Big Data Econometrics
Nowcasting & Early Estimates

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Introduction

We provide a primer on the use of big data in macroeconomic nowcasting and early estimation, with a special focus on the use in official Statistical Agencies and similar institutions.

We discuss:

- a typology of big data characteristics relevant for macroeconomic nowcasting and early estimates,
- various methods for feature extraction of big data sources to usable time series format,
- econometric methodologies which could be used for nowcasting with big data,
- empirical nowcasting results and gains in terms of increased timeliness for three key target variables in four countries, and
- various ways to evaluate and present nowcast estimates.

Introduction

Nowcasting and the construction of early estimates are concerned with the production of a preliminary estimate for the contemporaneous value of an indicator, which has not yet officially been released.

Leading examples are the GDP and its components, deflators, and fiscal variables, which are typically released at least 30-45 days after the end of the reference month or quarter, and later revised.

Nowcasts of monthly variables such as the HICP or confidence, sales, trade and labour market indicators could be also of interest.

Introduction

We focus on the use of big data for macroeconomic nowcasting and the production of early estimates, by surveying, developing and applying proper data handling techniques combined with state of the art econometric methods.

Big data have substantial potential in this context, as timely/continuous/large sets of data should provide new or complementary information with respect to standard economic indicators.

Our aim is to provide a useful guide for the applied researcher in official Statistical Agencies, or similar institutions, and present ways big data can be used in macroeconomic nowcasting to improve the quality of the early estimates, increase the timeliness of the releases, and complement the standard information with uncertainty and directional measures.

Methodological Issues

In our nowcasting context, we can summarize the potential methodological issues about the use of big data as follows.

First, do we get any relevant insights? In other words, can we improve nowcast precision by using big data?

This is mainly an empirical issue and, from the literature review, it seems that for some big data and target variables this is indeed the case.

Methodological Issues

Second, do we get a big data hubris?

As anticipated, we think of big data based indicators as complements to existing soft and hard data-based indicators, and therefore we do not get a big data hubris (though this is indeed the case sometimes even in some of the nowcasting studies, for example those trying to anticipate unemployment using only Google Trends).

Methodological Issues

Third, do we risk false positives?

Namely, can we get some big data based indicators that nowcast well just due to data snooping?

This risk is always present in empirical analysis and is magnified in our case by the size of the dataset since this requires the consideration of many indicators with the attendant risk that, by pure chance, some of them will perform well in sample.

Only a careful and honest statistical analysis can attenuate this risk. We suggest to compare alternative indicators and methods over a training sample, select the preferred approach or combine a few of them, and then test if they remain valid in a genuine (not previously used) sample (cross-validation).

Methodological Issues

Fourth, do we mistake correlations for causes?

Again, this is a common problem in empirical analysis and we will not be immune for it.

For example, a large number of internet searches for “filing for unemployment” can predict future unemployment without, naturally, causing it.

This is less of a problem in our nowcasting context, except perhaps at the level of economic interpretation of the results.

Methodological Issues

Fifth, do we use the proper econometric methods?

Here things are more complex because when the number of variables N is large we can no longer use standard methods and we have to resort to more complex procedures.

Some of these were developed in the statistical or machine learning literatures, often under the assumption of i.i.d. observations.

As this assumption is likely violated when nowcasting macroeconomic variables, we have to be careful in properly comparing and selecting methods that can also handle correlated and possibly heteroskedastic data.

This is especially the case since these methods are designed to provide a good control of false positives, but this control depends crucially on data being i.i.d.

Methodological Issues

To give an example, it is well known that exponential probability inequalities, that form the basis of most methods that control for false positives, have very different and weaker bounds for serially correlated data leading to the need for different choices for matters like tuning parameters used in the design of the methods. See, e.g., Roussas (1996) and the references therein for more information.

Overall, as we will see, a variety of methods are available, and they can be expected to perform differently in different situations, so that also the selection of the most promising approach is mainly application dependent.

Methodological Issues

Sixth, do we have instability due to Algorithm Dynamics or other causes (e.g., the financial crisis, more general institutional changes, the increasing use of internet, discontinuity in data provision, etc.)?

Instability is indeed often ignored in the current big data literature, while it is potentially relevant, as we know well from the economic forecasting literature.

Unfortunately, detecting and curing instability is complex, even more so in a big data context. However, some fixes can be tried, mostly borrowing from the recent econometric literature on handling structural breaks.

Also, recursive application of more sophisticated methods, such as the neural networks underlying ”deep learning”, can alleviate the problem of instability.

Methodological Issues

Finally, do we allow for variable and model uncertainty?

As we will see, it is indeed important to allow for both variable uncertainty, by considering various big data based indicators rather than a single one, and for model uncertainty, by comparing alternative procedures and then either selecting or combining the best performing ones.

Again, all issues associated with model selection and uncertainty are likely magnified due to the fact that large data also allow for larger classes of models to be considered, and model selection methods, such as information criteria, may need modifications in many respects.

Empirical Example

We now discuss an empirical example to illustrate some of the issues we have discussed so far, and various econometric methods.

We work with (many) standard economic indicators plus summaries based on big data: two big data based uncertainty indicators. This may seem restrictive but, as we have discussed, it is typically convenient to structure and reduce the dimensionality of big data prior to using them for macroeconomic forecasting.

We start with a description of the data used in the nowcasting exercise, and then discuss reasonable econometric methods for this application, evaluation criteria, and results.

Empirical Example

Data: Targets

We consider the four largest EU countries: Germany (DE), France (FR), Italy (IT) and the UK.

For each of them, we have collected data on three key monthly economic indicators: industrial production (IP), harmonised index of consumer prices (HICP) and unemployment rate (UR).

The datasets considered are made available by Eurostat and have been downloaded from their online dissemination database.

Empirical Example

Data: Predictors

Our set of monthly macroeconomic predictors includes various coincident and leading indicators plus additional key economic variables for each country.

Specifically, we consider: Bank Lending Rate, Bankruptcies, Building Permits, Capital Flows, Car Registrations, Construction Output, Consumer Credit, Core Consumer Prices, various CPI components, Crude Oil Production, Export Prices, Exports, Factory Orders, Gasoline Prices, House Price Index, Import Prices, Imports, Job Vacancies, Manufacturing Production, Mining Production, Money Supply M1, M2 and M3, New Orders, Private Sector Credit, Producer Prices, Steel Production, Unemployment Rate, Consumer Confidence Indicators and various surveys.

Our set of weekly variables includes mainly financial indicators: interest rates at various maturities and spreads, equity indexes, volatility indexes.

Finally, we have constructed two big data-based uncertainty indicators, one relying on Reuters news and the other on Google searches, which are discussed in more details below.

Empirical Example

Data: The Reuters Uncertainty Index

Using web-scraping procedures, we downloaded data from the Reuters news database and construct the uncertainty indexes. In particular, we used the following keywords:

- Germany: at least one of {uncertainty uncertain, uncertainty, uncertainties} and at least one of {Germany, German, Germans}.
- France: at least one of {uncertainty uncertain, uncertainty, uncertainties} and at least one of {France, French}.
- Italy: at least one of {uncertainty uncertain, uncertainty, uncertainties} and at least one of {Italy, Italian, Italians}.
- UK: at least one of {uncertainty uncertain, uncertainty, uncertainties} and at least one of {UK, Britain, British, United Kingdom, Briton}.

Empirical Example

Data: The Reuters Uncertainty Index

Following Eckley (2016), the empirical estimator for uncertainty/risk in our index is the number of articles containing at least one of the terms in the search dictionary over the total amount of articles published in each period:

$$U_t = \frac{m_t}{n_t}$$

where n_t is the total number of articles published in the given period, and m_t is the number of those articles that express uncertainty or risk.

Empirical Example

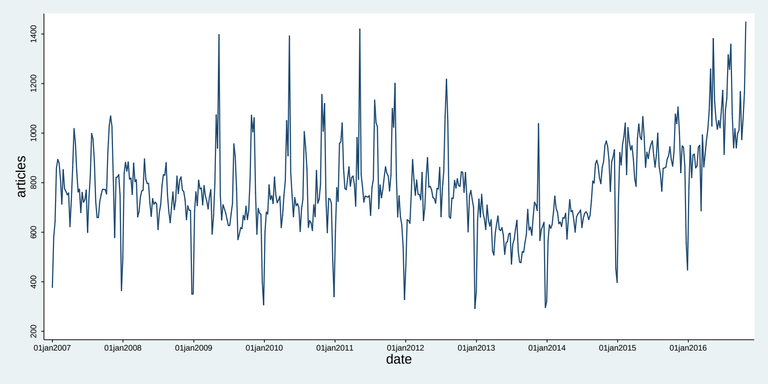
Data: The Reuters Uncertainty Index

The algorithm works by scanning each article body to detect words specified in a dictionary of terms. Each time an article is examined by the algorithm its date, URL, tags and file path are written to a csv file, together with an indicator that takes the value 1 if the article contains at least one of the words contained in the dictionary of terms.

After all articles have been examined, the code computes daily article frequencies for the total amount of articles and for the articles expressing uncertainty/risk, as well as the actual index U_t, i.e. the ratio between the two.

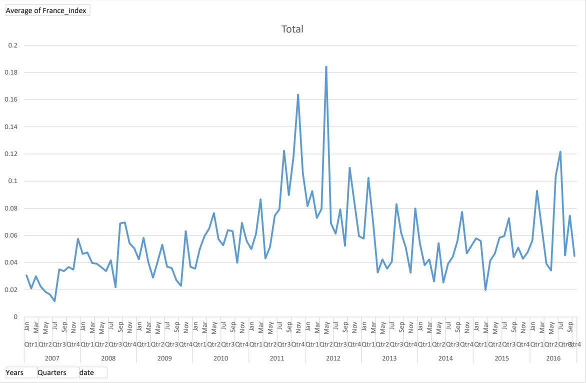
Reuters Uncertainty is strongly correlated with other uncertainty measures such as the Economic Policy Uncertainty index of Baker, Bloom and Davis (2016) and volatility indexes such as VIX.

Empirical Example



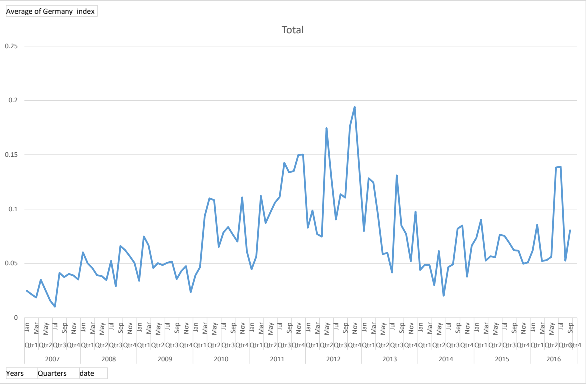
Weekly volume of articles.

Empirical Example



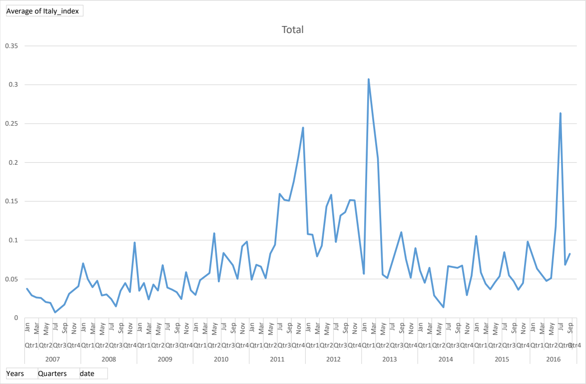
Reuters News Uncertainty Index.

