Nowcasting the Finnish economy with a large Bayesian vector autoregressive model

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Introduction

- Timely and accurate assessment of current macroeconomic activity is crucial for policymakers.
- Lag in the release of GPD figures is long (8-9 weeks) in Finland and the flash estimates (5-6 week publication lag) by the Statics Finland have performed poorly recently
  - Need for nowcasts
  - task is difficult due to volatility and structural break
  - models Bank of Finland has used, dynamic factor model and bridge models have been producing upward biased nowcasts
- We develop and apply a large Bayesian vector autoregressive (BVAR) model to nowcast quarterly GDP growth rate of the Finnish economy.
  - based on BVAR we are currently building a public nowcasting webpage containing news and contribution analysis

Introduction

- several papers have shown that DMFs and BVARs work well in terms of short term forecasting e.g. Giannonen et al. (2015), Banbura et al (2015)
- our general research question is, how do dynamic multivariate models for large cross-sections, DMF and BVAR, perform when the data is much different than normally used in the evaluations (US or euro area data)
  - volatility
  - structural break
- do perform well compared to simple statistical models well in terms of RMSE
- only BVAR (in log levels) produces unbiased nowcasts

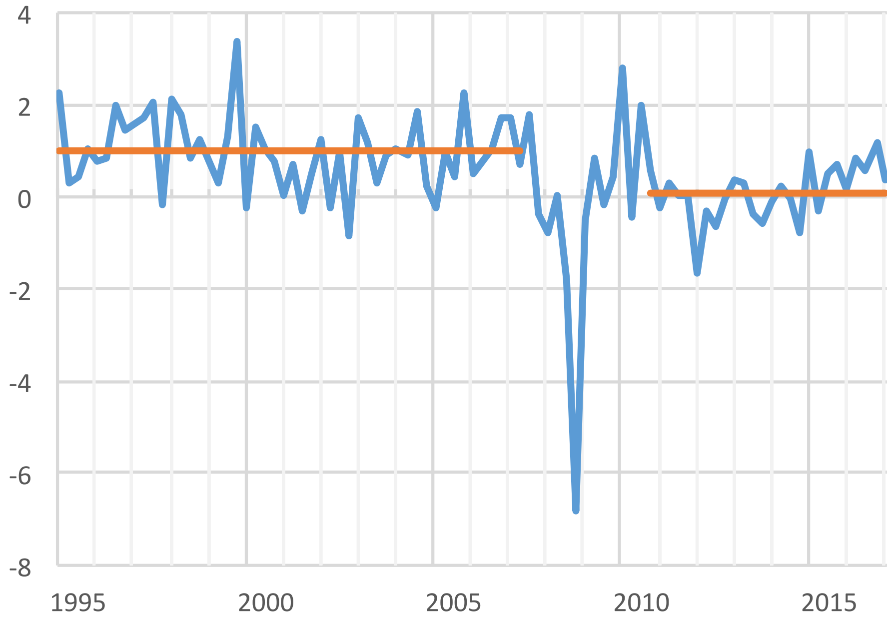
Introduction

- new approach to deal with mixed frequency data
- we illustrate that in order to get well behaving nowcasts from large BVAR, more shrinkage needs to be induced for the error var-cov matrix than in the standard Minnesota priors

