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Fiscal Nowcasting

Jacopo Cimadomo
European Central Bank

Domenico Giannone
Federal Reserve Bank of New York

Michele Lenza
European Central Bank

The opinions expressed herein are those of the authors and do not necessarily reflect those of the European Central Bank, the Eurosystem or the Federal Reserve Bank of New York

Plan of the talk

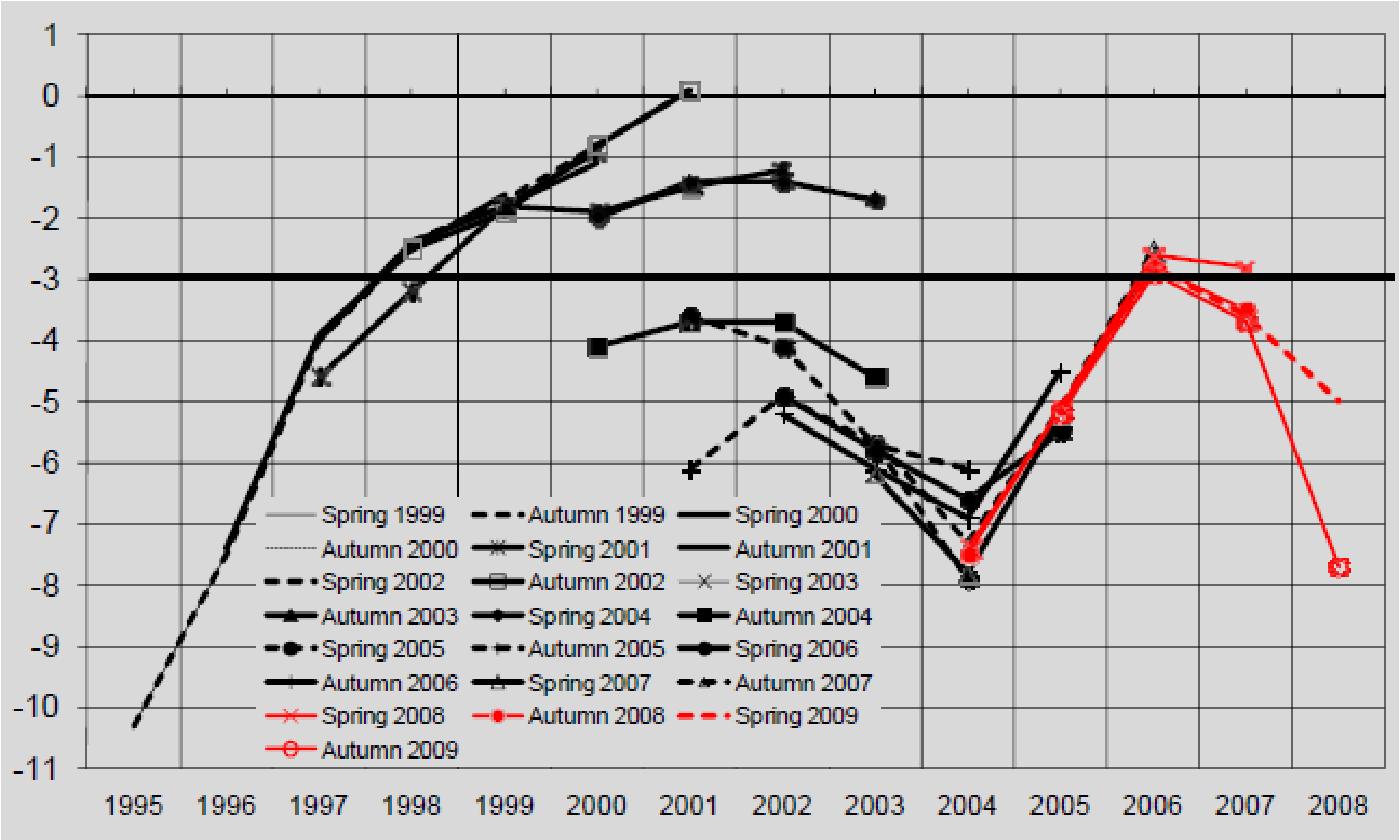
i	Motivation
ii	Contribution
iii	Related literature
iv	Data (Italy)
v	The now-casting problem
vi	Methodology
vii	Preliminary results
viii	Conclusions and on-going work

