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Fiscal monitoring with VARs

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Abstract

We design a Bayesian Mixed-Frequency Vector Autoregression (VAR) model for fiscal monitoring, i.e., to nowcast the government deficit-to-GDP ratio in real time and provide a narrative for its dynamics. The model incorporates both monthly cash and quarterly accrual fiscal indicators, together with other high-frequency macroeconomic and financial variables, as well as real GDP and the GDP deflator. Our model produces timely monthly density nowcasts of the annual deficit ratio, while governments and official institutions generally only publish their point predictions bi-annually. Based on a database of real-time vintages of macroeconomic, financial, and fiscal variables for Italy, we show that the nowcasts of the annual deficit-to-GDP ratio produced by our model are similarly or more accurate than those of the European Commission, depending on the month in which the nowcast is produced. Our scenario analysis compares the dynamics of the deficit ratio associated with a monetary policy shock and a typical recession, finding a more muted response in the latter case.

JEL Classification: C11, E52, E62, E63, H68.
Keywords: Nowcasting, Mixed-frequency, Government deficit, Cash data, Monetary policy shock, Monetary-fiscal interactions.

Non Technical Summary

Fiscal monitoring entails nowcasting key fiscal variables, such as the government deficit-to-GDP ratio, providing a narrative for the drivers of the fiscal outlook and running counterfactual scenarios. This paper proposes a mixed-frequency fiscal vector autoregressive (VAR) model to carry out fiscal monitoring within a unified empirical framework. Our empirical analysis focuses on Italy, which is an interesting case study, given that it has one of the highest debt-to-GDP ratios among advanced economies.

Forecasting the developments of the current-year deficit ratio in real-time, or "nowcasting ", is a particularly challenging task because it entails the prediction for different variables (government expenditures, government revenues and nominal GDP), potentially for relatively long forecasting horizons (e.g., up to a year when nowcasting the annual deficit at the beginning of the year). Moreover, quarterly government revenues and expenditures are released with a considerable delay, even longer than the typical delay for quarterly GDP releases. However, governments also publish *cash* data for revenues and expenditure, which have a monthly rather than a quarterly frequency, and are released rather timely. Cash data refer to the month in which the financial inflow or outflow is recorded in the Treasury account of the government, and not when the underlying transaction takes place (e.g., the period in which personal income is generated, or when a procurement is approved and budgeted), which is the case for the national account (accrual) quarterly data. The mixed frequency Bayesian VAR proposed in the paper aims at reaping the benefits of the timeliness of monthly cash data releases while, at the same time, filtering out the noise in their relationship with quarterly budget balance data induced by the different accounting procedures. The model also exploits the informational content of other (non-fiscal) monthly macroeconomic and financial variables, which turn out to be useful for deficit ratio nowcasting – for example, because they help tracking nominal GDP, the denominator of the deficit ratio.

We show that the density forecasts of the model accurately track the dynamics of the Italian budget deficit. Moreover, the median nowcasts are as accurate and, at times, more accurate than the judgmental nowcasts of the European Commission. This result is noteworthy because our model is very parsimonious and based only on statistical information. Instead, the Commission's nowcasts are based on a plethora of models, including almost two hundred variables, and embed also the judgment of fiscal and macro experts which, presumably, is informed by fiscal plans that are unlikely to be fully reflected in the variables of our model.

We also show how our approach can evaluate the “news” content of each data release, providing an economic narrative for the changes in the model predictions. In addition, we show that the model is able to capture well the transmission mechanisms of economic shocks, suggesting that it can be used also to run scenario analysis.

1 Introduction

Global public debt is elevated and projected to rise over the medium term (see, e.g., Dabla-Norris et al., 2025). In Europe, this renewed fiscal activism has been spurred by the need to achieve objectives of strategic independence in areas such as defense and the green transition. The push towards greater government spending, further amplified by the necessity to respond to geopolitical tensions and tariffs - with implications, for example, for public support to domestic industries - occurs amid rising yields in major economies and widening spreads in emerging markets.

In these circumstances, fiscal monitoring - i.e., predicting fiscal variables such as the government deficit-to-GDP ratio, providing a narrative for their triggers, and constructing scenarios - is key to detecting early signs of strain in public finances, to analyzing policy implications, and to taking adequate measures to address them.

This paper extends the nowcasting framework introduced to economics by Giannone et al. (2008) and Banbura et al. (2013) to the fiscal domain. Nowcasting the government deficit-to-GDP ratio is a particularly challenging task because it entails the prediction of different variables, i.e., government expenditures, government revenues, and nominal GDP. Moreover, quarterly government revenues and expenditures are released with a considerable delay, even longer than the typical delay for quarterly GDP releases, and are subject to large revision errors.

To date, fiscal monitoring has relied primarily on expert judgment and institutional practices, whereas we develop a rigorous econometric framework that formalizes this process and provides a systematic, data-driven approach to tracking and interpreting fiscal developments in real time. Our approach relies on the mixed-frequency Bayesian VAR described in Cimadomo et al. (2022). This model is an ideal tool for fiscal monitoring. First, it can generate accurate and timely signals about the key fiscal variables and the risks surrounding their outlook, thanks to its ability to exploit higher-frequency data and produce density forecasts and, second, it can track the joint dynamics of the economy simultaneously across variables and horizons to build a narrative for the evolution of the fiscal quantities of interest.

We apply this methodology to Italy, which is an interesting case study in light of its high debt-to-GDP ratio and of the fact that its monetary policy is decided at the euro area level, but our approach could easily be applied to other countries as well. Our model includes a set of quarterly variables (fiscal expenditures and revenues, real GDP, and the GDP deflator) and a set of monthly macroeconomic variables (consumer prices - HICP, industrial production, industrial turnover, economic sentiment, and long-term bond yields). We also include the monthly cash data for the revenues and expenditures of the Italian Treasury. Cash data - which reflect the moment at which fiscal transactions are settled, while quarterly fiscal variables are based on the accrual accounting principle - provide a timely but noisy signal for quarterly fiscal revenues and expenditures and, ultimately, the deficit-to-GDP ratio. Some earlier studies have used cash data (see, e.g., Perez, 2007, Pedregal and Pérez, 2010, Onorante et al., 2010, and Hughes Hallett et al., 2010) to improve the forecasting and monitoring of the annual general government deficit. Relative to these papers, we take a multivariate approach, which encompasses all the components of the deficit-to-GDP ratio and allows us to track how it builds up and to construct scenarios. Another important advantage of our model is that it produces not only point forecasts but also predictive densities, which account for uncertainty in the estimation as well as in the economy.

We evaluate the ability of the density forecasts of our model to track the Italian budget deficit ratio, based on the data available to the forecasters in real time. We start by comparing the nowcasting accuracy of the median forecasts from our model with those of the European Commission, which only provides point forecasts. We find that the accuracy of our model is similar, and at times superior, to that of the European Commission. This result is remarkable, given that our model is very parsimonious and based only on statistical information, while the Commission's forecasts are based on a plethora of models and include almost two hundred variables and judgment from fiscal and macro experts. The judgmental component is plausibly quite important, as it can be informed by fiscal plans that are unlikely to be fully reflected in the variables included in statistical models like ours. Broadening the focus of the analysis to density forecasts, we find that they generally appear to be centered around the outcomes, and the uncertainty around the median forecasts for the budget deficit of a specific year shrinks over the course of the year as more information on the budget balance becomes available. Moreover, we conduct a case study evaluating the budget deficit outlook in 2020 through the lens of our model. We find that the model density forecasts project a very large increase in uncertainty over the course of the year and, already in June, assign a high probability to a value for the budget deficit which had never been experienced in our sample, but which eventually materialized. We conclude that our density forecasts can be used to reliably quantify the risks surrounding the fiscal outlook in Italy. An additional advantage of our approach, compared to the Commission's forecasts - and forecasts from other international institutions - is that we can easily update the forecasts at each point at which new information becomes available. Our forecasting evaluation suggests that our BVAR model has strong empirical foundations.