Introduction

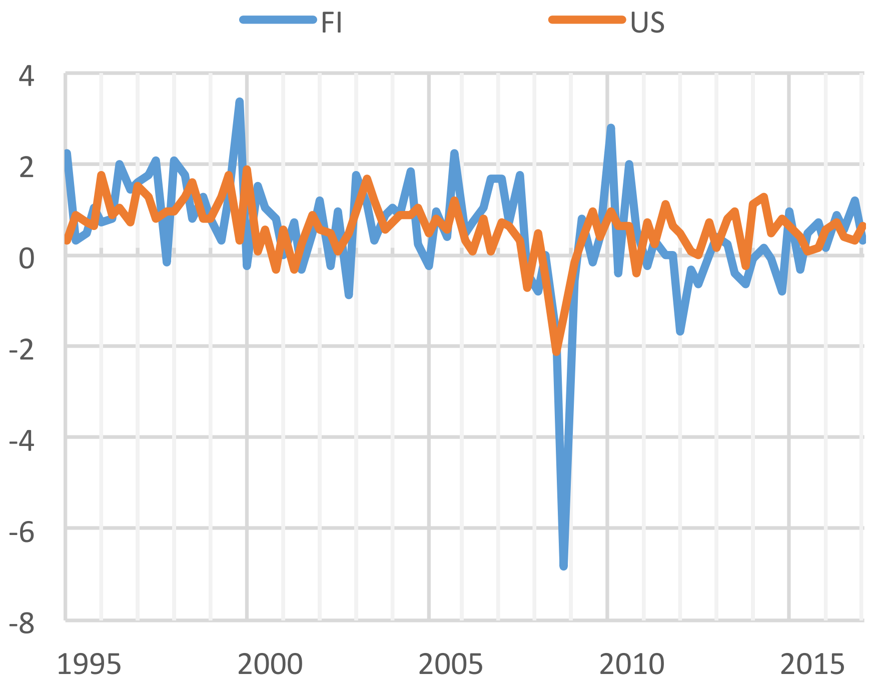
1. Look at the challenging data
2. Our approach
3. Forecasting evaluation results
4. Applications

