Forecasting Industrial Production with Factor Models: Case of Turkey

December 2014

Mahmut Günay

Yıldırım Beyazıt University and Central Bank of the Republic of Turkey*

*Views expressed in this presentation are those of the author and do not necessarily represent the official views of the Central Bank of the Republic of Turkey

"Those who have knowledge, don't predict. Those who predict, don't have knowledge.
--Lao Tzu, 6th Century BC Chinese Poet

- Source: http://www1.secam.ex.ac.uk/famous-forecasting-quotes.dhtml

"Prediction is very difficult, especially if it's about the future." --Nils Bohr, Nobel laureate in Physics

- This quote serves as a warning of the importance of testing a forecasting model out-of-sample. It's often easy to find a model that fits the past data well--perhaps too well!--but quite another matter to find a model that correctly identifies those features of the past data which will be replicated in the future.

- Source: http://www1.secam.ex.ac.uk/famous-forecasting-quotes.dhtml

"An economist is an expert who will know tomorrow why the things he predicted yesterday didn't happen today. "
--Evan Esar

- Post-analysis of predictions is often very revealing especially concerning model weaknesses.

- Source: http://www1.secam.ex.ac.uk/famous-forecasting-quotes.dhtml

- Date: July, 2005.
- INTERVIEWER: *Tell me, what is the worst-case scenario? We have so many economists coming on our air saying 'Oh, this is a bubble, and it's going to burst, and this is going to be a real issue for the economy.' Some say it could even cause a recession at some point. What is the worst-case scenario if in fact we were to see prices come down substantially across the country?*

  Mr. B: *Well, I guess I don't buy your premise. It's a pretty unlikely possibility. We've never had a decline in house prices on a nationwide basis. So, what I think what is more likely is that house prices will slow, maybe stabilize, might slow consumption spending a bit. I don't think it's gonna drive the economy too far from its full employment path, though.*
- *Source: http://www.cepr.net/index.php/bernanke-greatest-hits*

- So, why try to forecast future?

- **Accuracy is not the only thing we look for forecasts. We look for following features in forecasts.**
- **Let,** $\boldsymbol{e_t}^{\boldsymbol{t-i}} = \boldsymbol{Y_t} - \boldsymbol{Y_t}^{\boldsymbol{t-i}}$**,**
  - Y_t: Realization
  - $Y_t{}^{t-i}$:Forecast for period t at period t-i.
- Forecasts should be unbiased.
  - $\boldsymbol{e_t}^{\boldsymbol{t-i}} = \boldsymbol{\alpha} + \boldsymbol{u_t}$ $\quad unbiased \Rightarrow \alpha$=0

- Weak efficiency
  - $\boldsymbol{Y_t} = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{Y_t}^{\boldsymbol{t-i}} + \boldsymbol{u_t}$ $\qquad unbiased \Rightarrow \alpha = 0,$
    $weak\ efficient \Rightarrow \beta = 1$
- Strong efficiency
- $\boldsymbol{Y_t} = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{Y_t}^{\boldsymbol{t-i}} + \boldsymbol{\gamma}\boldsymbol{Z_{t-i}} + \boldsymbol{u_t}$

- $unbiasedness \Rightarrow \alpha = 0,$
  Strong efficiency$\Rightarrow \beta = 1\ and\ \gamma$=0

Source: Hackworth et al (2013).
http://www.bankofengland.co.uk/publications/Documents/quarterlybulletin/2013/qb130405.pdf

‘Understading MPC’s Forecast Performance Since Mid-2010’. 2013. C. Hackworth, A. Radia, N. Roberts. Quarterly Bullettin. Page 349:

Table 1 Regression results on one quarter ahead projections[a][b][c]

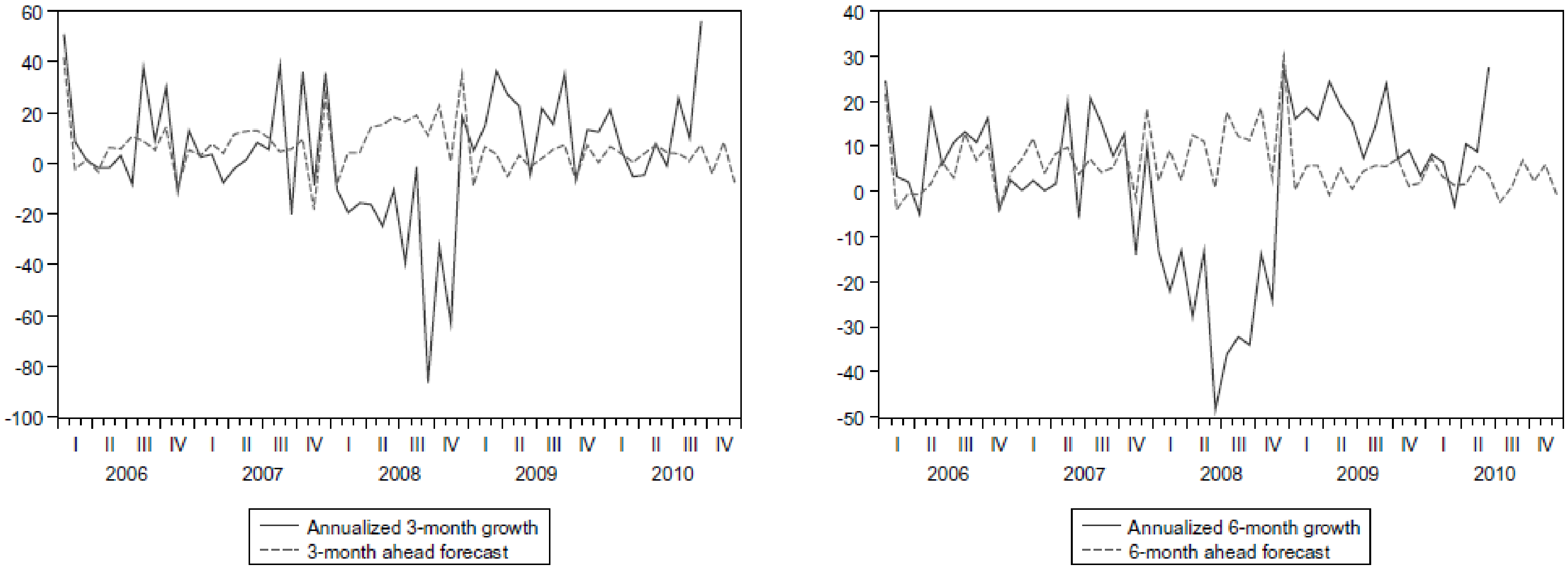
	Hypothesis	Inflation	Quarterly GDP growth[d]
Bias	$\alpha = 0$	**0.0 (0.58)**	**-0.1 (0.13)**
Weak efficiency	$\alpha = 0$	0.2 (0.01)	**-0.1 (0.12)**
	$\beta = 1$	0.9 (0.01)	**1.0 (0.52)**
Strong efficiency[e]	$\gamma = 0$		
(i) Previous outturn less expectation		**-0.1 (0.26)**	0.4 (0.00)
(ii) Previous outturn		**0.0 (0.94)**	-0.2 (0.04)
(iii) Change in exchange rate		**0.0 (0.30)**	**0.0 (0.26)**
(iv) CIPS business activity index			1.2 (0.00)
(v) Import prices		**0.0 (0.41)**	

(a) For mean projection based on market expectations for interest rates. RPIX forecasts made between August 1997 and November 2003, CPI forecasts made between February 2004 and May 2013. GDP forecasts made between August 1997 and May 2013.
(b) Figures are in bold if the p-value associated with each test (in parentheses) is greater than 0.05, or in other words if at the 95% confidence level, there is no significant evidence that projections are biased or inefficient.
(c) Each indicator is included in a separate regression. We do not report the constant and coefficient on expectations in this table, for brevity. Where the indicator shows evidence for statistical significance, the significance of the estimates for α and β are the same as for weak efficiency.
(d) Using real-time GDP data, including the Bank's estimates for past growth since November 2007, as these most closely relate to forecasts made at that time.
(e) Using real-time data for previous outturn, forecast and import price inflation, as these were available at the time the forecast was made.

Bold face indicates efficient forecast.

Industrial Production Forecasts for Turkey by Altug and Uluceviz (2012).

Figure 1. **IP growth, 2006:1-2010:12**



Source: Altug, Sumru and Erhan Uluceviz (2013), "Identifying leading indicators of real activity and inflation for Turkey, 1988-2010: A pseudo out-of-sample forecasting approach", *OECD Journal: Journal of Business Cycle Measurement and Analysis*

- **“We are facing a data tsunami”.**

Source: http://publik.tuwien.ac.at/files/PubDat_189756.pdf, page 3. Quote belongs to Bart de Moor.

- Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors.
- For example, it is possible that variations in four observed variables mainly reflect the variations in two unobserved variables. Factor analysis searches for such joint variations in response to unobserved latent variables.
- Originally, from Spearman (1905) observation that school children's scores on a wide variety of seemingly unrelated subjects were positively correlated, which led him to postulate that a general mental ability, or g, underlies and shapes human cognitive performance.

