

# Improving model-based near-term GDP forecasts by subjective forecasts: a real-time exercise for the G7-countries

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Disclaimer: views expressed do not necessarily reflect official position of De Nederlandsche Bank

# Introduction

## Research question

- Are predictions of professional analysts able to improve GDP forecasts for the nearby quarters generated by purely statistical procedures in **real-time**?

## Motivation

- Several papers indicate that professional analysts could enhance mechanical linear models, e.g. Liebermann (2014) and Giannone, Reichlin and Small (2008) for the US, Jansen, Jin en de Winter (2016) for the euro area;

## Goals

- Extend previous research to G7 countries (CA, US, UK, JA, DE, FR, IT) in a truly **real-time** setting;
- Provide new evidence on the practical issue how policy makers should combine forecasts of mechanical models and 'judgmental' forecasts of professional analysts.

## Main message

Forecasts of professional analysts can enhance the forecasting accuracy of state-of-the-art mechanical nowcasting models via simple combination schemes, especially in volatile times.

# Agenda

- Model
- Data & real-time setup
- Outcome
- Conclusion

## Workhorse Dynamic factor model (DFM)

Doz, Giannone and Reichlin (2011), Bańbura and Rünstler (2011), den Reijer (2013), Schumacher, Breitung (2008), Jansen et al. (2016)

### Intuition

- Extract information from panel of indicators in a few factors that account for co-movement among variables;
- Use factors to forecast GDP;
- Allow (VAR) dynamics between factors;
- Estimation of coefficients is straightforward: Principal Component Analysis & Ordinary Least Squares;
- Use temporal aggregation constraint to mix monthly and quarterly frequencies;
- Cast model in state-space form to generate forecasts.

# Real-time database: monthly variables

## Monthly variables

Real-time vintages for approx. 40 headline “market moving” indicators that are readily available to economic agents (e.g. Bańbura et al., 2013, Bańbura and Modugno, 2014)

### Part I: Domestic economy

- Hard, quantitative information on production & expenditures;
- Consumer and producer prices;
- Financial variables (prices & volumes);
- Soft, qualitative information from surveys amongst consumers & producers.

### Part II: Global variables

- Oil and commodity prices;
- Semiconductor sales, Baltic Dry Index, S&P VIX, World trade (CPB).

### Part III: Key data on two most important trade partners

- Imports, exports, industrial production, composite leading indicator (OECD);
- Ifo, INSEE, ISEA and BNB for DE, FR & IT.

# Real-time database: Data sources

## Sources monthly indicators and GDP

- ALFRED database St. Louis;
- OECD Main Economic Indicators Database;
- Bloomberg;
- CPB, EC, IFO, INSEE, ISEA, BNB, BoJ, BALTEX.

## Source professional analysts

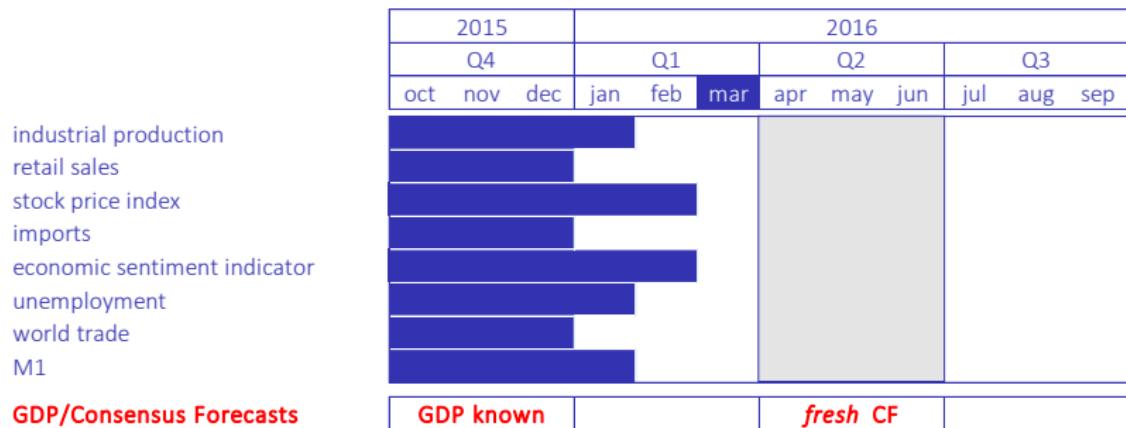
- New dataset of average forecasts of professional analysts
- Constructed from paper copies of **Consensus Forecasts**;
- Well known for yearly forecasts (**monthly** publication frequency);
- Less well for quarterly forecasts (**quarterly** publication frequency).

