Nowcasting at the EC-JRC

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[1] The views expressed are purely those of the writer and may not in any circumstance be regarded as stating an official position of the European Commission.

Nowcasting at the EC JRC

Activities at European Commission Joint Research Centre:

- In 2018, group on "Big Data and Economic Forecasting"
- Under COVID-19: **weekly nowcasting** of QoQ GDP
  $\rightarrow$ *policy support*
- Nowcasting Methods and data documented in paper
  $\rightarrow$ *scientific contribution*
- **Public database** published at JRC Data Catalogue
  $\rightarrow$ *dissemination*

Which skills and tools?

Modelling: econometrics, statistics, ML...

Coding: R, Python, Matlab, Stata, Java ...

Data: cloud computing, SQL, no-SQL ...

Soft skill: teamwork, policy support ...

Talk outline

1. Nowcasting and big data
   - Testing Big Data in a Big Crisis: Nowcasting Under Covid-19 *International Journal of Forecasting* (Barbaglia et al., 2023b)

2. Sentiment analysis of news data
   - Forecasting with Economic News *Journal of Business & Economic Statistics* (Barbaglia et al., 2023a)
   - Forecasting GDP in Europe with textual data *Journal of Applied Econometrics* (Barbaglia et al., 2024)

Testing big data in a big crisis

Background

- The COVID-19 was an unexpected and unprecedented shock for the world economy
- Policymakers need nowcasts of the economy's state to design timely policy actions
- Traditional economic forecast is unable to produce a quick assessment
  - The COVID-19 crisis is a structural change in the models
  - Macro data come with a lag $\rightarrow$ effects of COVID-19 are not visible
- Joining nowcasting techniques and timely available "big data" could improve the impact assessment
  - Bayesian Model Averaging (BMA)

Paper's contribution

Main novelties:

1. Bayesian methodology to merge a vast amount of data, classical and sophisticated forecasting methods

   $\rightarrow$ innovative "selection" prior: economic survey

2. Collection of a large data set for macroeconomic forecasting in Europe

   $\rightarrow$ Traditional macro (fat) data

   $\rightarrow$ Alternative big data

3. Nowcasting exercice assessing the COVID-19 crisis

   $\rightarrow$ Valuable predictors and models

Data in the working paper

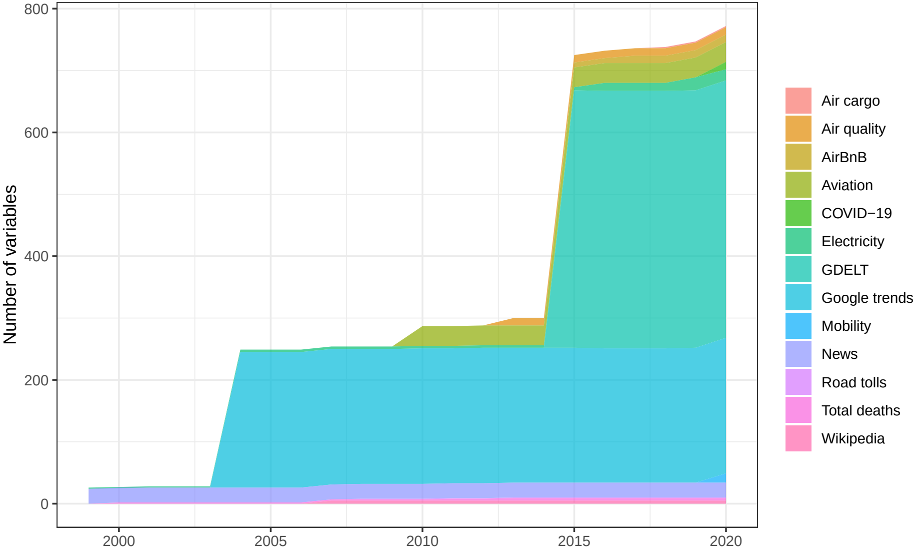
- **Monthly** averages from 1995 to now
- Germany, France, Italy and Spain ($>$1,000 time-series)
- **Fat Data**: Traditional macro-financial data and surveys
  - Official statistics, Surveys on business and consumers sentiments, Stock markets indexes and volatilities, ...

