European Commission

JRC TECHNICAL REPORT

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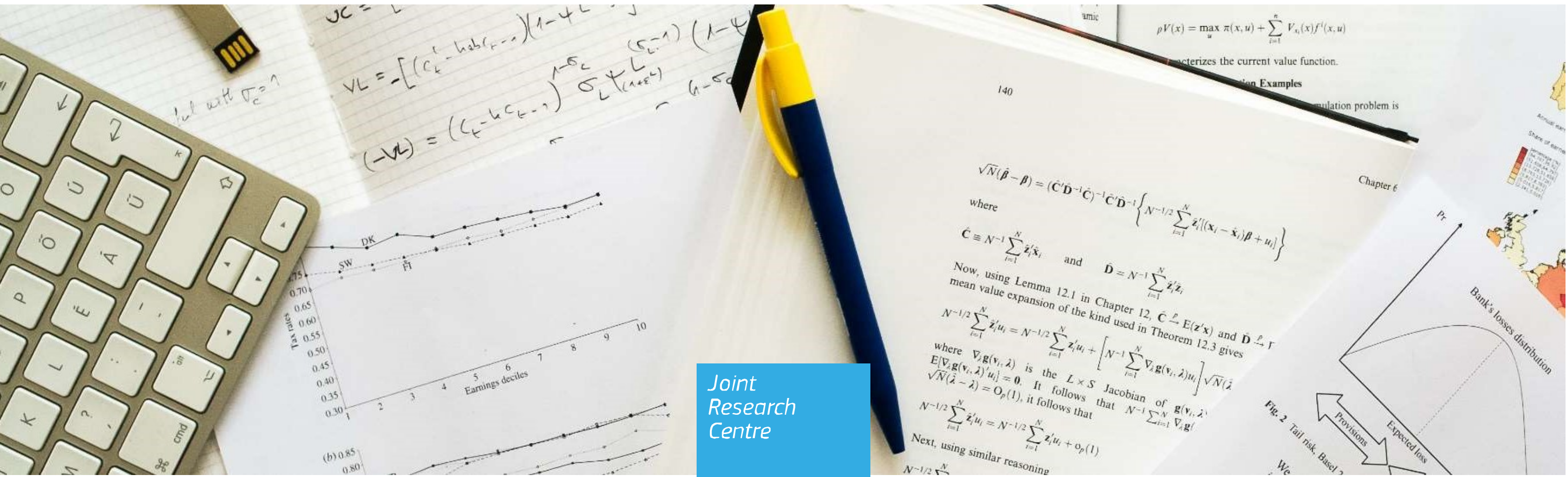
2022

JRC Working Papers in Economics and Finance, 2022/6



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EU Science Hub
https://ec.europa.eu/jrc

JRC129073

Ispra: European Commission, 2022

How to cite this report: Barbaglia L., Frattarolo L., Onorante L., Pericoli F. M., Ratto M. and Tiozzo Pezzoli L., *Testing big data in a big crisis: Nowcasting under COVID-19*, European Commission, Ispra, 2022, JRC129073

Testing big data in a big crisis: Nowcasting under COVID-19

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Abstract

During the COVID-19 pandemic, economists have struggled to obtain reliable economic predictions, with standard models becoming outdated and their forecasting performance deteriorating rapidly. This paper presents two novelties that could be adopted by forecasting institutions in unconventional times. The first innovation is the construction of an extensive data set for macroeconomic forecasting in Europe. We collect more than a thousand time series from conventional and unconventional sources, complementing traditional macroeconomic variables with timely big data indicators and assessing their added value at nowcasting. The second novelty consists of a methodology to merge an enormous amount of non-encompassing data with a large battery of classical and more sophisticated forecasting methods in a seamlessly dynamic Bayesian framework. Specifically, we introduce an innovative "selection prior" that is used not as a way to influence model outcomes, but as a selecting device among competing models. By applying this methodology to the COVID-19 crisis, we show which variables are good predictors for nowcasting Gross Domestic Product and draw lessons for dealing with possible future crises.

Keywords: Bayesian Model Averaging, Big Data, COVID-19 Pandemic, Nowcasting
JEL: C11, C30, E3, E37

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Executive Summary

This paper assesses the economic impact of the COVID-19 pandemic in real time by closely monitoring Gross Domestic Product (GDP) developments for the four largest economies in the Euro Area, namely Germany, Italy, Spain and France. Economic forecasting to design timely policy actions is a demanding task in the wake of the COVID-19 crisis at least for two main reasons. First, standard linear models typically struggle to capture the unexpected large slowdown in economic activity. Second, traditional macroeconomic data are available only at monthly or quarterly frequencies and released with delay. This work joins high-frequency data and a range of state-of-the-art forecasting techniques, including non-linear and "Big Data" models in order to face these major challenges. The novelties are along two main directions. First, we construct a big data set composed by traditional and alternative indicators to forecast GDP in the wake of the pandemic. We complement series that already proved to be an useful proxy of economic developments (such as electricity figures, text-based sentiment indicators or Google trends) with series that have not been tested, such as AirB&B review figures, air cargo and air quality statistics, measures of media attention and sentiment extracted from the Global Database of Events and Tone (GDELT) database, mobility indicators based on mobile phone data and aviation figures. Summing to more than a thousand variables, this makes our data set one of the biggest macroeconomic data set to date. The second novelty is a new methodology to merge an enormous amount of data with a large battery of classical econometric models with some machine learning models. Results from the empirical analysis highlight the added-value of the proposed forecasting strategy both at point and density forecasting during unstable times. Big data variables appear to be particularly important at nowcasting GDP in the second and third quarters of 2020 and in the first quarter of 2021.

Our main conclusions are the following. First, the COVID-19 period emphasizes to an extreme point two aspects that forecasters have known for a long time: no single model should be trusted, and models need to be adapted and changed over time. A two-step process based on developing different models and using model averaging proved to be the key success for this real-time nowcasting exercise in our institution. Second, in periods of abrupt change, it is crucial to enlarge, update and adapt the information set as much as possible. Timely big data signals reveal to be decisive during the pandemic but additional information sources are needed to filter out any noise component. In our case, information about lockdown policies in the form of a prior was crucial to increase the signal-to-noise ratio of the big data. However, our experience shows also that far from the pandemic outbreak, traditional data become more relevant and already includes the response to pandemic shocks. Looking ahead, the solution to ignore the outliers as in Lenza and Primiceri (2022) becomes increasingly realistic. Finally, uncertainty is a key component of the nowcast and should always be communicated. Our results show that the forecasts performed particularly well in terms of densities. This is due both to the improvement in mean given by the big data and to the correct evaluation of the (abnormally high) uncertainty surrounding the nowcasts.

1. Introduction

During the COVID-19 pandemic, traditional forecasting models became outdated, and their performance rapidly deteriorated. Several factors undermined their functioning. First, the COVID-19 crisis itself represented an unexpected and unprecedented shock to the world economy, and no past observations could provide a relevant signal about its potential economic impact. Second, social distancing measures imposed by governments to contain the spread of the pandemic affected both the supply and demand sides of the economy, reduced disposable income and consumption, ultimately increasing unemployment: the incertitude around government restrictions and policy support made it very difficult to assess their impact on national economies (see Ferrara and Sheng, 2022 and references therein).

Despite these challenges, policymakers need short-term forecasts and nowcasts of the current state of the economy to design timely policy actions and evaluate their effectiveness in contrasting the pandemic's adverse consequences and preserving societal well-being (Ferrara et al., 2022). Although being important priorities in any policy agenda, readily-available predictions are very difficult to obtain, this task being even more challenging in a period of global distress. Sharing the innovative tools and expertise developed in this experience could help other policymakers assess the economy's real-time monitoring, providing them with a more informed and up-to-date starting point for forecast and scenario analysis.

This paper presents two major novelties that could be adopted by forecasting institutions in unconventional times. The first innovation consists in the production of a new macroeconomic data set able to consistently enlarge the standard information set at policymakers' disposal. Many economic variables produced by statistical agencies and used by forecasters are available only at monthly (e.g., industrial production) or quarterly frequencies (e.g., national account variables, such as Gross Domestic Product), usually released with a substantial delay and subject to successive revisions. Although such macroeconomic series contain relevant and accurate information about the state of the economy, their poor timeliness might prevent them to capture unexpected shocks during highly uncertain times. Recent studies have provided evidence of the usefulness of fast-moving measurements extracted from big data sources to complement the information of classical economic variables (see Buono et al., 2017 for a review). For example, alternative indicators, like electricity consumption (see Blonz and Williams, 2020), tone and polarity extracted from text (Thorsrud, 2020; Algaba et al., 2021; Ashwin et al., 2021; Barbaglia et al., 2022), traffic and road tolls (Askitas and Zimmermann, 2013), Google data (Choi and Varian, 2012; Ferrara and Simoni, 2022; Aaronson et al., 2022) or mobility reports (Sampi and Jooste, 2020), have proved to be useful to track economic activity in real-time. Other studies (see for instance, Lewis et al., 2020; Eraslan and Götz, 2021; Woloszko, 2020), instead, merge some of the above alternative sources in few factors aimed to represent the real-time reactions of the economic agents to unanticipated shocks.

In this paper, we assess the usefulness of traditional and alternative indicators to nowcast Gross Domestic Product (GDP) in the wake of the pandemic. We complement a large amount of conventional monthly macro series (fat data) with a set of timely high-frequency alternative indicators (big data). Among the big data variables, we include series that have already been proved to be a useful proxy of economic developments, such as electricity figures, text-based sentiment indicators or Google trends. Moreover, among the big data variables, we add series that have not been tested in an economic nowcasting exercise: these big data sources include

AirB&B review figures, air cargo and air quality statistics, measures of media attention and sentiment extracted from the Global Database of Events and Tone (GDELT) database of Leetaru and Schrodt (2013), mobility indicators based on mobile phone data of Santamaria et al. (2020) and aviation figures by Iacus et al. (2020). Summing to more than a thousand variables, this makes our data set one of the biggest macroeconomic data set to date.

