Dynamic Factor Model
with Infinite Dimensional Factor Space: Forecasting

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Abstract. The paper compares the pseudo real-time forecasting performance of three Dynamic Factor Models: (i) The standard principal-component model, Stock and Watson (2002a), (ii) The model based on generalized principal components, Forni et al. (2005), (iii) The model recently proposed in Forni et al. (2015) and Forni et al. (2016). We employ a large monthly dataset of macroeconomic and financial time series for the US economy, which includes the Great Moderation, the Great Recession and the subsequent recovery. Using a rolling window for estimation and prediction, we find that (iii) neatly outperforms

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(i) and (ii) in the Great Moderation period for both Industrial Production and Inflation, and for Inflation over the full sample. However, (iii) is outperfomed by (i) and (ii) over the full sample for Industrial Production.

1 Introduction

This paper compares the pseudo real-time forecasting performance of three Large-Dimensional Dynamic Factor Models for the US monthly macroeconomic dataset over the period February 1985 to August 2014, this including the so-called Great Moderation and the Great Recession.

Large-Dimensional Dynamic Factor Models represent each variable in the dataset as decomposed into a *common component*, driven by a small (as compared to the number of series in the dataset) number of *common factors* and an *idiosyncratic component*. The latter are assumed to be orthogonal across different variables or only weakly correlated, so that the covariance of the variables is mostly accounted for by the common components. Typically, the asymptotic results are obtained for n, the number of series, and T, the number of observations for each series, both tending to infinity. Among the different versions of the Dynamic Factor Model we selected:

(i) SW. The model introduced in Stock and Watson (2002a,b). The factors are estimated by means of the standard Principal Components of the variables in the dataset. The forecast of the variable of interest, call it y_t, is obtained by regressing y_{t+h} on the factors and the variable y_t, plus possibly lags of the factors and y_t.

(ii) FHLR. A variant of the previous model which has been proposed in Forni et al. (2005). In a first step the covariances of the common and the idiosyncratic components are estimated using a frequency-domain method introduced in Forni et al. (2000). In the second step such covariances are employed to estimate the factors by means of Generalized Principal Components.

(iii) FHLZ. Both models (i) and (ii) assume that the space spanned by the common components at any time t stays finite-dimensional as n tends to infinity. In two recent papers, (Forni et al., 2016, 2015), it is assumed that a finite number of common shocks drive the common components, though the common components themselves are allowed to span an infinite-dimensional space. The dynamic relationship between the variables and the factors in this model is more general as compared to (i) and (ii). However, its estimation is rather complex and no systematic comparison with (i) and (ii) has as yet been produced[1].

The literature comparing SW and FHLR has reached mixed conclusions so far. Using US data, Boivin and Ng (2005) found that SW generally outperforms FHLR, whereas D'Agostino and Giannone (2012) found the two methods to perform equally well in their sample even if different performances are found in subsamples. In particular, FHLR fares better during the Great Moderation, consistently with the results in the present paper. Schumacher (2007), using German data, finds that FHLR provides more accurate forecasts of the GDP. A similar result is obtained in den Reijer (2005) with Dutch macroeconomic data.

Let us point out that here we only consider the three factor models outlined above. In particular, we do not consider variants of the Dynamic Factor Model or of the estimation method such as Peña and Poncela (2004), Kapetanios and Marcellino (2009) (which is included in Schumacher (2007)), Doz et al. (2011b), Doz et al. (2011a). Comparison with such variants and alternative shrinkage methods, see e.g. Stock and Watson (2012) and Kim and Swanson (2014), are left to future research. For a review and evaluation of forecast results with Dynamic Factor Models see Eickmeier and Ziegler (2008).

In the present paper we extend the comparisons in Boivin and Ng (2005) and D'Agostino and Giannone (2012) to more recent US data and include the new FHLZ forecasting model. We use a dataset of US macroeconomic and financial monthly time series spanning from January 1959 to August 2014 thus including the Great Moderation, the Great Recession and the subsequent recovery.

[1]See however Forni et al. (2016), in which forecasts obtained with models (i) and (iii) are compared using simulated data and quarterly macroeconomic US data.

A distinctive feature of our exercise is that we use a fairly large subsample, February 1960 to December 1984, to calibrate the models, i.e. to decide which method should be used to determine the number of factors, the number of lags of the factors or of the variable to be predicted, etc. The selected models are then run and compared in the remaining sample: January 1985 to August 2014.

Our results are:

(I) In the Great Moderation period, in which the assumption of stationarity of the series in the dataset (after suitable transformations) underlying all factor models is by and large fulfilled, FHLZ neatly outperforms the other factor models and the univariate AR model both for Industrial Production and Inflation. FHLZ also prevails over the other factor models in the full sample for Inflation, though all factor models loose ground with respect to the AR model. This deterioration is the result of a bad performance of the factor models during the crisis.

(II) In the full sample FHLR and SW outperform FHLZ and AR for Industrial Production. Again, this reversal in the order among the factor models is completely accounted for by their performance in the crisis period.

(III) We also run forecasts for all single series in the dataset and find that, over the full sample, FHLZ is the best method for the nominal variables, consistently with (I) above, whereas FHLR is the best for real variables.

The structure of the paper is as follows. In Section 2 the factor models considered are outlined and the particular features of FHLZ are discussed. In Section 3 we describe the calibration of the models. In Section 4 we describe and discuss the results. Section 5 concludes.

2 Three forecasting methods

Let us start with the general form of the Large-Dimensional Dynamic Factor Model:

$$x_{it} = \chi_{it} + \xi_{it} = \frac{c_{i1}(L)}{d_{i1}(L)} u_{1t} + \frac{c_{i2}(L)}{d_{i2}(L)} u_{2t} + \cdots + \frac{c_{iq}(L)}{d_{iq}(L)} u_{qt} + \xi_{it}, \tag{2.1}$$

where L is the lag operator, $t =\in \mathbb{Z}$, $i \in \mathbb{N}$,

$$c_{if}(L) = c_{if,0} + c_{if,1}L + \ldots + c_{if,s_1}L^{s_1}, \quad d_{if}(L) = d_{if,0} + d_{if,1}L + \ldots + d_{if,s_2}L^{s_2},$$

$\mathbf{u}_t = (u_{1t}\ u_{2t}\ \cdots\ u_{qt})'$ is a q-dimensional orthonormal white noise.

The processes χ_{it}, are called the *common components*, they are driven by the *common shocks* $\mathbf{u}_t$, also called the *dynamic (common) factors*. We assume that the polynomials $d_{if}(L)$ are stable so that χ_{it} is stationary and is co-stationary with χ_{jt} for all $i, j \in \mathbb{N}$. The processes ξ_{it} are called the *idiosyncratic components*. We assume that ξ_{it} is stationary and co-stationary with ξ_{jt} for all $i, j \in \mathbb{N}$. Moreover, ξ_{it} and $\mathbf{u}_t$ are orthogonal for all $i \in \mathbb{N}$ so that ξ_{it} and χ_{jt} are orthogonal for all $i, j \in \mathbb{N}$. The assumptions above trivially imply that the observable process x_{it} is stationary and costationary with x_{jt}, for all $i, j \in \mathbb{N}$.

Assumptions on the eigenvalues of the spectral density of the vector processes

$$\boldsymbol{\chi}_{nt} = (\chi_{1t}\ \chi_{2t}\ \cdots\ \chi_{nt})', \quad \boldsymbol{\xi}_{nt} = (\xi_{1t}\ \xi_{2t}\ \cdots\ \xi_{nt})',$$

not specified here, imply that the common shocks and the common components (and therefore the idiosyncratic components) can be recovered as limits of linear combinations of the first n observables x_{it}, as n tends to infinity. Roughly speaking, while the common components are "strongly correlated" through the common shocks, the idiosyncratic components are either orthogonal to one another or only "weakly correlated", so that if we take a linear combination of the first n variables and n is large, the idiosyncratic component becomes negligible, as compared to the common component. A detailed description of assumptions and results can be found in Forni et al. (2016, 2015).

Suppose now that for a given $\bar{t}$ the common components

$$\chi_{i\bar{t}} = \frac{c_{i1}(L)}{d_{i1}(L)} u_{1\bar{t}} + \frac{c_{i2}(L)}{d_{i2}(L)} u_{2\bar{t}} + \cdots + \frac{c_{iq}(L)}{d_{iq}(L)} u_{q\bar{t}}, \qquad i \in \mathbb{N},$$

span a finite-dimensional vector space $S_{\bar{t}}$ and denote by r its dimension. Stationarity of the common and idiosyncratic components implies that the same occurs for all $t \in \mathbb{Z}$, that the dimension of S_t is independent of t and there exists a "stationary basis"

$$\mathbf{F}_t = (F_{1t} \ F_{2t} \ \cdots \ F_{rt})$$

such that (2.1) can be rewritten in the *static form*

$$x_{it} = \lambda_{i1} F_{1t} + \lambda_{i2} F_{2t} + \cdots + \lambda_{ir} F_{rt} + \xi_{it}, \tag{2.2}$$

see Forni et al. (2009). Moreover, $r \geq q$, i.e. the number of the so-called *static factors* F_{ht} is at least equal to the number of dynamic factors. For example, if $q = 2$ and

$$\chi_{it} = \frac{c_{i1}}{1 - dL} u_{1t} + c_{i2} u_{2t} + c_{i3} u_{2,t-1}, \tag{2.3}$$

then the model has the static representation, with $r = 3$,

$$\lambda_{ij} = c_{ij}, \quad F_{1t} = (1 - dL)^{-1} u_{1t}, \quad F_{2t} = u_{2t}, \quad F_{3t} = u_{2,t-1}.$$

Model (2.2), i.e. the finite-dimension assumption, has been almost universally adopted in the literature on Dynamic Factor Models, we only mention here the seminal papers Stock and Watson (2002b), Stock and Watson (2002a) and Bai and Ng (2002), Forni et al. (2005). Under the finite-dimension assumption, the factors F_{jt} and the loadings λ_{ij} can be estimated using the first r standard principal components, or generalized principal components as in Forni et al. (2005), of the first n observables x_{it}.

The general model (2.1), with no finite-dimension assumption, has been studied in Forni and Lippi (2011), Forni et al. (2015) and Forni et al. (2016), the last providing consistent estimators for the loadings $c_{if}(L)/d_{if}(L)$ and the dynamic factors u_{ft}.