Empirical Example



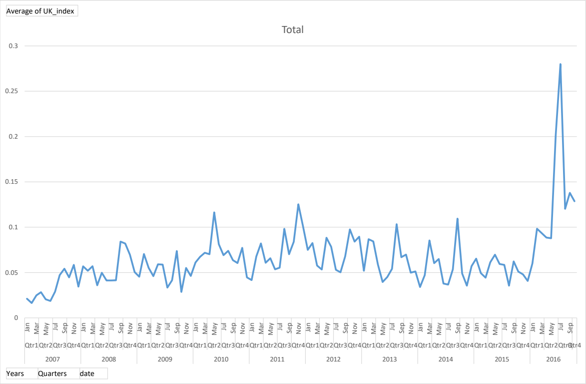
Reuters News Uncertainty Index.

Empirical Example



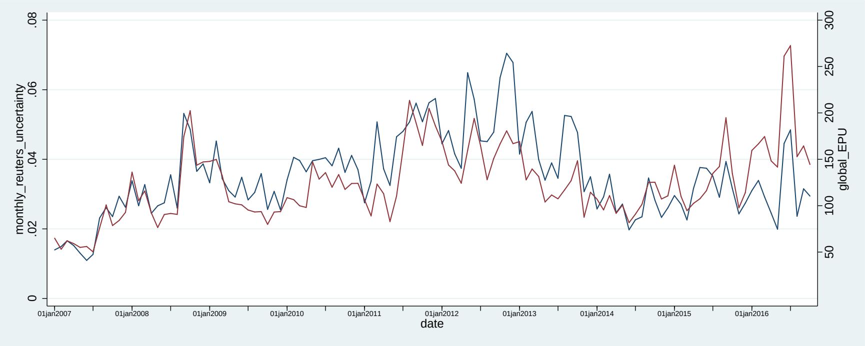
Reuters News Uncertainty Index.

Empirical Example



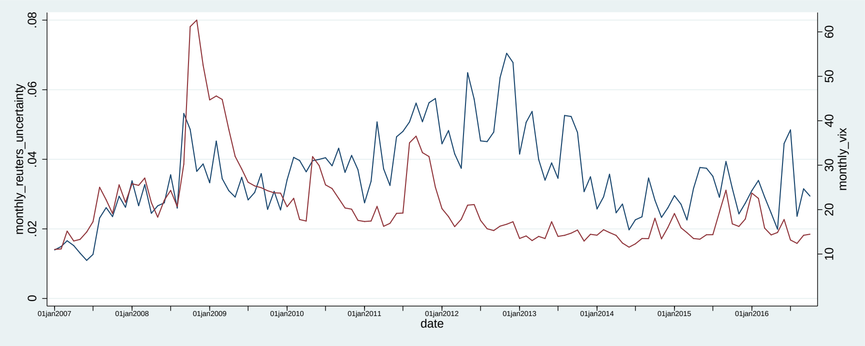
Reuters News Uncertainty Index.

Empirical Example



Line Plot of EPU Global index (red) and Reuters Uncertainty index (blue), monthly data.

Empirical Example



Line plot of VIX index (red) and Reuters Uncertainty index (blue).

Empirical Example

Data: The Google Uncertainty Index

The Google Uncertainty Index is based on the use of Google trends. For the general uncertainty and risk indexes, we consider four keywords, given that the searches are directed worldwide and the language barrier might jeopardise the result, and two keywords for the country-specific indexes using the domestic languages. In particular, we included the following Google Trends:

- Germany: for the German Google Uncertainty Index we use the keywords “unsicherheit” and “risiko” across web and news searches in the region of Germany.
- France: for the French Google Uncertainty Index we use the keywords “incertitude” and “risque” across web and news searches in the region of France.
- Italy: for the Italian Google Uncertainty Index we use the keywords “incertezza” and “rischio” across web and news searches in the region of Italy.
- UK: for the UK Google Uncertainty Index we use the keywords “uncertainty” and “risk” across web and news searches in the region of the UK.

Empirical Example

Data: The Google Uncertainty Index

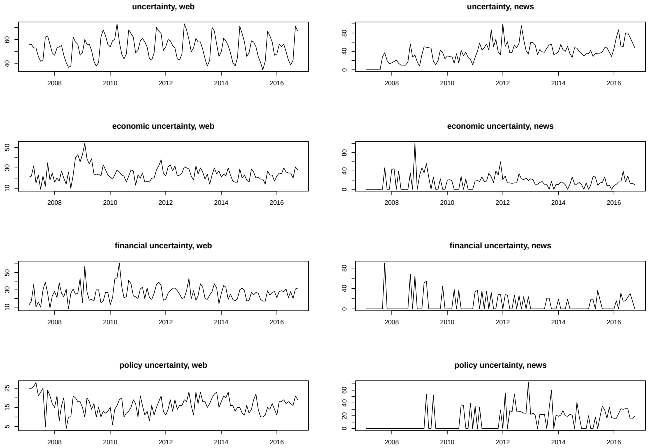
For the separate countries we use both “uncertainty” and “risk” keywords in order to cover more user profiles and obtain a more robust result.

Then, to construct each index we take the equally weighted average of the respective Google Trends.

We also try to use data-dependent weights based on the spectral entropy of each series. Lower spectral entropy values indicate that the series is more predictable.

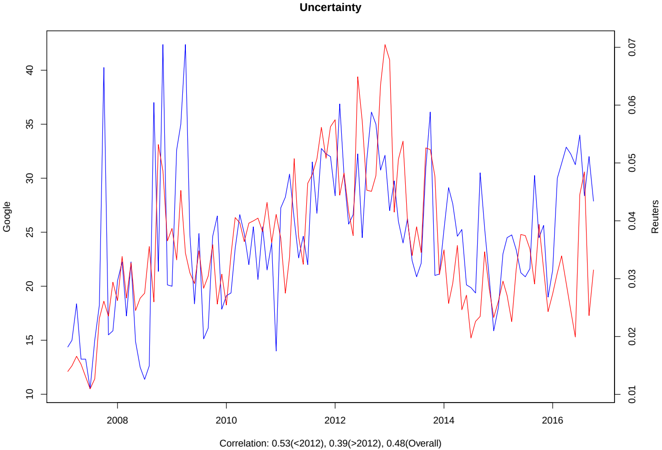
However, the resulting uncertainty indexes do not change significantly and we omit the results from presentation.

Empirical Example



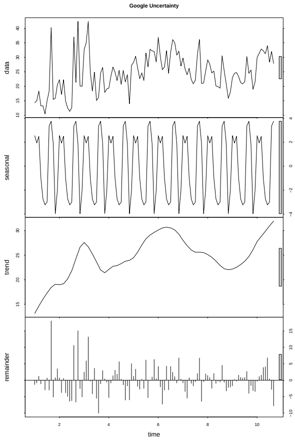
Google Trends to construct the General Uncertainty Index.

Empirical Example



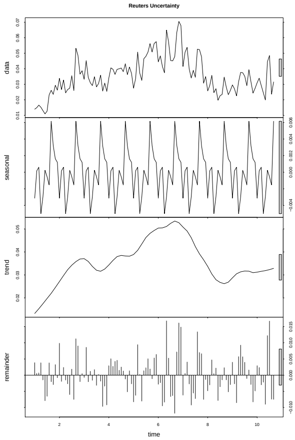
Comparing the General Uncertainty Index of Google (left axis, blue colour) to the corresponding Reuters index (right axis, red colour).

Empirical Example



Google Uncertainty Index, STL decomposition.

Empirical Example



Reuters Uncertainty Index, STL decomposition.

Empirical Example

Data: Transformations

To ensure that the variables under analysis are stationary, a pre-requisite for several of the econometric methods we will implement, we use a set of transformations, which include: (i) log, (ii) first difference, (iii) percentage change, (iv) log difference, (v) second log difference.

The specific transformation for each variable follows standard practice in the literature, see, e.g., McCracken and Ng (2015) as well as Stock and Watson (2002a and 2002b) among others.

We nowcast the period-to-period percentage change of IP, HICP and GDP and the period-to-period first difference of UR.

The nowcasts for most models are first produced using growth rates, and then translated to levels, as Eurostat and other official statistical agencies typically publish their nowcasts in levels.

Empirical Example

Data: Timing, Mixed-Frequency & Unbalancedness

For each variable, we mark the publication delay and the day of the month that the release for this variable is due.

For example, suppose that industrial production for month T is released on the 25th day of the next month, month T+1. In that case, we note one time period publication lag (i.e., -1) and the 25th day as publication release.

Repeating this procedure for each variable allows us to construct a nowcasting exercise that is accurate (on average) in terms of the information which is available at each point in time.

For example, when we are about to construct nowcasting estimates five weeks prior to the official release, we use only the available information up to that point.

Empirical Example

Data: Timing, Mixed-Frequency & Unbalancedness

In our nowcasting exercise we transform weekly observations to monthly by averaging the available information in each month, as routinely done when constructing bridge models.

This creates an unbalanced panel of variables in which weekly-to-monthly variables have zero publication lag, i.e., information is up-to-date, but macroeconomic variables might have 1, 2, or more periods of publication lags.

In such cases of unavailable information, we assign missing values.

Empirical Example

Data: Timing, Mixed-Frequency & Unbalancedness

The U-MIDAS approach could also be an attractive alternative, in general, to deal with mixed frequency data. However, in our specific context the available sample is too short and the difference in sampling frequency can be rather high (when going from weekly to quarterly).

The MIDAS approach could reduce the number of parameters to be estimated but it would introduce non-linearity, which would make an estimation with a large number of explanatory variables practically unfeasible.

Hence, our preference for simple temporal aggregation. See Ghysels et al. (2004) and Foroni, Marcellino and Schumacher (2015), among others, for MIDAS and U-MIDAS models.

Limited experimentation with UMIDAS produced similar results.

Empirical Example

Data: Timing, Mixed-Frequency & Unbalancedness

To deal with the missing values at the end of the sample due to publication delays, we adjust each series by moving it forward so that the last observed data point matches the observed value in the dependent variable.

Other solutions could be to replace the missing values with the median or mean, or to use extrapolation employing a simple autoregressive (AR) or other model.

However, the median or mean could be different from the recent trend of the variables, and extrapolation is complex when dealing with a very large dataset.

Limited experimentation with extrapolation produced similar results.

Empirical Example

Data: Time Span

Because the Reuters Uncertainty Index starts in 2007, our monthly variables (including monthly targets) span from 2007-01-31 to 2016-10-31 (118 months).

The nowcasting exercise starts in 2014-01-31, to ensure that there is sufficient data to be used in the estimation also for the complex econometric models.

A lag of the target variable is included in most specifications, i.e., an autoregressive term. However, lags of the predictors are not included, to avoid overfitting due to the short sample span.

For the monthly variables, we have 34 evaluation periods (2014-01-31 to 2016-10-31). The short evaluation sample should be kept in mind when assessing the empirical results.

Empirical Example

Nowcasting Exercise

The nowcasting exercise is based on the algorithm described in the following steps.

1. First, we leave a number of observations, T^{OUT}, out-of-sample, in order to use them in the evaluation of the nowcasting performance of different models. In our experiments, $T^{OUT} = 34$ for the monthly targets.

2. The initial sample we use in the first round of estimation and nowcasting is $T_1^{IN} = \{1, .., (T - T^{OUT} + 1)\}$. Then, we estimate the parameters and produce the nowcasts from the various models. We construct nowcasts for $h = \{-5, -4, -3, -2, -1\}$ weeks prior to the target date when the official release is due. For each h, we keep the same target date, however we re-estimate and produce different nowcasts (updates) using all available information up to that time point. This produces five estimates for each corresponding target date.

Empirical Example

Nowcasting Exercise

3. We repeat Step 2 in a recursive manner, i.e. $T_2^{IN} = \{1, .., (T - T^{OUT} + 2)\}$ and generally $T_j^{IN} = \{1, .., (T - T^{OUT} + j)\}$. We stop when $T_j^{IN} = \{1, .., (T - 1)\}$, as we always need the true value of the next period to evaluate the nowcasts.

At the end of the above recursive procedure we end up with T^{OUT} nowcasts for each model under consideration.

