NBP Narodowy Bank Polski

NBP Working Paper No. 256

Forecasting with FAVAR: macroeconomic versus financial factors

Alessia Paccagnini

NBP Working Paper No. 256

Forecasting with FAVAR: macroeconomic versus financial factors

Alessia Paccagnini

Economic Institute
Warsaw, 2017

Alessia Paccagnini – University College Dublin, School of Economics;
alessia.paccagnini@ucd.ie

Acknowledgments
Part of this project has been undertaken while I was a visiting researcher at Narodowy Bank Polski. I would like to thank them for their support and hospitality and all participants at my seminar held at the NBP, in particular Michał Rubaszek. All errors are mine.

Published by:
Narodowy Bank Polski
Education & Publishing Department
ul. Świętokrzyska 11/21
00-919 Warszawa, Poland
phone +48 22 185 23 35
www.nbp.pl

ISSN 2084-624X

Contents

Abstract

We assess the predictive power of macroeconomic and financial latent factors on the key variables for the US economy before and after the recent Great Recession. We implement a forecasting horserace among Factor Augmented VAR (FAVAR), Classical, and Bayesian VAR models.

FAVAR models outperform others. Focusing only on macroeconomic or on financial latent factors, we find how the financial variables have not a driver role in forecasting the US economy including the Great Recession.

JEL CODES: C38, C53, C3, E32, E3

KEYWORDS: Factor Models, Factor Augmented VAR, VAR models, Bayesian VAR models, Forecasting

1 Introduction

Between 2007 and 2009, the United States economy experienced one of the most severe and long recession since the Great Depression. It renewed interest among economists to study how macroeconomic and financial variables played an important role as driver of economic fluctuations (Stock and Watson, 2012). Several studies evidence how financial markets, banking and housing sectors, and fall in consumption are the main determinants of this recent crisis (Grusky, Western, and Wimer, 2011; Palley, 2011; Bagliano and Morana, 2012; Del Negro, Giannoni, and Schorfheide, 2015; Kolasa and Rubaszek, 2015; Menno and Oliviero, 2016 among others).

This paper takes an empirical look at the power of latent factors to forecast some key macroeconomic variables before and after the Great Recession. As first research question, we assess the forecastability power of using latent factors in the framework of a Factor Augmented VAR (FAVAR) à la Bernanke, Boivin, and Eliasz (2005) and à la Boivin, Giannoni, and Mihov (2009). We compare the FAVAR approach with Classical and Bayesian VAR models focusing on three macroeconomic variables: Industrial Productivity, Short-term interest rate, and Inflation. As second research question, we investigate how disentagling the macroeconomic and financial latent factors we can improve our prediction for the three key macro variables. The latent factors are extracted using an updated version of the Stock and Watson (2002) large dataset of monthly macroeconomic and financial time series to study the economic fluctuations. We call "general economy latent factors" the ones extracted from the full dataset. Meanwhile, we call "macro latent factors" and "financial latent factors" the ones extracted, respectively, from only macro and only financial variables.

Our results indicate that the FAVAR models outperform Classical and Bayesian VAR models to forecast the Industrial Productivity, Short-term interest rate, and Inflation rate, due to the advantage of adding information through factors before and after the crisis.

However, when we estimate FAVAR models with only "macro or financial latent factors", we do not report any improvement before the Great Recession. While, after the recent crisis, FAVAR models with "macro latent factors" outperform the specifications with "general latent" and "financial latent" factors. This result suggests how during and after the recent crisis, the macroeconomic variables are the most important drivers of economic fluctuations.

Several papers discuss the importance of the latent factors in a factor model framework to forecast key macroeconomic variables (Korobolis, 2008: Banbura, Giannone, and Reichlin, 2010; Gupta and Kabundi, 2010; Stock and Watson, 2012, Eickemeier, Lemke, and Marcellino, 2015). We contribute to discuss the linkage between macroeconomic and financial variables to forecast the economic fluctuations including the recent crisis.

The remainder of the paper is organized as follows. Section 2 presents an overview of the econometric models implemented in the forecasting comparison. Section 3 discusses the empirical exercises presenting a description of the data and details about the forecasting evaluation. Section 4 reports main results about the comparison between FAVAR and BVAR models. Section 5 reports main results about the FAVAR models with "macro and financial latent factors". Section 6 concludes.

2 Econometric Models

Our empirical contribution focuses on the forecasting performance of Factor Augmented VAR models (FAVAR). We compare the predictability of FAVAR models against Classical and Bayesian VAR models.

This Section summarizes some technical details about the implemented econometric models.

2.1 Classical VAR

The standard unrestricted VAR, introduced in Sims (1980), is as follows:

$$Y_t = \alpha + A_1 Y_{t-1} + ... + A_p Y_{t-p} + \varepsilon_t, \tag{1}$$

where Y_t refers to the endogenous variables (Industrial Productivity, Short-term interest rate, and Inflation), ε_t is an n-dimensional Gaussian white noise with covariance matrix $E[\varepsilon_t \varepsilon_t'] = \Psi$, $\alpha = (\alpha_1, ..., \alpha_n)'$is an n-dimensional vector of constants, and $A_1, ..., A_p$ are $n \times n$ autoregressive matrices.

The Classical VAR is very well used econometric model to make forecasts and policy evaluations, but unfortunately the VAR produces poor out-of-sample forecasting performance due to a densely parametrization problem.

There are two common ways to overcome to this issue: Bayesian VAR and Factor Models.

2.2 Bayesian VAR

The Bayesian approach to VAR models has become popular to dealing with the overparmeterization problem as studied in Litterman (1981), Doan *et al.* (1984), Todd (1984), Litterman (1986) and Spencer (1993). One of main issues in using VAR models is that many parameters need to be estimated, although some of them may be insignificant. Instead of eliminating longer lags, the Bayesian VAR (BVAR) with prior shrinkage allows these coefficients to be near zero than the coefficients on shorter lags. Obviously, if there are strong effects from less important variables, the data can counter this assumption. Usually, the restrictions are imposed by specifying normal prior distributions with zero means and small standard deviations for all coefficients, with a decreasing standard deviation as the lags increase. The only exception is the coefficient on a variable's first lag that has a mean of unity. Litterman (1981) used a diffuse prior for the constant. The means of the prior are popularly called the "Minnesota Priors" due to the development of the idea at the University of Minnesota and the Federal Reserve Bank at Minneapolis[1].

The basic idea of the "Minnesota Priors" is that all the equations are "centered" around the random walk with drift; i.e., the prior mean can be associated with the following representation for Y_t:

$$Y_t = \alpha + Y_{t-1} + \varepsilon_t.$$

As summarized by Banbura et al. (2010), the prior means and variances can be written as follows:

$$E[(A_k)ij] = \begin{cases} 1, \; j = i, k = 1 \\ 0, \; \text{otherwise} \end{cases}, \tag{2}$$

$$V[(A_k)ij] = \begin{cases} \frac{\lambda^2}{k^2}, j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2}, \text{otherwise} \end{cases}, \tag{3}$$

where λ parameter controls the overall tightness of the prior belief[2], $\frac{1}{k^2}$ controls for the rate at which the prior variance shrinks more for increasing lag length, the ratio $\frac{\sigma_i^2}{\sigma_j^2}$ accounts for the different scale and variability of the data, and ϑ governs the extent to which the lags of other variables are 'less important' than the own lags.