    $\rightarrow$ We expand the dataset of Schumacher (2016)
- **Big Data**
  - Google searches
  - AirB&B
  - Aviation passengers
  - Media attention sentiment
  - ...

Big Data variables in the working paper

- Google searches: automotive market, holidays, job application, teleworking, unemployment benefits
- Wikipedia page views
- Air quality indicators
- Aviation passengers and Air Cargo figures
- News sentiment indicators
- GDELT news attention-sentiment (Growth, Labour, Diseases)
- Electricity prices and Energy Production
- AirB&B figures
- Mobile phone mobility data and Google mobility data
- Truck-tolls data
- COVID-19 cases and deaths

Big Data evolution



Public Database

In **Summer 2022**, we published some big data series on the **JRC Data Catalogue** `https://data.jrc.ec.europa.eu/collection/id-00373`

Euro Area Macro-economic nowcasting

Acronym: EANow

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Description

Conventional and unconventional data for nowcasting and forecasting the European economy. Monthly time series by country for France, Germany, Italy and Spain. Each data set gathers country-specific traditional macro-economic series from statistical agencies, as well as big data alternative variables that can provide timely signals of economic developments. Examples of big data variables are text-based sentiment measures, indicators of media attention on economic topics or air quality indicators. For details on the application of the data set for economic nowcasting, check out the work by Barbaglia et al., "Testing Big Data in a Big Crisis: Nowcasting under COVID-19" (March 25, 2022), Available at SSRN: https://ssrn.com/abstract=4066479.

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Datasets (4)

Search datasets

Last updated

DATASET | Last updated: 13 Sep 2022

Spain nowcasting

Models and Priors

The **model set**:

- DFM: Dynamic Factor Model (Giannone et al., 2008)
- MG-MIDAS: MIDAS for big data Modal Grids (Ghysels et al., 2020)
- MF-BVAR: Mixed-Freq Bayesian VAR (Schorfheide and Song, 2015)
- ML: Machine Learning combination of Neural Network, Stacked Ensembles regression, Random Forest, eXtreme Gradient Boosting
- ADL: Unrestricted equations

Bayesian Model averaging:

- Priors provide information on the effect of lockdown policy measures
- Priors select away models and variables that do not have predictive power in the crisis $\rightarrow$ discipline nowcasting (Wright, 2013)

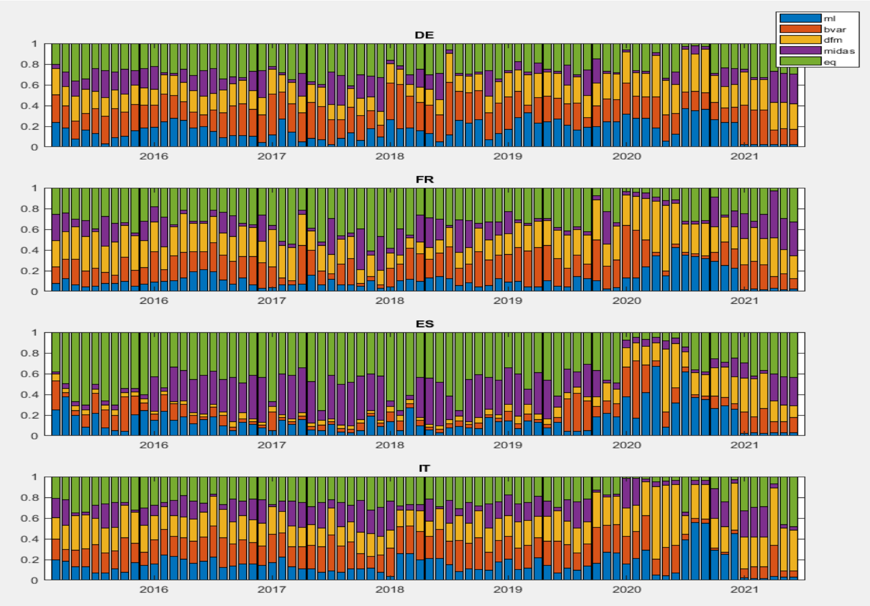
Forecasting Assessment

Table: Out-of-sample point forecast models evaluation in terms of MAFE relative to a random walk model.

