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Nowcasting – developing the sources and methods to improve high-frequency labour market forecasting

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Nowcasting – developing the sources and methods to improve high-frequency labour market forecasting

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INTRODUCTION

Forecasting unemployment dynamics is a significant concern for policymakers and welfare institutions. Timely decisions on passive and active labour market (LM) policies are increasingly seen as key for their efficiency and cost effectiveness. Reliable and real-time forecasts of employment/unemployment cycles and trends allow welfare institutions and/or governments of member states to make more informed and time-consistent decisions about the management of the LM. Indeed, the effectiveness of policies affecting the calibration of unemployment benefits, the provision of targeted wage/hiring subsidies, or the provision of training programmes can benefit from the high-frequency update of forecasts on the LM, as this might reduce the typical decision and implementation lags of policies.

Furthermore, reliable and very short-term forecasts of LM trends might generate efficiency improvements also in the management of public funding devoted to the LM, provided that this would reduce the indirect costs related to making funding available in contexts characterised by decision time constraints.

Lastly, improvements in policy effectiveness might also arise from the dissemination of these practices in a broader EU context, provided that the high-frequency business and LM cycle data characterising the economic evolution of EU countries, becomes increasingly synchronised.

Despite its relevance, official information about the LM is released with a substantial delay (about two and a half months for quarterly LM statistics; about one month for aggregate monthly provisional data for employment and unemployment). Italy is not an exception: the Italian National Institute of Statistics (Istituto Nazionale di Statistica - ISTAT) publishes a provisional estimate of national unemployment with a 1-month delay following the end of the month, whereas the revised values are typically released at the end of the quarter. Regional level unemployment rates are published on a quarterly basis, resulting in an even lower frequency and higher publication lag of around 14 weeks.

Short-term forecasting using high-frequency data, commonly called nowcasting (a term borrowed from weather “flash” forecasts), is a straightforward solution to information lag problems. In economic contexts, nowcasting is defined as the prediction of the present, the very near future and the very recent past[1].

In economics, nowcasting tools are becoming increasingly popular in the real-time prediction of macroeconomic aggregates such as industrial production, gross domestic product (GDP) and inflation, mainly from Central Bank’s research offices. The objective of this research note is to extend these methods (i.e., nowcasting tools) to the Italian LM analysis. As the Italian economy displays one of the most heterogeneous LM structures in the EU (huge differences between the north and the south of the country), we believe that the Italian economy can be challenging and vital for testing our methodological strategy.

[1] Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin. "Large Bayesian vector auto regressions." Journal of applied Econometrics 25, no. 1 (2010): 71-92.

A nowcasting approach to the analysis of LM trends implies merging real-time data on hiring and firing with high- and standard-frequency official data in a Vector Auto-Regressive (VAR) model to provide high-frequency forecasts (i.e., nowcasts) of specific segments of employment. By merging official releases with a high-dimensional set of high-frequency data, we can contribute to the estimation of the current LM dynamics and the understanding of their underlying developments in real-time.

The Italian legal system has made the communication of any contractual job agreement between two parties, as well as all its variations, mandatory. The communication is being sent to the Italian Ministry of Labour. Therefore, the collection of information on the private sector's LM hiring and firing events feeds an administrative data set which allows us to extract on a daily basis the number of individuals that are under such an agreement at national and regional levels. Given that the typical frequency of more standard data can only be exploited monthly or quarterly, the value of using "mandatory communications" as a weekly indicator[2] of employment is potentially of paramount importance for nowcasting the LM. Hence, "mandatory communications" are a great source of information that allows our model to produce weekly nowcasts.

Due to the considerable delay in publication of hard data (up to two and a half months after the reference period), there are periods of time when the only source of information is mandatory communications. We deal with this delay by filling the missing values as explained in section 2. Even after imputation though, it is the mandatory communications that move our nowcasts in the right direction, rather than imputed variables. Ideally, we would like to shrink waiting periods for hard data and have more data contributing to our nowcasts in real time. Italy's legal requirements for mandatory communications and the diversity of regional labour markets is why the example of the Italian economy was considered ideal for this paper. At a later stage, the same approach could be successfully applied to other economies for which high-frequency administrative data on labour market transitions are available.

The current work to develop the sources and methods to improve high-frequency labour market forecasting has established and treated every step of the research with the aim to make it as universal as possible. Moreover, special attention was paid to the front end of the code in order to make it more convenient to use. The application constructed to extract and automatically update data (explained in section 2) could be directly adapted to any EU country and any statistical institution. Moreover, the algorithms used to construct the nowcasts are universal as well, as long as a data set with the same structure as ours is constructed. Thus, the process of nowcasting described in this paper could be replicated for any country with similar administrative data on the labour market.

The remainder of the paper is organised as follows: section 2 deals with data definition and issues, the blocks of variables considered helpful in the nowcasting exercise, the issue of mixed frequencies and ragged edges, and their extraction and updating process. Section 3 presents the estimation

[2] We have verified that the aggregation of daily information at the weekly frequency ensures a better predictive performance of the model, possibly because of the "dilution" of unsystematic measurement errors.

methodology. Section 4 summarises some selected results and Section 5 concludes and provide some further research directions.

DATA ELABORATION

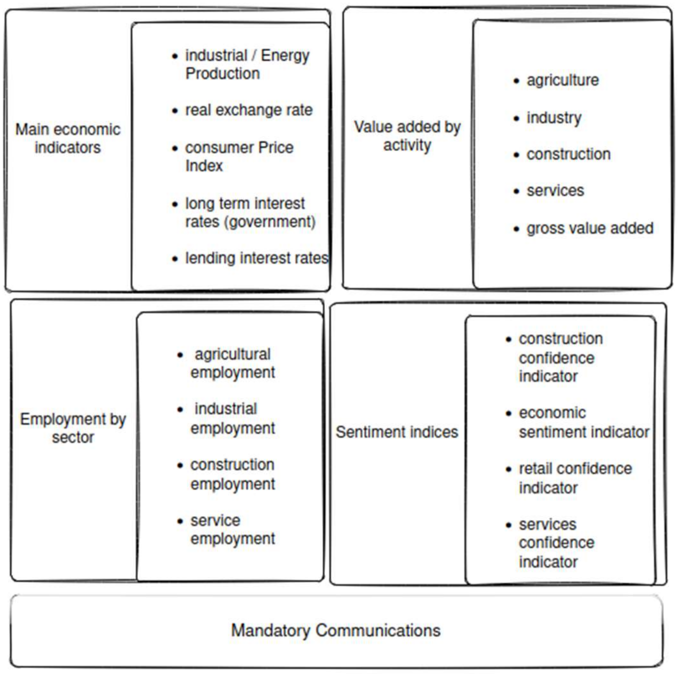
DATA SOURCES AND THE ITALIAN LABOUR MARKET'S "MANDATORY COMMUNICATIONS" DATABASE

Our analysis considers mixed frequency data including weekly, monthly, and quarterly observations, some of which start in 1980, and is gradually filled with observations up to 1999 when it is fully completed. First, the complete set is used for the imputation part of the analysis and then the imputed data set is reduced to the period 1999-20 for training and testing our models. All data are collected from Eurostat, OECD (Organisation for Economic Cooperation and Development), and the Ministry of Labour and Social Affairs of Italy. Figure 1 includes all the macroeconomic variables that contribute to the construction of the nowcasts.

We should first explain the "mandatory communications" variable in more detail.

Since 2007, Italian legislation has made the communications of the establishment, extension, transformation, or termination of an employment relationship an obligation to the employers (public administration and private companies). "Mandatory communications" is a time series reporting the number of individuals who had a contract of labour in force at a specific date. To our knowledge this kind of information has not been exploited yet in this field of research. We are confident that the variability in compulsory communications could help explain a large fraction of unemployment movements. Other variables we include in our dataset are main economic indicators, value-added by activity, employment data from different sectors, and sentiment indices. We present the composition of the data set in Figure 1.

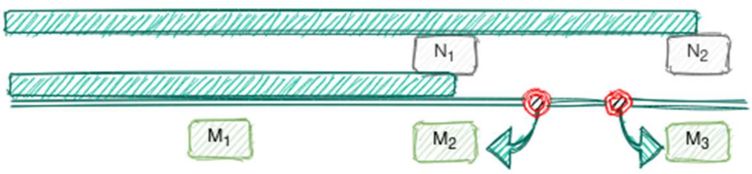
FIGURE 1: VARIABLES CONSIDERED IN THE ANALYSIS



EXTRACTING AND UPDATING THE DATA SET

A fundamental issue our analysis needs to deal with is the mixed frequencies. Data are published at different time frequencies, on different days, by various institutions that do not co-ordinate neither the publishing, nor the data updating frequency. For this reason, regularising the flow of data that we receive becomes an emerging issue.

FIGURE 2: ILLUSTRATIVE EXAMPLE OF THE WEEKLY UPDATING PROCESS



Variables published in the middle of the week are moved to the closest Monday to regulate the flow of information that the model receives. For instance, a variable published on Tuesday of week three is considered more related to the previous batch of observations. Therefore, it is transferred to the previous Monday, M2 and used for the nowcast N1.

We construct an automatic data collector which periodically visits the databanks from where we collect our data. The frequency that we consider most appropriate to update our data set is weekly for several reasons:

1. Most economical quantities are reported either monthly or quarterly with few flash estimates or revisions in between. Therefore, checking them daily, for instance, would not add any extra information to our analysis.
2. A weekly time aggregation of daily observations on “mandatory communications” reduces the potential bias from unsystematic measurement errors.
3. Having a homogeneous data set where all publications made during a specific week are transferred to the same day ensures better performance of the imputation methods used in the next steps of the analysis.

This is exactly the path that we followed: every Monday, our automatic data collection application visits all the websites that publish the information we are interested in; an economic measure published at the beginning of the week, e.g., Tuesday, is an observation that is more related to the previous week than the actual one and as such is moved to the closest Monday. The same procedure is followed with all variables as is indicatively shown in figure 2.

Aside from the algorithm that automatically updates our data set and saves vintages[3], an interface of the application called “UpData” was created to facilitate the extraction of the whole data set, of a small subset, or the target unemployment level at any time. The idea of having user-friendly software which deals with data asynchronously is fundamental for this project and is being developed as a separate experimental stage. To learn more about the specifics of this work, consider the process described in figure 3 in the next section.

DATA IMPUTATION

A fundamental part of nowcasting is dealing with missing values that appear among observations detected at different frequencies. Different frequencies or "ragged edges", as they are usually called, are issues that should be solved before feeding our data to any learning mechanism that will then provide nowcasts. For the majority of previous research, the Kalman filter/smoother was the most commonly applied method, frequently combined with the Expectation-Maximisation (EM) algorithm[4].

Without doubting the effectiveness of the Kalman filter, the importance of this choice requires further reflection. In order to explore other imputation paths, we compared the performances of different methods: simplest mean imputation, decision trees, random forests and forest-like mechanisms, the Bayesian ridge, k-nearest neighbours, the nuclear norm minimisation, and the Kalman filter combined with the EM algorithm. This paper does not describe all of them in detail but rather the general approach for choosing the optimal technique for our analysis.