However, some studies such as Sims (1992), Sims and Zha (1998), Robertson and Tallman (1999), and Banbura et al. (2010) suggest that we can obtain improvements in forecasting performance by imposing additional priors that constrain the sum of coeffi-

[1] The basic principle behind the "Minnesota" prior is that all equations are centered around a random walk with drift. This idea has been modified by Kadiyala and Karlsson (1997) and Sims and Zha (1998). In Ingram and Whiteman (1994), a real business cycle model is used to generate a prior for a reduced form VAR, as a development of the "Minnesota" priors procedure. Also, a prior is placed on the parameters of a simple linearized DSGE, which is then compared with a Bayesian VAR in a forecasting exercise. Smets and Wouters (2003) extend this to medium scale New Keynesian models used in policy analysis. This approach has the advantage of providing information about which behavioral mechanisms produce forecast error or policy scenarios. However, it seems that it often fails to empirically fit compared to models with no behavioral structure.

[2] If $\lambda = 0$, the posterior equals the prior and the data do not influence the estimates. If $\lambda \to \infty$, posterior expectations coincide with the ordinary least squares (OLS) estimates. Banbura et al. (2010) argue that the overall tightness governed by should be selected in relation to the size of the system. As the number of variables increases, the parameters should be shrunk more in order to avoid over-fitting. This point has been shown formally by De Mol et al. (2008).

cients. The procedure is a variation of the Minnesota prior involving linear combinations of the VAR coefficients as evidenced by Doan et al. (1984).

We can rewrite the VAR of Equation (1) in its error correction form as follows:

$$\Delta Y_t = \alpha - (I_n - A_1 - ... - A_p)Y_{t-1} + B_1 \Delta Y_{t-1} + ... + B_{p-1}\Delta Y_{t-p+1} + \varepsilon_t. \qquad (4)$$

A VAR in first differences implies the restriction $(I_n - A_1 - ... - A_p) = 0$. Following Doan et al. (1984), we set a prior that shrinks $\Pi = (I_n - A_1 - ... - A_p) = 0$.

Since this BVAR with Prior on the Sum of Coefficients produces better forecasting performance, we choose this BVAR in our empirical comparison.

2.3 Large Bayesian VAR

Introduced by Banbura et al. (2010), the Large BVAR has became very popular for forecasting and policy investigations when large datasets are available. The Large BVAR is an extension of the BVAR described in Subsection 2.2. We augment the Minnesota prior with an Inverse Wishart prior distribution for the covariance matrix of the residuals (as already discussed in Kadiyala and Karlsson, 1997 and Sims and Zha, 1998), and with a prior on the sum of the coefficients (as presented above and introduced by Doan et al., 1984).

While the original Litterman (1986) article assumes the covariance matrix of residuals to be $\Psi = diag(\sigma_1^2, ..., \sigma_n^2)$ to take into account the possible correlation among the residuals, Banbura et al. (2010) follow Kadiyala and Karlsson (1997) and Robertson and Tallman (1999) imposing a Normal Inverted Wishart prior (which retains the principles of the Minnesota prior and assumes $\vartheta = 1$).

We can rewrite Eq. (1) in the following companion form:

$$\underset{(T\times n)}{Y} = \underset{(T\times k)}{X}\underset{(k\times n)}{B} + \underset{(T\times n)}{E}, \qquad (5)$$

where

$Y = (Y_1, ..., Y_T)'$; $X = (X_1, ..., X_T)'$; $X_t = (Y'_{t-1}, ..., Y'_{t-p}, 1)$; $E = (\varepsilon_1, ..., \varepsilon_T)'$; $B = (A_1, ..., A_p, \alpha)$, and $k = np + 1$.

The Normal inverted Wishart prior has the form:

$$vec(B)|\Psi \sim N(vec(B_0), \Psi \otimes \Omega_0) \text{ and } \Psi \sim IW(S_0, \gamma_0),$$

where the prior parameters $B_0, \Omega_0, S_0, \gamma_0$ are chosen such that prior expectations and variances of B coincide with those implied by the Minnesota prior and the expectation of Ψ equals the fixed residual covariance matrix of the Minnesota prior as described in Kadiyala and Karlsson (1997). One of the advantage of the Normal inverted Wishart prior has the advantage is that it is a natural conjugate prior, which means that the posterior can be derived analytically and shown to belong to the same class of distributions – thus eliminating the need for posterior simulation.

We implement the prior by adding dummy observations. We can evidence that adding T_d dummy observations Y_d and X_d is equivalent to imposing the Normal Inverted Wishart prior with:

$B_0 = (X_d' X_d)^{-1} X_d Y_d$, $\Omega_0 = (X_d' X_d)^{-1}$, $S_0 = (Y_d - X_d B_0)'(Y_d - X_d B_0)$ and $\gamma_0 = T_d$ $-k$.

Banbura et al. (2010) define the dummies as follows to match the moments of the Minnesota Prior:

$$Y_d = \begin{pmatrix} diag(\delta_1\sigma_1, ..., \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ ... \\ diag(\sigma_1, ..., \sigma_n) \\ \\ 0_{1\times n} \end{pmatrix} \quad X_d = \begin{pmatrix} J \otimes diag(\delta_1\sigma_1, ..., \delta_n\sigma_n)/\lambda & 0_{np\times 1} \\ ... & ... \\ 0_{n\times np} & 0_{n\times 1} \\ ... & ... \\ 0_{1\times np} & \varphi \end{pmatrix},$$

where $J_p = diag(1, 2, ..., p)$.

Summing up, the first block of dummies imposes prior beliefs on the autoregressive coefficients, the second block implements the prior for the covariance matrix, and the third block reflects the uninformative prior for the intercept (φ is a very small number).

Banbura et al. (2010), following Litterman (1986) and Sims and Zha (1998), set the scale parameters σ_i^2 equal the variance of a residual from a univariate autoregressive model of order p for the variables y_{it}.

The regression model augmented with the dummies is as follows:

$$\underset{(T_*\times n)}{Y_*} = \underset{(T_*\times k)}{X_*}\underset{(k\times n)}{B} + \underset{(T_*\times n)}{E_*},$$

where $T_* = T + T_d$, $Y_* = (Y', Y_d')$, $X_* = (X', X_d')$, and $U_* = (U', U_d')$. We can ensure the existence of the prior expectation of Ψ adding an improper prior $\Psi \sim |\Psi|^{-(n+3)/2}$. In that case the posterior has the following form:

$$vec(B)|\Psi, Y \sim N(vec(\widetilde{B}), \Psi \otimes (X_*'X_*)^{-1}) \text{ and } \Psi|Y \sim IW(\widetilde{\Sigma}, T_d + 2 + T - k),$$

where $\widetilde{B} = (X_*'X_*)^{-1}X_*Y_*$ and $\widetilde{\Sigma} = (Y_* - X_*\widetilde{B})$. Note that the posterior expectation of the coefficients coincides with the OLS estimates of the regression of Y_* on X_*. It is possible to check that this corresponds to the posterior mean from the Minnesota prior. Computationally, the estimation is feasible since it only requires the inversion of a square matrix of dimension $k = np + 1$ as evidenced by Banbura et al. (2010). Adding dummy observations works as a regulation device to solve the matrix inversion problem.

