European Commission
Joint Research Centre

Nowcasting GDP during COVID-19

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Rationale

- The COVID-19 crisis is an unexpected and unprecedented shock for the entire world economy.
- Lockdown measures imposed by governments to contain the spread of the pandemic blocked the supply-side of the economy, reduce disposable income and consumption with a consequent increase in the number of unemployed people.
- Policymakers need nowcasts and short-term forecasts of the economy's actual 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, effects of COVID-19 are not visible
- Joining nowcasting techniques and timely available "big data" could improve the impact assessment

Outline

- We document the real-time experience in nowcasting GDP during the COVID-19 crisis within the European Commission - Joint Research Centre.
- We collect a data set of more than 200 variables per country:
  - We include traditional financial and economic indicators, as well as alternative data to capture timely the happening of economic shocks.
  - We implement a battery of forecasting models, including mixed-frequency models, dynamics factor models, vector autoregressions and a set of machine learning models.
  - The final nowcasts are obtained via Bayesian model averaging.
- We show the process in real time and we draw conclusions on the usefulness of traditional and big data during major crises

Data

- We enlarge the information set at policymakers' disposal.
- We keep a large amount of conventional monthly macro series (fat data)
- High-frequency big data indicators: Google searches concerning the automotive market, holidays, job applications, teleworking; Total views of Wikipedia pages. Country variables: Several air quality indicators (pollution as indicator of activity); Aviation, industries and passengers; Dow Jones news-based indicators on themes such as economy, unemployment, inflation; G-Delt news-based sentiment analysis, including macro, growth and general tone in the news; Electricity prices, Google searches (local language and concepts) on automotive, jobs, unemployment benefits; Total views of Wikipedia pages in the country; PMIs; AirBnB data; Indicator of mobility by country based on mobile phone data; Energy Production, Transmission & Distribution; Domestic Trade; Retail Trade; Google mobility indicators; truck-tolls data
- The database is being continuously expanded.
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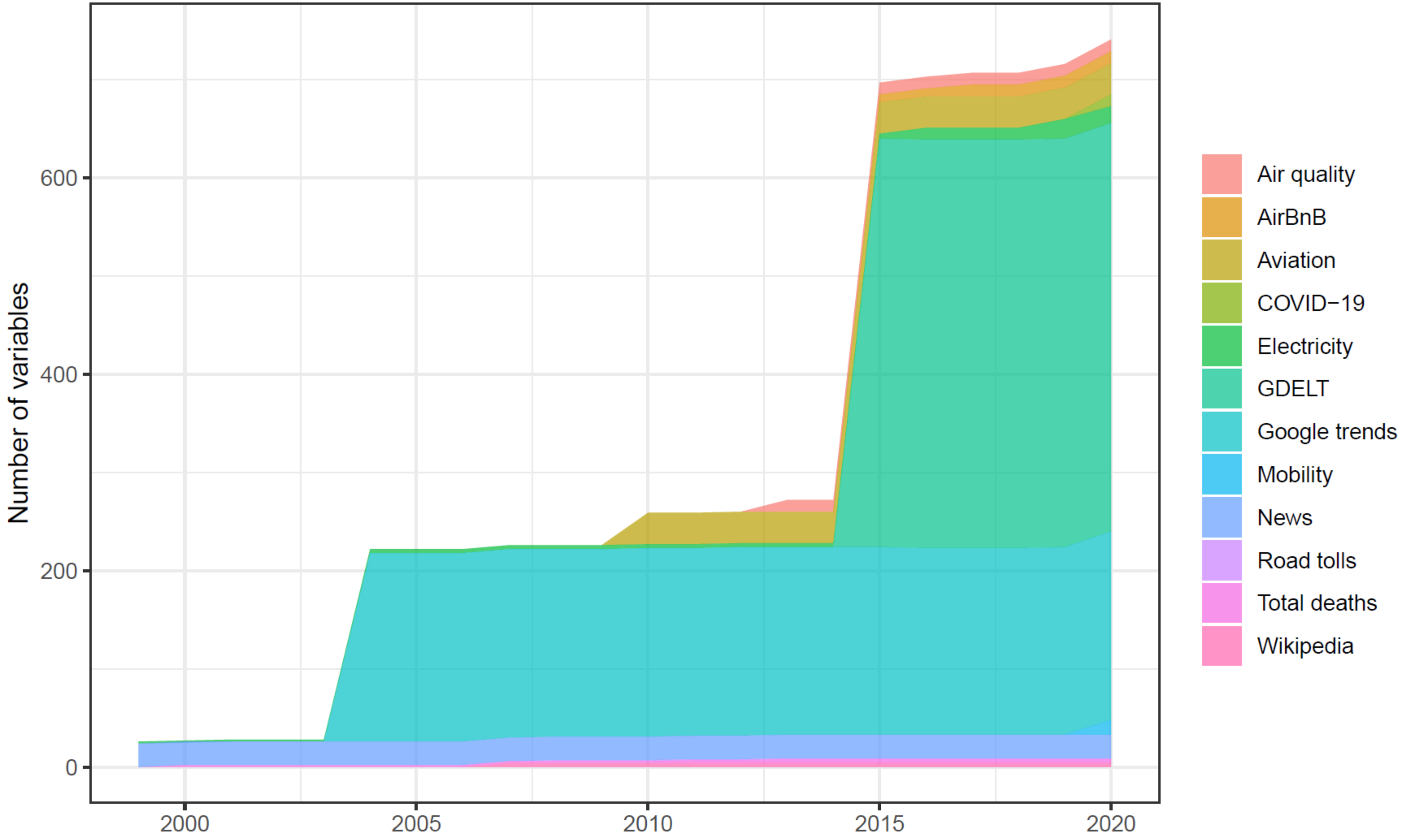
Data