In the special context of the pandemic, the selection of fast-moving indicators goes hand in hand with the use of modeling methodologies that account for both the quick changes in big data variables as well as the structural relations among standard macroeconomic time series. Recent studies have shown that relying only on one model could be dangerous since standard linear methodologies typically struggle to capture an abrupt change in economic activity (Goulet Coulombe et al., 2022; Huber et al., 2020), while more sophisticated econometric techniques might fail at accurately estimating the intensity of the recession (Carriero et al., 2020).

As a matter of fact, the second novelty of this work is a new methodology to merge an enormous amount of non-encompassing data with a large battery of classical econometric models - namely, autoregressive distributed lag models (ARDL), mixed-data sampling regressions (MIDAS), mixed-frequency Bayesian vector autoregression (VAR) and dynamic factors models (DFM) - with some machine learning (ML) forecasting models (such as random forest, extreme gradient boosting, stacked ensembles and neural networks) in a seamlessly dynamic Bayesian model averaging (BMA) framework. Specifically, we introduce an innovative selection prior that is used not as a way to influence model outcomes, but as a selecting device among competing models. Following Dietrich et al. (2022), we conduct an economist's survey in the second quarter of 2020 by asking experts about the effects of the lockdown measures on different economic activities. This allows us to set the Bayesian priors for model averaging consistently with the expected effects of governments' provisions implemented to stop the diffusion of COVID-19.

The advantage of using this policy information is twofold. It reduces the complexity of the nowcasting exercise by focusing only on the variables that are in line with the expected effects of policy measures. In addition, it permits to reduce the high level of complexity given the many different model specifications estimated. Model averaging allows us to produce the complete distribution of the nowcast, thus emphasizing the uncertainty and risk associated. The set of models and the database were dynamically expanded, making this project a particularly ground-breaking venture that Bayesian model averaging techniques could handle with a good degree of flexibility.

The empirical nowcasting assessment of GDP is performed for the four major economies in Europe, namely France, Germany, Spain and Italy, and spans an out-of-sample period going from the last quarter of 2011 to the second quarter of 2021. To separately assess our model during the COVID-19 crisis, in our nowcasting exercise we first consider data until the last quarter of 2019 and then we include pandemic observations by extending our sample till the second quarter of 2021. The results highlight the added-value of the proposed forecasting strategy both at point and density forecasting during unstable times. Big data variables appear to be particularly important at nowcasting GDP in the second and third quarters of 2020 and in the first quarter of 2021. Despite their relative minor importance in 2021, a consistent subset of big data variables is still selected among the most relevant regressors, indicating their usefulness at nowcasting.

The remainder of the paper is structured as follows. Section 2 provides an overview of nowcasting experiences during the pandemic. Section 3 describes the alternative big data used as explanatory variables and the model set, whereas the Bayesian model averaging approach and the definition of the prior are presented in Section 4. Sections 5 and 6 report on the real-time nowcasting experience during the pandemic and on the nowcast performance, respectively. Finally, Section 7 concludes.

2. Nowcasting the pandemic: academia and public institutions

Various approaches have been proposed in the literature about nowcasting during the pandemic. By leveraging previous experiences in public institutions and recent academic research we filter out data sources and modeling techniques that possibly fit the exceptional pandemic period and, starting from that, we develop our approach. The works of Lenza and Primiceri (2022) and Schorfheide et al. (2020) show how to handle linear VAR models as forecasting tools in presence of extreme observations during the COVID-19 pandemic. Building on the linear settings of the two papers above, Huber et al. (2020) develop a non-linear mixed-frequency Bayesian VAR to produce monthly nowcasts of GDP using additive regression trees, and claim that they are particularly suited when forecasting extreme values, like the ones observed during the pandemic. Jardet and Meunier (2022) fit factor-augmented MIDAS to forecast world GDP using a big data set of 190 series at monthly and weekly frequencies, showing large nowcasting gain in crisis periods. The importance of weekly frequencies to timely track the US economic activity is also explored by Lewis et al. (2020), who build a Weekly Economic Index extracting the first principal component out of 10 series, including retail sales, unemployment indexes, raw steel production, electricity output and traffic data. This indicator is regularly updated and available on St. Louis Fed Research website[2]. Similarly, Eraslan and Götz (2021) extract a common factor from a set of unconventional high-frequency indicators, which also include the number of flights passengers and the pedestrian frequency in shopping districts and construct a weekly activity index for Germany, that is updated regularly and available on the Deutsche Bundesbank website[3]. Richardson et al. (2021) focus on a much larger data set of 600 predictors to nowcast GDP in New Zealand. They show that a selected set of machine learning algorithms can outperform classic univariate forecasting methods. At the global scale, Diaz and Quiros (2020) use factor models and a set of worldwide commodity prices to extract a daily global tracker of economic activity. This index has good forecasting properties for global PMI during both normal and crisis periods.

Although the literature on nowcasting under the COVID-19 pandemic includes also other relevant works (among other works about nowcasting, we refer to Babii et al., 2022; Proietti et al., 2021), we now focus on the nowcasting experience in large public institutions, namely the Organisation for Economic Co-operation and Development (OECD), the Federal Reserve Bank of New York (NY-FED) and the European Central Bank (ECB). The OECD Weekly

[2] Available at `https://fred.stlouisfed.org/series/WEI`.

[3] `https://www.bundesbank.de/en/statistics/economic-activity-and-prices/weekly-activity-index/weekly-activity-index-for-the-german-economy-833976`.

Tracker of GDP[4] provides a weekly nowcast of GDP growth rates, using machine learning and Google Trends data and covering OECD and G20 countries. The Tracker is one of several indicators that feed into the OECD forecast process. The forecast is computed in two steps. First, a neural network for predicting GDP growth is estimated based on Google Trends search intensities at a quarterly frequency. Second, the quarterly model's elasticities are applied to the weekly Google Trends series to yield the nowcast. A detailed description of the methodology can be found in Woloszko (2020). The model based on Google Trends outperforms in the out-of-sample analysis an auto-regressive model that uses lags of year-on-year GDP growth. The paper also uses interpretability tools based on the Shapley value to understand the importance of different categories of searches in the forecast.

The NY-FED publishes weekly updates of the US GDP estimates and other macroeconomic variables in its *Nowcasting Report*[5]. The modeling approach combines Kalman-filtering techniques with dynamic factor models, which allow to parsimoniously represent the dynamics of a macroeconomic big data set. We refer to Giannone et al. (2008) and Bok et al. (2018) for a complete presentation of the methods. The input of the model consists of a selected set of market-moving indicators related to the current state of the economy about construction, manufacturing, consumption, income, labor and trade. Such indicators are also observed by market participants and enter the model as "news": the weekly update considers all the data as they become available, thus replicating the real-time information flow and its impact on current economic conditions. In particular, their approach replicates the traditional forecasting process, going from monitoring data releases, to forming and revising expectations as data are observed. In Bok et al. (2018), the authors find highly significant out-performance of their nowcast with respect to the naive AR(1) model.

In a recent work released in the ECB Working Paper series, Cimadomo et al. (2021) propose a mixed-frequency Bayesian VAR model and claim that it matches the performance of the NY-FED nowcasting tool. This technique provides a more general structure than dynamic factors models and allows the study of structural interactions across variables. As a consequence, an institution can easily build a narrative about the policy implications of an economic outlook, for instance via the use of standard tools like impulse response functions. Moreover, Bayesian VAR models allow to properly account for the forecast uncertainty, by targeting specific prior distribution choices. As a case study, they focus on US data that include standard macroeconomic variables as well as the text-based economic policy uncertainty indicators by Baker et al. (2016). In an application to nowcasting US GDP in the first quarter of 2020 under the COVID-19 pandemic, the authors show that the density associated to the nowcast of the proposed model is able to capture the economic slowdown caused by the anti-contagion restrictions, while that is not the case for the NY-FED benchmark methodology.

In sum, our approach owes a lot to the literature both with respect to the modeling choice (e.g., the inclusion of non-linear models or the adoption of a Bayesian framework) and to the input data (e.g., relying a large data set with conventional and unconventional data): we hope that reporting our experience could help other researchers and practitioners.

[4] Available at `http://www.oecd.org/economy/weekly-tracker-of-gdp-growth/`.

[5] The *Nowcasting Report* is available at `https://www.newyorkfed.org/research/policy/nowcast.html`.

3. A real-time story: nowcasting an outlier

This section illustrates two important aspects of our work. First, we describe the extensive and heterogeneous data set that we use to capture the real-time reactions of economic agents. Then, we briefly present the forecasting models, highlighting the advantages and disadvantages of each of them.

3.1. The information set

During our journey in nowcasting in the wake of the pandemic, our information set grew organically. We started with a few traditional macroeconomic variables and all the alternative high-frequency data sources that we could recover. Our opinion was that an unprecedented systematic shock could not be forecasted using history but only with quickly adapting variables. Once the first official data incorporating the effect of the COVID-19 crisis became available, we also expanded the set of traditional macroeconomic indicators. The data set is composed of *fat data*, or large amounts of traditional data, and of *big data*, real-time organic information stemming as a direct sub-product of human activities. Their role in nowcasting is quite different. On the one hand, fat data are large amounts of traditional macroeconomic series. They are published by statistical offices, come with varying delays, and are important for nowcasting in normal times. On the other hand, big data are fast-moving and might provide an early signal of the economic agents' reaction to a shock. Nevertheless, big data are no panacea as they are often not a representative sample of the whole population, since they do not stem from correct statistical sampling procedures, but are the direct product of some specific human activities. Therefore, they may only cover the activities of a population with a bias.

One of the main difficulties in the use of big data, mainly due to their novelty, is that they represent almost uncharted territory when economic forecasting is considered. In particular, the literature offers little guidance in selecting relevant big data variables, some of them may provide additional predictive power toward the variable of interest, some others, although intuitively correlated, may be, in practice, useless, because too noisy. Consider, as an example, the level of CO2. Our intuition suggests a correlation with the level of economic activity, but there is little literature about whether it works in practice. For instance, should you consider a sampling station located far away from productive structures, its signal may be more informative about weather and wind conditions, representing noise in a production-related perspective. Decades of econometric works have, instead, explored the statistical relations across traditional macroeconomic series, and one can rely on past experience to select the most important variables to use in a model. A classical example is industrial production: it is a well-documented and widely used explanatory variable at monthly frequency for GDP. Overall, traditional macroeconomic variables can be very informative for nowcasting purposes, despite their poor timeliness.

