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Nowcasting inflation with Lasso-regularized vector autoregressions and mixed frequency data

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Abstract

We evaluate the predictive performances of the least absolute shrinkage and selection operator (Lasso) as an alternative shrinkage method for high-dimensional vector autoregressions. The analysis extends the Lasso-based multiple equations regularization to a mixed/high-frequency data setting. Very short-term forecasting (nowcasting) is used to target the Euro area's inflation rate. We show that this approach can outperform more standard nowcasting tools in the literature, producing nowcasts that closely follow actual data movements. The proposed tool can overcome information and policy decision problems related to the substantial publishing delays of macroeconomic aggregates.

KEYWORDS

Nowcasting, Inflation, Model shrinkage methods, Lasso-VAR, Mixed frequency Data

1 | INTRODUCTION

Inflation is back and hitting the economy worldwide. There is a significant concern about how inflation will evolve, given its direct and uncontroversial effect on consumers, businesses, governments and central banks' expectations and incentives. In principle, everyone makes decisions based on present information and expectations, thus forecasts, of the price levels in the future. Because crucial statistics on key macroeconomic variables are available with a significant delay, real-time (or high-frequency) forecasting of the present and near future (nowcasting) is becoming increasingly relevant in economics (Bańbura et al., 2013).

The anticipation of the present state of the economy adds a critical dimension, timeliness, to the information sets upon which private agents and policymakers inform their decision processes. Unsurprisingly, the practice of nowcasting is becoming increasingly common at central banks and super-national economic institutions.[1]

Possibly because of their high-frequency forecasts, policymakers partially expected the current inflation hype and anticipated its emergence. The availability of increasingly accurate short-term inflation forecasts enriches the information on which policymakers form their decision processes. In this perspective, monitoring the variability of price levels at higher frequencies than the current publication timing is essential.

[1]The Board of Governors of the Federal Reserve implemented the first nowcasting model to provide high-frequency forecasts of GDP (Giannone et al., 2008). Since then, various versions of this seminal model have been built and implemented in other central banks, including the European Central Bank (Bańbura & Saiz, 2008) and the International Monetary Fund (Matheson, 2011).

Our paper contributes to the nowcasting literature on a specific aspect of the high-frequency forecasting practice, that is, on the model dimensionality reduction issue.

Nowcasting introduces three significant complications to the practical implementation of the analyses. First, including timely information from various sources implies that data are sampled at different frequencies and possibly in an asynchronous manner. Mixed frequency data inherently imply missing values for lower frequency inner observations (gaps) and outer observations (ragged edges). Second, the need to relate standard statistical information to high-frequency information from different sources implies that the information set is generally extensive. Nowadays, we can get a vast amount of information on the behavior of individual prices in the distance of a "click," so the issue is how to make the best use of this information. This second point leads to the third analytical complication, that is, the need to use model shrinkage methods to keep complexity to a computationally tractable level.

Model dimension issues arise particularly in multivariate dynamic settings, as in vector autoregressions (VARs), where the number of coefficients increases with the square of the variables in the VAR. The profligate parameter problem can make estimation infeasible or forecasts inaccurate in cases where the sample size is too small relative to the parameters' space. Here, the "horse race" among different missing data inputting methods and model shrinkage techniques comes to the fore.

Several approaches have been proposed for nowcasting in high-dimensional information settings, but only some pertain to the model shrinkage issue. On this latter terrain, reference studies in the nowcasting literature adopt either Bayesian shrinkage or dynamic factors convolutions, leading to large Bayesian VAR models (BVAR) and factor augmented VAR models (FAVAR), respectively.

This paper proposes the least absolute shrinkage and selection operator (Lasso) as an alternative (machine learning-based) shrinkage method for high-dimensional VARs estimated over mixed frequency data. Compared with other linear regularization methods, such as the Ridge regression and the Elastic Net estimator, the Lasso has the advantage of entirely excluding some information from the model.[2] The missing data inputting issue is instead aligned with the literature reference solutions. To the better of our knowledge, this is the first work in which a Lasso-based VAR regularizer is applied to nowcast Euro area HICP inflation considering a large, mixed frequency information set.

Results show that our machine learning approach is aligned with the BVAR model. At the same time, it can outperform the FAVAR model in the near-term prediction of both inflation and core inflation. Considering forecast sub-samples characterized by different degrees of price variability, we obtain that the Lasso-VAR tends to outperform all the tested model alternatives in periods of reduced price variability. These results are robust to some evaluation directions, such as the size of the information set (i.e., the inclusion of policy variables) and the consideration of core inflation as a target variable. We also show that other (linear) machine learning-based regularization methods, such as the Ridge and the Elastic Net, do not provide predictive improvements on the Lasso. We interpret this last finding as an indication that the selection step (i.e., the fact that the Lasso entirely excludes some variables/lags from the model by shrinking their parameters to precisely zero) is critical to avoid overfitting and poor forecasting in highly parameterized models. The consideration of extended forecast horizons, that is, moving from a nowcasting analysis to a forecasting analysis, shows that the BVAR modeling alternative attains the best predictive performances over the other model shrinkage approaches.

Our paper relates to two strands of literature. The first is the literature on short-term forecasting and nowcasting in high-dimensional information settings, which is becoming as vast as its importance for macroeconomic dynamics. To simplify, we can refer to a few significant works in the field. Giannone et al. (2008) evaluate the marginal effect of high-frequency information releases on current period (quarter) forecasts (nowcasts) in a factor model. Marcellino (2008) compare the predictive abilities of time-varying models, nonlinear time series models and artificial neural network models against standard ARMA models in predicting US GDP growth. Modugno (2011) uses mixed frequency data and a factor modeling framework to separate the effect on forecast revisions due to the inclusions of new data releases from that attached to the high-frequency dimension. Breitung and Roling (2015) propose a non-parametric approach to high-frequency forecasting using mixed frequency data and equations. Di Filippo (2015) uses dynamic model averaging and dynamic model selection to forecast US and Euro area price inflation, considering a large set of predictors. Hubrich and Skudelny (2017) propose using performance-based forecast combination methods to forecast HICP headline inflation. Cimadomo et al. (2022), following Giannone et al. (2008), apply the mixed frequency data approach to nowcasting within a Bayesian Vector Auto-Regression (BVAR) resembling the

[2] We verify this potential advantage in the robustness checks step. Other machine learning algorithms are not considered because their ability to allow for nonlinear relations would penalize the other benchmark models considered in the analysis, which are inherently linear.

modeling approach suggested by Bańbura et al. (2010).[3] Richardson et al. (2021) test the application of machine learning algorithms in a high-dimensional data setting to nowcast New Zealand's GDP. They show that these algorithms can significantly improve over a simple autoregressive benchmark and a dynamic factor model.

The second strand of literature is about using the Lasso as a shrinkage device in VARs. In this perspective, recent literature shows that Lasso-regularized VARs can provide an efficient solution to the "profligate parameterization" issue, as it ensures sparse structures. With the removal of over-parameterization and overfitting, the forecasts generated with these models can outperform those obtainable with benchmark single equation methods and the alternative multivariate methods developed for high-dimensional settings (Basu & Michailidis, 2015; Lin & Michailidis, 2017; Messner & Pinson, 2019; Nicholson et al., 2017, 2020).