This idea is based on the theoretical proof that Bayesian shrinkage is suitable when we deal with large models. As shown in Del Mol et al. (2008), the Bayesian forecast converges to the optimal forecast, provided that the tightness of the prior (degree of shrinkage) increases as more variables are added to the model. Intuitively, Bayesian shrinkage allows extracting the relevant signal from a large dataset, since macroeconomic series are highly collinear, so adding more information allows a tighter prior, filtering out the unsystematic component.

In this paper we consider the Large Bayesian VAR version with a prior on the sum of the coefficients as already discussed in case of BVAR.

2.4 Factor Augmented VAR

Alternative to Large BVAR, Factor Augmented VAR (FAVAR) has become very popular in the recent literature using big data. Stock and Watson (2002), Forni and Reichlin (1996, 1998) and Forni *et al.* (1999, 2000) have shown that very large macroeconomic datasets can be properly modelled using dynamic factor models, where the factors can be considered as an "exhaustive summary of the information " in the data. The rationale underlying dynamic factor models is that the behavior of several variables is driven by few common forces, the factors, plus idiosyncratic shocks. Hence, the factors-approach can be useful in alleviating the omitted variable problem in empirical analysis using traditional small-scale models. Bernanke and Boivin (2003) and Bernanke *et al.*

(2005) utilized factors in the estimation of VAR to generate a more general specification. Chudik and Pesaran (2011) illustrated how a VAR augmented by factors could help in keeping the number of estimated parameters under control without loosing relevant information.

Following Stock and Watson (2005b), we can consider a Dynamic Factor Model (DFM) in static form as follows:

$$Y_t = \Lambda F_t + D(L)Y_{t-1} + v_t, \tag{6}$$

$$F_t = \Phi(L)F_{t-1} + G\eta_t, \tag{7}$$

where Λ is $n \times f$ matrix, f is the number of static factors, and G is $f \times q$. Equation (6) is the measurement equation and Equation (7) is the state equation. The representation (6) and (7) is called the "static" for the DFM since F_t appears in measurement equation without any lags.

It is possible to write a VAR form of the DFM by substituting (7) into (6) as follows:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Phi(L) & 0 \\ \Lambda\Phi(L) & D(L) \end{bmatrix} \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{F_t} \\ \varepsilon_{X_t} \end{bmatrix}, \tag{8}$$

where

$$\begin{bmatrix} \varepsilon_{F_t} \\ \varepsilon_{X_t} \end{bmatrix} = \begin{bmatrix} I \\ \Lambda \end{bmatrix} G\eta_t + \begin{bmatrix} 0 \\ v_t \end{bmatrix}.$$

In our empirical analysis, we adopt the Factor Augmented VAR (FAVAR) as proposed by Bernanke, Boivin, and Eliasz (2005). To understand how we can estimate the factors, we need to add the relation between the "informational" time series X_t, the observed variables Y_t, and the factors F_t as follows:

$$X_t = \Lambda^f F + \Lambda^y Y_t + e_t, \tag{9}$$

where X_t denote an $N \times 1$ vector of economic time series and Y_t a vector of $M \times 1$ observable macroeconomic variables which are a subset of X_t[3], Λ^f is a $N \times k$ matrix of factor loadings, Λ^y is a $N \times M$ matrix of coefficients that bridge the observable Y_t

[3] In this context, most of the information contained in $\mathbf{X}_t$ is captured by $\mathbf{F}_t$, a $k \times 1$ vector of unobserved factors. The factors are interpreted as an addition to the observed variables, as common forces driving the dynamics of the economy.

and the macroeconomic dataset, and e_t is the vector of $N \times 1$ error terms. These terms are mean zero, normal distributed, and uncorrelated with a small cross-correlation. In fact, the estimator allows for some cross-correlation in e_t that must vanish as N goes to infinity. This representation nests also models where X_t depends on lagged values of the factors (Stock and Watson, 2002).

For the estimation of the FAVAR model equation (9), we follow the two-step principal components approach proposed by Bernanke *et al.* (2005). In the first step factors are obtained from the observation equation by imposing the orthogonality restriction $F'F/T = I$. This implies that $\hat{F} = \sqrt{T}\hat{G}$, where $\hat{G}$ are the eigenvectors corresponding to the K largest eigenvalues of XX', sorted in descending order. Stock and Watson (2002) showed that the factors can be consistently estimated by the first r principal components of X, even in the presence of moderate changes in the loading matrix Λ. For this result to hold it is important that the estimated number of factors, k, is larger or equal than the true number r. Bai and Ng (2002) proposed a set of selection criteria to choose k that are generalizations of the BIC and AIC criteria. In the second step, we estimate the FAVAR equation replacing F_t by $\hat{F}_t$. Following Bernanke *et al.* (2005), Y_t is removed from the space covered by the principal components. Boivin *et al.* (2009) impose the constraint that Y_t is one of the common components in the first step, guaranteeing that the estimated latent factors $\hat{F}_t$ recover the common dynamics which are not captured by Y_t. FAVAR models are estimated using both Maximum Likelihood estimation and Bayesian estimation with a prior of sum coefficients.

3 Empirical Strategy

3.1 Data

In the empirical analysis, we use an updated version (up 2012) of the dataset of Stock and Watson (2005a). This dataset contains 127 monthly macro and financial indicators covering a broad range of categories including, among others, income, industrial production, capacity, employment and unemployment, consumer prices, producer prices, wages, housing starts, inventories and orders, stock prices, interest rates for different maturities, exchange rates, and money aggregates.

The time span is from January 1972 to December 2012[4]. The estimation sample is from January 1984 to December 2012. We apply logarithms to most of the series, with the exception of those already expressed in rates. For non-stationary variables, considered in first differences by Stock and Watson (2005a).

We compare the forecasting performance of a Factor Augmented VAR with the performance reported by VARs and BVARs of different sizes (SMALL, MEDIUM, LARGE).

Our empirical analysis focuses on three macroeconomic variables. We use Industrial Production Index (IP) as an indicator of real economic activity. The Short-term monetary policy instrument is the Federal Funds Rate (FFR). The level of prices is measured by the consumer price index (CPI).

We consider the following VAR specifications: 1) SMALL. This is a small monetary VAR including the three key variables. 2) MEDIUM. We augment the SMALL VAR including Capital Utilization, Unemployment Rate, Average Weekly Hours: Manufacturing, Housing Starts, Personal Consumption Expenditures, Producer Price Index, 10-Year Treasury Constant Maturity Rate, M1, M2, Non-Borrowed Reserves, Total Reserves, S&P Common Stock Price Index, and VIX. 3) LARGE. This specification includes all the 127 macroeconomic indicators of Stock and Watson's dataset.

Appendix provides a detailed discussion of the data.

[4] The dataset is originally from January 1959 to December 2003. We update the data up 2012 using FED St. Louis as source. We stop at 2012 since we investigate about the Great Recession and its aftermath.

3.2 Forecast Evaluation

We evaluate the relative (to a random walk with drift process) forecast performance of BVARs and FAVAR for the three key series included in all specifications (IP, CPI, and FFR) using the Mean Square Forecast Error (MSFE). The lag length for VAR component is 13, while the one for the factors is 2. Parameters are estimated using the most recent 10 years observation (in a rolling scheme)[5].