On the other hand, alternative data can provide a timely indication of the reaction of economic agents to a shock, although their signal can potentially be very noisy and biased. In order to balance the informativeness of fat data and the timeliness of alternative indicators, we build a big data set that combine different data types: (i) traditional macroeconomic indicators, survey and financial data (*fat* data), and (ii) alternative data (*big* data). The first data type consists of monthly and quarterly survey-based indicators about business and

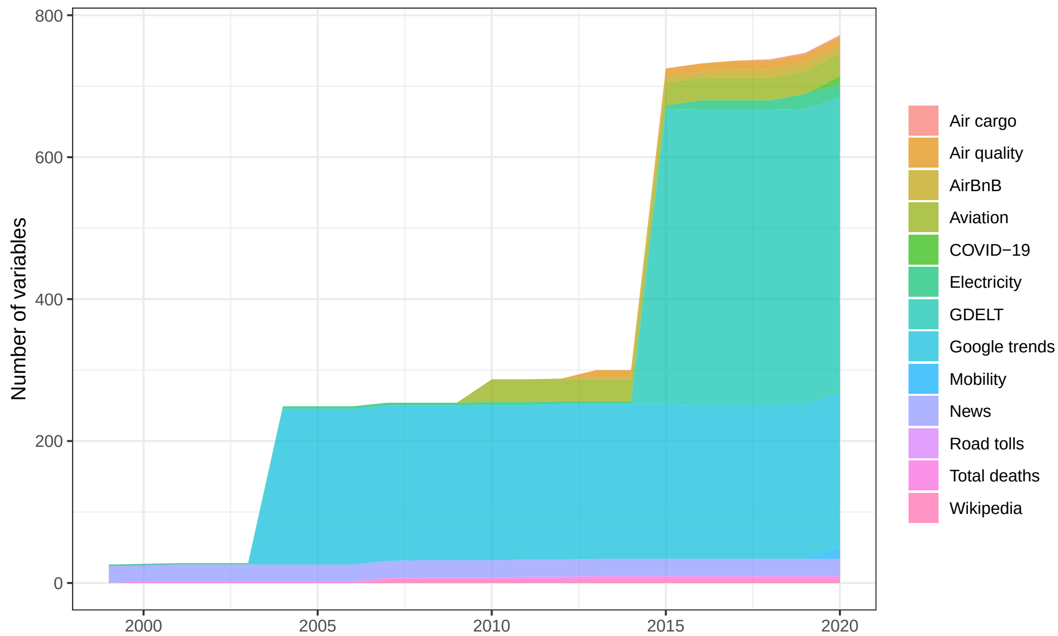

Figure 1: Number of big data variables available over time by variable group.

consumer sentiment, as well as official statistics and financial variables observed at daily frequency. Our selection includes and expands the financial and macroeconomic data set employed by Schumacher (2016). The second data type gathers a number of alternative data, that are, fast-moving variables about air quality, transport, energy production and consumption, internet searches, text-based sentiment indicators, as well as COVID-19 specific indicators. Such variables are not necessarily related to finance or to the current state of the economy, but they can provide a timely signal of the economic agents' reaction to the anti-contagion restrictions and their expectations about the future severity of the economic slowdown.

Focusing on alternative data, it is important to notice that the time span of their samples varies largely across variables. Figure 1 reports the number of time series available in each year of analysis by variable groups. A group of approximately 20 time series starts before the 2000s, including Wikipedia searches, total deaths, road tolls and news-based sentiment indicators (Barbaglia et al., 2021). Google trends represent almost 200 series which become available in 2004, together with electricity consumption and production statistics. The variables about the aviation sector, namely the number of passengers and average revenues of Iacus et al. (2020), and the air quality indicators become available in 2010 and 2013, respectively. In 2015, AirB&B review figures started alongside the hundreds of sentiment and media attention related measures extracted from the GDELT database (Consoli et al., 2021). Finally, in 2020 COVID-19 indicators entered the data set together with mobility indicators of Santamaria et al. (2020).

New data enter the model as they are available, thus reproducing the real-time information flow of vintages, expectations and revisions discussed in Bok et al. (2018). As of the outbreak of the pandemic, the data set has been updated weekly (Fridays, at 2.00 pm CET): in each update, we collect the latest available information for each series, starting from January 1995. Data are aggregated at monthly frequency by averaging. The final data set contains 1,134 series for the Euro Area as a whole and for the four largest European economies, namely France, Germany, Italy and Spain, making it, to the best of our knowledge, one of the biggest data set explored in the nowcasting literature. Appendix A and the tables within provide a detailed description of the data set and data transformation.

3.2. The model set

One model never fits all, and this is especially true during the COVID-19 crisis, when existing models seem to become quickly unreliable. In the tradition of forecasting under model uncertainty (Kapetanios et al., 2008), we use many models, including well-known econometric modeling strategies (ARDL, DFM or VAR), MIDAS, non-linear specifications such as ML models, to produce individual forecasts. We then combine their predictions in a second stage.

- ARDL: AutoRegressive Distributed Lag models. These are standard, unrestricted regressions where the dependent variable (GDP) is a function of its own past and of current and past values of an explanatory variable (x). We consider a high number of models, each featuring past values of GDP and one explanatory variable. We also consider transformations of the variables as additional regressors, therefore in different equations the same x variable may enter in levels, quarter-on-quarter or month-on-month growth rates, and in different lags (up to three months). Non-stationary specifications are dropped.

- DFM : The Dynamic Factor Model has proved to be a successful reduced-form econometric model both for nowcasting and forecasting purposes. This class of model is intensively employed by central banks and international organizations for monitoring the state of the business cycle, and computing short-term projections of macroeconomic variables such as growth and inflation. In this paper, we use the version of the model proposed by Giannone et al. (2008), which has been developed to nowcast quarterly series through indicators available at a higher frequency and subject to frequent revisions. The model is estimated in two stages. In the first stage, stationary monthly indicators are employed to estimate a monthly factor model via principal components, as in Stock and Watson (2002). In the second stage, the monthly factor is aggregated at the quarterly frequency, and is employed in a bridge equation to nowcast the quarterly series of interest. In our application, the principal components are extracted from a set of 20 indicators including the main aspects of the business cycle.

- MG-MIDAS: MIDAS estimation with big data using Modal Grids. MIDAS estimation handles regressors with lower frequency using temporal aggregation with a parametrized weight distribution (Ghysels et al., 2020). Once the aggregation is done, estimation is equivalent to OLS. The proposed method exploits this feature and, given the weight function, computes a grid of weights such that each set of weights has its mode on a different lag. Then aggregation is performed for each set of weights and each regressor, resulting in a number of new aggregated regressors equal to the number of original regressors multiplied by the number of weight sets. The selection of aggregated regressors is then performed using the generalized least squares screening (GLSS) proposed in Yousuf (2018). Values of parameters of the weight function originating the most significant aggregated regressors are stored and reused as initial values in a final maximum-likelihood estimation of the MIDAS regression. This methodology allows pre-selection among a big number of variables while maintaining contributions from a wide distribution of lags in the final estimation.

- MF-BVAR : Mixed-Frequency Bayesian Vector AutoRegression by Schorfheide and Song (2015). This approach allows to jointly model variables observed at quarterly frequencies (e.g., GDP) with monthly ones (e.g., unemployment). Similarly to Schorfheide et al. (2020), we adopt the standard setting for the Bayesian estimation of the model and select only a limited number of variables[6]. A major benefit of such a model is that it provides point and density forecasts, while jointly modeling multiple variables observed at mixed frequencies. As it is a linear multivariate model, it does not account for complex non-linear effects or interactions among variables.

- ML : Machine Learning combination of a deep Neural Network (NN), a Stacked Ensembles regression (SE), a Random Forest (RF) and an eXtreme Gradient Boosting (XGB) (we refer to Hastie et al., 2009 for an introduction to the first three techniques, while to Chen and Guestrin, 2016 for the XGB). The NN is a multi-layer network, based on a randomized five-fold cross-validation for parameter tuning and on a grid-search for the selection of the number and size of the hidden layers. The SE is a supervised algorithm that finds the optimal combination of a set of learners by "stacking". The RF is a "bagging" algorithm that generates a forest of classification trees, where each of these weak-learners is fitted on a random subset of rows and columns. On the other hand, the XGB is a "boosting" algorithm which fits the weak-learner on sequentially re-weighted versions of the data, including two penalties on a large number of leaves and on the leaf weight of the classification tree. Although the list of machine learning models is not exhaustive, the implemented models represent the most important machine learning techniques, ranging from boosting, bagging, penalized regression to neural networks. We feed the ML models with the full data set in real-time and with a one-quarter lag, and select the best model based on a squared loss: in the large majority of the cases, NN is the best performing model. We repeat the procedure on 100 bootstrap samples, and obtain a point forecast for the median and an associated density[7].

The breadth of our model set allows capturing various aspects of the economic dynamics that might play a key role in providing an accurate nowcast. Dynamic factor models represent a well-established nowcasting tool able to parsimoniously represent complex data structures. Linear mixed-frequency techniques model simultaneously monthly and quarterly frequency

[6] The input of the MF-BVAR are macroeconomic variables of interest (i.e., GDP, Unemployment rate and CPI), the business and consumer confidence indicators, the PMI activity indicators and a sentiment measure about the overall state of the economy.

[7] For further details on the hyper-parameters tuning, we refer to `http://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html`.

variables, account for their structural relations and provide a reliable long-term view of the future economic outlook (Schorfheide et al., 2020). Machine learning models are particularly suited to work with a large number of regressors and, most importantly, are able to promptly capture non-linear dynamics in the data (Richardson et al., 2021; Babii et al., 2022).