Empirical Example

Econometric Models

In the nowcasting exercise we employ several methodologies to assess the relative gains from more complex methods that can handle large datasets with respect to simpler procedures. Specifically, we consider:

- (7) Naive and AR models. The first group of models consists of some simple models which assume that the best nowcast is given by: the average of the last four periods ($Ave4$), the average of the last twelve periods ($Ave12$) and the average of the last twenty-four periods ($Ave24$). The ***Naive*** model uses the last observed value as the best nowcast (which coincides with that from a pure random walk model). Then, we include an $AR(1)$, $AR(4)$ and an $AR(p_{AIC})$ model where the p_{AIC} is determined via the Akaike's Information Criterion.
- (6) Simple Linear Regressions. These are simple specifications using the Google and Reuters Uncertainty Indexes with no, one or three lags of the target variable.

Empirical Example

Econometric Models

- (8) Various other univariate models working well in various forecasting competitions by the IJF (Hyndman and Khandakar (2008)).
  - AutoArima: chooses the best ARIMA(p,d,q) model using AIC. Transformation of the univariate series not necessary as the model handles integrated series.
  - ETS and BaggedETS: Exponential smoothing methods as in Hyndman et al. (2002) and Bergmeir et al. (2016). The methodology is fully automatic and performed extremely well on the M3-competition data. The bootstrapped series are obtained using the Box-Cox and Loess-based decomposition (BLD) bootstrap; see Bergmeir et al. (2016).

Empirical Example

Econometric Models

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  - BATS and TBATS: This class of models are exponential smoothing state space models with Box-Cox transformation, ARMA errors, Trend and Seasonal components. See De Livera et al. (2011).
  - Neural Networks (NN): This is a simple feed-forward neural network with a single hidden layer and lagged inputs.
  - Spline forecasts: this model produces local linear nowcasts using cubic smoothing splines.
  - Theta method: The theta decomposition method of Assimakopoulos and Nikolopoulos (2000).

Empirical Example

Econometric Models

- (16) Dynamic Factor Analysis (DFA). We use the default setup of Giannone, Reichlin and Small (2008) with $(q, r, p) = (2, 2, 1)$ where q is the dynamic rank, r is the static rank and p is the AR order of the state vector. We also try three more settings with $(q, r, p) = (3, 3, 1)$, $(q, r, p) = (4, 4, 1)$ and $(q, r, p) = (5, 5, 1)$. For each setting we use: (i) the set of macroeconomic and financial indicators only (MacroFin), (ii) the set of macroeconomic and financial indicators including the Google Uncertainty Indexes (MacroFin-Google), (iii) the set of macroeconomic and financial indicators including the Reuters Uncertainty Indexes (MacroFin-Reuters), and (iv) the set of macroeconomic and financial indicators including both the Google and the Reuters Uncertainty Indexes (MacroFin-GoogleReuters).

Empirical Example

Econometric Models

- (20) Partial Least Squares (PLS). We use PLS to extract one, two, three, four and five factors; the resulting models and nowcasts are labeled, respectively, $PLS(1)$, $PLS(2)$, $PLS(3)$, $PLS(4)$ and $PLS(5)$. As above, for each model we use MacroFin, MacroFin-Google, MacroFin-Reuters and MacroFin-GoogleReuters.
- (20) Sparse Principal Components (SPC). We use SPC to extract one, two, three, four and five factors; the resulting models and nowcasts are labeled, respectively, $SPC(1)$, $SPC(2)$, $SPC(3)$, $SPC(4)$ and $SPC(5)$. As above, for each model we use MacroFin, MacroFin-Google, MacroFin-Reuters and MacroFin-GoogleReuters.

Empirical Example

Econometric Models

- (8) LASSO and Elastic Net (EN). We use the standard 10-fold cross-validation to determine the value for λ in LASSO. The chosen value is the one which minimises the in-sample MSE. As above, we use MacroFin, MacroFin-Google, MacroFin-Reuters and MacroFin-GoogleReuters.
- (4) Spike and Slab (SS) regressions using MacroFin, MacroFin-Google, MacroFin-Reuters and MacroFin-GoogleReuters.
- (4) Data-Driven Automated Forecasting Strategies. On top of the above methodologies we introduce some automated data-driven *"forecasting strategies"*. Our idea is simple and intuitive: we suggest the use of a *"model rotation"* strategy which chooses the model with the smallest cumulative nowcast error. Furthermore, we use an equally-weighted average of the top three, five and ten models.

Empirical Example

Evaluation Criteria

Once we have computed T^{OUT} nowcasts for 5 to 1 weeks prior to the release, and transformed them in levels, we evaluate their performance using the mean absolute error and the root mean squared forecast error statistics defined as:

$$MAE_{i,h} = \frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} |e_{i,t}| \, ,$$

$$RMSFE_{i,h} = \left(\frac{1}{T^{OUT}} \sum_{t=1}^{T^{OUT}} e_{i,t}^2 \right)^{\frac{1}{2}} \, ,$$

where e_i is the out-of-sample forecast error (in levels) for model i and weekly nowcast h weeks prior to the release. We further calculate the Diebold and Mariano (1995) statistic for equal predictive accuracy

Empirical Example

Summary

The main goal of this exercise is to assess whether the use of big data, as proxied by Reuters news and Google searches in this research, can, either in isolation or in combination with high frequency economic and financial indicators, improve the precision of nowcasts and flash estimates.

We are interested in gains in terms of both standard measures such as MAE and MSE and in increased timeliness.

We find that the nowcast error decreases significantly when we estimate three, two and one weeks prior to the official release.

The inclusion of big data-based uncertainty indexes results in improved nowcasting performance.

In some cases even a simple linear regression model using the Reuters index and three lags of the target variable results in accurate and robust nowcasts.

Various univariate models also seem to perform well.

Empirical Example

		IT, Harmonised CPI								
		GOOGLE		REUTERS			GOOGLE		REUTERS	
		Estimate	P-value	Estimate	P-value		Estimate	P-value	Estimate	P-value
		Contemporaneous Regression					Predictive Regression			
$r=1$	α	109.442	0.000	110.651	0.000	α	109.820	0.000	110.716	0.000
	β	0.155	0.019	41.643	0.000	β	0.145	0.028	41.932	0.000
	R^2_{Adj}	0.043		0.149		R^2_{Adj}	0.037		0.156	
$r=2$	α	109.644	0.000	110.527	0.000	α	109.882	0.000	110.568	0.000
	β	0.146	0.029	42.367	0.000	β	0.141	0.033	42.939	0.000
	R^2_{Adj}	0.036		0.156		R^2_{Adj}	0.034		0.166	
$r=3$	α	109.501	0.000	110.502	0.000	α	110.039	0.000	110.597	0.000
	β	0.151	0.022	42.663	0.000	β	0.135	0.044	42.590	0.000
	R^2_{Adj}	0.040		0.158		R^2_{Adj}	0.030		0.163	
$r=4$	α	109.968	0.000	110.240	0.000	α	109.907	0.000	110.333	0.000
	β	0.130	0.055	44.149	0.000	β	0.135	0.043	44.115	0.000
	R^2_{Adj}	0.036		0.175		R^2_{Adj}	0.000		0.181	

Contemporaneous and predictive regressions using Eurostat vintages and uncertainty indexes in levels.

Empirical Example

		UK, Harmonised CPI								
		GOOGLE		REUTERS			GOOGLE		REUTERS	
		Estimate	P-value	Estimate	P-value		Estimate	P-value	Estimate	P-value
		Contemporaneous Regression					Predictive Regression			
$r=1$	α	98.936	0.000	111.060	0.000	α	99.166	0.000	111.204	0.000
	β	0.485	0.000	121.256	0.000	β	0.483	0.000	120.934	0.001
	R^2_{Adj}	0.263		0.086		R^2_{Adj}	0.267		0.088	
$r=2$	α	99.093	0.000	110.824	0.000	α	99.328	0.000	111.141	0.000
	β	0.479	0.000	123.411	0.001	β	0.478	0.000	120.438	0.001
	R^2_{Adj}	0.259		0.090		R^2_{Adj}	0.263		0.088	
$r=3$	α	99.102	0.000	110.997	0.000	α	99.261	0.000	110.653	0.000
	β	0.479	0.000	120.731	0.001	β	0.479	0.000	128.027	0.001
	R^2_{Adj}	0.259		0.086		R^2_{Adj}	0.266		0.100	
$r=4$	α	99.363	0.000	110.199	0.000	α	98.971	0.000	110.462	0.000
	β	0.469	0.000	130.082	0.001	β	0.482	0.000	127.951	0.001
	R^2_{Adj}	0.260		0.103		R^2_{Adj}	0.000		0.103	

Contemporaneous and predictive regressions using Eurostat vintages and uncertainty indexes in levels.

Empirical Example I

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	2.218	2.218	1.646	1.575	1.575	PLS(3)-MacroFin-GoogleReuters	1.81	1.825	1.271	1.204	1.205
Average(12)	1.78	1.78	1.299	1.229	1.229	PLS(3)-MacroFin-Reuters	1.803	1.812	1.269	1.209	1.21
Average(24)	1.781	1.781	1.297	1.229	1.229	PLS(4)-MacroFin	1.897	1.863	1.278	1.206	1.207
Naive	2.39	2.39	1.825	1.686	1.686	PLS(4)-MacroFin-Google	1.954	1.904	1.28	1.203	1.204
AR(1)	1.824	1.824	1.312	1.239	1.239	PLS(4)-MacroFin-GoogleReuters	1.951	1.9	1.28	1.201	1.202
AR(4)	1.324	1.324	0.693	0.577	0.577	PLS(4)-MacroFin-Reuters	1.894	1.86	1.277	1.205	1.206
AR(AIC)	1.242	1.242	0.552	0.362	0.362	PLS(5)-MacroFin	1.908	1.882	1.276	1.202	1.203
AutoArima	1.341	1.341	0.955	0.884	0.884	PLS(5)-MacroFin-Google	1.97	1.925	1.258	1.185	1.186
ETS	1.777	1.777	1.296	1.227	1.227	PLS(5)-MacroFin-GoogleReuters	1.969	1.919	1.261	1.186	1.187
BaggedETS	1.611	1.613	1.316	1.324	1.312	PLS(5)-MacroFin-Reuters	1.908	1.877	1.277	1.202	1.203
BATS	1.369	1.369	0.875	0.762	0.762	SPC(1)-MacroFin	1.808	1.798	1.307	1.246	1.246
TBATS	1.369	1.369	0.875	0.762	0.762	SPC(1)-MacroFin-Google	1.808	1.799	1.307	1.246	1.246
NN	1.275	1.252	0.571	0.31	0.325	SPC(1)-MacroFin-GoogleReuters	1.808	1.798	1.307	1.246	1.246
Spline	2.331	2.331	1.77	1.655	1.655	SPC(1)-MacroFin-Reuters	1.807	1.798	1.307	1.246	1.245
THETA	1.778	1.778	1.294	1.229	1.229	SPC(2)-MacroFin	1.796	1.801	1.314	1.249	1.247
Google	1.817	1.778	1.316	1.252	1.25	SPC(2)-MacroFin-Google	1.798	1.798	1.31	1.247	1.247
Google-L1	1.673	1.659	1.246	1.18	1.179	SPC(2)-MacroFin-GoogleReuters	1.797	1.799	1.311	1.248	1.248
Google-L3	**1.327**	**1.317**	**0.581**	**0.497**	**0.497**	SPC(2)-MacroFin-Reuters	1.8	1.801	1.313	1.247	1.248
Reuters	1.792	1.792	1.304	1.242	1.242	SPC(3)-MacroFin	1.772	1.794	1.305	1.247	1.246
Reuters-L1	1.655	1.657	1.185	1.125	1.125	SPC(3)-MacroFin-Google	1.773	1.797	1.307	1.245	1.249
Reuters-L3	**1.339**	**1.341**	**0.698**	**0.589**	**0.589**	SPC(3)-MacroFin-GoogleReuters	1.779	1.798	1.297	1.246	1.247
DFA(2)-MacroFin	1.775	1.796	1.315	1.249	1.249	SPC(3)-MacroFin-Reuters	1.773	1.796	1.31	1.247	1.247
DFA(2)-MacroFin-Google	1.774	1.796	1.314	1.25	1.25	SPC(4)-MacroFin	1.78	1.734	1.27	1.238	1.234
DFA(2)-MacroFin-GoogleReuters	1.774	1.796	1.314	1.25	1.25	SPC(4)-MacroFin-Google	1.779	1.74	1.259	1.238	1.238
DFA(2)-MacroFin-Reuters	1.775	1.797	1.316	1.25	1.25	SPC(4)-MacroFin-GoogleReuters	1.791	1.757	1.267	1.226	1.239