Source: http://en.wikipedia.org/wiki/Factor_analysis

- Psychology
- Marketing
- Finance
- Economics
  - Creating indices
  - Forecasting

Source: http://www.summitllc.us/wp-content/uploads/2013/02/Factor-Analysis-I-Summit-Presentation.pdf

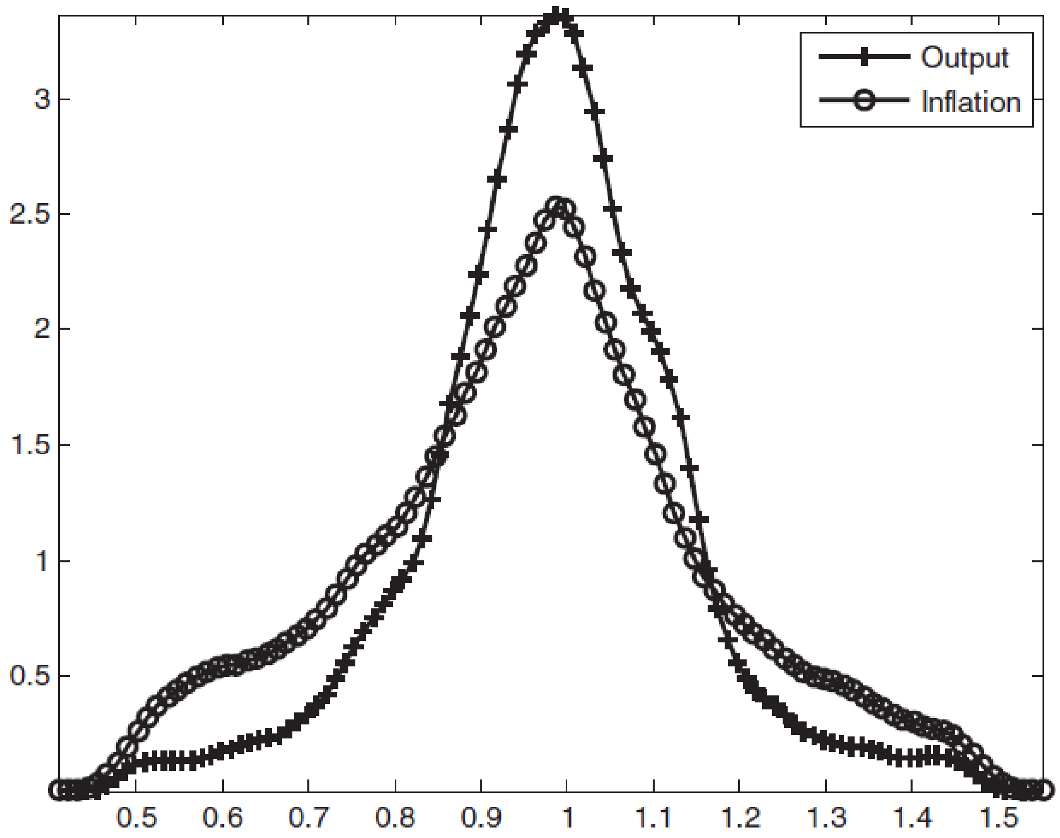
Factor Representation and Forecasting Equation

- $\boldsymbol{X}_{\boldsymbol{it}} = \boldsymbol{\lambda}_{\boldsymbol{i}}'\boldsymbol{F}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{it}}$
- X: Observed data
- F: Common Factors
- $\lambda_i' F_t$: Common component
- $\boldsymbol{e}_{\boldsymbol{it}}$: Idiosynratic component
- Note that factors, loadings and idiosyncratic components are not-observable.
- $\hat{Y}_{t+h/h}^{h} = \hat{\alpha}_h + \sum_{j=1}^{m} \widehat{\beta_{hj}}' \hat{F}_{T-j+1} + \sum_{j=1}^{p} \widehat{\gamma_{hj}}\, \hat{Y}_{T-j+1}$

How Successful are Dynamic Factor Models at Forecasting Output and Inflation? A Meta-Analytic Approach, Eickmeier and Ziegler (2008), Journal of Forecasting.

- A meta-analysis to survey existing factor forecast applications for output and inflation and assesses parameters that affect the forecast performance of factor models.
- Results suggest that factor models tend to outperform small models, whereas factor forecasts are slightly worse than pooled forecasts.
- Factor models deliver better predictions for US variables than for UK variables, for US output than for euro-area output and for euro-area inflation than for US inflation.
- The size of the dataset from which factors are extracted positively affects the relative factor forecast performance, whereas pre-selecting the variables included in the dataset did not improve factor forecasts in the past.
- Finally, the factor estimation technique may matter as well.

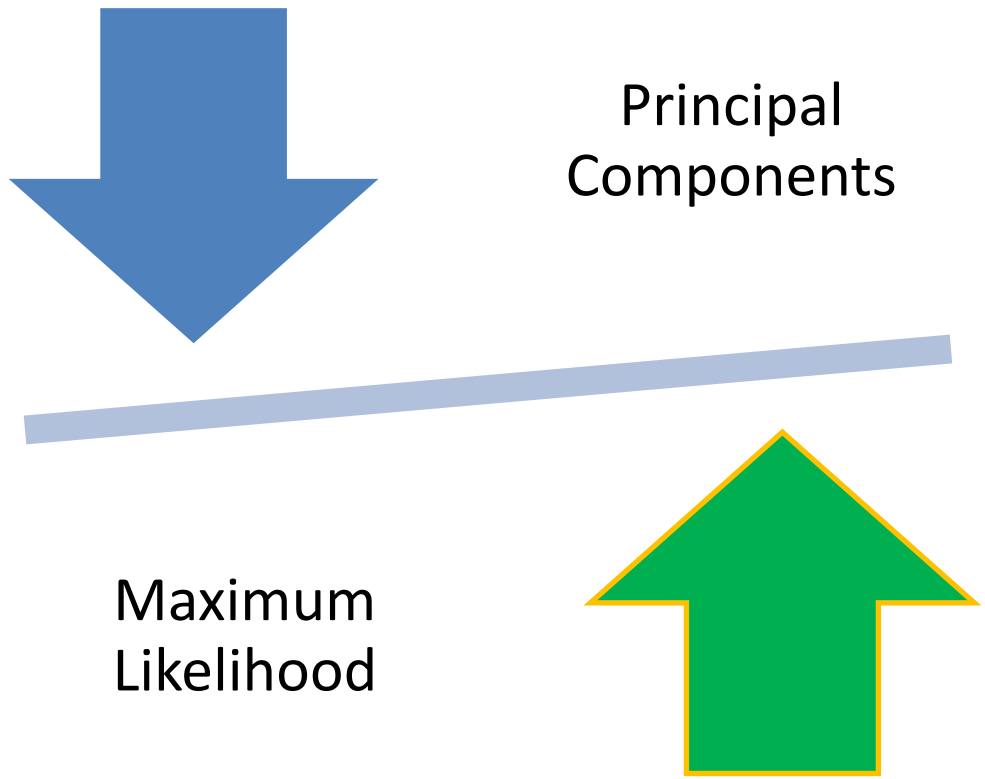
Eickmeier and Ziegler (2008), Figure 1



Issues we need to deal in this study…

- $\boldsymbol{X}_{\boldsymbol{it}} = \boldsymbol{\lambda}_{\boldsymbol{i}}'\boldsymbol{F}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{it}}$
- $\hat{Y}_{t+h/h}^{h} = \hat{\alpha}_h + \sum_{j=1}^{m} \widehat{\beta_{hj}}'\hat{F}_{T-j+1} + \sum_{j=1}^{p} \widehat{\gamma_{hj}}\,\hat{Y}_{T-j+1}$
- 1. How to get factors?
- 2. How many factors should we use?
- 3. h-period ahead forecast approach: direct or iterative?
- 4. Size and detail of the data set?
- 5. Pooling of bivariate forecasts or factor model forecasts?