4. Bayesian model averaging

4.1. Forecasting with BMA

Forecasting with many regressors under high model uncertainty is a challenging task. First, the presence of more than a thousand regressors makes standard econometrics unfeasible due to the curse of dimensionality. Additionally, the practice of estimating and using a single specification ignores model uncertainty, leading to over-confident inference: for this reason, we opt to combine the information contained in different forecasts having non-nested models and different information sets. BMA provides a coherent mechanism to account for model uncertainty while allowing to estimate in the presence of many regressors.

BMA has been made popular in the economic literature by Sala-i Martin et al. (2004) and later used in various economic applications (e.g., Proietti and Giovannelli, 2021 rely on BMA to nowcast monthly GDP). It allows the researcher to be agnostic on the specification, estimate a large battery of models and average them based on their forecasting accuracy. The advantages of BMA include the possibility of using parsimonious models that yield more stable estimates because of the fewer degrees of freedom that are used in individual models. Also, BMA can help identify important regressors, making the results more informative and easier to interpret. Crucially, it accounts for model uncertainty, and can be used as a tool to select the best indicators.

In this paper, BMA is used to deal with several econometric issues, including the short data span for some of the big data, the very high number of potentially relevant models, and the high risk of misspecification due to the size and noisiness of the database. It is important to note that in our case, as it is common practice when institutions use multiple models for forecasting, the models to be merged are non-nested. This raises specific problems because Bayesian posterior odds comparison is inconsistent for selecting between non-nested models. Hong and Preston (2012) study the case of non-nested model averaging and show that the averaging weights are non-degenerate even in large samples, as long as the models are sufficiently close to each other and none of them is the correct one. While Bayesian posterior odds and the Bayesian Information Criterion (BIC) are consistent for selecting among nested models, they are not consistent for selecting among non-nested models. Following Hong and Preston (2012), we resort to the Non-nested Information Criterion (NIC), which, in large samples, selects the most parsimonious model even if the models are non-nested. We check for the robustness of the BMA by using both the BIC and the NIC: in both cases, we exclude those models for which the number of parameters cannot be determined (e.g., neural networks).

We join the high number of available models and compute BMA weights on the basis of predictive likelihood. Predictive likelihood has the advantage, being an out-of-sample evaluation, to be robust to different parametrization choices and degrees of freedom. To take advantage of the growing sample and allow the models to progressively adapt to the crisis, the weights $w_{i,t}$ on the BMA are updated in real-time on an expanding estimation window:

$$w_{i,t} = Pr(M_i|y^{1:t-1}, X^{1:t-1}) \propto \prod_{\tau=1}^{t} Pr\left(y^{\tau}|y^{1:\tau-1}, X^{1:\tau-1}, M_i\right) Pr\left(M_{it}\right), \tag{1}$$

where M_i are the set of candidate models, $y^{1:t-1}$ is the past of the endogenous variable, y^t the value observed at time t, $X^{1:t-1}$ the exogenous variables available up to time $t-1$, $Pr(M_{it})$ is the prior probability of model M_i (note that it can vary over time), $Pr(M_i|y, X)$ is the posterior probability of model M_i. The weights are normalized at every t to sum to one.

An alternative, widely used technique is Bayesian Model Selection (BMS), where all the weight is given only the best model at each point in time:

$$w'_{it} = I(\underset{i}{\text{argmax}}\ w_{it}). \tag{2}$$

The model priors, $Pr(M_{it})$, are typically assumed to be equal, or a decreasing function of model complexity when simple models are preferred. In our case, we use an equal prior for most of the sample, but in t = 2020 Q2 and t = 2020 Q3 we introduce our survey-based prior detailed in the next section. BMS results are usually reported along with BMA, as the approach performs comparatively well in turbulent periods. However, BMS does not beat consistently the benchmark, because the choice of different models at each point in time often introduces "model noise".

4.2. The selection prior

A distinctive feature of the process of nowcasting was the increasing, massive amount of models and data sets. Among the models, for example, some were by construction highly reactive to new information (e.g., MG-MIDAS), while others put a higher emphasis on continuity and on the covariances among variables (e.g., MF-BVAR). ML models belong to yet another category, as they emphasize non-linearities to an extreme degree, but they are difficult to interpret. To complicate matters further, each class of models uses different information, exploiting a subset of the data used. We remind that the database is not only very extensive, including hundreds of traditional macro and big data time series, but it includes hundreds of untested "big data" series: some of them may provide good trackers of economic developments during the pandemic, but most would simply add noise.

Before COVID-19, we would start Bayesian Model Averaging (BMA) using an equal weight prior and derive the final BMA weights on the basis of past performance, but 2020 was not a normal year. When we started nowcasting, exceptional circumstances and policies were in place. In order to distinguish models that captured these exceptional circumstances from those that could not, we needed to include in our prior a selection device. For the second quarter of 2020, we decided to resort to an economists' survey. We exploited our institutional environment, the independent assessment of economic activity and policy intervention available to us by the internal European Commission (EC) channels to shape our priors and skim the space of models. Our survey involved 40 economists. We did not ask for a forecast of GDP directly, because this would have been very difficult and subjective. Instead, we focused on the effect of the lockdown measures on different economic activities. The survey only included the following main question: "According to your opinion, and looking at the country/region where you live, what is the fraction of activity levels which is lost

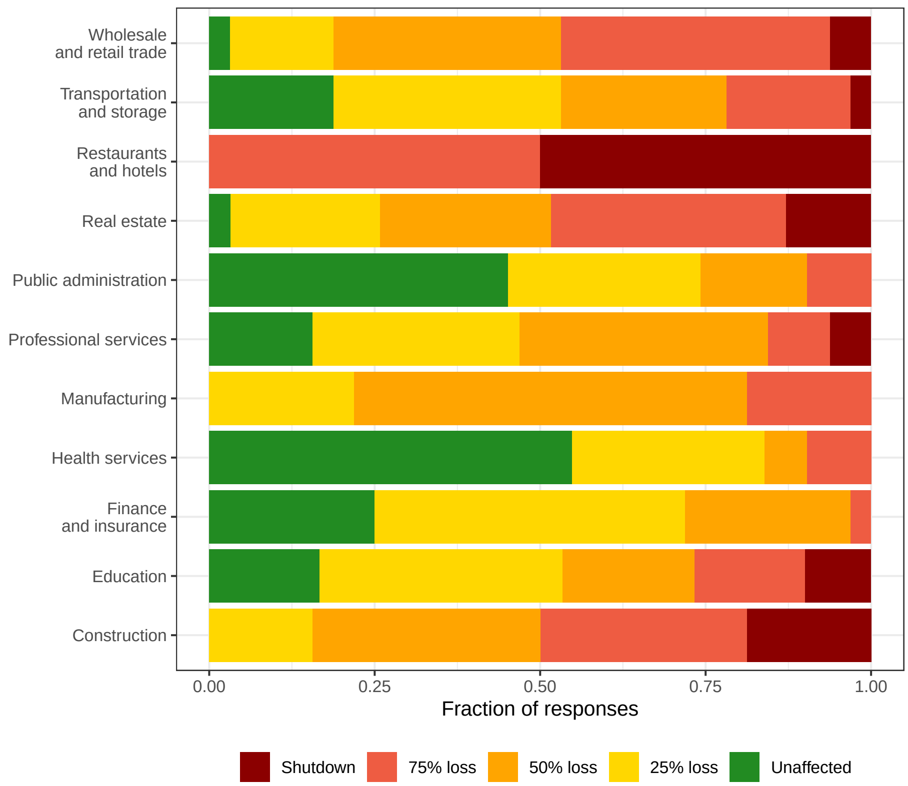

Figure 2: Survey of economists for 2020 Q2: answers to the question "According to your opinion, and looking at the country/region where you live, what is the fraction of activity levels which is lost due to lockdown, on a scale from 0 to 100, in these sectors of the economy?".

due to lockdown, on a scale from 0 to 100, in these sectors of the economy?". A list of NACE sectors followed, and for each sector the answer could be chosen between: (i) unaffected, (ii) 25% loss, (iii) 50% loss, (iv) 75% loss, (v) complete shutdown. Before leaving the survey, participants were asked about a self-assessment on how familiar they were with the economic situation and the country where they live, but these questions were not used in the analysis.

Figure 2 reports the results of the survey. Respondents agree homogeneously that restaurants and hotels would suffer most from the restriction measures imposed by governments, with half of them suggesting that this sector would go through a complete shutdown. Other activities that would be largely affected are wholesale and retail trade, real estate and construction, with more than half of the respondents indicating that the lockdown measures would cause at least a 75% loss. On the other hand, survey participants suggest that public administration, health services and financial activities would be unaffected by the pandemic restrictions. From these questions we evaluated the mean effect (common to all countries) of the lockdown as follows:

$$\mu_L = \frac{meanClosure * daysOfClosure}{90}, \tag{3}$$

where $meanClosure$ indicates the average closure of the economy resulting from the survey, aggregating the sectors according to their weight in GDP, $daysOfClosure$ is the number of

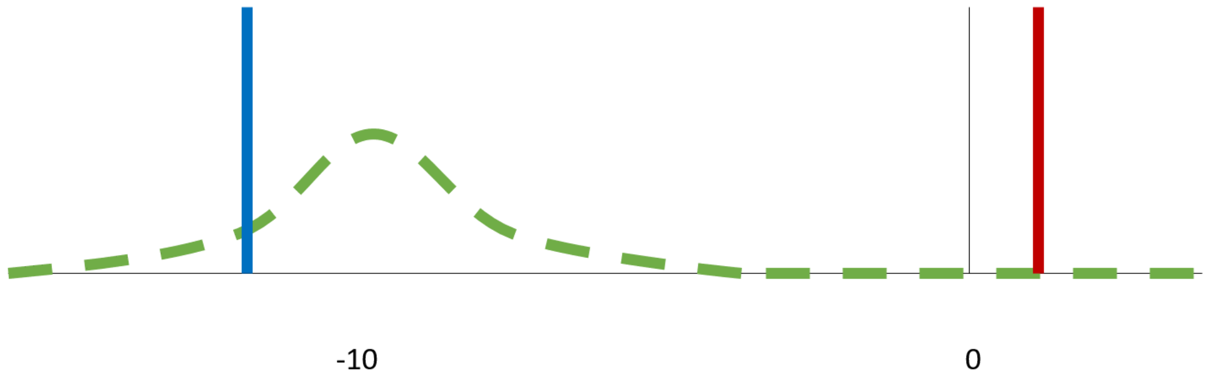

Figure 3: Example of the selection prior and two nowcasts.

days the lockdown was in place in the quarter (assumed to be of 90 days). The variance of the prior σ_L^2 is computed using the variability in single respondent assessment. The prior associated to each model forecasts M_{it} is obtained in the following equation:

$$Pr(M_{it}) \propto \left\{ \begin{array}{cc} \phi\left(\dfrac{M_{it} - \mu_L}{\sigma_L}\right) & t \in (2020\ Q2, 2020\ Q3) \\ \\ 1 & otherwise \end{array} \right\}, \tag{4}$$

where ϕ represents the standard normal density.