Motivation

- The government balance to GDP ratio is a synthetic indicator of state of public finances in one country, and it has a core role in the surveillance process (e.g., in the context of the EU fiscal framework)
- Timely monitoring the tendency of such ratio is of fundamental importance, especially for countries that exceeded the 3% of GDP.

The corrective arm of the Stability and Growth Pact (SGP) ensures that Member States adopt appropriate policy responses to correct excessive deficits by implementing the Excessive Deficit Procedure (EDP).

Greece: budget balance across different vintages (% of GDP)



Source: Castro et al. (2013)

Timeliness and frequency

- The general **government budget balance** is an accrual quarterly variable and released with a considerable delay.

➢ For EU countries: budget balance released only on the first business day of the fourth month after the end of the reference quarter.

For example, the budget balance for the 2nd quarter of 2018 has been released only at the beginning of October 2018.

➢ Problem of timeliness and sample frequency

➢ However: cash data for government revenue and expenditures (borrowing requirement) are available at the monthly frequency, and released more timely

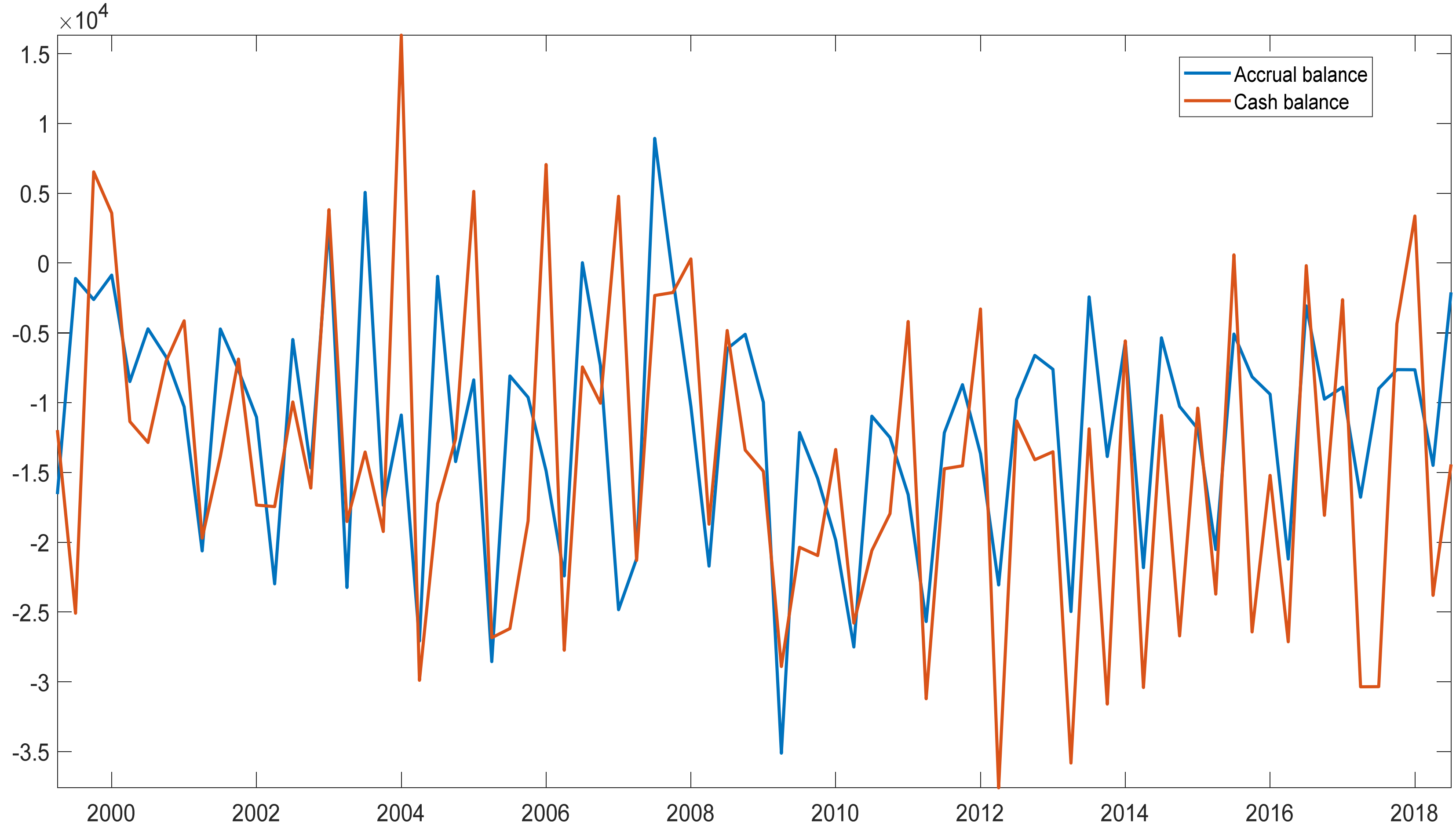
Cash vs. accrual fiscal data

- Accrual accounting (fiscal surveillance): records revenues and expenses <u>when they are incurred</u>, regardless of when cash is received (or paid) by (or to) the government.
- Cash accounting: receipts are recorded in the <u>period they are received</u>, and expenses are recorded in the <u>period in which they are actually paid</u> by the government.

Cash fiscal data

- At the beginning of month *tm*+2, most EU governments publish their cash flow (borrowing requirement) for month *tm*
  - *For example, in Italy: cash data for August 2018 have been released in early October 2018.*
  - *Some countries also publish early estimates at the beginning of month tm+1*
- The sum of the cash flows in the quarter do not exactly reflect the (accrual) budget balance of that quarter, due to different accounting methods and time lags.