We also illustrate the ability of our model to provide an economic narrative for its outcomes and to suggest their policy implications. Specifically, our approach can highlight the triggers of the changes in the predictions of the budget deficit and its sub-components when new information becomes available. The level of granularity of our analysis allows us to offer different, possibly complementary, descriptions of the expected dynamics of the budget deficit. In practice, we consider two possible options, both based on the concept of "news", i.e., the impact of each new data release on the revision of the deficit nowcast. First, we look at the news associated with the release of each individual variable and find that most variable releases carry important information for the budget deficit, with releases of cash data playing an important role. Second, we aggregate the news in the individual variables to show what they collectively imply for the four variables that enter the definition of the budget ratio, namely real GDP, the GDP deflator, fiscal expenditure, and fiscal revenues. This decomposition is helpful for drawing policy implications; for example, an increase in the deficit-to-GDP ratio due to, say, an economic recession may imply different policy reactions compared to a similar increase due entirely to a worsening of the fiscal balance. We find that the dynamics of fiscal revenues and expenditures are generally the major factor behind the dynamics in the deficit-to-GDP ratio.

Scenario analysis helps to capture unusual economic conditions and to complement density forecasts with an economic narrative. We show that our model can capture complex and nuanced transmission mechanisms and, hence, can enrich the analysis of the risks to the fiscal outlook. In more detail, first, we look at the reaction of the Italian economy to a monetary policy tightening. This standardized scenario, which we define as a "monetary recession", requires the identification of an exogenous monetary policy shock, which we carry out using an internal instrument approach based on the Jarociński and Karadi (2020) shocks. In this scenario, as expected, the Italian economy falls into a recession and the budget deficit substantially increases because of a drop in fiscal revenues due to the recession and an increase in fiscal expenditures due to the rise in interest rate expenditures. We compare this scenario to that of a "typical" recession, in which the same drop in GDP is entirely due to "business cycle shocks", i.e., the (unidentified) shocks which generally drive the business cycle in Italy. The most remarkable difference from the previous scenario is that, in the "typical recession" scenario, monetary policy acts to stabilize the economy by lowering interest rates. Hence, while fiscal revenues drop similarly to the case of a recession triggered by a monetary tightening, fiscal expenditures increase much less in this scenario, implying much more muted dynamics for the fiscal deficit compared to those prevailing in a monetary recession. Besides illustrating the ability of our model to conduct scenario analysis, the analysis just described also contributes from a novel angle to the debate on monetary and fiscal interactions, which has attracted considerable attention since the seminal work by Leeper (1991). Empirical evidence on how monetary and fiscal policy interact, and how fiscal policy affects the monetary transmission mechanism, is rather limited. Bianchi (2012) investigates how monetary policy shocks transmit to the US economy, depending on how monetary and fiscal policies have switched between active and passive regimes in the post-WWII period. Some papers have studied whether the transmission of monetary policy shocks is affected by the stance of fiscal policy. For example, Kloosterman et al. (2022) show that an expansionary monetary policy shock leads to an increase in inflation and output growth, but only when it occurs in an expansionary fiscal regime. Deb et al. (2023) examine how the fiscal policy stance affects monetary policy effectiveness across countries. Their results suggest that contractionary monetary policy shocks have stronger effects on output and prices when fiscal policy is also tighter. Closer to our work is Breitenlechner et al. (2024), which proposes a Bayesian proxy structural vector-autoregressive (BPSVAR) model for the US economy. They show that the impact of a monetary policy shock on prices is more than halved by the endogenous adjustment in public transfers, whereas the tax system significantly reduces the effect on output.

The rest of this paper is structured as follows. Section 2 outlines the model; Section 3 describes the dataset; Section 4 discusses the density nowcasts for the Italian deficit-to-GDP ratio and its triggers; Section 5 presents scenario analysis; and Section 6 concludes.

2 The model

Our target variable is the annual budget deficit-to-GDP ratio (b_{t_a}) of the Italian general government in a given year t_a. It is expressed as the difference between quarterly government expenditures (E_t) and revenues (R_t), summed over the four quarters of the year and deflated by nominal GDP (Y_t):

$$b_{t_a} = \frac{\sum_{t=t_a.Q1}^{t_a.Q4}(E_t - R_t)}{\sum_{t=t_a.Q1}^{t_a.Q4} Y_t}, \tag{1}$$

We generate monthly nowcasts of b_{t_a}, i.e., of the deficit-to-GDP ratio for the whole year t_a in each of the twelve months of the same year. Notice that this is not a trivial problem, given that, especially in the first months of the year, it requires forecasting the path of the budget deficit-to-GDP ratio - and hence, the path of the difference between expenditures and revenues over nominal GDP - several quarters ahead. This task has to be conducted based on no information for quarterly variables for year t_a until April (when real GDP for Q1 is released). However, our model can handle variables at higher frequency, which can be exploited to extract timely information. In particular, we use monthly cash data on revenues and expenditures, along with other monthly macro variables detailed in Section 3, to obtain a more timely estimate of the annual deficit-to-GDP ratio.

Our modelling approach is based on the latent BVAR (LBVAR) model of Cimadomo et al. (2022), which is designed to handle mixed-frequency data. In practice, the approach entails casting a Bayesian VAR model[1] in state-space form and modeling the low-frequency variables as latent, i.e., as higher-frequency processes that are sampled at a lower frequency than the one at which they are modeled. The estimates of the latent processes and the uncertainty around them are obtained by means of Kalman filtering techniques. To incorporate rich information while preventing overfitting, we use informative priors that have been widely used in traditional, single-frequency VARs (e.g. Banbura et al., 2010; Giannone et al., 2015).

We assume that the *levels* of our N (=11) variables (collected in the N-dimensional vector X_{t_m}) are described by the following monthly vector autoregressive process with p (=12) lags:

$$X_{t_m} = A_0 + A_1 X_{t_m-1} + \ldots + A_p X_{t_m-p} + e_{t_m}, \tag{2}$$

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

We address the potential over-parametrisation due to the rich specification by shrinking the model's coefficients toward those of the naïve and parsimonious random walk with drift model,

[1] These models have a long history; see Zadrozny (1990), Mittnik and Zadrozny (2004), Giannone et al. (2009), Schorfheide and Song, 2015, Brave et al., 2016, and McCracken et al. (2021).

$X_{i,t_m} = \delta_i + X_{i,t_m-1} + u_{i,t_m}$. De Mol et al. (2008) and Banbura et al. (2010) have shown that this approach reduces estimation uncertainty without introducing substantial bias. More specifically, we use a Normal-Inverted Wishart prior centred on a random walk model. For Σ, the covariance matrix of the residuals, we use an inverted Wishart with scale parameter given by a diagonal matrix Ψ (with ψ denoting the vector of its diagonal elements) and $d = N + 2$ degrees of freedom. This is the minimum number of degrees of freedom that guarantees the existence of the prior mean of Σ, which is equal to $\frac{\Psi}{(d-N-1)} = \Psi$. For the constant A_0 term, we use a flat prior. For the autoregressive coefficients $(A_1, \ldots, A_p)$, we use the Minnesota prior, as originally proposed by Litterman (1979), together with the sum-of-coefficients prior proposed by Doan, Litterman, and Sims (1984), which is intended to limit the explanatory power of the VAR's deterministic component. The Minnesota prior, conditional on the covariance matrix of the residuals, stipulates that the prior distribution of the autoregressive coefficients is normal with the following means and variances:

$$E(A_1) = I_N, \quad E(A_2) = \ldots = E(A_p) = 0_{N,N}, \tag{3}$$

$$Cov[(A_s)_{ij}, (A_r)_{hm}|\Sigma] = \lambda^2 \frac{\Sigma_{ih}}{s^2 \Psi_{ii}} \quad \text{if } m = j \text{ and } r = s, \text{ zero otherwise.} \tag{4}$$

Notice that the variance of this prior distribution decays with the lag, and coefficients associated with the same variables and lags in different equations are allowed to be correlated. The key hyperparameter is λ, which controls the scale of all the prior variances and covariances, and effectively determines the overall tightness of this prior. For $\lambda = 0$ the posterior equals the prior and the data do not influence the estimates. If $\lambda \to \infty$, on the other hand, posterior expectations coincide with the Ordinary Least Squares (OLS) estimates. The factor $\frac{1}{s^2}$ is the rate at which the prior variance decreases with increasing lag length and $\frac{\Sigma_{ii}}{\Psi_{jj}}$ accounts for the different scale and variability of the data. The "sum-of-coefficients" prior instead postulates that the sum of the coefficients associated with the own lags of each variable in the VAR equals one, while the sum of the coefficients associated with the lags of the other variables equals zero. The tightness by which this prior is enforced is described by the parameter μ. Summing up, the setting of these priors depends on the hyperparameters λ, ψ, and μ, which reflect the informativeness of the prior distribution for the model's coefficients. As in Giannone, Lenza, and Primiceri (2015), we treat these hyperparameters as random variables, we assume rather diffuse priors, and we conduct posterior inference on them.

