Did Financial Factors matter during the Great Recession?[*]

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Abstract

Yes, they mattered. To reply to this question, we assess the predictive content of macroeconomic and financial latent factors on the key variables (Industrial Productivity, Short-term interest rate, and Inflation) during the Great Recession period (2007 - 2009) in the United States. In this respect, we propose a forecasting analysis using a Factor Augmented VAR model. When we estimate the model with only financial factors, we improve the predictions in the short and medium horizons. Meanwhile, when we estimate the model with only macroeconomic factors, we improve the forecasting performance in the longer horizon.

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

**KEYWORDS**: Factor Models, Factor Augmented VAR, 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 drivers of economic fluctuations. In particular, recent empirical studies provide evidence how financial variables or indicators are suitable to predict the business cycle (see for example, English et al., 2005; Hatzius et al., 2010; Espinoza et al., 2012; Gilchrist and Zakrajšev, 2012; Stock and Watson, 2012; Andreou et al., 2013; and Chen and Ranciere, 2016). In addition, several studies evidence how financial markets, banking and housing sectors, and fall in consumption are the main determinants of this recent crisis (Grusky et al., 2011; Palley, 2011; Bagliano and Morana, 2012; Acosta-González et al., 2012; Del Negro et al., 2015; Kolasa and Rubaszek, 2015; Menno and Oliviero, 2016 among others). Look at the Graph 1[1], we can identify how the three key macroeconomic variables as Industrial Production Index, Consumer Price Index, and Effective Funds Rate face a quick fall from 2007 and after 2009 they experience a slow recovery (for more detail, see Dominguez and Shapiro, 2013; Lucchetta and Paradiso, 2014).

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[1]In the Graph 1, shaded areas indicate the US recessions.
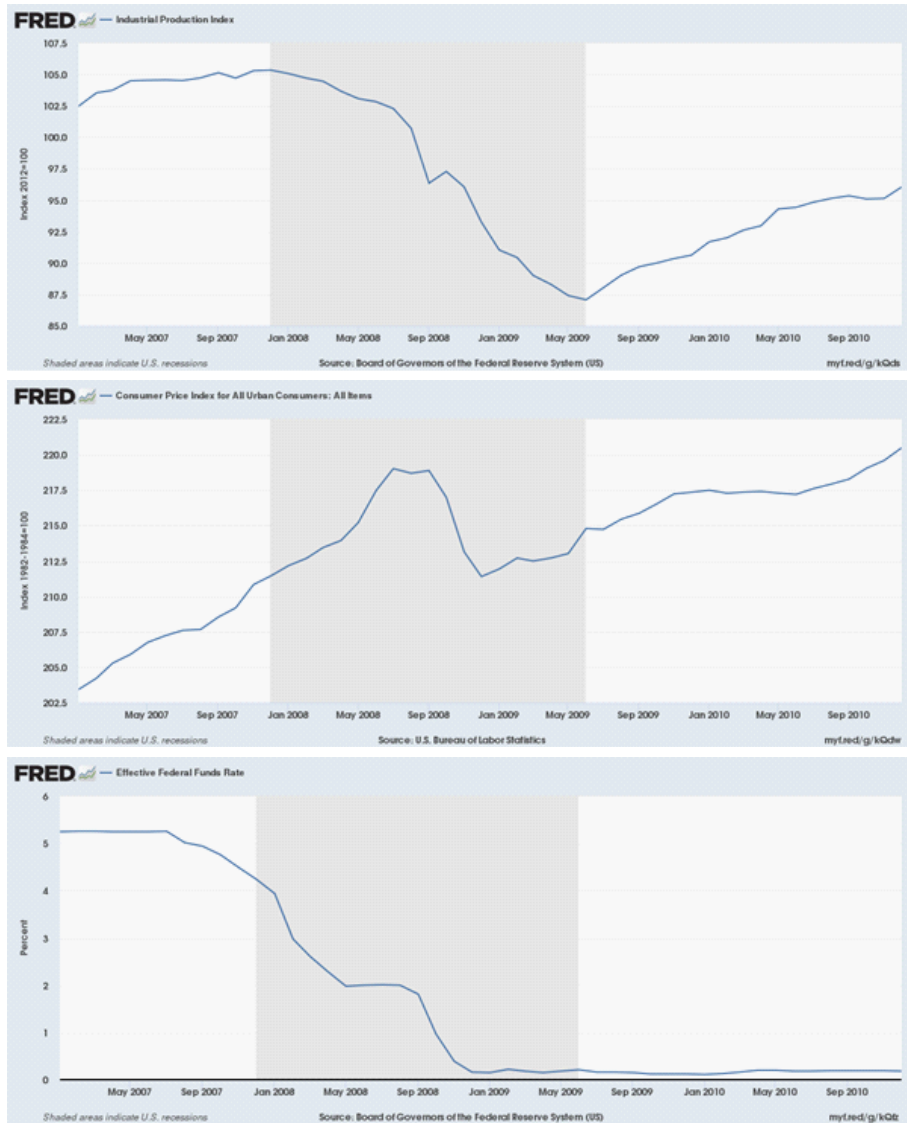
Graph 1: Industrial Production Index, Consumer Price Index, and Effective Federal Funds Rate.