- However, the cash flows reflect a large part of the items included in the budget balance data relevant for fiscal surveillance.

Italy: quarterly budget balance and cash borrowing requirement



This paper

- A new methodology, based on a mixed frequency vector autoregressive model (Schorfheide and Song, 2015; Brave Butters Justiniano 2016)
  - Reap the benefits of the timeliness in the releases of monthly cash data
  - Filter out the noise in the relationship with quarterly budget balance data induced by the different accounting procedures
- Exploiting both monthly and quarterly information:

  a *monthly* indicator of the *annual government balance*
- Apply this procedure to Italian data, but the aim is to build up an monitoring tool for all EA countries (and the US)

Literature review I

- Our paper at the intersection between the literature on **GDP nowcasting** and **fiscal forecasting**
- Literature on GDP nowcasting has developed very significantly over the last years.

➢ Giannone Reichlin Small (2008): evaluate impact that intra-monthly data releases have on the GDP growth nowcast.

➢ Kuzin Marcellino Schumacher (2011), Foroni and Marcellino (2014): compare the forecasting performance of MIDAS and MF-VAR models

➢ Banbura et al. (2013) survey the literature on economic nowcasting → models that formalize how market participants and policy makers read macroeconomic data releases in real-time.

➢ Schorfheide and Song (2015) and Brave et al. (2016): GDP nowcasting with mixed frequency BVARs

Literature review II

- The fiscal forecasting literature is quite limited
  - Some papers highlight that intra-annual data are available with short time lags can be used to derive accurate forecasts for end-of-year fiscal outcomes (see e.g. Pérez, 2007; Pedregal and Pérez, 2008; Onorante et al., 2008).
  - Based on MIDAS models, Asimakopoulos et al. (2012) assess the news content of quarterly fiscal data releases and their implications for the annual outturn.
  - Hughes-Hallet et al (2010) focus on monthly cash data to construct early warnings indicators for future deficit.
  - Carabotta and Claeys (2015): combine forecasts from both private and public agencies for Italy.