Predictions based on (2.2) and (2.1), described in Sections 2.1–2.3 and 2.2 respectively, are referred to as the *static* and the *dynamic* method, the first including SW and FHLR, the second FHLZ. On the other hand, we also refer to FHLR and FHLZ as *frequency-domain* methods, as both employ the spectral density matrix of the x's, and to SW as a *time-domain* method.

A motivation for studying the general model (2.1), as argued in FHLZ (2015), is that model (2.2) rules out cases as simple as

$$x_{it} = \frac{c_i}{1 - d_i L} u_t + \xi_{it}, \tag{2.4}$$

for $i \in \mathbb{N}$, where u_t is a scalar white noise and the coefficients d_i are drawn from, say, the uniform distribution between -0.8 and 0.8. For, unless d_i takes a finite number of values as $i \in \mathbb{N}$, the stochastic variables $\chi_{it} = c_i(1 - d_i L)^{-1} u_t$ span an infinite-dimensional space.

On the other hand, as pointed out in FHLZ (2015, end of Section 4.5), when a dataset is given, with finite n (number of variables) and T (number of observations), the static method might perform well even under misspecification, i.e. even if the data were generated by a model not fulfilling the finite-dimension assumption. In FHLZ (2014) the static and the dynamic methods have been applied to simulated data in several Monte Carlo experiments. A very short summary of the results is that: (i) when the data are generated by infinite-dimensional models like (2.4), the estimation of impulse-response functions and predictions obtained by the dynamic method are by far better than those obtained by the static method; (ii) when the data are generated under the finite-dimension assumption, model (2.2), still the dynamic method performs slightly better. In the present paper the comparison between the static and dynamic methods is conducted using empirical data, namely the US monthly macroeconomic dataset mentioned in the Introduction and fully described in Section 3.

2.1 Static method: SW

Given n, the number of series available, and T, the number of observations for each series, firstly the number r of static factors is estimated. Several criteria are available in the literature. In our exercise we make use of Bai and Ng (2002).

Secondly, let $\hat{\mathbf{\Gamma}}_n$ be the estimate of the covariance matrix of $\mathbf{x}_{nt} = (x_{1t}\ x_{2t}\ \cdots\ x_{nt})$. The first r principal components of $\mathbf{x}_{nt}$ are defined as

$$\hat{\mathbf{P}}_{nh}\mathbf{x}_{nt} = \mathbf{P}_{nh}(x_{1t}\ x_{2t}\ \cdots\ x_{nt})',$$

for $h = 1, 2, \ldots, r$, where $\hat{\mathbf{P}}_{nh}$ is the eigenvector corresponding to the h-th eigenvalue (in decreasing order) of $\hat{\mathbf{\Gamma}}_n$.

The SW forecasting equation for x_{it} is obtained by projecting $x_{i,t+h}$ on the space spanned by

$$\hat{\mathbf{F}}_t,\ \hat{\mathbf{F}}_{t-1}, \ldots,\ \hat{\mathbf{F}}_{t-g_1};\ x_{i,t},\ x_{i,t-1}, \ldots,\ x_{i,t-g_2}$$

where the presence of the terms $x_{i,t-k}$ can be motivated as possibly capturing auto-correlation in the idiosyncratic component ξ_{it}:

$$x^{SW}_{i,t+h|t} = \boldsymbol{\alpha}_i(L)\hat{\mathbf{F}}_t + \beta_i(L)x_{i,t}, \tag{2.5}$$

where $\boldsymbol{\alpha}_i(L)$ is a $1 \times r$ matrix polynomial of degree g_{i1} and $\beta_i(L)$ a scalar polynomial of degree g_{i2}.

Estimation of equation (2.5) requires determining three parameters:
(i) the number of static factors r,
(ii) the maximum lag g_{i1} for $\boldsymbol{\alpha}_i(L)$,
(iii) the maximum lag g_{i2} for $\beta_i(L)$.
This will be discussed in Section 3.2.

2.2 Dynamic method: FHLZ

Let us rewrite here for convenience the common components of model (2.1):

$$\chi_{it} = \frac{c_{i1}(L)}{d_{i1}(L)} u_{1t} + \frac{c_{i2}(L)}{d_{i2}(L)} u_{2t} + \cdots + \frac{c_{iq}(L)}{d_{iq}(L)} u_{qt}.$$

The basic result we are using is that the vector

$$\boldsymbol{\chi}_t = (\chi_{1t} \ \chi_{2t} \ \cdots \ \chi_{nt}, \ \cdots)',$$

which is an infinite (or large) dimensional vector driven by a finite (relatively small) number of shocks, has, under fairly general conditions, a blockwise autoregressive representation of the form

$$\begin{pmatrix} \mathbf{A}^1(L) & 0 & \cdots & 0 & \cdots \\ 0 & \mathbf{A}^2(L) & \cdots & 0 & \\ & & \ddots & & \\ 0 & 0 & \cdots & \mathbf{A}^k(L) & \\ \vdots & & & & \ddots \end{pmatrix} \boldsymbol{\chi_t} = \begin{pmatrix} \mathbf{R}^1 \\ \mathbf{R}^2 \\ \vdots \\ \mathbf{R}^k \\ \vdots \end{pmatrix} \mathbf{u}_t, \tag{2.6}$$

where $\mathbf{A}^k(L)$ is a $(q+1) \times (q+1)$ polynomial matrix *with finite degree* and $\mathbf{R}^k$ is $(q+1) \times q$. See Forni et al. (2015).

Denoting by $\mathbf{A}(L)$ and $\mathbf{R}$ the (infinite) matrices on the left- and right-hand sides of (2.6), using $\boldsymbol{\chi}_t = \mathbf{x}_t - \boldsymbol{\xi}_t$, and setting $\mathbf{Z}_t = \mathbf{A}(L)\mathbf{x}_t$:

$$\mathbf{Z}_t = \mathbf{R}\mathbf{u}_t + \mathbf{A}(L)\boldsymbol{\xi}_t. \tag{2.7}$$

Now, given n and T, estimation of the matrix polynomials $\mathbf{A}^k(L)$, the matrices $\mathbf{R}^k$ and the common shocks $\mathbf{u}_t$ is obtained by means of the procedure described below. We assume for convenience that n is an integer multiple of $q+1$, the size of the blocks.

(I) Estimation of the spectral density matrix of the x's, call it $\hat{\mathbf{\Sigma}}^x(\theta)$

$$\hat{\mathbf{\Sigma}}^x(\theta) = \frac{1}{2\pi}\sum_{k=-M}^{M} e^{-ik\theta} w_k \hat{\mathbf{\Gamma}}_k$$

where w_k are the weights of a kernel function. See, Forni et al. (2016).
(II) The spectral density matrix of the common components χ_{it}, call it $\hat{\mathbf{\Sigma}}^\chi(\theta)$, is obtained by means of the first q frequency-domain principal components of $\hat{\mathbf{\Sigma}}^x(\theta)$. See Forni et al. (2000), Forni et al. (2016).
(III) The autocovariance matrices of the χ's are obtained as

$$\hat{\mathbf{\Gamma}}_k^\chi = \int_{-\pi}^{\pi} e^{ik\theta}\hat{\mathbf{\Sigma}}^\chi(\theta)\, d\theta$$

See Forni et al. (2005), Forni et al. (2016).
(IV) The covariances $\hat{\mathbf{\Gamma}}_k^\chi$ are then used to compute the VAR matrices $\hat{\mathbf{A}}^k(L)$.
(V) Lastly, the shocks $\hat{\mathbf{u}}_t$ and the matrices $\hat{\mathbf{R}}^k$ are obtained by means of standard principal components of the estimated variables $\hat{\mathbf{Z}}_t$. See Forni et al. (2016).

The matrix $\mathbf{A}(L)$ in 2.6 can be inverted blockwise:

$$\boldsymbol{\chi}_t = [\mathbf{A}(L)]^{-1}\mathbf{R}\mathbf{u}_t = \mathbf{W}(L)\mathbf{u}_t = \mathbf{W}_0\mathbf{u}_t + \mathbf{W}_1\mathbf{u}_{t-1} + \cdots \tag{2.8}$$

Inversion of the estimated version of (2.6) gives

$$\hat{\boldsymbol{\chi}}_t = \left[\hat{\mathbf{A}}(L)\right]^{-1}\hat{\mathbf{R}}\hat{\mathbf{u}}_t = \widehat{\mathbf{W}}(L)\hat{\mathbf{u}}_t = \widehat{\mathbf{W}}_0\hat{\mathbf{u}}_t + \widehat{\mathbf{W}}_1\hat{\mathbf{u}}_{t-1} + \cdots, \tag{2.9}$$

where $\hat{\boldsymbol{\chi}}_t$ is n-dimensional, and the matrices $\hat{\mathbf{A}}(L)$, $\hat{\mathbf{R}}$ and $\widehat{\mathbf{W}}(L)$ are $n \times n$. and the corresponding prediction equation

$$x_{t+h|t}^{FHLZ} = \chi_{t+h|t}^{FHLZ} = \widehat{\mathbf{W}}_h\hat{\mathbf{u}}_t + \widehat{\mathbf{W}}_{h+1}\hat{\mathbf{u}}_{t-1} + \cdots \tag{2.10}$$

Estimation of FHLZ requires determining:
(i) the number of dynamic factors q,

(ii) the kernel and the lag window for the estimation of $\mathbf{\Sigma}^x(\theta)$,
(iii) the maximum lag for the matrix polynomials $\mathbf{A}^k(L)$.