The remainder of the paper is organized as follows. Section 2 deals with data issues. Here, we describe the data set, its continuous updating with mixed frequency information, how missing values are estimated, and the sample is re-balanced. Section 3 describes the econometric modeling strategy, the estimation, and its validation. Section 4 describes the nowcasting method and the metrics used to evaluate the out-of-sample model predictions. Here, we discuss the main results of the analysis from a comparative perspective. Section 5 describes some robustness checks. Section 6 concludes.

2 | DATA AND MISSING DATA IMPUTATION

Our analysis considers mixed frequency data, including weekly and monthly observations from September 2005 to August 2022. The benchmark model considers 31 variables, including inflation indicators for food, commodity, and electricity prices, changes in the broad money aggregate for the euro area (M3), and changes in bilateral and (nominal and real) effective exchange rates. Data are collected from Eurostat, the ECB Statistical Data Warehouse, Bloomberg, and the US Energy Information Administration (EIA). The complete dataset is described in Appendix A.

In the benchmark model estimates, we purposely left out monetary policy variables to produce nowcasts that are unconditional on information about policy measures. This choice, which is quite unconventional in forecasting, is justified by the fact that we aim to provide real-time forecasts (nowcasts) upon which policy decisions might be anchored. European Central Bank and US Federal Reserve's key policy variables are then included in the nowcasting models to verify the robustness of the main results to extensions of the information set.

Data are published at different time frequencies, on different days, by various institutions that do not coordinate the publishing or the data revision frequency. The first issue is providing a fixed weekly structure for the irregular and unstructured data flow. We attribute all the (working week) daily observations to the specific week they belong. This choice is consistent with the idea that data can be included in the conditioning set if known to the forecaster, no matter the publication day (i.e., their relative weight in the information content of the weekly observations).

We then estimate the unobserved weekly measures from lower frequency (monthly) data. For this purpose, we follow the latent observation VAR method (L-VAR) recently described in Cimadomo et al. (2022). This method treats the missing weekly observations as latent processes that can be inferred using the Kalman Filter (KF).[4] With this strategy, we build a structured weekly dataset such that even an irregular flow of information in the time dimension (i.e., mixed frequencies with ragged edges) can feed any high-dimensional forecasting model.

Provided that the information set is continuously updated in a real-time data environment, we follow the standard practice in the nowcasting literature by introducing data vintages.[5] In this way, we can produce nowcasts at any time by using the data being made available at the same time nowcasts are calculated.

In the remaining part of this section, we thoroughly explain the missing data imputation process we followed in our analysis.

[3]A (Kalman) filtering method has been suggested to estimate general equilibrium models by Canova and Ferroni (2011) in a data-rich environment.

[4]Cimadomo et al. (2022) evaluate the nowcasting performances of this approach against two alternative strategies. The first is the blocking VAR (B-VAR), in which the VAR is estimated at the joint (lower) data frequency. The higher-frequency observations are considered separate lower-frequency variables. This approach avoids the latent state definition of the VAR for missing higher-frequency data, limiting the use of Kalman recursions to fill the ragged edges generated by the asynchronous data release. The second alternative is labeled cubic root VAR (C-VAR) in a monthly-quarterly mixed frequency data environment. It starts from a lower-frequency model estimate and then maps it into a higher-frequency model using Kalman filtering techniques, as in the L-VAR.

[5]The vintage is a set of new data available at a particular moment in time, that is, in which the model is estimated.

2.1 | Imputation of high-frequency missing data

In a continuously updating mixed frequency information set by vintages, missing weekly observations emerge within known monthly observations (for data released at the monthly frequency) and at the end of the sample (when the last observation of a monthly frequency variable still needs to be released). In the latter case, the missing data generate a time-evolving sample's ragged edges. In order to get a complete weekly dataset, we need to estimate the motion of the monthly variables at a higher frequency than that available from official sources' releases. The KF can contribute to guessing the missing values between each monthly observation.[6]

In order to fill the missing weekly data, we adopt Cimadomo et al.'s (2022) latent observation VAR method (L-VAR).[7] The main difference is that our procedure considers a machine learning-regularized VAR instead of a Bayesian VAR.

The proposed strategy relies on KF techniques applied to the state-space representation of the VAR. The missing (weekly) values for the low-frequency observations are conceived as existing—albeit latent—processes for weekly variables that are observed only at the monthly frequency.

Specifically, the missing data imputing procedure goes as follows. First, a preliminary complete weekly dataset is obtained by interpolating monthly observations using splines. The preliminary weekly dataset is then used to initialize the Kalman recursions using a regularized VAR. For the benchmark estimates, the start coefficients for the KF consider a Lasso-VAR.[8] The state-space representation of the VAR is used to iteratively apply the Durbin and Koopman's (2001) simulation smoother, obtaining improved VAR and missing data estimates in each repetition of the procedure. The process is rerun until convergence—and thus the final complete weekly dataset—is achieved.

Because this process also yields nowcasts/forecasts conditional on the final dataset, a first one-month (four weeks) ahead forecast can be made. The procedure is then repeated for each new weekly data observation, obtaining weekly nowcasts. In fact, following each emission of new information, the KF is re-booted in order to provide corrected estimates. Figure 1 depicts the update-prediction procedure graphically. The red semi-circles are the observations released by official sources every four-time steps (weeks). The orange ones denote the output of the correction step, whereas the green semi-circles and lines result from the prediction step (this is where the data imputation occurs). The arrows show the direction of the KF updating process, starting from defining initial conditions to the final prediction step.

3 | THE ECONOMETRIC MODEL

Since the seminal work of Sims (1980), the VAR has become the most used methodological approach to empirical macroeconomic modeling. Despite their popularity, VAR models are often at risk of over-parameterization, leading to overfitting and poor forecast performances. Such a drawback of the methodology becomes particularly stringent in high-dimensional data settings.

The over-parameterization problem can be solved by artificially penalizing the model coefficients. Prior structures (or hyperparameters) in Bayesian settings or common factors-based structures are often employed to reach this goal. In the nowcasting literature, two are, in fact, the main modeling approaches to the high dimensionality issue: (i) large Bayesian VARs (BVAR) and

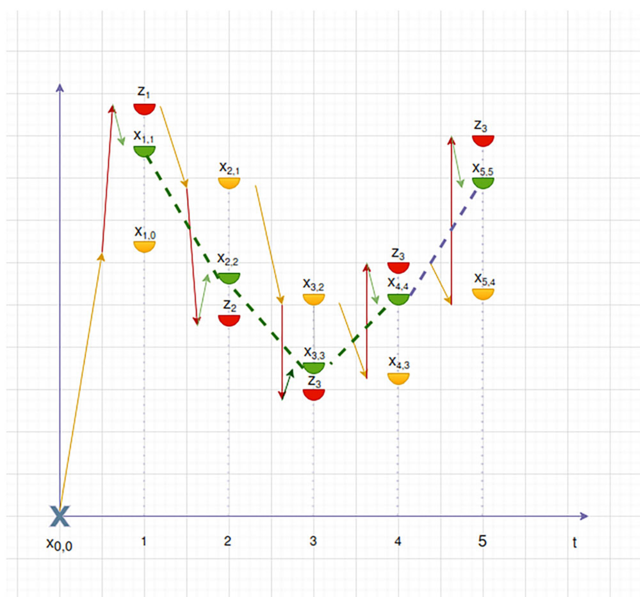

FIGURE 1 Graphical exemplification of the KF update-prediction procedure.

[6]The KF is designed to filter out the best guess for the latent state of a system in an environment characterized by the presence of a given level of noise.