To make an example, Figure 3 shows two models a Red and a Blue one. The colored bars show their point forecast in 2020 Q2, when lockdown policies led to the deepest part of the recession. The Red model includes variables that are either backward-looking (lags) or big data that do not react to the COVID-19 crisis. The Blue model, instead, includes a leading indicator for GDP during COVID-19. The green distribution is the prior calculated from the survey. In this case, the survey prior will lower the prior weights of the Red model in the BMA, while the prior weights of the Blue model in the BMA will be higher. The final weights of the two models in the BMA will depend, of course, on the posteriors, and it cannot be excluded that a high likelihood leads the Red model to dominate over the Blue one despite a worse prior. The estimated effect of the policies is not added to the no-policy forecast, but serves the purpose of selecting those models that react realistically to the crisis.

It should be noted that the use of survey information to twist forecasts is not new. For instance, the "democratic prior" in Wright (2013) uses the predictions of survey respondents as priors to discipline nowcasting. Here, contrary to them we do not twist the prediction of the models, but we use the survey more as a selection device. Our "selection prior" for model averaging fulfills two distinct purposes. First, it provides information about the effects of the lockdown measures. Given that their precise impact is unknown in real-time, we do not add it to the nowcast in a dogmatic additive manner, but as a Bayesian prior. The use of a prior to input the effect of governments' provisions improves on a simple additive policy measure as it accounts for the uncertainty around the existing estimations. Second, the prior is added while averaging across all models; each model will nowcast without prior, but some models (for example those that turn out to be completely unresponsive) will be dropped in the model averaging step. By providing additional information about an important component of the nowcast, the prior helps downplaying those models and variables that do not have predictive power during the crisis. In particular, variables that are non-reactive to the COVID-19 crisis are downplayed in the model averaging.

To summarize, the weights for model averaging in the BMA were calculated by using an equal weight prior before the pandemic. When the COVID-19 crisis hit the European economy in 2020 Q2 and lockdown policies were put in place, our prior was not equal weight anymore but we relied on the survey as a prior for the evaluation of the predictive likelihood of the 2020 Q2 forecast. In 2020 Q3, distancing measures were abandoned, thus $daysOfClosure$ dropped to zero while the σ_L is the same as in 2020 Q2. In the successive quarters an equal weight prior was restored.

The use of the survey allowed us to exploit big data in a way that avoids hand-picking, while accounting for unprecedented policy responses adopted by governments. Among the advantages of this prior, we highlight its "Bayesian" nature (i.e, it is drawn from a completely independent source of information) and the fact that it does not impose an exact evaluation of the policy effects. While we see the survey as a valuable addition, care must be exercised in generalizing the approach to different situations. In general, there is probably scope in including surveys as selection priors[8], but the solution is to be found on a case-by-case basis.

In summary, the forecast is produced in two steps. First, at each time t we estimate the individual models and produce the associated forecasts. Second, we use prior with equal weights for each type of model, with the exception of the policy prior during the first lockdown, and update it with the (predictive) likelihood to compute the final weights of the BMA. In line with the Bayesian concept of inclusion probabilities, we also assess the importance of the variables by attributing the weight of each model to the variables that appear in it.

5. Real-time forecasting during pandemic

The idea of having a two-steps process for nowcasting, including several non-nested models and a model averaging step, came from theoretical and institutional considerations. Bayesian econometrics has shown that model averaging hedges against major mistakes, and often performs better than most models of the averaged pool, therefore this seemed to be a good approach in a time of increased uncertainty. On the institutional side, the many different, non-nested models available at the EC Joint Research Centre were natural candidates as starting points, and the BMA provided a natural framework for their joint use and assessment. This approach proved to be remarkably resilient and flexible over time.

In the first months of 2020 Q2, it had become clear that the existing models were mostly missing the upcoming downturn. This led to additional research in two directions. On the one hand, we increased the space and type of models used in our forecasting applications. On the other hand, we performed a large-scale search for possible real-time indicators, which immediately led to the use of organic big data information. The first stream of expansion led

[8] We refer to the use of information as selection prior for big data. The use of surveys as additional models or for tilting model-based forecasts is already widely used in the literature. For a recent contribution and literature review, see, for instance, the work of Banbura et al. (2021).

to the use of mixed-frequency models (MF-BVAR, MIDAS) and non-linear frameworks (NN and other ML techniques) aiming at capturing extreme events. The second stream leveraged the wide range of research interests and data production at the EC Joint Research Centre and the help of DG ECFIN. As a result of this collaboration, we collected more than 1,000 time series[9].

When nowcasting for the third quarter of 2020, the opposite problem arose. In the months between July and September 2020, the confinement measures were removed in most places, therefore any plausible model would need to include a bounce back of GDP. Among the models adopted, both with traditional and big data, there were two prominent behaviours. On the one hand, models with an important autoregressive component tended back to baseline, but at a reduced speed. On the other hand, other models extrapolating on the estimated non-linearities (i.e., mostly ML models) would suggest an even further deterioration of the economic situation. Besides, linear or semi-linear models with big data would go in all possible directions, depending on the information set. For example, models including information on flight transportation or tourism, which remained subdued, due to remaining constraints to international movements and consumer choices, would still indicate economic degradation. On the opposite side, models considering information from industry, a sector that rebounded quickly, would suggest a prompt recovery.

This gave us the opportunity to further streamline the models used, by imposing the additional prior on 2020 Q3 that the measures would not apply, thereby lowering the prior weight of models very far away from a level recovery. From 2020 Q4 onward, the equal-weight prior was used to further re-weight the models. The BMA structure seamlessly accommodated this evolution.

5.1. Best variables

The breadth of the information set plays a key role alongside the flexible modeling strategy. After the release of each quarterly GDP, the BMA reassesses the pool of models and produces posterior probabilities (so-called inclusion probabilities of the BMA) for each explanatory variable. In this section, we use these posterior probabilities to identify and report the most important regressors in each quarter[10].

Figure 4 shows the proportion of *fat* and *big* data, as detailed in Section 3, among the best variables selected by the BMA modeling strategy when summing the variable contribution across all months within a quarter. Our real-time forecasting exercise started in the second quarter of 2020, when the first nowcasts were produced: in this period, big data played a key role as they could provide timely early-warning signals of the economic deterioration that the anti-pandemic restrictions were imposing in the European economy. Interestingly, the relevance of big data varies largely across countries. For example, approximately 80% of the best variables in Germany and Italy belonged to the big data group, against the 60% in France and Spain. Starting from 2020 Q3, the proportion of big data dropped, ranging

[9] Appendix A provides a summary of the data used with additional detail about the pre-processing requested by each model.

[10] BMA obtains the posterior inclusion probability of a candidate regressor by summing the posterior model probabilities across those models that include the variable, thus providing an indication of which regressors are most important.

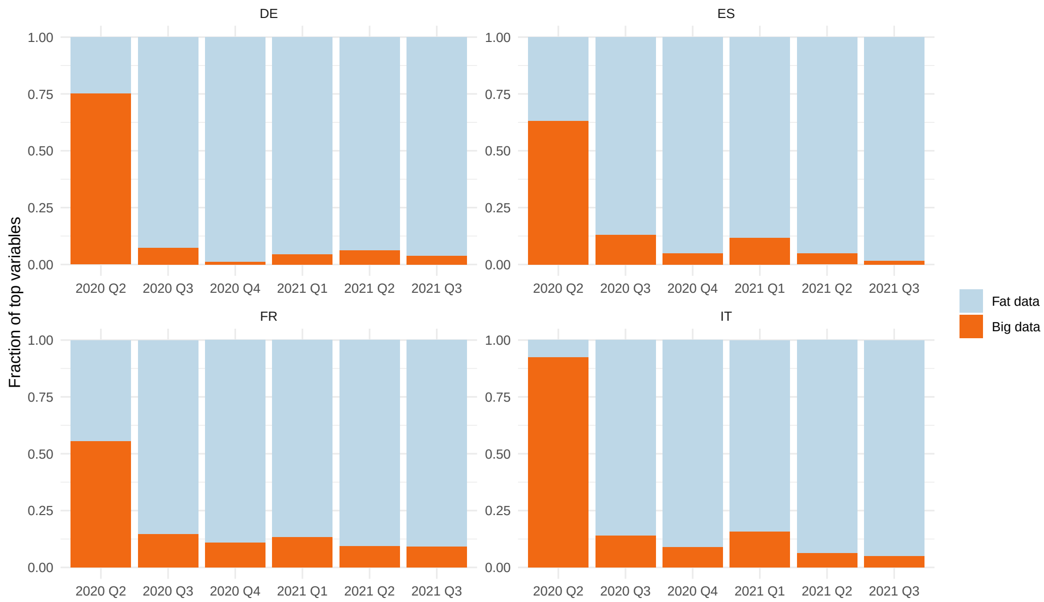

Figure 4: Best variables selected by BMA: fraction of *big* data and *fat* data.

between 10% and 15% in all countries. As a matter of fact, big data provided timely signals of the economic deterioration during the outbreak of the pandemic when severe restrictive measures were implemented to contain the spread of the virus. When the state of emergency reduced and lockdown policies progressively were lifted off, traditional macroeconomic and financial indicators largely replaced the alternative data sources. The drastic drop in the fraction of big data among best variables has also to be imputed to an important increase in the size of the information set: indeed, in the last quarter of 2020 we added approximately 60 new variables from Schumacher (2016), thus artificially increasing the proportion of fat data. It is worth noting that big data gained again relative importance in the first quarter of 2021, when the uncertainty induced by the vaccine campaigns efficacy and spread of new COVID-19 variants undermined again the European economic outlook. Despite the relatively minor importance of big data after 2020 Q2, a consistent subset of alternative indicators has been selected among the best variables.