Related modelling approaches

- Our modeling approach is based on a mixed-frequency Bayesian VAR model: treat the low frequency variables as the result of aggregation of a high frequency latent process.
- This approach has been used in previous work, based on Maximum Likelihood (or under flat priors) estimation (see, e.g., Giannone et al., 2009; and by Kuzin et al., 2011).
- We follow more recent work which use informative priors (see, in particular, Schorfheide and Song, 2015, and Brave et al., 2016).

Contribution

- Nowcast del government budget entails a lot of "art" (and judgement) [IMF, ECB, EC, CBO…]
- Our attempt: turn it into 'science' as it was the case for GDP
- There is a lot of information (cash data, survey?) to be included into models, but little has been done so far…
- Question: a small scale model including cash variables is enough, or we cannot avoid to rely on judgement?

Empirical analysis

- Focus: **end-of-the-year annual budget balance to GDP ratio**:

$$b_{ta} = \frac{\sum_{t=ta.Q1}^{ta.Q4} D_t}{\sum_{t=ta.Q1}^{ta.Q4} Y_t P_t},$$

- We specify a mixed-frequency VAR model that includes:

➢ **Quarterly data (3 variables)**: government revenues and expenditures; nominal GDP. Sample: 1999Q1 to 2018Q3

➢ **Monthly data (2 variables)**: cash revenues and expenditures for the general government. Sample: January 1999 to August 2018 (as observed in October 2018).

The now-casting problem

Date of now-cast	GDP	Fiscal accrual	Fiscal cash
15-Jan	ta-1.Q3	ta-1.Q3	ta-1.November
15-Feb	ta-1.Q3	ta-1.Q3	ta-1.December
15-Mar	ta-1.Q4	ta-1.Q3	ta.January
15-Apr	ta-1.Q4	ta-1.Q4	ta.February
15-May	ta-1.Q4	ta-1.Q4	ta.March
15-Jun	ta.Q1	ta-1.Q4	ta.April
15-Jul	ta.Q1	ta.Q1	ta.May
15-Aug	ta.Q1	ta.Q1	ta.June
15-Sep	ta.Q2	ta.Q1	ta.July
15-Oct	ta.Q2	ta.Q2	ta.August
15-Nov	ta.Q2	ta.Q2	ta.September
15-Dec	ta.Q3	ta.Q2	ta.October

The now-casting problem

		GDP	Revenues	Expenditures	CASH rev.	CASH Exp.
	2017 m1	NaN	NaN	NaN	34921	37042
	2017 m2	NaN	NaN	NaN	38562	30330
	2017 m3	428324	192111	175336	54445	31349
	2017 m4	NaN	NaN	NaN	38121	33003
	2017 m5	NaN	NaN	NaN	42242	34593
	2017 m6	430558	208093	199096	48216	38630
	2017 m7	NaN	NaN	NaN	31665	43100
	2017 m8	NaN	NaN	NaN	44786	43599
	2017 m9	433107	195164	187525	44474	28655
	2017 m10	NaN	NaN	NaN	38992	34095
	2017 m11	NaN	NaN	NaN	48288	41341
	2017 m12	434813	245395	237746	89505	105332
	2018 m1	NaN	NaN	NaN	34704	35336
	2018 m2	NaN	NaN	NaN	38358	32378
	2018 m3	437335	**192580**	**178079**	50891	29767
	2018 m4	NaN	NaN	NaN	39852	36830
15-Jul-18	2018 m5	NaN	NaN	NaN	**45866**	**37898**