1. Obtaining factors



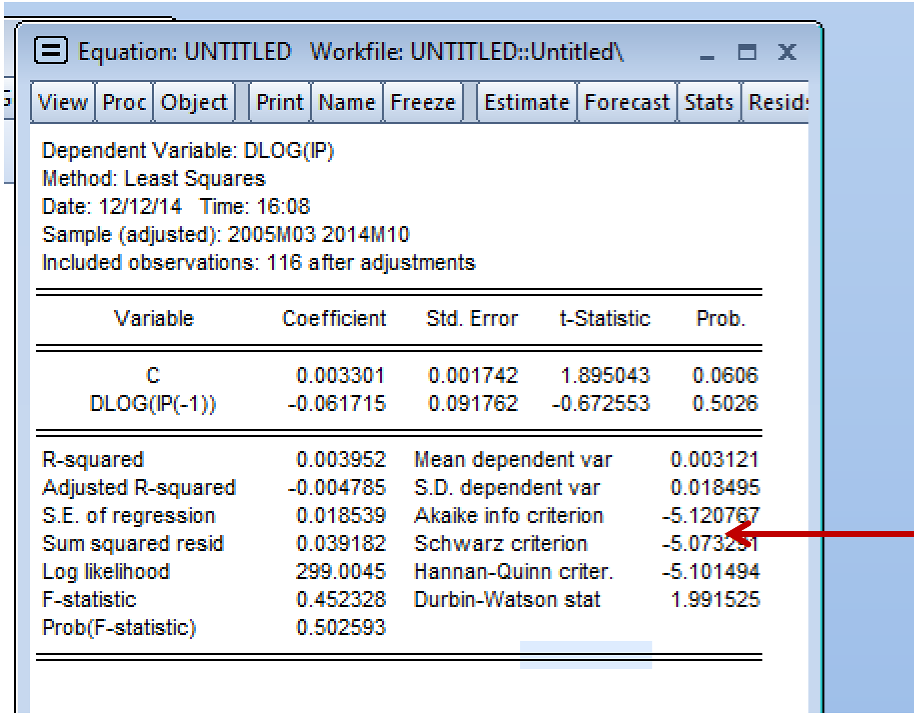
Obtaining Factors with Principal Components

- Stock and Watson (2002) show that
- $V(\tilde{F},\tilde{\Lambda}) = (NT)^{-1}\sum_i \sum_t (x_{it} - \tilde{\lambda}_i\tilde{F}_t)^2$
- We want to minimize the above loss function which implies that we maximize the part that is explained by the common component.
- $F = X'\hat{\Lambda}$/N solves the above minimization problem.
- $\hat{\Lambda} = eigenvectors\ of\ X'X\ corresponding\ to\ r\ largest\ eigenvalues.$

Obtaining Factors with Principal Components

- Another important contribution of this paper is that authors show that 'forecasts using estimated factors and parameters converges to optimal infeasible forecasts.
- Note that, factors and loadings are not uniquely identified. This is not a problem for the case of forecasting but if factors or loadings are used for other purposes, one should be careful in interpretation.

2. How many factors to use?


Equation: UNTITLED Workfile: UNTITLED::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resid

Dependent Variable: DLOG(IP)
Method: Least Squares
Date: 12/12/14 Time: 16:08
Sample (adjusted): 2005M03 2014M10
Included observations: 116 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003301	0.001742	1.895043	0.0606
DLOG(IP(-1))	-0.061715	0.091762	-0.672553	0.5026

R-squared	0.003952	Mean dependent var	0.003121
Adjusted R-squared	-0.004785	S.D. dependent var	0.018495
S.E. of regression	0.018539	Akaike info criterion	-5.120767
Sum squared resid	0.039182	Schwarz criterion	-5.073251
Log likelihood	299.0045	Hannan-Quinn criter.	-5.101494
F-statistic	0.452328	Durbin-Watson stat	1.991525
Prob(F-statistic)	0.502593		

BIC=T*ln(SSR/T)+k*ln(T)

SSR: Sum of squared residuals
k: number of estimated parameters
T: Sample size

Classical information criteria is not enough in the case of factor models as we need to consider both dimensions (time and number of variables).

Determining the Number of Factors in Approximate Factor Models, Bai and Ng (2002), Econometrica.

- If we know the number of factors, we can use BIC to determine the number of factors.
- But, when the factors are unknown and has to be estimated, BIC will not always consistently estimate number of factors.
- Let $\boldsymbol{V(k, \widehat{F^k}) = \min_{\Lambda} \frac{1}{N\,T} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i^{k\prime} \widehat{F_t^k})^2}$ be the sum of squared residuals when we estimate k factors. Aim is to come up with a criterion such that
- $PC(k) = V(k, \widehat{F^k})$+kg(N,T) can consistently estimate r.

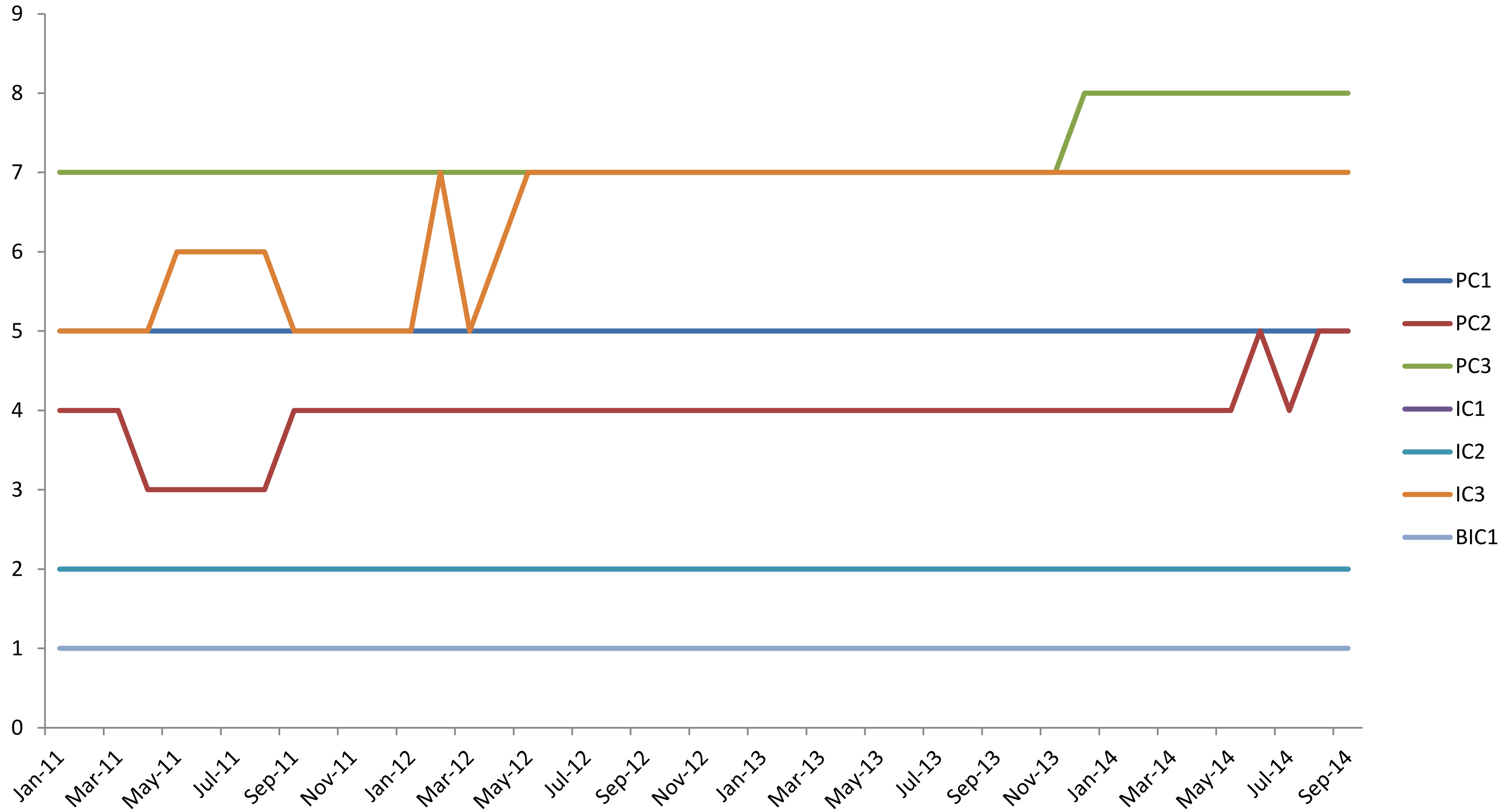
7 Criteria from Bai and Ng (2002)

- $PC_{p1}(k) = V(k, \widehat{F^k}) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln(\frac{NT}{N+T)})$
- $PC_{p2}(k) = V(k, \widehat{F^k}) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln C_{NT}^2$
- $PC_{p3}(k) = V(k, \widehat{F^k}) + k\hat{\sigma}^2 \left(\frac{lnC_{NT}^2}{C_{NT}^2}\right)$
  - Here, $\hat{\sigma}^2$ can be replaced by $V(kmax, \widehat{F^{kmax}})$
- $IC_{p1}(k) = \ln(V\left(k, \widehat{F^k}\right)) + k \left(\frac{N+T}{NT}\right) \ln(\frac{NT}{N+T)})$
- $IC_{p2}(k) = \ln(V\left(k, \widehat{F^k}\right)) + k \left(\frac{N+T}{NT}\right) \ln C_{NT}^2$
- $IC_{p3}(k) = \ln(V\left(k, \widehat{F^k}\right)) + k \left(\frac{lnC_{NT}^2}{C_{NT}^2}\right)$
- $BIC_3(k) = V(k, \widehat{F^k}) + k\hat{\sigma}^2 \left(\frac{(N+T-k)\ln(NT)}{NT}\right)$

Results from Bai and Ng (2002)

- 1 . PC1, PC2 and IC1, IC2 seem to perform better than PC3 and IC3.
- 2. In the presence of cross-section correlations, BIC3 has very good properties. Criteria can be used even though it does not satisfy all the conditions of Theorem 2.