The point forecasts are computed using the posterior mean of the parameters. We assume $\widehat{A}_j^{(\lambda,m)} = 1,...,p$ and $\widehat{c}^{(\lambda,m)}$ for the posterior mean of the autoregressive coefficients and the constant term of a given model (m) obtained by setting the overall tightness equal to λ. The point estimates of the h-step-ahead forecasts are denoted by: $Y_{t+h|t}^{(\lambda,m)} = (y_{1,t+h|t}^{(\lambda,m)}, ..., y_{n,t+h|t}^{(\lambda,m)})'$, where n is the number of variables included in model m. The point estimate of the one-step-ahead forecast is computed as: $\widehat{Y}_{t+h|t}^{(\lambda,m)} = \widehat{c}^{(\lambda,m)} + \widehat{A}_1^{(\lambda,m)} Y_t + ... + \widehat{A}_p^{(\lambda,m)} Y_{t-p+1}$. Forecasts h steps ahead are computed recursively.

The point forecasts are computed using the posterior mean of the parameters. Before calculating the forecasting performance, we set the overall tightness hyperparameter λ. The procedure follows these steps:

- We set the training sample (1972:01 - 1983:12) to compute the OLS estimation with a lag length fixed at $p = 13$ of the SMALL VAR (with the three macroeconomic key variables (IP, CPI, FFR)) as follows:

$$Fit = \frac{1}{3} \sum_i \frac{MSFE_i^{(\lambda,m)}}{MSFE_i^{(0)}} |_{\lambda=\infty, m=SMALL}, \tag{10}$$

where $MSFE_i^{(\lambda,m)} = \frac{1}{T-p-1} \sum_{t=p}^{T-2} (y_{i,t+1|t}^{(\lambda,m)} - y_{i,t+1})^2$ is the one step-ahead mean squared forecast error evaluated using the training samples $t = 1, ..., T-1$.

- We define a large grid for λ. Set the prior on the sum of the coefficients $\tau = k \times \lambda$, where k is the proportionality coefficient.

- We estimate the BVAR to get the fit corresponding to each prior λ.

- We search for λ yielding the desired fit, that is:

[5] Using a different rolling window (20 years or 5 years) does not change the qualitative results.

$$\lambda_m(Fit) = \arg\min_{\lambda} |Fit - \frac{1}{3} \sum_i \frac{MSFE_i^{(\lambda,m)}}{MSFE_i^{(0)}}|.$$

For more details, see Banbura et al. (2010).

4 FAVAR vs BVAR

We consider two evaluation samples: 1984:01 - 2007:09 (before the Great Recession) and 1984:01 - 2012:12 (including the Great Recession).

In the first step of our empirical analysis, we estimate Bayesian VAR considering the three subsets of variables: Small, Medium, and Large.

Table 1 and Table 2 report MSFE relative to the benchmark model (random walk with drift) for Industrial Productivity Index (IP), short term interest rate (FFR), and inflation (CPI) for forecast horizons $h = 1, 3, 6$, and 12 for SMALL (3 variables), MEDIUM (20 variables), and LARGE BVAR (127 variables) for the two samples respectively. The last row indicates the value of the shrinkage hyperparameter λ. As explained in Banbura et al. (2010), this hyperparameter has been set so as to maintain the in-sample fit fixed, which requires the degree of shrinkage, $1/\lambda$, to be larger when the size of the model becomes larger.

		SMALL OLS	MEDIUM BVAR	LARGE BVAR
h=1	IP	1.025	0.996	0.997
	FFR	1.397	0.997	0.995
	CPI	0.742**	0.995	1.000
h=3	IP	1.123	0.985	0.987
	FFR	2.352	0.988	0.986
	CPI	0.721**	0.986**	0.989**
h=6	IP	1.241	0.963	0.965
	FFR	3.009	0.968	0.967
	CPI	0.699**	0.967	0.967**
h=12	IP	1.268	0.923	0.925*
	FFR	2.944***	0.920	0.919**
	CPI	0.736**	0.936***	0.935***
	LAMBDA	Inf	0.004	0.001

Table 1: Relative MSFE, 1984:01 - 2007:09

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

		SMALL OLS	MEDIUM BVAR	LARGE BVAR
h=1	IP	1.010	0.995	0.995
	FFR	1.293	0.995	0.996
	CPI	0.818	0.996	1.000
h=3	IP	1.034	0.986	0.986
	FFR	2.134**	0.990	0.989
	CPI	1.044	0.987	0.989
h=6	IP	1.223	0.971	0.971**
	FFR	2.746***	0.977	0.977**
	CPI	1.409	0.968**	0.969*
h=12	IP	1.055	0.953***	0.953**
	FFR	2.656***	0.935**	0.935**
	CPI	1.027	0.939*	0.939**
	LAMBDA	Inf	0.004	0.001

Table 2: Relative MSFE, 1984:01 - 2012:12

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

Table 1 and Table 2 show that for both samples, the Medium BVAR outperforms the other models, the random walk, the Small OLS, and it produces similar results as ones reported by the Large BVAR. Consequently, adding information helps the researcher to improve the forecast for all variables. This outcome in favor of the Medium BVAR suggests that for macroeconomic forecasting we do not to use much sectorial information beyond the set of variables included in the medium scale since results are not improved. According to Diebold and Mariano (2005) test, BVAR models predicts better than Random Walk process in the long horizons ($h = 6$ and $h = 12$).

In the second step, we compare the forecasting ability of the Medium BVAR to FAVAR models estimated in both Maximum Likelihood and Bayesian methodologies.

As suggested by Bäurle (2013), we select the number of extracted factors using two different criteria: Bai and Ng (2002) and Alessi, Barigozzi, and Capasso (2010). In both cases, as reported by Figure 1, we are allowed to extract eight factors. The total percentage of the explanatory power of these factors is around 60%. The correlation matrix reported in Appendix shows a good (between 20% and 50% in absolute value) correlation between the first four factors and the three macro variables.

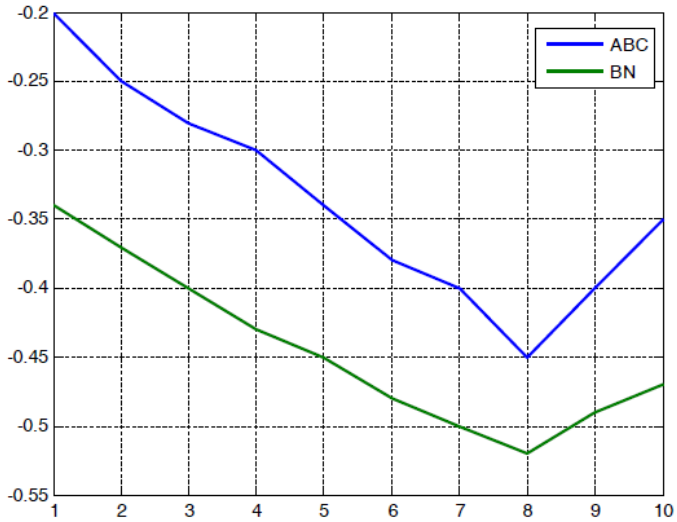

Figure 1: Comparison between Bai and Ng (2002) (BN) and Alessi et al. (2010) (ABC) Information Criteria

Factor	% Explanatory Power
1	22.38%
2	8.43%
3	7.10%
4	6.51%
5	4.47%
6	4.15%
7	3.83%
8	3.54%
Total	60.41%

Table 3: The percentage of the explanatory power of the extracted factors

Table 4 and Table 5 report MSFE relative to the benchmark model (random walk with drift) for Industrial Productivity Index (IP), short term interest rate (FFR), and inflation (CPI) for forecast horizons $h = 1, 3, 6$, and 12 for Medium BVAR, Factor Augmented VAR estimated with Maximum Likelihood and Bayesian methods, adding one, three, and eight factors.