The now-casting problem

		GDP	Revenues	Expenditures	CASH rev.	CASH Exp.
	2017 m1	NaN	NaN	NaN	34921	37042
	2017 m2	NaN	NaN	NaN	38562	30330
	2017 m3	428324	192111	175336	54445	31349
	2017 m4	NaN	NaN	NaN	38121	33003
	2017 m5	NaN	NaN	NaN	42242	34593
	2017 m6	430558	208093	199096	48216	38630
	2017 m7	NaN	NaN	NaN	31665	43100
	2017 m8	NaN	NaN	NaN	44786	43599
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	2018 m1	NaN	NaN	NaN	34704	35336
	2018 m2	NaN	NaN	NaN	38358	32378
	2018 m3	437335	192580	178079	50891	29767
	2018 m4	NaN	NaN	NaN	39852	36830
	2018 m5	NaN	NaN	NaN	45866	37898
15-Aug-18	2018 m6	NaN	NaN	NaN	**40964**	**37723**

The now-casting problem

		GDP	Revenues	Expenditures	CASH rev.	CASH Exp.
	2017 m1	NaN	NaN	NaN	34921	37042
	2017 m2	NaN	NaN	NaN	38562	30330
	2017 m3	428324	192111	175336	54445	31349
	2017 m4	NaN	NaN	NaN	38121	33003
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	2017 m6	430558	208093	199096	48216	38630
	2017 m7	NaN	NaN	NaN	31665	43100
	2017 m8	NaN	NaN	NaN	44786	43599
	2017 m9	433107	195164	187525	44474	28655
	2017 m10	NaN	NaN	NaN	38992	34095
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	2018 m1	NaN	NaN	NaN	34704	35336
	2018 m2	NaN	NaN	NaN	38358	32378
	2018 m3	437335	192580	178079	50891	29767
	2018 m4	NaN	NaN	NaN	39852	36830
	2018 m5	NaN	NaN	NaN	45866	37898
	2018 m6	**441751**	NaN	NaN	40964	37723
15-Sep-18	2018 m7	NaN	NaN	NaN	**36325**	**46895**

The now-casting problem

		GDP	Revenues	Expenditures	CASH rev.	CASH Exp.
	2017 m1	NaN	NaN	NaN	34921	37042
	2017 m2	NaN	NaN	NaN	38562	30330
	2017 m3	428324	192111	175336	54445	31349
	2017 m4	NaN	NaN	NaN	38121	33003
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	2017 m10	NaN	NaN	NaN	38992	34095
	2017 m11	NaN	NaN	NaN	48288	41341
	2017 m12	434813	245395	237746	89505	105332
	2018 m1	NaN	NaN	NaN	34704	35336
	2018 m2	NaN	NaN	NaN	38358	32378
	2018 m3	437335	192580	178079	50891	29767
	2018 m4	NaN	NaN	NaN	39852	36830
	2018 m5	NaN	NaN	NaN	45866	37898
	2018 m6	441751	**205611**	**203505**	40964	37723
	2018 m7	NaN	NaN	NaN	36325	46895
15-Oct-18	2018 m8	NaN	NaN	NaN	**38021**	**39099**

The now-casting problem

		GDP	Revenues	Expenditures	CASH rev.	CASH Exp.
	2017 m1	NaN	NaN	NaN	34921	37042
	2017 m2	NaN	NaN	NaN	38562	30330
	2017 m3	428324	192111	175336	54445	31349
	2017 m4	NaN	NaN	NaN	38121	33003
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	2018 m4	NaN	NaN	NaN	**39852**	**36830**
	2018 m5	NaN	NaN	NaN	**45866**	**37898**
	2018 m6	**441751**	**205611**	**203505**	**40964**	**37723**
	2018 m7	NaN	NaN	NaN	**36325**	**46895**
15-Oct-18	2018 m8	NaN	NaN	NaN	**38021**	**39099**
	2018 m9	NaN	NaN	NaN	NaN	NaN
	2018 m10	NaN	NaN	NaN	NaN	NaN
	2018 m11	?	?	?	?	?
	2018 m12	?	?	?	?	?