Criteria applied to a large panel of data that we will introduce later:



Testing the Number of Factors: An Empirical Assessment for a Forecasting Purpose; Barhoumi, Darne and Ferrara (2013), Oxford Bullettin of Economic and Statistics.

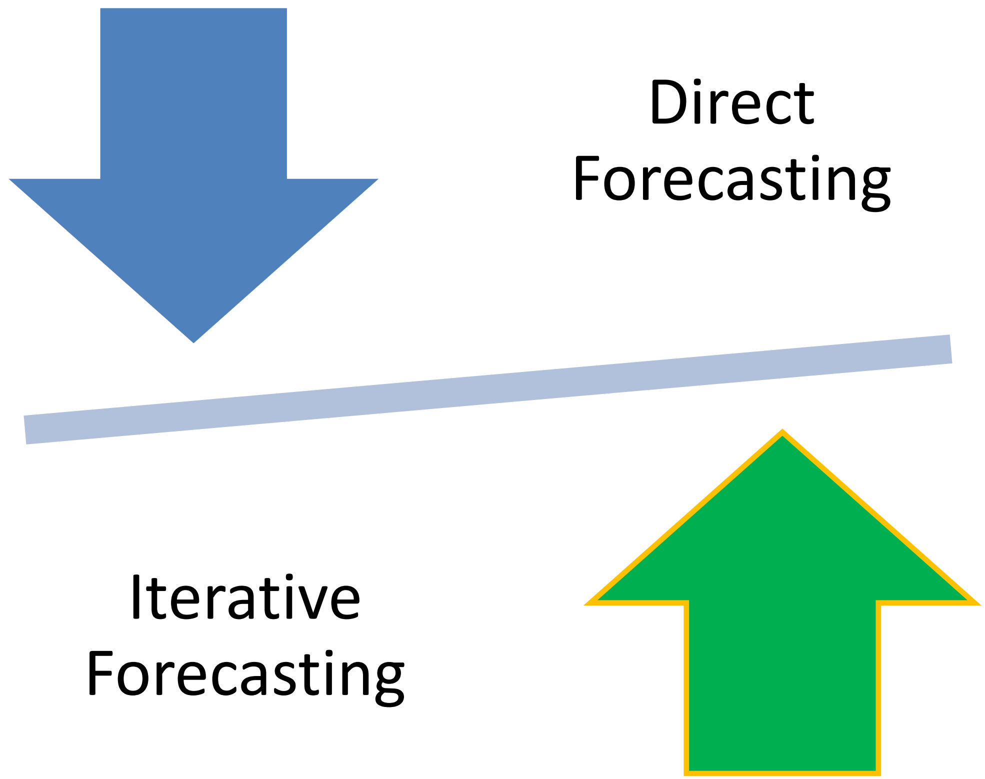
- Selects the number of factors, through a testing procedure, to include in the forecasting equation. Through an empirical exercise on French and German GDPs, assess the impact of a battery of recent statistical tests for the number of factors for a forecasting purpose. By implementing a rolling experience, also assess the stability of the results overtime.

TABLE 1

Evolution of estimated number of factors r for the various tests and the two countries

Method	Country	1993–98	1994–99	1995–00	1996–2001	1997–2002	1998–2003	1999–2004	2000–05	2001–06	2002–07	2003–08
Static factor models												
1-factor		1	1	1	1	1	1	1	1	1	1	1
Static factor models												
ABC	France	1	1	2	2	2	3	3	3	3	3	3
	Germany	2	1	1	1	1	2	3	3	4	3	3
BN02	France	4	4	4	4	4	4	4	4	3	3	3
	Germany	1	3	2	2	2	3	3	2	5	4	4
Dynamic factor models												
BN07	France	4	4	4	4	4	4	3	3	3	4	3
	Germany	4	2	2	3	3	3	5	4	3	2	4
HL	France	1	1	2	2	2	2	2	2	2	2	1
	Germany	3	3	3	3	3	3	3	2	2	2	3
BP	France	3	4	4	4	4	4	3	3	3	2	3
	Germany	3	4	3	3	3	4	5	5	5	5	4
AW	France	1	1	2	2	4	4	4	3	3	3	4
	Germany	4	4	4	5	5	5	5	3	3	2	4

3. Multi-step ahead forecasting



h-step Ahead Forecast Approach:
Stock and Watson (2003): Forecasting Output and Inflation: Role of Asset Prices

TABLE 3
PSEUDO OUT-OF-SAMPLE MEAN SQUARE FORECAST ERRORS:
1971–84 AND 1985–99, REAL GDP GROWTH, 4 QUARTERS AHEAD

Indicator	Transfor-mation	Canada		France		Germany		Italy		Japan		U.K.		U.S.	
		71–84	85–99	71–84	85–99	71–84	85–99	71–84	85–99	71–84	85–99	71–84	85–99	71–84	85–99
		Root Mean Square Forecast Error													
Univ. Autoregression		2.91	2.55	1.90	1.56	2.83	1.84	3.47	1.88	3.59	2.46	2.96	1.89	3.19	1.31
Univariate Forecasts		MSFE Relative to Univariate Autoregression													
$(1\text{-}L)y_t = \alpha + \varepsilon_t$		0.97	0.99		1.13	1.04	1.04	1.05	1.37	1.51	2.88	1.03	0.98	0.98	1.09
Bivariate Forecasts		MSFE Relative to Univariate Autoregression													
rovnght	level		0.74		1.57	0.30	1.48		1.48	1.21	0.89		1.13	0.78	1.42
rtbill	level	0.59	0.72		1.63		1.28		0.86			1.19	0.79	0.85	1.06
rbnds	level								0.92				0.87	0.92	1.29
rbndm	level							1.56	1.40					1.11	1.47
rbndl	level	0.80	0.94		1.59	0.46	2.12	1.16	1.55		0.88	1.00	0.96	1.18	1.66
rovnght	Δ		0.68		0.91	1.09	1.17		0.85	1.05	0.98		1.21	1.11	1.57
rtbill	Δ	1.05	1.03		0.98		1.37		0.48			1.24	1.11	1.32	1.63