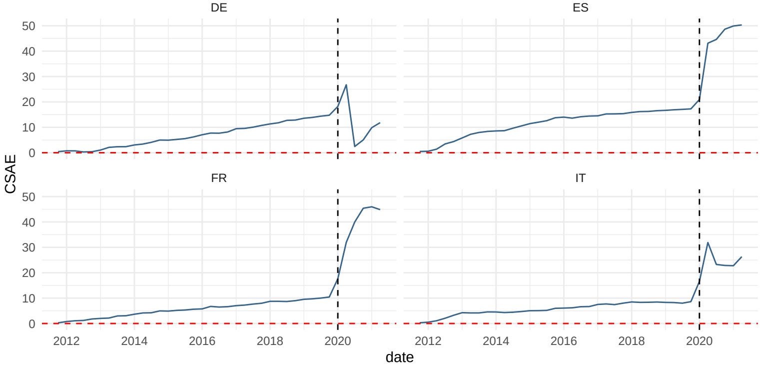
	France	**Germany**	**Italy**	**Spain**
Pre-COVID-19				
AR(1)	0.87^{***}	0.70^{***}	1.00	1.00
BMA - 1st month	0.86	0.72^{***}	1.28	1.67
BMA - 2nd month	0.19^{***}	0.19^{***}	0.49^{***}	0.61
BMA - 3rd month	0.18^{***}	0.14^{***}	0.41^{***}	0.56
COVID-19 Included				
AR(1)	1.00	0.73^{**}	0.89	1.06
BMA - 1st month	0.45	0.53^{**}	0.35	0.36
BMA - 2nd month	0.15^{*}	0.19^{***}	0.26^{*}	0.19^{*}
BMA - 3rd month	0.08^{*}	0.17^{***}	0.33^{**}	0.19^{*}

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

Model Predictive Likelihood



CSAE: big vs fat data



Relative difference in Cumulative Sum of Absolute Errors (CASE) of the proposed model with big and fat data with respect to the model with only fat data: if > 0, then the proposed model performs better.

Additional slides

Forecasting with Economic News

Traditional data for Economic Forecasting

Forecasting models usually rely on statistical agency data
$\rightarrow$ these regressors are *tested*, *reliable*, *deseasonalized* ...

Policy support: provide a timely update of the economic nowcasts

Traditional data might suffer from:

- long publication **delays** (e.g., 30 days for GDP)
- **infrequent** publications (e.g., quarterly)
- **revisions** of official statistics

Can alternative data provide meaningful signals to **complement** them?

Textual data for Economic Forecasting

Promising alternative data types for macroeconomic forecasting are:

- transaction data
- administrative data
- ...

Can **text** serve as an alternative regressor? Some *advantages*:

- easily obtainable (except for long time series)
- high-frequency and timely: delays come from retrieval and processing
- statements that are backward/current/forward looking
- flexible: news talk about many and various topics

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US Economic Sentiment Measures

Smoothed with a a 30−day MA. Grey area: NBER recessions

Forecasting setup

The goal is to predict the *first release* in day d in period t

- In-sample and out-of-sample with expanding window from 2007
- Consider forecast horizons h from 1 week to 1 year
- Include all available information at time $d - h$

Real-time variables:

- Dependent variables: GDP
- additional regressors: industrial production, unemployment and CPI
- Economic **soft indicators** added one at the time:
  - survey-based indicators: EC business & consumers confidence
  - news-based indicators

Forecasting models augmented with sentiment

The forecasting model:

$$Y_t^d = \alpha_h + \eta_h S_{d-h} + X_{d-h}^{'} \beta_h + \epsilon_t^d$$

- **ARX**: the model that includes own lags and additional macro variables ($\eta_h = 0$)
- **ARXS**: ARX model with soft-indicators

Estimation with the *double-lasso* (Belloni et al., 2014) and out-of-sample assesment with the *Multi-horizon SPA* test (Quaedvlieg, 2021)

Unrestricted MIDAS approach (Marcellino and Schumacher, 2010)