[7]In a frequentist setting, this strategy has been applied in Giannone et al. (2008), Mariano and Murasawa (2010), Kuzin et al. (2011) and Foroni et al. (2015). Eraker et al. (2014), Schorfheide and Song (2015), Cimadomo and D'Agostino (2016), and Brave et al. (2019) apply the latent variable approach within Bayesian settings.

[8]Other regularization strategies for linear models (Ridge and Elastic Net) are also considered to evaluate the robustness of results to the use of alternative machine learning-based model shrinkage methods.

(ii) dynamic factor and factor augmented VAR models (DFM-FAVAR).

A non-exhaustive summary of literature in which these approaches are proposed is, for DFMs-FAVARs, Stock and Watson (2002a), Stock and Watson (2002b), Giannone et al. (2008), Aruoba et al. (2009), and Cascaldi-Garcia et al. (2021). On the side of BVARs (2021), some significant contributions are Banbura et al. (2010), Koop and Onorante (2019) and, more recently, Cimadomo et al. (2022). Higgins (2014) proposes the joint consideration of the two approaches in a high-dimensional forecasting setting.

We propose a Lasso-based regularization as an alternative approach to overfitting issues in high-dimensional VARs, seeking to improve their real-time predictive performances (Basu & Michailidis, 2015; Lin & Michailidis, 2017; Messner & Pinson, 2019; Nicholson et al., 2017, 2020).

3.1 | The Lasso-VAR

The Lasso is a method for automatic variable selection and parameter shrinkage used to select the most informative predictors of a target variable from a large set of variables and parameters. A peculiarity of the approach is that the information set (i.e., number of variables) might be even larger than the sample size. This peculiarity makes high-dimensional modeling and forecasting feasible for any degree of model dimension and complexity.

The Lasso has been initially developed for single equation settings by Tibshirani (1996). The Lasso approaches curve fitting as a quadratic programming problem, where the objective function penalizes the total size of the regression coefficients based on the value of a tuning parameter, λ. In doing so, the Lasso can drive the coefficients of irrelevant variables to zero, thus performing the automatic variable selection. The strength of the penalty must be tuned. The stronger the penalty, the higher the number of coefficients shrunk to zero. The model is thus forced to select only the most important predictors, that is, those with the highest contribution to the prediction of the target variable.

Let $\{x_t\}_{t=1}^{T}$ be a k dimensional vector including time series that follow a VAR process of order p. All the variables are entered in first differences in the VAR, such that it considers aggregate, commodity-specific and currency-specific relative prices inflation rates. We have verified with Phillips–Perron tests that all the time series included in the VAR are stationary (non-stationarity test results are provided in Appendix A).

We fix the maximum order of lag p to 12 periods (thus one quarter). The chosen lag order is higher than the one indicated by the Akaike Information Criterion, suggesting a four-week lag order. This choice allows the model to capture economically plausible lags in the transmission dynamics from specific commodity price variations to other prices and aggregate inflation.[9]

$$\begin{aligned} X_t = A_1 X_{t-1} + \ldots + A_p X_{t-p} + u_t \\ u_t \sim N(0, \Sigma_u) \end{aligned} \tag{1}$$

where each A_i is a $k \times k$ matrix of coefficients for the endogenous variables, and $\mathbf{u}_t \sim (\mathbf{0}, \Sigma_u)$ is the vector of reduced-form errors. Because we standardize data before modeling, the VAR does not consider the k-dimensional intercept vector.

The LASSO objective function is minimized as follows:

$$\hat{\mathbf{A}}(\lambda) = \arg\min_{\mathbf{A}} \frac{1}{T} \|\mathbf{AZ} - \mathbf{Y}\|_2^2 + \lambda \|\mathbf{A}\|_1, \tag{2}$$

where λ is the shrinkage parameter, whose calibration targets the out-of-sample model's predictive ability, that is, the minimization of the forecast error. The optimization problem is solved by applying a coordinate descent numerical procedure, as explained in Kim et al. (2007) and Friedman et al. (2010).

3.2 | Lasso-VAR time series cross-validation

As immediately evident from Equation 2, λ is the most critical parameter in the Lasso framework. Its calibration is based on selecting the best predicting model, which should not be sample-specific. To minimize the risk of a sample-specific calibration, a cross-validation stage, based on sample splitting, is thus employed for getting the "optimal" value for λ.

In this respect, the data set is divided into a training and a test sample. The test set is for final evaluation, whereas the training set is split into five subsets. We follow an expanding window (more precisely, an "anchored walk forward") approach to cross-validation Carta et al. (2021).[10]

The anchored walk forward (five-fold) cross-validation method implies a gradually expanding training

[9]Nicholson et al. (2020) fix the maximum order of lag of the VAR to the number of periods included in the lower frequency dating, such as four weeks or 22 trading days in a month.

[10]Time series cross-validation essentially considers time dependence, such that the training set includes observations temporally preceding those in the test set.

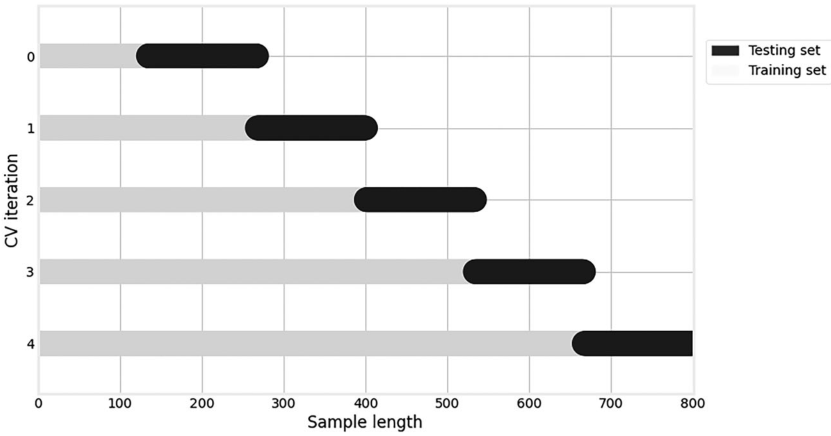

FIGURE 2 Graphical example of the five-split time series cross-validation.

set, pushing forward a fixed dimension test set. The 5-split time series cross-validation method is exemplified in Figure 2, where the length of training and test sets is shown on the horizontal axis. In contrast, the five cross-validation iterations are shown on the vertical axis.

4 | RESULTS AND MODEL COMPARISONS

After estimating the sparse model resulting from the cross-validated Lasso-VAR, we proceed to short-term forecasting, considering a sample spanning from July 2019 to August 2022. Consistent with the idea of nowcasting (i.e., forecasting the present or very near future), we are interested in a four periods-ahead forecast exercise, thus covering one month given the weekly update of the high-frequency information. In the robustness checks, we also consider extensions of the forecasting window to 8 and 12 periods ahead, moving from a typical nowcasting analysis to forecasting.

We thus restrict the information set to the one that would be available during the week in which the nowcast is performed. Following Diebold's (2020) approach to using information vintages, we build 165 weekly data releases (the weeks between July 2019 and August 2022). These releases are imputed using the methodology described in Section 2 to deal with the missing data issues related to mixed frequencies and ragged edges. During the weekly nowcasting exercises, we consider one other vintage per nowcast up to the date in which one additional monthly information is released. We then move to the next vintage of data.