Figure 5 reports the detailed proportion of best variables taken from the big data presented in Table A.4 in the online appendix. In the first quarter of the analysis, we observe that a number of fast-moving variables provide an early signal of the economic unexpected economic degradation caused by the pandemic. Electricity represents approximately 25% of the best variables in Germany, with consistent proportions also in Italy and Spain: the early days of the lockdown saw an abrupt change in the consumption and production patterns of households and firms, which caused an unprecedented reduction of any economic activity. Air quality indicators report a slowdown in the industrial and transportation sectors through a reduction in the level of pollution and are selected in Germany, while AirB&B occupation figures are picked out in Germany, Spain and Italy, representing the limited travel possibilities. The GDELT indicators that measure media attention and sentiment provide a very useful signal for Italy, where they represent approximately three quarters of the best

Figure 5: Best variables selected by BMA: focus on *big* data.

variables. Starting from the third quarter of 2020 the proportion of big data stabilizes and some variables seem to be consistently selected. Aviation figures from Iacus et al. (2020) are present in all successive quarters in Germany and France. The text-based sentiment indicators about the current state of economic activity by Barbaglia et al. (2021) are selected in France and Spain, while Google trends and air cargo figures are among the best variables in France, Spain and Italy.

Taking a deeper look at the big data variables that have the most important contribution to GDP nowcasting during the pandemic, we can observe some common patterns. First, the variables that are selected among the best ones are timely, meaning that they are published with no delay and provide a swift signal of the unexpected shock caused by the pandemic. They are not necessarily high-frequency, as among the best variables we find daily (e.g., electricity or news indicators), weekly (e.g., air-cargo) as well as monthly (e.g., Google trends or aviation) frequencies: this suggests that the frequency of publication is not a key feature, as long as the variables are available with no delay and provide a clear signal. Second, the variables need to have a long-enough time series. For instance, no indicator of social mobility or about the COVID-19 official statistics in terms of confirmed cases, deaths and recovery is selected among the best variables: even though they provided a timely and high-frequency signal of the pandemic development, their time series length is too short to bring additional information to the forecasting models. Third, if we look at the big data indicators about news and media coverage in our sample (i.e., GDELT, Google trends and news), we observe that certain topics are more prominent than others. Among the Google trends that were selected as the best variables, there is a clear prevalence of job-related topics: for instance, internet searches about unemployment, social security or job-search (e.g., "curriculum vitae" or "motivation letter") appear to be among the best variables in all countries. The importance of job-related topics is also confirmed when looking at which GDELT indicators are selected, where the media attention on labor and macroeconomic issues seem a relevant predictor for GDP. As for the text-based indicators from news, the most important indicator is the one collecting a general sentiment about the state of the economy, while other indicators about inflation, financial markets or industrial production are not selected.

While the results in terms of the most important predictors are inherently linked to the specific economic conditions imposed by the pandemic, we can generalize a few insights about nowcasting with big data that might be useful in future crisis. First, having access to a large number of regressors is a very relevant feature, as no single indicator proves to be the best regressor across countries and quarters. Then, the variables need to have a long-enough time series such to be included in the forecasting models. Finally, it is important to include fast-moving big data variables that provide information about areas of the economic activity linked to official statistics (e.g., media attention about unemployment), since their timely signal can anticipate the future outcome of the official figure that will be published with a delay.

6. Out-of-sample nowcast assessment

This section provides an out-of-sample assessment of the nowcasting performance of the proposed BMA model for the four countries in the analysis. We produce GDP monthly out-of-sample nowcasts from the last quarter of 2011 using an expanding window setting, which we prefer over a rolling setup given the short time length of the quarterly dependent variable. To separately assess our model during the COVID-19 crisis, we first run our nowcasting exercise considering data until the last quarter of 2019 and then we include pandemic observations by extending our sample until the second quarter of 2021. The nowcasts of the proposed model are assessed against two benchmarks, namely an AutoRegressive (AR) process of order 1 and a random walk (RW). Notice that for each quarter, we report the nowcast performance of the BMA at the end of each month included in the quarter. On the other hand, for the RW and AR(1) we obtain one unique nowcast for each quarter. We evaluate the model performance both in the terms of point accuracy and density nowcast[11].

6.1. Point nowcasting

We assess the point accuracy of the BMA model in terms of mean absolute forecast error (MAFE)[12]. Being y_t the GDP actual values at time t and $\hat{y}_t^h$ the out-of-sample nowcasted GDP values for the proposed model at horizon h with $1 \leq h \leq 3$, we define $\epsilon_t^h = \hat{y}_t^h - y_t$ the out-of-sample nowcast errors. Notice that h refers to 3 different sets of nowcasts. More precisely, the first set refers to the nowcast that is made in the first month of the quarter, that is January, April, July and October. The second set considers the nowcast that is made in the second month of the quarter, that is February, May, August and November. The third

[11] For the easiness of exposition, we do not report single model performances. Indeed, this evaluation is already incorporated in the second step of the BMA approach. We report the evolution of the predictive likelihood attached to each model in the out-of-sample period in Appendix B.

[12] We check for the robustness of the results to the choice of the performance metric by looking also at the root mean squared forecast error and the mean absolute percentage error, obtaining similar conclusions.

set considers the nowcast that is made in the third month of the quarter, that is March, June, September and December. Our MAFE metric is as follows:

$$MAFE_h = \frac{1}{T^*} \sum_{t=1}^{T^*} |\epsilon_t^h|, \tag{5}$$

where T^* is the total number of nowcasts produced, namely 33 nowcasts when we consider the out-of-sample period going from 2011 Q4 to 2019 Q4 and 39 nowcasts when we include the pandemic observations till 2021 Q2.

We report the results relative to the MAFE of the RW: a value smaller than unity, indicates a better performance than the benchmark. Notice that results are shown across different horizons to analyse the performance of the proposed model relative to the RW one as we approach the release date. We have also calculated the corrected version of the Diebold and Mariano (1995) test proposed by Harvey et al. (1997) to check whether the performance of the BMA model is significantly better than the RW benchmark one. The null hypothesis is that the two models have equal predictive accuracy, while the alternative one is that the BMA model has higher predictive accuracy than the benchmark[13].

The upper part of Table 1 reports the median point nowcast relative to the RW for the AR(1) and BMA models in the three nested months when excluding the COVID-19 crisis period from the time sample. In all countries, the BMA outperforms the RW benchmark as well as the AR(1). As expected, the nowcast performance of the BMA improves as time passes. Its relative MAFE decreases over the months within each quarter correctly representing the information flow (Bok et al., 2018): the closer you get to the end of the quarter, the easier it is to make a nowcast. The performance gains obtained by BMA are always visible if you consider the nowcast in the second and third months of the quarter, where we observe relative gains of approximately four times than the benchmark. In Germany, the BMA nowcasts are significantly more accurate than the RW ones in all three months in the quarter, while in France and Italy only the second and third months are to be preferred over the benchmark. On the other hand, in Spain we observe no statistically significant difference among the nowcasts.

If we include the COVID-19 crisis in the time sample, the results confirm the figures discussed above. The lower part of Table 1 reports the point nowcast performance considering the expanding window until the end of 2021. In all countries, except for France, the relative gains over the benchmark become greater than in the pre-COVID-19 period. In particular, the German BMA nowcasts are significantly different than the RW ones at 5% significance in all three months within the quarter. In the remaining countries, the significance is limited to the second and third months, and it is at the 10% confidence level.

What is the added-value of big data relative to fat data? We consider a BMA model that contains only fat data as a benchmark to be compared with the proposed BMA model containing both big and fat data. In Figure 6 we plot the difference in Cumulative Sum of Absolute Errors (CSAE) between these two models. Positive values indicate that the model with big and fat data performs better than the benchmark model with only fat data

[13]Notice that our out-of-sample exercise is performed in pseudo-real time and we use the last available revised GDP data as July 25^{th} 2022.

Table 1: Out-of-sample point forecast models evaluation in terms of MAFE relative to a random walk model. We also show the corrected version of Diebold and Mariano (1995) test statistics proposed by Harvey et al. (1997) for equal predictive accuracy (under absolute loss function). Specifically, ***, ** and * denote a Diebold-Mariano significance at 1, 5 and 10 percent respectively. Evaluation period from 2011 Q4 to 2019 Q4 (top) and 2011 Q4 to 2021 Q4 (bottom).

	France	**Germany**	**Italy**	**Spain**
Pre-COVID-19				
AR(1)	0.87***	0.70***	1.00	1.00
BMA - 1^{st} month	0.84	0.72***	1.29	1.67
BMA - 2^{nd} month	0.29***	0.19***	0.56**	0.61
BMA - 3^{rd} month	0.29***	0.14***	0.48***	0.56
COVID-19 Included				
AR(1)	0.99	0.73**	0.89	1.07
BMA - 1^{st} month	0.44	0.54**	0.36	0.36
BMA - 2^{nd} month	0.17*	0.20***	0.26*	0.19*
BMA - 3^{rd} month	0.10*	0.18***	0.34*	0.19*

*Notes: *** 1%, ** 5%, * 10% significance.*

(Goyal and Welch, 2003). Until 2019, the proposed model consistently performs better than the benchmark and it accumulates a gain of approximately 10-15 percentage points in all countries. With the advent of the COVID-19 pandemic, the relative gains of big data increase swiftly, with an upward spike in CSAE across all countries. In Spain and France, the added-value of big data is very pronounced and grows monotonically across all quarters of 2020, while it stabilizes in 2021. On the other hand, in Germany, and to a lesser extent also in Italy, the BMA model with big data seems to provide an added-value only in the first two quarters of 2020 while its performance deteriorates in the remaining quarters of that year. In 2021, big data brings back their relevance and revert the negative trend of the later part of the previous year. Overall, the evidence in Figure 6 highlights the added-value of big data relative to fat data across the whole out-of-sample period (i.e., the proposed model attains a lower cumulative of absolute errors than the benchmark at the end of the time sample), with big data delivering the most pronounced gains in the first months of the pandemic[14].