- Different starting points
- Very noisy
- High frequency

- Econometric challenges



Models

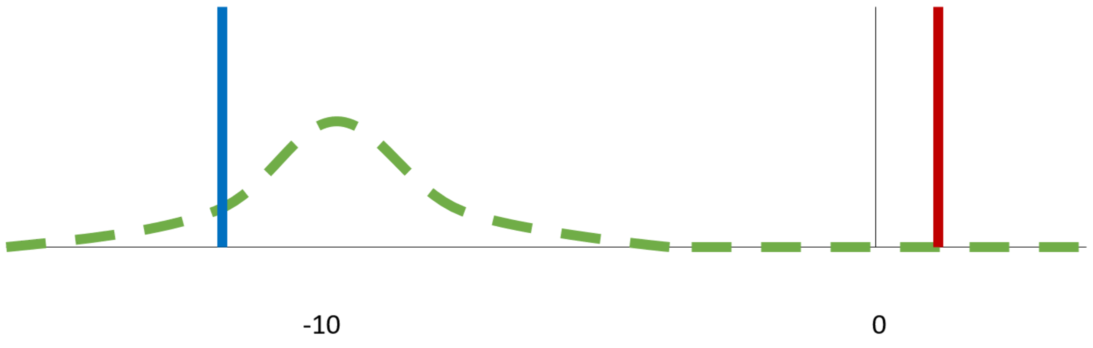
- Dynamic Factor Model with mixed frequency Giannone et al. (2008)
  - MG-MIDAS, MIDAS estimation with big data using Modal Grids: Ghysels et al. (2020).
  - MF-BVAR : Mixed-Frequency Bayesian Vector AutoRegression: Schorfheide and Song (2015)
  - ML : Machine Learning combination of a deep Neural Network (NN), a Stacked Ensembles regression (SE), a Random Forest (RF) and an eXtreme Gradient Boosting (XGB)
  - Unrestricted equations
  - Agnostic nowcasting (thick modelling)
- Priors for model averaging fulfil two distinct purposes:
  - Provide information about the effects of the policy measures, not in a dogmatic additive manner, but as a Bayesian prior (accounts for the uncertainty)
  - The prior selects away those models and variables that do not have predictive power in the crisis.