4.1 | Evaluation of the Lasso-VAR nowcasting performances

A standard dynamic (recursive) forecasting method is applied to calculate the near-term out-of-sample forecast:

$$X_{T+h|T} = c + A_1 X_{T+h-1|T} + \ldots + A_p X_{T+h-p|T} \tag{3}$$

In order to provide a first evaluation of the performances of a real-time approach to inflation forecasting, the Survey of Professional Forecasters (SPF) estimate of the Euro area HICP inflation is first taken into account.

We acknowledge that the comparison with the SPF is only partially legitimate because the latter is not based on nowcasts. The reference to the SPF is only to highlight the potential improvements in forecasting macro-aggregates coming from the use of higher frequency information and efficient model shrinkage methods, as compared with an established methodology within the operation of central banks.[11]

Figure 3 compares Lasso-VAR-based nowcasts, realized HICP inflation and SPF estimates. The figure also reports the nowcasts' 95% confidence intervals, obtained from bootstrapped forecast errors.[12] We also include the forecasts obtainable by a simple linear extrapolation of inflation from its past, obtained by a naive AR(2) process (Cimadomo et al., 2022). Unsurprisingly, the nowcasting approach outperforms the AR(2) model, because the latter neglects the information embedded in the higher frequency variables. The predictive improvement obtained with the Lasso-VAR nowcasts on the naive benchmark is particularly evident when relevant changes in dynamics are building up, possibly due to unexpected shocks.

[11]The SPF is a quarterly survey conducted by the European Central Bank, reflecting the average perception of approximately 90 experts regarding their expectations about the dynamics of a set of leading macroeconomic indicators. In the first month of each quarter, the participants (experts affiliated with financial or non-financial institutions within the Euro area) declare their expectations regarding the HICP inflation rate, GDP growth and unemployment (and their degree of uncertainty). Expectations are formed after having been provided with all the information available up to that date.

[12]Because forecast errors are normally distributed according to the Shapiro–Wilk, D'Agostino and Pearson, and Anderson-Darling tests for normality, we have verified that analytical and bootstrapped confidence intervals are only marginally different.

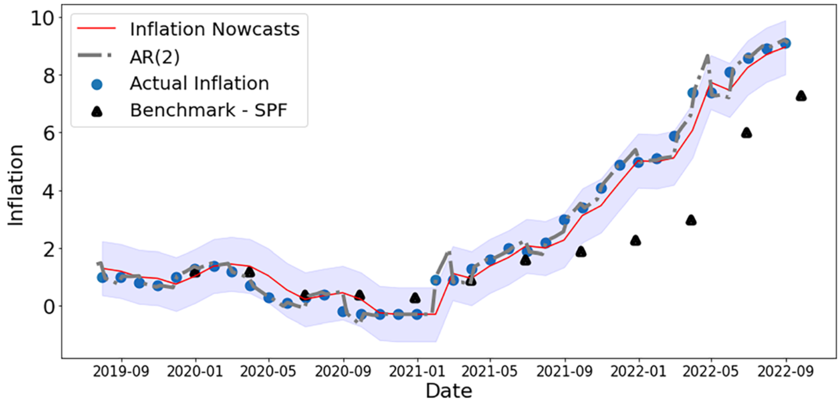

FIGURE 3 Nowcasts, actual HICP inflation and SPF estimates. *Notes*: Nowcasts' 95% confidence intervals are obtained from bootstrapped forecast errors.

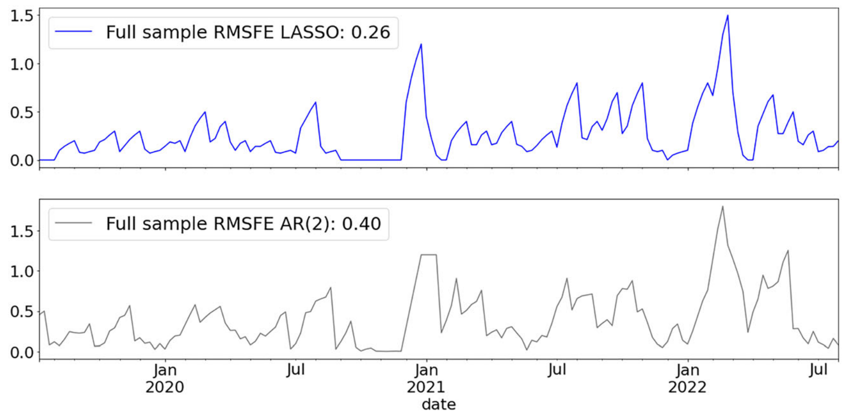

FIGURE 4 Root mean squared forecast error.

In order to evaluate the forecasting model performances over objective metrics, the Root Mean Squared Forecast Error (RMSFE) is adopted and calculated on out-of-sample residuals.

$$RMSFE = \sqrt{\left(\frac{1}{H}\right)\sum\nolimits_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{4}$$

A critical step in evaluating the nowcasting results is deciding to which values these nowcasts are to be compared. We do not have the actual values of the weekly inflation rate within two consequent months, and the model is trained and tested on subsets including both actual inflation data (at the monthly frequency) and imputed data (at the weekly frequency). Consistent with the standard approach in the literature, we calculate the ex-post RMSFE considering weekly point HICP inflation nowcasts and the realized HICP inflation, which is observed at the monthly frequency. This approach highlights the role of the arrival of new high-frequency information for forecasting performances.

Figure 4 depicts the dynamics of the RMSFE for the Lasso-VAR-based nowcasts and for the AR(2) benchmark over the entire (weekly) sample spanning from July 2019 to August 2022. The graphs highlight that the forecast errors increase with time, possibly reflecting the build-up of inflationary pressures at the end of 2021.

The behavior of the forecast errors over the weekly sample indicates that the forecasting accuracy improves as more weekly information becomes available over the month. This result is better depicted in Figure 5, in which we report, for every week in a month, the average RMSFEs for the point HICP inflation nowcasts in the month, calculated over the entire sample (July 2019 to August 2022). The behavior of the average forecast error over subsequent weeks indicates that the proposed Lasso-VAR is a valid nowcasting tool. As more information becomes available each week of the month, the forecast error decreases. Such a decrease does not materialize for the naive AR(2) benchmark, denoting an RMSFE slightly lower than the Lasso-VAR at the beginning of the month, then increasing with the (weekly) forecast horizon. This difference in the average RMSFE behavior over the weeks in the month highlights the informational advantage arising from the efficient use of higher-frequency information.

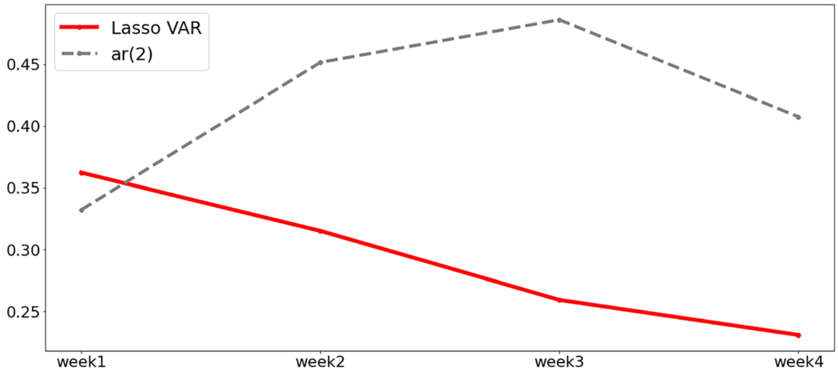

FIGURE 5 Nowcasting performance per week of the month. *Notes*: The line denotes average monthly RMSFEs for weekly point HICP inflation nowcasts for the sample July 2019 to August 2022.