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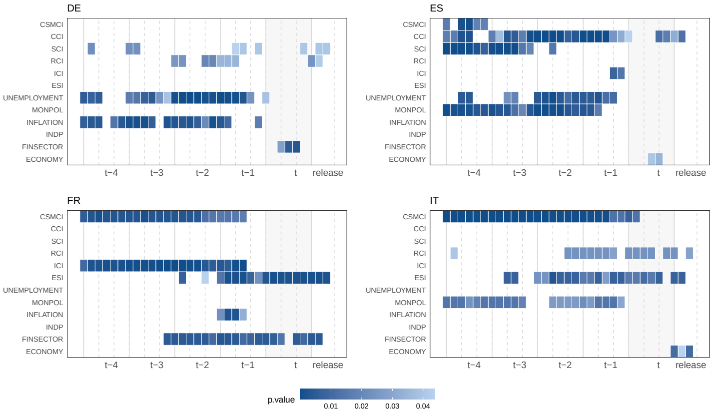
Double-lasso variable selection

In order to asses the which sentiment measures are most relevant for forecasting, we rely on the **double-lasso** (Belloni et al., 2014)

1. Select variables using a standard lasso
2. Select additional variables regressing the sentiment measures on the controls in $\boldsymbol{X}_t$
3. *Post-lasso* estimate using the variables selected in steps 1 & 2

The double-lasso reduces the risk of omitting relevant features and delivers consistent estimates.

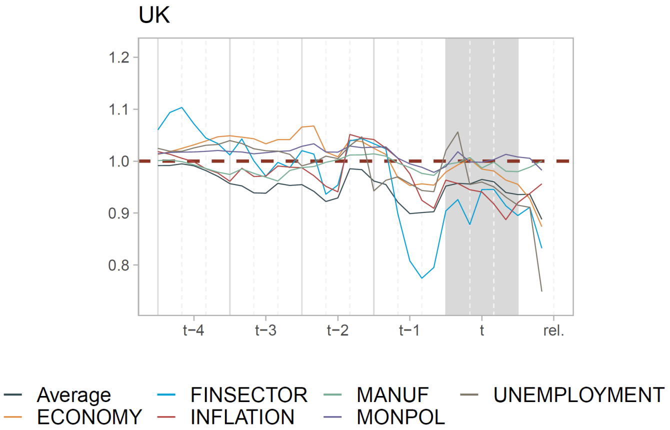
Significance of η_h with adaptive BH MT correction



- Both surveys and news are useful in fore/now-casting
- Sentiment about topics not covered in the news is often selected (e.g., *financial sector* and *monetary policy*)

Forecast gains by horizon: QoQ GDP in UK

MSFE relative to a model with macro and survey information:
⇒ If below 1, then better than benchmark model



Conclusions

- Big data can provide a timely signal during crisis
  - → Selected variables differs across quarters and countries
  - → Selected variables focus on labour market issues
  - → Variables having too short time-series are not selected
  - → Decrease importance in normal time
- BMA select dynamically among many different models
  - → Single model can not be trusted, dynamic model choice
- Informative prior
  - → Filter out non-reacting models and big data noise

References I

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. The quarterly journal of economics 131, 1593–1636.

Barbaglia, L., Consoli, S., Manzan, S., 2023a. Forecasting with economic news. Journal of Business & Economic Statistics 41, 708–719.

Barbaglia, L., Consoli, S., Manzan, S., 2024. Forecasting GDP in Europe with textual data. Journal of Applied Econometrics 39, 338–355.

Barbaglia, L., Frattarolo, L., Onorante, L., Pericoli, F., Tiozzo Pezzoli, L., 2023b. Testing big data in a big crisis: Nowcasting under covid-19. International Journal of Forecasting 39.

Belloni, A., Chernozhukov, V., Hansen, C., 2014. Inference on treatment effects after selection among high-dimensional controls. The Review of Economic Studies 81, 608–650.

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. American Economic Review 112, 1194–1225.

References II

Consoli, S., Pezzoli, L.T., Tosetti, E., 2021. Emotions in macroeconomic news and their impact on the european bond market. Journal of International Money and Finance 118, 102472.

Consoli, S., Pezzoli, L.T., Tosetti, E., 2022. Neural forecasting of the italian sovereign bond market with economic news. Journal of the Royal Statistical Society - Series A .