## Analyze period 1999-2014

- For each country: **188 Snapshots** of the monthly data & GDP;
- For each country: **60 Snapshots** of the quarterly Consensus Forecasts;
- All data aligned to the second Monday of the month.

# Real-time database: flow of monthly data & forecasts

## Forecast, month 3 (FC m3) for 2016Q2



# Real-time database: flow of monthly data & forecasts

## Nowcast, month 1 (NC m1) for 2016Q2

	2015			2016								
	Q4			Q1			Q2			Q3		
	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep
	industrial production											
retail sales												
stock price index												
imports												
economic sentiment indicator												
unemployment												
world trade												
M1												
GDP/Consensus Forecasts	GDP known			1 mnth. old CF								

# Real-time database: flow of monthly data & forecasts

## Nowcast, month 2 (NC m2) for 2016Q2

	2015			2016								
	Q4			Q1			Q2			Q3		
	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep
industrial production												
retail sales												
stock price index												
imports												
economic sentiment indicator												
unemployment												
world trade												
M1												
GDP/Consensus Forecasts	GDP known			2 mnth. old CF								

# Real-time database: flow of monthly data & forecasts

## Nowcast, month 3 (NC m3) for 2016Q2

	2015			2016								
	Q4			Q1			Q2			Q3		
	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep
	industrial production											
retail sales												
stock price index												
imports												
economic sentiment indicator												
unemployment												
world trade												
M1												
GDP/Consensus Forecasts	GDP known			fresh CF								

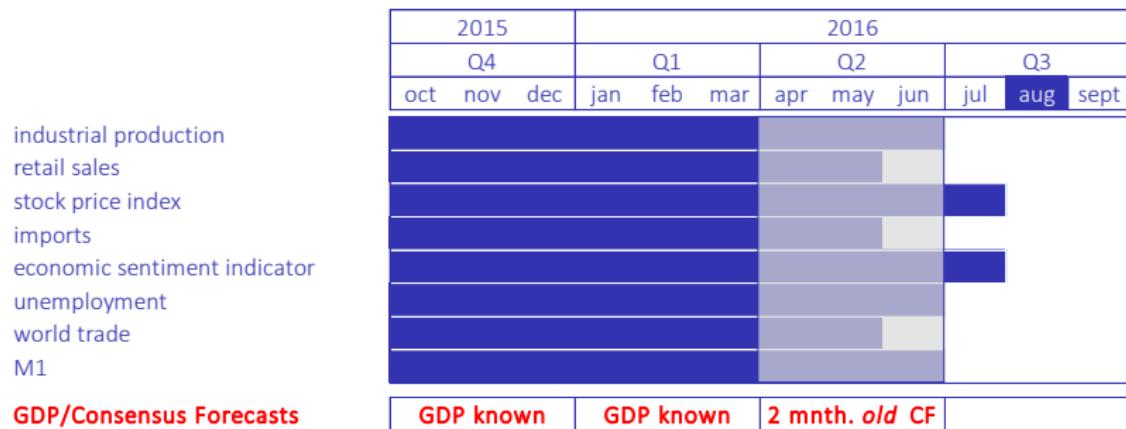
# Real-time database: flow of monthly data & forecasts

## Backcast, month 1 (BC m1) for 2016Q2

	2015			2016								
	Q4			Q1			Q2			Q3		
	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep
	industrial production											
retail sales												
stock price index												
imports												
economic sentiment indicator												
unemployment												
world trade												
M1												
GDP/Consensus Forecasts	GDP known			GDP known			1 mnth. old CF					

# Real-time database: flow of monthly data & forecasts

## Backcast, month 2 (BC m2) for 2016Q2



# Real-time database: flow of monthly data & forecasts

## GDP 2016Q2 known

	2015			2016								
	Q4			Q1			Q2			Q3		
	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep
	industrial production									known		
retail sales												
stock price index										known		
imports												
economic sentiment indicator										known		
unemployment										known		
world trade												
M1										known		
GDP/Consensus Forecasts				GDP known			GDP known			GDP known		

# Real-time database: Forecast design

## Timing of forecast exercise for second quarter GDP growth

Forecast type	Month	DFM	Consensus
Forecast	3	March	new
Nowcast	1	April	1 month old
	2	May	2 months oud
	3	June	new
Backcast	1	Juli	1 month old
	2	August	2 months old

# Outcome: preliminaries

## Graphical presentation outcomes

- Averages for G-7 countries, measures of differences between countries;
- All country results and robustness tests are in DNB Working Paper nr. 507;
- Tables therein show if models are equal in “economic” and “statistical” term: 10% rule and Diebold Mariano (1995) test.