Priors for model averaging – chosing models

- Predictive likelikhood

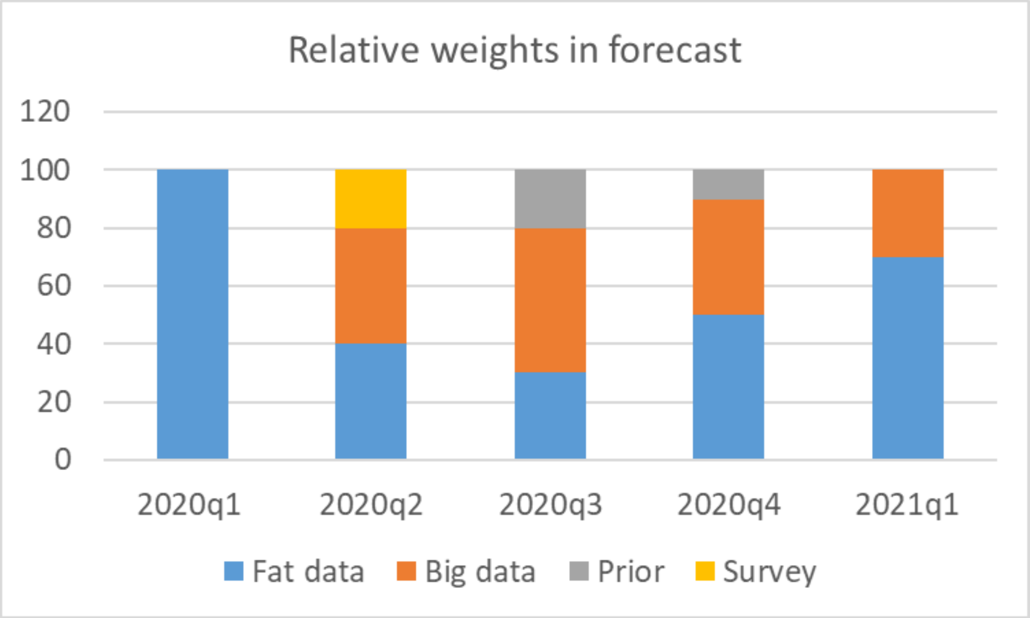
$$Pr(M_i|y^{1:t-1}, X^t) = w_{i,t} \propto \frac{Pr\left(y_t|y^{1:t-1}, X^t, M_i\right) Pr\left(M_i\right)}{\sum_{j=1}^{K} Pr\left(y_t|y^{1:t-1}, X_t, M_j\right) Pr\left(M_j\right)}.$$

- Prior is needed for policy measures (lockdown)