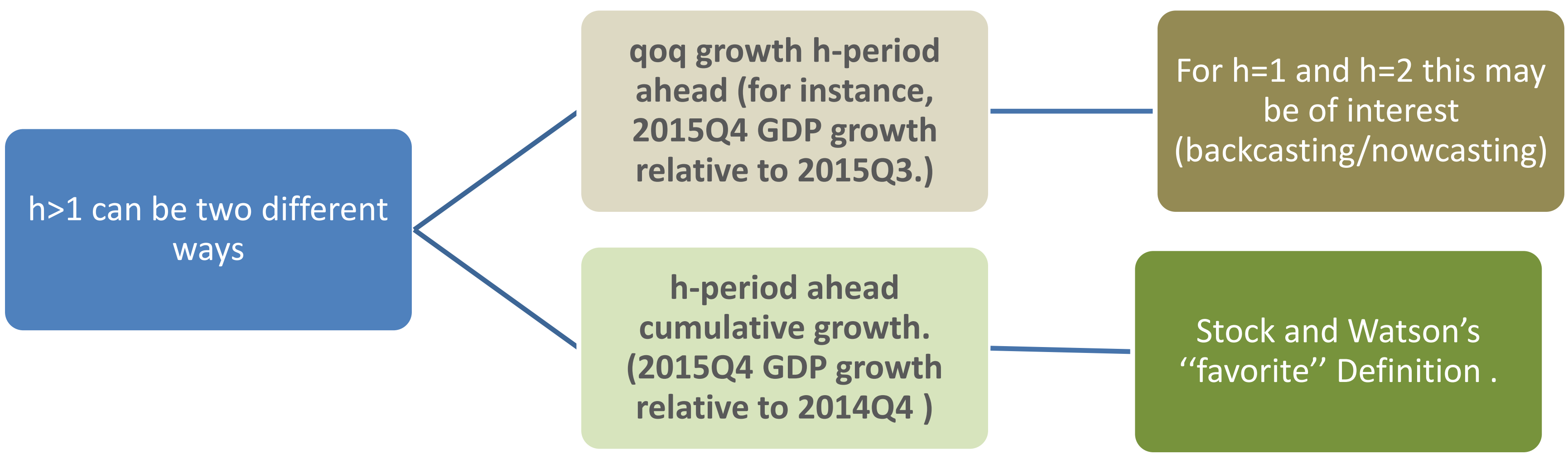
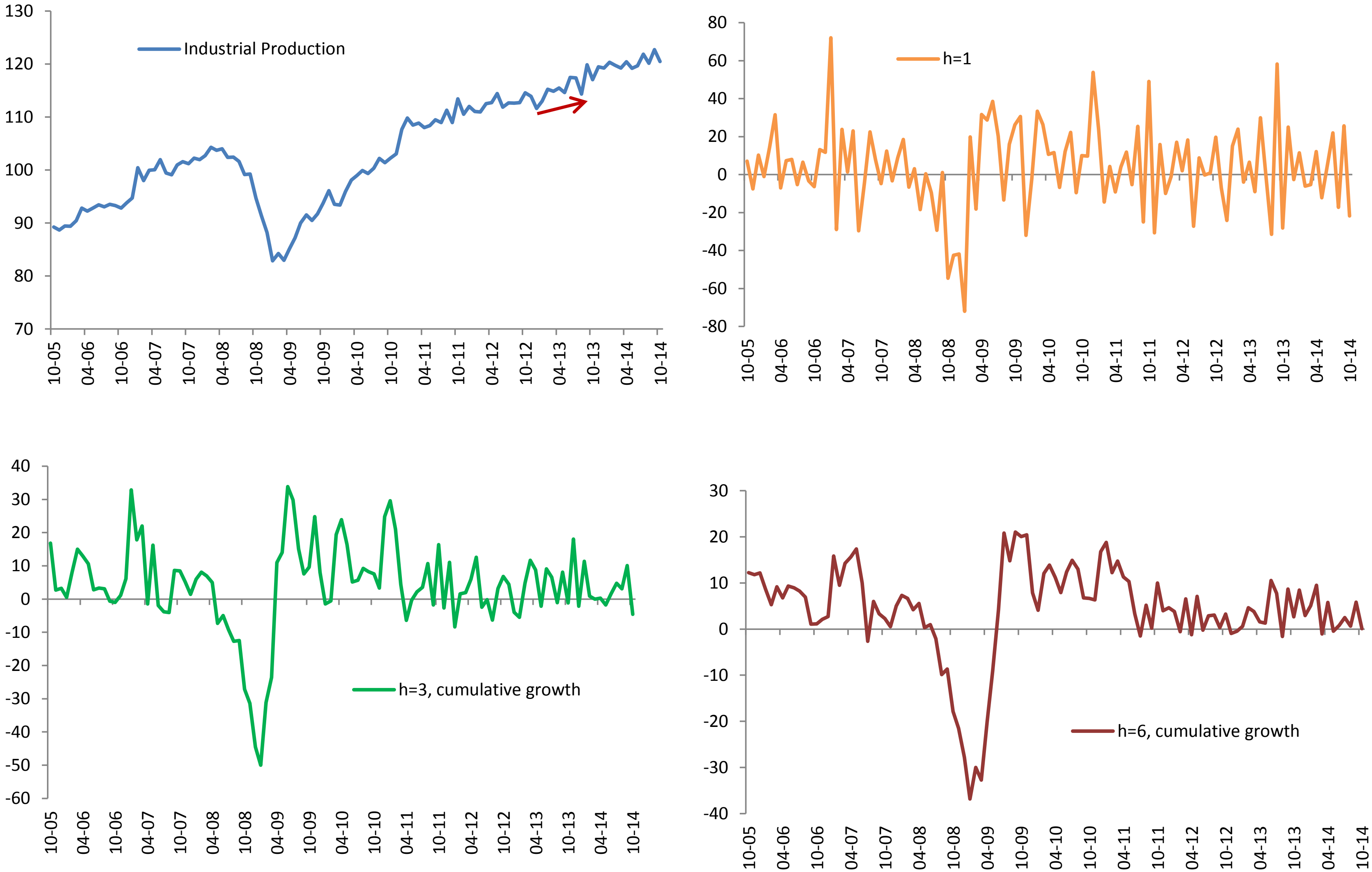

h>1 can be two different ways
qoq growth h-period ahead (for instance, 2015Q4 GDP growth relative to 2015Q3.)
For h=1 and h=2 this may be of interest (backcasting/nowcasting)
h-period ahead cumulative growth. (2015Q4 GDP growth relative to 2014Q4)
Stock and Watson's "favorite" Definition .

Illustration of h-period ahead



Annualized growth rates.

Iterative Approach

- Let us work on an AR(1) Model
- $\boldsymbol{y_{t+1}} = \alpha + \beta y_t + u_{t+1}$
- $\widehat{\boldsymbol{y_{t+1}}} = \hat{\alpha} + \hat{\beta} y_t$
- $\widehat{\boldsymbol{y_{t+2}}} = \hat{\alpha} + \hat{\beta}\widehat{\boldsymbol{y_{t+1}}} = \hat{\alpha} + \hat{\beta}(\widehat{\alpha} + \hat{\beta} y_t)$
- Let h=2 and y: log-difference:
  - Then, cumulative growth in h=2: $\widehat{y_{t+1}}+\widehat{\boldsymbol{y_{t+2}}}$

Iterative Approach

- Suppose that we have an additional indicator for forecasting y.
- $y_{t+1} = \alpha + \beta y_t + \gamma x_t + u_{t+1}$
- $\widehat{y_{t+1}} = \hat{\alpha} + \hat{\beta} y_t + \hat{\delta} x_t$
- $\widehat{y_{t+2}} = \hat{\alpha} + \hat{\beta} \widehat{y_{t+1}} + \hat{\delta} \widehat{x_{t+1}}$
- We need a forecast for x(t+1) as well for forecasting y(t+2). We need to use a VAR.

Iterative Approach

- $Y_{t+1}^{h} = \beta_0 + \beta_1(L)F_t + \beta_2(L)Y_t + u_{t+1}$
- **We estimate one equation and iterate h times to get h period ahead forecasts.**

Direct-Approach to h-step ahead forecasting

- $Y_{t+h}^{h} = \beta_0 + \beta_1(L)F_t + \beta_2(L)Y_t + u_{t+h}^{h}$
- $Y_{t+h}^{h} = ln\left(\frac{Q_{t+h}}{Q_t}\right)$
- $Y_t = \Delta lnQ_t$
- **Q: Industrial production**
- **For each horizon 'h' we estimate a different equation.**

- Source: Stock and Watson, 2004. 'Combination Forecasts of Output Growth in a Seven-Country Data Set'.

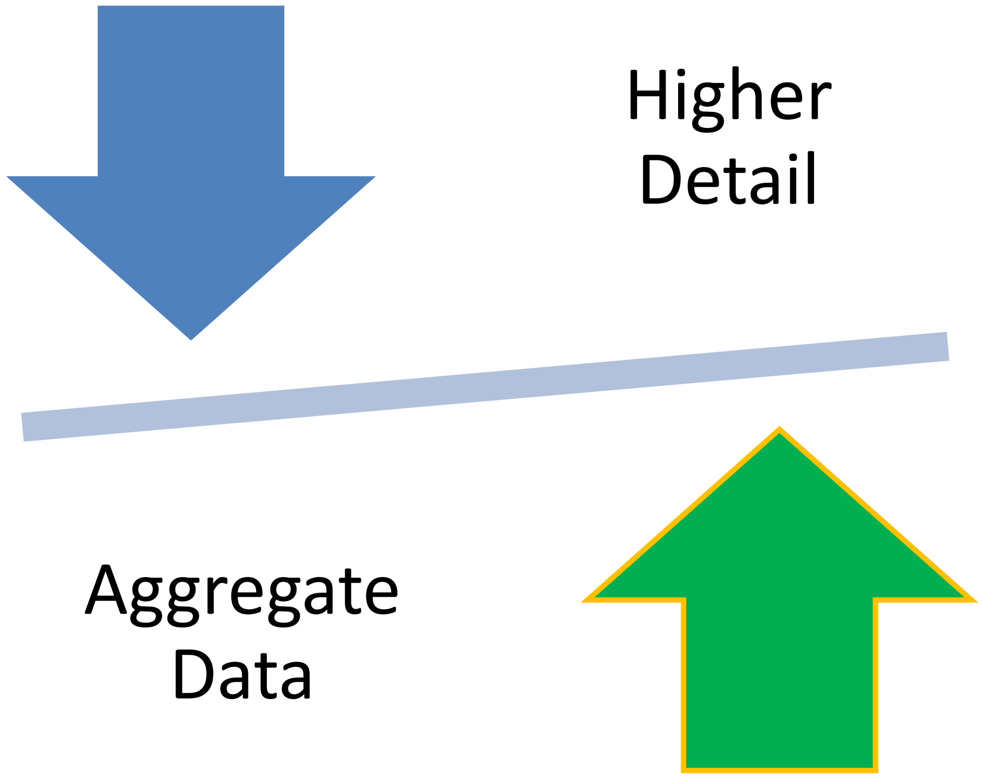
A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series (2006), Marcellino, Stock and Watson, Journal of Econometrics.

- “Iterated” multiperiod ahead time series forecasts are made using a one-period ahead model, iterated forward for the desired number of periods, whereas “direct” forecasts are made using a horizon-specific estimated model, where the dependent variable is the multi-period ahead value being forecasted. Which approach is better is an empirical matter: **in theory, iterated forecasts are more efficient if correctly specified, but direct forecasts are more robust to model misspecification.** This paper compares empirical iterated and direct forecasts from linear univariate and bivariate models by applying simulated out-of-sample methods to 171 U.S. monthly macroeconomic time series spanning 1959 – 2002. The iterated forecasts typically outperform the direct forecasts, particularly if the models can select long lag specifications. **The relative performance of the iterated forecasts improves with the forecast horizon.**

Taieb ve Hyndman (2012), Recursive and direct multi-step forecasting: the best of both worlds

- «Traditionally, multi-step forecasting has been handled recursively, where a single time series model is estimated and each forecast is computed using previous forecasts. More recently, direct calculation of multi-step forecasting has been proposed, where a separate time series model for each forecasting horizon is estimated, and forecasts are computed only on the observed data. Choosing between these different strategies involves a trade-off between bias and estimation variance. Recursive forecasting is biased when the underlying model is nonlinear, but direct forecasting has higher variance because it uses fewer observations when estimating the model, especially for longer forecast horizons. The literature on this topic often involves comparing the recursive and direct strategies, and discussing the conditions under which one or other is better. For example, **Ing (2003) shows that in the linear case, the recursive MSE is greater than the direct MSE. Chevillon (2007) concludes that the direct strategy is most beneficial when the model is misspecified**.»