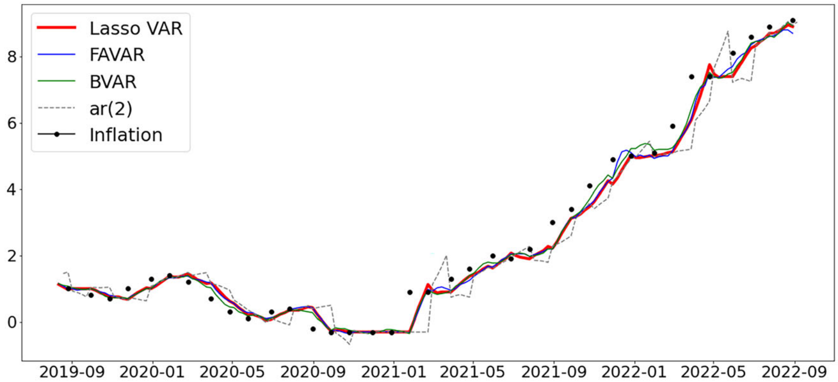

FIGURE 6 Nowcasts: Lasso-VAR versus FAVAR, BVAR and AR(2).

4.2 | Model comparisons

We compare the performance of our Lasso-VAR-based nowcasting approach to two modeling benchmarks in the literature, the FAVAR and the BVAR. Because our main focus is to evaluate the relative forecasting abilities of the methodologies, the model comparisons are performed on standardized experimental features. The information set and the missing values imputation strategy are the same across model specifications, and the maximum lag order is fixed to 12 in all model shrinkage alternatives. For the FAVAR model, the number of top factors identified by the largest eigenvectors is defined such that they jointly explain about 85% of the variation in the data. In our analysis, this threshold is reached with three factors.

Even in this case, the forecast performances of our nowcasting strategy are tested considering an extended period spanning from July 2019 to August 2022. Reference to an extended sample allows us to verify whether model comparison results are sample-dependent, an issue that emerged in recent literature (de Bondt et al., 2021; Dauphin et al., 2022). To better highlight this point, the forecasting period over which model comparisons are evaluated is divided into three reference periods: a pre-COVID-19 period, spanning from July 2019 to February 2020; a COVID-19 crisis period, spanning from March 2020 to September 2021 (i.e., when the European mass vaccination campaign was almost completed, allowing for a generalized relaxation of non-pharmaceutical containment measures); a post-COVID-19/Energy crisis period, starting from October 2022 and still ongoing.

Figure 6 depicts the Lasso-VAR, the FAVAR and BVAR-based average weekly nowcasts for the sample from July 2019 to August 2022, along with the realized inflation values. The nowcasts are compared with those obtained with the naive AR(2) benchmark.

The figure shows that all the nowcasting model alternatives can closely follow the actual inflation rate, providing policymakers with valuable real-time information about inflation.

To give an idea of the relative nowcasting abilities of the three model competitors, Table 1 summarizes their RMSFEs (and that of the naive AR(2) model benchmark) in the three sub-samples. The table also reports, with bold values, whether the results from the model's predictive accuracy comparison tests are significant. These tests are based on the corrected (Diebold & Mariano, 1995) statistics (Harvey et al., 1997), taking the Lasso-VAR as a reference.

The table shows that the three nowcasting alternatives have similar predictive properties, with the Lasso-VAR significantly outperforming the FAVAR and the

TABLE 1 Model comparisons: RMSFE and Diebold–Mariano test results.

		pre-COVID-19 sample	COVID-19 sample	Energy crisis sample	Full sample
h=4	Lasso-VAR	0.144	0.239	0.379	0.261
	FAVAR	**0.153**	**0.262**	0.401	**0.281**
	BVAR	**0.152**	0.235	0.364	0.256
	AR(2)	**0.200**	**0.386**	**0.546**	**0.407**

Notes: Bold values indicate that the predictive performance of the Lasso VAR is statistically different from those obtained by the other models. The reference test is the Diebold and Mariano's (1995) test of differences in the model's predictive accuracy. The reference statistics consider the Harvey et al. (1997)'s correction for small samples.

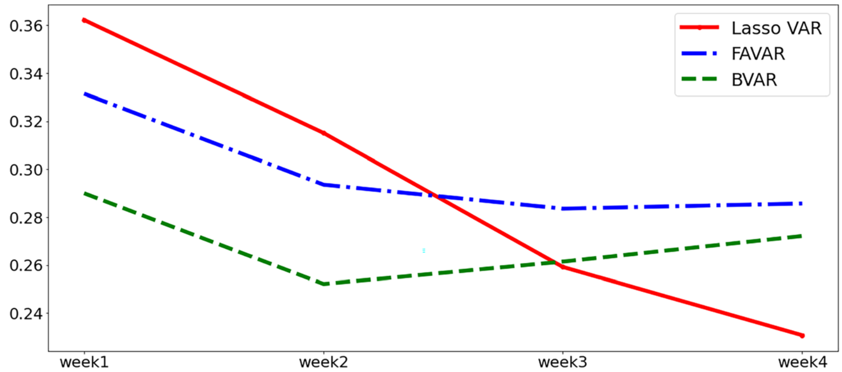

FIGURE 7 Models' nowcasting performance per week of the month. *Notes*: The line denotes average monthly RMSFEs for weekly point HICP inflation nowcasts for the sample July 2019 to August 2022.

AR(2) benchmark in the total nowcast sample. In "normal times," the Lasso-VAR outperforms all the alternative methods, reaching the minimum RMSFE across model competitors. With the increase of the HICP volatility registered during the COVID-19 and the energy crisis periods, the BVAR marginally outperformed the Lasso-VAR in terms of RMSFE (the difference in the predictive performances is not statistically significant). The latter, however, continues to perform significantly better than the FAVAR and the AR(2). The relative decrease in the nowcasting abilities of the Lasso-VAR in the heightened price volatility periods is entirely due to a loss of accuracy in two specific episodes. One between February 2021 and March 2021 and one just before May 2022 (see Figures 3, 4, and 6). We speculate that the Lasso shrinkage (which sets to exactly zero some of the VAR coefficients) might become inaccurate when some sudden shocks hit the economy (possibly the COVID-19 shock in February-March 2021 and the energy prices turmoils from the Russian-Ukrainian war in May 2022). The three nowcasting tools outperform the AR(2) model, whose RMSFE is significantly higher by 45% to 59%.

A further comparison of the models' nowcasting properties can be obtained from the average RMSFEs for the weekly point HICP inflation nowcasts in the month. Figure 7 replicates the information included in Figure 5 for the Lasso-VAR (and for the AR(2) benchmark), adding the same information for the FAVAR and the BVAR. The performance of the three models is, on average, similar. For the Lasso-VAR and the FAVAR, it shows monotonic improvements in accuracy as new information becomes available during the month. The Lasso-VAR attains the minimum (and least) average RMSFE at the end of the month. The BVAR attains its minimum average RMSFE in the second week of the month.

5 | ROBUSTNESS CHECKS

The robustness of the results described in the previous section can be evaluated in several ways. Here, we focus on four significant aspects of the analysis: (i) the extension of the information set to the inclusion of high-frequency (weekly) and standard-frequency (monthly) policy variables; (ii) the extension of the forecasting window up to 12 weeks (approximately one quarter); (iii) the use of alternative machine learning-based regularization tools in the class of linear models; (iv) the application of the Lasso-VAR procedure to perform core inflation nowcasts.