2.3 Static, frequency-domain method: FHLR

The procedure goes like in the previous section, steps (I) through (III), so obtaining

$$\widehat{\mathbf{\Gamma}}_k^\chi, \quad \widehat{\mathbf{\Gamma}}_k^\xi, \quad k \in \mathbb{Z}.$$

However, unlike in the previous section, it is assumed that the space spanned by the common components has finite dimension r. Instead of using the standard principal components, which are based on the covariances $\mathbf{\Gamma}_0^x$, the covariances $\mathbf{\Gamma}_0^\chi$ and $\mathbf{\Gamma}_0^\xi$ are employed to estimate a basis in the factor space by means of generalized principal components (the estimated variance of the idiosyncratic is taken into account):

$$\widehat{\mathbf{G}}_t = \left(\widehat{G}_{1t}, \ \widehat{G}_{2t}, \ \ldots, \ \widehat{G}_{rt}\right) = \mathbf{P}^{G,r}\mathbf{x}_{nt}$$

where $\mathbf{P}^{G,r}$ is $n \times r$ and has the eigenvectors associated with the first r generalized eigenvalues of $\left(\mathbf{\Gamma}_0^\chi, \ \mathbf{\Gamma}_0^\xi\right)$ on the columns. The covariances $\mathbf{\Gamma}_h^\chi$ and $\mathbf{\Gamma}_h^\xi$ are then employed to project $\chi_{i,t+h}$ on the factors:

$$x_{i,t+h|t}^{FHLR} = \chi_{i,t+h|t}^{FHLR} = \boldsymbol{\gamma}_h \widehat{\mathbf{G}}_t, \tag{2.11}$$

with $\boldsymbol{\gamma}_h = \widehat{\boldsymbol{\Gamma}}_{\boldsymbol{h}}^{\boldsymbol{\chi}} \widehat{\boldsymbol{z}}^{\boldsymbol{g}'} \left(\widehat{\boldsymbol{z}}^{g} \widehat{\boldsymbol{\Gamma}}_{\mathbf{0}} \widehat{\boldsymbol{z}}^{\boldsymbol{g}'}\right)^{-1}$ (a dynamically more complex version, allowing for lags of the factors and x_{it}, as in (2.5), can be obtained in the same way). This predictor is based on Forni, Hallin, Lippi and Reichlin (2000, 2005). We refer to it as FHLR.

Although this method assumes a finite number of static factors, like SW, the dynamic structure of the dataset is exploited in the calculation of the covariance matrices $\mathbf{\Gamma}_k^\chi$ and $\mathbf{\Gamma}_k^\xi$. Estimation requires determining:
(i) the number of dynamic factors q (like in FHLZ),
(ii) kernel and lag window for the estimation of $\mathbf{\Sigma}^x(\theta)$ (like in FHLZ),

(iii) the number of static factors.

3 Data and Calibration of the Models

3.1 Data description, transformations, forecasts

The dataset consists of 115 U.S. macroeconomic and financial time series observed at monthly frequency between January 1959 and August 2014. The series are grouped into 12 main categories, see the Appendix for details.

To achieve stationarity the series are transformed into first difference of the logarithm (mainly real variables), first difference of yearly difference of the logarithm (prices and wages), first difference (interest rates). A few stationary series are taken in levels, see the Appendix for details. No treatment for outliers is applied.

Let $\mathbf{X_t} = (X_{1t},\ X_{2t},\ \dots,\ X_{nt})'$ be the raw dataset and $\mathbf{Z}_t = (Z_{1t},\ Z_{2t},\ \dots,\ Z_{nt})'$ its stationary version after the transformations are applied. The models are estimated using $\mathbf{Z}_t$ and the forecasts of $Z_{i,t+h}$, denoted $\hat{Z}_{i,t+h|t}$ are computed (for simplicity, $\hat{Z}_{i,t+h|t}$ contains no reference to the model used to compute it).

On the other hand, the targets of the final forecasts have been usually defined in the literature using our US monthly macroeconomic dataset, see e.g. Stock and Watson (2002b), D'Agostino and Giannone (2012), as the *level* of the (log of) Industrial Production Index (and of the real variables) and the *change*, yearly or monthly, of the (log of) Consumer Price Index (and of prices and wages). As Industrial Production, $\mathrm{IP}_t = X_{1t}$, is transformed by first difference of the logarithm, the target at time $t + h$ is

$$W_{1,t+h|t} = \log \mathrm{IP}_{t+h} - \log \mathrm{IP}_t = Z_{1,t+1} + \cdots + Z_{1,t+h},$$

so that

$$\hat{W}_{1,t+h|t} = \hat{Z}_{1,t+1|t} + \cdots + \hat{Z}_{1,t+h|t},$$

and the prediction error, normalized for the horizon's length,

$$\mathrm{FE}_{1,t,h} = \frac{1}{h}(\hat{W}_{1,t+h|t} - W_{1,t+h}) = \frac{1}{h}\Big((\hat{Z}_{1,t+1|t} - Z_{1,t+1}) + \cdots + (\hat{Z}_{1,t+h|t} - Z_{1,t+h})\Big).$$

For the consumer price index $\mathrm{CPI}_t = X_{77,t}$, which is transformed by $(1-L)(1-L^{12})\log$, the target is defined as

$$W_{77,t+h|t} = (1-L^{12})\log \mathrm{CPI}_{t+h} - (1-L^{12})\log \mathrm{CPI}_t.$$

Its forecast is obtained in the same way as $\hat{W}_{1,t+h|t}$. For series taken in levels the target is the series itself. Forecasts of the targets $W_{i,t+h}$ are computed and compared for $h = 6, 12, 24$ months ahead.

In addition to SW, FHLZ, FHLR, we compute forecasts obtained with a univariate AR. For all four methods we use a *rolling ten-year window* $[t-119,\ t]$, and the models are re-estimated for each t. The sample is split into a *calibration pre-sample*, from February 1960 (some observations at the beginning of the sample are lost due to the difference transformations) to January 1985, and the *sample proper*, from February 1985 to August 2014. The ten years from February 1975 to January 1985 are used to produce the first forecasts within the sample. Thus we start by predicting July 1985, January 1986, January 1987 for $h = 6,\ 12,\ 24$ respectively. The last forecast is 2014 for all horizons.

For each predictive model, the forecasting performance is evaluated by its mean square forecast error (MSFE), which is defined as follows:

$$\mathrm{MSFE}^m_{i,h} = \frac{1}{(T_1-h)-T_0+1}\sum_{\tau=T_0}^{T_1-h} \mathrm{FE}^2_{i,\tau,h}, \tag{3.1}$$

where (i) T_0 and T_1 denote the first and the last dates of the sample, (ii) the superscript m stands for the model used and ranges over SW, FHLR, FHLZ, AR. Replacing the limits of the summation in (3.1) with any time interval within the sample we can measure local forecasting performances. We also use the cumulated sums:

$$\sum_{\tau=T_0}^{t} \mathrm{FE}_{i,\tau,h}^2, \tag{3.2}$$

as a function of t, see Figure 1 in Section 4.1.

3.2 Calibration

The pre-sample period, February 1960 to January 1985, is used to calibrate the methods SW, FHLZ, FHLR and AR, i.e. to compare the forecasting performance of different specifications for each method. The best is then used in the sample for comparison between methods.

To illustrate calibration, consider for example the SW method and let $i = 1$, Industrial Production. A crucial parameter is the number r of static factors. We can determine it in different ways. In particular:

SW_1. Let $\mathbf{P}$ be the time interval starting with the 120-th date and ending with the last date in the pre-sample. For each $t \in \mathbf{P}$ the number r is determined, using the ten-year window $[t-119,\ t]$, according to Bai and Ng's criterion IC_2, see Bai and Ng (2002)[2]. No lags are allowed for the factors or the variable to be predicted, thus the prediction equation is (2.5) with $\beta_i(L) = 0$ and $\boldsymbol{\alpha}_i(L)$ of degree zero. The model is estimated over the window $[t-119,\ t]$ and the forecasts for $W_{i,t+h}$ computed. As $t+h$ varies from $120+h$ to the end of the pre-sample, we compute a mean square forecast error for each horizon, call it $\mathrm{MSFE}_{1,h}^{\mathrm{SW}_1}$.

SW_2. The parameter r is kept fixed as the window moves in the pre-sample. Again, no lag for the factors or the variable to be predicted are allowed. With r varying between, say, 3 and 7 we obtain five specifications with corresponding $\mathrm{MSFE}_{1,h}^{\mathrm{SW}_2,j}$, $j = 3, \ldots, 7$.

Note that different specifications can differ in the value of some parameters: different fixed values of r in SW_2, or in the procedure: fixed r as opposed to r determined by the Bai and Ng's criterion. Moreover, each of the six specifications

[2]We have run some experiments with other criteria, such as Alessi et al. (2010), Onatski (2009), with no significant differences.

above can be augmented by including lags of the predicted variable and the factors in the prediction equation, see Section 3.2.1.

To compare specifications m_1 and m_2 of method m at horizon $h = 6,\ 12,\ 24$ we use the ratio

$$\mathrm{RMSFE}_{i,h}^{m_1/m_2} = \frac{\mathrm{MSFE}_{i,h}^{m_1}}{\mathrm{MSFE}_{i,h}^{m_2}}. \tag{3.3}$$

Because in many cases no specification prevails uniformly across different horizons, we choose according to the average of the ratio (3.3) over all three horizons. The calibration procedure is limited to aggregate industrial production, $\mathrm{IP}_t = X_{1,t}$, consumer price, $\mathrm{CPI}_t = X_{77,t}$. The chosen specifications are then used, respectively, in the forecast of disaggregated real and nominal variables.

3.2.1 Calibration of SW.

It is easily seen that detailed consideration of all alternatives leads to thousands of alternatives:

(i) Like in SW_1, the number r is determined by one of Bai and Ng's criteria.

(ii) Like in SW_2, the number r is fixed as the window moves, with r to be chosen within an interval of values.

(iii) Lags are allowed for the variable to be predicted and the order of the polynomial $\beta_i(L)$ in (2.5) is determined by the AIC or the BIC criterion. Alternatives are the criterion and the maximum lag used in its application.

(iv) Same as in (ii) for the lags of the factors, i.e. the vector polynomial $\boldsymbol{\alpha}_i(L)$. Again, there are alternative critera and maximum lags.

(v) Same as in (ii) and (iii) with lags for both the factors and the predicted variable.

(vi) The lags in (iii), (iv) and (v) can be kept fixed as the window moves and be chosen within intervals of values.

On the other hand, choosing SW_1 and SW_2 as benchmarks and running some examples from categories (iii) to (vi), we find no evidence that lags in the factors and the predicted variable, in addition to the factors at t, do help predicting CPI_{t+h} or IP_{t+h}, for $h = 6,\ 12,\ 24$, in the pre-sample period. Thus we limit our exploration of the "cartesian product" of the alternatives outlined above to the following steps.