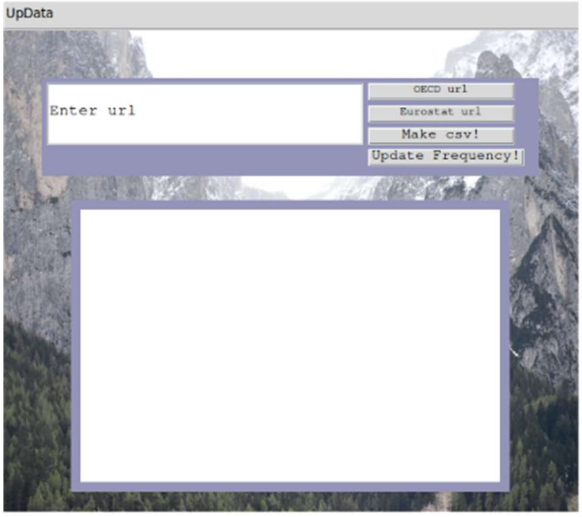
Ideally, an optimal imputation method can recover the true observations of a data set after being removed from it in an evaluation setting. We cannot do that in practice since we do not have any true observations in weekly frequencies to compare them with imputations. We have to rely on the second-best solution and compare the actual observations with the imputed ones, lying a one-time

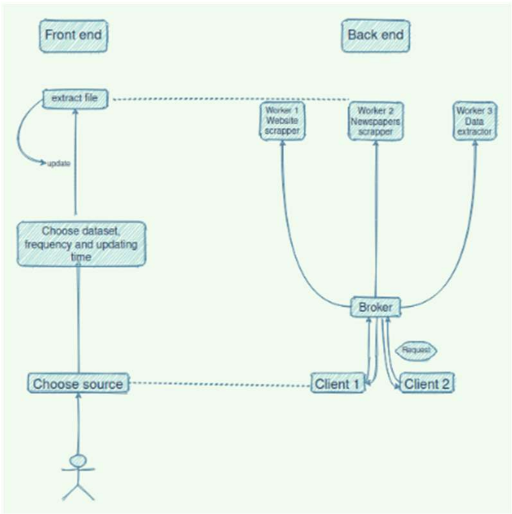
[3] Vintage is a set of new data available at the particular moment in time.
[4] Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin. "Large Bayesian vector auto regressions." Journal of applied Econometrics 25, no. 1 (2010): 71-92.

step before them. The idea is that if the imputation mechanism works correctly, the transition from one observation to the other should be smooth (minimise their internal variability), and imputed observations around an actual value should be very close to it.

FIGURE 3: ILLUSTRATIVE EXAMPLE OF THE WEEKLY UPDATING PROCESS

(A) THE MECHANISM BEHIND ”UPDATA" **(B) INTERFACE OF ”UPDATA"**





Note: Fig. 3(A): The mechanism of collecting and updating data works as follows: the broker distributes the ”job”, after receiving a request from the server (us), to several workers who independently finish their part and asynchronously send their response to the broker who completes the final data set just like a puzzle. The simplicity of this mechanism makes it extremely useful. After having constructed this ”main skeleton,” we can add workers and facilitate the simultaneous use by multiple users with very little effort.
Fig. 3(B): The user inserts the query/ies of the variable/s they are interested in (which are provided by the institutions), selects the source of his query and extracts the data set he needs only once, or sets the desired frequency for executing an immediate extraction and subsequent ones at the specified frequency.

METHODOLOGY

LASSO-VAR

Since the seminal work of Sims published in 1980[5], the Vector Auto-Regression (VAR) model has become the most used methodology in empirical macroeconomic modelling. The success of VAR models can be attributed to their flexibility and intuitive model specification. Despite their popularity, VAR models come with the danger of over‑parameterisation, which can lead to overfitting issues and poor forecasts. Regularisation is one of the selection techniques used to solve this problem. In general, the over-parameterisation problem can be solved by artificially penalising model coefficients. Prior structures in Bayesian settings (or hyperparameters) are often employed to reach this goal.

Of all the most common methodologies providing regularised linear regression models (the Least Absolute Selection and Shrinkage Operator (LASSO) Regression, the Ridge Regression and the Elastic-Net), we decided to use a combination of the LASSO technique with the VAR in two different variations: the LASSO-Selection-VAR and the LASSO-VAR. The former is a two-step approach in which we first apply the LASSO to select the most informative variables/lags in terms of predictive ability and then re-estimate these variables/lags in a reduced VAR model to perform an unbiased short-term forecast. The latter technique estimates VAR directly using LASSO instead of OLS.

MODEL ESTIMATION

The LASSO is a method for automatic variable selection which can be used to select predictors X* of a target variable Y from a more extensive set of potential or candidate predictors X[6]. Developed for a single equation setting by Tibshirani in 1996[7], the LASSO formulates curve fitting as a quadratic programming problem, where the objective function penalises the total size of the regression coefficients, based on the value of a tuning parameter “lambda”. 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, where the more potent the penalty, the higher the number of coefficients that shrink to zero. Hence, the model selects only the most important predictors, with the highest contribution to the prediction of our target variable.

The standard LASSO VAR loss function can be expressed as in Nicholson et al.[8]:

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[5] Sims, C. A., and H. Uhlig. "Econometrica: Journal of the Econometric Society." (1980): 1.
[6] Jones, Clive. “VARIABLE SELECTION PROCEDURES – THE LASSO” Business Forecast Blog. Last modified March 4, 2014. https://businessforecastblog.com/tag/predictive-analytics/page/10/
[7] Tibshirani, Robert. "Regression shrinkage and selection via the lasso." Journal of the Royal Statistical Society: Series B (Methodological) 58, no. 1 (1996): 267-288.
[8] Nicholson, William B., David S. Matteson, and Jacob Bien. "Structured regularization for large vector autoregressions." Cornell University (2014).

$$\frac{1}{2}||Y - BZ||_2^2 + \lambda||B||_1$$

Where $|.|_r$ represents both vector and matrix L_r norms, $\lambda > 0$ is a scalar penalty parameter that controls the degree of shrinkage. The L1 penalty works as a sparsity-inducing term over the individual entries of the coefficient matrix B, pushing some of the coefficients to zero in an element-wise manner.

To construct a sparse B matrix, we perform LASSO regression for each individual variable (setting it as a target). Each equation is solved separately and then stacked in the B matrix. Below, we present a detailed derivation.

We follow the notation from Stanford Computer Science course[9], where m are observations and n are variables. We are also using summations rather than matrix notation for clearer understanding.

We start from the LASSO loss function:

$$RSS^{lasso}(\theta) = RSS^{(OLS)}(\theta) + \lambda_{|}|\theta|_{|1}\frac{1}{2}\sum_{i=1}^{m}\left[y^{(i)} - \sum_{j=0}^{n}\theta_j\, x_j^{(i)}\right]^2 + \lambda\sum_{j=1}^{n}{}_{|}\theta_j\,|$$

Solving the OLS term:

$$\frac{\partial}{\partial\theta_j}RSS^{OLS}(\theta) = -\sum_{i=1}^{m}x_j^{(i)}\left[y^{(i)} - \sum_{j=0}^{n}\theta_j\, x_j^{(i)}\right] - \sum_{i=1}^{m}x_j^{(i)}\left[y^{(i)} - \sum_{k\neq j}^{n}\theta_k\, x_k^{(i)} - \theta_j x_j^{(i)}\right]$$
$$-\sum_{i=1}^{m}x_j^{(i)}\left[y^{(i)} - \sum_{k\neq j}^{n}\theta_k\, x_k^{(i)}\right] + \theta_j\sum_{i=1}^{m}\left(x_j^{(i)}\right)^2 \triangleq \rho_j + \theta_j z_j$$

Where we define ρ_j and the normalising constant z_j for notational simplicity.

Solving the L1 term

The main obstacle with this term is that the absolute function is undefined at $\theta = 0$. Therefore, we perform the coordinate descent to:

- Perform coordinate-wise optimisation where only one feature is considered at each stop, and all others are treated as constants.
- Make use of sub-derivatives and sub-differentials, which are extensions of the notions of derivative for non-differentiable functions.

We need to combine the two points because the sub-differential approach to the LASSO regression does not have a closed form solution in the multivariate case (except for the special case of orthogonal features).

The coordinate descent allows us to isolate θ_j as in the following equation:

[9] Andrew Ng, "CS229 - Machine Learning." (Course, Standford, 2020)

$$\lambda \sum_{j=1}^{n} |\theta_j| = \lambda|\theta_j| + \lambda \sum_{k\neq j}^{n} |\theta_k|$$

Hence, we can optimise this equation as a function of θ_j, reducing it to a univariate problem. Using the definition of the sub-differential as a non-empty, closed interval $[a,b]$where a and b are the one-sided limits of the derivative, we get the following equation for the sub-differential $\partial_{\theta_j}\lambda|\theta|_1$

$$\partial_{\theta_j}\lambda = \sum_{j=1}^{n} |\theta_j| = |x| = \begin{cases} \{-\lambda\}, if\theta_j < 0 \\ [-\lambda,\lambda], if\theta_j = 0 \\ \{\lambda\}, if\theta_j > 0 \end{cases}$$

Finally, by combining everything together we get the complete LASSO loss function which is convex and non-differentiable.

$$RSS^{lasso}(\theta) = RSS^{OLS}(\theta) + \lambda||\theta||_1 \triangleq f(\theta) + g(\theta)$$

Property 1.1:
A convex function is differentiable at a point x_0 *if and only if the subdifferential set is made up of only one point, which is the derivative at* x_0
Property 1.2:
Moreau-Rockafellar theorem: If f *and* g *are both convex functions with subdifferentials* $\partial\mathrm{f}$ *and* $\partial\mathrm{g}$ *then the subdifferential of* $\mathrm{f}+\mathrm{g}$ *is* $\partial(\mathrm{f}+\mathrm{g}) = \partial\mathrm{f} + \partial\mathrm{g}$
Property 1.3:
Stationary condition: A point x_0 *is the global minimum of a convex function* f *if and only if the zero is contained in the subdifferential*

Now we can use these properties to compute the sub-differential of the LASSO loss function and then set it to zero to find the minimum:

$$\partial_{\theta_j}RSS^{lasso}(\theta) = \partial_{\theta_j}RSS^{OLS}(\theta) + \partial_{\theta_j}\lambda||\theta||_1$$
$$0 = -\rho_j + \theta_j z_j + \partial_{\theta_j}\lambda||\theta_j||$$

$$0 = \begin{cases} -\rho_j + \theta_j z_j - \lambda, & if\theta_j < 0 \\ [-\rho_j - \lambda, -\rho_j + \lambda], & if\theta_j = 0 \\ -\rho_j + \theta_j z_j - \lambda, & if\theta_j > 0 \end{cases}$$

In the second statement, we must ensure that the closed interval contains a zero so that $\theta_j = 0$ is a global minimum:

$$0 \in [-\rho j - \lambda, -\rho j + \lambda]$$
$$-\rho j - \lambda \leq 0$$
$$-\rho j + \lambda \geq 0$$
$$-\lambda \leq \rho j \leq \lambda$$

By solving for θ_j the first and third statement and by combining with the above we get:

$$\begin{cases} \theta_j = \dfrac{\rho_j + \lambda}{z_j}, & for \quad \rho_j \leftarrow \lambda \\ \theta_j = 0, \quad for & -\lambda \leq \{\rho_j \leq \lambda \\ \theta_j = \dfrac{\rho_j - \lambda}{z_j}, & for \quad \rho_j > \lambda \end{cases}$$

This is known as the soft thresholding function $\frac{1}{z_j}S(\rho_j,\lambda)$ where $\frac{1}{z_j}$ is a normalising constant which is equal to 1 when the data is normalised.
Hence, we have the next procedure to update coordinate descent:

For $j = 0,1,\dots,n$
Compute $\rho_j = \sum_{i=1}^{m} x_j^{(i)} \left[y^{(i)} - \sum_{k\neq j}^{n} \theta_k\, x_k^{(i)}\right]$
Compute $z_j = \sum_{i=1}^{m} \left(x_j^{(i)}\right)^2$
Set $\theta_j = \frac{1}{z_j}S(\rho_j,\lambda)$

This procedure must be repeated until the maximum number of iterations is reached, which has to be large enough in order to reach convergence.