## Forecast accuracy against the flash GDP release

- Paper shows sensitivity results for **pseudo real-time design**, real-time forecasts against **final GDP**.

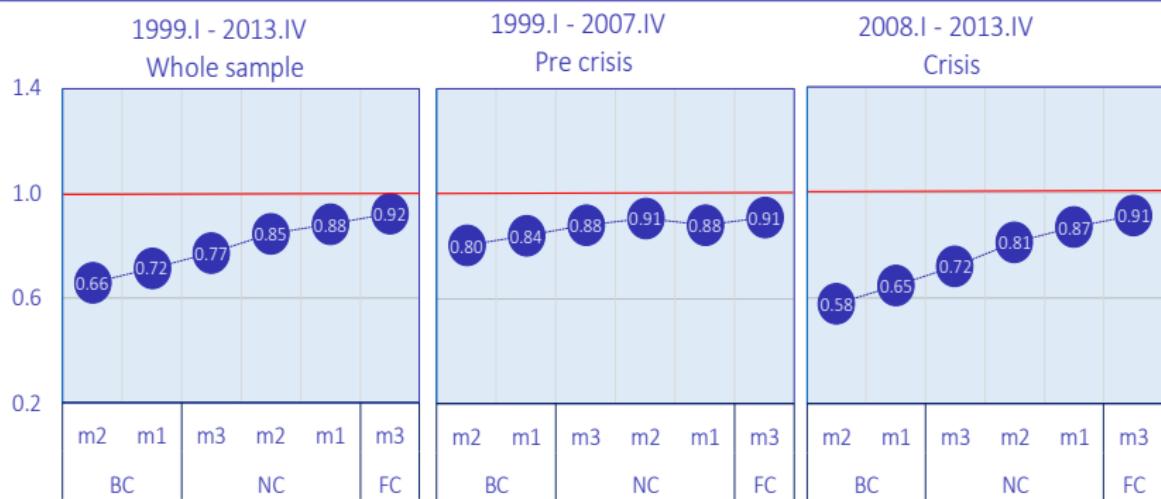
## Dynamic factor model specification

- 15 year rolling window;
- Unweighted average of forecasts of 40+ DFM-specifications estimated each month;
- Paper shows sensitivity results for **different rolling window size** (10 year) and **expanding window**

The Root Mean Squared Error (RMSFE) is our measure of forecast accuracy

# Outcome: average G7 countries

## Dynamic factor model vs. Random Walk

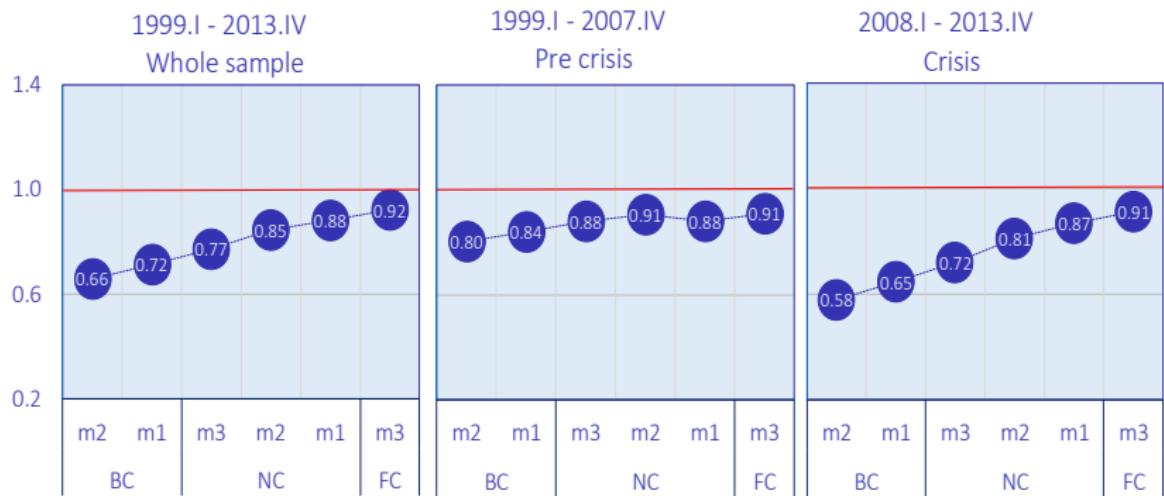


Source: DNB.

Note: RMSFE Dynamic Factor Model divided by RMSFE Random Walk; average G-7; BC = Backcast, NC=Nowcast, FC=Forecast.