S1. We compute the ratios $\text{RMSFE}_{i,h}^{m_1/m_2}$ where: (1) m_2 is SW_2 with r equal to 5, (2) m_1 is either SW_1 or SW_2 with $r = 1, \ldots, 8$, (3) $i = 1$ (IP) or $i = 77$ (CPI), (4) $h = 6,\ 12,\ 24$. The results are reported in Table 1, Panel SW:*S1.* We see that the best models are: (I) SW_2 with $r = 6$ for IP with $r = 7, 8$ very close, (II) SW_2 with $r = 5$ for CPI, the second best being SW_1. The two best models are denoted by $\text{SW}_2(6)$ and $\text{SW}_2(5)$ respectively.
S2. Now we run the prediction equation (2.5) with $r = 6$, $r = 5$ for IP and CPI respectvely, augmented with lags for the predicted variable. The degree of $\beta_i(L)$ is determined by the AIC and the BIC criteria setting the maximum number of lags to 15. The results are reported in the Panel SW:*S2* of Table 1, the benchmark for the RMSFE being $\text{SW}_2(6)$ for IP and $\text{SW}_2(5)$ for CPI. For both IP and CPI the best result is obtained using the BIC criterion. On average they are are worse though not far from $\text{SW}_2(6)$ and $\text{SW}_2(5)$ respectively.
S3 and S4. Now the models $\text{SW}_2(6)$ and $\text{SW}_2(5)$ augmented with lags of the factors are run. The degree of $\boldsymbol{\alpha}_i(L)$ is determined by the AIC and the BIC criteria setting the maximum numer of lags to 15. Again, the results are worse as compared to $\text{SW}_2(6)$ and $\text{SW}_2(5)$ and are not reported, with the exception of that obtained with the BIC criterion for IP, which is 1.03 on average over h. Lastly, $\text{SW}_2(6)$ and $\text{SW}_2(5)$ are augmented with both lags of the factors and of the predicted variable. The results are very poor (see Table 1, Panel SW:*S3, S4*).

In conclusion, our exploration of the space of possible SW specifications points to $\text{SW}_2(6)$ and $\text{SW}_2(5)$ as good models for IP and CPI respectively. They are our first choice for SW in the in-sample comparison.

3.2.2 Calibration of FHLZ

S1, order of the variables. FHLZ is based on equations (2.9) and (2.10), which are obtained from inversion of (2.6). Now, a change in the order of the variables x_{it} and χ_{it} obviously causes a change in the matrices $\mathbf{A}^k(L)$ and $\mathbf{R}^k$ in (2.6). However, under mild assumptions, see Forni et al. (2016), no change occurs in the (infinite) moving average polynomials in (2.8). For example, the q moving average polynomials of χ_{1t}

in (2.8) do not change if the variables χ_{it}, $i = 2, \ldots, q+1$ are replaced by other variables in the first block of size $q+1$.

Things change when $\mathbf{A}^k(L)$ and $\mathbf{R}^k$ are replaced by their estimated counterparts $\hat{\mathbf{A}}^k(L)$ and $\hat{\mathbf{R}}^k$. Because the idiosyncratic components have not yet been erased and because their size is heterogeneous, each of the estimated polynomials in (2.8) depends on the grouping of the variables x_{it}. An obvious course of action, see Forni et al. (2016), consists in averaging over the predictions produced using different random permutations of the x's. We determine the number of permutations N_{per} by the procedure described below.

(i) Preliminary comparisons suggest the following specification. The Triangular Kernel and $B = 30$ (the bandwidth corresponding to a five-year window) for the estimation of the spectral density of the observable vector. The dimension q is determined at each t by means of the Hallin-Liška criterion, see Hallin and Liška (2007). We then determine the order of the $(q+1)$-dimensional VAR's by the BIC criterion with maximum lag 5.

(ii) Let $s_1, \ldots, s_{10}$ be 10 seeds (random number generators). Using the Matlab command `randsample`, we produce N_{per} permutations for each seed.

(iii) Denote by $\text{AMSFE}(N_{\text{per}}, s_k, h, i)$ the average of the MSFE, over the N_{per} permutations corresponding to the seed s_k, the horizon h and the variable i, the latter being either IP or CPI.

(iv) We then define:

$$\mu(N_{\text{per}}, h, i) = \max_k \left(\text{AMSFE}(N_{per}, s_k, h, i)\right) / \min_k \left(\text{AMSFE}(N_{per}, s_k, h, i)\right),$$

the maximum ratio between AMSFE's across seeds, and

$$\nu(N_{\text{per}}, i) = \max_h \mu(N_{\text{per}}, h, i).$$

In the Panel FHLZ: *S1* of Table 2 we report the values of $\nu(N_{\text{per}}, i)$ for IP and CPI, for N_{per} taking some values from 1 to 150. We see that ν gets stabilized for N_{per} between 50 and 150. All the specifications compared below are run with $N_{\text{per}} = 100$.

The remaining steps of the calibration of FHLZ are the following.

S2. We compare the specification described in (i) above with the one in which the BIC is replaced by the AIC criterion to determine order of the $(q+1)$-dimensional VAR's. In both cases the maximum lag 5 and $N_{\text{per}} = 100$. The results are shown in the Panel FHLZ: *S2* of Table 2, with the model using the BIC criterion taken as benchmark. The AIC criterion shows some advantage and is therefore adopted. Call it FHLZ1.

S3 and S4. We try different maxima for the maximum lag in the AIC criterion, from 3 to 7. Taking FHLZ1 as benchmark, the best result is 1.000 (see Table 2, Panel FHLZ: *S3*). The same flatness is obtained when we try different values for the bandwidth: 25, 35 and 40 (see Table 2, Panel FHLZ: *S4*). Thus we stick to FHLZ1 as our preferred specification.

Some experiments using fixed values for q or the alternative criterion to determine q in Onatski (2009) do not produce significant changes.[3] The same applies to different shapes of the Kernel for the estimation of the spectral density.

3.2.3 Calibration of FHLR

S1. We use the Triangular Kernel, determine q by the Hallin-Liška criterion, and compare the results with different values of B. We choose $B = 40$, which improves CPI predictions at 12- and especially 24-step ahead with respect to those obtained with $B = 30$ (see Table 3).

4 Results

4.1 Industrial Production and Inflation

We now compare the performance of the factor models in the prediction of IP and CPI over the sample starting with February 1985. For FHLZ and FHLR we stick to the specifications selected in the previous section. For SW we ran in the sample

[3]The criterion to determine q in Amengual and Watson (2007) only applies under the finite-dimension assumption, see Section 2.

several of the specifications that were discarded in the pre-sample. None of them outperforms $\mathrm{SW}_2(5)$ for CPI. However, $\mathrm{SW}_2(5)$ outperforms $\mathrm{SW}_2(6)$ for IP, the latter having been selected in the calibration. Table 4 reports the results obtained with both $\mathrm{SW}_2(5)$ and $\mathrm{SW}_2(6)$ for IP. However, when commenting on SW we always refer to $\mathrm{SW}_2(5)$, i.e. the specification performing better in the sample.

The common benchmark for the factor models is the univariate AR. We determine the number of lags for each window by the BIC criterion with maximum lag 13. This is the best among several specifications in the sample.

In Table 4 we report the average performance, measured by the RMSFE, of the three factor models relative to AR for our main variables of interest, namely IP and CPI. We give results for the Great Moderation, or pre-crisis period, starting with February 1985 and ending at December 2007, the beginning of the Great Recession (from December 2007 to June 2009), Panel A, and the *full sample* period, from February 1985 to September 2014, Panel B. We use one, two or three asterisks to indicate that the null of equal performance of the three factor models relative to AR is rejected at the 1%, 5%, 10% significance level, respectively, by the Diebold-Mariano test, see Diebold and Mariano (1995). One, two or three daggers indicate the for FHLZ or FHLR same with respect to SW. All the p-values are reported in Table 5.

The reason for splitting the sample is that the forecast performance of all methods, absolute and relative to one another, changes dramatically during the Great Recession. This is clearly illustrated in the lower graph in Figure 1, which shows the cumulated sum of the square forecast errors for CPI for all methods at horizon 6, see (3.2). The shaded areas correspond to recessionary periods according to the NBER. We observe a steady increase of the cumulated sums in the pre-crisis period, a dramatic jump during the Great Recession, followed by another period of steady increase after the crisis. All the crossings take place during or immediately after the Great Recession. The graphs for the other horizons and for IP show the same pattern.[4]

[4] Using the graph of the MSFEs at t instead of the cumulated sums would give a less clear picture of the relative performance.

Further graphic evidence is provided in Figures 2 and 3. The solid line is the graph of the difference between the Square Forecast Error with methods m_1 and m_2, FHLZ and SW for example, relative to IP and CPI, at each horizon, normalized by its estimated standard deviation and smoothed by a centered moving average of length $m = 61$, with the coefficients equal to $1/m$. Giacomini and Rossi (2010) use it to test against the null of equal local performance of two forecasting methods. The zero horizontal line indicates equal performance, the dotted lines indicate the 5% critical values, so that m_1 outperforms (underperforms) m_2 locally, at the 5% significance level, when the solid line is below (above) the lower (upper) dashed line. Because the moving averages are centered of length 61, the last 30 values are not computed or graphed.

- IP. We see that on average FHLZ outperforms the other three methods in the pre-crisis period, significantly both with respect to AR and SW, see Panel A in Table 4. The performance of FHLZ is somewhat improving before the crisis with respect to the three other methods at horizons 12 and 24, see Figure 2. During the crisis, see again Figure 2, SW and FHLR behave significantly better than FHLZ and AR, while AR performs significantly better than FHLZ. However, with the end of the crisis almost all the solid lines are clearly heading back to the pre-crisis pattern. On average over the whole sample, FHLZ is outperformed by FHLR and SW at horizons 6 and 12. All methods do better than AR with the exception of SW at horizon 24, see Panel B in Table 4.

- CPI. In the pre-crisis period, FHLZ outperforms significantly the other methods on average, see Panel A in Table 4. In this case the crisis has a negative effect on the performance of all three factor methods as compared to AR, see Figure 3. However, on average over the full sample, the best method remains FHLZ, with the exception of horizon 24, for which it is outperformed by SW. In many cases, though not as regularly as for IP, with the end of the crisis the solid lines in Figure 3 go back to the pre-crisis pattern.