Ghysels, E., Kvedaras, V., Zemlys-Balevicius, V., 2020. Chapter 4 - mixed data sampling (midas) regression models, in: Vinod, H.D., Rao, C. (Eds.), Financial, Macro and Micro Econometrics Using R. Elsevier. volume 42 of *Handbook of Statistics*, pp. 117 – 153.

Giannone, D., Reichlin, L., Small, D., 2008. Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics 55, 665–676.

Leetaru, K., Schrodt, P.A., 2013. Gdelt: Global data on events, location, and tone, 1979–2012, in: ISA annual convention, Citeseer. pp. 1–49.

References III

Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries and 10-ks. Journal of Finance 66, 35–65.

Marcellino, M., Schumacher, C., 2010. Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. Oxford Bulletin of Economics and Statistics 72, 518–550.

Martindale, C., 1987. Narrative pattern analysis: A quantitative method for inferring the symbolic meaning of narratives, in: Literary Discourse: Aspects of Cognitive and Social Psychological Approaches, Halasz L. (ed). De Gruyter, pp. 167–181.

Quaedvlieg, R., 2021. Multi-horizon forecast comparison. Journal of Business & Economic Statistics 39, 40–53.

Schorfheide, F., Song, D., 2015. Real-time forecasting with a mixed-frequency var. Journal of Business & Economic Statistics 33, 366–380.

References IV

Schumacher, C., 2016. A comparison of midas and bridge equations. International Journal of Forecasting 32, 257–270.

Strapparava, C., Valitutti, A., 2004. WordNet-Affect: An affective extension of WordNet. Proceedings of the 4th International Conference on Language Resources and Evaluation (LREC 2004) , 1083–1086.

Wright, J.H., 2013. Evaluating Real Time Var Forecasts With An Informative Democratic Prior. Journal of Applied Econometrics 28, 762–776.

Additional Material

Public Database

Four distinct data sets (DE, ES, FR and IT), for each data set:

- $\sim$ 300 monthly time series
- Updated **weekly** by Friday 2h00pm CET
- Main file published in .CSV format
- Past real-time observations available in the **Vintages** folder
- Separate **metadata** file providing a detail description of each variable

Time series in the public database

We publish a subset of the time series:

1. Air quality indicators from the European Environmental Agency
2. Financial indicators from DBnomics and Schumacher (2016)
3. Uncertainty indicators by Baker et al. (2016) and Caldara and Iacoviello (2022) $\rightarrow$ *not present in the WP!*
4. Wikipedia page views
5. Google trends
6. News-based sentiment indicators (Barbaglia et al., 2024, 2023a)
7. GDELT media attention and sentiment (Consoli et al., 2021, 2022)

Google trends

Country-specific search volume indexes:

- **France** : *adecco, agence emploi, annulation assurance, assistance sociale, assurance chômage, assurance voyage, auto1, autoscout, autoscout24, bon coin voiture, bureau emploi, cadremploi, chomage partiel, chomage technique, chomage, curriculum vitae, curriculum* ...
- **Italy** : *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* ...
- ...

News-based sentiment indicators

Country-specific sentiment indicators by Barbaglia et al. (2023a):

- **Fine-grained aspect-based sentiment**
- **Topics**: economy, unemployment, inflation, monetary policy, manufacturing, financial markets
- **Full-text articles** by Dow Jones Factiva for DE, ES, FR and IT:
  - DE: Suddeutsche Zeitung, Der Spiegel, Die Tageszeitung
  - ES: El Mundo, ABC, Expansion, La Vanguardia, Cinco Días, El País
  - FR: Le Monde, Le Figaro, Les Echos, La Tribune
  - IT: La Stampa, Corriere della Sera, Sole24Ore, Giornale, Repubblica
- English translation based on **neural machine translation**
- *Update frequency* depends on input data availability

GDELT

Global Database of Events, Language, Tone (Leetaru and Schrodt, 2013):

- **Open-source** platform on worldwide news collected from broadcast, print and web news in more than 65 languages
  $\rightarrow$ select only outlets from the countries of interest
- **Structured news data** (people, organizations, topics ...) and million of themes from common used practitioners topical **taxonomies**
- From February 2015 to now
- Dimension: around 11-12 TB of textual data, growing $\sim$1TB each year (over 88 million articles and 150,000 news outlets yearly)
- **Real-time**: a .CSV file every 15 minutes