Shift in in the growth rate of Finnish real GDP

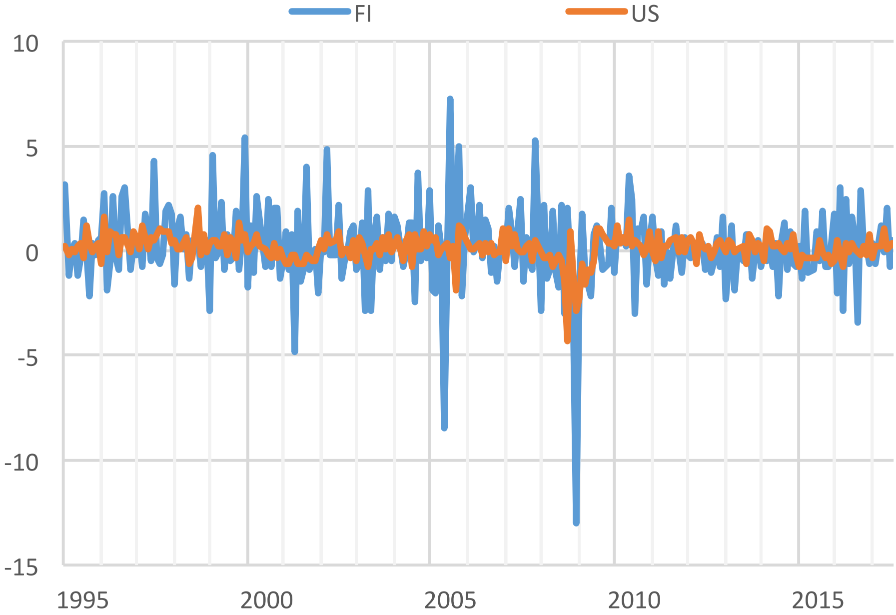


Average QoQ growth 1995-2007 1%
Average QoQ "growth" 2011- 0.1%

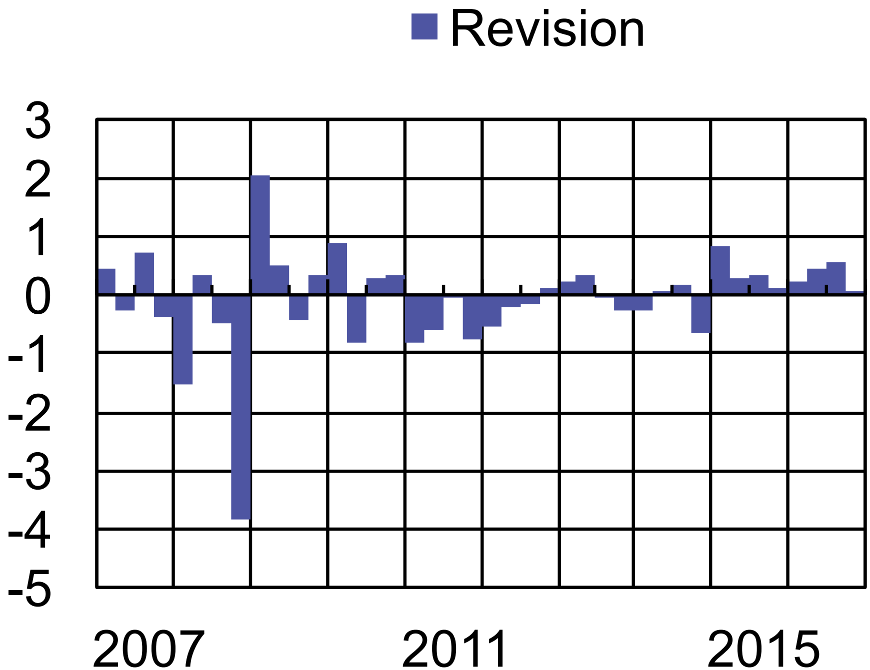
Volatile quarterly growth rate of Finnish real GDP



Volatility of monthly indicators, IP



Large revisions in Finnish GDP



Statistics Finland Flash estimates for QoQ GDP growth

	Latest vintage	Flash	Difference
2015Q1	-0,78	-0,10	-0,68
2015Q2	1,00	-0,40	1,40
2015Q3	-0,28	-0,60	0,32
2015Q4	0,50	-0,10	0,60
2016Q1	0,72	0,40	0,32
2016Q2	0,18	0,30	-0,12
2016Q3	0,85	0,50	0,35
2016Q4	0,59	-0,50	1,09
2017Q1	1,17	1,60	-0,43
2017Q2	0,36	-0,50	0,86

Our approach

- Recently renewed interest on large BVARs since work as well as factor models Giannone et al (2015),Banbura et al (2015)
- Curse of dimensionality is dealt with Bayesian shrinkage, using Minnesota type priors
- We estimate the VAR on undifferenced data - contains long run information
  - wanted to see if this produces less upward biased forecasts as factor model on differenced data
  - differencing amplifies the noise component the in data and Finnish data is volatile
- New approach to estimate VAR on mixed frequency data
- Kalman filter/smoother

BVAR

- VAR with n variables and p lags

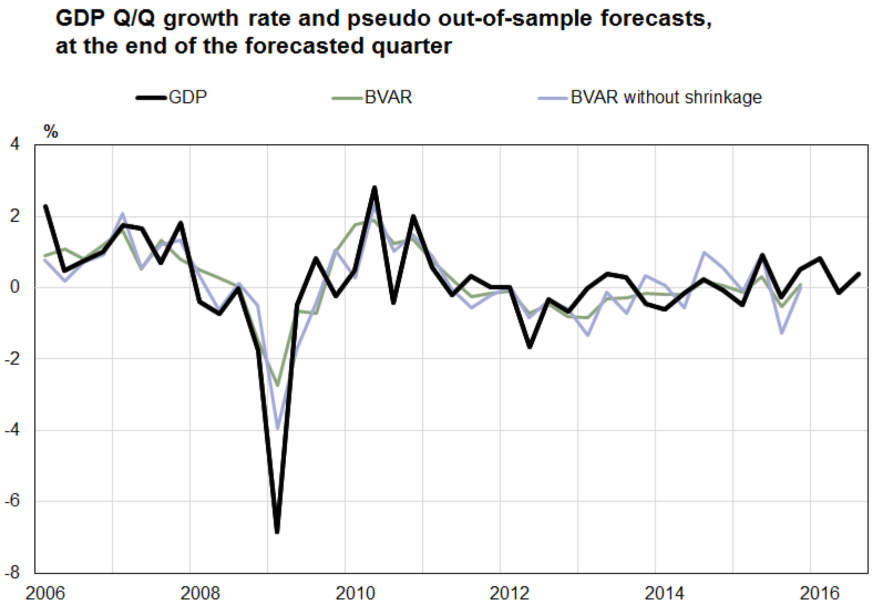
$$y_t = c + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma) \quad (1)$$