# Outcome: average G7 countries

## Dynamic factor model vs. Random Walk



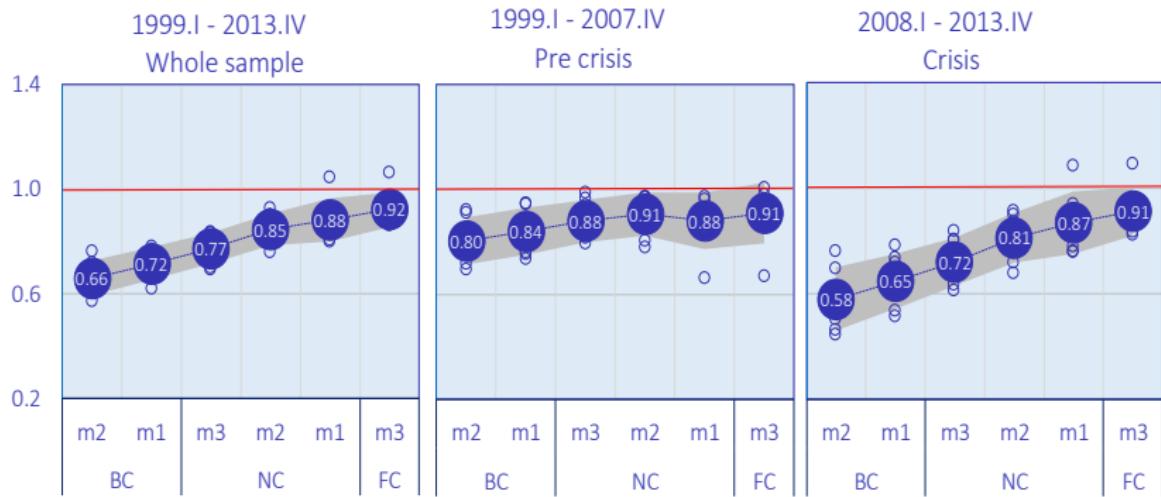
Source: DNB.

Note: RMSFE Dynamic Factor Model divided by RMSFE Random Walk; average G-7; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Incorporating monthly information pays off (all  $rRMSFES < 1$ );
- ②  $rRMSFE$  post-crisis << pre-crisis;
- ③ DFM's relatively strength is now- and backcasting.

# Outcome: average G7 countries & country results

## Dynamic factor model vs. Random Walk



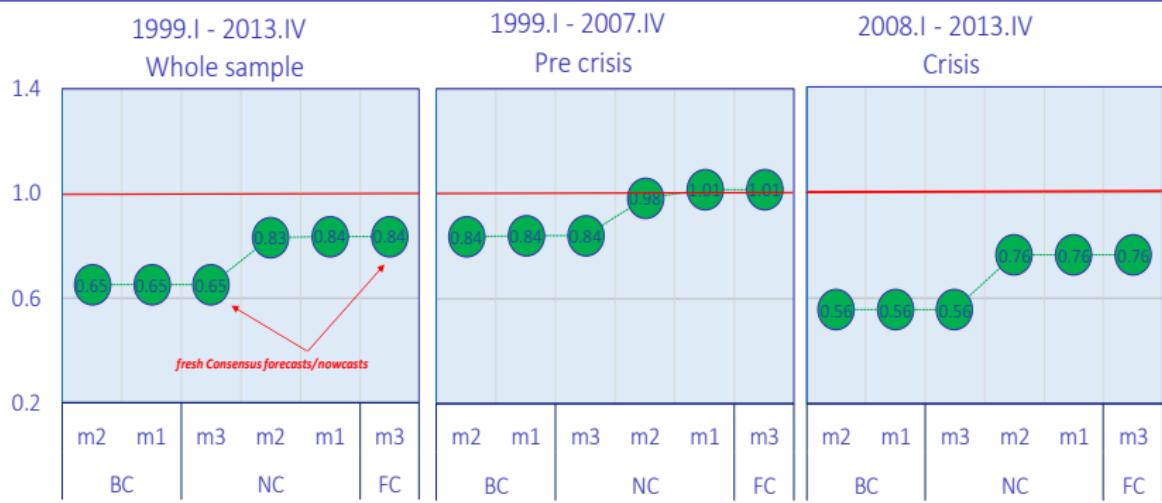
Source: DNB.