6.2. Density nowcasting

We evaluate the entire nowcast distribution performance of our BMA model against a bootstrapped RW density by considering percentile scoring (see Hong et al., 2016 for more details)[15]. For each time period t and set of nowcasts h, we construct nowcast errors for all the percentiles of the nowcasting density, namely $\epsilon^h_{q_i,t} = \hat{y}^h_{q_i,t} - y^h_t$ where $\hat{y}^h_{q_i,t}$ is the GDP nowcast

[14] As robustness checks, we compare the forecast performance of the proposed method against two additional benchmarks, namely a BMA model without policy prior, thus assigning equal prior weights across models, and an equally-weighted average models' forecasts in the same spirit of Stock and Watson (2004). The proposed BMA performs significantly better than these additional benchmarks, thus confirming the added value of the policy prior. The detailed results are available upon request.

[15] We have done some robustness checks and used other measures for the density nowcast assessment such as the Continuous ranked probability score (CRPS) of Matheson and Winkler (1976). Results are similar to those reported in the paper and are available upon request.

Figure 6: Relative difference in Cumulative Sum of Absolute Errors of the proposed model with big and fat data with respect to the model with only fat data: if above zero, then the proposed model performs better. The vertical line corresponds to 2020 Q1.

at percentile q_i, with $i = 1, 2, ..., 99$. For each percentile we obtain a loss score by evaluating the associated nowcast error through the pinball loss function[16]. Scores are then averaged across all percentiles for all time periods to assess the full nowcast distribution. We report the density predictive score results relative to the ones of the RW: a value smaller than unity, indicates a better performance than the benchmark. We also generate bootstrapped densities for the AR(1) following the procedure of Thombs and Schucany (1990). As for the point nowcast evaluation, results are shown across different horizons to analyse the performance of the BMA model relative to the RW as we approach the release date.

Table 2 reports the assessment using the pinball loss score. Regardless of the period considered, the performance of the BMA model improves when we approach the release date. Thus, as noticed for the point nowcast assessment, the information flow is correctly represented. As it regards the pre-COVID-19 period, in all countries we observe some relative gains with respect to RW as well as the AR(1) with the only exception of Spain. These improvements are mostly related to the second and third months of the quarter while in the first month only the BMA model for Germany outperforms the benchmark but archives similar performance as an AR(1).

These enhancements become greater for all the countries and all months in the quarter when we include the pandemic period in our out-of-sample exercise. The BMA becomes definitively the better model when compared against the RW as well as the relative performance of the AR(1). Generally, the relative gains of our model with respect to a RW across countries and horizons are approximately two times greater than the ones obtained in normal times. We notice that, when including the COVID-19 crisis for France, the relative gains can reach around three times the ones that are obtained when the pandemic period is excluded

[16]We refer to Yu et al. (2018) for a presentation of the pinball loss function.

Table 2: Out-of-sample density forecast models evaluation in terms of pinball loss metrics relative to a random walk model. Evaluation period from 2011 Q4 to 2019 Q4 (top) and 2011 Q4 to 2021 Q4 (bottom).

	France	**Germany**	**Italy**	**Spain**
Pre-COVID-19				
AR(1)	1.00	0.79	1.02	1.00
BMA - 1^{st} month	1.00	0.79	1.07	1.88
BMA - 2^{nd} month	0.85	0.70	0.98	1.72
BMA - 3^{rd} month	0.85	0.67	0.93	1.68
COVID-19 Included				
AR(1)	1.08	0.77	0.95	1.07
BMA - 1^{st} month	0.63	0.65	0.52	0.57
BMA - 2^{nd} month	0.35	0.52	0.51	0.48
BMA - 3^{rd} month	0.30	0.50	0.53	0.48

from the analysis.

7. Conclusions

Economic forecasting under COVID-19 was a challenging task, due to the high incertitude on the development of the pandemic and to the need of providing accurate figures to policy-makers. While documenting the experience of nowcasting GDP during the COVID-19 pandemic at the European Commission Joint Research Centre, this paper proposes two major novelties. First, we study a novel data set of more than a thousand variables taken from traditional and big data sources. Second, we forecast GDP relying on a Bayesian model averaging (BMA) framework with an innovative "selection prior".

Our results show the importance of timely information brought by big data to forecast a fast-moving economic environment. Overall, the BMA aggregation of the forecasts from our heterogeneous pool of traditional and machine learning models outperforms the standard random walk and autoregressive benchmarks. Moreover, the extent of these improvements in forecast accuracy increases when we include the pandemic period in our exercise. More specifically, during the pre-COVID-19 period, when evaluating the whole nowcasting distribution, results favor the BMA in the second and third months of the quarter for the majority of countries in the analysis. The pandemic period inclusion extends the BMA advantage to all horizons and all countries. We report, in some cases, a threefold increase in performance compared to the accuracy in the pre-pandemic sample.

Our main conclusions are the following. First, the COVID-19 period emphasizes to an extreme point two aspects that forecasters have known for a long time: no single model should be trusted, and models need to be adapted and changed over time. A two-step process based on developing different models and using model averaging proved to be the key success for this real-time nowcasting exercise in our institution.

Second, in periods of abrupt change, it is crucial to enlarge, update and adapt the information set as much as possible. Timely big data signals reveal to be decisive during the pandemic but additional information sources are needed to filter out any noise component. In our case, information about lockdown policies in the form of a prior was crucial to increase the signal-to-noise ratio of the big data. However, our experience shows also that far from the pandemic outbreak, traditional data become more relevant and already includes the response to pandemic shocks. Looking ahead, the solution to ignore the outliers as in Lenza and Primiceri (2022) becomes increasingly realistic.

Finally, uncertainty is a key component of the nowcast and should always be communicated. Our results show that the forecasts performed particularly well in terms of densities. This is due both to the improvement in mean given by the big data and to the correct evaluation of the (abnormally high) uncertainty surrounding the nowcasts.

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Appendix A. Data description

This section provides additional details about the data set and detailed information on the transformation applied for each variable. We select data starting in January 1995 until the most recent release available. Our data set is updated with the most recently available information every week and the variables observed at weekly or daily frequencies are aggregated by taking the monthly averages. Most data are publicly available, few data series are confidential and were provided by internal sources of the European Commission.

Table A.3 reports the variables included as additional regressors in our models falling under the "fat" data category. We consider stock and volatility indexes to proxy the present state of financial markets. We crawl the complete DBnomics[17] data sets to extract, at monthly frequency, all financial and macro-economic variables related to the countries under analysis. Moreover, we include the complete list of variables described in Schumacher (2016).

Variable	Frequency	Start	Description
CDS	daily	2007-01	Credit Default Swaps at country and global level from Datastream `https://www.refinitiv.com/en/products/datastream-macroeconomic-analysis`
Confidence	monthly	1995-01	Sentiment indicators seasonally adjusted about construction, economic, industrial, retail, consumer and service confidence. Source Eurostat
DBnomics	daily	1995-01	Financial and macro-economic variables selected by crawling `https://db.nomics.world/`
Employment	quarterly	1995 Q1	Active people (from 15-64 years) seasonal adjusted, not calendar adjusted, hour worked and people seeking for a job. Source Eurostat `https://ec.europa.eu/eurostat`
PMI	monthly	1996-01	Purchasing Managers' Index indicators about composite output, business activity, output, orders and employment (source EC internal)
Schumacher	monthly	1995-01	Financial and macro-economic variables from Schumacher (2016)
Sotck	daily	2001-01	Stock market indexes from Bloomberg `www.bloomberg.com`
Volatility	daily	2000-01	Global market realized volatility from Bloomberg `www.bloomberg.com`

Table A.3: Independent variables: fat data.

Table A.4 describes all the regressors defined as "big" data, namely variables extracted from alternative sources that are non commonly used in economic forecasting (e.g., air quality, mobility and news indicators among others). This type of data has three main advantages: (i) they are commonly observed at a higher frequency (e.g., daily) than standard official

[17] DBnomics available at `https://db.nomics.world/`.

economic statistics, (ii) they are released in real-time, with short or no publication delay and no later revision, (iii) they may provide early warnings when a rapid deterioration of economic conditions occurs. However, the signal extracted from these alternative data sources is often noisy and its relevance for forecasting purposes is harder to evaluate. Furthermore, alternative data are available with separate starting dates, raising doubts on how to properly compare different models across time points.

The majority of the big data variables in Table A.4 are publicly available and collected from published sources: for instance, aviation figures are collected from Iacus et al. (2020), mobility information based on mobile phone data come from Santamaria et al. (2020) or text-based sentiment indicators are downloaded from Barbaglia et al. (2021). Among all the variables listed in Table A.4, the GDELT indicators and Google trends are the only big data that are a novel addition to the final data set. From GDELT we extract media attention, sentiment and emotion indicators belonging to five main topics: macroeconomics and structural policies, economic growth, social protection and labour, macroeconomic vulnerability and debt, and disease. The GDELT platform[18] collects real-time news stories worldwide and, by using "state of art" natural language processing techniques (see Leetaru and Schrodt, 2013), extracts themes according to popular domain expert topical taxonomies and retrieves sentiments and emotions from news. From this vast amount of data, we select only the narratives from newspapers belonging to the four countries of interest and focus on articles having at least two keywords related to each specified theme. We have used the World Bank Topical Taxonomy to understand the primary focus (topic) of each article and select the relevant narratives. From this subset of news, we construct three different sets of indicators. The first one captures media attention through the five topics mentioned above (news volume). For each country and for each topic, our measure is the count of the total number of stories focusing on each specific theme normalized by the overall number of stories published in a country. The second set of indicators provides the tonality measures of the selected news calculated using a generalist GDELT built-in dictionary and three dimensions of the Loughran and McDonald (2011) dictionary: positive, negative and uncertainty. We normalize these metrics by the overall number of stories published in a country and the number of news related to the topics of interest. The last set of indicators includes the emotional connotation of the selected narratives. We collect the word count of emotions belonging to two dictionaries, namely the Regressive Imagery dictionary of Martindale (1987) and the WordNet Affect of Strapparava and Valitutti (2004). From the first dictionary we consider only its anxiety dimension, while from the second one we select the following dimensions: anger, contempt, disgust, fear, happiness, sadness and surprise. We also retrieve the happiness score proposed by Dodds et al. (2014). All the emotional measures are normalized by the overall number of stories published in a country and the number of news that are associated with the topics of interest.