IT, HICP, Actual RMSFE

Empirical Example II

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	1.757	1.792	1.313	1.249	1.249	SPC(4)-MacroFin-Reuters	1.782	1.746	1.274	1.239	1.234
DFA(3)-MacroFin-Google	1.757	1.792	1.311	1.248	1.248	SPC(5)-MacroFin	1.783	1.737	1.257	1.231	1.227
DFA(3)-MacroFin-GoogleReuters	1.757	1.793	1.311	1.248	1.248	SPC(5)-MacroFin-Google	1.774	1.733	1.263	1.232	1.221
DFA(3)-MacroFin-Reuters	1.757	1.793	1.313	1.249	1.249	SPC(5)-MacroFin-GoogleReuters	1.773	1.734	1.263	1.216	1.223
DFA(4)-MacroFin	1.759	1.765	1.279	1.242	1.242	SPC(5)-MacroFin-Reuters	1.774	1.739	1.261	1.222	1.227
DFA(4)-MacroFin-Google	1.757	1.749	1.276	1.239	1.238	LASSO-MacroFin	1.692	1.702	1.178	1.135	1.135
DFA(4)-MacroFin-GoogleReuters	1.757	1.757	1.277	1.239	1.239	LASSO-MacroFin-Google	1.739	1.645	1.19	1.129	1.143
DFA(4)-MacroFin-Reuters	1.759	1.769	1.28	1.243	1.243	LASSO-MacroFin-GoogleReuters	1.658	1.673	1.189	1.149	1.139
DFA(5)-MacroFin	1.754	1.731	1.271	1.229	1.23	LASSO-MacroFin-Reuters	1.754	1.679	1.171	1.136	1.129
DFA(5)-MacroFin-Google	1.751	1.727	1.27	1.228	1.229	EN-MacroFin	1.694	1.639	1.186	1.137	1.135
DFA(5)-MacroFin-GoogleReuters	1.751	1.726	1.269	1.228	1.229	EN-MacroFin-Google	1.731	1.656	1.184	1.152	1.145
DFA(5)-MacroFin-Reuters	1.754	1.73	1.271	1.229	1.23	EN-MacroFin-GoogleReuters	1.738	1.661	1.191	1.151	1.143
PLS(1)-MacroFin	1.789	1.789	1.306	1.257	1.258	EN-MacroFin-Reuters	1.684	1.678	1.194	1.135	1.143
PLS(1)-MacroFin-Google	1.79	1.789	1.312	1.264	1.265	SSlab-MacroFin	1.709	1.709	1.214	1.161	1.153
PLS(1)-MacroFin-GoogleReuters	1.79	1.789	1.312	1.263	1.264	SSlab-MacroFin-Google	1.707	1.707	1.21	1.143	1.157
PLS(1)-MacroFin-Reuters	1.789	1.789	1.306	1.256	1.257	SSlab-MacroFin-GoogleReuters	1.711	1.703	1.216	1.155	1.149
PLS(2)-MacroFin	1.789	1.786	1.295	1.239	1.239	SSlab-MacroFin-Reuters	1.707	1.711	1.215	1.155	1.156
PLS(2)-MacroFin-Google	1.789	1.787	1.291	1.235	1.236	Best1	**1.344**	**1.379**	**0.778**	**0.617**	**0.62**
PLS(2)-MacroFin-GoogleReuters	1.789	1.787	1.29	1.234	1.235	Best3	1.32	1.316	0.709	0.574	0.574
PLS(2)-MacroFin-Reuters	1.789	1.786	1.294	1.238	1.239	Best5	1.365	1.334	0.733	0.613	0.615
PLS(3)-MacroFin	1.803	1.813	1.27	1.21	1.211	Best10	1.411	1.418	0.822	0.723	0.725
PLS(3)-MacroFin-Google	1.811	1.826	1.272	1.205	1.207						

IT, HICP, Actual RMSFE

Empirical Example I

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	0.431	0.431	0.351	0.351	0.351	PLS(3)-MacroFin-GoogleReuters	0.402	0.4	0.332	0.324	0.324
Average(12)	0.378	0.378	0.322	0.313	0.313	PLS(3)-MacroFin-Reuters	0.405	0.402	0.336	0.329	0.329
Average(24)	0.383	0.383	0.331	0.32	0.32	PLS(4)-MacroFin	0.395	0.402	0.339	0.329	0.329
Naive	0.513	0.513	0.462	0.484	0.484	PLS(4)-MacroFin-Google	0.4	0.408	0.338	0.326	0.326
AR(1)	0.395	0.395	0.365	0.358	0.358	PLS(4)-MacroFin-GoogleReuters	0.4	0.409	0.338	0.326	0.326
AR(4)	0.404	0.405	0.365	0.356	0.356	PLS(4)-MacroFin-Reuters	0.394	0.403	0.339	0.33	0.33
AR(AIC)	0.369	0.368	0.264	0.257	0.257	PLS(5)-MacroFin	0.405	0.404	0.341	0.33	0.33
AutoArima	0.401	0.401	0.358	0.349	0.349	PLS(5)-MacroFin-Google	0.404	0.408	0.338	0.324	0.324
ETS	0.393	0.393	0.352	0.341	0.341	PLS(5)-MacroFin-GoogleReuters	0.402	0.407	0.338	0.325	0.325
BaggedETS	0.427	0.419	0.367	0.353	0.351	PLS(5)-MacroFin-Reuters	0.402	0.404	0.341	0.33	0.33
BATS	0.388	0.388	0.347	0.336	0.336	SPC(1)-MacroFin	0.393	0.392	0.361	0.354	0.355
TBATS	0.388	0.388	0.347	0.336	0.336	SPC(1)-MacroFin-Google	0.393	0.393	0.361	0.354	0.354
NN	0.386	0.386	0.354	0.306	0.313	SPC(1)-MacroFin-GoogleReuters	0.393	0.393	0.361	0.354	0.354
Spline	0.439	0.439	0.373	0.376	0.376	SPC(1)-MacroFin-Reuters	0.393	0.393	0.361	0.354	0.354
THETA	0.372	0.372	0.316	0.311	0.311	SPC(2)-MacroFin	0.393	0.395	0.367	0.36	0.361
Google	0.366	0.397	0.319	0.311	0.311	SPC(2)-MacroFin-Google	0.393	0.395	0.368	0.361	0.361
Google-L1	0.391	0.423	0.316	0.308	0.308	SPC(2)-MacroFin-GoogleReuters	0.393	0.396	0.367	0.362	0.361
Google-L3	**0.345**	**0.38**	**0.295**	**0.284**	**0.285**	SPC(2)-MacroFin-Reuters	0.393	0.395	0.367	0.361	0.361
Reuters	0.373	0.376	0.357	0.354	0.354	SPC(3)-MacroFin	0.368	0.379	0.35	0.342	0.342
Reuters-L1	0.38	0.382	0.355	0.351	0.35	SPC(3)-MacroFin-Google	0.367	0.365	0.342	0.336	0.332
Reuters-L3	0.403	0.405	0.371	0.362	0.362	SPC(3)-MacroFin-GoogleReuters	0.367	0.364	0.344	0.333	0.335
DFA(2)-MacroFin	0.392	0.393	0.371	0.364	0.364	SPC(3)-MacroFin-Reuters	0.361	0.36	0.351	0.342	0.344
DFA(2)-MacroFin-Google	0.392	0.393	0.372	0.364	0.364	SPC(4)-MacroFin	0.365	0.352	0.334	0.335	0.333
DFA(2)-MacroFin-GoogleReuters	0.392	0.394	0.372	0.364	0.365	SPC(4)-MacroFin-Google	0.361	0.339	0.327	0.319	0.324
DFA(2)-MacroFin-Reuters	0.392	0.393	0.371	0.364	0.364	SPC(4)-MacroFin-GoogleReuters	0.359	0.349	0.324	0.322	0.326

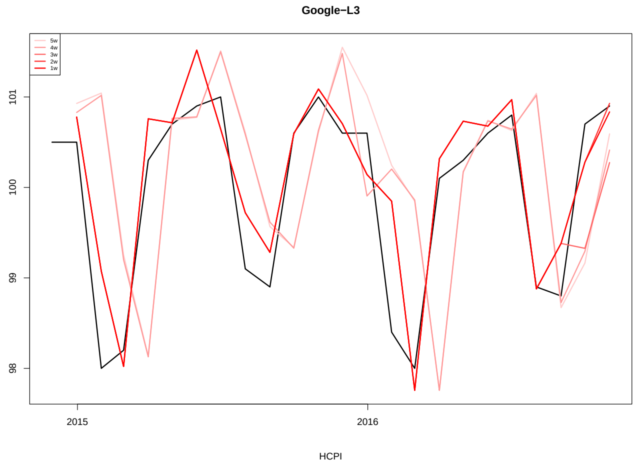
UK, HICP, Actual RMSFE

Empirical Example II

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	0.367	0.37	0.363	0.355	0.355	SPC(4)-MacroFin-Reuters	0.364	0.35	0.337	0.334	0.332
DFA(3)-MacroFin-Google	0.366	0.366	0.356	0.348	0.348	SPC(5)-MacroFin	0.358	0.34	0.326	0.324	0.326
DFA(3)-MacroFin-GoogleReuters	0.367	0.366	0.356	0.347	0.347	SPC(5)-MacroFin-Google	0.35	0.332	0.316	0.314	0.315
DFA(3)-MacroFin-Reuters	0.365	0.371	0.363	0.354	0.355	SPC(5)-MacroFin-GoogleReuters	0.351	0.334	0.316	0.317	0.316
DFA(4)-MacroFin	0.366	0.361	0.348	0.34	0.34	SPC(5)-MacroFin-Reuters	0.358	0.339	0.329	0.328	0.325
DFA(4)-MacroFin-Google	0.36	0.356	0.34	0.331	0.331	LASSO-MacroFin	0.32	0.322	0.314	0.298	0.295
DFA(4)-MacroFin-GoogleReuters	0.36	0.357	0.341	0.333	0.333	LASSO-MacroFin-Google	0.315	0.32	0.307	0.287	0.293
DFA(4)-MacroFin-Reuters	0.367	0.362	0.35	0.342	0.342	LASSO-MacroFin-GoogleReuters	0.321	0.314	0.308	0.288	0.287
DFA(5)-MacroFin	0.362	0.352	0.338	0.335	0.335	LASSO-MacroFin-Reuters	0.325	0.319	0.315	0.297	0.297
DFA(5)-MacroFin-Google	0.353	0.349	0.33	0.325	0.325	EN-MacroFin	0.317	0.316	0.312	0.308	0.3
DFA(5)-MacroFin-GoogleReuters	0.355	0.352	0.331	0.326	0.326	EN-MacroFin-Google	0.313	0.316	0.31	0.289	0.289
DFA(5)-MacroFin-Reuters	0.363	0.355	0.34	0.336	0.336	EN-MacroFin-GoogleReuters	0.322	0.314	0.312	0.292	0.29
PLS(1)-MacroFin	0.393	0.392	0.35	0.346	0.346	EN-MacroFin-Reuters	0.312	0.312	0.322	0.3	0.3
PLS(1)-MacroFin-Google	0.394	0.393	0.352	0.348	0.348	SSlab-MacroFin	0.315	0.319	0.313	0.297	0.299
PLS(1)-MacroFin-GoogleReuters	0.394	0.393	0.352	0.347	0.347	SSlab-MacroFin-Google	0.314	0.32	0.313	0.297	0.297
PLS(1)-MacroFin-Reuters	0.393	0.392	0.349	0.346	0.346	SSlab-MacroFin-GoogleReuters	0.315	0.32	0.313	0.297	0.295
PLS(2)-MacroFin	0.406	0.404	0.358	0.351	0.352	SSlab-MacroFin-Reuters	0.314	0.319	0.313	0.297	0.297
PLS(2)-MacroFin-Google	0.409	0.407	0.356	0.348	0.349	Best1	0.35	0.368	0.348	0.334	0.331
PLS(2)-MacroFin-GoogleReuters	0.408	0.406	0.356	0.349	0.349	Best3	0.325	0.332	0.299	0.302	0.301
PLS(2)-MacroFin-Reuters	0.405	0.403	0.358	0.351	0.352	Best5	0.33	0.329	0.306	0.305	0.305
PLS(3)-MacroFin	0.408	0.404	0.336	0.328	0.328	Best10	0.32	0.323	0.32	0.308	0.308
PLS(3)-MacroFin-Google	0.405	0.403	0.332	0.324	0.324						