This paper takes an empirical look at the power of financial factors to forecast some key macroeconomic variables (Industrial Productivity, Short-term interest rate, and Inflation) during the Great Recession. To reply to our research question, we estimate a Factor Augmented VAR (FAVAR) à la Bernanke, Boivin, and Eliasz (2005) two steps approach. In the first step, we extract the latent factors or factors using Principal Component Analysis from a large dataset composed of macroeconomic and financial time series. In the second step,

we estimate the augmented VAR with factors which is implemented in a forecasting analysis. To investigate the effect of macroeconomic and financial factors, we extract factors from only macro and only financial variables. As main results, we discover how financial factors improve the forecasting of the three key macroeconomic variables in the short run; meanwhile in the long run the macroeconomic factors outperform.

Our results contribute the recent empirical literature which assesses the role of financial variables to forecast the business cycle proposing some different features. Differently from Hatzius et al. (2010), we ignore financial condition indices to measure financial shocks, which are replaced, in our framework, by financial factors extracted using Principal Component approach. Moreover, in our analysis, all data are in monthly frequency, as discussed in Stock and Watson (2012), and we do not estimate a mixed frequency model as implemented in Andreou et al. (2013). Our results are qualitatively similar to Espinoza et al. (2012), even if, contrary to them, we do not estimate FAVAR models with real time data which could offer precise forecasting analysis (see Stark and Croushore, 2002 for details).

The rest of this paper is organized as follows. Section 2 discusses the empirical exercise with a description of the data and details about the forecasting evaluation. Section 3 concludes.

2   Empirical Strategy and Results

In our empirical analysis, we implement the Factor Augmented VAR (FAVAR) which is the reduced form VAR of the Dynamic Factor Model (Stock and Watson, 2005b). The model is estimated following the two-step principal components approach illustrated in Bernanke, Boivin, and Eliasz (2005). For technical details, see Appendix.

We evaluate the relative (to a random walk with drift process) forecast performance of the three key macroeconomic variables (Industrial Productivity (IP), Short-term interest rate (FFR), and Inflation (CPI)) using a Factor Augmented VAR à la Bernanke, Boivin, and Eliasz (2005). We measure the prediction ability using the Mean Square Forecast Error (MSFE) calculated for forecast horizons $h = 1, 3, 6,$ and 12. The factors or latent variables are extracted using Principal Component Analysis from a large dataset composed of 128 monthly time series macroeconomic and financial variables from 1984 to 2009 for the United States[2]. As suggested by Bäurle (2013), we select the number of extracted factors using two different criteria: Bai and Ng (2002) and Alessi et al. (2010). Both criteria suggest a maximum of three factors. First, we extract three factors from the whole dataset; second, we extract three

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[2]The dataset is provided by the FED St.Louis https://research.stlouisfed.org/econ/mccracken/fred-databases/. For more detail, see McCracken and Ng (2016). 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).