  where y, c and ϵ are $n \times 1$ vectors, each A is $n \times n$ and Σ is $n \times n$ are matrices
- VAR with Litterman prior, shrinks towards independent unit root process
- in addition sum-of-coefficients and dummy-initial-observation priors
- VAR contains over 40 variables, all the relevant that Statistics Finland publishes on monthly or quarterly basis and few exogenous variables

Shrinkage for Σ

- We induce more shrinkage for the error covariance matrix, Σ than in the traditional Litterman prior.
- As in the Litterman prior, prior for Σ is diagonal but it has higher weight in our application
- This is crucial for the behavior of nowcast, since nowcasts are obtained with Kalman filter and the updating is based on Σ
- as Σ is almost 50×50 matrix and some of the elements can be very poorly estimated
- we reduce the correlations and this affects also on Kalman updating

Shrinkage for Σ



Estimation procedure

Data consists of monthly and quarterly data. We estimate a VAR for monthly data only and a VAR for data that consists of time-aggregated monthly data and quarterly data.

1. Use monthly VAR and Kalman filter to fill missing observations till the end of the latest quarter we have any observations.
2. Do time-aggregation in Kalman filter and get forecast error var-cov matrix for time aggregated data. When time-aggregated data point contains forecasts, it is treaded as observed with a measurement error. We obtain var-cov matrix for the measurement errors from the output of the Kalman filter.
3. Use quarterly VAR and Kalman filter to forecast GDP conditional on observed quarterly data and monthly data that is time-aggregated. Take into account that part of the time aggregated monthly data contains measurement errors. Feed in the var-cov matrix from step 2

On solving the mixed frequency problem

- Schorfheide and Song (2015) specify VAR on monthly frequency and treat monthly GDP as unobserved variable
- McCracken et al. (2015) specify monthly variables on different months of a quarter as different variables, triples the number of paramters
- due to noisy monthly series we prefer time aggregation

Forecast evaluation

- pseudo out-of-sample evaluation against competing models taking into account the publication lags of different variables
  - data begins from 1995, evaluation period is 2006-2015
- very short real real-time comparison against the flash estimates of Statistics Finland

Competing models

- **Bridge models** are simple linear regression models which forecast GDP quarter-to-quarter growth rate y_t using a single monthly indicator x_t, which has been aggregated to the quarterly level.