		Medium BVAR	FAVAR 1 fact	BFAVAR 1 fact	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	0.996	1.048	0.925	1.060	0.903	1.127	0.899
	FFR	0.997	1.384	0.898	1.415	0.729**	1.924	0.834**
	CPI	0.995	0.764**	0.708**	0.707**	0.728**	0.768**	0.682**
h=3	IP	0.985	1.131	0.840***	1.122	0.809**	1.185	0.822**
	FFR	0.988	2.026	0.911**	2.013	0.793**	1.752	0.759**
	CPI	0.986**	0.748**	0.613***	0.717**	0.684***	0.769*	0.637***
h=6	IP	0.963	1.270	0.836**	1.99	0.810	1.328	0.810
	FFR	0.968	2.505	1.080*	2.098	0.890	1.950	0.841
	CPI	0.967	0.746**	0.506***	0.673**	0.644**	0.731**	0.583**
h=12	IP	0.923	1.297	0.778**	1.365	0.771**	1.410	0.755**
	FFR	0.920	2.537	1.168	2.141***	0.938	2.147***	0.921
	CPI	0.936***	0.822**	0.468***	0.720**	0.621***	0.774**	0.557***

Table 4: Relative MSFE, 1984:01 - 2007:09

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

		Medium BVAR	FAVAR 1 fact	BFAVAR 1 factor	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	0.995	0.918	0.922	0.820	0.903	1.025	0.849
	FFR	0.995	1.314	1.351	0.743**	0.729**	1.768	0.819**
	CPI	0.996	0.863	0.896	0.782**	0.728**	0.742*	0.735**
h=3	IP	0.986	0.813	0.798	0.702**	0.809**	0.973**	0.798**
	FFR	0.990	1.956	1.990	0.826	0.793***	1.577	0.749**
	CPI	0.987	1.201	1.131	0.823	0.684***	0.693	0.738**
h=6	IP	0.971	0.972**	0.942*	0.778**	0.810	1.119	0.849
	FFR	0.977	2.490**	2.237**	0.918	0.890	1.754**	0.835
	CPI	0.968**	1.633	1.350	0.785	0.644**	0.750	0.657***
h=12	IP	0.953***	1.208	1.201	0.834	0.771**	1.279	0.798*
	FFR	0.935**	2.621***	2.386**	0.931	0.938	1.922*	0.911
	CPI	0.939*	1.336	1.092	0.697	0.621**	0.797	0.582**

Table 5: Relative MSFE, 1984:01 - 2012:12

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

Table 4 and Table 5 show FAVAR models outperform BVAR. In particular, estimating a FAVAR with 3 and 8 factors we improve our results. As main advantage of using FAVAR is that we can focus on the three key macroeconomic variables taking advantage of additional information through factors. The best results are reported using the Bayesian estimation of FAVAR.

5 Macroeconomic and Financial Variables

In Section 4, we investigate the forecastability of FAVAR models versus BVAR models. Factors are extracted on the dataset composed of both macroeconomic and financial variables. Hence, we call them "general economy latent factors". In this Section, we investigate if the good forecastability of FAVAR is more driven by macroeconomic or financial factors. We split the dataset in two groups: macroeconomic and financial variables, hence we extract factors from each group. Consequently, we have "macro and financial latent factors". We repeat the same forecasting exercise as presented in Section 4.

Table 6 and Table 7 show the FAVAR models (Maximum Likelihood (FAVAR) and Bayesian estimation (BFAVAR)) with 1, 3, and 8 macroeconomic factors. As reported for the FAVAR models with "general economy latent factors", FAVAR with 3 and 8 factors outperform the others.

		FAVAR 1 fact	BFAVAR 1 factor	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	1.051	0.930	1.129	0.912	1.127	0.899
	FFR	1.416	0.909	1.759	0.800	1.924	0.834**
	CPI	0.753**	0.702**	0.682***	0.691***	0.768***	0.682***
h=3	IP	1.131	0.840**	1.199	0.846	1.185	0.822
	FFR	2.236*	0.960	2.073	0.782	1.752	0.759**
	CPI	0.752	0.611***	0.703***	0.649***	0.769**	0.637***
h=6	IP	1.257	0.824	1.306	0.829	1.328	0.810
	FFR	2.833**	1.123	2.319	0.878	1.950	0.841
	CPI	0.758*	0.494**	0.694**	0.601**	0.731**	0.583***
h=12	IP	1.264	0.752**	1.314	0.770**	1.410	0.755
	FFR	2.797**	1.208	2.356	0.944	2.147*	0.921***
	CPI	0.831**	0.450***	0.769**	0.573**	0.774	0.557

Table 6: Macroeconomic Factors, Relative MSFE, 1984:01 - 2007:09

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically sig-

nificant different from 1 - Diebold and Mariano (1995).

		FAVAR 1 fact	BFAVAR 1 factor	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	0.932	0.860	1.010	0.850	1.006	0.835
	FFR	1.327	0.896	1.634	0.814	1.787	0.844
	CPI	0.859**	0.771**	0.837**	0.754**	0.912**	0.758*
h=3	IP	0.847**	0.743**	0.912	0.779**	0.892*	0.759*
	FFR	2.080	0.992*	1.965	0.814**	1.713*	0.793**
	CPI	1.191	0.785***	1.111	0.778**	1.147	0.776
h=6	IP	0.998	0.821	1.009	0.848**	1.009	0.834
	FFR	2.642	1.165	2.214*	0.894	1.893*	0.860**
	CPI	1.632	0.730**	1.27	0.734	1.351	0.724
h=12	IP	1.074	0.808**	1.089	0.848	1.104	0.837*
	FFR	2.582	1.194	2.181**	0.932	1.992	0.911**
	CPI	1.169	0.597**	0.967	0.639***	0.966	0.626

Table 7: Macroeconomic Factors, Relative MSFE, 1984:01 - 2012:12

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

Table 8 and Table 9 show the FAVAR models the FAVAR models (Maximum Likelihood (FAVAR) and Bayesian estimation (BFAVAR)) with 1, 3, and 8 financial factors. As reported for the FAVAR models with "general economy latent factors", FAVAR with 3 and 8 factors outperform the others.