4. Data Selection



Short-term forecasting of GDP using large monthly datasets – A pseudo real-time forecast evaluation exercise (2008), by K. Barhoumi, S. Benk, R. Cristadoro, A. Den Reijer, A. Jakaitiene, P. Jelonek, A. Rua, G. Rünstler, K. Ruth and C. Van Nieuwenhuyze Working Paper Research 133, National Bank of Belgium.

Tables

Table 1: Datasets

		No of series	Production and sales	Surveys	*of which* Financial	Prices	Other	Sample start
Euro area	EA	85	25	25	24	0	11	1991 M1
Belgium	BE	393	25	262	50	42	14	1991 M1
Germany	DE	111	55	19	32	4	1	1991 M1
France	FR	118	19	96	0	2	1	1991 M1
Italy	IT	84	27	24	10	20	3	1991 M1
Netherlands	NL	76	8	33	8	23	4	1991 M1
Portugal	PT	141	32	78	12	10	9	1991 M1
Lithuania	LT	103	35	21	12	33	1	1995 M1
Hungary	HU	80	33	9	12	11	15	1998 M1
Poland	PL	81	16	30	10	11	14	1997 M1

Are more data always better for factor analysis?, 2006, Jean Boivin and Serena Ng, Journal of Econometrics.

- Factors estimated from large macroeconomic panels are being used in an increasing number of applications. However, little is known about how the size and the composition of the data affect the factor estimates. In this paper, we question whether it is possible to use more series to extract the factors, and yet the resulting factors are less useful for forecasting, and the answer is yes.
- Such a problem tends to arise when the idiosyncratic errors are cross-correlated. It can also arise if forecasting power is provided by a factor that is dominant in a small dataset but is a dominated factor in a larger dataset. In a real time forecasting exercise, **we find that factors extracted from as few as 40 pre-screened series often yield satisfactory or even better results than using all 147 series.**
- Weighting the data by their properties when constructing the factors also lead to improved forecasts. Our simulation analysis is unique in that special attention is paid to cross-correlated idiosyncratic errors, and we also allow the factors to have stronger loadings on some groups of series than others. It thus allows us to better understand the properties of the principal components estimator in empirical applications.

Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP?, 2010, Barhouimi, Darne and Ferrara, Journal of Forecasting .

- This paper compares the GDP forecasting performance of alternative factor models based on monthly time series for the French economy.
- These models are based on static and dynamic principal components obtained using time and frequency domain methods. We question whether it is more appropriate to use aggregate or disaggregate data to extract the factors used in forecasting equations.
- The forecasting accuracy is evaluated for various forecast horizons considering both rolling and recursive schemes.
- **We empirically show that static factors, estimated from a small database, lead to competitive results**, especially for nowcasting.

Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP?, 2010, Barhouimi, Darne and Ferrara, Journal of Forecasting .

APPENDIX: DATABASE DESCRIPTION

1. Small database

The small database consists in 20 variables including:

A **Prices**: (1) Consumer price index (Insee); (2) Oil price Brent (Datastream).

B **Financial data**: (1) Rate of return on long-term Government loans (monetary and financial statistics); (2) Treasury bonds with maturity of 13 weeks (monetary and financial statistics); (3) Reference rate of regulated loans in housing (monetary and financial statistics); (4) French stock index CAC40 (Datastream).

C **Soft data**: (1) Business sentiment indicator in industry (BdF); (2) Consumer sentiment indicator (Insee); (3) Services sentiment indicator (BdF); (4) Assessment of order-book levels (Eurostat); (5) Assessment of export order-book levels (Eurostat); (6) Production expectations for the months ahead (Eurostat); (7) Changes in retails sales (Insee).

D **Hard data**: (1) Household consumption in manufactured goods (Insee); (2) Industrial production index (Insee); (3) Exportations (Insee); (4) Importations (Insee); (5) Industrial car registrations (CCFA); (6) New car registrations (CCFA); (7) Declared housing starts (Ministry of Equipment).

Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP?, 2010, Barhouimi, Darne and Ferrara, Journal of Forecasting .

3. Large database

For large database a sectorial disaggregation is applied for some data when possible.

A11 **Consumer price index**. Each price data item defined in A(1) is disaggregated as: (1) Agri-food; (2) Tobacco; (3) Manufactured goods; (4) Energy; (5) Services.

C11 **Business survey in industry**. Each soft data item defined in C1 is disaggregated as: (1) Intermediate goods; (2) Capital goods; (3) Automotive industry; (4) Consumer goods; (5) Agri-food industries.

C71 **Changes in retails sales**. Each soft data item defined in C(7) is disaggregated as: (1) New cars; (2) Old cars; (3) Textiles and clothing; (4) Furniture; (5) Shoes; (6) Household electrical goods; (7) Electronics; (8) Hardware shops; (9) Watches and jewelers; (10) Agri-foods excluding meat; (11) Books and papers; (12) Meat.

D11 **Household consumption**. Each hard data item defined in D(1) is disaggregated as: (1) Cars; (2) Textile and leather; (3) Other manufactured goods; (4) Furnishing; (5) Household electrical; (6) Electronics.

D12 **Industrial production index**. Each hard data item defined in D(2) is disaggregated as: (1) Intermediate goods; (2) Capital goods; (3) Automotive industry; (4) Consumer goods; (5) Energy products.

‘Small’ Data Set in This Study.
Data are seasonally adjusted and transformed to log-difference or differenced.

1. Industrial Production
2. Export Quantity Index
3. Import Quantity Index
4. Borsa Istanbul-30
5. Business Tendency Survey- Assesment of General Situation
6. Capacity Utilization
7. CNBC-e Consumer Confidence Index
8. Inflation
9. Euro/Dollar Parity
10. Dollar Exchange Rate
11. TL Deposit Interest Rate
12. Dollar Deposit Interest Rate
13. TL Commercial Credit Interest Rate
14. Euro Commercial Credit Interest Rate
15. TL Consumer Credit Interest Rate
16. Benchmark Interest Rate
17. EU-Industrial Production
18. EU Consumer Confidence
19. EU-Business Confidence
20. Commodity Price Index
21. VIX
22. SP 500

Increasing Detail

Small	Medium	Large
• Industrial Production	• Intermediate • Capital • Non-durable • Durable • Energy	• Mining • Food • Beverage • Tobacco • Textile • Apparel • Leather • Wood • Paper • Media • Refined petroleum • Chemical • Pharmaceutical • Rubber • Other Mineral • Basic Metal • Fabricated Metal • Electronic and Optical • Electrical Equipment • Machinery and Equipment • Motor Vehicles • Other Transport • Furniture • Other manufacturing • Repair of mach-eq • Electricity, gas and steam

Increasing Detail

Small	Medium	Large
• Consumer Confidence	• Question 1 • Question 2 • Question 3 • Question 4 • Question 5	• Question 1 • Question 2 • Question 3 • Question 4 • Question 5

- For the small set we have 22 series, for medium we have 63 and for the large series we have 167 series.
- Series are, if appropriate, log-transformed and used in first differences for stationarity.

- RESULTS

Factor Representation and Forecasting Equation

- $\boldsymbol{X}_{\boldsymbol{it}} = \boldsymbol{\lambda}_{\boldsymbol{i}}' \boldsymbol{F}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{it}}$
- $\hat{Y}_{t+h/h}^{h} = \hat{\alpha}_h + \sum_{j=1}^{m} \widehat{\beta_{hj}}' \hat{F}_{T-j+1} + \sum_{j=1}^{p} \widehat{\gamma_{hj}} \, \hat{Y}_{T-j+1}$
- Number of factors determined by Bai and Ng (2002).
- m and p are determined by BIC following Stock and Watson (2002).

Recursive Pseudo Out of Sample Forecasting

Estimate in 2005M02-(2012m10-h) to get h step ahead forecast. Get forecasts for h=1 to 12.

Extend sample by one period. Estimate In 2005M02-(2012m11-h) to get h step ahead forecast. Get forecasts for h=1 to 12.