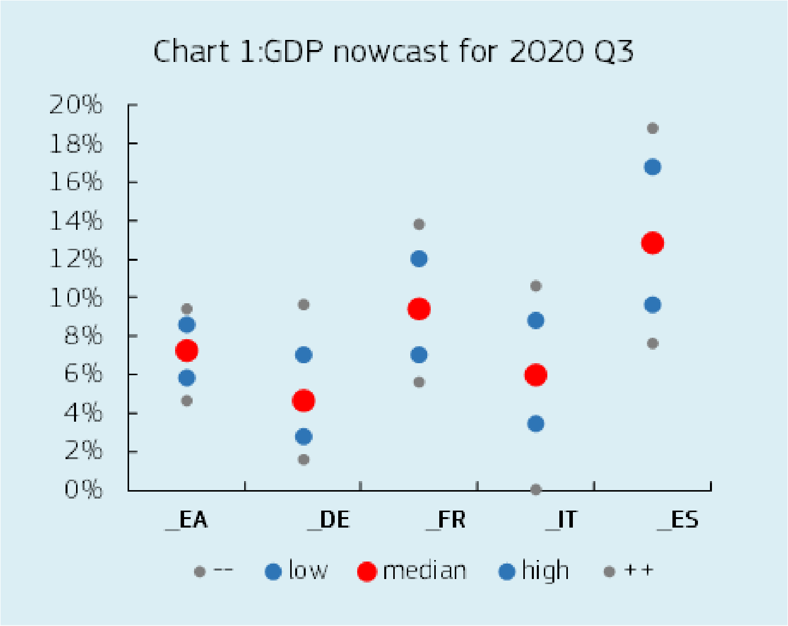
Some lessons

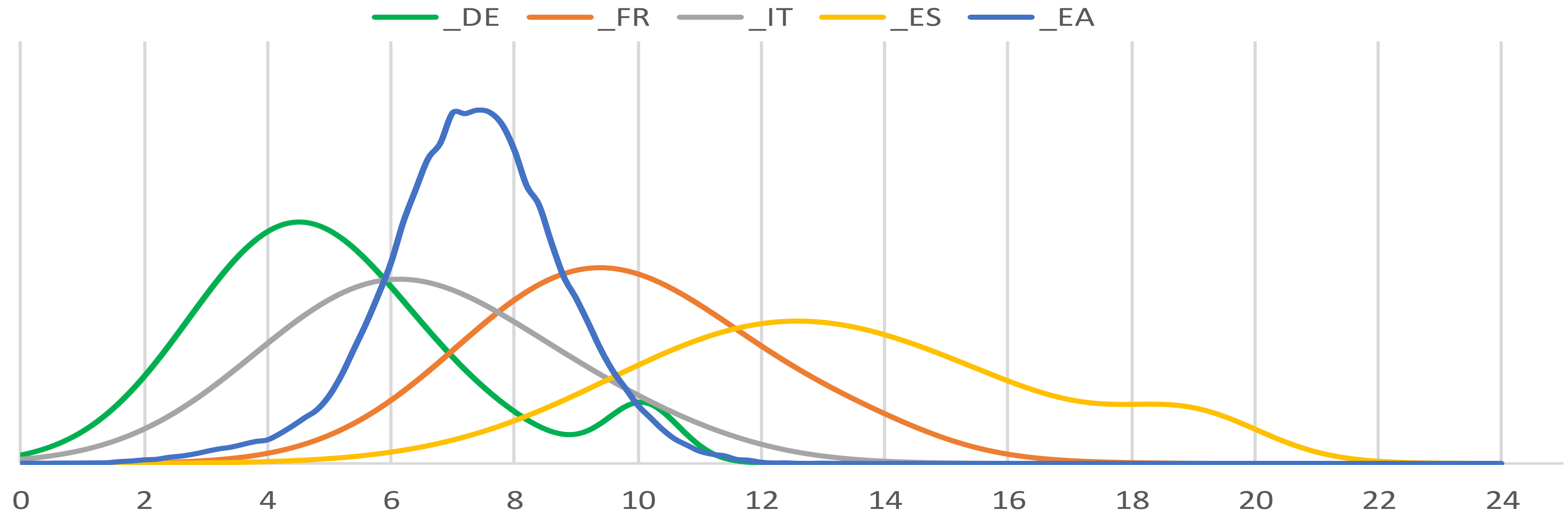
- Models: use many, change over time.
  - On model does not fit all. Models change over time. In our case, also because models and variables are very linked in many cases.
- Variables: from big data to normality (fat data)
  - Big data to capture behaviour. Variables shift over time. Categories of variables as well, big data timely but noisy, with traditional data increasing in importance over time.
- Policies as lose priors: from subjective to objective
  - Priors always matter for policy. Subjective better than calculated, due to noise?