To partially understand our results let us recall that the factor models employed here are based on the assumption of stationarity and co-stationarity (after suitable transformations) of the variables in the dataset, while the AR method only requires stationarity of the variable to be predicted. During the Great Moderation, when such assumptions are by and large fulfilled, the relative performance of the factor models and the AR change little (see again the pre-crisis period in Figures 2 and 3 as well as in the lower graph in Figure 1). In particular, FHLZ outperforms the other methods, consistently with the results obtained with simulated stationary data in Forni et al. (2016).

On the other hand, as soon as the crisis breaks out the covariance structure of the dataset changes abruptly. This is roughly but convincingly described in the upper graph in Figure 1, where we plot the sum of squares

$$\sum_{\tau=1}^{t} \sum_{i=1}^{115} z_{i\tau}^2,$$

where z_{it} is equal to Z_{it} after standardization. We observe a steady growth except for the recession periods, with a particularly sharp increase in the slope during the Great Recession. The latter corresponds to the dramatic deterioration of the predictive performance of all methods. More specifically, the sudden change in the covariance structure of the dataset may affect the forecasting performance of the factor and AR models in two ways:

(I) The targets themselves exhibit instability. This is the only possible cause of deterioration for the AR model. Figure 4 shows the target variables, i.e. $\log(\text{IP})$ and $(1 - L^{12})\log(\text{CPI})$. Though both variables are non-stationary, a marked change of behaviour of IP in the Great Recession is fairly obvious, both absolutely and in comparison to CPI, which only exhibits a mild increase in volatility.

(II) The estimation of the factors and of the loadings, i.e. the coefficients in (2.5), (2.10), (2.11), take time to adjust. This only affects the factor models.

In the case of CPI, where (I) is less important as a cause of prediction deterioration, all factor models loose ground with respect to the AR model. FHLZ remains the best method, though by little with respect to AR. Moreover, in this relatively less unstable situation, the performance of the factor models relative to one another does not change much.

In the case of Industrial Production, with both (I) and (II) affecting the predictions, FHLR and SW, which are simpler as compared to FHLZ, exhibit more robustness with respct to FHLZ and AR. [5]

4.2 Forecasting the whole dataset

The pseudo real-time exercise is then extended for each time series in the dataset. We should recall that a good forecasting performance of factor models can be expected when the variable contains a substantial common component. On the other hand, if the dynamic behaviour of a variable is dominated by that of its idiosyncratic component, then univariate methods are likely to prevail. Therefore, as in Stock and Watson (2012), we exclude from the evaluation the variables associated with a superior forecasting performance of AR. Precisely, in our exercise we rule out the variables whose AR prediction is at least 10 percent more accurate for at least one predictive horizon and for all the three factor models. We find 23 such variables. In particular, those belonging to the housing category (category 4 in Table 8) do not survive[6]. For real variables we use the specification adopted for IP, while for the nominal variables that adopted for CPI.

For every group of variables, in Table 6 we report the mean RMSE within the group. The best performance is given in bold. We see that FHLZ and FHLR generally perform better than SW, the latter being the most accurate only for the employment 6 and 12 steps ahead. All in all, FHLR is more accurate for the real variables, i.e. IP, Employment, Unemployment Rate, Inventories, while FHLZ is more accurate for nominal variables, i.e. Prices, Wages, Interest Rates, Money and Stock Prices. For

[5]The effect of data instability on forecasting with factor models has been studied in D'Agostino et al. (2007), D'Agostino et al. (2013), Clements (2015).

[6]These conclusions apply to our monthly dataset. In other works, with quarterly datasets, dynamic factor models are successfully applied to housing market data, see Luciani (2015), Stock and Watson (2008) and Moench and Ng (2011).

Exchange Rates and Wages at horizon 12 the AR is still the most accurate model. Considering median values rather than means we obtain similar results.

In Table 7 the distribution of the RMSE of the models is calculated excluding the same variables as before. Only FHLZ improves at every horizon upon AR for more than the half of the series. FHLR does so only 24-step ahead, is less accurate than AR 6-step ahead by 4.1 percent and 2.1 percent 12-step ahead. Furthermore, FHLZ is roughly as accurate as AR even at his 75-th percentile. SW is outperformed by frequency domain models at most percentiles and horizons. His performance deteriorates as the predictive horizon increases while the contrary holds for FHLR and FHLZ. Within the frequency domain methods FHLZ performs better at the 95-th percentile and FHLR is more accurate at the 5-th percentile.

5 Conclusions

The paper has compared the forecasting performance of FHLZ, FHLR and SW over a time period including the Great Moderation, the Great Depression and the subsequent recovery. We find that during the Great Moderation, when the dataset is relatively stationary (after suitable transformations), FHLZ neatly prevails for both IP and CPI.

Over the full sample, the performance of FHLZ remains the best for CPI, though all factor models loose ground with respect to the simple AR model. FHLR and SW, in this order, become the best models over the full sample for IP, thus exhibiting more robustness than FHLZ in a situation where both the target variable and the whole dataset undergo instability.

Forecasting each single series in the dataset for the full sample confirms the above results, with FHLZ being the best method for the nominal variables, FHLR for the real variables.

The two methods based on frequency-domain estimation methods, FHLZ and FHLR, perform very well. The more general dynamic structure of FHLZ is an advantage in "stationary" periods but may be a weakness in some cases during periods of instability.

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Table 1: Calibration: SW

Panel SW: *S1* - number of static factors

h	IP(1)	IP(2)	IP(3)	IP(4)	IP(5)	IP(6)	IP(7)	IP(8)	IP(BN)
6	1.562	1.066	1.040	1.069	1.0	0.911	0.928	0.932	0.963
12	1.469	0.987	0.961	1.014	1.0	0.915	0.967	0.969	1.004
24	1.095	0.910	0.931	0.983	1.0	0.952	0.934	0.949	0.994
mean	1.376	0.988	0.977	1.022	1.0	0.926	0.943	0.950	0.987

h	CPI(1)	CPI(2)	CPI(3)	CPI(4)	CPI(5)	CPI(6)	CPI(7)	CPI(8)	CPI(BN)
6	1.179	1.164	1.034	1.017	1.0	1.055	1.114	1.151	1.010
12	1.173	1.252	1.095	1.051	1.0	1.080	1.209	1.240	1.025
24	1.338	1.289	1.167	1.148	1.0	1.036	1.059	1.122	1.093
mean	1.230	1.235	1.099	1.072	1.0	1.057	1.127	1.171	1.043

Panel SW: *S2* - target lag order $\beta_i\left(L\right)$

h	IP(1)	CPI(1)	IP(BIC)	CPI(BIC)	IP(AIC)	CPI(AIC)
6	1.0	1.0	1.003	1.095	0.999	0.963
12	1.0	1.0	1.048	1.074	1.047	1.011
24	1.0	1.0	1.040	1.028	1.048	1.123
mean	1.0	1.0	1.030	1.066	1.031	1.033

Panel SW: *S3* - factors lag order $\alpha_i\left(L\right)$

h	IP(0)	CPI(0)	IP(BIC)	CPI(BIC)	IP(AIC)	CPI(AIC)
6	1.0	1.0	1.101	1.121	1.424	1.206
12	1.0	1.0	1.034	1.258	1.070	1.432
24	1.0	1.0	1.008	1.129	1.145	1.349
mean	1.0	1.0	1.048	1.169	1.213	1.329

Panel SW: *S4* - target and factors lag order $\beta_i\left(L\right)$, $\alpha_i\left(L\right)$

h	IP(1,0)	CPI(1,0)	IP(BIC,BIC)	CPI(BIC,BIC)	IP(AIC,AIC)	CPI(AIC,AIC)
6	1.0	1.0	1.134	1.126	1.418	1.120
12	1.0	1.0	1.069	1.287	1.140	1.275
24	1.0	1.0	1.048	1.195	1.234	1.532
mean	1.0	1.0	1.084	1.203	1.264	1.309

Table 2: Calibration: FHLZ

Panel FHLZ: *S1* - order of the variables

N_{per}	1	10	25	50	100	150
IP	1.348	1.103	1.064	1.040	1.027	1.021
CPI	1.494	1.150	1.083	1.068	1.045	1.041

Panel FHLZ: *S2* - lag order criterion

h	IP(AIC)	CPI(AIC)	IP(BIC)	CPI(BIC)
6	0.980	0.960	1.0	1.0
12	0.982	0.965	1.0	1.0
24	0.975	0.980	1.0	1.0
mean	0.979	0.968	1.0	1.0

Panel FHLZ: *S3* - max lag order

h	IP(3)	CPI(3)	IP(4)	CPI(4)	IP(5)	CPI(5)	IP(6)	CPI(6)	IP(7)	CPI(7)
6	1.002	1.001	1.000	1.001	1.0	1.0	1.000	1.000	0.999	1.000
12	1.002	1.001	1.001	1.001	1.0	1.0	1.000	1.000	1.000	1.000
24	1.001	1.001	1.000	1.001	1.0	1.0	1.000	1.000	1.000	1.000
mean	1.002	1.001	1.000	1.001	1.0	1.0	1.000	1.000	1.000	1.000

Panel FHLZ: *S4* - bandwidth

h	IP(25)	CPI(25)	IP(30)	CPI(30)	IP(35)	CPI(35)	IP(40)	CPI(40)
6	0.998	1.003	1.0	1.0	0.998	0.996	1.004	0.997
12	0.996	1.002	1.0	1.0	1.000	1.000	1.003	1.000
24	0.994	1.000	1.0	1.0	1.002	1.000	1.006	1.000
mean	0.996	1.002	1.0	1.0	1.000	0.999	1.004	0.999

Table 3: Calibration: FHLR

FHLR: *S1* - bandwidth

h	IP(25)	CPI(25)	IP(30)	CPI(30)	IP(35)	CPI(35)	IP(40)	CPI(40)
6	1.018	1.011	1.0	1.0	1.011	1.004	1.008	1.012
12	1.006	1.030	1.0	1.0	1.005	0.996	0.995	0.985
24	0.992	1.042	1.0	1.0	1.012	0.971	1.002	0.943
mean	1.006	1.028	1.0	1.0	1.009	0.990	1.001	0.980