The first robustness check enriches the information set by including the monetary policy rates. Three of six policy rates are observed at the highest frequency (daily, thus moved to weekly): the ECB's Marginal lending facility rate, the Deposit facility rate and the Main refinancing operations rate. The other rates are available at a monthly frequency: the ECB's shadow interest rate (Wu & Xia, 2020), the US Federal Funds rate and its shadow rate (Wu & Xia, 2016).[13] With this data extension, the number of variables (thus equations) considered in the VARs increases from 31 to 37. The missing data imputing procedures and the dynamic model specifications are fixed to those used for the no-policy variables model estimates. Results, summarized in Table B1 in Appendix C, show that including policy variables does not alter the near-term (four weeks ahead) models' predictive properties. This result is constant across model alternatives.

With the second check, we verify whether our methodology, specifically designed for very short-term forecasts, maintains its predictive properties even at larger forecasting horizons, that is, moving from a nowcasting analysis to a forecasting analysis. We also consider eight and 12-week-ahead forecasts along with the four-week ahead forecasts. Results are summarized in Table C1 in Appendix C. Unsurprisingly, the predictive abilities of the Lasso-VAR, the FAVAR and the BVAR, summarized in the values of the RMSFE, worsen with the size of the forecasting periods. There are, however, signals that the predictive abilities of the Lasso-VAR tend to be outperformed by the alternative methods when the forecast period is extended, with the BVAR prevailing on the other model shrinkage methods.

The third robustness check verifies whether we can improve the nowcasting properties by considering alternative regularization methods for the VAR. In the class of linear models, the Ridge and the Elastic Net estimators are "natural" machine learning competitors for the Lasso. The former replaces a quadratic penalty to the Lasso coefficients' mass, that is, it relies on the following optimization problem:

$$\hat{\mathbf{A}}(\lambda) = \arg\min_{\mathbf{A}} \frac{1}{T}\|\mathbf{AZ}-\mathbf{Y}\|_2^2 + \lambda\|\mathbf{A}\|_2, \tag{5}$$

By penalizing the sum of squared coefficients (the so-called L2 penalty) instead of the sum of their absolute values (L1 penalty) as in the Lasso, the VAR coefficients are shrunk but not set to exactly zero.

The Elastic Net estimator combines the L1 and L2 penalties to minimize the following loss function:

$$\hat{\mathbf{A}}(\lambda) = \arg\min_{\mathbf{A}} \frac{1}{2T}\|\mathbf{AZ}-\mathbf{Y}\|_2^2 + \lambda\left(\frac{1-\alpha}{2}\|\mathbf{A}\|_2 + \alpha\|\mathbf{A}\|_1\right), \tag{6}$$

where α is the mixing parameter between Ridge (α=0) and Lasso (α=1). The Ridge/Lasso penalty parameter λ is cross-validated over five-time series folds, with α calibrated over a grid of values between 0 and 1.

Results, summarized in Table C2 in Appendix C, show that, for our nowcasting sample and the 31 variables dataset, the Lasso-VAR ensures a lower RMSFE than the Ridge and Elastic Net-regularized VARs. This result holds irrespective of the particular sub-sample being considered.

With the fourth robustness check, we verify whether the predictive abilities of the different high-dimensional VAR methods are also confirmed for Euro area core inflation. This variable is within the information set used for the estimates. The nowcast graph and the related RMSFEs, depicted in Figure C1 and Table C3 of Appendix A, respectively, show that the tested VAR-based methodologies perform very well in nowcasting core inflation in "normal" times (the pre-COVID-19 period) while worsening in the COVID-19 period. This result is likely related to the specificity of the information set employed for the estimates, in which 10 out of 31 variables are energy prices, the most important predictors of the increase in HICP price variability. The models' predictive performances denote an improvement in the following energy crisis period, signaling that the rise of energy prices is increasingly embedded in the other components of the price level, thus augmenting their predictive content for core inflation.

6 | CONCLUSIONS

Nowcasting tools are becoming increasingly popular in real-time predicting macroeconomic aggregates such as industrial production, gross domestic product and inflation, particularly within the central banks' research offices.

This work contributes to the nowcasting approach by evaluating the performances of the Least absolute shrinkage and selection operator Vector Auto Regression (Lasso-VAR) in the near-term prediction of aggregate Euro area inflation. The Lasso-VAR performances are

[13]The shadow rates are included in the model as a measure of the monetary policy stance during the zero-lower-bound periods. They are defined as the monthly interest rates implied by a multi-factor shadow rate term structure (yield curve) model. Wu and Xia's (2016, 2020) rates are obtained as a linear combination of three latent factors following a VAR(1) process. An extended Kalman filter estimates the latent factors and the shadow rate. The main characteristic of the shadow rate is that it is not bounded to zero, whereas it equals the policy rate when this is above its lower bound (0.25 % for the US and 0 for the Eurozone).

compared with well-established model shrinkage strategies adopted in high dimensional, mixed frequency data settings: the factor augmented vector auto regression (FAVAR) and the Bayesian vector auto regression (BVAR) models. Emerging literature shows that the Lasso strategy efficiently handles dimensionality reduction, generating the sparsity through which the resulting adequately-fitted VAR can outperform both FAVARs models and BVARs in high-dimensional settings.

We merge real-time high-frequency data and standard-frequency data released by official sources. We describe the different stages of the analysis, from the imputation of the missing high-frequency data to the estimation of the sparse structure and the comparative evaluation of the model's forecasting performances.

The modeling approach being proposed performed relatively well as a nowcasting tool. We show that the Lasso-VAR can closely follow the actual inflation rate and effectively handle real-time information. The forecasting accuracy improves as more high-frequency data become available over time. In "normal times" environments (pre-COVID-19 sample), the Lasso-VAR outperforms the alternative methods, reaching the lowest forecast error across model competitors. With the recent increase in the price volatility registered during the COVID-19 and the energy crisis periods, the Lasso-VAR cannot significantly outperform the BVAR, even if it continues to perform better than the FAVAR and the naive AR(2) model benchmark. For the complete nowcast sample considered in our study (July 2019 to August 2022), the Lasso-VAR continues to outperform the FAVAR and the AR(2) benchmark, and its nowcasting ability remains statistically aligned with that of the BVAR.

These results suggest that machine learning-based model shrinkage methods provide a valid and efficient alternative to well-established methods used in nowcasting. A possible advantage is that they can handle high-dimensional information sets, a feature which becomes increasingly appealing with the availability of real-time information. That could significantly improve the forecasting abilities of these methods. The inclusion of real-time "soft" information to detect the drivers of nowcast revisions, the application of the proposed approach to nowcast country-specific information and inflation components are possible avenues for future research.

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DATA AVAILABILITY STATEMENT

The data supporting this study's findings are available from the sources in Table A1. The specific sample used in this paper is available from the corresponding author upon request.

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APPENDIX A

A.1 | DATASET

We provide a summary of the dataset used in the analyses. Table A1 describes the time series data. Information about their frequency and the source and codes for retrieving the data are provided. Table A2 summarizes the results of the Phillips–Perron non-stationarity tests. The tests are performed on the series entered in the VARs, thus considering differenced price levels (inflation), whereas interest rates are tested in levels.

TABLE A1 Summary of data, frequency of observations, and source.