Note: RMSFE Dynamic Factor Model divided by RMSFE Random Walk; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① **Variability (grey area):  $\pm 1$  standard deviation;**
- ② **All countries relatively close together;**

# Outcome: average G7 countries

## Consensus Forecasts vs. Random Walk



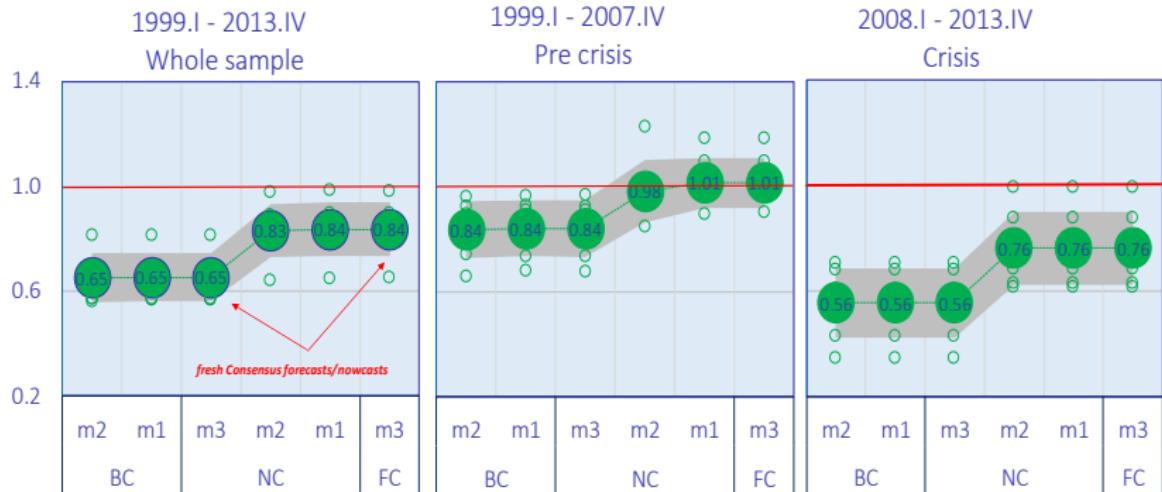
Source: DNB.

Note: RMSFE Quarterly Consensus Forecasts divided by RMSFE Random Walk; average G-7; BC = Backcast, NC=Nowcast, FC=Forecast.

### ① Very steep learning curve

# Outcome: average G7 countries & country results

## Consensus Forecasts vs. Random Walk



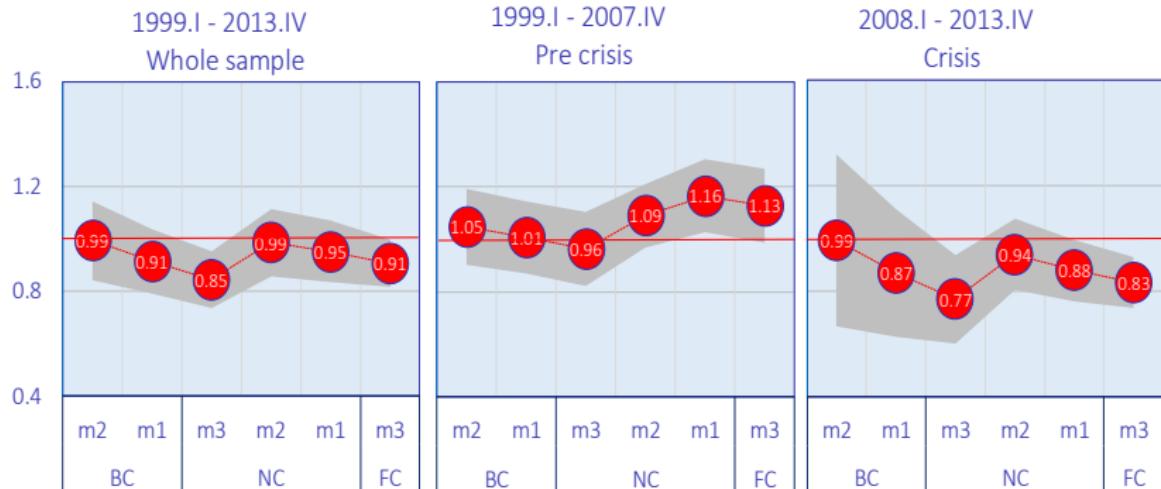
Source: DNB.

Note: RMSFE Quarterly Consensus Forecasts divided by RMSFE Random Walk; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Japan has worst performance;
- ② The remarkable case of Canada → post- versus pre-crisis.

# Outcome: average G7 countries

## Consensus Forecasts vs. Dynamic Factor Model



Source: DNB.

Note: RMSFE Quarterly Consensus Forecasts divided by Dynamic Factor Model; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① fresh CF nowcasts always better than DFM → driven by crisis;
- ② DFM catches up in between fresh CF's → especially during crisis;

# Outcome: encompassing test

Formal investigation of value added Consensus Forecasts versus the DFM forecasts.