The second step involves a standard reduced VAR estimation environment. A VAR system contains a set of n variables, each of which is expressed as a linear function of p lags of itself and of all of the other n – 1 variables, plus a deterministic component and an error term.

A VAR(p) model can thus be written as:

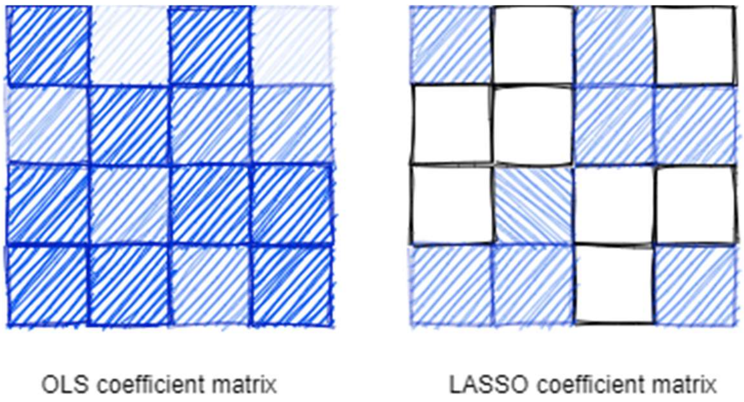
$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u$$

Hence, to produce reliable forecasts, variables must be transformed into stationary before being fed in the model. Non-stationarity is tested by utilising the Phillips-Perron (PP) test. The PP test allows controlling for higher-order autoregressive processes by correcting the reference distribution considering the zero-frequency spectral density (long-run memory). With the LASSO-VAR, instead of using OLS to estimate the coefficient matrix

$$\Phi = (X'X)^{-1}X'Y$$

leading to a parameter space of (potentially) size $n^2 \times p$ (hence given a very high number of coefficients), the dimensionality problem is reduced by estimating a sparse coefficient matrix, where a major part of variables will be pushed to 0 and thus automatically removed from the model.

FIGURE 4: ILLUSTRATIVE EXAMPLE OF THE WEEKLY UPDATING PROCESS



After estimating the resulting model, we proceed to forecast. We are interested in forecasting four steps in the present environment, thus covering a one-month period given our weekly reference frequency. The standard forecasting algorithm is used to calculate the out-of-sample forecast:

$$Y_{T+h|T} = \Pi_1 Y_{T+h|T} + \cdots + \Pi_p Y_{T+h-p|T}$$

As new data becomes available (vintages), the procedure is repeated and the resulting model re-estimated, providing updated nowcasts in quasi real-time.

CALIBRATION OF THE LASSO: AN EVALUATION OF PREDICTIVE PERFORMANCE

As it can be seen above, lambda (λ), is the most important parameter for the LASSO framework. Hence, in order to select the best predicting model, we need to introduce cross validation. We use cross validation to select the best hyper-parameters for our model. We follow a standard approach which can be seen in many applications. Our data is divided into a training and a test sample. The test set is being held for final evaluation, whereas the training set is split into 5 subsets, by a 5-fold cross validation.

The general procedure works as follows[10]:

a. We shuffle our data set randomly;
b. Split the data set in 5 groups;
c. For every group we:
    i. Take the group as test data set;
    ii. Take the remaining groups as a training data set;
    iii. We fit a model on the training set and evaluate it on the test set;

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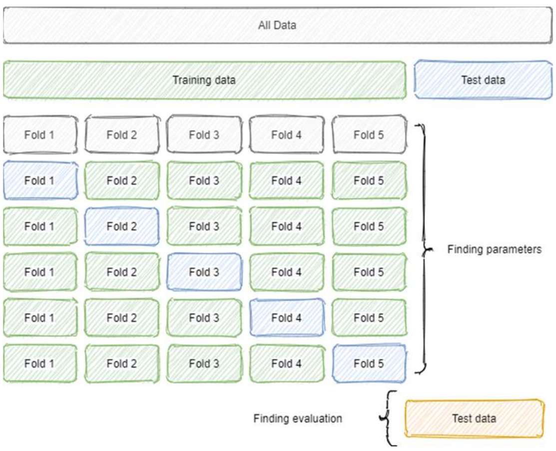
[10] Savitha, G., and P. Jidesh. "A fully-automated system for identification and classification of subsolid nodules in lung computed tomographic scans." Biomedical Signal Processing and Control 53 (2019): 101586.

iv. We keep the evaluation score and discard the model.

d. Summarise the performance of the model using the sample of model evaluation scores.

Moreover, every observation in the data is assigned to a separate group and it remains there throughout the procedure. Therefore, every sample is being used in the test set once to train the model k-1 times, where k in our case is 5.

FIGURE 5: ILLUSTRATIVE EXAMPLE OF THE WEEKLY UPDATING PROCESS



This approach can be computationally expensive but does not waste too much data (as is the case when fixing an arbitrary validation set), which is a major advantage in problems such as inverse inference where the number of samples is very small11.

The value of k is chosen so that each train/test group of data set is big enough to be statistically representative. In our analysis we choose k=5 as it is the most common value used in various applications. The performance measure being reported is the average of the computed values. After this step our data set is reduced to the optimal number of variables/lags to be used in the VAR modelling environment.

BENCHMARKS FOR MODEL COMPARISON

As the first benchmark comparison model, we employ the Factor Augmented VAR. We follow the approach developed by Bernanke in 2005[12]. He assumes that the joint dynamics is given by the following equation (F_t', Y_t'):

[11] Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel et al. "Scikit-learn: Machine learning in Python." the Journal of machine Learning research 12 (2011): 2825-2830.

[12] Bernanke, Ben S., Jean Boivin, and Piotr Eliasz. "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach." The Quarterly journal of economics 120, no. 1 (2005): 387-422.

$$F_tY_t = \Phi(L)F_{t-1}Y_{t-1} + v_t$$

Where $\Phi(L)$ is a comfortable lag polynomial of finite order p and the error term, v_t, is zero mean with covariance matrix Σ. The vector Y_t contains observable variables and the F_t unobservable factors, which are supposed to influence the macroeconomic variables. The factors can be thought of as underlying economic phenomena that cannot be explained with a single observable variable but with a convolution of several macroeconomic time series. The unobserved k factors are extracted from a large set of indicators of size n, X_t, providing relevant information about the fundamentals of the economy. The relation between the factors and the variables in the set are provided by the following observation relation:

$$X_t = \Lambda^F F_t + \Lambda^Y Y_t + e_t$$

where Λ^F is of size n x k and Λ^Y of n x m are factor loadings and e_t is a zero-mean vector of disturbances. To identify the model, a standard normalisation is imposed as proposed by Bernanke[13]. Specifically, the principal components are set to $C'C = I$, where C(.) denotes the common space spanned by the factors of X_t in each block.

To estimate our FAVAR model we follow a two-step approach: in the first step, we extract factors by performing a principal component analysis (PCA), whereas in the second step the FAVAR equation is estimated including the factor estimates.

Our second benchmark model is the Large Bayesian VAR. In this case we follow the approach developed by Bańbura, Giannone and Reichlin[14]. The basic idea of this methodology is to use *quasi* Minnesota prior belief to overcome the curse of dimensionality. This approach develops the standard Bayesian shrinkage procedure suggested by Litterman (1986a)[15], using modifications proposed by Kadiyala and Karlsson in 1997[16] and Sims and Zha (1998)[17]. For more details see Bańbura et al., (2010)[18].

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[13] Bernanke, Boivin, and Eliasz. "Measuring the effects of monetary policy" 387-422.
[14] Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin. "Large Bayesian vector auto regressions." Journal of applied Econometrics 25, no. 1 (2010): 71-92.
[15] Litterman, Robert B. "Forecasting with Bayesian vector autoregressions—five years of experience." Journal of Business & Economic Statistics 4, no. 1 (1986): 25-38.
[16] Kadiyala, K. Rao, and Sune Karlsson. "Numerical methods for estimation and inference in Bayesian VAR models." Journal of Applied Econometrics 12, no. 2 (1997): 99-132.
[17] Sims, Christopher A., and Tao Zha. "Bayesian methods for dynamic multivariate models." International Economic Review (1998): 949-968.
[18] Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin. "Large Bayesian vector auto regressions." Journal of applied Econometrics 25, no. 1 (2010): 71-92.