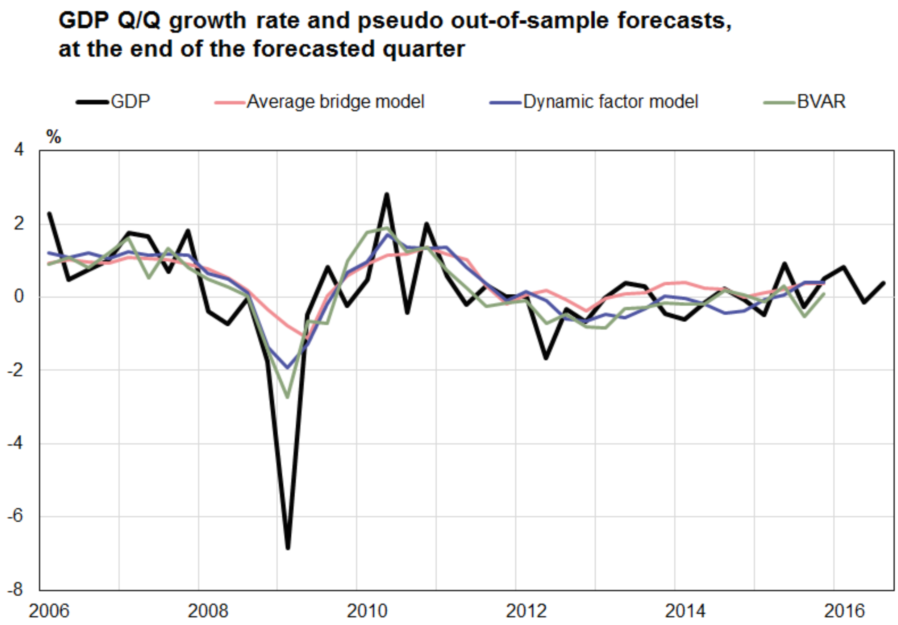
$$y_t = \alpha + \beta_1 x_t + \beta_2 x_{t-1} + e_t,$$

- **Dynamic factor** model based on Giannone et al. (2008)

$$\begin{aligned} Y_t &= \mu + \Lambda F_t + E_t, \quad E_t \sim i.i.d.\ N(0, \Sigma_E) \\ F_t &= \Phi(L) F_t + U_t, \quad U_t \sim i.i.d.\ N(0, \Sigma_U) \end{aligned}$$

- **Random Walk** and **AR(1)**

Pseudo out-of-sample nowcasts at the end of the target quarter



Forecasting performance

	Horizon	Root squared mean error		Mean absolute error		Mean error	
	months from the end of forecasted quarter	2006-2015	2006-2015 exl. 2009	2006-2015	2006-2015 exl. 2009	2006-2015	2006-2015 exl. 2009
RW	4	1,93	1,08	1,16	0,84	0,03	0,10
	1	1,75	1,23	1,20	0,95	0,00	0,04
AR	4	1,55	0,96	0,94	0,73	0,29	0,17
	1	1,50	1,00	0,97	0,76	0,19	0,13
Bridge model	5	1,38	0,90	0,88	0,72	0,38	0,27
	4	1,37	0,90	0,88	0,72	0,37	0,27
	3	1,36	0,90	0,87	0,71	0,37	0,27
	2	1,29	0,85	0,80	0,66	0,34	0,22
	1	1,26	0,82	0,77	0,63	0,33	0,21
	0	1,25	0,81	0,77	0,63	0,32	0,21
Factor model	5	1,53	0,93	0,95	0,74	0,43	0,31
	4	1,42	0,97	0,92	0,75	0,35	0,27
	3	1,22	0,92	0,83	0,69	0,30	0,24
	2	1,17	0,86	0,80	0,69	0,32	0,21
	1	1,02	0,75	0,74	0,63	0,22	0,13
	0	1,07	0,73	0,72	0,59	0,19	0,10
	-1	1,08	0,71	0,71	0,58	0,20	0,11
BVAR	5	1,43	0,97	0,90	0,77	0,21	0,05
	4	1,37	0,96	0,91	0,79	0,19	0,07
	3	1,34	0,92	0,88	0,76	0,19	0,06
	2	1,17	0,78	0,77	0,64	0,17	0,05
	1	1,05	0,68	0,68	0,57	0,11	0,01
	0	0,97	0,68	0,66	0,54	0,08	-0,01
	-1	0,93	0,70	0,64	0,54	0,05	-0,04

Mean error

- What explains the differences in the mean errors?
- Both dynamic factor model and BVAR are linear time series model that use same data set
- But the curse of dimensionality is treated differently...
- ...and factor model uses differenced data
  - trending series in log-diffs, others in diffs
  - this is needed since starting values for factors are obtained by estimating principal components
- test the role of differencing by running BVAR with data in diffs