To estimate the model, we use the algorithm developed in Cimadomo et al. (2022), which extends the hierarchical approach of Giannone et al. (2015) to handle the missing data problem due, in this paper, to the mixed frequency of the variables and the different data releases which generate a so-called "ragged edge" at the end of our sample. The latter issue emerges because, in order to provide a realistic assessment of the challenges faced in nowcasting the state of Italian public finances, we take into account the real-time data availability faced by practitioners. In practice, we have reconstructed the data availability that a practitioner would face on the 15th day of each of the twelve months of the year.

The algorithm. A schematic representation of our recursive algorithm for month t_m and forecast horizon h is as follows:

1. Initialization: $X(0)_{t_m}$ is obtained by interpolating the missing values at the end of the sample (i.e., the "ragged edge") by means of standard univariate non-parametric interpolation techniques.

2. First draw of the parameters from their posterior distribution based on Giannone et al. (2015), conditional on the initialization of the variables: $A(1)_0, \ldots, A(1)_p$.

3. First draw of the past, present, and future of the variables conditional on $A(1)_0, \ldots, A(1)_p$: $X(1)_0, \ldots, X(1)_{t_m}, \ldots, X(1)_{t_m+h}$, using the simulation smoother of Durbin and Koopman (2001).

4. Second draw of the parameters from their posterior distribution, conditional on the previous draw of the variables.

5. Second draw of the past, present, and future of the variables conditional on $A(2)_0, \ldots, A(2)_p$: $X(2)_0, \ldots, X(2)_{t_m}, \ldots, X(2)_{t_m+h}$.

6. Iterate steps 4 and 5 M times.[2]

Table 1: **Data availability for Italy in the dates of the nowcast production.**

	Quarterly			Monthly		
Date of nowcast	**Real GDP** YR	**GDP Defl.** YD	**Fiscal accrual** TOR_Q TOE_Q	**Fiscal cash** TOR_M TOE_M	**Other monthly variables** $HICP, IR$ IP, ESI	ITI
15-Jan	$t_a - 1.Q3$	$t_a - 1.Q3$	$t_a - 1.Q3$	$t_a - 1.Nov$	$t_a - 1.Dec$	$t_a - 1.Oct$
15-Feb	$t_a - 1.Q4$	$t_a - 1.Q3$	$t_a - 1.Q3$	$t_a - 1.Dec$	$t_a.Jan$	$t_a - 1.Nov$
15-Mar	$t_a - 1.Q4$	$t_a - 1.Q4$	$t_a - 1.Q3$	$t_a.Jan$	$t_a.Feb$	$t_a - 1.Dec$
15-Apr	$t_a - 1.Q4$	$t_a - 1.Q4$	$t_a - 1.Q4$	$t_a.Feb$	$t_a.Mar$	$t_a.Jan$
15-May	$t_a.Q1$	$t_a - 1.Q4$	$t_a - 1.Q4$	$t_a.Mar$	$t_a.Apr$	$t_a.Feb$
15-Jun	$t_a.Q1$	$t_a.Q1$	$t_a - 1.Q4$	$t_a.Apr$	$t_a.May$	$t_a.Mar$
15-Jul	$t_a.Q1$	$t_a.Q1$	$t_a.Q1$	$t_a.May$	$t_a.Jun$	$t_a.Apr$
15-Aug	$t_a.Q2$	$t_a.Q1$	$t_a.Q1$	$t_a.Jun$	$t_a.Jul$	$t_a.May$
15-Sep	$t_a.Q2$	$t_a.Q2$	$t_a.Q1$	$t_a.Jul$	$t_a.Aug$	$t_a.Jun$
15-Oct	$t_a.Q2$	$t_a.Q2$	$t_a.Q2$	$t_a.Aug$	$t_a.Sep$	$t_a.Jul$
15-Nov	$t_a.Q3$	$t_a.Q2$	$t_a.Q2$	$t_a.Sep$	$t_a.Oct$	$t_a.Aug$
15-Dec	$t_a.Q3$	$t_a.Q3$	$t_a.Q2$	$t_a.Oct$	$t_a.Nov$	$t_a.Sep$

Notes: The table reports the data available at the date of the nowcast (first column), where "t_a" represents the nowcast year. So, for example, $t_a - 1.Q3$ means that the last available data point is for quarter 3 of year $t_a - 1$. The data availability is shown for both quarterly variables: real GDP (YR), GDP deflator (YD), government revenues (TOR) and expenditures (TOE), and monthly variables: government revenues and expenditures, HICP, the 10-year bond interest rate (IR), industrial production (IP), the Economic Sentiment Indicator (ESI) and industrial turnover index (ITI).

3 Data

Our database includes 208 real-time monthly vintages of Italian data - from January 2007 to April 2024 - intended to mimic the information set of the fiscal expert at the time of the forecast.[3] The starting year of each vintage of data is 2002, for all time series. For example, the April 2024 vintage includes quarterly data for real GDP, the GDP deflator and general government revenues (TOR) and expenditures (TOE) over the period 2002Q1 to 2023Q4. All quarterly data are collected from the European Commission's database, while the monthly cash data for the central government revenues and expenditures are published by the Italian Ministry of Finance and are available until month $t_m - 2$.[4] We include five more monthly variables: the HICP index, the yield on the 10-year Italian bond, the industrial production index excluding construction

[2] In practice, multiple chains can be run in parallel and later combined.

[3] On the use of real-time data for forecasting and policy analysis, see Croushore and Stark (2001), Croushore and Stark (2003), Giannone et al. (2012), and Croushore (2011).

[4] Figure A1 shows monthly cash data for the central government, together with quarterly accrual data for the general government, for expenditures, revenues, and the difference between the two (i.e., the deficit), from the April 2024 vintage. The Figure indicates that the medium-low frequency developments in the data on cash flows are definitely in line with the medium-low frequency in the quarterly accrual data, for the three variables. Overall, due to the more timely releases of cash data, they can be a very important asset in order to predict the budget balance in real time. However, cash data are also considerably noisier than budget balance data and modelling devices should be used in order to appropriately filter out such noise without eliminating too much of their informative content.

(IP), the "Economic Sentiment Indicator" (ESI) for the euro area, published by the European Commission. These variables are all available until month $t_m - 1$. Moreover, we include the Industrial Turnover Index (ITI), which is available until month $t_m - 3$.[5] More details on the data source and transformations can be found in Table A1 in Appendix. The data availability on the 15^{th} of each month for the eleven variables used in our empirical application is reported in Table 1.