NOWCASTING IN PRACTICE: RESULTS AND FUTURE IMPROVEMENTS

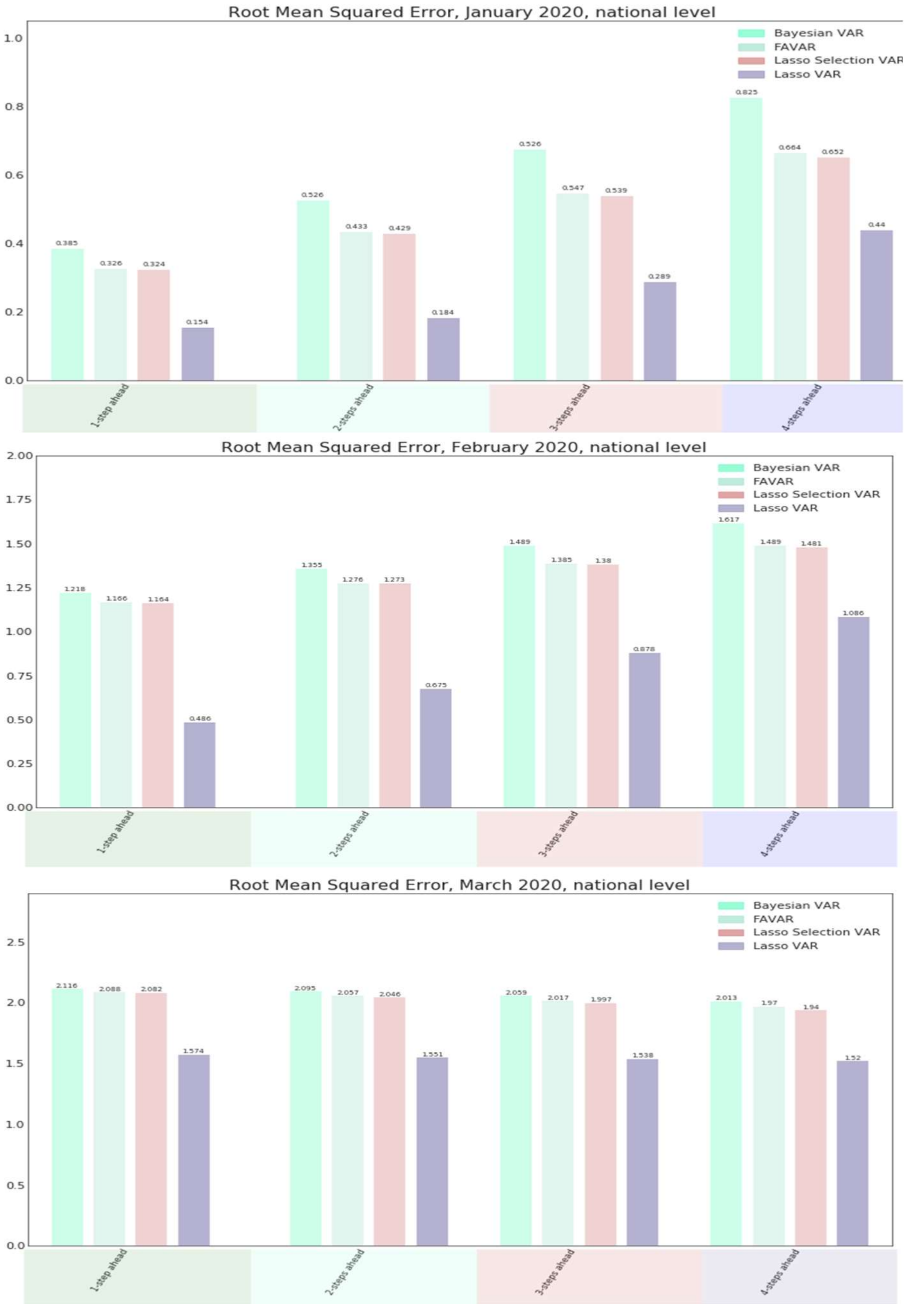
We test the performance of the model focusing on the first quarter of 2021. To objectively assess the precision of the nowcasts we need to restrict our information set to the one available on the day when the nowcast would be calculated. Following Diebold's[19] reasoning regarding how information vintages should be perceived, we construct three vintages of data using "expanding sample estimation and vintage information": one for the beginning of each month of the quarter (i.e., 30 December 2019, 27 January 2020, and 24 February 2020 for nowcasting performed in January, February and March, respectively). After that, we impute them as described in section 2 in order to deal with the mixed frequency and ragged edges issues. During the weekly nowcasting estimation, we use one vintage up to the publishing date of additional data; after that, we move to the following vintage data set.

One crucial step in evaluating the nowcasting results is deciding which values these nowcasts will be compared to. We do not have the actual values of the weekly unemployment rate during the model's training or during this testing phase; if we had them, this research would not take place after all. To solve this issue, we impute the full information set, which ends in December 2020. The imputed values that bridge the monthly unemployment rates are the closest we can get to the actual rate. The difference between imputing the full information set and imputing the vintage sets is as follows: in the former case, the Kalman Filter can depict the movement from one month to the next one during the first quarter of 2020 since it considers both the starting and ending points in the data set and fills the gap between them. When imputing the vintages, on the other hand, because of missing information, some of the values calculated by the Kalman Filter may diverge from the actual unemployment rate even in a monthly frequency because the ending point may be unknown.

Figure 6 shows the performance of the Lasso-Selection VAR, Lasso VAR, and the two benchmarks we considered, for each of the three months of the first quarter of 2020, considering one, two, three and four steps-ahead nowcasts. Detailed information of the measures of fit (root mean squared error and mean absolute error) concerning the national, regional and macro-regional unemployment levels is reported in appendix A. We can immediately notice the expected deterioration of the performance of all models as the quarter evolves: the more outdated the data is, the less precise the nowcasts will be.

[19] Foroni, Claudia, Massimiliano Marcellino, Dalibor Stevanovic, Edward Glaeser, Hyunjin Kim, Michael Luca, Máximo Camacho, Gabriel Pérez-Quirós, and Pilar Poncela. "Measuring real activity in real time: Exiting the Great Recession and entering the pandemic recession.", 2021

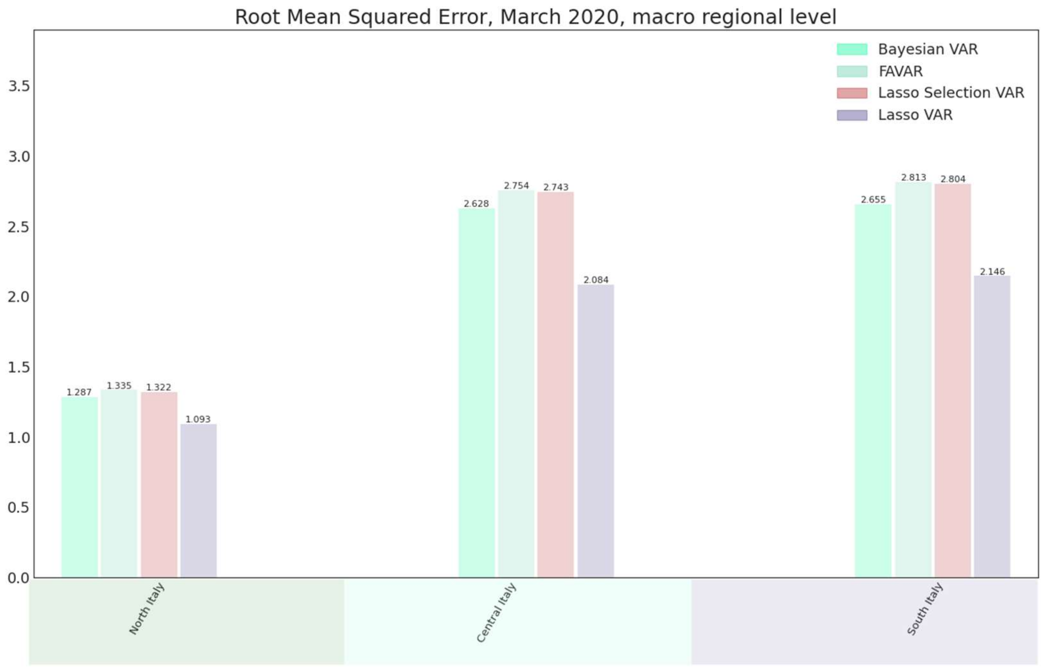
FIGURE 6: COMPARISON OF THE MODELS BASED ON ROOT MEAN SQUARED ERROR



It is clear that the Lasso VAR setting outperforms the rest of the models. During the months of January and February, the Lasso VAR model is performing considerably better (it achieves an average RMSE decrease of 47% and 42%, respectively); whereas, for the last month of the quarter, even though the lack of up-to-date information decreases the efficiency of all models, the Lasso VAR remains prevalent (reaches a 23% decrease in terms of RMSE).

Even though the Lasso-VAR is performing better compared to the other models, an improvement is still required in two directions: data provision and estimation improvement. At a regional level the nowcasts follow approximately the same pattern, with Lasso VAR outperforming the alternative models in most cases, as shown in the Appendix. Figure 7 shows the performance of all models for nowcasts calculated during March 2020, which we consider to be the most challenging period for nowcasting because of limited information at a macro-regional level.[20]

FIGURE 7: RMSE ON MACRO REGIONAL

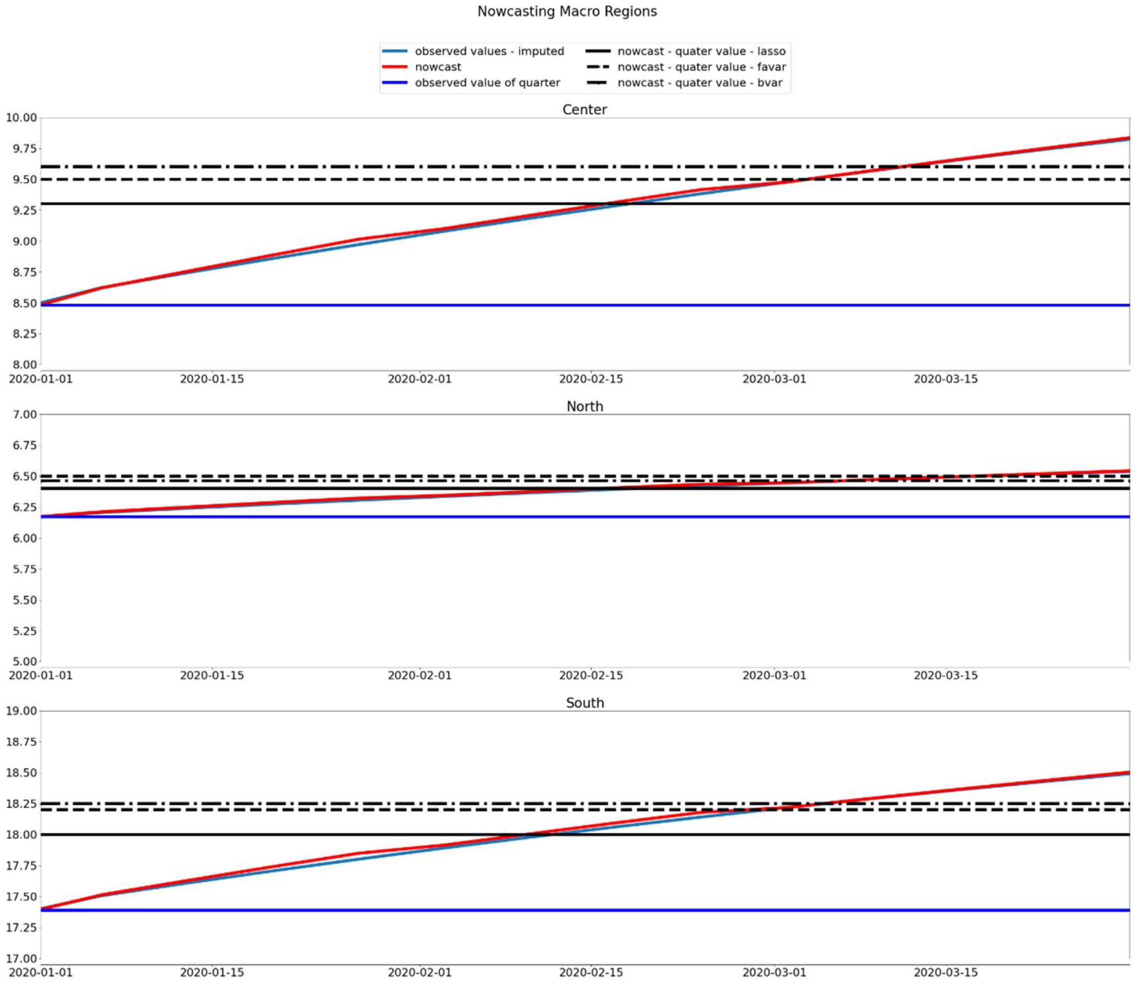


In Figure 8, we plot nowcast values together with observed imputed values. Regional data are coming with a substantial lag, in quarterly frequency, making it troublesome to graph the model's performance. We approach this problem by taking into consideration the first quarter of 2020. We plot nowcast weekly values across the quarter in weekly frequency. These are not "real" values, so we add a horizontal line representing the official quarterly value (blue line in the figure below).