In this empirical exercise, we stop at 2009 since we investigate about the recent Great Recession and subsequent slow recovery period. Moreover, from 2008 the US experienced the unconventional monetary policy tools.

factors from only macro and from only financial variables. 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)[3]. The estimation sample is from 1984:01 to 2007:08, while the pseudo-out-of-sample forecasts are from 2007:09 to 2009:12.

Table 1[4] reports the MSFE ratios calculated for the three key macroeconomic variables. The first column refers to the FAVAR model with three factors extracted from the whole dataset. The second column refers to the FAVAR with three factors extracted from the macroeconomic variables, while the last column refers to FAVAR with three factors extracted from financial variables.

We note how the MSFE suggests a good forecasting performance in favor of the FAVAR model against the random walk with drift. According to the second and third column, we evidence how the financial factors help the FAVAR model to forecast better IP, FFR, and CPI in 1-month, 3-month, and 6-month steps ahead. These results are statistical significant using Diebold and Mariano (1995) test. However, the macroeconomic factors improve the forecasting performance of the FAVAR in the longer horizon, 12-month steps ahead.

A robustness analysis provides evidence how these results are typically about the Great Recession and the subsequent slow recovery (see Appendix). In particular, considering the crisis between 1981 and 1982[5], we note how financial factors do not outperform in predicting economic activity and they are not statistically significant as during the 2007 - 2009 crisis. Moreover, if we extend the sample until 2017[6], the prediction power of financial factors is still relevant but not statistically significant. However, we can agree with Stock and Watson (2012), that during the Great Recession, the business cycle can be explained using the same financial factors used to explain previous recessionary periods.

We can read these results in the light of Boivin and Ng (2006) and Bai and Ng (2008). Boivin and Ng (2006) have stressed out how there could be a trade-off between quality of the data and their quantity. They show how it is possible to have worse forecasting performance when we include irrelevant variables in the dataset used to extract principal components. If we check the first 10 series which explain the marginal R-Squared in case of the whole dataset,

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

[4]In the Table 1, we report of horizon = 1, 3, 6, and 12 the MSFE for the three models: FAVAR (with 3 factors extracted from all dataset), FAVAR with Macro Factors (with 3 factors extracted from only macro variables of the dataset), and FAVAR with Financial Factors (with 3 factors extracted from only financial variables of the dataset). The MSFE ratio for FAVAR is with respect the random walk model with drift. The MSFE ratio for FAVAR with Macro and Financial Factors is with respect the FAVAR model. For FAVAR with Macro and Financial factors, we report the Diebold and Mariano (1995) test: * (10%),** (5%),***(1%) significance levels for which relative RSME is statistically significant different from 1 - Diebold and Mariano (1995).

[5]McCracken and Ng (2016) dataset starts originally from 1959. Hence, we repeat the forecasting exercise considering as estimation sample from 1959:01 to 1981:06 and the pseudo-out-of-sample forecasts are from 1981:07 to 1982:12.

[6]The estimation sample is from 1984:01 to 2007:08 and the pseudo-out-of-sample forecasts are from 2007:09 to 2017:11.

we note how financial variables are relevant, but not exclusive[7]. Moreover, the FAVAR with factors extracted from the whole dataset outperforms the FAVAR with factors extracted from the only macro variable dataset. Hence, we can affirm how in this case financial variables are important to improve forecasts and our approach is not far from the "target predictors" proposed by Bai and Ng (2008).

		FAVAR (MSFE ratio with RW)	FAVAR Macro Factors (MSFE ratio with FAVAR)	FAVAR Financial Factors (MSFE ratio with FAVAR)
h=1	IP	0.976	0.962**	0.850**
	FFR	0.894	1.026	0.765**
	CPI	0.914	1.137	0.930**
h=3	IP	0.892	1.030	0.950*
	FFR	0.934	0.956*	0.874**
	CPI	0.874	0.999	0.973**
h=6	IP	0.930	1.048	0.850**
	FFR	0.974	1.005	0.980**
	CPI	1.002	1.139**	0.875***
h=12	IP	0.878	0.768***	1.095*
	FFR	0.954	0.873**	0.994
	CPI	0.973	0.987**	1.029

Table 1: Relative MSFE, 2007:09 - 2009:12.