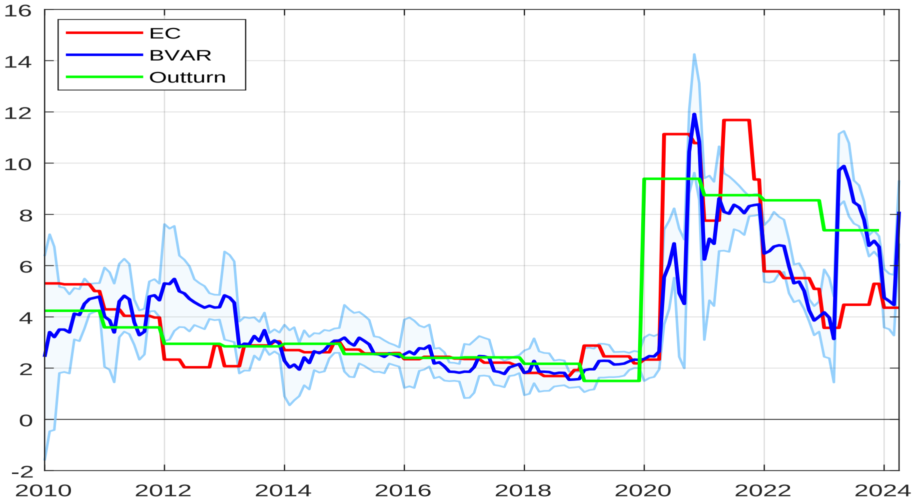
Table 1 describes both the different timeliness of the variables and their different sample frequency. In columns 2 and 3, we report the available releases of real GDP and the GDP deflator at each mid-month nowcasting round. National accounts are released with a quarterly frequency: the flash estimate of real GDP is released at the end of the first month after the reference quarter, while the GDP deflator is released around the middle of the third month following the reference quarter. Hence, for example, the nowcasts of the deficit-to-GDP ratio produced in February are based on real GDP for the fourth quarter of the previous year ($t_a - 1$) and GDP deflator data until the third quarter $t_a - 1$. In mid-March, instead, the release of GDP deflator for the fourth quarter of the previous year becomes available, while quarterly government accounts are released with a few weeks' delay compared to Quarterly National accounts, generally at the beginning of the fourth month after the end of the reference quarter. Hence, in March, the nowcasts are still based on fiscal accrual data only until Q3 of the previous year, and the fourth quarter release will only be factored in the nowcasts from April onward. Cash data on borrowing requirements, by contrast, are released with monthly frequency at the beginning of each month (the second business day of the month) and refer to two months prior (e.g., the data for December of the previous year becomes available in February of the current year). While noisier, cash data exhibit clear informational content for accrual variables, due to their more timely releases and can provide relevant predictive content for the budget balance in real time.

4 Fiscal nowcasts and news

In this section, we report the monthly nowcast over the fifteen months of the reference year plus three months of the subsequent year (January, February, and March). The estimates produced in these three months are generally defined as "backcast", i.e., estimates for year $t_a - 1$ based

[5] We use truly real-time vintages from Government Finance Statistics (GFS) and ECB Databases for GDP, quarterly revenues and expenditures. For monthly variables, we use pseudo-real time data, given that past vintages are not available for the full sample. However, monthly cash data and the other monthly variables in the dataset are only marginally revised across vintages.

Figure 1: Nowcast for the current year deficit-to-GDP ratio:
BVAR, European Commission and final outturn

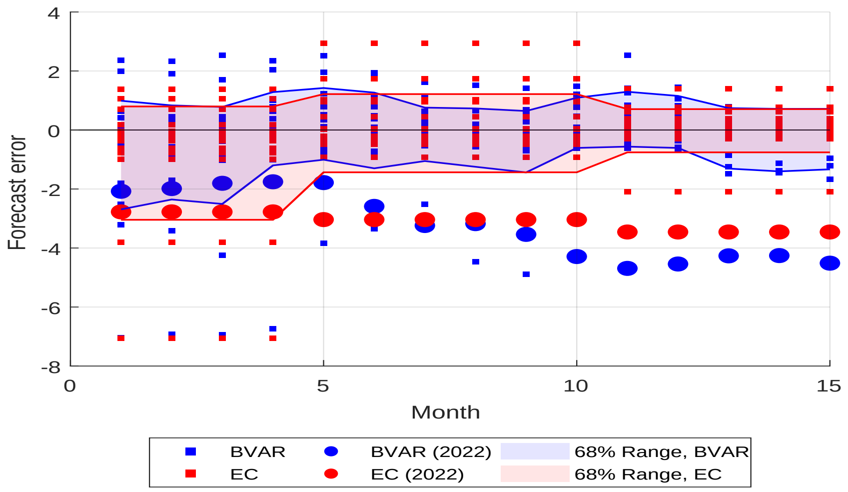


Notes: The deficit-to-GDP ratio is expressed in percent of GDP. The green line indicates the outturn, as published by the European Commission and Italian statistical agency (ISTAT) in April 2024. The BVAR nowcast is in blue (point estimate), together with the 16-84 uncertainty bands. The red line is the European Commission's forecast. The nowcast is conducted for the period 2010-2023, whereas the period 2002-2009 is used to initialise the model's estimates.

on information available in different vintages of year t_a. The evaluation sample for the nowcasts ranges from 2010 to 2023. The last vintage of data used in our real-time analysis is April 2024 which includes monthly data up to March 2024 and quarterly data up to 2023Q4. The availability of 2023Q4 allows us to evaluate the forecast accuracy up to 2023, given that the annual outturn for this year was published in April 2024 (first release).

Figure 1 reports the results. The green line indicates the outturn, as published by the Italian statistical agency (ISTAT) and the European Commission in April 2024. We plot the point nowcast from the BVAR model in dark blue, together with the 16-84 uncertainty bands in light blue. The red line is the European Commission's forecast, which is updated in May and November of each year and, hence, can take three different values in the course of each year. Our model generally accurately tracks the dynamics of the deficit-to-GDP ratio and, as expected, the uncertainty around the median BVAR nowcasts shrinks in the course of each year, when new information becomes available. Going into more detail, the BVAR nowcasts track the final outcome very closely from 2010 until the Covid crisis of 2020, with the exception of 2012, in which our model overshoots the final outcome, while the Commission's forecast is too optimistic, pointing to a lower deficit ratio than the final outcome.

Figure 2: Range of nowcast errors over the 15 months



Notes: The figure shows the range of nowcast errors (defined as deficit forecast for the current year minus realised deficit, in percentage points of GDP) over the fifteen months of projections for a given year.

The response to the Covid crisis generated a large expansion of the deficit ratio, which reaches about 9% of GDP in 2020 (green line). The BVAR's nowcast started picking up in May 2020, based on monthly macroeconomic and financial variables up to April 2020, and cash indicators up to March 2020, as does the Commission's. Both overshoot the final outcome for 2020. The 2021 Commission's forecast exceeds the final outcome by more than two percentage points, i.e., about 12% of GDP against a final outcome of 8.9% of GDP, while the BVAR nowcast turns out to be more accurate than the Commission's in that year. Both the BVAR model and the Commission largely undershoot the final outturn in 2022, mainly due to large ex-post revisions to the deficit brought about by delayed effects on public accounts of the "Superbonus 110%".[6] The BVAR model accurately processes signals of a further deterioration of the underlying fiscal indicators in 2023, and produces a nowcast for the deficit ratio for that year which is closer to the final outcome than the projections of the European Commission. The first four months of 2024 show a further decline of the deficit nowcast, which is however reversed in the last vintage of the sample (April 2024), indicating a new sudden deterioration.

[6] Superbonus 110% was a measure introduced by the Italian government on 19 May 2020. It consisted in a series of development mechanisms, deductions and refunds for building interventions, with the aim of modernizing construction and improving infrastructure. It aimed at improving energy efficiency and supporting the real estate and construction sector, which was deeply affected by the Covid-19 pandemic. The initial estimate of its cost was of 36 billion euro. In April 2024, a new estimate indicated that the total cost was instead of around 160 billion euro (around 8% of Italian GDP), over several years from 2021. Such revisions strongly impacted ex-post on the estimates for the deficit ratio, especially for 2022 and 2023 (see documentation provided by the Italian Statistical Agency, ISTAT). On the role of the Superbonus 110% for the Italian economy, see the analysis by Corsello and Ercolani (2024).

