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Nowcasting GDP through the lens of economic states

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Abstract

Common sense tells that historical data are more informative for the estimation of today's nowcasting models when observed in a similar economic state as today. We operationalise this intuition by proposing a state-based weighted estimation procedure of GDP nowcasting models, in which observations are weighted based on the similarity with the current economic state. For this end, we also construct new state variables for measuring the similarity of economic time periods using news data, in addition to traditional variables. We find that the state-based weighting of observations leads to economically significant nowcasting gains for predicting GDP growth in Belgium as compared to traditional unweighted approaches.

Keywords: GDP growth, Media news, Nowcasting, Sentometrics, State variables

JEL Codes: C32, C51, C53, C55

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Non-technical summary

Timely economic policy making requires estimates of real activity of the ongoing quarter, while official numbers are only released over a month after the reference period has ended. A solution is to use other more timely economic indicators and econometric models to estimate the current GDP growth. This approach is called nowcasting.

When estimating these models, it is common to treat all historical data equally. However, it seems self-evident that we learn more about current economic growth dynamics from historical data observed in a similar economic state. If we are experiencing a crisis right now, we can learn more from previous crisis periods than from non-crisis periods. In this paper, we operationalize this idea by using weights based on variables that assess the state of the economy. Comparing the current state to historical states, we assign appropriate weights to the observations in the sample: we overweight observations with a similar state to the current state, and underweight dissimilar observations.

We apply our approach to nowcasting GDP growth in Belgium. We find that our state-based weighting approach is useful for improving GDP nowcasting accuracy in periods of economic turbulence such as the financial crisis and the COVID-19 crisis.

TABLE OF CONTENTS

"If history repeats itself, and the unexpected always happens, how incapable must Man be of learning from experience."

– George Bernard Shaw

1 Introduction

Timely economic policy making requires estimates of real activity of the ongoing quarter, while official numbers are only released over a month after the reference period has ended. Obtaining such a nowcast of economic growth is challenging when the economy transitions from sluggish economic growth to a turbulent period (Lewis et al., 2022). In case of turbulence, it seems self-evident that we learn more about current economic growth dynamics from historical data observed in a similar economic state. This view contrasts with the widespread approach of treating all historical data equally. Such models, with equally weighted observations, fail when they are needed the most: at a turning point of economic states. This state-dependency can be incorporated in the estimator, by overweighting historical observations similar to the current state.

In this study, we capture the state similarity using a combination of media news data and financial variables, and use this to improve the estimation of the model parameters. The use of textual media data for assessing the current state of the economy is natural for at least three reasons. First, the media report about the economy. The qualitative information of news articles (e.g., attention to recession, the tone about the economy) can be expected to be a source of information about the current state of the economy. Second, the media continuously report on economic events and agents, and thereby spread information which may influence the economic decision–making process (Hollanders and Vliegenthart, 2011; Larsen et al., 2021; Gambetti et al., 2023). Third, the media news articles are available in real time and at a daily frequency, enabling us to extract timely information about the current state.

Our main contribution is to provide a new method to model time variation in economic relationships by weighting the historical observations based on their similarity to the current state, which is easily applicable to any nowcasting model. Our approach mimics the popular practice among tactical investors to tilt their position towards the asset classes that have performed best in economically similar periods, based on the "Investment Clock" of Greetham and Hartnett (2004). In the context of risk analysis, Meucci (2010) proposes risk-based simulation analysis, in which historical observations receive a higher weight when they correspond to observations that are closer to the current economic situation. Economic and financial time series are subject to various instabilities, including changes in the behaviour of economic agents and exogenous shocks, which can lead to misspecification of models. Time-varying models provide a flexible framework for capturing these instabilities and modelling the dynamics of the system.

A large number of researchers have shown the importance of time variation in economic relationships, and several methods have been developed to take it into account. The Markov regime switching model of Hamilton (1989) distinguishes for example between a low and a high mean value for economic growth. Under this model, the states are latent. An alternative approach is to use a threshold model in which the economic state is determined by an observable variable (see e.g. Hansen 2000; Caner and Hansen 2004; Boudt et al. 2017). Typically, these models are estimated by imposing assumptions on the time dimension. Orbe et al. (2005) for example, estimate time-varying parameters using non-parametric regression, where the kernel function is explicitly dependent on the time. Our approach however aims to capture the time-varying nature of the parameters through a structure where we impose the historical observations in a similar state getting a higher weight while estimating the time-varying parameters.