Table 4: Mean Square Forecast Error Relative to AR

Panel A : Pre Crisis $(1985:1-2007:11)$

IP				
	FHLZ	FHLR	$SW_2(5)$	$SW_2(6)$
h=6	$0.847^{***\dagger\dagger}$	$0.986^{\dagger\dagger}$	1.054	1.064
h=12	$0.897^{***\dagger}$	$0.995^{\dagger\dagger}$	1.100	1.192
h=24	$0.968^{*\dagger}$	$0.960^{\dagger\dagger}$	1.137	1.323
mean	0.904	0.980	1.097	1.193

CPI			
	FHLZ	FHLR	SW
h=6	$0.920^{*\dagger}$	1.022	1.040
h=12	$0.840^{**\dagger}$	$0.941^{\dagger\dagger}$	1.025
h=24	0.862^{***}	0.823	0.850
mean	0.874	0.929	0.972

Panel B : Full Sample $(1985:1-2014:8)$

IP				
	FHLZ	FHLR	$SW_2(5)$	$SW_2(6)$
h=6	0.950	0.868	0.861	0.904
h=12	0.942	0.879	0.862	0.982
h=24	0.970	$0.929^{**\dagger\dagger}$	1.061	1.174
mean	0.954	0.892	0.928	1.020

CPI			
	FHLZ	FHLR	SW
h=6	$0.948^{\dagger\dagger}$	1.086	1.144
h=12	$0.997^{\dagger\dagger\dagger}$	1.152	1.060
h=24	1.037	1.014	0.953
mean	0.994	1.084	1.052

We use one, two or three asterisks to indicate that the null of equal performance of the three factor models relative to AR is rejected at the 1%, 5%, 10% significance level, respectively, by the Diebold-Mariano test. One, two or three daggers indicate the for FHLZ or FHLR same with respect to SW. All the p-values are reported in Table 5.

Table 5: Diebold-Mariano test: p-values

Panel A : Pre Crisis $(1985:1-2007:11)$

IP							
	FHLZ vs SW_2 (5)	FHLR vs SW_2 (5)	FHLZ vs FHLR	FHLZ vs AR	FHLR vs AR	SW_2 (5) vs AR	SW_2 (6) vs AR
h=6	0.049	0.027	0.097	0.003	0.444	0.679	0.722
h=12	0.051	0.031	0.109	0.000	0.479	0.776	0.937
h=24	0.068	0.044	0.560	0.094	0.254	0.909	0.976

CPI						
	FHLZ vs SW	FHLR vs SW	FHLZ vs FHLR	FHLZ vs AR	FHLR vs AR	SW vs AR
h=6	0.071	0.218	0.077	0.091	0.527	0.583
h=12	0.074	0.016	0.154	0.019	0.309	0.528
h=24	0.523	0.319	0.605	0.007	0.174	0.259

Panel B : Full Sample $(1985:1-2014:8)$

IP							
	FHLZ vs SW_2 (5)	FHLR vs SW_2 (5)	FHLZ vs FHLR	FHLZ vs AR	FHLR vs AR	SW_2 (5) vs AR	SW_2 (6) vs AR
h=6	0.712	0.542	0.765	0.300	0.130	0.130	0.226
h=12	0.708	0.630	0.727	0.500	0.152	0.189	0.463
h=24	0.129	0.012	0.783	0.500	0.019	0.980	0.939

CPI						
	FHLZ vs SW	FHLR vs SW	FHLZ vs FHLR	FHLZ vs AR	FHLR vs AR	SW vs AR
h=6	0.025	0.210	0.052	0.393	0.670	0.740
h=12	0.001	0.767	0.032	0.493	0.729	0.644
h=24	0.735	0.784	0.612	0.600	0.545	0.364

Table 6: Mean RMSE by category

FHLZ			
	h=6	h=12	h=24
IP	0.948	0.923	0.976
Employment	1.131	1.069	0.979
Unemployment Rate	0.873	0.907	0.938
Inventories	1.005	0.927	0.984
Prices	**0.978**	1.008	**0.987**
Wages	**0.977**	**0.990**	**0.986**
Interest Rates	**0.989**	**0.983**	**0.950**
Money	**0.870**	**0.864**	**0.753**
Exchange Rates	1.015	1.014	1.010
Stock Prices	**0.975**	**0.972**	**0.945**

FHLR			
	h=6	h=12	h=24
IP	**0.929**	**0.902**	**0.966**
Employment	0.985	0.947	**0.908**
Unemployment Rate	**0.666**	**0.723**	**0.853**
Inventories	**0.951**	**0.893**	**0.970**
Prices	1.111	1.153	1.035
Wages	1.077	1.049	0.967
Interest Rates	1.123	1.138	1.074
Money	0.900	0.930	0.790
Exchange Rates	1.072	1.067	1.014
Stock Prices	1.020	1.090	1.011

SW			
	h=6	h=12	h=24
IP	0.950	0.915	1.114
Employment	**0.939**	**0.940**	1.005
Unemployment Rate	0.684	0.737	0.968
Inventories	1.037	0.973	1.239
Prices	1.224	1.162	1.069
Wages	1.151	1.121	1.123
Interest Rates	1.321	1.521	1.546
Money	0.980	0.936	0.878
Exchange Rates	1.176	1.148	1.137
Stock Prices	1.248	1.340	1.305

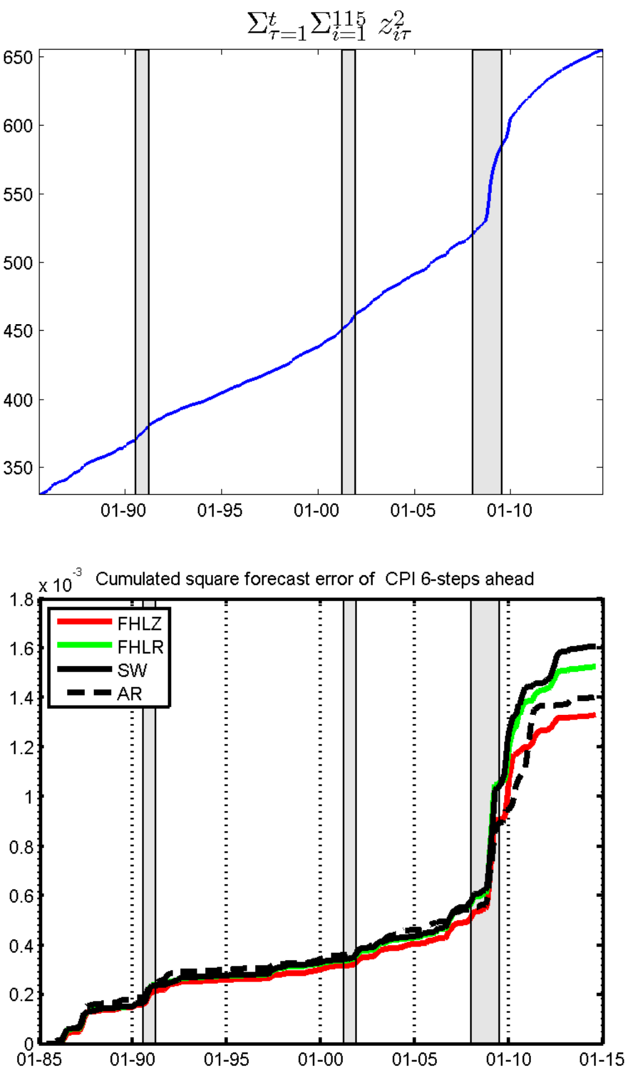
Table 7: Distribution RMSE

FHLZ					
Percentile:	0.05	0.25	0.50	0.75	0.95
h=6	0.819	0.925	0.987	1.018	1.219
h=12	0.845	0.924	0.982	1.013	1.136
h=24	0.817	0.942	0.983	1.012	1.068

FHLR					
Percentile:	0.05	0.25	0.50	0.75	0.95
h=6	0.639	0.933	1.041	1.122	1.183
h=12	0.696	0.915	1.021	1.136	1.257
h=24	0.775	0.900	0.981	1.057	1.210

SW					
Percentile:	0.05	0.25	0.50	0.75	0.95
h=6	0.650	0.955	1.120	1.226	1.382
h=12	0.667	0.910	1.071	1.189	1.613
h=24	0.730	0.963	1.075	1.286	1.626

Figure 1: Graph of $\sum_{\tau=1}^{t}\sum_{i=1}^{115} z_{i\tau}^2$ and Cumulated Sum of Square Forecast Error, 6-step ahead, CPI



Shaded areas indicate NBER recession dates

Figure 2: Fluctuation test (IP)