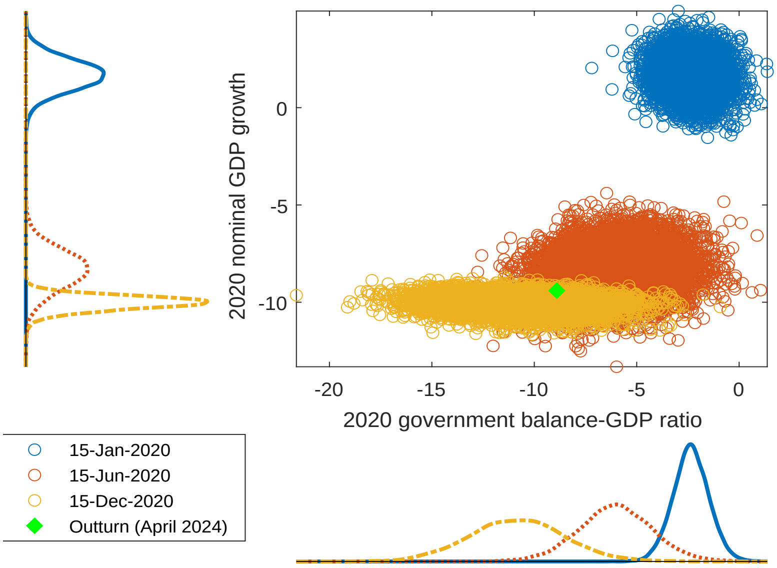
Figure 2 shows the evolution of the nowcast errors distribution over the fifteen months of the year. It indicates that errors are typically centered around zero. However, there are a few large negative outliers for the first months of the year (until month 4) which are due to the performance of the model in 2020, when it took some time before incorporating new information about the Covid crisis (see also Figure 1). Moreover, the negative outliers between month 9 and 15 are due to the effects of the "Superbonus 110%". Once again, the chart shows that uncertainty around the forecast tends to decline as new information becomes available. Despite the difference in size and complexity of the two forecasting approaches, our forecast is comparable and, at times, better than the Commission's, as also evident in Table C1 in Appendix, which reports the Root Mean Squared Errors (RMSE) for both the BVAR and the Commission's forecast.[7]

It should be stressed that, unlike the Commission's forecast, our model is very parsimonious, including only eleven variables and no judgment. The judgmental component for fiscal nowcasts is likely to be beneficial in terms of prediction accuracy, since it can be informed by fiscal plans which are unlikely to be fully reflected in the variables included in statistical models, such as ours. An additional advantage of our approach is that it produces a monthly indicator of the deficit ratio, thereby also providing estimates in the months between the May and November updates of the Commission's forecast.

Given the unprecedented volatility associated with the Covid pandemic, it is instructive to focus more specifically on the evolution of our fiscal nowcasts in the course of 2020. Figure 3 reports the joint distribution of the government balance-to-GDP ratio (the negative of the deficit ratio) and the GDP growth nowcasts during the Covid crisis of 2020. It shows the joint distribution in three different nowcast vintages: January 2020 (blue circles), before the onset of the Covid crisis; June 2020 (dark orange circles), at the peak of the Covid crisis; and December 2020 (light orange circles), when uncertainty around the Covid crisis started to dissipate. The nowcast produced in January 2020 indicates a low mean value for the deficit ratio, around 2% of GDP, in line with previous years and historical regularities. The uncertainty around the point estimate was also low, as indicated by the blue "cloud" of scattered points (draws). The model shows an explosion of uncertainty at the peak of the Covid crisis, in June 2020, but a mean estimate which was already quite close to the ex-post final values for GDP growth and the deficit, indicating that the model was fast and accurate in incorporating the informational content of

[7] The "Superbonus" in 2022 is the cause of the worse performance of the BVAR after month 11, but eliminating that observation from the evaluation sample (dotted lines in Table C1), one can see that the RMSEs of the BVAR are almost identical to the Commission's ones.

Figure 3: Joint nowcast of GDP growth and government balance ratio for 2020



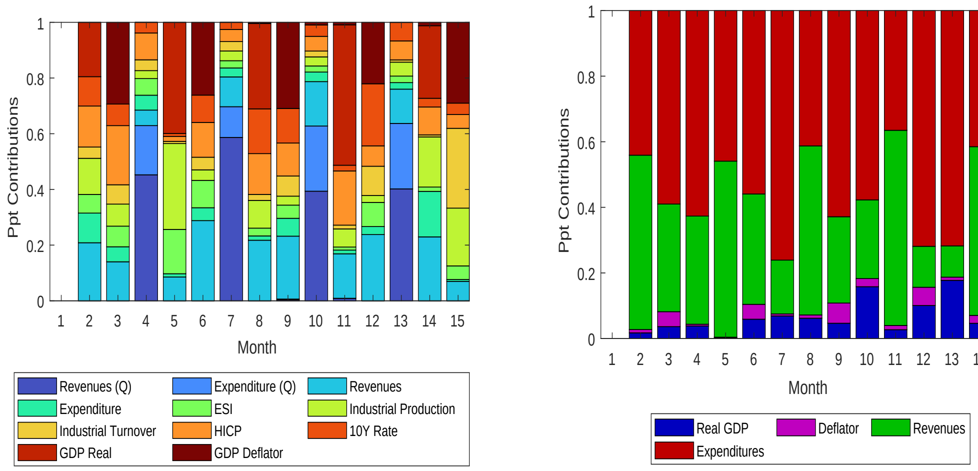
Notes: The figure shows the joint distribution of the nowcast of nominal GDP growth on the vertical axis and (horizontal axis) of the government balance-to-GDP ratio (i.e. the negative of the deficit-to-GDP ratio) as produced in three different vintages during the Covid-19 crisis: January 2020, June 2020 and December 2020. The chart also show the final outcome, as of April 2024.

new releases. By December 2020, with the flow of further information about macroeconomic and fiscal developments, the uncertainty around the GDP nowcast shrank, while the uncertainty around the balance-to-GDP ratio remained quite elevated.

Our BVAR approach also allows us to evaluate the "news" content of data releases, i.e., the percentage point contributions of the release of each of the model's variables to the monthly revision of the deficit-to-GDP ratio nowcast. This analysis plays a key role for fiscal monitoring by providing a narrative for the fiscal outlook and, possibly, policy implications. Against this background, besides looking at the news attached to individual variables, we also suggest cumulating all the news to define, respectively, the implied news for real GDP, the GDP deflator, fiscal revenues and fiscal expenditures, which are the four building blocks of the deficit-to-GDP ratio. If this analysis suggests, say, that the fiscal outlook is expected to deteriorate mainly due to the dynamics in fiscal variables rather than because of expected economic slack, it may suggest the need for a fiscal consolidation, rather than more general economic support policies.

As an illustrative example of news analysis, Figure 4 shows the average absolute contributions to the revisions in the nowcast of the deficit ratio for our full evaluation sample. The graph on the left reports the average absolute contributions to the revisions in the nowcast from the

Figure 4: Average Absolute Contributions of Data News to the deficit-to-GDP Ratio, Normalized



Notes: The figures shows the average absolute contributions in percentage points of the eleven quarterly and monthly variables in the model to the (monthly) revisions of the deficit-to-GDP ratio nowcast over 2010:2023. In the right hand side graph the variables are aggregated