Recent nowcasting literature has concentrated on methods to address the challenges posed by the extreme COVID-19 observations. Barbaglia et al. (2023c) introduce a selection prior in a Bayesian setting as a way to select between competing models. Artemova et al. (2021) propose using a weighted maximum likelihood estimator, and recommend cross-validation to select the best weighting method. Schorfheide and Song (2021) suggest excluding the pandemic observations, while Lenza and Primiceri (2022) propose to downweight the COVID-19 observations by explicitly estimating heteroscedasticity factors. Carriero et al. (2022) and Eraslan and Schröder (2023) recommend adding stochastic volatility to a Bayesian VAR and DFM approach, respectively. This enables the modeller to address historical outlying observations during normal times, but may not necessarily facilitate the accurate nowcasting of extreme observations during similar extreme periods. Our approach allows to dynamically downweight observations from crisis periods in normal times, while keeping the ability to dynamically increase the weights during future crisis periods. It can be applied to all kinds of estimation methods and is tractable and easy to implement. While this paper focuses on nowcasting models, our approach is also applicable to other, more general time series models.

Our second contribution is the introduction of a novel news–based state variable, namely the use of the correlation between economic sentiment from popular newspapers. This state variable indicates major economic events happening. The intuition comes from Nimark and Pitschner (2019). They state that economic agents cannot monitor all economic events. Agents need to rely on news providers. These news providers make state-dependent decisions on what events to cover. On a slow news day, different outlets will most likely cover different events. During an important economic event however, all news providers will cover this event and have a similar sentiment, leading to a high correlation. Our correlation between economic sentiment index thus tends to spike in periods when few economic events dominate the news narratives.

Our third contribution is to complement the existing nowcasting literature on the gains from using media news data. A growing literature shows the added value of news-based variables for the prediction of economic variables such as consumer confidence (Algaba et al., 2023), inflation (Larsen et al., 2021) and economic growth (Ardia et al., 2019; Thorsrud, 2020). In recent work, Barbaglia et al. (2023b) and Ellingsen et al. (2022) show the added value of enriching traditional macroeconomic and financial data with textual media news data when now–forecasting the quarterly GDP growth rate in the US, while Barbaglia et al. (2023a) focus on European countries. In the current literature, the news-based variables are added as predictors in an existing model, without adapting the estimation procedure. In this paper, we keep the prediction model and the predictors as they are in the benchmark approach – without news-based variables. Instead, we study the use of news data for improving the estimation of the model parameters. We are the first to introduce news-based variables this way into a modelling framework.

We illustrate our methodology by nowcasting economic growth for the Belgian economy. We rely on all major Belgian newspaper outlets. We find over the period January 2000 to June 2023, that the correlation between economic sentiment of popular newspapers peaks during crisis periods. Additionally, we find that the news sentiment correlation peaks during periods when the economy performs highly above average. We additionally show the gains for nowcasting Belgian GDP growth over the out-of-sample period January 2008 to June 2023. We integrate the state-based weights in the estimation of the nowcasting model using an approach without and with predictors. For the former we use the historical mean, which has been used as a benchmark model and can outperform more advanced nowcasting models in expansion periods (Siliverstovs and Wochner, 2021; Siliverstovs, 2021a,b). For the latter we use the BREL nowcasting approach by Piette (2016) that combines the use of bridge equations to solve the mixed-frequency problem, and the use of elastic net for handling the high-dimensionality. BREL is the current state-of-the-art nowcasting approach used by the National Bank of Belgium to produce the nowcasts published in the quarterly business cycle monitor. We find that this weighted approach yields an economically significant nowcasting accuracy improvement for several news–based and financial state variables.

The remainder of the paper proceeds as follows. Section 2 introduces the methodology. Section 3 discusses the news corpus, the macroeconomic data and the computation of the news-based state variables. Section 4 illustrates the state-based weights. Section 5 and section 6 present the nowcasting results. Section 7 concludes.

2 Methodology

We denote the variable to predict by y_t, where $t = 1, \ldots, T$ is a time index and T is the time of the nowcast. We require y_t to be covariance stationary. Let x_t be the $M \times 1$ vector of predictors available at time t, possibly including lags thereof. Assume we are currently at time t and y_t is not yet observed but x_t is. Then we use x_t to predict y_t. The prediction function $m(\cdot)$ includes a parameter vector θ_t and a hyperparameter vector η_t that may vary over time:

$$y_t = m(x_t; \theta_t, \eta_t) + \epsilon_t. \tag{1}$$

The hyperparameter η_t allows for the potential use of variable selection methods.