Additionally, we calculate the average unemployment rate in the first quarter nowcast using three different models to create three horizontal lines representing nowcast quarterly values. Now, this can be used for comparison with the official observed value. We can see that we overestimate the actual value for the macro regions of Centre and South, while for the North nowcasted value is very close to the observed one. Since we have a data gap going on for the whole quarter, we argue that this result can be significant for the early assessment of labour market trends at the macro-regional level. Moreover, LASSO VAR performs better than the other two benchmark models in all three macro-regions.

[20] Macro-regions are the first-level NUTS of the European Union.

FIGURE 8: NOWCASTING MACRO REGIONS



CONCLUSION AND FURTHER RESEARCH

Traditional macroeconomic variables are usually only available in quarterly or monthly frequency and are therefore not fully representative of the current economic and labour market situation. More reliable and real-time forecasts (that can be obtained by nowcasting methods), would allow decision makers to make more informed and time-consistent decisions including the calibration of unemployment benefits, the provision of targeted wage/hiring subsidies, or the provision of training programmes.

Nowcasting traditional economic variables demand high-frequency variables that can grasp the dynamics of the target variable and can therefore closely represent dynamics in the labour market. Without high-frequency variables, we would find ourselves in a standard modelling environment that cannot provide timely updates on developments in an economy, such as employment and unemployment or economic output. In this context, data stemming from “mandatory communications” are a great source of information, which are included in our model and allow it to produce weekly nowcasts. To achieve higher accuracy, adding other high-frequency variables such as “Cassa Integrazione Guadagni” (Redundancy Fund) data, energy consumption or job postings on websites and in newspapers would likely improve its performance.

Therefore, we plan to create a real-time coincident index that will portray the state of the economy, making use of sentiment indexes and text analysis techniques combined with high-frequency financial market data. We are confident that this separate project will improve the nowcasting process as well. The other direction we aim to explore is alternative nowcasting techniques. Borrowing ideas from machine learning models, we have some preliminary evidence that some techniques could catch patterns that more traditional methods have not been able to and could therefore lead to even better nowcasts.

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APPENDIX A: IMPUTATION METHOD

Imputation or up sampling is made after experimenting with several other methods, making use of the combination of the Expectation Maximisation (EM) algorithm and the Kalman Smoother.
The logic of the EM algorithm is iterative as in Zhang et al.[21]:

(i) initially we make a guess over the parameters describing the distribution of the variable with the missing observations.
For k=1, 2… iterations:
-Expectation step:
(ii) Compute the log-likelihood (optional),
(iii) Use the parameters to obtain the smoothed values of the hidden states and their correlations, for t= 1,2, …, T (Kalman smoother)

$$J_{t-1} = P_{t-1}^{t-1} A^T (P_t^{t-1})^{-1}$$
$$x_{t-1}^n = x_{t-1}^{t-1} + J_{t-1}(x_t^n - A x_{t-1}^{t-1})$$
$$P_{t-1}^n = P_{t-1}^{t-1} + J_{t-1}(P_t^n - P_t^{t-1}) J_{t-1}^T$$

The matrix J is the smoothing gain, which is analogue to the Kalman gain K. The initial values for the smoother are the final estimates of the filter, x_n^n and P_n^n.
-Maximisation step:

$$G(\Theta) = E(logL | y_1, \dots, y_n)$$

However, since the hidden states x_t are unknown, only the expected value of the log-likelihood conditioned on $y_1, \dots, y_n$ is accessible. For detailed derivations refer to Shumvay and Stoffer (1982)[22].
(iv)Use the smoothed values to calculate the updated parameters that maximise the expected likelihood of the observed variables (where the expectation is taken over the unobserved ones).
(v)Repeat Steps (ii) – (iv) to convergence.

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[21] Huang, Chengliang, Xiao-Ping Zhang, and Fang Wang. "Approaches in Using Expectation Maximization Algorithm for Maximum Likelihood Estimation of The Parameters of a Constrained State Space Model with an External Input Series." In CS & IT Conference Proceedings, vol. 6, no. 5. CS & IT Conference Proceedings, 2016.
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APPENDIX B: MEASURES OF FIT

The RMSE and the MAE, resulting from the nowcasting process for the first quarter of 2020, are reported in detail below. Tables 1-6 are dedicated to reporting results about the Lasso VAR model. In those, information can be extracted about the RMSE and the MAE at the national, macro regional, and regional level up to four horizons/weeks ahead.

Tables 7-9 report the same information in a more compressed form for the rest of the models, reporting information at all levels for each month of the first quarter 2020 (e.g. the suffix "01_20" is referring to nowcasts conducted during January, etc.).

TABLE 1: LASSO VAR ROOT MEAN SQUARED ERROR
JANUARY 2020

Region	Horizon h=1	Horizon h=2	Horizon h=3	Horizon h=4
Abruzzo	0.164	0.201	0.323	0.502
Basilicata	0.066	0.078	0.124	0.194
Bolzano	0.046	0.054	0.085	0.132
Calabria	0.185	0.216	0.330	0.495
Campania	0.148	0.181	0.285	0.436
Centro	0.033	0.041	0.065	0.100
Emilia-Romagna	0.015	0.018	0.032	0.053
Friuli-Venezia Giulia	0.042	0.053	0.087	0.134
Lazio	0.104	0.128	0.200	0.307
Liguria	0.089	0.104	0.159	0.237
Lombardia	0.086	0.105	0.168	0.260
Marche	0.018	0.028	0.053	0.089

Molise	**0.172**	**0.213**	**0.334**	**0.501**
North	**0.030**	**0.038**	**0.062**	**0.098**
North-East	**0.034**	**0.042**	**0.068**	**0.106**
North-West	**0.027**	**0.034**	**0.056**	**0.089**
Piemonte	**0.058**	**0.070**	**0.106**	**0.156**
Puglia	**0.047**	**0.054**	**0.076**	**0.105**
Sardegna	**0.212**	**0.264**	**0.423**	**0.651**
Sicilia	**0.069**	**0.081**	**0.122**	**0.178**
South	**0.034**	**0.044**	**0.074**	**0.119**
Toscana	**0.034**	**0.040**	**0.062**	**0.093**
Trentino	**0.022**	**0.024**	**0.038**	**0.060**
Trento	**0.025**	**0.028**	**0.044**	**0.067**
Umbria	**0.141**	**0.162**	**0.243**	**0.360**
Vale d'Aosta	**0.093**	**0.113**	**0.174**	**0.263**
Veneto	**0.047**	**0.058**	**0.092**	**0.141**
National level	**0.154**	**0.184**	**0.289**	**0.440**

TABLE 2: LASSO VAR MEAN ABSOLUTE ERROR JANUARY 2020

Region	**Horizon h=1**	**Horizon h=2**	**Horizon h=3**	**Horizon h=4**
North	**0.026**	**0.031**	**0.048**	**0.080**
North-West	**0.024**	**0.028**	**0.044**	**0.074**
Piemonte	**0.050**	**0.059**	**0.086**	**0.127**

Vale d'Aosta	0.081	0.093	0.136	0.211
Liguria	0.076	0.086	0.123	0.192
Lombardia	0.074	0.087	0.130	0.209
North-East	0.029	0.035	0.053	0.085
Trentino	0.019	0.020	0.029	0.050
Bolzano	0.040	0.045	0.066	0.106
Trento	0.022	0.023	0.033	0.058
Veneto	0.041	0.048	0.072	0.113
Friuli-Venezia Giulia	0.037	0.044	0.067	0.108
Emilia-Romagna	0.013	0.015	0.025	0.045
Centro	0.028	0.036	0.055	0.079
Toscana	0.029	0.032	0.048	0.081
Umbria	0.122	0.134	0.187	0.293
Marche	0.016	0.024	0.042	0.072
Lazio	0.089	0.107	0.162	0.247
South	0.030	0.037	0.059	0.095
Abruzzo	0.143	0.167	0.249	0.399
Molise	0.150	0.176	0.260	0.405
Campania	0.128	0.150	0.224	0.350
Puglia	0.041	0.047	0.063	0.086
Basilicata	0.057	0.064	0.096	0.161

Calabria	0.160	0.177	0.255	0.410
Sicilia	0.059	0.066	0.094	0.146
Sardegna	0.184	0.218	0.327	0.522
National level	0.133	0.151	0.224	0.363

TABLE 3: LASSO VAR ROOT MEAN SQUARED ERROR FEBRUARY 2020

Region	Horizon h=1	Horizon h=2	Horizon h=3	Horizon h=4
Abruzzo	0.519	0.751	1.028	1.337
Basilicata	0.218	0.310	0.413	0.526
Bolzano	0.146	0.207	0.278	0.355
Calabria	0.578	0.790	1.001	1.207
Campania	0.451	0.650	0.885	1.144
Centro	0.090	0.143	0.214	0.302
Emilia-Romagna	0.054	0.082	0.117	0.159
Friuli-Venezia Giulia	0.133	0.190	0.259	0.332
Lazio	0.309	0.455	0.635	0.839
Liguria	0.271	0.370	0.471	0.569
Lombardia	0.271	0.389	0.524	0.672
Marche	0.059	0.103	0.171	0.257
Molise	0.518	0.719	0.938	1.151
North	0.099	0.144	0.199	0.261

North-East	0.107	0.155	0.214	0.280
North-West	0.090	0.131	0.182	0.239
Piemonte	0.166	0.234	0.312	0.394
Puglia	0.127	0.170	0.210	0.244
Sardegna	0.656	0.945	1.287	1.660
Sicilia	0.207	0.277	0.341	0.397
South	0.107	0.166	0.246	0.342
Toscana	0.111	0.148	0.183	0.214
Trentino	0.072	0.102	0.135	0.171
Trento	0.084	0.116	0.150	0.186
Umbria	0.430	0.584	0.733	0.875
Vale d'Aosta	0.282	0.397	0.525	0.658
Veneto	0.144	0.208	0.284	0.368
National level	0.486	0.675	0.878	1.086

TABLE 4: LASSO VAR MEAN ABSOLUTE ERROR
FEBRUARY 2020

Region	Horizon h=1	Horizon h=2	Horizon h=3	Horizon h=4
North	0.111	0.161	0.220	0.285
North-West	0.102	0.147	0.201	0.262
Piemonte	0.184	0.258	0.340	0.424
Vale d'Aosta	0.314	0.438	0.572	0.710
Liguria	0.298	0.403	0.506	0.603

Lombardia	**0.304**	**0.431**	**0.575**	**0.730**
North-East	**0.120**	**0.173**	**0.236**	**0.305**
Trentino	**0.080**	**0.113**	**0.148**	**0.187**
Bolzano	**0.163**	**0.230**	**0.305**	**0.386**
Trento	**0.093**	**0.128**	**0.164**	**0.201**
Veneto	**0.161**	**0.231**	**0.312**	**0.401**
Friuli-Venezia Giulia	**0.148**	**0.211**	**0.283**	**0.360**
Emilia-Romagna	**0.062**	**0.093**	**0.132**	**0.178**
Centro	**0.105**	**0.164**	**0.243**	**0.338**
Toscana	**0.121**	**0.160**	**0.195**	**0.225**
Umbria	**0.472**	**0.634**	**0.786**	**0.925**
Marche	**0.071**	**0.122**	**0.198**	**0.293**
Lazio	**0.349**	**0.510**	**0.703**	**0.921**
South	**0.123**	**0.190**	**0.277**	**0.381**
Abruzzo	**0.583**	**0.838**	**1.134**	**1.461**
Molise	**0.570**	**0.783**	**1.005**	**1.217**
Campania	**0.505**	**0.722**	**0.973**	**1.244**
Puglia	**0.139**	**0.183**	**0.222**	**0.254**
Basilicata	**0.243**	**0.343**	**0.452**	**0.571**
Calabria	**0.636**	**0.861**	**1.077**	**1.282**
Sicilia	**0.225**	**0.297**	**0.361**	**0.411**