## Weighted average

E.g. Bates en Granger (1969), Stekler (1991) and Jansen, Jin, de Winter (2016)

$$y_{t+h|t}^Q = \beta \hat{y}_{\text{cs}(t+h|t)}^Q + (1 - \beta) \hat{y}_{\text{dfm}(t+h|t)}^Q + \varepsilon_t \quad (1)$$

$\beta$  restricted to [0,1] interval.

## Linear combination

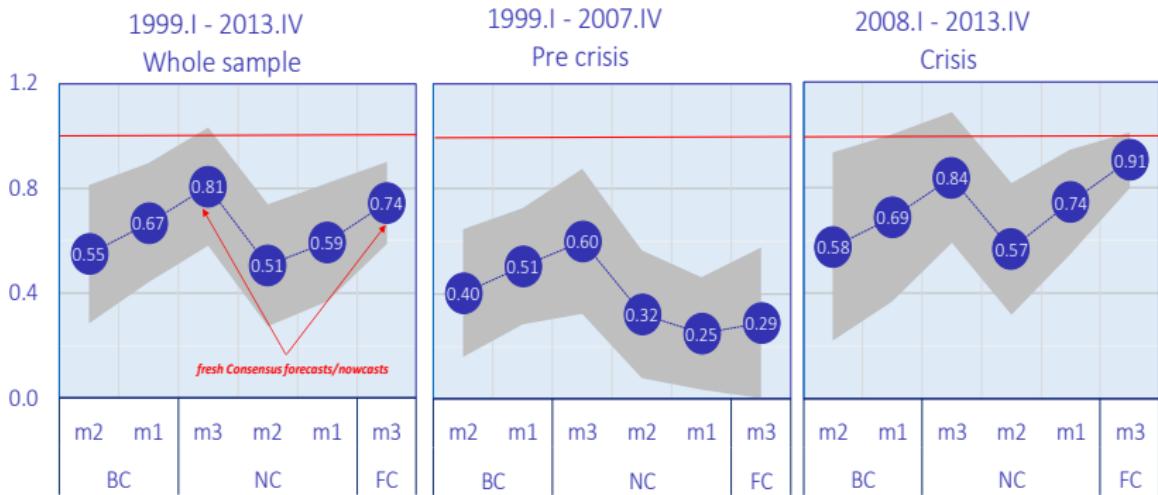
E.g. Granger en Ramathan (1984), Fair en Shiller (1990) and Liebermann (2014)

$$y_{t+h|t}^Q = \alpha + \beta \hat{y}_{\text{cs}(t+h|t)}^Q + \gamma \hat{y}_{\text{dfm}(t+h|t)}^Q + \varepsilon_t \quad (2)$$

All coefficients unrestricted. Advantage: Can neutralize bias in forecasts (Timmerman, 2006)

# Outcome: average G7 countries & country results

## Coefficient Weighted average



Source: DNB.

Note: Weight ( $\beta$ ) of Consensus Forecasts in encompassing test (weighted average specification).

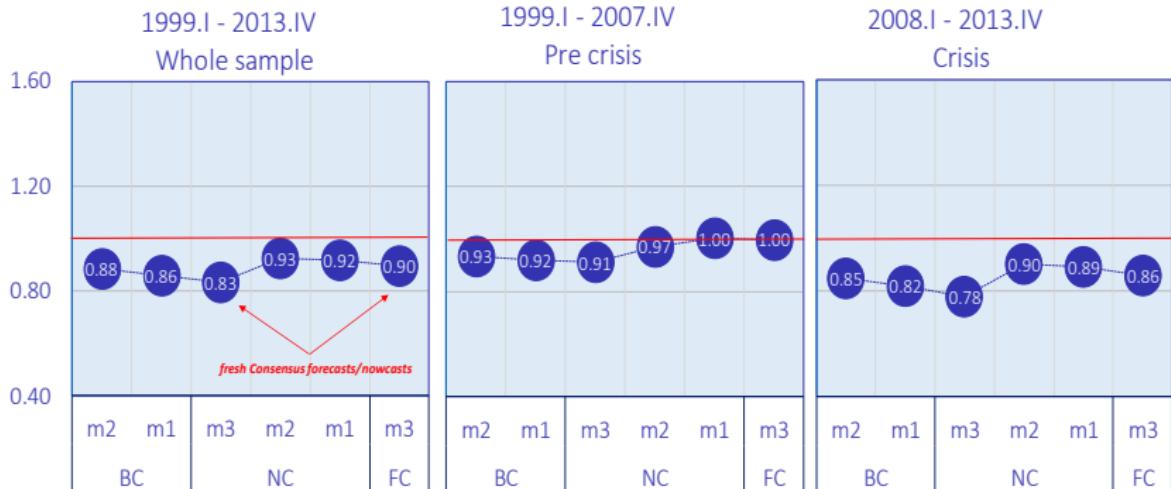
- ① Pre-crisis  $\beta < 0.5$ , after crisis  $\beta > 0.5$ ;
- ② Corner solutions are rare  $\rightarrow \beta(CA) = 0$  pre-crisis;
- ③ Hints at possible forecasting advantage of combining;