Variable name	Frequency	Source	Code
HICP	Monthly	ECB	ICP.M.IT.N.000000.4.ANR
HICP - Processed food incl. alcohol and tobacco	Monthly	ECB	ICP.M.IT.N.FOODPR.4.ANR
HICP - Unprocessed food	Monthly	ECB	ICP.M.IT.N.FOODUN.4.ANR
HICP - Industrial goods excluding energy	Monthly	ECB	ICP.M.IT.N.IGXE00.4.ANR
HICP - Energy	Monthly	ECB	ICP.M.IT.N.NRGY00.4.ANR
HICP - Services	Monthly	ECB	ICP.M.IT.N.SERV00.4.ANR
Food, import weighted	Monthly	ECB	STS.M.I8.N.ECPE.CFOOD0.3.000
Non food, import weighted	Monthly	ECB	STS.M.I8.N.ECPE.CNFOOD.3.000
Total non-energy commodity, import weighted	Monthly	ECB	STS.M.I8.N.ECPE.CTOTNE.3.000
Food, use weighted	Monthly	ECB	STS.M.I8.N.UWIE.CFOOD0.3.000
Non-food, use weighted	Monthly	ECB	STS.M.I8.N.UWIE.CNFOOD.3.000
Total non-energy commodity, use weighted	Monthly	ECB	STS.M.I8.N.UWIE.CTOTNE.3.000
Global Natural Gas	Monthly	EC	EC Weekly Oil Bulletin
EUA CO2	Weekly	Bloomberg	-
Euro Super 95	Weekly	EC	EC Weekly Oil Bulletin
Diesel	Weekly	EC	EC Weekly Oil Bulletin
Gas oil	Weekly	EC	EC Weekly Oil Bulletin
Heating Oil	Weekly	EC	EC Weekly Oil Bulletin
LPG	Weekly	EC	EC Weekly Oil Bulletin
Brent	Weekly	EIA	EC Weekly Oil Bulletin
Power - ITA	Weekly	Bloomberg	-
Power - FRA	Weekly	Bloomberg	-
Power - DE	Weekly	Bloomberg	-
Power - ESP	Weekly	Bloomberg	-
USD/EUR	Weekly	ECB	EXR.D.USD.EUR.SP00.A
YEN/EUR	Weekly	ECB	EXR.D.JPY.EUR.SP00.A
GBP/EUR	Weekly	ECB	EXR.D.GBP.EUR.SP00.A
RMB/EUR	Weekly	ECB	EXR.D.CNY.EUR.SP00.A
Nominal effective exchange rate, eurozone	Monthly	EC	ERT_EFF_IC_M
Real effective exchange rate, eurozone	Monthly	EC	ERT_EFF_IC_
Marginal lending facility	Weekly	ECB	FM.B.U2.EUR.4F.KR.MLFR.LEV
Deposit facility	Weekly	ECB	M.B.U2.EUR.4F.KR.DFR.LEV
Main refinancing operations	Weekly	ECB	FM.B.U2.EUR.4F.KR.MRR_FR.LEV
Shadow rate ECB	Monthly	Wu-Xia shadow rates	ECB_WU_XIA_M
Shadow rate US	Monthly	Wu-Xia shadow rates	US_WU_XIA_M
Federal funds rate	Monthly	FRED	FEDFUNDS
Monetary aggregate M3	Monthly	ECB	BSI.M.U2.Y.V.M30.X.I.U2.2300.Z01.A

TABLE A2 Philips–Perron tests for non-stationarity.

Variable name	Test statistic	*p*-value	Variable name	Test statistic	*p*-value
HICP	−7.9074	0.05	Brent	−18.8200	0.00
HICP - Processed food incl. alcohol and tobacco	−4.4884	0.00	Power - ITA	−30.6786	0.00
HICP - Unprocessed food	−7.6619	0.00	Power - FRA	−37.6345	0.00
HICP - Industrial goods excluding energy	−7.7836	0.00	Power - DE	−39.2505	0.00
HICP - Energy	−6.4242	0.00	Power - ESP	−28.4744	0.00
HICP - Services	−9.2710	0.00	USD/EUR	−17.0097	0.00
Food, import weighted	−7.3260	−7.33	YEN/EUR	−18.2911	0.00
Non food, import weighted	−6.9617	−6.96	GBP/EUR	−18.1924	0.00
Total non-energy commodity, import weighted	−7.1914	−7.19	RMB/EUR	−17.1134	0.00
Food, use weighted	−7.2363	−7.24	Nominal effective exchange rate, eurozone	−7.0695	0.00
Non-food, use weighted	−6.9343	−6.93	Real effective exchange rate, eurozone	−7.2795	0.00
Total non-energy commodity, use weighted	−7.1080	−7.11	Marginal lending facility	−20.7241	0.02
Global Natural Gas	−6.3165	0.00	Deposit facility	−22.2143	0.03
EUA CO2	−24.3585	0.00	Main refinancing operations	−19.9126	0.02
Euro Super 95	−15.3554	0.00	Shadow Rate ECB	−8.2463	0.00
Diesel	−14.6733	0.00	Shadow rate US	−8.1027	0.02
Gas oil	−18.4698	0.00	Federal Funds Rate	−5.3728	0.00
Heating Oil	−19.8784	0.00	Monetary aggregate M3	−7.6345	0.00
LPG	−13.1760	0.00			

APPENDIX B: ADDITIONAL RESULTS

Table B1 summarizes the RMSFE of the different models at the end of each month for different forecasting horizons.

TABLE B1 Monthly RMSFE.

	h=4				h=8			h=12		
date	lasso	favar	lbvar	ar(2)	lasso	favar	lbvar	lasso	favar	lbvar
2019-09-30	0.172	0.142	0.108	0.208	0.167	0.125	0.121	0.231	0.222	0.246
2019-10-31	0.084	0.131	0.056	0.216	0.153	0.166	0.094	0.202	0.194	0.181
2019-11-30	0.254	0.156	0.188	0.179	0.138	0.119	0.184	0.108	0.088	0.125
2019-12-31	0.184	0.260	0.270	0.346	0.403	0.355	0.388	0.422	0.332	0.432
2020-01-31	0.107	0.169	0.137	0.083	0.281	0.272	0.244	0.421	0.396	0.381
2020-02-29	0.164	0.119	0.087	0.138	0.113	0.122	0.078	0.123	0.125	0.104
2020-03-31	0.313	0.350	0.245	0.429	0.423	0.445	0.300	0.435	0.463	0.317
2020-04-30	0.294	0.344	0.181	0.475	0.522	0.519	0.313	0.667	0.696	0.444