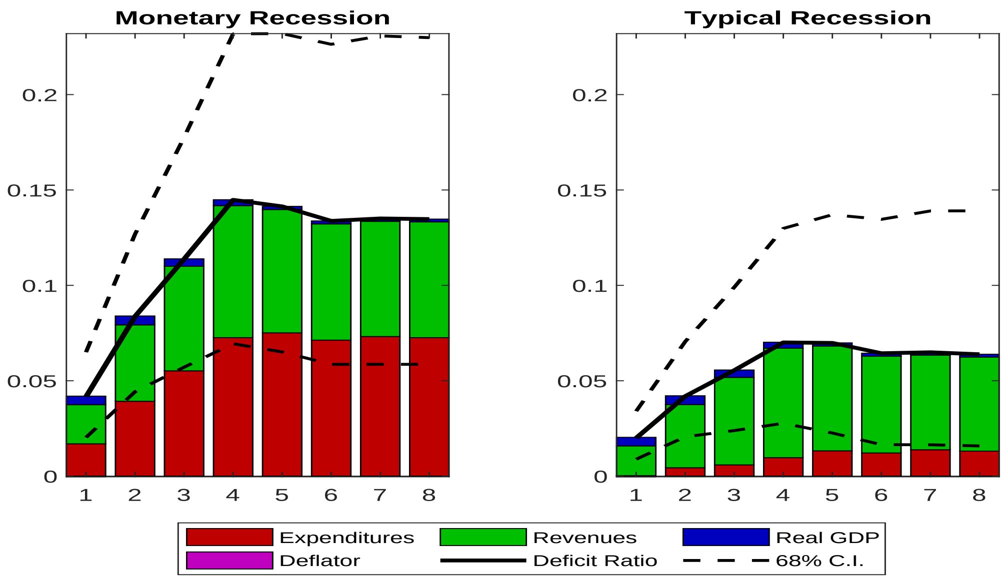
individual predictors, while on the right we aggregate the news of individual variables for each of the four building blocks of the deficit-to-GDP ratio, along the lines defined above. As regards the individual variables, we show that most of the variable releases carry important information for the budget deficit, with releases of cash data playing an important role. This result can be seen as an ex-post validation of our choice of variables. Aggregating the news across the four building blocks of the deficit-to-GDP ratio shows that the dynamics of fiscal revenues and expenditures are generally the major factor behind the dynamics in the deficit-to-GDP ratio in Italy.

5 Scenario on deficit-to-GDP ratios

Scenario analysis is a useful tool to capture the economic dynamics associated with unusual economic conditions, and to complement density forecasts with an economic narrative. We show that our model is particularly well-suited for conducting scenario analysis on the deficit-to-GDP ratio, by studying two stylized scenarios: an economic recession triggered by a monetary tightening, defined as “monetary recession”, and that of a “typical recession”, i.e., a recession due to the shocks which typically drive the business cycle in Italy.

Figure 5 reports the outcomes of our scenario analysis, in terms of the evolution of the deficit-

Figure 5



Notes: The figures show the response of the deficit-to-GDP ratio (black solid line) to a 1 standard deviation monetary policy shock (left panel) and a generalized business cycle shock that generates a recession of the same magnitude (right). The color bars report the contributions of fiscal revenues (green), fiscal expenditures (red), real GDP (blue) and the GDP deflator (violet) to the evolution of the deficit-to-GDP ratio.

to-GDP ratio (black solid line) in the two scenarios. On the left, we report the results for the "monetary recession" and on the right we report the results for the "typical recession". The color bars in the charts refer to the contributions of fiscal revenues (green), fiscal expenditures (red), real GDP (blue) and the GDP deflator (violet) to the evolution of the deficit-to-GDP ratio. The responses of all the individual model's variables in these two scenarios can be seen in Figures C1 and C2 in Appendix.

The monetary recession is implemented using the proxy for monetary policy surprises developed by Jarociński and Karadi (2020), based on the so-called "poor man's" sign restrictions. Fed funds futures surprises are taken as proxies for monetary policy shocks in months in which stock price surprises have the opposite sign, whereas central bank information shocks are those that move the two variables in the same direction; in all other months, the proxy is set to zero.[8] We include the proxy as an additional endogenous variable, ordered first, in the VAR used in the previous sections and identify shocks using a Cholesky decomposition. This reflects the assumption that monetary policy shocks can affect the other endogenous variables contemporaneously,

[8] This approach implicitly assumes that, in each month, the shock can be classified either as a pure monetary policy shock or as a pure central bank information shock.

whereas the reverse does not hold.

For the typical recession, we impose the same peak-to-trough decline in GDP as in the monetary recession, but attribute the downturn to a sequence of forecast errors in GDP.[9] These reduced-form disturbances can be expressed as weighted sums of the (unobserved) structural shocks, with weights proportional to their contribution to GDP growth forecast-error variance.

In the monetary recession scenario, fiscal expenditures increase substantially, due to the automatic stabilizers and the increased cost of debt. Fiscal revenues fall as a consequence of the contraction of the tax base caused by the reduction in economic activity, which further increases the deficit sizably and persistently. The dynamics of nominal GDP do not appear to play a relevant role in the evolution of the budget deficit. In the typical recession scenario, the dynamic response of the deficit-to-GDP ratio is substantially smaller. The most remarkable difference from the previous scenario is that, in this scenario, monetary policy acts to stabilize the economy by lowering interest rates. Hence, while fiscal revenues drop similarly to the case of a monetary recession, fiscal expenditures increase much less, implying that the budget deficit-to-GDP ratio displays much more muted dynamics.

This simple experiment showcases the model's ability to complement the analysis of the risks to the outlook by running counterfactual scenarios, capturing complex and nuanced transmission mechanisms.

6 Conclusions

This paper proposes a mixed-frequency BVAR model based on Cimadomo et al. (2022) to carry out fiscal monitoring. This methodology exploits information from monthly cash data and other high-frequency macroeconomic and financial variables, in order to produce density nowcasts of the annual government deficit-to-GDP ratio and provide a narrative for its evolution over time. In addition, the model captures complex and nuanced transmission mechanisms and, hence, can enrich the analysis of the risks to the fiscal outlook by running counterfactual scenarios.

We present an empirical application on Italian data, but a similar analysis could also be imple-

[9] Impulse responses to shocks defined in terms of forecast errors are often referred to as generalized impulse response functions. As shown by Del Negro et al. (2020), these impulse responses are closely related to those associated with the business-cycle shock proposed by Giannone et al. (2019), defined as the linear combination of structural shocks that explains most of GDP variation at business-cycle frequencies. Business-cycle shocks have been increasingly studied and used in recent years; see Angeletos et al. (2020); Bianchi et al. (2023); Ascari and Fosso (2024); Carriero and Volpicella (2025); Crump et al. (2025); Dou et al. (2025).

mented for other economies such as the United States and Japan, which have exhibited large fiscal imbalances in recent years. In general, this tool can be particularly helpful for fiscal monitoring in crisis times, such as the European Sovereign Debt crisis of 2010-2012 or the Covid crisis of 2020-2021, and more generally when economic and political uncertainty is high, which can lead to large and unexpected changes in fiscal variables. Under these circumstances, fiscal experts typically closely monitor fiscal developments, and construct scenarios based on the transmission of different shocks to the government deficit, debt, and other fiscal variables.

In our counterfactual scenario, we estimate the effects of monetary policy on the fiscal balance, which is relevant in light of the recent debate on "monetary-fiscal" interactions in the euro area and other advanced economies, where one of the questions at stake was about the fiscal implications of monetary tightening in the context of the post-Covid inflation cycle.

