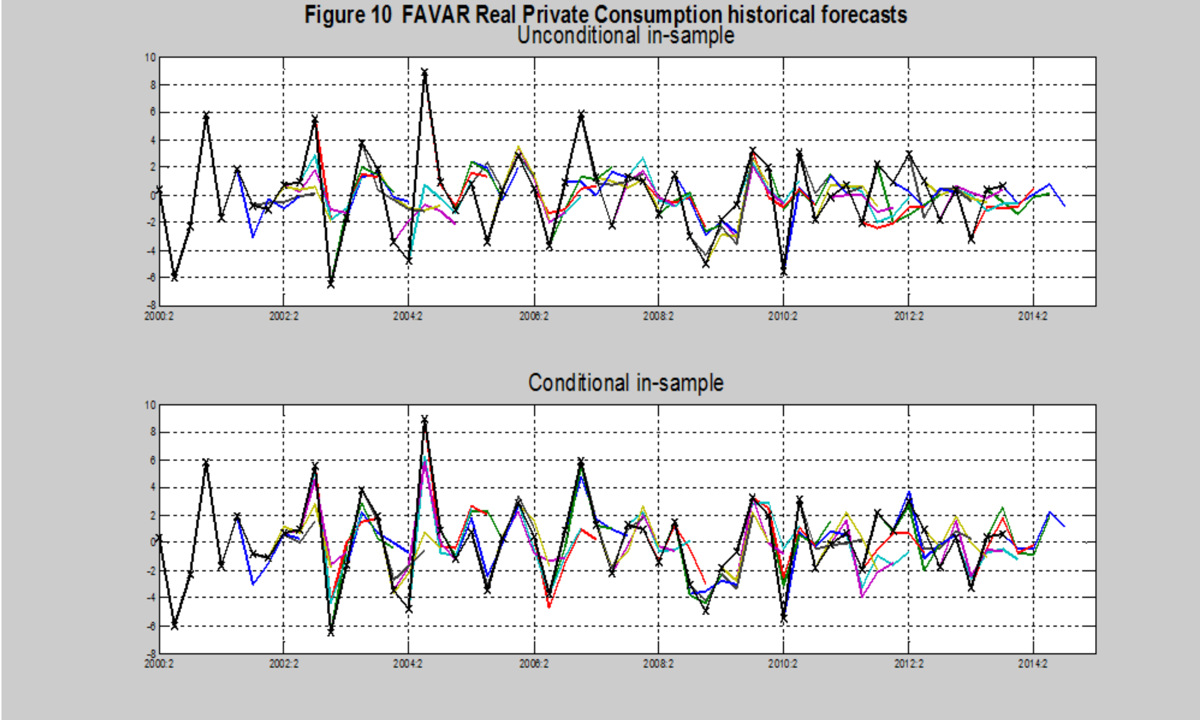


Figure 10 FAVAR Real Private Consumption historical forecasts



References

[1] Assenmacher-Wesche, Katrin, and M. Hashem 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.

[2] Bai, Jushan, and Serena Ng (2002). "Determining the Number of Factors in Approximate Factor Models," *Econometrica* 70(1): 191-221.

[3] Banbura, Marta, Domenico Giannone, and Lucrezia Reichlin (2010). "Large Bayesian vector auto regressions," *Journal of Applied Econometrics* 25 (1): 71-92.

[4] Banbura, Marta, Domenico Giannone, and Michele Lenza (2014). "Conditional Forecasts and Scenario Analysis with Vector Autoregressions for Large Cross-Sections," CEPR Discussion Paper No. DP9931.

[5] Bell, Venetia, Lai Wah Co, Sophie Stone, and Gavin Wallis (2014). "Nowcasting UK GDP Growth," *Bank of England Quarterly Bulletin* 54(1): 58-64.

[6] 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.

[7] Canova, Fabio (1999). "Vector Autoregressive Models: Specification, Estimation, Inference and Forecasting" in *Handbook of Applied Econometrics: Macroeconomics*, eds. M. Hashem Pesaran and Michael R. Wickens (Oxford: Blackwell).

[8] Clements, Michael P., and David F. Hendry (2002). "Pooling of Forecasts," *Econometrics Journal* 5: 1-26.

[9] Ciccareli, Matteo, and 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.

[10] Commandeur, Jacques J. F., Siem Jan Koopman, and Marius Ooms (2011). "Statistical Software for State Space Methods," *Journal of Statistical Software* 41(1).

[11] Doan, Thomas, Robert Litterman, and Christopher A. Sims (1984)., "Forecasting and Conditional Projection Using Realistic Prior Distributions," *Econometric Reviews* 3: 1-100.

[12] Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin (2007). "A two-step estimator for large approximate dynamic factor models based on Kalman filtering," CEPR Discussion paper 6043.

[13] Giannone, Domenico, Lucrezia Reichlin, and David Small (2008). "Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases," *Journal of Monetary Economics* 55: 665-676.

[14] Giannone, Domenico, Lucrezia Reichlin, and Luca Sala (2005). "Monetary policy in real time," in NBER Macroeconomics Annual 2004, Vol. 19 (Cambridge, MA: MIT Press).

[15] Jarocinski, Marek (2010). “Conditional forecasts and uncertainty about forecast revisions in vector autoregressions,” *Economics Letters* 108(3): 257–259.

[16] Litterman, Richard (1986). “Forecasting with Bayesian Vector Autoregressions-Five Years of Experience,” *Journal of Business and Economic Statistics* 4: 25-38.

[17] Matheson, Troy D. (2010). “An analysis of the informational content of New Zealand data releases: The importance of business opinion surveys,” *Economic Modelling* 27: 304-314.

[18] Matheson, Troy D. (2011). “New Indicators for Tracking Growth in Real Time,” IMF Working Paper No. 11/43.

[19] Sims, Christopher A. (1992). “Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy,” *European Economic Review* 36, 975-1000.

[20] Stock, James, and Mark Watson (1989). “New Indexes of Coincident and Leading Economic Indicators,” NBER Macroeconomics Annual (4) (Cambridge, MA: MIT Press)

[21] Stock, James, and Mark Watson (2002a). “Forecasting Using Principal Components from a Large Number of Predictors,” *Journal of the American Statistical Association* 97: 147–162.

[22] Stratford, Kate (2013). “Nowcasting world GDP and trade using global indicators,” *Bank of England Quarterly Bulletin* 53(3): 233-43.