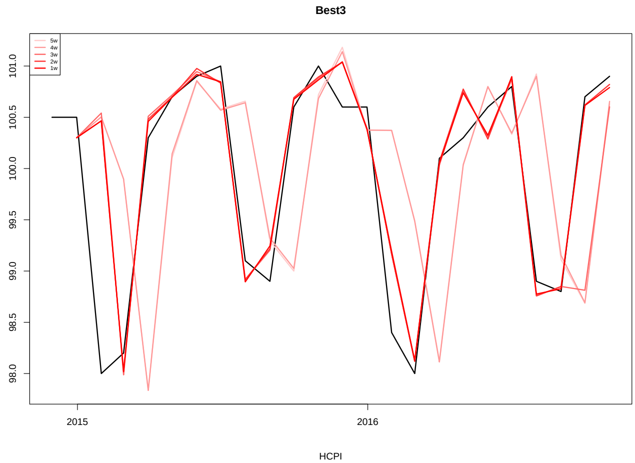
UK, HICP, Actual RMSFE

Empirical Example



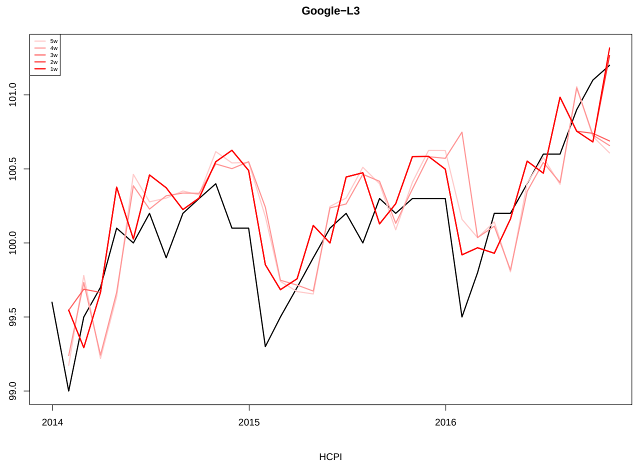
IT, HICP, Google-based Uncertainty Index.

Empirical Example



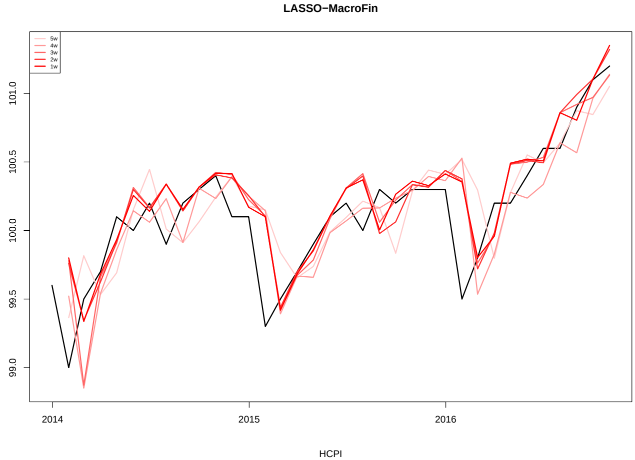
IT, HICP, about 50% of the times a big data index is used.

Empirical Example



UK, HICP.

Empirical Example



UK, HICP.

Further Evaluation & Metrics Robustness

While point nowcasts and forecasts are routinely computed and reported, also in official publications, there is growing interest in providing also measures of uncertainty around the point forecasts, and possibly other complementary information, such as directional forecasts.

Hence, we briefly review density and interval forecasts and methods for their evaluation.

Then, we apply them empirically, as a continuation of the nowcasting exercise, to assess whether the big data based indicators can also yield gains in terms of reducing uncertainty and/or improving directional accuracy.

Further Evaluation & Metrics Robustness

Interval and density forecasts

Assuming that the model used to generate the flash estimates of forecasts is correctly specified and with normal errors, and that the sample size T is large so that parameter estimation error can be ignored, it is

$$\left(\frac{y_{T+h} - \hat{y}_{T+h}}{\sqrt{V(e_{T+h})}}\right) \sim N(0,1), \tag{1}$$

where $\hat{y}_{T+h}$ indicates the forecast and e_{T+h} the forecast error, $e_{T+h} = y_{T+h} - \hat{y}_{T+h}$. Equation (1) implies

$$y_{T+h} \sim N(\hat{y}_{T+h}, V(e_{T+h})), \tag{2}$$

which is the expression for the *density forecast* of y_{T+h}.

Further Evaluation & Metrics Robustness

Interval and density forecasts

The density forecast can be used to assign probabilities to specific events of interest concerning the future behaviour of the variable y. For example, if y is inflation, with the formula in (2) we can compute the probability that inflation in period $T+h$ will be higher than 2%.

Another use of the forecast density is to construct *interval forecasts* for y_{T+h}. A $[1-\alpha]\%$ forecast interval is represented as

$$\hat{y}_{T+h} - c_{\alpha/2}\sqrt{V(e_{T+h})}; \hat{y}_{T+h} + c_{\alpha/2}\sqrt{V(e_{T+h})}, \tag{3}$$

where $c_{\alpha/2}$ is the $(\alpha/2)\%$ critical value for the standard normal density. For example, a 95% confidence interval is given by

$$\hat{y}_{T+h} - 1.96\sqrt{V(e_{T+h})}; \hat{y}_{T+h} + 1.96\sqrt{V(e_{T+h})}. \tag{4}$$

Further Evaluation & Metrics Robustness

Interval and density forecasts

Finally, density forecasts and confidence intervals can be also constructed with different assumptions on the distribution of the error term, though the derivations are more complex.

Also, as long as the distribution of the error is symmetric, the density (and the interval forecasts) will be centered around the optimal point forecast that coincides, as said, with the future expected value of the dependent variable, conditional on the available information set.

Finally, in the case of nonlinear models, simulation methods are generally required to approximate the density forecasts.

Further Evaluation & Metrics Robustness

Interval and density forecasts

For the evaluation of point forecasts we just compare the forecast and actual values, for the density forecasts we must instead compare the entire forecast and actual densities, or the corresponding CDFs, which makes the evaluation more complex.

A related approach to probabilistically evaluate density forecasts is based on likelihood ratio tests, see Berkowitz (2001). Specifically, let us assume the model:

$$z_t - \mu = \rho \left(z_{t-1} - \mu \right) + \epsilon_t,$$

with $\epsilon_t \sim N\left(0,1\right)$ and, as before, $z_t = \Phi^{-1}\left[\int_{-\infty}^{y_t} f\left(u\right) du\right]$ is the inverse standard normal distribution function with $f\left(y_t\right)$ being the probability density of y_t.

Further Evaluation & Metrics Robustness

Interval and density forecasts

Then, three alternative likelihood ratio tests can be used:

$$LR_1 = -2(L(0,1,\widehat{\rho}) - L\left(\widehat{\mu},\widehat{\sigma}_{\epsilon}^2,\widehat{\rho}\right))$$

$$LR_2 = -2(L\left(\widehat{\mu},\widehat{\sigma}_{\epsilon}^2,0\right) - L\left(\widehat{\mu},\widehat{\sigma}_{\epsilon}^2,\widehat{\rho}\right))$$

$$LR_3 = -2(L(0,1,0) - L\left(\widehat{\mu},\widehat{\sigma}_{\epsilon}^2,\widehat{\rho}\right))$$

where $L(\cdot)$ is the likelihood as a function of the unknown parameters; for more information see Berkowitz (2001). LR_1 tests for the zero mean of the series and unity of the residuals variance. LR_2 tests for independence and LR_3 is the joint test.

Further Evaluation & Metrics Robustness

Directional forecasts

let us assume that the variable of interest is negative in period t, $R_t = 1$, if the unobservable variable s_t is larger than zero, where the evolution of s_t is governed by

$$s_t = \beta' y_{t-1} + e_t. \tag{5}$$

Therefore,

$$\Pr(R_t = 1) = \Pr(s_t > 0) = F(\beta' y_{t-1}), \tag{6}$$

where $F(.)$ is either the cumulative normal distribution function (Probit model), or the logistic function (Logit model). The model can be estimated by maximum likelihood, and the estimated parameters combined with current values of the leading indicators y to provide an estimate of the probability of observing a negative value in period $t+1$, i.e.,

$$\widehat{R}_{t+1} = \Pr(R_{t+1} = 1) = F(\widehat{\beta}' y_t). \tag{7}$$

Further Evaluation & Metrics Robustness

Directional forecasts

Note that, as in the case of dynamic estimation, a different model specification is required for each forecast horizon. For example, if a h-step ahead prediction is of interest, the model in (5) should be substituted with

$$s_t = \gamma_h' y_{t-h} + u_{t,h}. \tag{8}$$

This approach typically introduces serial correlation and heteroskedasticity into the error term $u_{t,h}$, so that the Logit specification combined with nonlinear least squares estimation and robust estimation of the standard errors of the parameters can be preferred over standard maximum likelihood estimation.

Further Evaluation & Metrics Robustness

Directional forecasts

As an alternative, the model in (5) could be complemented with an auxiliary specification for y_t, say,

$$y_t = Ay_{t-1} + v_t \tag{9}$$

so that

$$\Pr(R_{t+h} = 1) = \Pr(s_{t+h} > 0) = \Pr(\beta' A^{h-1} y_t + \eta_{t+h-1} + e_{t+h} > 0) = F_{\eta+e}(\beta' A^{h-1} y_t) \tag{10}$$

with $\eta_{t+h-1} = \beta' v_{t+h-1} + \beta' A v_{t+h-2} + ... + \beta' A^{h-1} v_t$. In general, the derivation of $F_{\eta+e}(.)$ is quite complicated, and the specification of the auxiliary model for y_t can introduce additional noise, so that the direct approach seems empirically preferable.

Further Evaluation & Metrics Robustness

Evaluation of Directional forecasts

When the target variable, R_t, is a binary indicator while the (out of sample) forecast is a probability of recession, $\widehat{R}_t$, evaluation criteria similar to the MSFE can be introduced. Specifically, Diebold and Rudebusch (1989) defined the accuracy of the forecast as

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(R_t - \widehat{R}_t)^2, \tag{11}$$

where QPS stands for quadratic probability score. The range of QPS is $[0, 2]$, with 0 for perfect accuracy.

Further Evaluation & Metrics Robustness

Evaluation of Directional forecasts

A similar loss function that assigns more weight to larger forecast errors is the log probability score,

$$LPS = -\frac{1}{T}\sum_{t=1}^{T}\left((1-R_t)\log(1-\widehat{R}_t) + R_t \log \widehat{R}_t\right). \quad (12)$$

The range of LPS is $[0,\infty]$, with 0 for perfect accuracy.