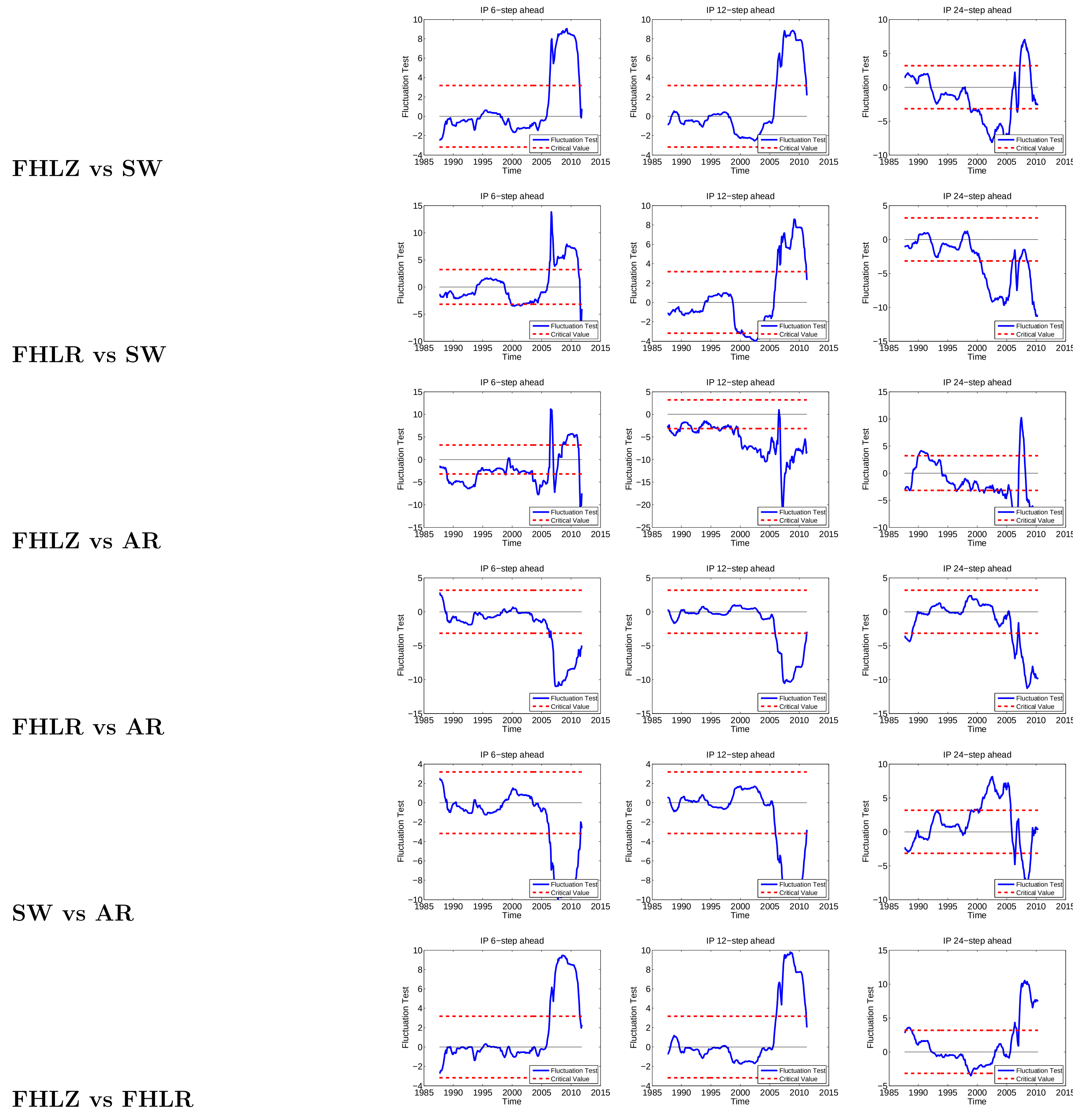
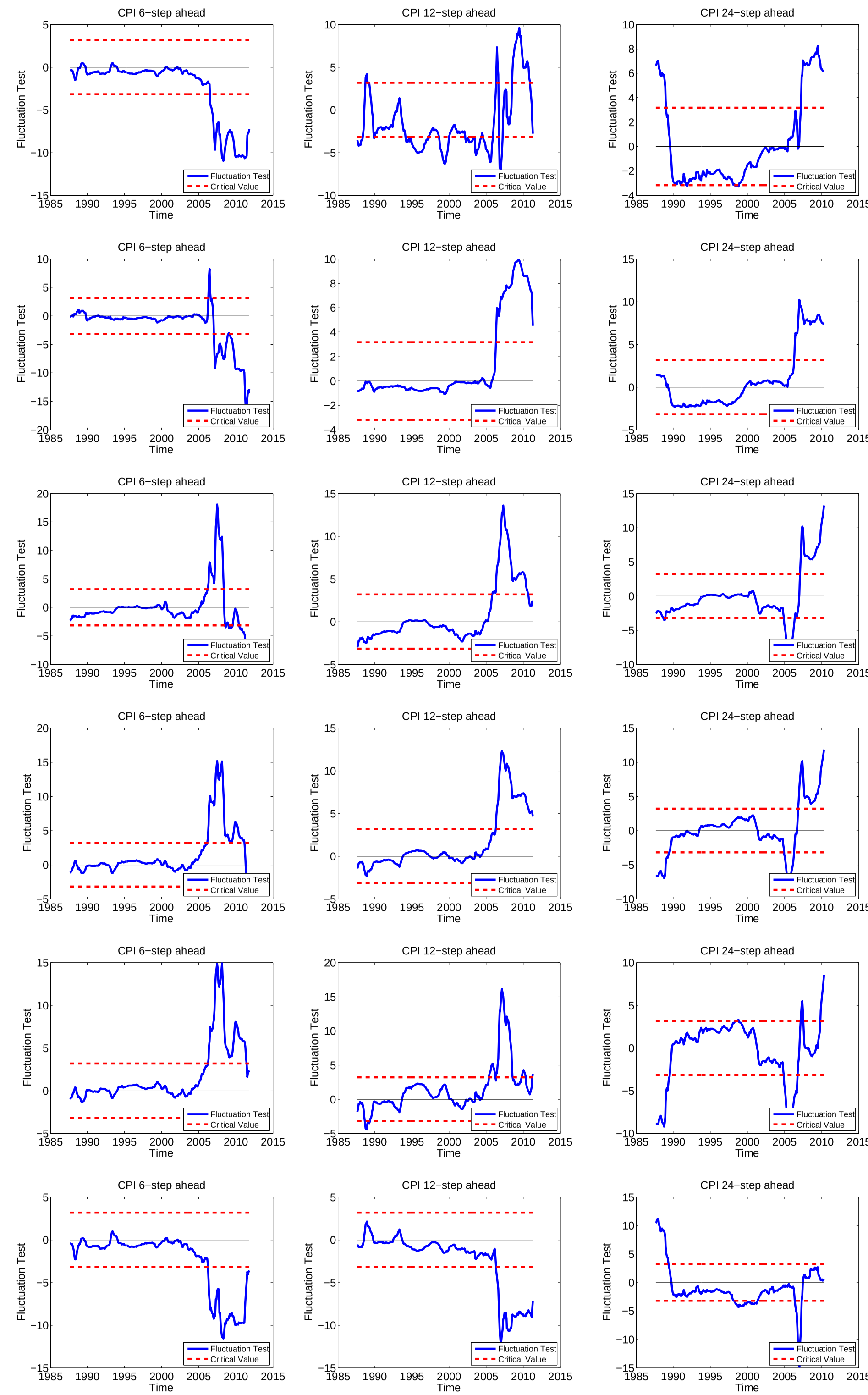


Figure 3: Fluctuation test (CPI)



FHLZ vs SW

FHLR vs SW

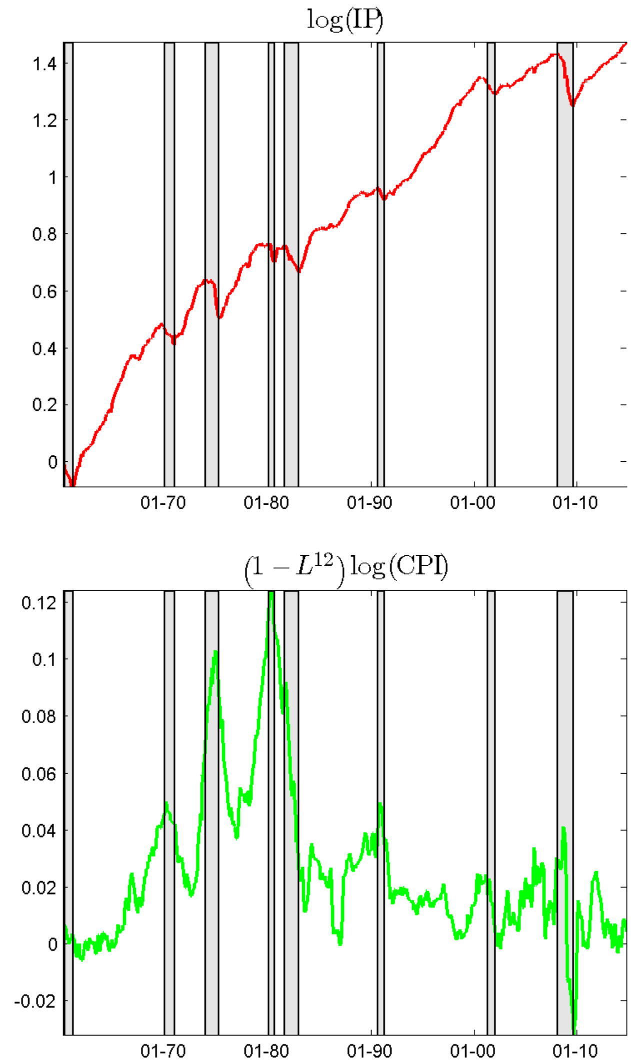
FHLZ vs AR

FHLR vs AR

SW vs AR

FHLZ vs FHLR

Figure 4: Target variables, log(IP) and $(1 - L^{12})\log(\text{CPI})$



Shaded areas indicate NBER recession dates

Appendix: Dataset and transformations

We give here a description of the dataset, the transformation applied to each series and the category to which they belong. We use an updated version of the database in Stock and Watson (2012) and their classification in categories. Stock and Watson's monthly section consists of 108 US macroeconomic time series over the period from January 1959 through December 2009. All the series could be updated through August 2014, with the exception of

1. Index Of Help-Wanted Advertising In Newspapers (1967=100;Sa),
2. Employment: Ratio; Help-Wanted Ads:No. Unemployed Clf,

which were therefore excluded. The following Consumer Price series, used in Stock and Watson (2005), have been added:

1. Consumer Price Index for All Urban Consumers: All Items Less Food,
2. Consumer Price Index for All Urban Consumers: All items less medical care,
3. Consumer Price Index for All Urban Consumers: All items less shelter,
4. Consumer Price Index for All Urban Consumers: Apparel,
5. Consumer Price Index for All Urban Consumers: Commodities,
6. Consumer Price Index for All Urban Consumers: Durables,
7. Consumer Price Index for All Urban Consumers: Medical Care,
8. Consumer Price Index for All Urban Consumers: Services,
9. Consumer Price Index for All Urban Consumers: Transportation,

The final database contains 115 monthly macroeconomic time series. While this work was yet in preparation, a similar, publicly available[7] and constantly updated

[7] The website is: `http://research.stlouisfed.org/econ/mccracken/sel/`.

dataset described by McCracken and Ng (2015) has been made available by the Federal Reserve Bank of St. Louis. We leave its analysis to future research.