Mean error

	BVAR		
horizon	log-levels	log-differenced	all differenced
5	0,21	0,31	0,50
4	0,19	0,29	0,48
3	0,19	0,29	0,45
2	0,17	0,20	0,31
1	0,11	0,04	0,16
0	0,08	0,05	0,13
-1	0,05	0,05	0,12
	Excluding 2009		
5	0,05	0,17	0,37
4	0,07	0,21	0,37
3	0,06	0,20	0,36
2	0,05	0,08	0,20
1	0,01	-0,07	0,07
0	-0,01	-0,08	0,02
-1	-0,04	-0,08	0,01

Mean error

- when all variables are differenced it is clear that a positive bias emerges during a long downturn.
  - e.g. differenced unemployment rate does not have information on the state of the economy, only about the change in the state of the economy
- this is less clear when trending variables are in log-diffs and others in levels

Real real-time comparison with Flash estimates

- for a year now we have been using BVAR for nowcasting and stored the nowcasts
- Flash estimates are by Statistics Finland (6 weeks after the end of the quarter)

	Latest vintage	Flash	BVAR
2016Q3	0,85	0,50	0,93
2016Q4	0,59	-0,50	0,35
2017Q1	1,17	1,60	0,86
2017Q2	0,36	-0,50	0,33

Summarizing our findings

- dynamic multivariate models for large cross-sections, BVARs & DMF, forecast relatively accurately also with volatile data and in the presence of a structural break in terms of RMSE
- however, to get unbiased forecasts in a presence of structural break, model specified on log-levels data seems to perform better than on differenced data
- mixed frequency problem can be dealt with a computationally simple approach
- BVAR is useful tool for nowcasting, but error var-cov matrix needs more shrinkage than in the traditional Minnesota prior
- for this short period, our nowcasts have been comparable or even better than the flash estimates by the Statisic Finland

Applications

We use BVAR for

- news analysis
- contribution analysis
- reporting uncertainty

News analysis

- as in Banbura and Modugno (2014)
- what matters is the unexpected component in the releases, not the releases itself
- allows to find the most important data releases
  - less weight for volatile variables