Some lessons - 2

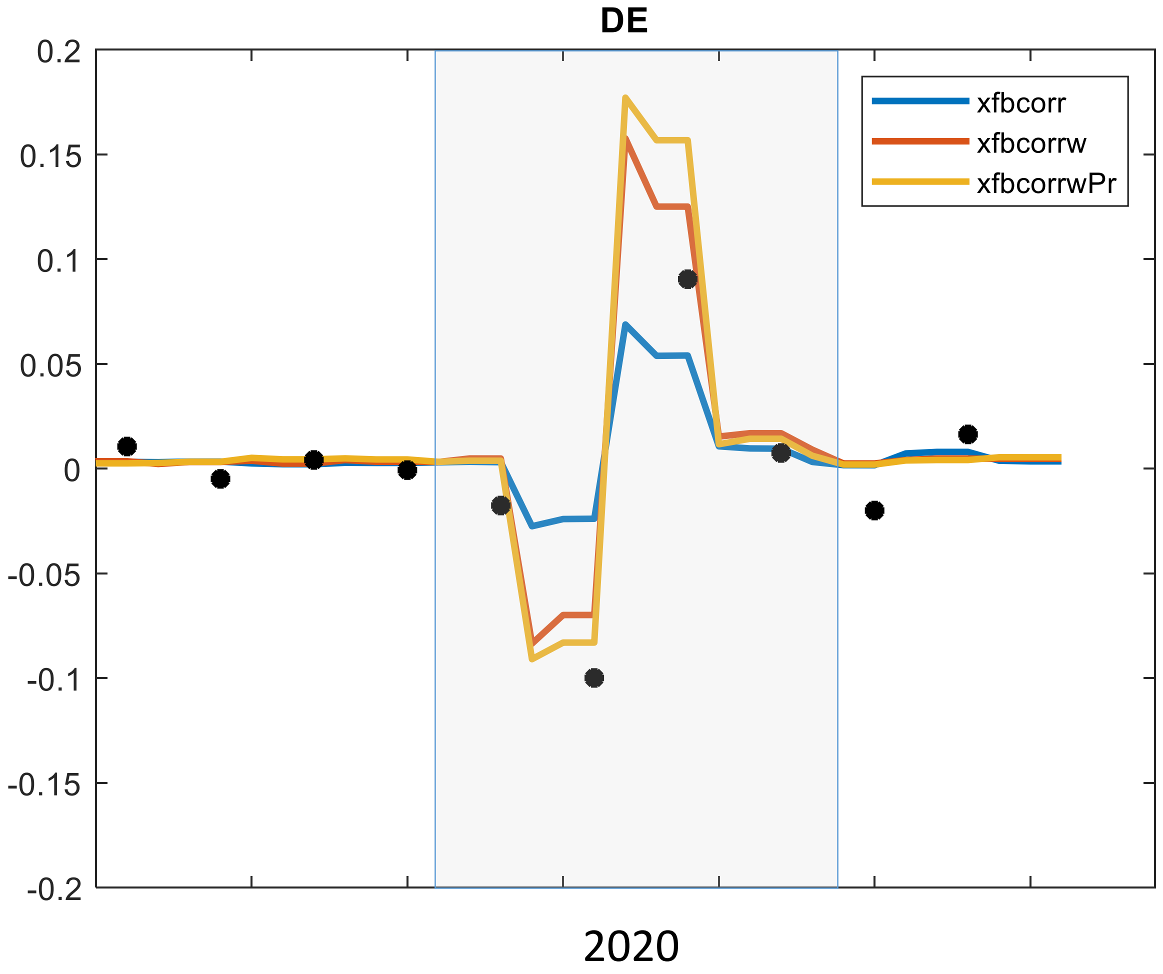
- It is difficult to get the numbers right.
  - Judgemental forecast of the country desks hard to beat
  - Errors are highly correlated with theirs
- Accounting for uncertainty is essential
  - Provides information about what we do not know