With respect to Google Trends, we download language-specific queries about automotive market, holidays, job market conditions and teleworking. For France, we look for the following keywords: "adecco, agence emploi, annulation assurance, assistance sociale,

[18]GDELT platform available at `https://www.gdeltproject.org/`.

assurance chômage, assurance voyage, auto1, autoscout, autoscout24, bon coin voiture, bureau emploi, cadremploi, chomage partiel, chomage technique, chomage, curriculum vitae, curriculum, cv, doccasion, glassdoor, indeed, indemnisation, job, jobijoba, keljob, la centrale, lettre de motivation, linkedin, manpower, mastercard assurance, mercedes benz, modèle de cv, monster, offre demploi, pole emploi, pole-emploi, poste vacant, récession, randstad, recession, recrut, resume, salon emploi, stepstone, télétravail, travail, unemployment, vacances annulation, visa assurance, voiture occasion". For Germany, we look for the following keywords: "aaa auto, adecco, arbeitsagentur, arbeitslos, arbeitslosengeld, arbeitslosenversicherung, arbeitslosigkeit, auto1, autobazar, autoscout, bewerbung, curriculum vitae, curriculum, glassdoor, hotelstornierung, indeed, job, jobbörse, jobs.de, jobware, jobworld, kurzarbeiter, kurzarbeitergeld, linkedin, manpower, mercedes benz, motivationsschreiben, randstad, recession, reiserücktrittsversicherung, reiseversicherung, resume, rezession, soziale unterstützung, stellenanzeigen, stepstone, telearbeit, unemployment, urlaubsstornierung, vita". For Italy, we look for the following keywords: "aaa auto, adecco, aiuti per disoccupati, annunci lavoro, aspi, assicurazione annullamento, auto usate, auto1, autoscout, autoscout24, bancalavoro, careerjet, cassa integrazione, cercalavoro, cliccalavoro, curriculum da compilare, curriculum vitae, curriculum, cv, disoccupati, disoccupazione, domanda di disoccupazione, domanda di lavoro, fiera del lavoro, gi group, glassdoor, indeed, indennità di disoccupazione, infojobs, inps disoccupazione, inps, job, lavori, lavoro subito.it, lavoro, lettera di presentazione, linkedin, manpower, mercedes benz, mini aspi, monster, naspi, offerta di lavoro, randstad, recession, recessione, resume, seconda mano, telelavoro, trabajo, ufficio di lavoro, unemployment". For Spain, we look for the following keywords: "aaa auto, adecco, aplicacion trabajo, asistencia social, auto1, autocasion, autoscout, carta de motivación, cotizacion, curriculum vitae, curriculum, cv, desempleo, desocupado, empleo, erte, feria de trabajo, gi group, glassdoor, indeed, infoempleo, infojobs, job, linkedin, manpower, mercedes benz, milanuncios empleo, modelos curriculum, monster, ofertas de empleo, oficina de trabajo, parado, parados, paro, plantilla curriculum, prestaciones, randstad, recesión, recession, resume, segunda mano, seguro cancelación, seguro de viaje, stepstone, subsidios, teletrabajo, teletrabajo, trabajo, unemployment, vita".

Model-specific transformations

In our application, we rely on BMA to produce the final forecasts based on the individual predictions provided by our set of models. Each of the underlying models requires specific treatment on the input and deals with the issues associated with imperfect data structures (e.g., times series with different start dates, missing values or "ragged edge" as in Wallis, 1986) in different ways. As each of the models deals with input data differently, we decided not to apply any transformation to the data set, except for the ones suggested in the original work. For instance, the text-based indicators by Barbaglia et al. (2021) are standardized to have mean zero and variance one. Here below we now provide detailed information on the transformation applied to the input data by each model.

For the ARDL unrestricted equations we adopt several transformations for each big data variable. We consider each transformation of a variable as an additional regressor, therefore in different equations the same variable may enter in levels, quarter-on quarter or month-on-month growth rates, and with different lags (up to three months). Non-stationary specifications are dropped.

Variable	Frequency	Start	Description
AirB&B	daily	2015-01	AirB&B number of reviews daily, last 14 days and one-day ahead forecast (source EC internal)
Air cargo	weekly	2018-01	Cargo flown in m^3 and tons (source EC internal)
Air quality	daily	2013-01	PM10, PM2.5, CO and NO2 indicators from the European Environment Agency
Aviation	monthly	2010-01	Number of passengers and average revenues from Iacus et al. (2020)
COVID-19	daily	2020-01	COVID-19 confirmed cases, deaths and recovered form John Hopkings repository `https://github.com/CSSEGISandData/COVID-19`
Electricity	daily	2016-01	Price and volume electricity consumption (corrected by weather conditions) and energy production (source EC internal)
GDELT	daily	2015-03	Sentiment indicators (tone, volume and emotions) about macroeconomy, economic growth, labour market and diseases as in Consoli et al. (2021)
Google trends	monthly	2004-01	Google searches concerning the automotive market, holidays, job market conditions and teleworking (in local language) from `https://trends.google.com`.
Mobility (phone)	daily	2020-01	Mobility indicators based on mobile phone data from Santamaria et al. (2020)
News	daily	1995-01	Sentiment indicators about the economy, financial sector, manufacturing, inflation and monetary policy from Barbaglia et al. (2021)
Road tolls	daily	2008-01	Truck Toll Mileage Index for Germany, Calendar Adjusted from `www.destatis.de`
Total deaths	weekly	2000-01	Total deaths by Eurostat
Wikipedia	daily	2007-01	Wikipedia page views from `https://wikimedia.org/api/`

Table A.4: Independent variables: big data.

The DFM picks up, for each country in the analysis, only 20 variables at monthly frequency. More precisely, the model contains: six text-based sentiment indicators by Barbaglia et al. (2021) related to the overall state of the economy, financial sector, industrial production, inflation and monopoly (these are daily variables that are aggregated monthly by averaging); six indicators produced by the Eurostat such as construction, consumer, industrial, retail and service confidence indicators and an economic sentiment indicator; five surveys from the European Commission which are the composite PMI output index, the construction PMI total activity index, manufacturing PMI new orders index, manufacturing PMI index, services PMI business activity index; two confidence indicators from OECD namely the consumers opinion surveys and the business tendency surveys (manufacturing). These variables enter in the model without any transformation since they are stationary by construction (see European Union, 2006 and the appendix of Giannone et al., 2009 for more details). For all the variables we consider a sample period which starts in 2000 and goes till the last monthly available observation. No missing values are allowed in the model estimation procedure.

The MG-MIDAS, thanks to the GLSS step, is able to use all the available monthly variables that have no missing observations. Variables are stationarized by differencing if an Augmented Dickey-Fuller test is accepted. This conservative procedure could result in overdifferentiation because we are not considering any correction for multiple testing (e.g., Bonferroni), but the model inference remains valid. The lags considered for the MIDAS weights are selected estimating different models for different set of lags and then selecting using Bayesian Information Criteria. Different variables could enter in the different lagged models according to their missing value structure. This takes also into consideration the ragged edge issue.

The MF-BVAR considers only a limited subset of the available variables, namely GDP, unemployment rate, CPI, the business and consumer confidence indicators, the PMI activity indicator and text-based sentiment measure about the overall state of the economy. Following Schorfheide and Song (2015), the variables enter the model in log levels, with the exception of the unemployment rate which is not log-transformed. The series that are available at weekly or daily frequency are monthly aggregated by averaging. In this way, variables that enter the MF-BVAR are either quarterly or monthly. We select the input variables such that no missing values are present at the begging of the sample. As it regards the presence of ragged edges, we fill the monthly series with missing data as in Ankargren and Jonéus (2021).

The ML models consider the full data set as input. The variables are aggregated at quarterly frequency by averaging and taken as percentage returns (e.g., the target variable GDP is log-transformed and taken in first difference). We expand the cross-section of the input data by adding a one-quarter lag observation for each variable. As it regards the presence of incomplete data structures, each ML model deals with missing values in a different way[19]. For instance, NN deals with missing entries by mean imputation, while RF and XGB consider missing values as separate categorical labels.

[19] We refer to `http://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html` for the detail on how each ML models deal with missing values.

Appendix B. Model predictive likelihood

Figure B.7 reports the predictive likelihood attached to each model listed in the main paper, namely autoregressive distributed lag models (ARDL), mixed-data sampling regressions (MIDAS), mixed-frequency Bayesian vector autoregression (MF-BVAR) and dynamic factors models (DFM), with some machine learning (ML) forecasting models. At each point in time, the predictive likelihood of each model is measured and reported (after normalization), so that a bar twice as big as another also reflects a predictive likelihood ratios of two among model types. The models' weights seems to be relatively stable before the pandemic, while the COVID-19 crisis imposes a different weighting scheme. On the one hand, in 2020 we observe higher weights attached to the ML and DFM models, which include big data variables as additional regressors and are able to more easily fit the non-linear shock imposed by the pandemic on the national economies. On the other hand, the weights attached to the MF-BVAR, MIDAS and the BMA equations are relatively smaller in 2020: while these models are dominant in normal times, their performance is drastically reduced with the pandemic breakthrough.

Figure B.7: Normalized predictive likelihood of each class of models (*ml*: Machine Learning, *bvar*: Mixed-Frequency Bayesian Vector AutoRegression, *midas*: Mixed Data Sampling, *dfm*: Dynamic Factor Model, *eq*: Bayesian Model Averaging unrestricted equations) at monthly frequency.

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