3   Concluding Remarks

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) during the Great Recession period. For this purpose, we propose a forecasting analysis using a Factor Augmented VAR model. When we estimate the model with only financial factors, we improve the predictions in the short and medium horizons. Meanwhile, when we estimate the model with only macroeconomic factors, we improve the forecasting performance in the longer horizon.

According to these results, we can conclude how the financial factors played an important role to predict the business cycle variables during the short and medium run. In particular,

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[7]Among the first 10 variables which contribute the marginal R-Squared we find industrial production indices, inflation indicators, and treasury bill rates.

to explain the quick fall at the start of the Great Recession.

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4 Appendix

4.1 Factor Augmented VAR

In the recent literature about big data applied to time series, Factor Augmented VAR (FAVAR) has become very popular. Stock and Watson (2002), Forni and Reichlin (1996, 1998) and Forni, Hallin, Lippi and Reichlin (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 main purpose of using dynamic factor models is to take into account the behavior of several variables which is determined by a few common latent variables, called factors in addition to idiosyncratic shocks. Consequently, the use of factors helps the researcher to face with the "curse of dimensionality" adding factors to small-scale models and improving the shocks identification and forecasting analysis. In this direction, Bernanke and Boivin (2003) and Bernanke, Boivin, and Eliasz (2005) implement factors in the estimation of VAR to generate a more general specification. Meanwhile, Chudik and Pesaran (2011) illustrate 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:

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

$$F_t = \Phi(L)F_{t-1} + G\eta_t, \tag{2}$$

where Λ is $n \times f$ matrix, f is the number of static factors, and G is $f \times q$. Equation (1) is the measurement equation and Equation (2) is the state equation. The representation (1) and (2) is called the "static" for the DFM since F_t appears in measurement equation without any lags.

It is possible to derive a VAR form of the DFM by substituting (2) into (1) as follows:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Phi(L) & 0 \\ \Lambda\Phi(L) & D(L) \end{bmatrix} \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{F_t} \\ \varepsilon_{X_t} \end{bmatrix}, \tag{3}$$

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:

$$X_t = \Lambda^f F + \Lambda^y Y_t + e_t, \tag{4}$$

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[8], 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 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). The FAVAR model equation (4), is estimated following the two-step principal components approach illustrated in Bernanke, Boivin, and Eliasz (2005). The number of factors are selected according to Bai and Ng (2002) and Alessi, Barigozzi, and Capasso (2010). For

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[8]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.

more technical detail, see Bernanke, Boivin, and Eliasz (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, Boivin, and Eliasz (2005), Y_t is removed from the space covered by the principal components. Boivin, Giannoni, and Mihov (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.

4.2   Robustness Exercises

		Forecast period: 1981:07 - 1982:12		Forecast period: 2007:09 - 2017:11	
		FAVAR 3 macro factors	FAVAR 3 financial factors	FAVAR 3 macro factors	FAVAR 3 financial factors
h=1	IP	0.84	0.73	0.91	0.83
	FFR	0.77	0.81*	0.94	0.92
	CPI	1.19	0.90	0.95	0.90
h=3	IP	0.59	0.58	0.93	0.91 *
	FFR	0.98**	1.46	0.90 *	0.93
	CPI	1.84	1.03	1.00	0.91
h=6	IP	0.75	0.76	0.88*	0.95
	FFR	1.60	0.97	1.00	0.98 *
	CPI	2.90	1.09	1.13**	0.78
h=12	IP	0.84	0.93	0.71*	1.02
	FFR	0.80	0.87	0.98	0.99
	CPI	1.02	1.09	0.84**	1.03

Table Appendix: Relative MSFE