		FAVAR 1 fact	BFAVAR 1 factor	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	1.037	0.940	1.175	0.934	1.127	0.954
	FFR	1.192	0.768	1.593	0.950	1.924	1.002
	CPI	0.755***	0.704**	0.796**	0.790**	0.768**	0.790**
h=3	IP	1.089	0.870	1.221	0.849	1.185	0.867
	FFR	1.781	0.946	2.388	1.055	1.752	1.047
	CPI	0.736**	0.599**	0.21**	0.732***	0.769**	0.706**
h=6	IP	1.245	0.854	1.388	0.931	1.328	0.837
	FFR	2.137	1.107	2.289	1.060	1.950	1.019
	CPI	0.699**	0.471**	0.639**	0.682**	0.731**	0.642**
h=12	IP	1.343	0.796**	1.611	0.785**	1.410**	0.776**
	FFR	2.451	1.168	2.645	1.042	2.147	1.018
	CPI	0.727**	0.409**	0.649**	0.646***	0.774	0.619***

Table 8: Financial Factors, Relative MSFE, 1984:01 - 2007:09

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

		FAVAR 1 fact	BFAVAR 1 factor	FAVAR 3 fact	BFAVAR 3 fact	FAVAR 8 fact	BFAVAR 8 fact
h=1	IP	0.948	0.850	1.047	0.864	1.006	0.884
	FFR	1.150	0.782	1.514	0.916	1.787*	0.966
	CPI	0.754**	0.714**	0.804	0.809**	0.912	0.819**
h=3	IP	0.871**	0.726*	0.931	0.769***	0.892	0.795***
	FFR	1.834	1.035	2.381	1.031	1.713	1.020
	CPI	1.123	0.772***	1.133	0.839	1.147	0.829
h=6	IP	1.061	0.768**	1.150	0.817	1.009	0.836
	FFR	2.393**	1.230	2.690**	1.045	1.893*	1.008
	CPI	1.607	0.703**	1.559**	0.793**	1.351*	0.771**
h=12	IP	1.385	0.858***	1.842**	0.856**	1.104	0.855***
	FFR	2.970**	1.234	3.846**	1.013	1.992	0.992**
	CPI	1.587	0.580***	1.764**	0.709***	0.966*	0.689**

Table 9: Financial Factors, Relative MSFE, 1984:01 - 2012:12

* (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

Table 6, Table 7, Table 8, and Table 9 report results similar in qualitative terms to results discussed in case of FAVAR models with "general economy latent factors". To understand the contribution of extracting only macroeconomic or only financial factors, we calculate the ratio of the MSFE of the Bayesian FAVAR with 3 macro or financial factors to the MSFE of the Bayesian FAVAR with factors extracted from the full dataset.

		BFAVAR 3 macro fact	BFAVAR 3 financial fact
h=1	IP	0.941	0.957
	FFR	1.117	1.257
	CPI	1.036	1.111
h=3	IP	0.963	0.951
	FFR	1.026	1.300
	CPI	1.137	1.227
h=6	IP	1.048	1.009
	FFR	1.005	1.175
	CPI	1.139	1.231
h=12	IP	1.100	1.110
	FFR	0.994	1.080
	CPI	1.029	1.142

Table 10: ratio MSFE of BFAVAR, 1984:01 - 2007:09

		BFAVAR 3 macro fact	BFAVAR 3 financial fact
h=1	IP	1.010	1.035
	FFR	1.097	1.303
	CPI	0.949	1.085
h=3	IP	1.045	1.049
	FFR	0.986	1.330
	CPI	0.949	1.070
h=6	IP	1.024	1.026
	FFR	0.986	1.191
	CPI	0.933	1.059
h=12	IP	0.999	1.018
	FFR	1.007	1.111
	CPI	0.923	1.040

Table 11: ratio MSFE of BFAVAR, 1984:01 - 2012:12

As main result, before the Great Recession, we can estimate the FAVAR models using "general economy latent factors", ignoring the difference between macro and financial variables. Instead, after the Great Recession, the BFAVAR with only macro factors outperforms the BFAVAR with financial and with general economy factors.

It seems the aftermath of the Great Recession period is explained better using macroeconomic variables.

So far, we evaluate the forecasting ability of these models on two samples: 1984 - 2007 and 1984 - 2012. Hence, we extend the first sample adding the years after the peak of the recent crisis. To focus on the period of the Great Recession, we repeat the forecasting exercise focusing only on the period after the Great Recession, 2007: 10 - 2012:12. Table 12 reports the ratio of the MSFE of the Bayesian FAVAR with 3 macro or financial factors to the MSFE of the Bayesian FAVAR with general economy latent factors. In qualitative terms, results do not change. The macroeconomic latent factors are the most important driver for the economic fluctuations during and after the Great Recession.

		BFAVAR 3 macro fact	BFAVAR 3 financial fact
h=1	IP	0.945	1.065
	FFR	1.002	1.103
	CPI	0.932	1.095
h=3	IP	0.985	1.119
	FFR	0.956	1.130
	CPI	0.972	1.003
h=6	IP	0.932	1.123
	FFR	0.978	1.167
	CPI	0.953	1.003
h=12	IP	0.942	1.003
	FFR	1.001	1.141
	CPI	0.924	1.120

Table 12: ratio MSFE of BFAVAR, 2007:10 - 2012:12

6 Conclusions

In this paper, we assess the predictive content of macroeconomic and financial latent factors on the key variables (Industrial Productivity, Short-term interest rate, and Inflation) before and after the Great Recession period. In this respect, we propose a forecasting horserace among Factor Augmented VAR (FAVAR), Classical, and Bayesian VAR models. We show that adding latent factor to a VAR structure improves the forecasting performance for the three key macroeconomic variables. We extract latent factors only from macro or financial variables to investigate if the good prediction is driven by a specific category of factors. Before the crisis, there is no evidence of improvement using only macro or financial variables. Including the Great Recession, there is a positive evidence in favor of inflation and short term interest rate.

References

[1] Alessi L, Barigozzi M, Capasso M (2010) Improved penalization for determining the number of factors in approximate factor models, Statistics & Probability Letters, Elsevier, vol. 80(23-24), pages 1806-1813, December.

[2] Bagliano FC, Morana C (2012) The Great Recession: US dynamics and spillovers to the world economy, Journal of Banking & Finance, Volume 36, Issue 1, Pages 1-13.

[3] Bai J, Ng S (2002) Determining the Number of Factors in Approximate Factor Models, Econometrica, 70.

[4] Banbura M, Giannone D, Reichlin L (2010) Large Bayesian vector auto regressions, Journal of Applied Econometrics, John Wiley & Sons, Ltd., vol. 25(1), pages 71-92.

[5] Bäurle G (2013) Structural Dynamic Factor Analysis Using Prior Information From Macroeconomic Theory, Journal of Business & Economic Statistics, Taylor & Francis Journals, vol. 31(2), pages 136-150, April.

[6] Bernanke BS, Boivin J (2003) Monetary Policy in a Data-Rich Environment, Journal of Monetary Economics 50 (3), 525-546.

[7] Bernanke BS, Boivin J and Eliasz P (2005) Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach, The Quarterly Journal of Economics, MIT Press, vol. 120(1), pages 387-422, January.

[8] Boivin J, Giannoni MP and Mihov I (2009) Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data, American Economic Review, American Economic Association, vol. 99(1), 350-84.

[9] Chudik A, Pesaran MH (2009) Infinite Dimensional VARs and Factor Models, Working Paper Series 998, European Central Bank.

[10] De Mol C, Giannone D, Reichlin L (2008) Forecasting using a large number of predictors: is Bayesian regression a valid alternative to principal components? Journal of Econometrics 146: 318–328.

[11] Del Negro M, Giannoni MP, Schorfheide F (2015) Inflation in the Great Recession and New Keynesian Models, American Economic Journal: Macroeconomics, 7(1): 168-96.

[12] Diebold FX, Mariano RS (1995) Comparing predictive accuracy, Journal of Business and Economic Statistics, 13(3), 253-263.