## Combining forecasts in real-time

- Weighted average versus Linear combination → heterogeneous picture;
- This advantage is hard to use in real time;
- Unweighted average of schemes is optimal ("insurance principal");
- Simple average over both combination-schemes evaluated over last 1,2,3 and 4 year period;

# Outcome: average G7 countries & country results

## Average combination rules versus dynamic factor model



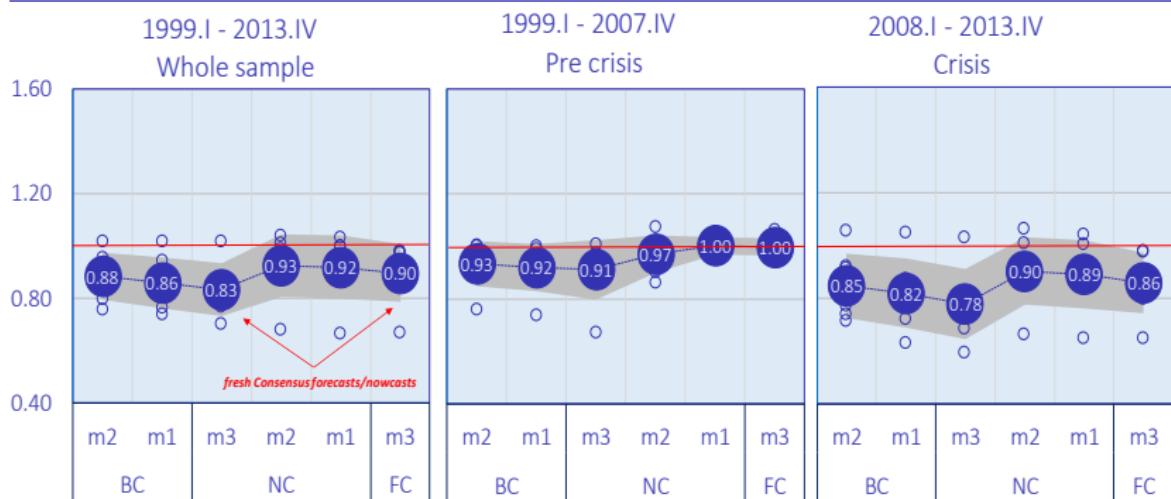
Source: DNB.

Note: RMSFE Combination DFM and Quarterly CF divided by RMSFE DFM; average G-7; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Post-crisis combination always better than DFM alone;
- ② Especially when Consensus forecasts are freshly released;

# Outcome: average G7 countries & country results

## Average combination rules versus dynamic factor model



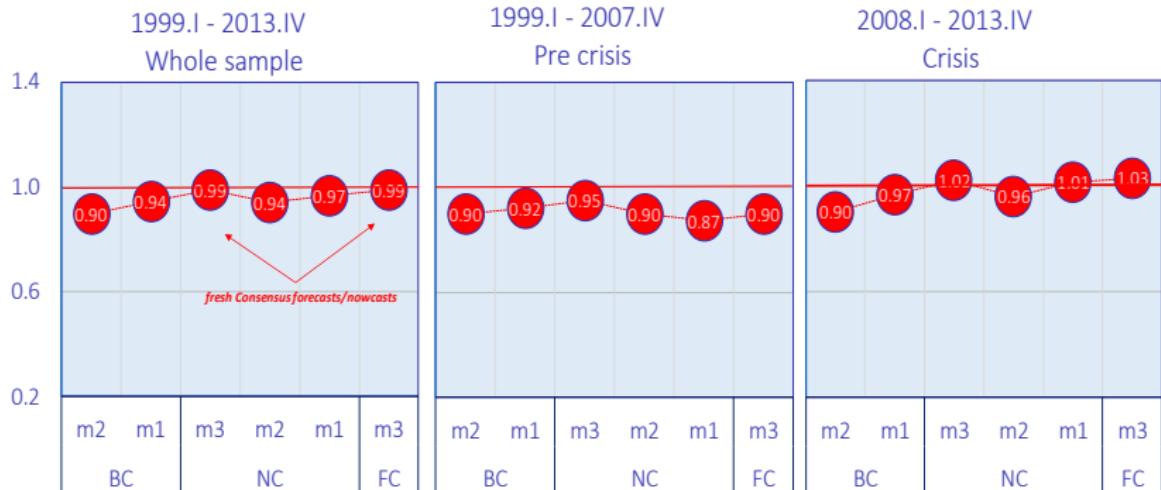
Source: DNB.