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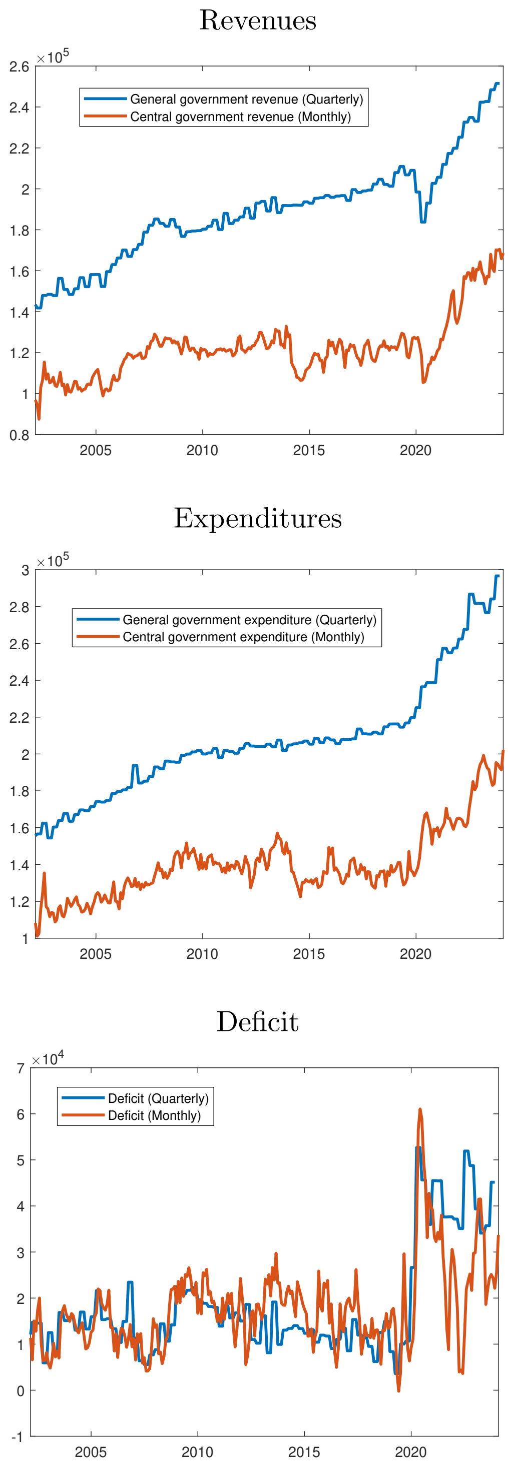
A Variable definitions and transformations

Table A1: Data and timing of releases

Variable	Frequency	Publication timing	Transformation	Prior	Code	Source
Real Gross Domestic Product	q	m+2	log-level	wn	YR	ECB
Deflator of Gross Domestic Product	q	m+3	log-level	wn	YD	ECB
General govt. total revenues	q	m+4	log-level, SA	wn	TORQ	ISTAT, ECB
General govt. total expenditures	q	m+4	log-level, SA	wn	TOEQ	ISTAT, ECB
Central govt. cash revenues	m	m+2	log-level, SA	wn	TORM	Ministry of Finance
Central govt. cash expenditures	m	m+2	log-level, SA	wn	TORM	Ministry of Finance
Industrial turnover index	m	m+3	log-level	wn	ITI	Haver Analytics
Industrial production excl. construction	m	m+2	log-level	wn	IP	Haver Analytics
Harmonized Consumer Price Index	m	m+1	log-level, SA	wn	HICP	Haver Analytics
10-years govt. benchmark bond yield	m	m+1	level	wn	IR	ECB
Economic Sentiment Indicator (euro area)	m	m+1	level	wn	ESI	European Commission

Notes: The table describes the eleven variables included in the baseline VAR. The publication time refers to the month after the end of the reference quarter of month. For example, GDP of 2023Q3 was published in March 2024 (m+3). Some variables (indicated with 'SA') have been seasonally adjusted using the X-13 toolbox of Matlab.

Figure A1:
Government nominal revenues, expenditures and deficit:
cash (monthly) and accrual (quarterly) data



Notes: The charts show monthly cash data for the central government (published by the Ministry of Finance) and quarterly accrual data for the general government (published by ISTAT), from the last vintage (April 2024). Quarterly data are up to 2023Q4 while monthly data are up to February 2024. Data are seasonally adjusted using the US Census Bureau's X-13 ARIMA-SEATS program. Units are millions of euro.

B Computing "News" on the annual deficit-to-GDP ratio

To compute the contributions of individual data releases ("news") to the revision of our target variable defined in (1) between two successive vintages $v0$ and $v1$, $b_{ta}^{v1} - b_{ta}^{v0}$, we need to relate the components of the annual deficit-to-GDP ratio, which are all expressed in (sums of) quarterly levels, to the variables as they enter our model, namely in natural logs. Once that is done, the same method to compute news described in Cimadomo et al. (2022), which is based on Bańbura and Modugno (2014), can be applied.

The first step, which involves no approximation, is to rewrite the annual deficit-to-GDP ratio as the weighted sum of quarterly deficit-to-GDP ratios:

$$b_{t_a} = \frac{\sum_{t=t_a.Q1}^{t_a.Q4} (E_t - R_t)}{\sum_{t=t_a.Q1}^{t_a.Q4} Y_t} = \sum_{t=t_a.Q1}^{t_a.Q4} \frac{Y_t}{Y_A} \left(\frac{E_t - R_t}{Y_t} \right) \tag{B1}$$

where $Y_A \equiv \sum_{s=t_a.Q1}^{t_a.Q4} Y_s$. Nominal GDP in turn is the product of real GDP and its deflator: $Y_A = P_A Z_A = \sum_{s=t_a.Q1}^{t_a.Q4} P_s Z_s$. A revision to the annual ratio, $b_{t_a}^{v1} - b_{t_a}^{v0}$, can therefore be written as the sum of four quarterly revisions. For a given quarter t, the revision is

$$\frac{Y_t^{v1}}{Y_A^{v1}} \left(\frac{E_t^{v1} - R_t^{v1}}{Y_t^{v1}} \right) - \frac{Y_t^{v0}}{Y_A^{v0}} \left(\frac{E_t^{v0} - R_t^{v0}}{Y_t^{v0}} \right) \tag{B2}$$

The second step, which does involve two approximations, is to relate each quarterly deficit-to-GDP ratio to the model variables expressed in natural logs, on which (additive) news contributions can be computed. To do that, rewrite equation (B2) in terms of (weighted) percent changes in expenditures and revenues:

$$\begin{aligned}
\frac{Y_t^{v1}}{Y_A^{v1}} \left(\frac{E_t^{v1} - R_t^{v1}}{Y_t^{v1}} \right) - \frac{Y_t^{v0}}{Y_A^{v0}} \left(\frac{E_t^{v0} - R_t^{v0}}{Y_t^{v0}} \right) &= \frac{E_t^{v1} - R_t^{v1}}{Y_A^{v1}} - \frac{E_t^{v0} - R_t^{v0}}{Y_A^{v0}} \\
&= \frac{Y_A^{v0}}{Y_A^{v1}} \frac{E_t^{v1} - R_t^{v1}}{Y_A^{v0}} - \frac{E_t^{v0} - R_t^{v0}}{Y_A^{v0}} \\
&= \frac{\frac{Y_A^{v0}}{Y_A^{v1}} E_t^{v1} - E_t^{v0}}{Y_A^{v0}} - \frac{\frac{Y_A^{v0}}{Y_A^{v1}} R_t^{v1} - R_t^{v0}}{Y_A^{v0}} \\
&= \frac{E_t^{v0}}{Y_A^{v0}} \frac{\frac{Y_A^{v0}}{Y_A^{v1}} E_t^{v1} - E_t^{v0}}{E_t^{v0}} - \frac{R_t^{v0}}{Y_A^{v0}} \frac{\frac{Y_A^{v0}}{Y_A^{v1}} R_t^{v1} - R_t^{v0}}{R_t^{v0}}
\end{aligned} \tag{B3}$$

The expenditure and revenue terms can then be approximated in terms of log differences, which can be computed (and decomposed into news contributions) from the variables in our model (lowercase variables denoting natural logs). For expenditures:

$$\begin{aligned}
\frac{E_t^{v0}}{Y_A^{v0}} \frac{\frac{Y_A^{v0}}{Y_A^{v1}} E_t^{v1} - E_t^{v0}}{E_t^{v0}} &\approx \frac{E_t^{v0}}{Y_A^{v0}} \left(e_t^{v1} - e_t^{v0} - \left(y_A^{v1} - y_A^{v0} \right) \right) \\
&\approx \frac{E_t^{v0}}{Y_A^{v0}} \left(e_t^{v1} - e_t^{v0} - \sum_{s=t_a.Q1}^{t_a.Q4} \frac{Y_s^{v0}}{Y_A^{v0}} \left(y_s^{v1} - y_s^{v0} \right) \right)
\end{aligned} \tag{B4}$$

where the second approximation exploits the fact that $y_A^{v1} - y_A^{v0} \approx \frac{Y_A^{v1} - Y_A^{v0}}{Y_A^{v0}} = \sum_{s=t_a.Q1}^{t_a.Q4} \frac{Y_s^{v0}}{Y_A^{v0}} \left(\frac{Y_s^{v1} - Y_s^{v0}}{Y_s^{v0}} \right) \approx \sum_{s=t_a.Q1}^{t_a.Q4} \frac{Y_s^{v0}}{Y_A^{v0}} \left(y_s^{v1} - y_s^{v0} \right)$. The expression for revenues is analogous.