Sardegna	**0.735**	**1.049**	**1.412**	**1.802**
National level	**0.537**	**0.740**	**0.951**	**1.162**

TABLE 5: LASSO VAR ROOT MEAN SQUARED ERROR MARCH 2020

Region	Horizon h=1	Horizon h=2	Horizon h=3	Horizon h=4
Abruzzo	**3.733**	**4.264**	**4.831**	**5.424**
Basilicata	**1.344**	**1.495**	**1.647**	**1.797**
Bolzano	**0.913**	**1.017**	**1.124**	**1.231**
Calabria	**1.904**	**1.795**	**1.599**	**1.328**
Campania	**2.901**	**3.263**	**3.644**	**4.032**
Centro	**1.190**	**1.452**	**1.753**	**2.084**
Emilia-Romagna	**0.592**	**0.709**	**0.840**	**0.982**
Friuli-Venezia Giulia	**0.809**	**0.902**	**0.998**	**1.094**
Lazio	**2.463**	**2.859**	**3.296**	**3.758**
Liguria	**0.853**	**0.795**	**0.697**	**0.565**
Lombardia	**1.659**	**1.848**	**2.042**	**2.234**
Marche	**1.242**	**1.558**	**1.926**	**2.335**
Molise	**1.645**	**1.558**	**1.407**	**1.191**
North	**0.737**	**0.847**	**0.967**	**1.093**
North-East	**0.761**	**0.871**	**0.989**	**1.113**
North-West	**0.701**	**0.810**	**0.929**	**1.055**

Piemonte	0.811	0.867	0.916	0.956
Puglia	0.200	0.151	0.175	0.293
Sardegna	4.140	4.643	5.168	5.698
Sicilia	0.303	0.237	0.312	0.529
South	1.255	1.518	1.818	2.146
Toscana	0.241	0.191	0.140	0.141
Trentino	0.470	0.525	0.581	0.638
Trento	0.444	0.476	0.503	0.526
Umbria	1.201	1.064	0.864	0.632
Vale d'Aosta	1.444	1.552	1.646	1.726
Veneto	0.945	1.068	1.198	1.330
National level	2.041	2.091	2.096	2.053

TABLE 6: LASSO VAR MEAN ABSOLUTE ERROR MARCH 2020

Region	Horizon h=1	Horizon h=2	Horizon h=3	Horizon h=4
North	0.784	0.898	1.020	1.147
North-West	0.748	0.861	0.982	1.109
Piemonte	0.833	0.885	0.930	0.968
Vale d'Aosta	1.489	1.591	1.679	1.753
Liguria	0.811	0.726	0.598	0.431
Lombardia	1.740	1.931	2.124	2.314
North-East	0.808	0.921	1.041	1.165

Trentino	0.494	0.550	0.606	0.663
Bolzano	0.958	1.064	1.171	1.277
Trento	0.458	0.488	0.514	0.535
Veneto	0.997	1.122	1.253	1.385
Friuli-Venezia Giulia	0.849	0.943	1.039	1.136
Emilia-Romagna	0.641	0.763	0.899	1.043
Centro	1.297	1.574	1.887	2.226
Toscana	0.198	0.153	0.142	0.173
Umbria	1.100	0.908	0.655	0.517
Marche	1.368	1.704	2.088	2.510
Lazio	2.632	3.043	3.489	3.958
South	1.363	1.640	1.951	2.288
Abruzzo	3.962	4.508	5.086	5.686
Molise	1.573	1.438	1.239	0.975
Campania	3.055	3.424	3.808	4.196
Puglia	0.165	0.166	0.218	0.329
Basilicata	1.410	1.561	1.712	1.860
Calabria	1.826	1.664	1.411	1.081
Sicilia	0.255	0.273	0.378	0.582
Sardegna	4.356	4.866	5.394	5.925
National level	2.052	2.078	2.060	1.996

TABLE 7: BAYESIAN VAR MEASURES OF FIT
KANUARY-MARCH 2020

Region	Horizon h=1		Horizon h=2		Horizon h=3		Horizon h=4	
	rmse	mae	rmse	mae	rmse	mae	rmse	mae
national_01_20	0.385	0.385	0.526	0.511	0.674	0.641	0.825	0.772
national_02_20	1.218	1.218	1.355	1.349	1.489	1.475	1.617	1.594
National_03_20	2.116	2.116	2.095	2.094	2.059	2.059	2.013	2.010
Abruzzo_01_20	0.209	0.209	0.257	0.253	0.315	0.305	0.386	0.365
Abruzzo_02_20	1.287	1.287	1.415	1.410	1.555	1.541	1.706	1.679
Abruzzo_03_20	5.617	5.617	5.911	5.904	6.205	6.188	6.497	6.466
Basilicata_01_20	0.209	0.209	0.299	0.289	0.396	0.372	0.499	0.460
Basilicata_02_20	0.627	0.627	0.728	0.722	0.832	0.818	0.941	0.916
Basilicata_03_20	1.897	1.897	1.983	1.981	2.062	2.058	2.133	2.127
Bolzano_01_20	0.049	0.049	0.067	0.065	0.091	0.085	0.118	0.108
Bolzano_02_20	0.376	0.376	0.424	0.421	0.475	0.468	0.528	0.517
Bolzano_03_20	1.309	1.309	1.374	1.373	1.439	1.436	1.502	1.496
Calabria_01_20	0.497	0.497	0.679	0.659	0.867	0.824	1.056	0.989
Calabria_02_20	1.438	1.438	1.593	1.586	1.739	1.724	1.873	1.850
Calabria_03_20	1.274	1.274	1.131	1.121	0.991	0.954	0.867	0.778
Campania_01_20	0.156	0.156	0.181	0.179	0.215	0.210	0.258	0.246
Campania_02_20	1.049	1.049	1.128	1.125	1.212	1.205	1.301	1.288
Campania_03_20	4.082	4.082	4.235	4.233	4.385	4.378	4.529	4.518

Centro_01_20	0.038	0.038	0.068	0.063	0.093	0.085	0.111	0.102
Centro_02_20	0.205	0.205	0.215	0.214	0.231	0.230	0.256	0.252
Centro_03_20	2.137	2.137	2.298	2.293	2.463	2.449	2.628	2.605
Emilia-Romagna_01_20	0.031	0.031	0.042	0.041	0.055	0.052	0.069	0.064
Emilia-Romagna_02_20	0.156	0.156	0.177	0.176	0.202	0.199	0.229	0.223
Emilia-Romagna_03_20	1.027	1.027	1.103	1.100	1.178	1.172	1.252	1.242
Friuli-Venezia Giulia_01_20	0.015	0.015	0.018	0.017	0.025	0.023	0.036	0.032
Friuli-Venezia Giulia_02_20	0.239	0.239	0.243	0.243	0.252	0.251	0.263	0.262
Friuli-Venezia Giulia_03_20	0.967	0.967	0.961	0.961	0.958	0.958	0.957	0.957
Lazio_01_20	0.052	0.052	0.046	0.045	0.045	0.045	0.054	0.052
Lazio_02_20	0.708	0.708	0.755	0.754	0.811	0.806	0.876	0.867
Lazio_03_20	3.831	3.831	4.037	4.032	4.243	4.231	4.447	4.425
Liguria_01_20	0.187	0.187	0.253	0.246	0.324	0.308	0.397	0.372
Liguria_02_20	0.628	0.628	0.685	0.683	0.740	0.735	0.791	0.783
Liguria_03_20	0.508	0.508	0.433	0.425	0.365	0.336	0.317	0.262
Lombardia_01_20	0.128	0.128	0.162	0.159	0.203	0.195	0.249	0.234
Lombardia_02_20	0.651	0.651	0.710	0.707	0.772	0.766	0.837	0.827
Lombardia_03_20	2.284	2.284	2.367	2.366	2.447	2.444	2.522	2.517
Marche_01_20	0.041	0.041	0.066	0.062	0.085	0.080	0.098	0.092

Marche_02_20	0.179	0.179	0.208	0.206	0.249	0.242	0.302	0.288
Marche_03_20	2.448	2.448	2.677	2.668	2.914	2.891	3.155	3.115
Molise_01_20	0.125	0.125	0.117	0.116	0.112	0.111	0.108	0.108
Molise_02_20	0.988	0.988	0.989	0.989	0.982	0.982	0.965	0.964
Molise_03_20	0.921	0.921	0.750	0.723	0.615	0.519	0.553	0.464
North_01_20	0.043	0.043	0.054	0.053	0.067	0.065	0.083	0.078
North_02_20	0.244	0.244	0.267	0.266	0.292	0.290	0.320	0.315
North_03_20	1.120	1.120	1.177	1.176	1.233	1.230	1.287	1.282
North-East_01_20	0.045	0.045	0.057	0.056	0.070	0.068	0.087	0.082
North-East_02_20	0.260	0.260	0.285	0.284	0.312	0.309	0.341	0.336
North-East_03_20	1.137	1.137	1.193	1.192	1.248	1.245	1.300	1.295
North-West_01_20	0.041	0.041	0.052	0.051	0.065	0.063	0.081	0.076
North-West_02_20	0.225	0.225	0.247	0.246	0.271	0.268	0.297	0.293
North-West_03_20	1.084	1.084	1.141	1.140	1.197	1.194	1.251	1.246
Piemonte_01_20	0.045	0.045	0.047	0.047	0.054	0.053	0.063	0.061
Piemonte_02_20	0.359	0.359	0.381	0.380	0.404	0.402	0.427	0.424
Piemonte_03_20	0.951	0.951	0.962	0.962	0.974	0.973	0.987	0.986
Puglia_01_20	0.063	0.063	0.078	0.076	0.093	0.091	0.109	0.105
Puglia_02_20	0.262	0.262	0.274	0.274	0.283	0.283	0.289	0.288
Puglia_03_20	0.258	0.258	0.350	0.340	0.448	0.426	0.547	0.513
Sardegna_01_20	0.237	0.237	0.279	0.276	0.333	0.325	0.400	0.382