[13] Doan T, Litterman R, Sims C (1984) Forecasting and Conditional Projections Using Realistic Prior Distributions, Econometric Reviews, 3, 1-100.

[14] Eickmeier S, Lemke W, Marcellino M (2015) A Classical Time Varying FAVAR Model: Estimation, Forecasting, and Structural Analysis, Journal of the Royal Statistical Society, Series A. Statistics in Society, 178, 493–533.

[15] Forni M, Reichlin L. (1996): Dynamic Common Factors in Large Cross-Sections, Empirical Economics, 21, 27-42.

[16] Forni M, Reichlin L. (1998): Let's Get Real: A Dynamic Factor Analytical Approach to Disaggregated Business Cycle, Review of Economic Studies, 65, 453-474.

[17] Forni M, Hallin M, Lippi M and Reichlin L. (1999): Reference Cycles: The NBER Methodology Revisited, mimeo.

[18] Forni M, Hallin M, Lippi M and Reichlin L. (2000): The Generalized Dynamic-Factor Model: Identification And Estimation, The Review of Economic and Statistics, MIT Press, vol. 82(4), pages 540-554, November.

[19] Grusky B, Western B, Wimer C, The Great Recession, Russell Sage Foundation, 2011.

[20] Gupta R, Kabundi A (2010) Forecasting macroeconomic variables in a small open economy: a comparison between small- and large-scale models, Volume 29, Issue 1-2, January - March 2010, Pages 168–185.

[21] Ingram B, Whiteman C (1994) Supplanting the Minnesota Prior - Forecasting Macroeconomics Time Series using Real Business Cycle Model Priors, Journal of Monetary Economics, 34, 497-510.

[22] Kadiyala KR, Karlsson S (1997) Numerical Methods for Estimation and Inference in Bayesian VAR-Models, Journal of Applied Econometrics, 12(2), 99-132.

[23] Kolasa M, Rubaszek M (2015) Forecasting with DSGE models with financial frictions. International Journal of Forecasting 31, 1-19.

[24] Korobilis D (2008) Forecasting in vector autoregressions with many predictors, in Siddhartha Chib, William Griffiths, Gary Koop, Dek Terrell (ed.) Bayesian Econometrics (Advances in Econometrics, Volume 23) Emerald Group Publishing Limited, pp.403 - 431.

[25] Litterman RB (1981) A Bayesian Procedure for Forecasting with Vector Autoregressions, Working Paper, Federal Reserve Bank of Minneapolis.

[26] Litterman RB (1986) Forecasting with Bayesian Vector Autoregressions: Five Years of Experience, Journal of Business and Statistics 4(1), 25–38.

[27] Menno D, Oliviero T (2016), Financial intermediation, house prices, and the welfare effects of the US great recession, CSEF Working Paper No. 373.

[28] Palley T (2011) America's flawed paradigm: macroeconomic causes of the financial crisis and great recession, Empirica, 38:3-17.

[29] Robertson JC, Tallman EW (1999) Vector autoregressions: forecasting and reality. Economic Review Q1: 4–18.

[30] Sims CA (1980) Macroeconomics and reality, Econometrica, 48(1), 1-48.

[31] Sims CA (1992) Bayesian inference for multivariate time series with trend. Mimeo Yale University.

[32] Sims, CA (2002) Solving Linear Rational Expectations Models, Computational Economics, 20 (1-2), 1-20.

[33] Sims CA, Zha T (1998) Bayesian Methods for Dynamic Multivariate Models, International Economic Review, 39, 949-968.

[34] Spencer DE (1993) Developing a Bayesian Vector Autoregression Forecasting Model, International Journal of Forecasting 9(3), 407–421.

[35] Stock JH, Watson WM (2001) Vector autoregressions, Journal of Economic Perspectives, 15, 101-115.

[36] Stock JH, Watson WM (2002) Macroeconomic Forecasting Using Diffusion Indexes, Journal of Business Economics and Statistics, XX:II, 147-162.

[37] Stock JH, Watson MW (2005a). An empirical comparison of methods for forecasting using many predictors. Manuscript, Princeton University.

[38] Stock JH, Watson MW (2005b). Implications of dynamic factor models for VAR analysis. Manuscript, Princeton University.

[39] Stock JH, Watson MW (2012). Disentangling the Channels of the 2007-2009 Recession. Brookings Papers on Economic Activity, Spring 2012.

[40] Todd RM (1984) Improving Economic Forecasting with Bayesian Vector Autoregression, Quarterly Review, Federal Reserve Bank of Minneapolis.

7 Appendix

7.1 Data

The source of the data is the Federal Reserve Economic Data - Federal Reserve Bank of Saint Louis (http://research.stlouisfed.org/fred2/). In order to construct the FAVAR we extract factors from a balanced panel of 127 monthly macroeconomic and financial time series, following the dataset built by Stock and Watson (2002) and Stock and Watson (2005a). The dataset involves several measures of industrial production, interest rates, various price indices, employment and other important macroeconomic and also financial variables. In the following Table, the first column has the series acronym, the third the series description, the fourth the transformation codes and the fifth column denotes a macroeconomic variable with 1 and a financial one with 0. The transformed series are tested using the Box-Jenkins procedure and the Dickey-Fuller test. Following Bernanke *et al.* (2005), the transformation codes are as follows: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm; 6 - second difference; 7 - second difference of logarithm.

Date	Long Desc.	Tcode	MACRO
INDPRO	IP: Total index	5	1
IPFINAL	Industrial Production: Final Products (Market Group)	5	1
IPCONGD	IP: Consumer goods	5	1
IPMAT	Industrial Production: Materials	5	1
IPDMAT	Industrial Production: Durable Materials	5	1
IPNMAT	Industrial Production: nondurable Materials	5	1
MCUMFN	Capu Man. (Fred post 1972, Older serious before 1972)	1	1
TCU	Capacity Utilization: Total Industry	1	1
IPDCONGD	Industrial Production: Durable Consumer Goods	5	1
IP.B51110.S	IP: Automotive products	5	1
IPNCONGD	Industrial Production: Nondurable Consumer Goods	5	1
IPBUSEQ	Industrial Production: Business Equipment	5	1
IP.B51220.S	IP: Consumer Energy Products	5	1
MANEMP	All Employees: Manufacturing	5	1
PAYEMS	Total Nonfarm Payrolls: All Employees	5	1
SRVPRD	All Employees: Service-Providing Industries	5	1
USGOOD	All Employees: Goods-Producing Industries	5	1
USGOVT	All Employees: Government	5	1
USPRIV	All Employees: Total Private Industries	5	1
CES9091000001	Federal	5	1
CES9092000001	State government	5	1
CES9093000001	Local government	5	1
DMANEMP	All Employees: Durable Goods Manufacturing	5	1
NDMANEMP	All Employees: Nondurable Goods Manufacturing	5	1
USCONS	All Employees: Construction	5	1
USEHS	All Employees: Education & Health Services	5	1
USFIRE	All Employees: Financial Activities	5	1
USINFO	All Employees: Information Services	5	1