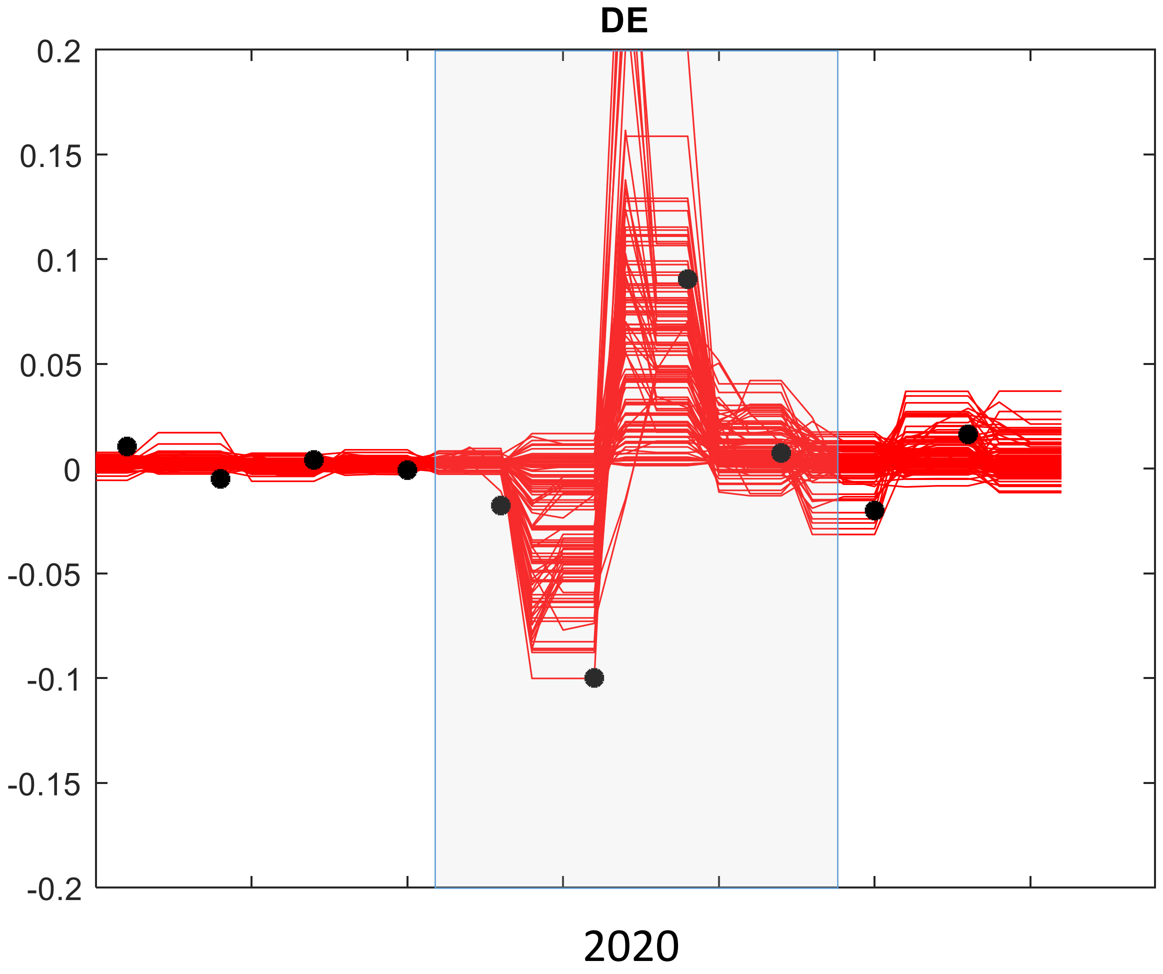
Ex post: which big data matter

- 80 Macro, financial, labour market indicators
- 9 Surveys (PMI)
- CAS-Gdelt Growth
- Google:
  aaa_auto, autoscout, curriculum_vitae, glassdoor, indeed, job, job_application, mercedes_benz, motivationsschreiben, randstad



Ex post: which big data matter

- Lags
  - 5 lag 0
  - 28 lag 1
  - 43 lag 2
  - 36 lag 3
- Means
  - 80 Q-o-q
  - 30 M-o-m
  - 2 levels (BuBa)
- Uncertainty



Thanks

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