Sardegna_02_20	1.503	1.503	1.608	1.605	1.720	1.712	1.839	1.823
Sardegna_03_20	5.724	5.724	5.905	5.903	6.081	6.075	6.250	6.239
Sicilia_01_20	0.160	0.160	0.211	0.206	0.262	0.251	0.310	0.294
Sicilia_02_20	0.446	0.446	0.472	0.472	0.491	0.489	0.500	0.499
Sicilia_03_20	0.508	0.508	0.678	0.661	0.857	0.818	1.038	0.977
South_01_20	0.011	0.011	0.029	0.025	0.041	0.036	0.047	0.042
South_02_20	0.260	0.260	0.281	0.280	0.309	0.306	0.344	0.338
South_03_20	2.192	2.192	2.344	2.339	2.499	2.488	2.655	2.635
Toscana_01_20	0.092	0.092	0.126	0.122	0.161	0.153	0.197	0.184
Toscana_02_20	0.271	0.271	0.302	0.300	0.331	0.328	0.357	0.352
Toscana_03_20	0.045	0.045	0.113	0.099	0.179	0.155	0.245	0.211
Trentino_01_20	0.056	0.056	0.078	0.076	0.103	0.097	0.129	0.120
Trentino_02_20	0.204	0.204	0.236	0.234	0.270	0.265	0.306	0.298
Trentino_03_20	0.683	0.683	0.722	0.721	0.762	0.759	0.801	0.797
Trento_01_20	0.073	0.073	0.102	0.098	0.133	0.126	0.166	0.154
Trento_02_20	0.227	0.227	0.259	0.258	0.293	0.289	0.328	0.321
Trento_03_20	0.568	0.568	0.591	0.591	0.614	0.613	0.636	0.634
Umbria_01_20	0.375	0.375	0.513	0.498	0.656	0.623	0.798	0.748
Umbria_02_20	1.042	1.042	1.146	1.141	1.241	1.232	1.324	1.311
Umbria_03_20	0.436	0.436	0.316	0.267	0.303	0.270	0.424	0.369
Vale d_Aosta_01_20	0.116	0.116	0.137	0.136	0.163	0.159	0.192	0.184

Vale d_Aosta_02_20	0.634	0.634	0.671	0.670	0.708	0.705	0.744	0.740
Vale d_Aosta_03_20	1.712	1.712	1.716	1.715	1.714	1.714	1.709	1.709
Veneto_01_20	0.063	0.063	0.078	0.077	0.097	0.094	0.119	0.112
Veneto_02_20	0.349	0.349	0.382	0.381	0.417	0.414	0.455	0.448
Veneto_03_20	1.354	1.354	1.409	1.408	1.464	1.461	1.515	1.511

TABLE 8: FAVAR MEASURES OF FIT JANUARY-MARCH 2020

Region	Horizon h=1		Horizon h=2		Horizon h=3		Horizon h=4	
	rmse	mae	rmse	mae	rmse	mae	rmse	mae
national_01_20	0.326	0.326	0.433	0.422	0.547	0.522	0.664	0.624
national_02_20	1.166	1.166	1.276	1.272	1.385	1.375	1.489	1.472
National_03_20	2.088	2.088	2.057	2.057	2.017	2.016	1.970	1.967
Abruzzo_01_20	0.323	0.323	0.439	0.427	0.570	0.540	0.716	0.664
Abruzzo_02_20	1.376	1.376	1.559	1.550	1.761	1.735	1.980	1.933
Abruzzo_03_20	5.654	5.654	5.973	5.965	6.297	6.276	6.623	6.586
Basilicata_01_20	0.151	0.151	0.216	0.208	0.295	0.275	0.391	0.354
Basilicata_02_20	0.568	0.568	0.641	0.637	0.721	0.711	0.810	0.791
Basilicata_03_20	1.868	1.868	1.945	1.943	2.020	2.016	2.093	2.087
Bolzano_01_20	0.094	0.094	0.127	0.123	0.162	0.154	0.198	0.186
Bolzano_02_20	0.377	0.377	0.421	0.418	0.466	0.461	0.513	0.504
Bolzano_03_20	1.275	1.275	1.327	1.326	1.378	1.375	1.427	1.422

Calabria_01_20	**0.407**	**0.407**	**0.545**	**0.531**	**0.693**	**0.661**	**0.847**	**0.794**
Calabria_02_20	**1.352**	**1.352**	**1.460**	**1.456**	**1.557**	**1.549**	**1.639**	**1.628**
Calabria_03_20	**1.182**	**1.182**	**0.997**	**0.976**	**0.833**	**0.751**	**0.728**	**0.614**
Campania_01_20	**0.285**	**0.285**	**0.387**	**0.376**	**0.501**	**0.475**	**0.630**	**0.585**
Campania_02_20	**1.160**	**1.160**	**1.304**	**1.297**	**1.460**	**1.441**	**1.627**	**1.593**
Campania_03_20	**4.151**	**4.151**	**4.345**	**4.341**	**4.538**	**4.528**	**4.730**	**4.712**
Centro_01_20	**0.045**	**0.045**	**0.063**	**0.061**	**0.085**	**0.080**	**0.114**	**0.103**
Centro_02_20	**0.282**	**0.282**	**0.337**	**0.333**	**0.403**	**0.392**	**0.481**	**0.459**
Centro_03_20	**2.180**	**2.180**	**2.367**	**2.360**	**2.559**	**2.542**	**2.754**	**2.724**
Emilia-Romagna_01_20	**0.033**	**0.033**	**0.049**	**0.047**	**0.069**	**0.064**	**0.095**	**0.085**
Emilia-Romagna_02_20	**0.164**	**0.164**	**0.192**	**0.190**	**0.225**	**0.220**	**0.264**	**0.254**
Emilia-Romagna_03_20	**1.032**	**1.032**	**1.112**	**1.109**	**1.193**	**1.186**	**1.273**	**1.262**
Friuli-Venezia Giulia_01_20	**0.084**	**0.084**	**0.114**	**0.111**	**0.149**	**0.141**	**0.188**	**0.174**
Friuli-Venezia Giulia_02_20	**0.337**	**0.337**	**0.379**	**0.377**	**0.425**	**0.420**	**0.475**	**0.465**
Friuli-Venezia Giulia_03_20	**1.126**	**1.126**	**1.173**	**1.173**	**1.221**	**1.219**	**1.269**	**1.265**
Lazio_01_20	**0.185**	**0.185**	**0.251**	**0.244**	**0.325**	**0.308**	**0.409**	**0.380**
Lazio_02_20	**0.834**	**0.834**	**0.952**	**0.946**	**1.085**	**1.067**	**1.232**	**1.199**
Lazio_03_20	**3.904**	**3.904**	**4.151**	**4.144**	**4.400**	**4.383**	**4.648**	**4.618**
Liguria_01_20	**0.185**	**0.185**	**0.243**	**0.237**	**0.302**	**0.290**	**0.360**	**0.341**
Liguria_02_20	**0.621**	**0.621**	**0.664**	**0.663**	**0.700**	**0.697**	**0.724**	**0.721**
Liguria_03_20	**0.474**	**0.474**	**0.383**	**0.368**	**0.313**	**0.252**	**0.298**	**0.251**

Lombardia_01_20	0.174	0.174	0.235	0.228	0.302	0.287	0.377	0.351
Lombardia_02_20	0.694	0.694	0.778	0.774	0.868	0.857	0.964	0.945
Lombardia_03_20	2.302	2.302	2.395	2.394	2.487	2.482	2.575	2.568
Marche_01_20	0.021	0.021	0.034	0.032	0.055	0.049	0.085	0.072
Marche_02_20	0.217	0.217	0.271	0.267	0.337	0.324	0.417	0.392
Marche_03_20	2.459	2.459	2.697	2.687	2.944	2.920	3.198	3.155
Molise_01_20	0.344	0.344	0.450	0.440	0.557	0.535	0.661	0.627
Molise_02_20	1.168	1.168	1.257	1.254	1.336	1.330	1.400	1.392
Molise_03_20	0.979	0.979	0.823	0.804	0.688	0.620	0.599	0.499
North_01_20	0.061	0.061	0.085	0.082	0.112	0.105	0.144	0.132
North_02_20	0.264	0.264	0.301	0.299	0.343	0.337	0.390	0.379
North_03_20	1.134	1.134	1.201	1.199	1.268	1.264	1.335	1.328
North-East_01_20	0.065	0.065	0.089	0.086	0.115	0.109	0.145	0.135
North-East_02_20	0.280	0.280	0.318	0.316	0.359	0.354	0.405	0.395
North-East_03_20	1.151	1.151	1.215	1.214	1.281	1.277	1.346	1.339
North-West_01_20	0.056	0.056	0.078	0.076	0.105	0.099	0.137	0.125
North-West_02_20	0.244	0.244	0.280	0.278	0.321	0.316	0.368	0.357
North-West_03_20	1.098	1.098	1.166	1.164	1.233	1.229	1.301	1.293
Piemonte_01_20	0.102	0.102	0.130	0.127	0.154	0.149	0.172	0.167
Piemonte_02_20	0.400	0.400	0.438	0.437	0.475	0.471	0.508	0.503
Piemonte_03_20	0.959	0.959	0.972	0.972	0.984	0.984	0.996	0.996
Puglia_01_20	0.082	0.082	0.097	0.096	0.103	0.102	0.100	0.099

Puglia_02_20	0.271	0.271	0.281	0.280	0.282	0.282	0.275	0.275
Puglia_03_20	0.284	0.284	0.395	0.383	0.514	0.486	0.637	0.592
Sardegna_01_20	0.410	0.410	0.549	0.535	0.702	0.668	0.866	0.810
Sardegna_02_20	1.672	1.672	1.873	1.863	2.086	2.061	2.308	2.264
Sardegna_03_20	5.878	5.878	6.144	6.138	6.408	6.394	6.669	6.645
Sicilia_01_20	0.143	0.143	0.182	0.178	0.216	0.209	0.242	0.234
Sicilia_02_20	0.439	0.439	0.457	0.457	0.466	0.466	0.464	0.463
Sicilia_03_20	0.529	0.529	0.718	0.698	0.917	0.873	1.122	1.051
South_01_20	0.060	0.060	0.087	0.084	0.123	0.114	0.168	0.150
South_02_20	0.321	0.321	0.380	0.376	0.449	0.438	0.532	0.510
South_03_20	2.244	2.244	2.429	2.422	2.620	2.603	2.813	2.784
Toscana_01_20	0.080	0.080	0.106	0.104	0.132	0.127	0.157	0.149
Toscana_02_20	0.247	0.247	0.260	0.260	0.270	0.269	0.273	0.273
Toscana_03_20	0.073	0.073	0.161	0.144	0.250	0.219	0.341	0.296
Trentino_01_20	0.048	0.048	0.065	0.063	0.084	0.080	0.103	0.096
Trentino_02_20	0.191	0.191	0.213	0.212	0.235	0.232	0.257	0.253
Trentino_03_20	0.664	0.664	0.690	0.690	0.716	0.715	0.740	0.738
Trento_01_20	0.058	0.058	0.078	0.076	0.099	0.095	0.120	0.113
Trento_02_20	0.214	0.214	0.235	0.234	0.254	0.252	0.272	0.269
Trento_03_20	0.541	0.541	0.546	0.546	0.549	0.549	0.549	0.549
Umbria_01_20	0.303	0.303	0.401	0.391	0.502	0.481	0.602	0.569
Umbria_02_20	0.983	0.983	1.050	1.048	1.104	1.100	1.141	1.136

Umbria_03_20	0.370	0.370	0.263	0.206	0.359	0.303	0.582	0.474
Vale d_Aosta_01_20	0.187	0.187	0.253	0.246	0.327	0.311	0.409	0.380
Vale d_Aosta_02_20	0.701	0.701	0.778	0.775	0.859	0.850	0.945	0.929
Vale d_Aosta_03_20	1.770	1.770	1.806	1.806	1.841	1.841	1.875	1.874
Veneto_01_20	0.089	0.089	0.120	0.117	0.154	0.146	0.191	0.178
Veneto_02_20	0.371	0.371	0.419	0.416	0.470	0.464	0.525	0.514
Veneto_03_20	1.370	1.370	1.436	1.435	1.502	1.498	1.567	1.561