Date	Long Desc.	Tcode	MACRO
USLAH	All Employees: Leisure & Hospitality	5	1
USMINE	All Employees: Natural Resources & Mining	5	1
USPBS	All Employees: Professional & Business Services	5	1
USSERV	All Employees: Other Services	5	1
USTPU	All Employees: Trade, Transportation & Utilities	5	1
USTRADE	All Employees: Retail Trade	5	1
USWTRADE	All Employees: Wholesale Trade	5	1
CE160V	Emp Total (Household Survey)	5	1
CLF16OV	Civilian Labor Force	5	1
LNS11300000	LaborForce Participation Rate (16 Over) SA	2	1
UNRATE	Urate	2	1
URATE_ST	Urate Short Term (< 27 weeks)	2	1
URATE_LT	Urate Long Term (>= 27 weeks)	2	1
LNS14000012	Unemployment Rate - 16-19 yrs	2	1
LNS14000025	Unemployment Rate - 20 yrs. & over, Men	2	1
LNS14000026	Unemployment Rate - 20 yrs. & over, Women	2	1
UEMPLT5	Number Unemployed for Less than 5 Weeks	5	1
UEMP5TO14	Number Unemployed for 5-14 Weeks	5	1
UEMP15T26	Civilians Unemployed for 15-26 Weeks	5	1
UEMP27OV	Number Unemployed for 27 Weeks & over	5	1
LNS13023621	Unemployment Level - Job Losers	5	1
LNS13023557	Unemployment Level - Reentrants to Labor Force	5	1
LNS13023705	Unemployment Level - Job Leavers	5	1
LNS13023569	Unemployment Level - New Entrants	5	1
LNS12032194	Employment Level - Part-Time for Economic Reasons, All Industries	5	1
AWHMAN	Average Weekly Hours: Manufacturing	1	1
AWHNONAG	Average Weekly Hours: Total Private Industrie	2	1
AWOTMAN	Average Weekly Hours: Overtime: Manufacturing	2	1
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started	5	1
HOUST5F	Privately Owned Housing Starts: 5-Unit Structures or More	5	1
HOUSTMW	Housing Starts in Midwest Census Region	5	1
HOUSTNE	Housing Starts in Northeast Census Region	5	1
HOUSTS	Housing Starts in South Census Region	5	1
HOUSTW	Housing Starts in West Census Region	5	1
PERMIT	New Private Housing Units Authorized by Building Permit	5	1
A0M009	Construction contracts (mil. sq. ft.) (Copyright, McGraw-Hill)	4	1
A0M007	Mfrs' new orders durable goods industries (bil. chain 2000 $)	5	1
A0M008	Mfrs' new orders, consumer goods and materials (mil. 1982 $)	5	1
A1M092	Mfrs' unfilled orders durable goods indus. (bil. chain 2000 $)	5	1
A0M032	Index of supplier deliveries -- vendor performance (pct.)	1	1
A0M027	Mfrs' new orders, nondefense capital goods (mil. 1982 $)	5	1
A0M070	Manufacturing and trade inventories (bil. Chain 2005 $)	5	1
A0M057	Manufacturing and trade sales (mil. Chain 2005 $)	5	1
A0M059	Sales of retail stores (mil. Chain 2000 $)	5	1
PPIACO	Producer Price Index: All Commodities	6	1
WPU0531	PPI: Natural Gas	5	1
WPU0561	PPI: Crude Petroleum	5	1
PCEPI	Personal Consumption Expenditures: Chain-type Price Index	6	1
PCEPILFE	Personal Consumption Expenditures: Chain-Type Price Index Less Food and Energy	6	1
PPIFGS	Producer Price Index: Finished Goods	6	1
PPIFCF	Producer Price Index: Finished Consumer Foods	6	1

Date	Long Desc.	Tcode	MACRO
PPIFCG	Producer Price Index: Finished Consumer Goods	6	1
PPIIDC	Producer Price Index: Industrial Commodities	6	1
PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components	6	1
CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items	6	1
CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	6	1
CES2000000008	Average Hourly Earnings: Construction	5	1
CES3000000008	Average Hourly Earnings: Manufacturing	5	1
AHETPI	Average Hourly Earnings: Total Private Industries	5	1
AAA	Moody's Seasoned Aaa Corporate Bond Yield	2	1
BAA	Moody's Seasoned Baa Corporate Bond Yield	2	0
FEDFUNDS	Effective Federal Funds Rate	2	0
CPF3M	3-Month AA Financial Commercial Paper Rate post 1997 … linked to XLI CP90 before 1997	2	0
CP90_Tbill	CP3FM-TB3MS	1	0
GS1	1-Year Treasury Constant Maturity Rate	2	0
GS10	10-Year Treasury Constant Maturity Rate	2	0
MORTG	30-Year Conventional Mortgage Rate	2	0
TB3MS	3-Month Treasury Bill: Secondary Market Rate	2	0
TB6MS	6-Month Treasury Bill: Secondary Market Rate	2	0
MED3	3-Month Eurodollar Deposit Rate (London)	2	0
Med3_tb3m	MED3-TB3MS (Version of TED Spread)	1	0
AAA_GS10	AAA-GS10 Spread	1	0
BAA_GS10	BAA-GS10 Spread	1	0
MRTG_GS10	Mortg-GS10 Spread	1	0
tb6m_tb3m	tb6m-tb3m	1	0
GS1_tb3m	GS1_Tb3m	1	0
GS10_tb3m	GS10_Tb3m	1	0
BOGAMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements	5	0
BOGNONBR	Non-Borrowed Reserves of Depository Institutions	5	0
BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	5	0
CONSUMER	Consumer (Individual) Loans at All Commercial Banks	5	0
M1SL	M1 Money Stock	5	0
M2SL	M2SL	5	0
MZMSL	MZM Money Stock	5	0
NONBORTAF	Non-Borrowed Reserves of Depository Institutions Plus Term Auction Credit	5	0
NONREVSL	Total Nonrevolving Credit Outstanding	5	0
REALLN	Real Estate Loans at All Commercial Banks	5	0
TRARR	Board of Governors Total Reserves, Adjusted for Changes in Reserve Requirements	5	0
REVOLSL	Total Revolving Credit Outstanding	5	0
TOTALSL	Total Consumer Credit Outstanding	5	0
FSPCOM	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	5	0
FSDJ	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE	5	0
mvol	VXO (Linked by N. Bloom) .. Average daily VIX from 2009 ->	1	0
TWEXMMTH	FRB Nominal Major Currencies Dollar Index (Linked to EXRUS in 1973:1)	5	0
EXSZUS	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$) Fred, 1971 ? EXRSW previous	5	0
EXJPUS	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$), Fred 1971- EXRJAN previous	5	0
EXUSUK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND), Fred 1971->, EXRUK Previous	5	0
EXCAUS	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$) ? Fred, 1971 -> EXRCAN previous	5	0
U0M083	Consumer expectations NSA (Copyright, University of Michigan)	1	1

Table A1. Description Dataset

7.2 Correlation Matrix between "general economy latent factors" and Macro variables

The correlation matrix between "general economy latent factors" and Macroeconomic variables shows a good (between 20% and 50% in absolute value) correlation between the first four factors and the three macro variables.

	1	2	3	4	5	6	7	8
IP	0.64	-0.15	0.29	-0.47	0.16	-0.12	0.28	-0.03
FFR	0.47	-0.15	0.57	0.31	-0.18	0.03	-0.12	-0.01
CPI	0.25	0.22	-0.19	0.26	0.11	-0.20	0.24	0.28

Table A2. Correlation Matrix Factors and Macro variables www.nbp.pl