Note: RMSFE Combination DFM and Quarterly CF divided by RMSFE DFM; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Japan is the outlier: RMSFE combination > RMSFE DFM;

# Outcome: average G7 countries & country results

## Average combination rules versus quarterly consensus forecasts



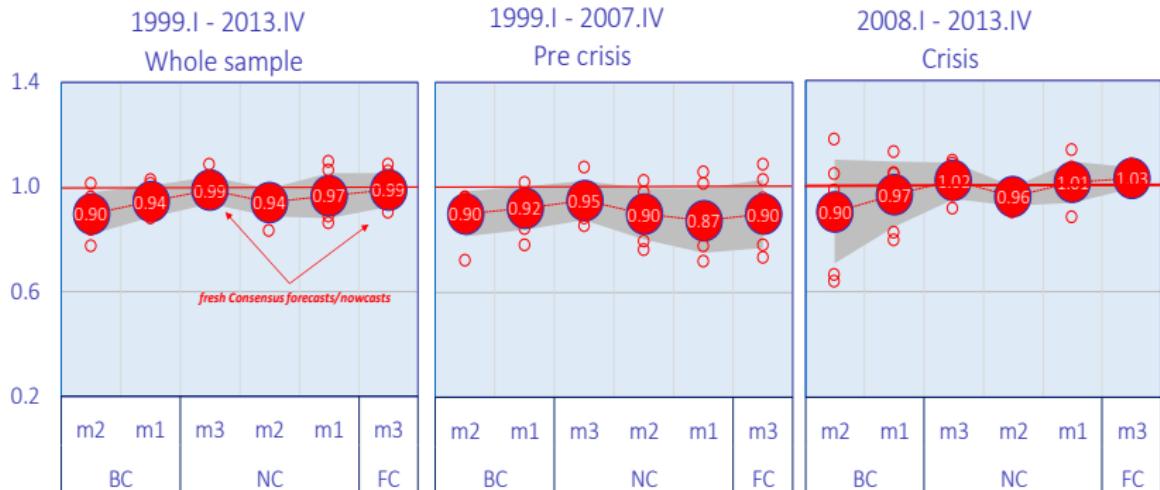
Source: DNB.

Note: RMSFE Combination DFM and Quarterly CF divided by RMSFE CF; average G-7; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Very hard to beat a fresh Consensus Forecast;
- ② Value added of DFM quite limited in post-crisis period;

# Outcome: average G7 countries & country results

## Average combination rules versus quarterly consensus forecasts



Source: DNB.

Note: RMSFE Combination DFM and Quarterly CF divided by RMSFE CF; BC = Backcast, NC=Nowcast, FC=Forecast.

- ① Although there are some exceptions...;
- ② ...Italy & Japan post-crisis, Canada pre-crisis;

# Outcome: weight Consensus Forecast over time

Weight ( $\beta$ ) "fresh" Consensus forecasts in weighted average combination scheme



# Conclusion

## Different angles, one constant refrain...

- Predictive power subjective Consensus forecasts has improved relative to predictions from the dynamic factor model over time

## Why?

- Analysts used less advanced models at beginning of our evaluation period;
- Analysts put more effort in forecasting during volatile periods (Lundquist and Stekler, 2012);
- Forecasts analysts = monthly data + models + expert opinion;
- Dynamic factor model not well equipped to deal with breaks (Castle et al., 2015);

## Still (large) value added nowcasting models..

- Consensus forecasts are released once a quarter: can become outdated rather quickly;
- “Black-Box” versus “Story-Telling”
- You can learn from model mistakes...

# Conclusion

## Conclusions

- ① Monthly statistical indicators contain valuable information that can be extracted with DFM (nowcast, backcasts);
- ② Consensus forecasts improve after the crisis, making them a tough competitor to the DFM;
- ③ Relative forecasting advantage N3>F3 (some information);
- ④ Combination enhances the forecasting accuracy of the DFM, even when Consensus forecasts are somewhat dated;
- ⑤ Average of weighting schemes optimal, but differences small;

## Future research

- How can statistical models be made more robust to extreme observations in real-time (heuristic, fully taking into account breaks inside model)
- In-depth investigation into the forecasting strategies of professional analysts

# Thank you for your attention!

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