Further Evaluation & Metrics Robustness

Evaluation of Directional forecasts

A third option, is the Sign Success Ratio (SSR) defined as:

$$SSR_{i,h} = \frac{\sum_{j=1}^{Eval} I\left(\text{Sign}\left(\widehat{y}_{i,T_j+h}^{f}\right)\right)}{Eval}, \tag{13}$$

where h is the forecast horizon, $I\left(\text{Sign}\left(\widehat{y}_{i,T_j+h}^{f}\right)\right)$ is an indicator function that receives the value 1 if $\text{Sign}\left(\widehat{y}_{i,T_j+h}^{f}\right) = \text{Sign}\left(y_{i,T_{j+h}}\right)$ and 0 otherwise, and $Eval$ indicates the number of the evaluation periods.

A large SSR indicates that the specified model correctly predicts the "direction" of the target during the cross-validation period. This statistic is a percentage and, as such, it is easier to interpret and communicate than QPS or LPS. For example, a 95% SSR indicates that the underlying model has correctly predicted the direction of the target over 95% of the evaluation period.

Further Evaluation & Metrics Robustness

Empirical Gains

Overall, the results for GDP are rather heterogeneous in terms of best forecasting procedures, but sequential selection and averaging of the best models over a training simple often delivers good directional and interval forecasts.

Models with the big data based uncertainty indicators have a mixed performance, as well as those based on large macro and financial information sets.

Simple univariate models tend to do well in terms of directional forecasts, but often produce too wide interval forecasts, which contain 100% of the realizations rather than only 60% of them.

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	8.7	8.7	26.09	30.43	30.43	PLS(3)-MacroFin-GoogleReuters	21.74	17.39	43.48	52.17	52.17
Average(12)	30.43	30.43	34.78	34.78	34.78	PLS(3)-MacroFin-Reuters	21.74	21.74	47.83	52.17	52.17
Average(24)	30.43	30.43	43.48	47.83	47.83	PLS(4)-MacroFin	21.74	21.74	43.48	52.17	52.17
Naive	26.09	26.09	47.83	52.17	52.17	PLS(4)-MacroFin-Google	26.09	26.09	39.13	47.83	47.83
AR(1)	30.43	30.43	60.87	65.22	65.22	PLS(4)-MacroFin-GoogleReuters	26.09	26.09	39.13	47.83	47.83
AR(4)	43.48	43.48	69.57	73.91	73.91	PLS(4)-MacroFin-Reuters	26.09	26.09	43.48	52.17	52.17
AR(AIC)	52.17	52.17	69.57	73.91	73.91	PLS(5)-MacroFin	26.09	30.43	43.48	52.17	52.17
AutoArima	43.48	43.48	60.87	65.22	65.22	PLS(5)-MacroFin-Google	30.43	30.43	43.48	52.17	52.17
ETS	30.43	30.43	30.43	30.43	30.43	PLS(5)-MacroFin-GoogleReuters	30.43	30.43	43.48	52.17	52.17
BaggedETS	34.78	34.78	34.78	30.43	30.43	PLS(5)-MacroFin-Reuters	26.09	34.78	43.48	52.17	52.17
BATS	47.83	47.83	65.22	69.57	69.57	SPC(1)-MacroFin	26.09	26.09	52.17	56.52	56.52
TBATS	47.83	47.83	65.22	69.57	69.57	SPC(1)-MacroFin-Google	26.09	26.09	52.17	56.52	56.52
NN	39.13	43.48	65.22	73.91	73.91	SPC(1)-MacroFin-GoogleReuters	26.09	26.09	52.17	56.52	56.52
Spline	30.43	30.43	52.17	56.52	56.52	SPC(1)-MacroFin-Reuters	26.09	26.09	52.17	56.52	56.52
THETA	30.43	30.43	52.17	56.52	56.52	SPC(2)-MacroFin	26.09	26.09	52.17	56.52	56.52
Google	30.43	30.43	56.52	56.52	56.52	SPC(2)-MacroFin-Google	26.09	26.09	52.17	56.52	56.52
Google-L1	30.43	34.78	52.17	52.17	52.17	SPC(2)-MacroFin-GoogleReuters	26.09	26.09	52.17	56.52	56.52
Google-L3	56.52	56.52	73.91	78.26	78.26	SPC(2)-MacroFin-Reuters	26.09	26.09	52.17	56.52	56.52
Reuters	26.09	26.09	52.17	56.52	56.52	SPC(3)-MacroFin	30.43	26.09	43.48	47.83	47.83
Reuters-L1	34.78	34.78	47.83	52.17	52.17	SPC(3)-MacroFin-Google	30.43	26.09	39.13	47.83	47.83
Reuters-L3	43.48	43.48	78.26	82.61	82.61	SPC(3)-MacroFin-GoogleReuters	30.43	26.09	39.13	43.48	47.83
DFA(2)-MacroFin	26.09	26.09	47.83	52.17	52.17	SPC(3)-MacroFin-Reuters	30.43	26.09	43.48	47.83	47.83
DFA(2)-MacroFin-Google	30.43	26.09	47.83	52.17	52.17	SPC(4)-MacroFin	26.09	26.09	47.83	47.83	47.83
DFA(2)-MacroFin-GoogleReuters	30.43	26.09	47.83	52.17	52.17	SPC(4)-MacroFin-Google	26.09	26.09	52.17	56.52	47.83
DFA(2)-MacroFin-Reuters	26.09	26.09	47.83	52.17	52.17	SPC(4)-MacroFin-GoogleReuters	26.09	26.09	47.83	52.17	56.52

IT, HICP, SSR

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	30.43	26.09	39.13	43.48	43.48	SPC(4)-MacroFin-Reuters	26.09	21.74	52.17	52.17	56.52
DFA(3)-MacroFin-Google	30.43	26.09	39.13	43.48	43.48	SPC(5)-MacroFin	26.09	39.13	52.17	47.83	52.17
DFA(3)-MacroFin-GoogleReuters	30.43	26.09	39.13	43.48	43.48	SPC(5)-MacroFin-Google	26.09	39.13	47.83	43.48	56.52
DFA(3)-MacroFin-Reuters	30.43	26.09	39.13	43.48	43.48	SPC(5)-MacroFin-GoogleReuters	26.09	39.13	43.48	47.83	52.17
DFA(4)-MacroFin	30.43	30.43	39.13	43.48	43.48	SPC(5)-MacroFin-Reuters	26.09	43.48	47.83	47.83	47.83
DFA(4)-MacroFin-Google	34.78	34.78	43.48	47.83	47.83	LASSO-MacroFin	39.13	43.48	43.48	52.17	47.83
DFA(4)-MacroFin-GoogleReuters	34.78	30.43	43.48	47.83	47.83	LASSO-MacroFin-Google	34.78	39.13	43.48	52.17	47.83
DFA(4)-MacroFin-Reuters	30.43	30.43	39.13	43.48	43.48	LASSO-MacroFin-GoogleReuters	30.43	39.13	47.83	52.17	52.17
DFA(5)-MacroFin	30.43	43.48	43.48	47.83	47.83	LASSO-MacroFin-Reuters	39.13	43.48	43.48	52.17	52.17
DFA(5)-MacroFin-Google	30.43	43.48	43.48	47.83	47.83	EN-MacroFin	39.13	43.48	47.83	47.83	52.17
DFA(5)-MacroFin-GoogleReuters	30.43	43.48	43.48	47.83	47.83	EN-MacroFin-Google	26.09	39.13	47.83	52.17	52.17
DFA(5)-MacroFin-Reuters	30.43	43.48	43.48	47.83	47.83	EN-MacroFin-GoogleReuters	26.09	39.13	47.83	47.83	52.17
PLS(1)-MacroFin	26.09	26.09	56.52	56.52	56.52	EN-MacroFin-Reuters	39.13	43.48	47.83	47.83	47.83
PLS(1)-MacroFin-Google	26.09	26.09	52.17	52.17	52.17	SSlab-MacroFin	34.78	34.78	47.83	52.17	52.17
PLS(1)-MacroFin-GoogleReuters	26.09	26.09	56.52	56.52	56.52	SSlab-MacroFin-Google	34.78	34.78	52.17	52.17	52.17
PLS(1)-MacroFin-Reuters	26.09	26.09	56.52	56.52	56.52	SSlab-MacroFin-GoogleReuters	34.78	34.78	47.83	52.17	52.17
PLS(2)-MacroFin	26.09	26.09	47.83	52.17	52.17	SSlab-MacroFin-Reuters	34.78	34.78	47.83	52.17	52.17
PLS(2)-MacroFin-Google	26.09	26.09	47.83	52.17	52.17	Best1	34.78	30.43	60.87	65.22	65.22
PLS(2)-MacroFin-GoogleReuters	26.09	26.09	47.83	52.17	52.17	Best3	34.78	34.78	65.22	73.91	78.26
PLS(2)-MacroFin-Reuters	26.09	26.09	47.83	52.17	52.17	Best5	39.13	52.17	69.57	73.91	73.91
PLS(3)-MacroFin	21.74	26.09	47.83	52.17	52.17	Best10	34.78	39.13	69.57	73.91	73.91
PLS(3)-MacroFin-Google	21.74	17.39	52.17	56.52	56.52						

IT, HICP, SSR

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	32.35	32.35	50	47.06	50	PLS(3)-MacroFin-GoogleReuters	58.82	61.76	70.59	73.53	73.53
Average(12)	20.59	17.65	29.41	32.35	38.24	PLS(3)-MacroFin-Reuters	61.76	64.71	73.53	76.47	76.47
Average(24)	14.71	14.71	29.41	26.47	29.41	PLS(4)-MacroFin	61.76	61.76	73.53	76.47	76.47
Naive	67.65	67.65	82.35	79.41	79.41	PLS(4)-MacroFin-Google	55.88	55.88	61.76	67.65	67.65
AR(1)	85.29	88.24	85.29	85.29	88.24	PLS(4)-MacroFin-GoogleReuters	55.88	55.88	64.71	70.59	70.59
AR(4)	76.47	82.35	85.29	88.24	85.29	PLS(4)-MacroFin-Reuters	61.76	61.76	76.47	79.41	79.41
AR(AIC)	58.82	55.88	58.82	61.76	61.76	PLS(5)-MacroFin	50	52.94	73.53	76.47	76.47
AutoArima	76.47	76.47	79.41	88.24	91.18	PLS(5)-MacroFin-Google	50	52.94	67.65	70.59	70.59
ETS	79.41	79.41	85.29	85.29	85.29	PLS(5)-MacroFin-GoogleReuters	50	52.94	67.65	70.59	70.59
BaggedETS	38.24	38.24	55.88	61.76	67.65	PLS(5)-MacroFin-Reuters	50	52.94	73.53	76.47	76.47
BATS	79.41	79.41	85.29	85.29	85.29	SPC(1)-MacroFin	61.76	67.65	73.53	79.41	79.41
TBATS	79.41	79.41	85.29	85.29	85.29	SPC(1)-MacroFin-Google	64.71	67.65	73.53	79.41	79.41
NN	47.06	47.06	61.76	67.65	64.71	SPC(1)-MacroFin-GoogleReuters	61.76	67.65	73.53	76.47	76.47
Spline	76.47	76.47	82.35	79.41	79.41	SPC(1)-MacroFin-Reuters	61.76	64.71	73.53	79.41	79.41
THETA	82.35	82.35	91.18	91.18	91.18	SPC(2)-MacroFin	64.71	64.71	76.47	79.41	79.41
Google	61.76	64.71	67.65	70.59	70.59	SPC(2)-MacroFin-Google	64.71	64.71	76.47	76.47	76.47
Google-L1	52.94	50	58.82	61.76	61.76	SPC(2)-MacroFin-GoogleReuters	64.71	64.71	73.53	76.47	76.47
Google-L3	55.88	55.88	58.82	61.76	61.76	SPC(2)-MacroFin-Reuters	64.71	64.71	76.47	79.41	79.41
Reuters	67.65	70.59	73.53	76.47	76.47	SPC(3)-MacroFin	64.71	55.88	73.53	79.41	79.41
Reuters-L1	61.76	64.71	73.53	76.47	76.47	SPC(3)-MacroFin-Google	61.76	58.82	76.47	79.41	79.41
Reuters-L3	61.76	64.71	76.47	79.41	79.41	SPC(3)-MacroFin-GoogleReuters	61.76	58.82	73.53	79.41	79.41
DFA(2)-MacroFin	61.76	61.76	70.59	76.47	76.47	SPC(3)-MacroFin-Reuters	67.65	58.82	73.53	79.41	79.41
DFA(2)-MacroFin-Google	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin	58.82	61.76	76.47	79.41	79.41
DFA(2)-MacroFin-GoogleReuters	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin-Google	61.76	58.82	76.47	79.41	76.47
DFA(2)-MacroFin-Reuters	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin-GoogleReuters	64.71	58.82	76.47	79.41	79.41

IT, HICP, Actual coverage rates of 60% interval forecasts.