Methodology

- We assume that the *annualized log-levels* of our N (=5) variables (collected in the N-dimensional vector X_{tm}) are described by the following monthly vector autoregressive process with p (=13) lags:

$$X_{tm} = A_0 + A_1 X_{tm-1} + \ldots + A_p X_{tm-p} + e_{tm}$$

where A_p is the $N*N$ matrix collecting the coefficients of the p-th lag and e_{tm} is a normally distributed multivariate white noise error with covariance matrix Σ.

Methodology

- The rich dynamics in our VAR model imply that we face an issue of over-fitting, owing to the large number of parameters (the so-called "curse of dimensionality").

- We address this issue by shrinking the model's coefficients toward those of the naïve and parsimonious random walk with drift model, $X_{i,tm} = \delta_i + X_{i,tm-1} + u_{i,tm}$ (De Mol et al. (2008) and Banbura et al. (2010))

- In practice, we assume N-IW priors and we parameterise them by imposing a Minnesota and two sum-of-coefficients priors. The hyperparameters are also treated as random variables and drawn from their posterior (as in Giannone et al., 2015)

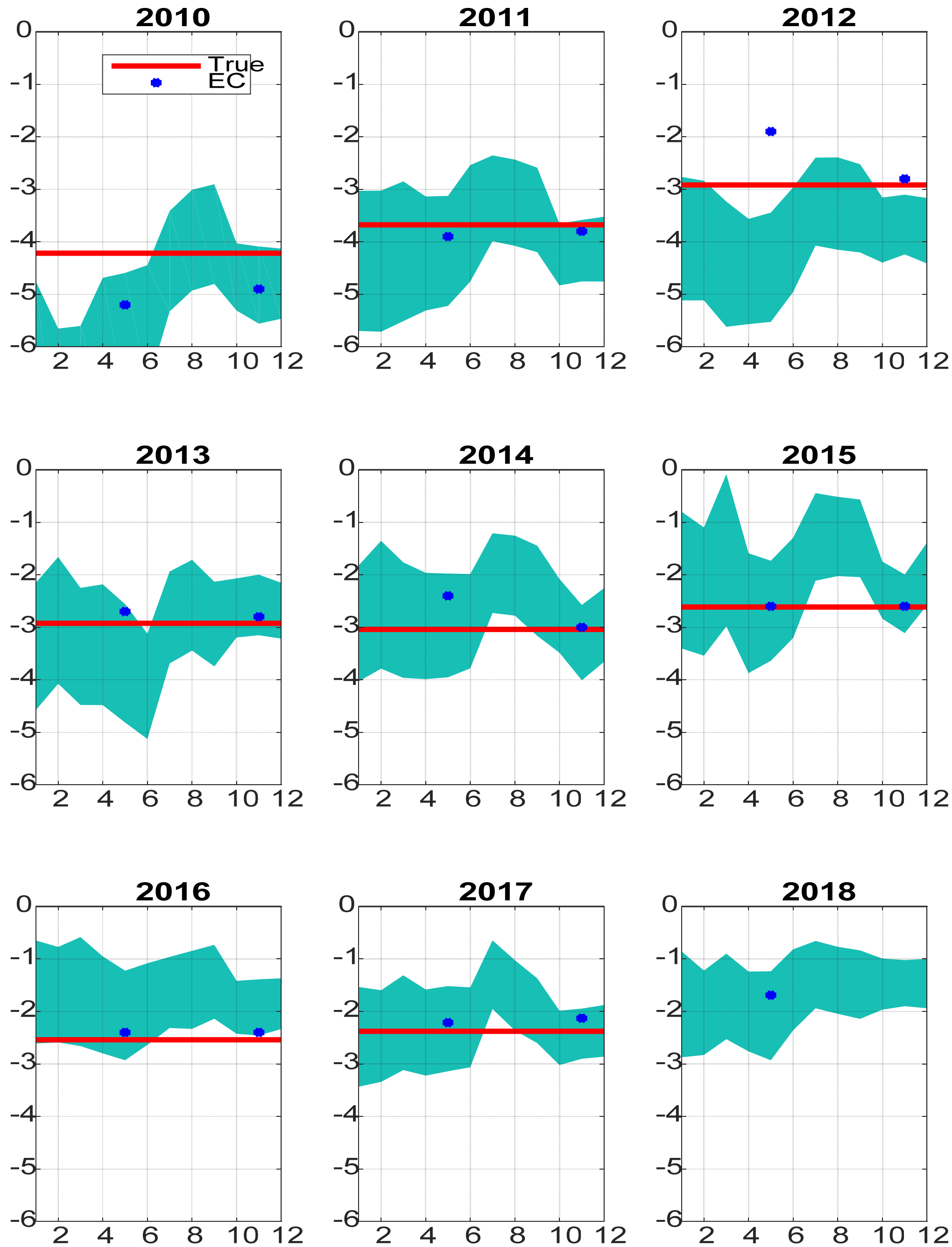
Overview of the estimation algorithm

- We estimate the model by iteratively taking the following steps (details in the paper):

    1. Draw of the missing data *conditional* on a draw from the posterior of the model parameters and prior hyperparameters;

    2. Draw the prior hyperparameters and the parameters conditional on the previous draw of the variables.

Results


2010
2011
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2016
2017
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EC
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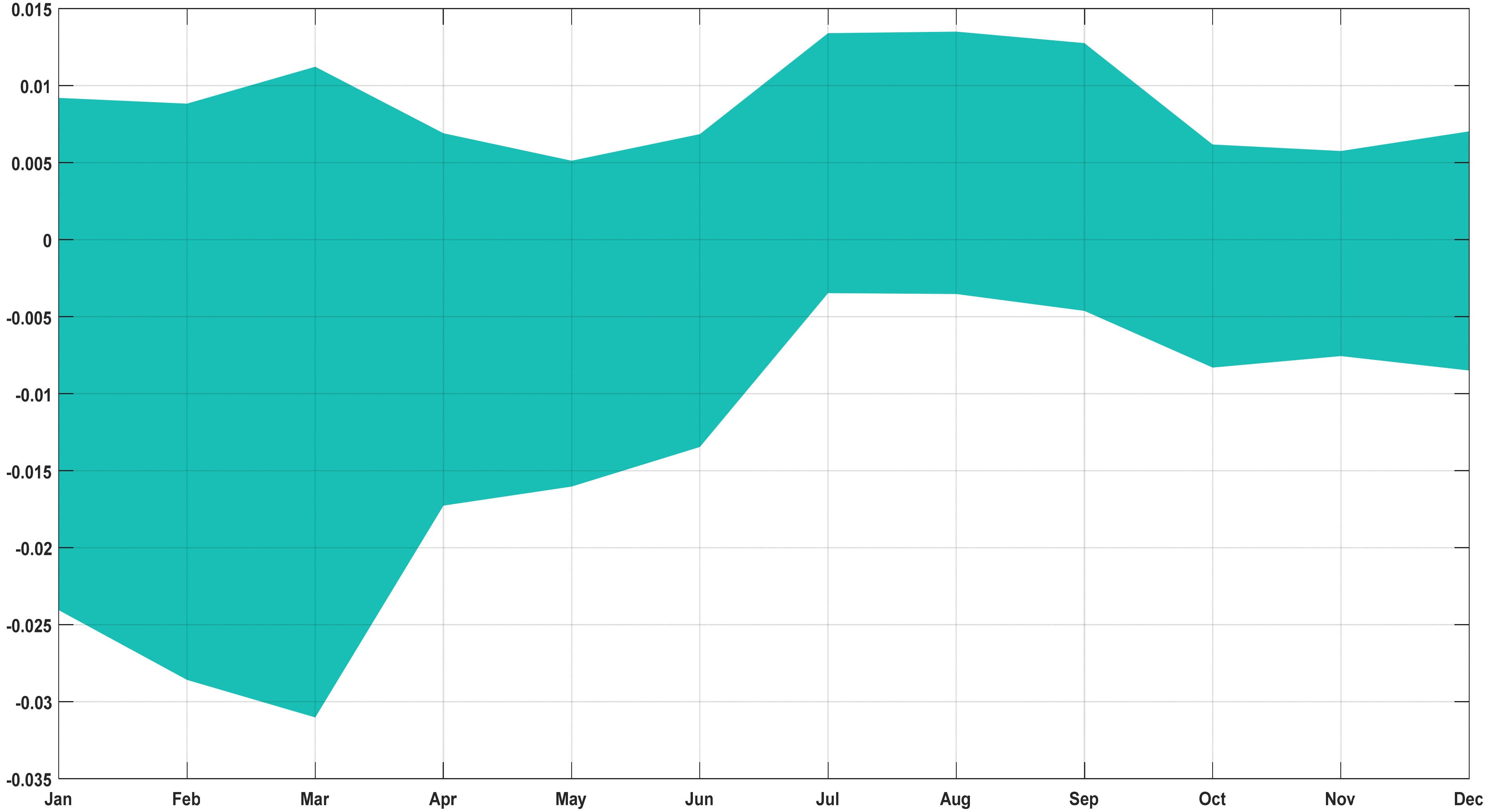
-1
-2
-3
-4
-5
-6
2
4
6
8
10
12