TABLE 9: LASSO SELECTION VAR MEASURES OF FIT JANUARY-MARCH 2020

Region	Horizon h=1		Horizon h=2		Horizon h=3		Horizon h=4	
	rmse	mae	rmse	mae	rmse	mae	rmse	mae
national_01_20	0.324	0.324	0.429	0.418	0.539	0.516	0.652	0.614
national_02_20	1.164	1.164	1.273	1.269	1.380	1.370	1.481	1.465
National_03_20	2.082	2.082	2.046	2.045	1.997	1.996	1.940	1.936
Abruzzo_01_20	0.329	0.329	0.452	0.438	0.593	0.561	0.754	0.696
Abruzzo_02_20	1.376	1.376	1.559	1.549	1.760	1.734	1.979	1.932
Abruzzo_03_20	5.650	5.650	5.966	5.958	6.286	6.266	6.607	6.571
Basilicata_01_20	0.133	0.133	0.172	0.169	0.212	0.204	0.252	0.239
Basilicata_02_20	0.565	0.565	0.633	0.629	0.705	0.696	0.781	0.766
Basilicata_03_20	1.867	1.867	1.941	1.940	2.012	2.009	2.078	2.073
Bolzano_01_20	0.091	0.091	0.121	0.118	0.152	0.145	0.185	0.174
Bolzano_02_20	0.378	0.378	0.424	0.422	0.474	0.468	0.527	0.516

Bolzano_03_20	1.278	1.278	1.333	1.332	1.388	1.386	1.444	1.439
Calabria_01_20	0.405	0.405	0.541	0.527	0.687	0.655	0.838	0.786
Calabria_02_20	1.353	1.353	1.462	1.458	1.561	1.553	1.647	1.635
Calabria_03_20	1.189	1.189	1.010	0.990	0.849	0.776	0.738	0.613
Campania_01_20	0.289	0.289	0.396	0.385	0.518	0.490	0.654	0.605
Campania_02_20	1.159	1.159	1.303	1.295	1.457	1.439	1.622	1.589
Campania_03_20	4.147	4.147	4.337	4.333	4.526	4.516	4.710	4.693
Centro_01_20	0.048	0.048	0.070	0.068	0.098	0.091	0.133	0.120
Centro_02_20	0.282	0.282	0.338	0.334	0.404	0.393	0.482	0.461
Centro_03_20	2.178	2.178	2.362	2.356	2.552	2.535	2.743	2.714
Emilia-Romagna_01_20	0.033	0.033	0.048	0.046	0.068	0.063	0.093	0.083
Emilia-Romagna_02_20	0.163	0.163	0.190	0.188	0.221	0.217	0.257	0.248
Emilia-Romagna_03_20	1.031	1.031	1.108	1.105	1.186	1.180	1.262	1.252
Friuli-Venezia Giulia_01_20	0.090	0.090	0.129	0.124	0.176	0.164	0.231	0.210
Friuli-Venezia Giulia_02_20	0.336	0.336	0.377	0.375	0.421	0.416	0.468	0.459
Friuli-Venezia Giulia_03_20	1.122	1.122	1.165	1.165	1.207	1.205	1.247	1.244
Lazio_01_20	0.195	0.195	0.275	0.265	0.370	0.347	0.484	0.442
Lazio_02_20	0.834	0.834	0.954	0.947	1.089	1.071	1.241	1.206
Lazio_03_20	3.900	3.900	4.142	4.135	4.384	4.368	4.623	4.595

Liguria_01_20	**0.182**	**0.182**	**0.235**	**0.230**	**0.287**	**0.277**	**0.335**	**0.320**
Liguria_02_20	**0.623**	**0.623**	**0.669**	**0.667**	**0.707**	**0.704**	**0.735**	**0.731**
Liguria_03_20	**0.480**	**0.480**	**0.393**	**0.381**	**0.323**	**0.274**	**0.294**	**0.250**
Lombardia_01_20	**0.173**	**0.173**	**0.233**	**0.227**	**0.299**	**0.284**	**0.370**	**0.345**
Lombardia_02_20	**0.694**	**0.694**	**0.777**	**0.773**	**0.867**	**0.857**	**0.962**	**0.943**
Lombardia_03_20	**2.301**	**2.301**	**2.394**	**2.392**	**2.484**	**2.479**	**2.570**	**2.563**
Marche_01_20	**0.030**	**0.030**	**0.054**	**0.050**	**0.092**	**0.080**	**0.146**	**0.121**
Marche_02_20	**0.221**	**0.221**	**0.279**	**0.274**	**0.353**	**0.338**	**0.445**	**0.415**
Marche_03_20	**2.457**	**2.457**	**2.692**	**2.683**	**2.936**	**2.912**	**3.184**	**3.142**
Molise_01_20	**0.346**	**0.346**	**0.457**	**0.446**	**0.573**	**0.548**	**0.690**	**0.651**
Molise_02_20	**1.172**	**1.172**	**1.268**	**1.264**	**1.356**	**1.349**	**1.435**	**1.424**
Molise_03_20	**0.981**	**0.981**	**0.827**	**0.808**	**0.692**	**0.628**	**0.602**	**0.497**
North_01_20	**0.063**	**0.063**	**0.088**	**0.085**	**0.117**	**0.110**	**0.152**	**0.139**
North_02_20	**0.263**	**0.263**	**0.299**	**0.297**	**0.339**	**0.334**	**0.383**	**0.373**
North_03_20	**1.132**	**1.132**	**1.196**	**1.195**	**1.260**	**1.256**	**1.322**	**1.315**
North-East_01_20	**0.068**	**0.068**	**0.095**	**0.092**	**0.127**	**0.120**	**0.165**	**0.151**
North-East_02_20	**0.280**	**0.280**	**0.318**	**0.316**	**0.359**	**0.354**	**0.405**	**0.395**
North-East_03_20	**1.148**	**1.148**	**1.210**	**1.208**	**1.271**	**1.268**	**1.332**	**1.325**
North-West_01_20	**0.055**	**0.055**	**0.074**	**0.072**	**0.096**	**0.091**	**0.120**	**0.111**
North-West_02_20	**0.243**	**0.243**	**0.277**	**0.275**	**0.315**	**0.310**	**0.357**	**0.348**
North-West_03_20	**1.098**	**1.098**	**1.164**	**1.162**	**1.230**	**1.226**	**1.296**	**1.288**
Piemonte_01_20	**0.110**	**0.110**	**0.150**	**0.145**	**0.193**	**0.183**	**0.240**	**0.224**

Piemonte_02_20	**0.404**	**0.404**	**0.448**	**0.446**	**0.494**	**0.489**	**0.542**	**0.533**
Piemonte_03_20	**0.958**	**0.958**	**0.972**	**0.972**	**0.985**	**0.985**	**0.998**	**0.998**
Puglia_01_20	**0.089**	**0.089**	**0.111**	**0.109**	**0.129**	**0.126**	**0.140**	**0.137**
Puglia_02_20	**0.272**	**0.272**	**0.284**	**0.284**	**0.289**	**0.289**	**0.286**	**0.286**
Puglia_03_20	**0.287**	**0.287**	**0.400**	**0.387**	**0.521**	**0.492**	**0.646**	**0.600**
Sardegna_01_20	**0.424**	**0.424**	**0.585**	**0.567**	**0.772**	**0.728**	**0.985**	**0.908**
Sardegna_02_20	**1.678**	**1.678**	**1.888**	**1.878**	**2.117**	**2.089**	**2.364**	**2.313**
Sardegna_03_20	**5.873**	**5.873**	**6.132**	**6.126**	**6.387**	**6.374**	**6.635**	**6.613**
Sicilia_01_20	**0.147**	**0.147**	**0.192**	**0.188**	**0.238**	**0.228**	**0.281**	**0.267**
Sicilia_02_20	**0.440**	**0.440**	**0.460**	**0.459**	**0.471**	**0.470**	**0.472**	**0.471**
Sicilia_03_20	**0.530**	**0.530**	**0.719**	**0.699**	**0.920**	**0.875**	**1.128**	**1.055**
South_01_20	**0.063**	**0.063**	**0.095**	**0.091**	**0.138**	**0.126**	**0.194**	**0.171**
South_02_20	**0.321**	**0.321**	**0.380**	**0.376**	**0.450**	**0.439**	**0.533**	**0.511**
South_03_20	**2.243**	**2.243**	**2.425**	**2.419**	**2.614**	**2.597**	**2.804**	**2.775**
Toscana_01_20	**0.073**	**0.073**	**0.089**	**0.088**	**0.101**	**0.099**	**0.107**	**0.105**
Toscana_02_20	**0.247**	**0.247**	**0.262**	**0.262**	**0.273**	**0.272**	**0.279**	**0.279**
Toscana_03_20	**0.069**	**0.069**	**0.151**	**0.135**	**0.232**	**0.204**	**0.314**	**0.273**
Trentino_01_20	**0.047**	**0.047**	**0.063**	**0.061**	**0.083**	**0.078**	**0.105**	**0.097**
Trentino_02_20	**0.192**	**0.192**	**0.217**	**0.215**	**0.243**	**0.240**	**0.272**	**0.266**
Trentino_03_20	**0.667**	**0.667**	**0.697**	**0.697**	**0.728**	**0.726**	**0.759**	**0.756**
Trento_01_20	**0.043**	**0.043**	**0.044**	**0.044**	**0.039**	**0.038**	**0.036**	**0.034**
Trento_02_20	**0.214**	**0.214**	**0.235**	**0.234**	**0.254**	**0.252**	**0.271**	**0.268**

Trento_03_20	**0.545**	**0.545**	**0.555**	**0.555**	**0.566**	**0.565**	**0.575**	**0.575**
Umbria_01_20	**0.300**	**0.300**	**0.393**	**0.384**	**0.488**	**0.468**	**0.580**	**0.550**
Umbria_02_20	**0.984**	**0.984**	**1.053**	**1.051**	**1.110**	**1.106**	**1.152**	**1.147**
Umbria_03_20	**0.372**	**0.372**	**0.264**	**0.203**	**0.350**	**0.294**	**0.562**	**0.457**
Vale d_Aosta_01_20	**0.197**	**0.197**	**0.276**	**0.267**	**0.369**	**0.347**	**0.476**	**0.436**
Vale d_Aosta_02_20	**0.701**	**0.701**	**0.779**	**0.776**	**0.861**	**0.852**	**0.947**	**0.931**
Vale d_Aosta_03_20	**1.757**	**1.757**	**1.783**	**1.782**	**1.803**	**1.802**	**1.818**	**1.817**
Veneto_01_20	**0.092**	**0.092**	**0.126**	**0.122**	**0.165**	**0.156**	**0.209**	**0.193**
Veneto_02_20	**0.372**	**0.372**	**0.421**	**0.418**	**0.474**	**0.468**	**0.534**	**0.521**
Veneto_03_20	**1.369**	**1.369**	**1.434**	**1.432**	**1.498**	**1.494**	**1.561**	**1.555**