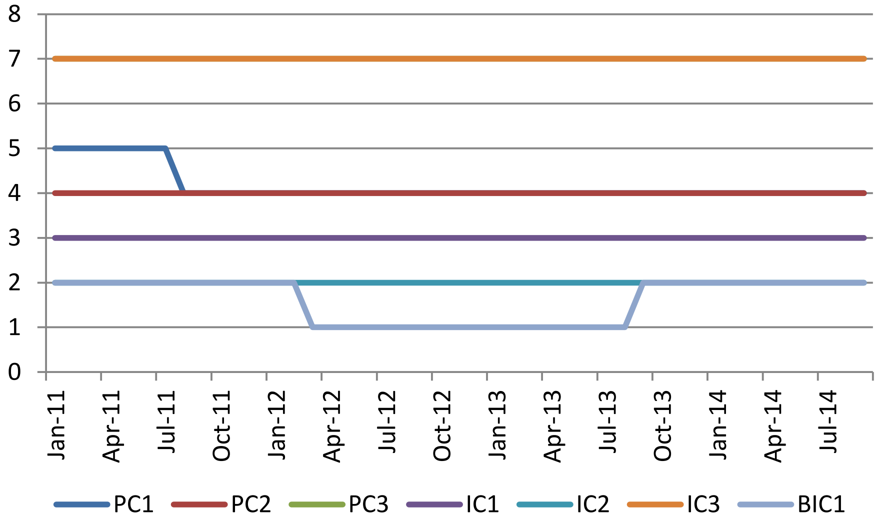
Extend sample by one month

…

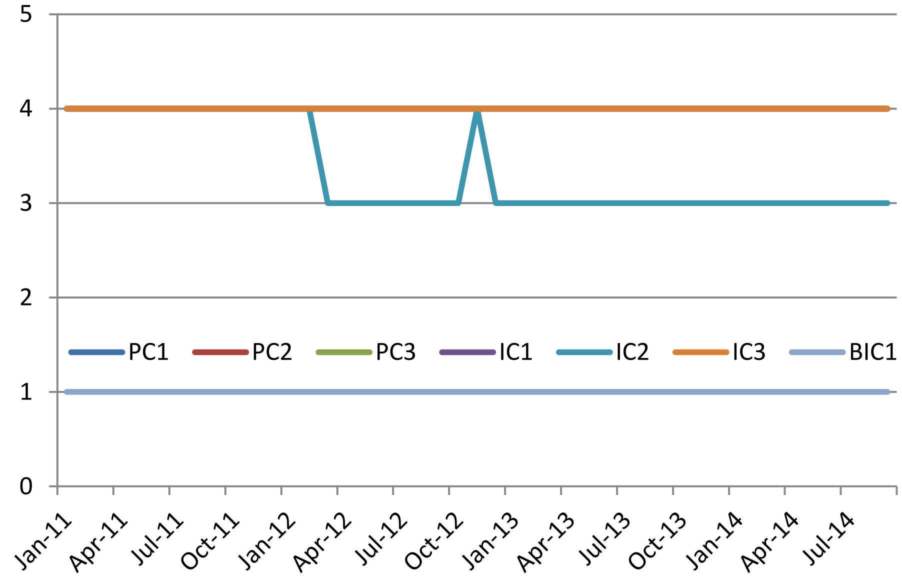
Estimate In 2005M02-(2014M09-h) to get h step ahead forecast. Get forecasts for h=1 to 12.

Number of Factors with BN02 for Medium and Small Sized Data Set

Medium



Small



Factor Representation and Forecasting Equation

- Consider k=7, max(m)=max(p)=4.
- We need to consider each combination and find the minimuım BIC equation. With k=7 and lag of dependent variable, we need to try 4^8 =65,536 combinations at each recursion for each data set for each multistep forecasting approach for each BN2002 criteria, and in the case of direct forecasting for each h.
- For instance,
- Y=f(F1,F1,F2,F3,F4,F5,F6,F7, dY)
- Y=f(F1,F1(-1),F2,F3,F4,F5,F6,F7,dY)
- Y=f(F1,**F1(-1)**,F2,F2(-1),F3,F4,F5,F6,F7,dY)
- Y=f(F1,**F1(-1)**,F2,F2(-1),F3,F4,F5,F6,F7,dY, **dY(-1)**)

October 2012- September 2014 Relative RMSEs

Large Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	0.99	0.81	0.38	0.25	5
BN2002_criter2	1.03	0.65	0.39	0.27	5
BN2002_criter3	0.78	0.53	0.43	0.29	8
BN2002_criter4	1.00	1.00	1.05	1.18	2
BN2002_criter5	1.00	1.00	1.05	1.18	2
BN2002_criter6	0.78	0.53	0.42	0.28	7
BN2002_criter7	0.99	1.12	1.12	1.19	1

Medium Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	1.06	0.97	0.65	0.97	4
BN2002_criter2	1.06	0.97	0.65	0.97	4
BN2002_criter3	0.79	0.42	0.33	0.26	7
BN2002_criter4	0.97	0.91	0.70	1.18	3
BN2002_criter5	0.95	0.90	1.16	1.59	2
BN2002_criter6	0.79	0.42	0.33	0.26	7
BN2002_criter7	0.91	0.90	1.14	1.77	2

Small Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	1.02	0.83	0.69	0.55	4
BN2002_criter2	1.02	0.83	0.69	0.55	4
BN2002_criter3	1.02	0.83	0.69	0.55	4
BN2002_criter4	1.02	0.83	0.69	0.55	4
BN2002_criter5	1.02	0.94	0.90	0.66	3
BN2002_criter6	1.04	0.84	0.69	0.54	4
BN2002_criter7	0.91	0.94	1.05	1.29	1

October 2012- September 2014 Relative RMSEs depending on Data Set

	VAR							Direct			
	Large/small							Large/small			
	h=3	h=6	h=9	h=12				h=3	h=6	h=9	h=12
BN2002_criter1	0.95	1.00	1.02	0.92			BN2002_criter1	0.98	1.04	1.82	2.03
BN2002_criter2	0.94	0.99	0.99	0.90			BN2002_criter2	0.94	1.27	1.74	1.79
BN2002_criter3	1.02	1.03	1.07	0.92			BN2002_criter3	1.33	1.62	1.69	1.76
BN2002_criter4	0.95	0.95	0.96	0.89			BN2002_criter4	0.96	0.79	0.63	0.42
BN2002_criter5	0.95	1.01	0.99	0.89			BN2002_criter5	0.96	0.94	0.86	0.50
BN2002_criter6	1.01	1.02	1.06	0.95			BN2002_criter6	1.33	1.63	1.73	1.83
BN2002_criter7	0.89	0.94	0.99	0.91			BN2002_criter7	0.81	0.79	0.93	0.99
	Medium/small							Medium/small			
BN2002_criter1	1.03	0.99	1.00	0.94			BN2002_criter1	0.97	0.83	1.23	0.61
BN2002_criter2	1.03	0.99	1.00	0.94			BN2002_criter2	0.97	0.83	1.23	0.60
BN2002_criter3	1.05	1.04	1.06	0.99			BN2002_criter3	1.32	1.91	2.06	1.94
BN2002_criter4	1.02	0.98	0.99	0.94			BN2002_criter4	1.07	0.86	1.14	0.56
BN2002_criter5	1.02	1.03	1.02	0.93			BN2002_criter5	1.06	1.02	0.91	0.53
BN2002_criter6	1.04	1.03	1.06	1.00			BN2002_criter6	1.32	1.91	2.06	1.94
BN2002_criter7	1.00	1.01	0.97	0.86			BN2002_criter7	0.99	1.01	1.02	0.94

- Results indicate that relative performance of direct vs iterative forecasts and the effect of data set size on forecast performance depends on the number of factors which are obtained by different criteria.

October 2012-September 2014 Best Performing models

Lowest RMSE				
	h=3	h=6	h=9	h=12
BN2002	BIC3	BIC3	BIC3	IC1 & IC2
VAR or Direct	VAR	Direct	Direct	Direct
Data Set	Large	Large	Large	Large
Number of Factors	1	1	2	2

Second Lowest RMSE				
	h=3	h=6	h=9	h=12
BN2002	BIC3	BIC3	IC1 and IC2	BIC3
VAR or Direct	Direct	VAR	Direct	Direct
Data Set	Large	Large	Large	Medium
Number of Factors	1	1	2	2

Stability of Forecast Performance: Stock ve Watson (2003): Forecasting Output and Inflation: Role of Asset Prices, Table 4

B. Output (N = 211)

		1971–84 Out-of-Sample Period		
		Relative MSFE < 1	Relative MSFE > 1	Total
1985–99 Out-of-Sample Period	Relative MSFE < 1	0.10	0.16	0.26
	Relative MSFE > 1	0.21	0.53	0.74
	Total	0.31	0.69	1.00

Notes: Each table shows the fraction of relative means square forecast errors (MSFE) less than 1 or greater than 1 for each sample period, relative to the univariate autoregressive benchmark. Results shown are pooled for all pairs of asset price predictors and inflation measures (part A) or output measures (part B) for all countries at horizon $h = 4$.