Forecast errors over the 12 months



Conclusions

- This paper describes a methodology to extract information from monthly cash data in order to now-cast the annual budget balance ratio to GDP.
- The methodology we propose is able to handle both staggered data releases and missing data in the estimation sample in a unified framework and its outcome is the predictive distribution of the budget balance ratio.
- Our empirical application, in this paper, is on Italian data. We provide quite an accurate account of the Italian budget balance to GDP ratio, which allows us to conclude that our model is able to successfully extract information from the noisy cash flow data.

Thank you

Ongoing work

- Apply to other countries (e.g. EA big-5 and the US)
- Evaluation of density forecasts; extend evaluation also to forecasts and back-casts
- Extension of the cross-section of data in order to improve forecast accuracy (for example, including monthly surveys to better forecast GDP)
- Perform a truly real-time exercise and forecast comparison (IMF, EC, OECD).

Algorithm

- We tackle the issue of missing data by setting up a recursive procedure that:

  1. Balances the database by providing a draw of the missing data *conditional* on a draw from the posterior of the model parameters;

  2. Provides another draw of the parameters conditional on the previous draw of the variables.

Algorithm

- Recursive algorithm for the panel available in month t_m and forecast horizon *h*:

1. Initialization: $\mathbf{X(0)_{tm}}$ is obtained by interpolating the unbalanced panel by means of standard univariate non-parametric interpolation techniques.

2. First draw of the parameters from their posterior distribution, conditional on initialization of the variables: $\mathbf{A(1)_0} \ldots \mathbf{A(1)_p}$.

3. First draw of the past, present and future of the variables from the distribution of their conditional expectation, conditional on $A(1)_0 \ldots A(1)_p$: $\mathbf{X(1)_0} \ldots \mathbf{X(1)_{tm}} \ldots \mathbf{X(1)_{tm+h}}$ by means of the simulation smoother of Carter and Kohn (1994).

4. Second draw of parameters from their posterior distribution, conditional on previous draw of the variables conditional on $X(1)_0 \ldots X(1)_{tm}$: $\mathbf{A(2)_0} \ldots \mathbf{A(2)_p}$.

5. Second draw of the past, present and future of the variables from the distribution of their conditional expectation, conditional on $A(2)_0 \ldots A(2)_p$: $\mathbf{X(2)_0} \ldots \mathbf{X(2)_{tm}} \ldots \mathbf{X(2)_{tm+h}}$ by means of the simulation smoother of Carter and Kohn (1994).

6. Iterate 4 and 5 *M* times.