News analysis

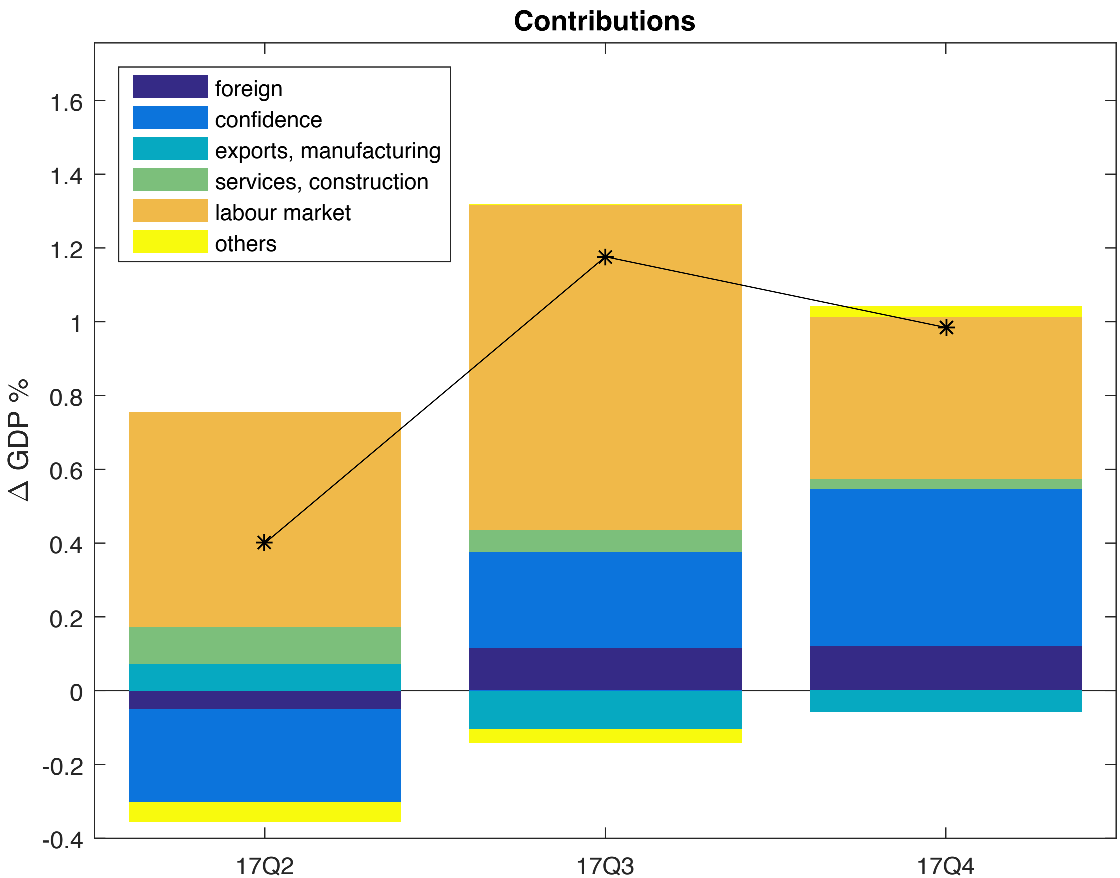
Variable			Latest observation (A)	Previous observation	Forecast (B)	News (A-B)	Changes in GDP forecasts 2016Q4	2017Q1	2017Q2
Granted building permits	M12	lnΔ M/M	-24,19	-0,59	-46,69	22,50	0,00	-0,01	0,01
Volume index of newbuilding	M12	lnΔ M/M	-0,14	0,17	0,05	-0,19	0,00	-0,01	-0,01
Building starts	M12	lnΔ M/M	21,78	-7,92	5,09	16,70	-0,07	-0,02	0,07
Building completions	M12	lnΔ M/M	1,04	31,42	-10,55	11,60	0,01	0,00	-0,01
World trade	M12	lnΔ M/M	0,49	2,53	1,28	-0,79	-0,03	-0,07	-0,02
Employed, ages 15-74	M1	lnΔ M/M	-0,20	0,32	0,06	-0,27	0,00	-0,04	-0,03
Unemployment rate, ages 15-74	M1	%	8,96	8,38	8,31	0,64	0,00	-0,06	-0,07
Jobs vacant	M1	lnΔ M/M	-6,35	2,62	4,39	-10,74	0,00	-0,29	-0,13
Unemployment rate (Employment Service Stats)	M1	%	12,53	12,73	12,69	-0,16	0,00	0,24	0,12
Unemployed jobseekers	M1	lnΔ M/M	-1,81	-1,23	-0,42	-1,39	0,00	0,26	0,12
Consumer price index	M1	lnΔ M/M	-0,60	0,25	0,15	-0,76	0,00	-0,03	0,04
Producer price index, manufacturing	M1	lnΔ M/M	0,77	0,78	0,41	0,36	0,00	0,00	0,00
Export price index	M1	lnΔ M/M	0,79	1,28	-0,07	0,85	0,00	0,01	-0,01
Import price index	M1	lnΔ M/M	1,36	2,85	0,63	0,73	0,00	0,01	0,01
Consumer survey: Own economy	M2	-	9,00	8,80	8,83	0,17	0,00	0,02	0,01
Consumer survey: Finland's economy	M2	-	14,90	15,30	15,71	-0,81	0,00	0,00	-0,01
Business confidence, Manufacturing	M2	-	1,50	3,60	5,36	-3,86	0,00	-0,05	-0,06
Business confidence, Construction	M2	-	3,30	3,80	3,61	-0,31	0,00	0,00	0,00
Business confidence, Manufacturing prod	M2	-	12,80	17,40	19,54	-6,74	0,00	-0,04	-0,04
USA pmi (ISM), manufacturing	M2	-	57,70	56,00	55,90	1,80	0,00	0,02	0,03
German IFO-index	M2	-	118,40	116,90	117,99	0,41	0,00	0,01	0,01
Economic sentiment indicator, Eurozone	M2	-	108,00	107,90	108,53	-0,53	0,00	-0,02	-0,03
Effect of revisions							-0,07	0,02	0,03