January 2011-September 2012 Relative RMSEs by Direct vs Iterative Forecasts

Large Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	0.84	0.75	0.60	0.46	5
BN2002_criter2	0.82	0.91	0.71	0.57	5
BN2002_criter3	0.80	0.69	0.53	0.53	8
BN2002_criter4	0.99	0.97	0.83	0.79	2
BN2002_criter5	0.99	0.97	0.83	0.79	2
BN2002_criter6	0.81	0.84	0.64	0.60	7
BN2002_criter7	0.98	0.99	0.91	0.80	1

Medium Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	0.87	0.86	1.11	0.79	4
BN2002_criter2	0.87	0.83	1.19	0.89	4
BN2002_criter3	0.77	0.93	1.15	1.10	7
BN2002_criter4	0.96	0.93	1.05	0.88	3
BN2002_criter5	0.97	0.95	0.85	0.78	2
BN2002_criter6	0.77	0.93	1.15	1.10	7
BN2002_criter7	0.97	0.95	0.85	0.78	2

Small Data Set	VAR/Direct				
	h=3	h=6	h=9	h=12	Number of Factors
BN2002_criter1	0.83	0.76	0.69	0.88	4
BN2002_criter2	0.83	0.76	0.69	0.88	4
BN2002_criter3	0.83	0.76	0.69	0.88	4
BN2002_criter4	0.83	0.76	0.69	0.88	4
BN2002_criter5	0.83	0.76	0.75	0.66	3
BN2002_criter6	0.86	0.81	0.74	0.95	4
BN2002_criter7	0.87	0.96	0.87	0.78	1

January 2011-September 2012 Relative RMSEs by Data Set Size

Large/small

	h=3	h=6	h=9	h=12
BN2002_criter1	1.00	0.96	1.05	1.08
BN2002_criter2	0.96	0.90	1.01	1.04
BN2002_criter3	1.01	1.01	1.09	1.09
BN2002_criter4	1.02	0.97	1.03	1.10
BN2002_criter5	1.02	0.98	1.03	1.10
BN2002_criter6	0.95	0.92	0.97	1.03
BN2002_criter7	1.03	0.99	0.92	0.97

Large/small

	h=3	h=6	h=9	h=12
BN2002_criter1	0.98	0.97	1.21	2.09
BN2002_criter2	0.98	0.75	0.98	1.61
BN2002_criter3	1.05	1.12	1.41	1.81
BN2002_criter4	0.86	0.76	0.86	1.22
BN2002_criter5	0.86	0.76	0.93	0.91
BN2002_criter6	1.02	0.89	1.12	1.63
BN2002_criter7	0.91	0.97	0.88	0.95

Medium/small

BN2002_criter1	0.99	1.01	1.02	1.07
BN2002_criter2	1.01	1.01	1.02	1.07
BN2002_criter3	0.98	1.00	1.04	1.06
BN2002_criter4	1.00	1.02	1.01	1.06
BN2002_criter5	1.00	1.02	1.00	1.06
BN2002_criter6	0.95	0.95	0.97	0.99
BN2002_criter7	1.01	1.02	0.94	0.99

Medium/small

BN2002_criter1	0.94	0.90	0.64	1.18
BN2002_criter2	0.95	0.93	0.59	1.05
BN2002_criter3	1.07	0.82	0.63	0.85
BN2002_criter4	0.87	0.83	0.66	1.06
BN2002_criter5	0.86	0.81	0.88	0.89
BN2002_criter6	1.07	0.82	0.63	0.85
BN2002_criter7	0.90	1.03	0.96	0.99

January 2011-September 2012 Best Performing models

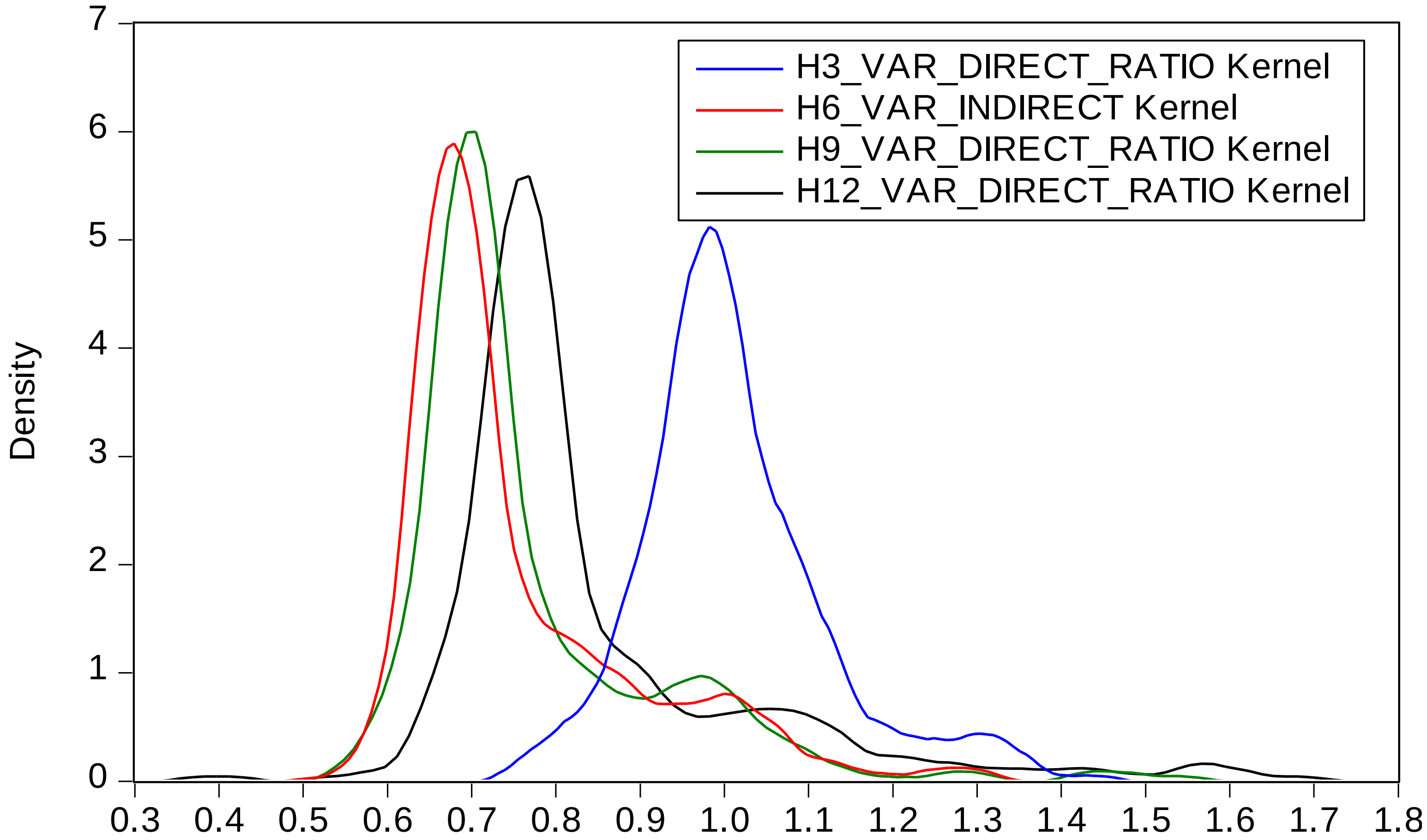
Lowest RMSE				
	h=3	h=6	h=9	h=12
BN2002	PC2	PC2	PC2	PC3 & IC3
VAR or Direct	VAR	VAR	Direct	Direct
Data Set	Large	Large	Medium	Medium
Number of Factors	5	5	7	7
Second Lowest RMSE				
	h=3	h=6	h=9	h=12
BN2002	IC3	IC1 & IC 2	PC3 and IC3	PC1, PC2, IC1 and IC2
VAR or Direct	VAR	VAR	Direct	Direct
Data Set	Medium	Large	Medium	Small
Number of Factors	5	5	7	4

- How can we deal with **dimensionality** problem?
    - A. Factor Models
    - B. Multiple bi-variate direct forecast equations.
    - C. Multiple bi-variate VARs

Pooling bivariate forecasts vs Factor Model

- We consider 267 indicators.
- We get forecasts from each of these using bivariate models with direct and iterative approach.
- We take the average of forecasts for each period and do the horse race with factor models.

Direct vs Iterative Bi-variate Model Forecasts



October 2012-September 2014 Relative RMSEs

	h=3	h=6	h=9	h=12
Factor Model		+		+
Average of Direct bi-variate Forecasts				
Average of Direct bi-variate VAR Forecasts	+		+	

Lowest RMSE				
	h=3	h=6	h=9	h=12
BN2002	BIC3	BIC3	BIC3	IC1 & IC2
VAR or Direct	VAR	Direct	Direct	Direct
Data Set	Large	Large	Large	Large
Number of Factors	1	1	2	2

- We make a systematic evaluation of how performance of factor models change depending on the criterion for selecting number of factors, mutli-step ahead forecast approach and size of the data set.
- Results reveal that relative performance changes with different specifications which is a warning signal about the use of factor models forecasts.
- Time period where we do the evaluations also effects forecasts.
- We also considered pooling bi-variate forecasts rather than using a factor model. There are cases where pooling is more efficient than factor model forecasts.
- It will be informative to apply the same systematic approach to other type of variables such as price and financial data.