GDELT

Extract media attention, sentiment and emotion indicators belonging to five main **topics** by the World Bank Topical Taxonomy:

- Macroeconomics and structural policies
- Economic growth
- Social protection and labour
- Macroeconomic vulnerability and debt
- Disease

Build three sets of indicators by topic-country (Consoli et al., 2021, 2022):

- **Count**: normalized number of stories
- **Tonality**: positive, negative and uncertainty categories by Loughran and McDonald (2011)
- **Emotions** : Regressive Imagery dictionary by Martindale (1987) and the WordNet Affect by Strapparava and Valitutti (2004)

Survey-based Informative Prior

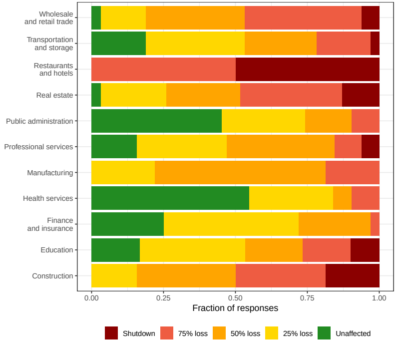
"According to your opinion, and looking at the country/region where you live, what is the fraction of activity levels which is lost due to lockdown, on a scale from 0 to 100, in these sectors of the economy?"

Mean effect of the lockdown:

$$\mu = \frac{meanClosure * daysOfClosure}{90}$$

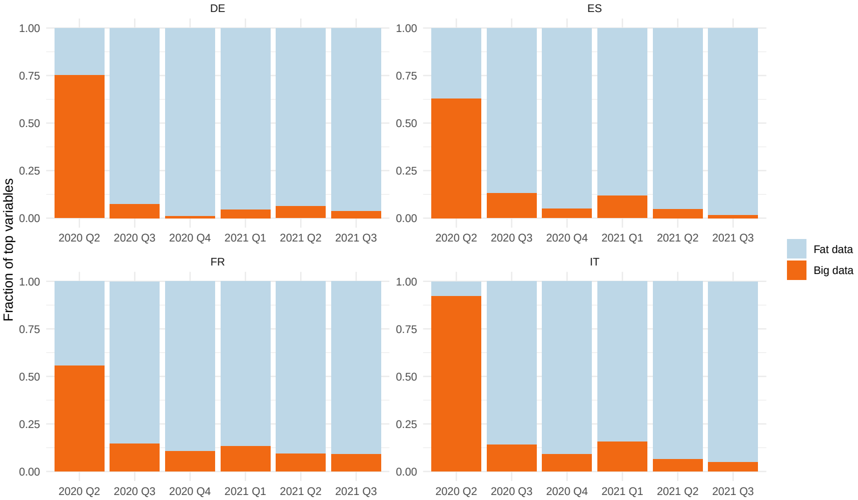
Prior associated to each model forecast:

$$Pr(M_{it}) \propto \begin{cases} \phi\left(\frac{M_{it} - \mu_L}{\sigma_L}\right) & t \in (2020Q2, Q3) \\ 1 & otherwise \end{cases}$$



Big Data or Fat Data?

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



Which data help the most?

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

Additional Results (I)

Table: Out-of-sample point forecast evaluation for the BMA model in terms of MAFE relative to a BMA model with only fat data and Bloomberg surveys

	France	**Germany**	**Italy**	**Spain**
Pre-COVID-19				
BMAfat - 1^{st} month	1.06	1.16	1.14	0.91
BMAfat - 2^{nd} month	0.38^{*}	0.33^{***}	0.51^{***}	0.34^{***}
BMAfat - 3^{rd} month	0.39^{**}	0.24^{***}	0.46^{***}	0.32^{***}
BMA Bloomberg - 3^{rd} month	0.53^{***}	0.32^{***}	0.61^{**}	0.68^{*}
COVID-19 Included				
BMAfat - 1^{st} month	1.05	1.50	0.80	0.77
BMAfat - 2^{nd} month	0.40^{**}	0.54^{*}	0.60^{*}	0.41^{***}
BMAfat - 3^{rd} month	0.23^{**}	0.48^{**}	0.77	0.42^{***}
BMA Bloomberg- 3^{rd} month	0.63	0.97	2.03	1.10

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

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