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	61.76	58.82	73.53	79.41	79.41	SPC(4)-MacroFin-Reuters	64.71	61.76	76.47	79.41	79.41
DFA(3)-MacroFin-Google	61.76	58.82	73.53	79.41	79.41	SPC(5)-MacroFin	64.71	67.65	79.41	79.41	79.41
DFA(3)-MacroFin-GoogleReuters	61.76	58.82	73.53	79.41	79.41	SPC(5)-MacroFin-Google	58.82	64.71	79.41	79.41	76.47
DFA(3)-MacroFin-Reuters	61.76	58.82	73.53	79.41	79.41	SPC(5)-MacroFin-GoogleReuters	61.76	67.65	82.35	79.41	76.47
DFA(4)-MacroFin	64.71	58.82	73.53	79.41	79.41	SPC(5)-MacroFin-Reuters	61.76	67.65	79.41	79.41	79.41
DFA(4)-MacroFin-Google	64.71	55.88	73.53	79.41	79.41	LASSO-MacroFin	44.12	23.53	67.65	70.59	70.59
DFA(4)-MacroFin-GoogleReuters	64.71	55.88	73.53	79.41	79.41	LASSO-MacroFin-Google	47.06	23.53	64.71	70.59	70.59
DFA(4)-MacroFin-Reuters	64.71	58.82	73.53	79.41	79.41	LASSO-MacroFin-GoogleReuters	47.06	23.53	61.76	67.65	67.65
DFA(5)-MacroFin	67.65	61.76	76.47	79.41	79.41	LASSO-MacroFin-Reuters	44.12	23.53	70.59	73.53	76.47
DFA(5)-MacroFin-Google	67.65	64.71	76.47	79.41	79.41	EN-MacroFin	44.12	23.53	67.65	70.59	73.53
DFA(5)-MacroFin-GoogleReuters	67.65	61.76	76.47	79.41	79.41	EN-MacroFin-Google	44.12	23.53	61.76	70.59	70.59
DFA(5)-MacroFin-Reuters	67.65	61.76	76.47	79.41	79.41	EN-MacroFin-GoogleReuters	50	20.59	58.82	67.65	67.65
PLS(1)-MacroFin	61.76	64.71	76.47	76.47	76.47	EN-MacroFin-Reuters	47.06	20.59	61.76	73.53	73.53
PLS(1)-MacroFin-Google	61.76	67.65	76.47	76.47	76.47	SSlab-MacroFin	41.18	23.53	70.59	73.53	76.47
PLS(1)-MacroFin-GoogleReuters	61.76	67.65	76.47	76.47	76.47	SSlab-MacroFin-Google	44.12	23.53	70.59	76.47	76.47
PLS(1)-MacroFin-Reuters	61.76	64.71	76.47	76.47	76.47	SSlab-MacroFin-GoogleReuters	44.12	23.53	70.59	76.47	76.47
PLS(2)-MacroFin	64.71	67.65	73.53	76.47	76.47	SSlab-MacroFin-Reuters	41.18	23.53	70.59	76.47	73.53
PLS(2)-MacroFin-Google	64.71	67.65	73.53	76.47	76.47	Best1	50	32.35	58.82	61.76	61.76
PLS(2)-MacroFin-GoogleReuters	64.71	67.65	73.53	76.47	76.47	Best3	44.12	38.24	82.35	70.59	73.53
PLS(2)-MacroFin-Reuters	64.71	67.65	73.53	76.47	76.47	Best5	44.12	32.35	73.53	79.41	79.41
PLS(3)-MacroFin	61.76	61.76	70.59	73.53	73.53	Best10	52.94	38.24	76.47	79.41	79.41
PLS(3)-MacroFin-Google	58.82	61.76	67.65	70.59	70.59						

IT, HICP, Actual coverage rates of 60% interval forecasts.

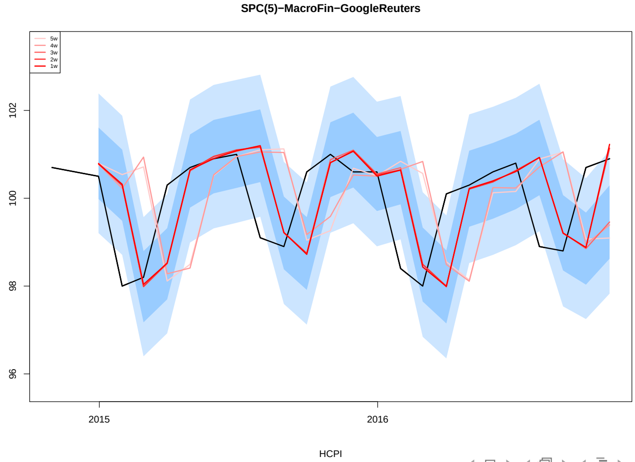
Further Evaluation & Metrics Robustness

Empirical Gains

IT, Google-based Uncertainty Index, 60% Intervals (dark blue), 90% Intervals (light blue)

Further Evaluation & Metrics Robustness

Empirical Gains



IT, Sparse PCA including Google & Reuters, 60% Intervals (dark blue), 90% Intervals (light blue)

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	35.29	35.29	38.24	41.18	41.18	PLS(3)-MacroFin-GoogleReuters	52.94	47.06	58.82	64.71	64.71
Average(12)	44.12	44.12	50	55.88	55.88	PLS(3)-MacroFin-Reuters	52.94	50	58.82	64.71	64.71
Average(24)	44.12	44.12	55.88	61.76	61.76	PLS(4)-MacroFin	58.82	55.88	61.76	64.71	64.71
Naive	61.76	61.76	38.24	38.24	38.24	PLS(4)-MacroFin-Google	58.82	58.82	61.76	64.71	64.71
AR(1)	58.82	58.82	55.88	61.76	61.76	PLS(4)-MacroFin-GoogleReuters	58.82	55.88	61.76	64.71	64.71
AR(4)	47.06	47.06	55.88	61.76	61.76	PLS(4)-MacroFin-Reuters	58.82	55.88	61.76	64.71	64.71
AR(AIC)	50	50	55.88	58.82	58.82	PLS(5)-MacroFin	55.88	55.88	58.82	64.71	64.71
AutoArima	41.18	41.18	55.88	61.76	61.76	PLS(5)-MacroFin-Google	52.94	55.88	58.82	64.71	64.71
ETS	50	50	55.88	61.76	61.76	PLS(5)-MacroFin-GoogleReuters	52.94	55.88	58.82	64.71	64.71
BaggedETS	50	50	47.06	50	50	PLS(5)-MacroFin-Reuters	55.88	55.88	58.82	64.71	64.71
BATS	44.12	44.12	55.88	61.76	61.76	SPC(1)-MacroFin	52.94	52.94	55.88	61.76	61.76
TBATS	44.12	44.12	55.88	61.76	61.76	SPC(1)-MacroFin-Google	52.94	55.88	55.88	61.76	61.76
NN	44.12	44.12	41.18	47.06	44.12	SPC(1)-MacroFin-GoogleReuters	52.94	52.94	55.88	61.76	61.76
Spline	44.12	44.12	38.24	41.18	41.18	SPC(1)-MacroFin-Reuters	52.94	52.94	55.88	61.76	61.76
THETA	41.18	41.18	55.88	61.76	61.76	SPC(2)-MacroFin	61.76	58.82	58.82	61.76	61.76
Google	58.82	52.94	61.76	64.71	67.65	SPC(2)-MacroFin-Google	61.76	55.88	58.82	61.76	61.76
Google-L1	47.06	50	70.59	67.65	70.59	SPC(2)-MacroFin-GoogleReuters	58.82	58.82	58.82	61.76	61.76
Google-L3	55.88	52.94	70.59	73.53	73.53	SPC(2)-MacroFin-Reuters	61.76	58.82	58.82	61.76	61.76
Reuters	58.82	58.82	58.82	61.76	61.76	SPC(3)-MacroFin	52.94	55.88	58.82	61.76	61.76
Reuters-L1	52.94	52.94	58.82	61.76	61.76	SPC(3)-MacroFin-Google	55.88	55.88	58.82	64.71	64.71
Reuters-L3	52.94	52.94	58.82	61.76	61.76	SPC(3)-MacroFin-GoogleReuters	55.88	55.88	58.82	64.71	64.71
DFA(2)-MacroFin	55.88	52.94	58.82	61.76	61.76	SPC(3)-MacroFin-Reuters	52.94	55.88	58.82	61.76	61.76
DFA(2)-MacroFin-Google	55.88	52.94	58.82	61.76	61.76	SPC(4)-MacroFin	52.94	52.94	58.82	61.76	61.76
DFA(2)-MacroFin-GoogleReuters	55.88	52.94	58.82	61.76	61.76	SPC(4)-MacroFin-Google	55.88	50	58.82	64.71	64.71
DFA(2)-MacroFin-Reuters	55.88	52.94	58.82	61.76	61.76	SPC(4)-MacroFin-GoogleReuters	55.88	47.06	58.82	64.71	64.71