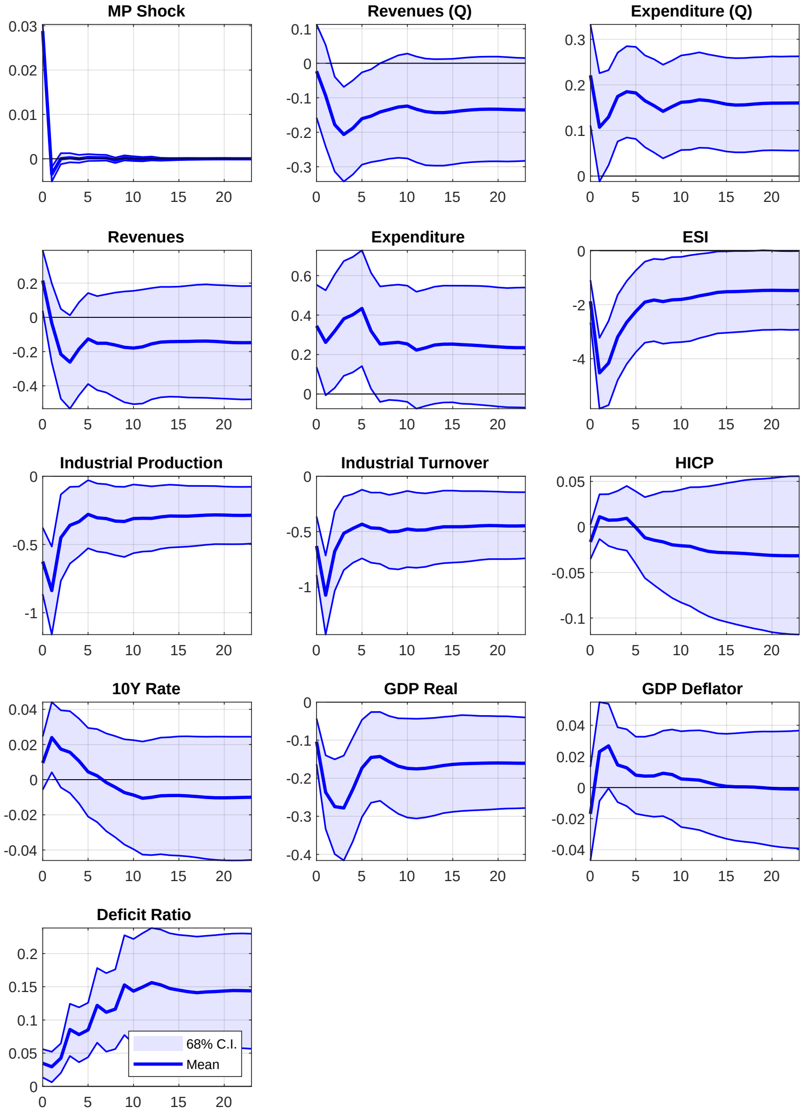
C Additional results

Table C1: **Root Mean Square Error (RMSE): BVAR vs. Commission's forecasts**

Month	EC	BVAR	EC ex.2022	BVAR ex.2022
1	2.36	2.46	2.32	2.49
2	2.36	2.36	2.32	2.39
3	2.36	2.46	2.32	2.50
4	2.36	2.11	2.32	2.13
5	1.53	1.51	1.34	1.49
6	1.53	1.44	1.34	1.30
7	1.53	1.25	1.34	0.94
8	1.53	1.57	1.34	1.37
9	1.53	1.70	1.34	1.47
10	1.53	1.35	1.34	0.73
11	1.20	1.56	0.79	0.96
12	1.20	1.42	0.79	0.76
13	1.20	1.36	0.79	0.77
14	1.20	1.38	0.79	0.80
15	1.20	1.43	0.79	0.80

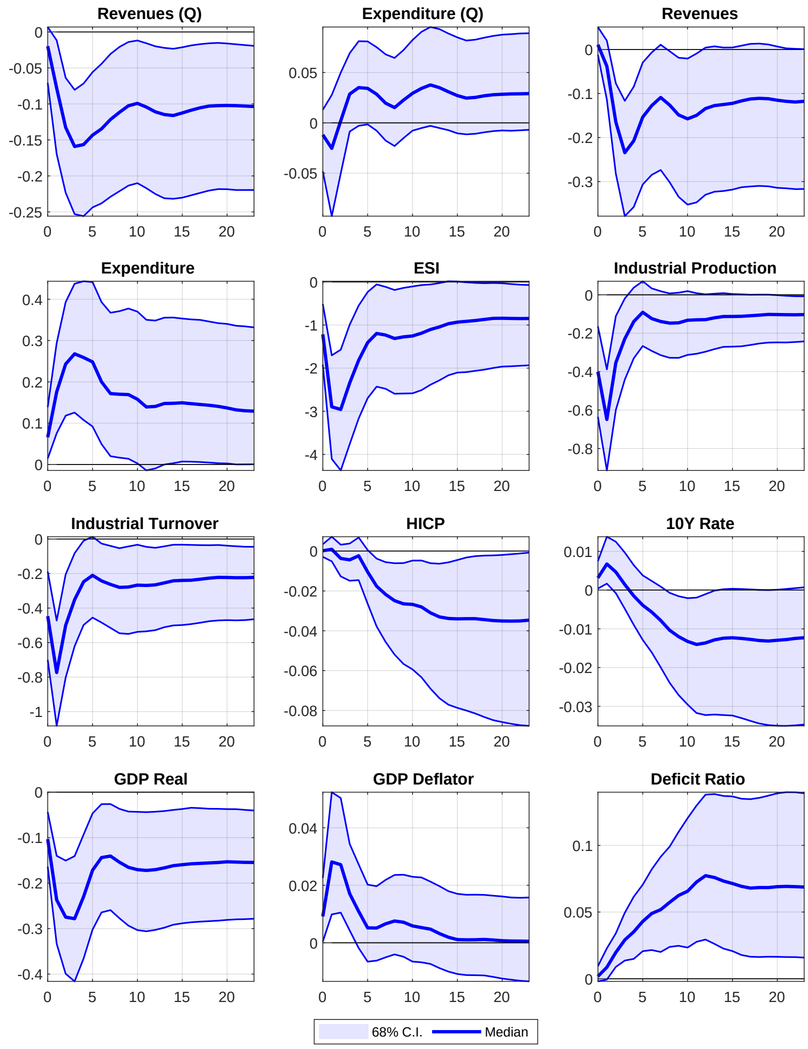
Notes: Root Mean Square error of the nowcast of the annual deficit-to-GDP ratio evaluated each month of the relevant year over the period 2010-2023, including (Columns 1 and 2) or excluding 2022 (Columns 3 and 4). The RMSE for months 13 to 15 is computed on the "backcast" for year $t-1$ as produced between January (month 13) and March (month 15) of year t.

Figure C1: Responses to a monetary policy shock



Notes: The figure shows the responses of the VAR variables to a one-standard-deviation monetary policy shock from Jarociński and Karadi (2020). The deficit ratio is computed based on the impulse responses of revenues, expenditures, real GDP and the GDP deflator.

Figure C2: Counterfactual



Notes: The figure shows the responses of the VAR variables to a generalized impulse response with GDP ordered first. A series of shocks is scaled to deliver the same GDP response as a one-standard-deviation monetary policy shock. The deficit ratio is computed based on the impulse responses of revenues, expenditures, real GDP and the GDP deflator.

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