TABLE B1 (Continued)

	h=4				h=8			h=12		
date	lasso	favar	lbvar	ar(2)	lasso	favar	lbvar	lasso	favar	lbvar
2020-05-31	0.165	0.200	0.094	0.213	0.347	0.350	0.078	0.521	0.565	0.238
2020-06-30	0.159	0.125	0.135	0.172	0.145	0.135	0.135	0.175	0.250	0.200
2020-07-31	0.084	0.106	0.119	0.316	0.209	0.147	0.250	0.198	0.060	0.331
2020-08-31	0.369	0.390	0.290	0.383	0.313	0.418	0.285	0.260	0.395	0.205
2020-09-30	0.092	0.269	0.200	0.537	0.416	0.553	0.234	0.481	0.700	0.319
2020-10-31	0.000	0.069	0.100	0.193	0.125	0.238	0.144	0.273	0.529	0.104
2020-11-30	0.000	0.005	0.025	0.017	0.012	0.050	0.105	0.068	0.202	0.152
2020-12-31	0.000	0.031	0.056	0.003	0.000	0.066	0.019	0.008	0.110	0.104
2021-01-31	0.922	0.738	0.737	0.752	0.756	0.703	0.700	0.763	0.663	0.760
2021-02-28	0.160	0.388	0.375	0.958	0.775	0.778	0.759	0.925	0.871	0.879
2021-03-31	0.256	0.180	0.290	0.566	0.360	0.240	0.448	0.687	0.578	0.730
2021-04-30	0.225	0.281	0.300	0.538	0.375	0.306	0.488	0.456	0.308	0.646
2021-05-31	0.295	0.290	0.175	0.251	0.368	0.405	0.355	0.505	0.465	0.595
2021-06-30	0.112	0.150	0.144	0.134	0.122	0.131	0.091	0.223	0.248	0.227
2021-07-31	0.221	0.088	0.100	0.209	0.138	0.022	0.047	0.175	0.060	0.062
2021-08-31	0.516	0.535	0.560	0.662	0.615	0.497	0.588	0.643	0.440	0.543
2021-09-30	0.296	0.431	0.438	0.599	0.744	0.700	0.741	0.921	0.775	0.875
2021-10-31	0.497	0.513	0.394	0.437	0.772	0.700	0.622	1.017	0.965	0.917
2021-11-30	0.551	0.545	0.405	0.689	0.838	0.735	0.453	1.097	0.975	0.732
2021-12-31	0.128	0.169	0.169	0.166	0.469	0.316	0.153	0.733	0.281	0.175
2022-01-31	0.066	0.125	0.195	0.193	0.135	0.175	0.428	0.307	0.238	0.345
2022-02-28	0.572	0.600	0.412	0.519	0.453	0.778	0.344	0.485	0.608	0.315
2022-03-31	1.080	1.113	1.000	1.448	1.331	1.484	1.244	1.433	1.800	1.025
2022-04-30	0.260	0.381	0.294	0.775	0.866	0.872	0.716	1.248	1.477	1.131
2022-05-31	0.412	0.325	0.415	0.736	0.410	0.340	0.390	0.773	0.703	0.662
2022-06-30	0.329	0.362	0.444	0.879	0.694	0.331	0.616	0.712	0.340	0.615
2022-07-31	0.241	0.231	0.337	0.197	0.347	0.259	0.456	0.612	0.302	0.633
2022-08-31	0.124	0.235	0.225	0.094	0.210	0.273	0.460	0.285	0.242	0.542

APPENDIX C: ROBUSTNESS CHECKS

In this section, the results from robustness checks are reported. The table summarizes the RMSFE results of the different models, considering the inclusion of the six monetary policy measures detailed in Section 5. For the Eurozone, these are the Marginal lending facility, the Deposit facility, the Main refinancing operations rates, and the Wu and Shadow's (2020) shadow interest rate. The Federal Funds rate and the Wu and Xia's (2016) shadow rate are considered for the US. Table C2 reports the RMSFE results for different forecast horizons. Table C3 summarizes the RMSFEs obtained considering alternative machine learning regularization methods for the VAR (Ridge and Elastic Net). Figure C1 displays the nowcasts of the model alternatives for Euro area core inflation. Table C4 summarizes the RMSFEs obtained by the different models for Euro area core inflation.

TABLE C1 Model comparisons: RMSFE with and without policy variables.

		Pre-COVID-19 sample		COVID-19 sample		Energy crisis sample		Full sample	
		No policy	Policy	No policy	Policy	No policy	Policy	No policy	Policy
h=4	Lasso-VAR	0.144	0.146	0.239	0.240	0.379	0.387	0.261	0.264
	FAVAR	**0.153**	**0.153**	**0.262**	**0.262**	0.401	0.401	**0.281**	**0.281**
	BVAR	**0.152**	**0.152**	0.235	0.235	0.364	0.364	0.256	0.256

Note: Bold values indicate that the predictive performance of the Lasso VAR is statistically different from those obtained by the other models. The reference test is the Diebold and Mariano's (1995) test of differences in the model's predictive accuracy. The reference statistics consider the Harvey et al.'s (1997)'s correction for small samples.

TABLE C2 RMSFE across different models and forecast horizon.

		Pre-COVID-19 sample	COVID-19 sample	Energy crisis sample	Full sample
h = 4	Lasso-VAR	0.144	0.239	0.379	0.261
	FAVAR	**0.153**	**0.262**	0.401	**0.281**
	BVAR	**0.152**	0.235	0.364	0.256
h=8	Lasso-VAR	0.204	0.353	0.577	0.388
	FAVAR	0.198	0.351	0.541	0.376
	BVAR	0.208	0.310	0.498	0.345
h=12	Lasso-VAR	0.234	0.437	0.777	0.496
	FAVAR	0.220	0.440	0.683	0.467
	BVAR	0.252	0.396	0.620	0.433

Note: Bold values indicate that the predictive performance of the Lasso VAR is statistically different from those obtained by the other models. The reference test is the Diebold and Mariano's (1995)'s test of differences in the model's predictive accuracy. The reference statistics consider the Harvey et al.'s (1997) correction for small samples.

TABLE C3 RMSFE Lasso-ridge-elastic net.

		Pre-COVID-19 sample	COVID-19 sample	Energy crisis sample	Full sample
h=4	Lasso-VAR	0.144	0.239	0.379	0.261
	Ridge-VAR	**0.147**	**0.251**	0.38	0.268
	Elastic Net-VAR	**0.154**	**0.258**	0.425	**0.286**

Note: Bold values indicate that the predictive performance of the Lasso VAR is statistically different from those obtained by the other models. The reference test is the Diebold and Mariano's (1995) test of differences in the model's predictive accuracy. The reference statistics consider the Harvey et al.'s (1997) correction for small samples.

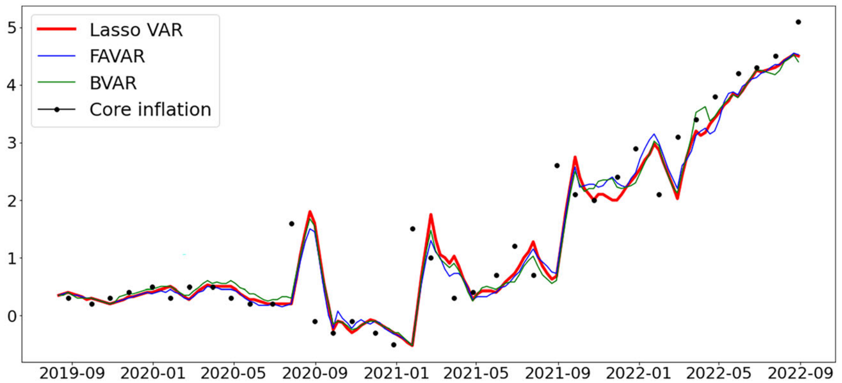

FIGURE C1 Nowcasting core inflation: Lasso-VAR versus FAVAR and BVAR.

TABLE C4 RMSFE core inflation.

		Pre-COVID-19 sample	COVID-19 sample	Energy crisis sample	Full sample
h=4	Lasso-VAR	0.089	0.420	0.306	0.320
	FAVAR	0.087	0.408	**0.332**	0.321
	BVAR	**0.073**	0.433	0.317	0.327

Note: Bold values indicate that the predictive performance of the Lasso VAR is statistically different from those obtained by the other models. The reference test is the Diebold and Mariano's (1995) test of differences in the model's predictive accuracy. The reference statistics consider the Harvey et al.'s (1997) correction for small samples.

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