	GDP forecasts 2016Q4	2017Q1	2017Q2
Pre-update	0,35	1,18	0,83
Post-update	**0,21**	**0,95**	**0,79**

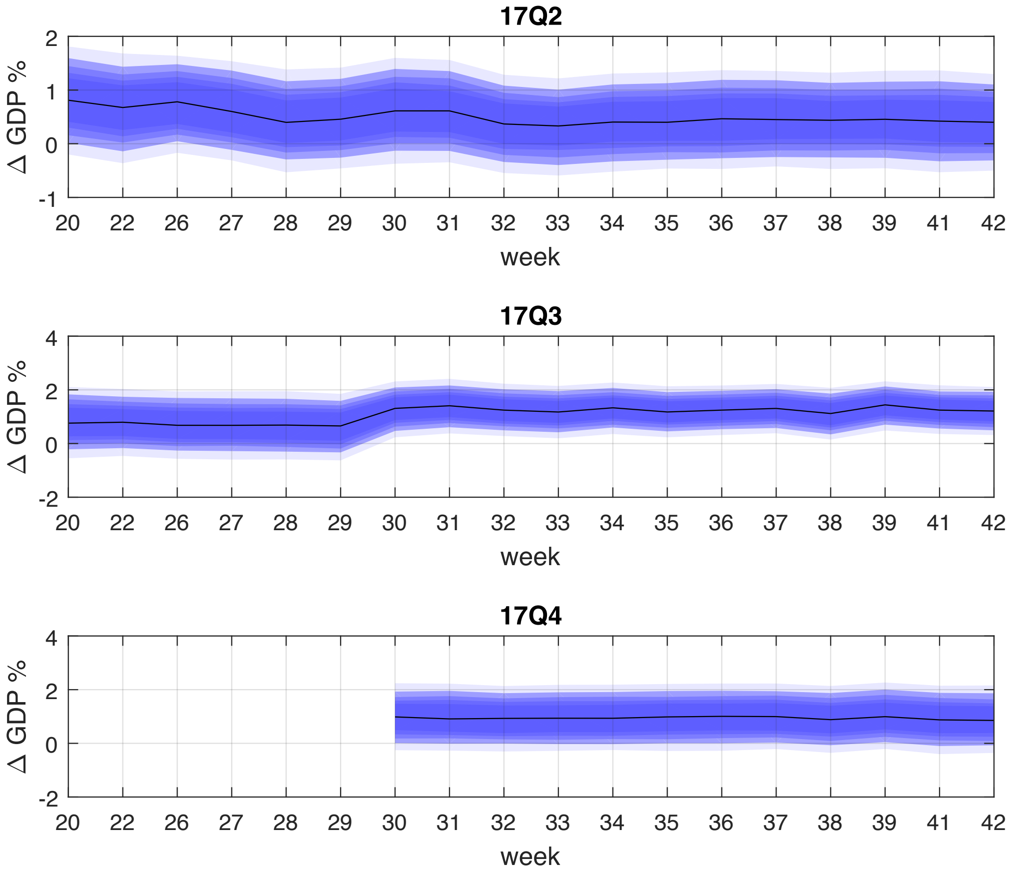
Contribution analysis

- as in Koopman and Harvey (2003)
- express forecasts as a weighted sum of observations
- summarizes the whole data

Contribution analysis



Reporting uncertainty



- currently Matlab produces an html document that is published in BoF's intranet
- but we are working to open a public webpage to publish our nowcasts by the end of this year

Thank you for your attention!