UK, HICP, SSR

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	55.88	50	58.82	61.76	61.76	SPC(4)-MacroFin-Reuters	50	52.94	58.82	61.76	61.76
DFA(3)-MacroFin-Google	52.94	55.88	55.88	61.76	61.76	SPC(5)-MacroFin	55.88	50	58.82	61.76	61.76
DFA(3)-MacroFin-GoogleReuters	50	55.88	55.88	61.76	61.76	SPC(5)-MacroFin-Google	55.88	50	58.82	61.76	64.71
DFA(3)-MacroFin-Reuters	55.88	50	58.82	61.76	61.76	SPC(5)-MacroFin-GoogleReuters	55.88	44.12	61.76	61.76	64.71
DFA(4)-MacroFin	55.88	52.94	58.82	61.76	61.76	SPC(5)-MacroFin-Reuters	58.82	47.06	55.88	61.76	61.76
DFA(4)-MacroFin-Google	52.94	50	58.82	64.71	64.71	LASSO-MacroFin	52.94	55.88	61.76	64.71	64.71
DFA(4)-MacroFin-GoogleReuters	52.94	50	58.82	64.71	64.71	LASSO-MacroFin-Google	55.88	52.94	70.59	73.53	73.53
DFA(4)-MacroFin-Reuters	55.88	52.94	58.82	61.76	61.76	LASSO-MacroFin-GoogleReuters	55.88	52.94	70.59	73.53	73.53
DFA(5)-MacroFin	58.82	52.94	55.88	61.76	61.76	LASSO-MacroFin-Reuters	52.94	55.88	64.71	67.65	67.65
DFA(5)-MacroFin-Google	55.88	52.94	58.82	64.71	64.71	EN-MacroFin	55.88	55.88	61.76	64.71	64.71
DFA(5)-MacroFin-GoogleReuters	55.88	52.94	58.82	64.71	64.71	EN-MacroFin-Google	50	52.94	67.65	70.59	70.59
DFA(5)-MacroFin-Reuters	58.82	52.94	55.88	61.76	61.76	EN-MacroFin-GoogleReuters	55.88	52.94	67.65	70.59	73.53
PLS(1)-MacroFin	55.88	52.94	55.88	61.76	61.76	EN-MacroFin-Reuters	58.82	55.88	61.76	64.71	64.71
PLS(1)-MacroFin-Google	55.88	52.94	55.88	61.76	61.76	SSlab-MacroFin	55.88	55.88	67.65	70.59	67.65
PLS(1)-MacroFin-GoogleReuters	55.88	52.94	55.88	61.76	61.76	SSlab-MacroFin-Google	55.88	55.88	67.65	70.59	70.59
PLS(1)-MacroFin-Reuters	55.88	52.94	55.88	61.76	61.76	SSlab-MacroFin-GoogleReuters	55.88	58.82	67.65	70.59	70.59
PLS(2)-MacroFin	52.94	47.06	58.82	61.76	61.76	SSlab-MacroFin-Reuters	55.88	55.88	67.65	70.59	70.59
PLS(2)-MacroFin-Google	50	47.06	61.76	64.71	64.71	Best1	64.71	61.76	50	52.94	55.88
PLS(2)-MacroFin-GoogleReuters	52.94	47.06	61.76	64.71	64.71	Best3	52.94	58.82	61.76	64.71	67.65
PLS(2)-MacroFin-Reuters	52.94	47.06	58.82	61.76	61.76	Best5	52.94	55.88	64.71	70.59	70.59
PLS(3)-MacroFin	52.94	50	61.76	64.71	64.71	Best10	58.82	55.88	64.71	70.59	70.59
PLS(3)-MacroFin-Google	52.94	47.06	61.76	64.71	64.71						

UK, HICP, SSR

Further Evaluation & Metrics Robustness

Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w	Model	-5w	-4w	-3w	-2w	-1w
Average(4)	32.35	32.35	50	47.06	50	PLS(3)-MacroFin-GoogleReuters	58.82	61.76	70.59	73.53	73.53
Average(12)	20.59	17.65	29.41	32.35	38.24	PLS(3)-MacroFin-Reuters	61.76	64.71	73.53	76.47	76.47
Average(24)	14.71	14.71	29.41	26.47	29.41	PLS(4)-MacroFin	61.76	61.76	73.53	76.47	76.47
Naive	67.65	67.65	82.35	79.41	79.41	PLS(4)-MacroFin-Google	55.88	55.88	61.76	67.65	67.65
AR(1)	85.29	88.24	85.29	85.29	88.24	PLS(4)-MacroFin-GoogleReuters	55.88	55.88	64.71	70.59	70.59
AR(4)	76.47	82.35	85.29	88.24	85.29	PLS(4)-MacroFin-Reuters	61.76	61.76	76.47	79.41	79.41
AR(AIC)	58.82	55.88	58.82	61.76	61.76	PLS(5)-MacroFin	50	52.94	73.53	76.47	76.47
AutoArima	76.47	76.47	79.41	88.24	91.18	PLS(5)-MacroFin-Google	50	52.94	67.65	70.59	70.59
ETS	79.41	79.41	85.29	85.29	85.29	PLS(5)-MacroFin-GoogleReuters	50	52.94	67.65	70.59	70.59
BaggedETS	38.24	38.24	55.88	61.76	67.65	PLS(5)-MacroFin-Reuters	50	52.94	73.53	76.47	76.47
BATS	79.41	79.41	85.29	85.29	85.29	SPC(1)-MacroFin	61.76	67.65	73.53	79.41	79.41
TBATS	79.41	79.41	85.29	85.29	85.29	SPC(1)-MacroFin-Google	64.71	67.65	73.53	79.41	79.41
NN	47.06	47.06	61.76	67.65	64.71	SPC(1)-MacroFin-GoogleReuters	61.76	67.65	73.53	76.47	76.47
Spline	76.47	76.47	82.35	79.41	79.41	SPC(1)-MacroFin-Reuters	61.76	64.71	73.53	79.41	79.41
THETA	82.35	82.35	91.18	91.18	91.18	SPC(2)-MacroFin	64.71	64.71	76.47	79.41	79.41
Google	61.76	64.71	67.65	70.59	70.59	SPC(2)-MacroFin-Google	64.71	64.71	76.47	76.47	76.47
Google-L1	52.94	50	58.82	61.76	61.76	SPC(2)-MacroFin-GoogleReuters	64.71	64.71	73.53	76.47	76.47
Google-L3	55.88	55.88	58.82	61.76	61.76	SPC(2)-MacroFin-Reuters	64.71	64.71	76.47	79.41	79.41
Reuters	67.65	70.59	73.53	76.47	76.47	SPC(3)-MacroFin	64.71	55.88	73.53	79.41	79.41
Reuters-L1	61.76	64.71	73.53	76.47	76.47	SPC(3)-MacroFin-Google	61.76	58.82	76.47	79.41	79.41
Reuters-L3	61.76	64.71	76.47	79.41	79.41	SPC(3)-MacroFin-GoogleReuters	61.76	58.82	73.53	79.41	79.41
DFA(2)-MacroFin	61.76	61.76	70.59	76.47	76.47	SPC(3)-MacroFin-Reuters	67.65	58.82	73.53	79.41	79.41
DFA(2)-MacroFin-Google	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin	58.82	61.76	76.47	79.41	79.41
DFA(2)-MacroFin-GoogleReuters	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin-Google	61.76	58.82	76.47	79.41	76.47
DFA(2)-MacroFin-Reuters	61.76	61.76	70.59	76.47	76.47	SPC(4)-MacroFin-GoogleReuters	64.71	58.82	76.47	79.41	79.41

UK, HICP, Actual coverage rates of 60% interval forecasts.

Further Evaluation & Metrics Robustness

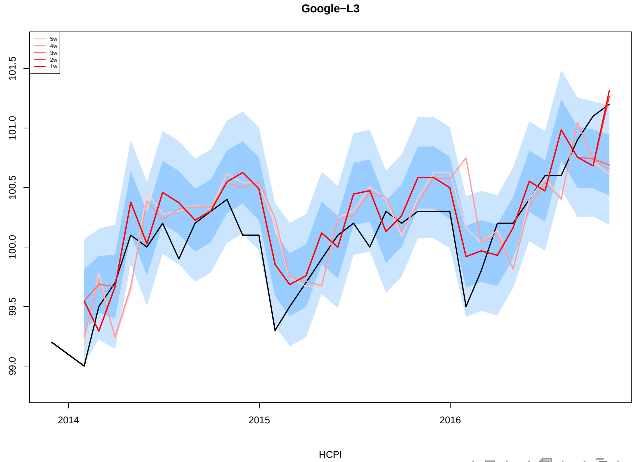
Empirical Gains

Model	-5w	-4w	-3w	-2w	-1w
DFA(3)-MacroFin	61.76	58.82	73.53	79.41	79.41
DFA(3)-MacroFin-Google	61.76	58.82	73.53	79.41	79.41
DFA(3)-MacroFin-GoogleReuters	61.76	58.82	73.53	79.41	79.41
DFA(3)-MacroFin-Reuters	61.76	58.82	73.53	79.41	79.41
DFA(4)-MacroFin	64.71	58.82	73.53	79.41	79.41
DFA(4)-MacroFin-Google	64.71	55.88	73.53	79.41	79.41
DFA(4)-MacroFin-GoogleReuters	64.71	55.88	73.53	79.41	79.41
DFA(4)-MacroFin-Reuters	64.71	58.82	73.53	79.41	79.41
DFA(5)-MacroFin	67.65	61.76	76.47	79.41	79.41
DFA(5)-MacroFin-Google	67.65	64.71	76.47	79.41	79.41
DFA(5)-MacroFin-GoogleReuters	67.65	61.76	76.47	79.41	79.41
DFA(5)-MacroFin-Reuters	67.65	61.76	76.47	79.41	79.41
PLS(1)-MacroFin	61.76	64.71	76.47	76.47	76.47
PLS(1)-MacroFin-Google	61.76	67.65	76.47	76.47	76.47
PLS(1)-MacroFin-GoogleReuters	61.76	67.65	76.47	76.47	76.47
PLS(1)-MacroFin-Reuters	61.76	64.71	76.47	76.47	76.47
PLS(2)-MacroFin	64.71	67.65	73.53	76.47	76.47
PLS(2)-MacroFin-Google	64.71	67.65	73.53	76.47	76.47
PLS(2)-MacroFin-GoogleReuters	64.71	67.65	73.53	76.47	76.47
PLS(2)-MacroFin-Reuters	64.71	67.65	73.53	76.47	76.47
PLS(3)-MacroFin	61.76	61.76	70.59	73.53	73.53
PLS(3)-MacroFin-Google	58.82	61.76	67.65	70.59	70.59
SPC(4)-MacroFin-Reuters	64.71	61.76	76.47	79.41	79.41
SPC(5)-MacroFin	64.71	67.65	79.41	79.41	79.41
SPC(5)-MacroFin-Google	58.82	64.71	79.41	79.41	76.47
SPC(5)-MacroFin-GoogleReuters	61.76	67.65	82.35	79.41	76.47
SPC(5)-MacroFin-Reuters	61.76	67.65	79.41	79.41	79.41
LASSO-MacroFin	44.12	23.53	67.65	70.59	70.59
LASSO-MacroFin-Google	47.06	23.53	64.71	70.59	70.59
LASSO-MacroFin-GoogleReuters	47.06	23.53	61.76	67.65	67.65
LASSO-MacroFin-Reuters	44.12	23.53	70.59	73.53	76.47
EN-MacroFin	44.12	23.53	67.65	70.59	73.53
EN-MacroFin-Google	44.12	23.53	61.76	70.59	70.59
EN-MacroFin-GoogleReuters	50	20.59	58.82	67.65	67.65
EN-MacroFin-Reuters	47.06	20.59	61.76	73.53	73.53
SSlab-MacroFin	41.18	23.53	70.59	73.53	76.47
SSlab-MacroFin-Google	44.12	23.53	70.59	76.47	76.47
SSlab-MacroFin-GoogleReuters	44.12	23.53	70.59	76.47	76.47
SSlab-MacroFin-Reuters	41.18	23.53	70.59	76.47	73.53
Best1	50	32.35	58.82	61.76	61.76
Best3	44.12	38.24	82.35	70.59	73.53
Best5	44.12	32.35	73.53	79.41	79.41
Best10	52.94	38.24	76.47	79.41	79.41

UK, HICP, Actual coverage rates of 60% interval forecasts.

Further Evaluation & Metrics Robustness

Empirical Gains



UK, Google-based Uncertainty Index, 60% Intervals (dark blue), 90% Intervals (light blue)

Conclusions & Overall Recommendations

We have developed a typology of big data and discussed various ways to move from unstructured big data to time series. We have also introduced ways to deal with seasonality and outliers before and after the transformation.

We have considered a variety of econometric methods suited for large (though not huge) datasets, and implemented them in an empirical nowcasting exercise for key economic variables for the four largest European countries. The exercise has shown the timeliness gains that can be obtained by adding big data based indicators to the usual set of explanatory variables.

Particular series, such as consumer prices and unemployment, tend to benefit more compared to industrial production. We have also discussed standard evaluation measures, and some extensions related to density and directional forecasting.

Conclusions & Overall Recommendations

We believe our analysis has highlighted the potential benefits associated with the use of big data.

However, there are also costs that should be considered, for example, for data collection, storage and handling, and there are also potential issues in terms of data quality, confidentiality, and reliability of provision.

Overall, our suggestion is to take a pragmatic approach that balances potential gains and costs from the use of big data for nowcasting macroeconomic indicators, in addition to standard indicators.