The Transformation Codes, Tcode in Table 8, are as follows. Calling X_t a raw series, the transformations adopted are:

$$Z_t = \begin{cases} X_t & \text{if Tcode=1} \\ (1-L)X_t & \text{if Tcode=2} \\ (1-L)(1-L^{12})X_t & \text{if Tcode=3} \\ \log X_t & \text{if Tcode=4} \\ (1-L)\log X_t & \text{if Tcode=5} \\ (1-L)(1-L^{12})\log X_t & \text{if Tcode=6} \end{cases}$$

Table 8: List of the series

N	Mnemonic	Description	Tcode	Category
1	USIPTOT.G	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA	5	2
2	USIPMPROH	US INDL PROD - PRDS, TOTAL VOLN	5	2
3	USIPMFING	US INDL PROD - FINAL PRODUCTS, TOTAL VOLA	5	2
4	USIPMCOGG	US INDL PROD - CONSUMER GOODS VOLA	5	2
5	USIPMDUCG	US INDL PROD - DURABLE CONSUMER GOODS VOLA	5	2
6	USIPMNOCG	US INDL PROD - NONDURABLE CONSUMER GOODS VOLA	5	2
7	USIPMBUQG	US INDL PROD - BUSINESS EQUIPMENT VOLA	5	2
8	USIPMMATG	US INDL PROD - MATERIALS, TOTAL VOLA	5	2
9	USIPMDUMH	US INDL PROD - DURABLE GOODS MATERIALS VOLN	5	2
10	USIPMNDMG	US INDL PROD - NONDURB GOODS MATERIALS VOLA	5	2
11	USIPMFGSG	US INDUSTRIAL PRODUCTION - MANUFACTURING (SIC) VOLA	5	2
12	USIP512UG	US INDL PROD - RESIDENTIAL UTILITIES VOLA	5	2
13	USIP512FG	US INDL PROD - FUELS VOLA	5	2
14	NAPM	ISM Manufacturing: PMI Composite Index	1	2
15	MCUMFN	Capacity Utilization: Manufacturing (NAICS)	1	2
16	AHE: goods	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - GOODS-PRODUCING	6	8
17	AHE: const	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION	6	8
18	AHE: mfg	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG	6	8
19	Real AHE: goods	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - GOODS-PRODUCING	5	8
20	Real AHE: const	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION	5	8
21	Real AHE: mfg	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG	5	8
22	USEMIP..O	US EMPLOYED - TOTAL PRIVATE VOLA	5	3
23	USEMPG..O	US EMPLOYED - GOODS-PRODUCING VOLA	5	3
24	CES1021000001	EMPLOYEES, NONFARM - MINING	5	3
25	USEM23..O	US EMPLOYED - CONSTRUCTION VOLA	5	3
26	USEMPMANO	US EMPLOYED - MANUFACTURING VOLA	5	3
27	USEMIMD.O	US EMPLOYED - DURABLE GOODS VOLA	5	3
28	USEMIMN.O	US EMPLOYED - NONDURABLE GOODS VOLA	5	3
29	USEMPS..O	US EMPLOYED - SERVICE-PROVIDING VOLA	5	3
30	USEMIT..O	US EMPLOYED - TRADE, TRANSPORTATION, & UTILITIES VOLA	5	3
31	USEM42..O	US EMPLOYED - WHOLESALE TRADE VOLA	5	3
32	USEMIR..O	US EMPLOYED - RETAIL TRADE VOLA	5	3
33	USEMIF..O	US EMPLOYED - FINANCIAL ACTIVITIES VOLA	5	3
34	USEMIG..O	US EMPLOYED - GOVERNMENT VOLA	5	3
35	USEMPTOTO	US TOTAL CIVILIAN EMPLOYMENT VOLA	5	3
36	USEMPALLO	US EMPLOYED - NONFARM INDUSTRIES TOTAL (PAYROLL SURVEY) VOLA	5	3
37	UNRATE	Civilian Unemployment Rate	2	4
38	UEMPMEAN	Average (Mean) Duration of Unemployment	2	4
39	USUNWK5.O	US UNEMPLOYED FOR LESS THAN 5 WEEKS VOLA	5	4
40	USUNWK14O	US UNEMPLOYED FOR 5 TO 14 WEEKS VOLA	5	4
41	USUNPLNGE	US UNEMPLOYED FOR 15 WEEKS OR MORE VOLA	5	4
42	USUNWK26O	US UNEMPLOYED FOR 15 TO 26 WEEKS VOLA	5	4
43	USUNWK27O	US UNEMPLOYED FOR 27 WEEKS & OVER VOLA	5	4
44	USHKPG..P	US AVG HOURS PROD WRKRS-GOODS-PRODUCING VOLN	1	3
45	USHXPMANO	US AVG OVERTIME HOURS - MANUFACTURING VOLA	2	3
46	USHOUSATE	US NEW PRIVATE HOUSING UNITS AUTHORIZED BY BLDG.PERMIT (AR) VOLA	4	5
47	USHOUSE.O	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA	4	5
48	HOUSTNE	Housing Starts in Northeast Census Region	4	5
49	HOUSTMW	Housing Starts in Midwest Census Region	4	5
50	HOUSTS	Housing Starts in South Census Region	4	5
51	HOUSTW	Housing Starts in West Census Region	4	5
52	FEDFUNDS	Effective Federal Funds Rate	2	9
53	TB3MS	3-Month Treasury Bill: Secondary Market Rate	2	9
54	TB6MS	6-Month Treasury Bill: Secondary Market Rate	2	9
55	GS1	1-Year Treasury Constant Maturity Rate	2	9
56	GS5	5-Year Treasury Constant Maturity Rate	2	9
57	GS10	10-Year Treasury Constant Maturity Rate	2	9
58	AAA	Moody's Seasoned Aaa Corporate Bond Yield	2	9

- Continued on next page -

Table 8 – continued from previous page

59	BAA	Moody's Seasoned Baa Corporate Bond Yield	2	9
60	Sfygm6	fygm6-fygm3	1	9
61	Sfygt1	fygt1-fygm3	1	9
62	Sfygt10	fygt10-fygm3	1	9
63	sFYAAAC	FYAAAC-Fygt10	1	9
64	sFYBAAC	FYBAAC-Fygt10	1	9
65	M1SL	M1 Money Stock	6	10
66	MZMSL	MZM Money Stock	6	10
67	M2SL	M2 Money Stock	6	10
68	BOGAMBSL	Board of Governors Monetary Base, Adj. for Changes in Res. Requirements	6	10
69	USTOTRSAB	US TOTAL RESERVES OF DEPOSITORY INSTITUTIONS CURA	6	10
70	USNBRRSAB	US NONBORROWED RESERVES OF DEPOSITORY INSTITUTIONS CURA	3	10
71	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	6	10
72	NONREVSL	Total Nonrevolving Credit Owned and Securitized, Outstanding	6	10
73	USCP...CE	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ	6	7
74	USCONDUCE	US CHAIN-TYPE PRICE INDEX FOR PCE - DURABLES SADJ	6	7
75	USCONNDCE	US CHAIN-TYPE PRICE INDEX FOR PCE - NONDURABLE GOODS SADJ	6	7
76	USCONSRCE	US CHAIN-TYPE PRICE INDEX FOR PCE - SERVICES SADJ	6	7
77	CPIAUCSL	CPI for All Urban Consumers: All Items	6	7
78	CPILFESL	CPI for All Urban Consumers: All Items Less Food & Energy	6	7
79	PCEPILFE	PCE Excluding Food and Energy (Chain-Type Price Index)	6	7
80	PPIFGS	PPI: Finished Goods	6	7
81	PPIFCG	PPI: Finished Consumer Goods	6	7
82	PPIITM	PPI: Intermediate Materials: Supplies & Components	6	7
83	PPICRM	PPI: Crude Materials for Further Processing	6	7
84	PWCMSAR	Real PPI:CRUDE MATERIALS (82=100,SA) (PWSMSA/PCEPILFE)	5	7
85	CRBSPOT	CRB BLS Spot Index (1967=100) - PRICE INDEX	6	7
86	PSCCOMR	Real SPOT MARKET PRICE INDEX (PSCCOM/PCEPILFE)	5	7
87	USPCIPCOF	US PPI - CRUDE PETROLEUM NADJ	6	7
88	PW561R	PPI Crude (Relative to Core PCE) (pw561/PCEPiLFE)	5	7
89	NAPMPRI	ISM Manufacturing: Prices Index	1	7
90	EXRUS	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	5	11
91	EXSZUS	Switzerland / U.S. Foreign Exchange Rate	5	11
92	EXJPUS	Japan / U.S. Foreign Exchange Rate	5	11
93	EXUSUK	U.S. / U.K. Foreign Exchange Rate	5	11
94	EXCAUS	Canada / U.S. Foreign Exchange Rate	5	11
95	US500STK	US STANDARD & POOR'S INDEX OF 500 COMMON STOCKS(MONTHLY AVE NADJ	5	12
96	USS&PIND	US STANDARD & POORS' SHARE PRICE INDEX - INDUSTRIALS (EP)	5	12
97	USSPDIVY	US STANDARD AND POORS' 500 COMPOSITE - DIVIDEND YLD	2	12
98	USSPRPER	US STANDARD AND POORS' 500 COMPOSITE - REAL P/E RATIO	2	12
99	USSHRPRCF	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ	5	12
100	USUMCONEH	US UNIV OF MICHIGAN CONSUMER SENTIMENT - EXPECTATIONS VOLN	2	13
101	NAPM	ISM Manufacturing: PMI Composite Index	1	6
102	NAPMNOI	ISM Manufacturing: New Orders Index	1	6
103	NAPMSDI	ISM Manufacturing: Supplier Deliveries Index	1	6
104	NAPMII	ISM Manufacturing: Inventories Index	1	6
105	USIPNOMAD	US MANUFACTURERS NEW ORDERS, CONSUMER GOODS & MATERIALS CONA	5	6
106	USNONDCGD	US MANUFACTURERS NEW ORDERS - NONDEFENSE CAPITAL GOODS CONA	5	6
107	CPIULFSL	CPI for All Urban Consumers: All Items Less Food	6	7
108	CUSR0000SA0L5	CPI for All Urban Consumers: All items less medical care	6	7
109	CUSR0000SA0L2	CPI for All Urban Consumers: All items less shelter	6	7
110	CPIAPPSL	CPI for All Urban Consumers: Apparel	6	7
111	CUSR0000SAC	CPI for All Urban Consumers: Commodities	6	7
112	CUSR0000SAD	CPI for All Urban Consumers: Durables	6	7
113	CPIMEDSL	CPI for All Urban Consumers: Medical Care	6	7
114	CUSR0000SAS	CPI for All Urban Consumers: Services	6	7
115	CPITRNSL	CPI for All Urban Consumers: Transportation	6	7