2.1 State–based weighted least squares estimation

We use the weighted least squares criterion as objective function for estimation of θ_t. The weight of a historical observation t depends on how different the current state variable z_T is from its past value z_t. At time T, y_t is observed for $t = 1, \ldots, T-1$ and x_t is observed for all $t = 1, \ldots, T$. The objective function M_T to be minimised at time T is:

$$M_T(\theta, \eta) = \sum_{t=1}^{T-1} w_t \left(y_t - m(x_t; \theta_T, \eta_T)\right)^2, \tag{2}$$

with $w_t \geq 0$ the weights. It nests the standard least squares estimator by setting $w_t = 1$. Let $\hat{\theta}$ be the resulting parameter estimate. The estimated model can then be used to predict y_T as:

$$\hat{y}_T = m(x_T; \hat{\theta}_T, \hat{\eta}_T). \tag{3}$$

The choice of state variable to compute the weights is crucial for the accuracy of the estimated model. We want the weights to reflect similarity of historical observations to the current state. Specifically, we specify the weight function such that it gives a higher weight to historical observations similar to the current state at time T and smaller weights to observations that are different from the current state. The weights are based on a state variable z_t that represents the current state of the economy. In the next section, the choice of state variable will be further discussed. We use a kernel function to map the difference between a historical observation z_t and the target value z_T into weights. Using a kernel function K_σ, the weights are given by:

$$w_t = K_\sigma(z_t - z_T) \qquad \text{for} \quad t = 1, \ldots, T-1. \tag{4}$$

We recommend using a smooth kernel function with unbounded support such that all observations receive a positive non-zero weight. In the application, we will use the Gaussian kernel, to assure smooth transition from one state to another. This kernel is given by $K_\sigma(v) = \exp(-v^2/2\sigma^2)$, where σ is the standard deviation of the state variable in the historical sample. These weights will be close to one for observations that are very similar to the current state. Weights will be closer to zero if this is not the case.

This weighted estimation procedure can be easily introduced in other estimation methods, such as elastic net (Zou and Hastie, 2005). Elastic net combines LASSO (Tibshirani, 1996) and ridge regression (Hoerl and Kennard, 1970). When weights are introduced, the objective function to be minimised with respect to θ at time T is:

$$M_T(\theta; \lambda) = \frac{1}{2(T-1)} \sum_{t=1}^{T-1} w_t \left(y_t - m_T(x_t; \theta)\right)^2 + \lambda_1 \left[\frac{1-\lambda_2}{2} \|\theta\|_2^2 + \lambda_2 \|\theta\|_1\right], \tag{5}$$

with $w_t \geq 0$, $\|.\|_p = \left(\sum_{i=1}^n |.|^p\right)^{1/p}$ and λ_i being the corresponding penalty coefficients.

Finally, note that the weighted least squares in the context of a linear model is still explicit and hence computationally simple. Throughout the paper, we use the sum of squared prediction errors as the estimation criterion. The proposed state-based weighted approach can be extended, without major modifications, to other estimation methods. Artemova et al. (2021) use a weighted maximum likelihood estimator for forecasting. A crucial difference between their estimator and ours is that we require the weights to depend on $z_t - z_T$, while Artemova et al. (2021) calibrate the weights based on z_t.

2.2 The case of multiple state variables

The above methodology can also be applied to a d-dimensional state variable, instead of a single state variable. In this case, there are d weights for a given time point t, denoted by $w_{t,1}, \ldots, w_{t,d}$, which can be aggregated into a composite weight using a function $g(.)$ such that:

$$w_t = g(w_{1,t}, \ldots, w_{d,t}) \text{ for } t = 1, \ldots, T-1. \tag{6}$$

Here, g(.) is an aggregation function such as the arithmetic mean, or the maximum. In our analysis, we use the arithmetic mean as the main approach and use the maximum as a robustness check (see Appendix F).

Figure 1 illustrates our methodology through a practical example with 40 observations ($T = 40$) and 2 state variables ($k = 2$). We thus have 39 historical observations and the last observation ($t = 40$), serves as the target observation (the red observation in Figure 1). Examining the graph reveals two distinct declines in the state variables around index 5 and 30 along with a notable peak near index 20. These observations, being farthest from the target, receive lower weights, as clearly observed in Figure 1. The weights for the other observations are closer to one.

In this example, we aggregate the weights using the arithmetic mean. The resulting composite weights offer insight into the relative importance of each observation, effectively highlighting key features, such as the declines in the state variables and the positive outlier near index 20. Note that we don't have a weight for $t = 40$, since we compare each historical observation to this target observation.

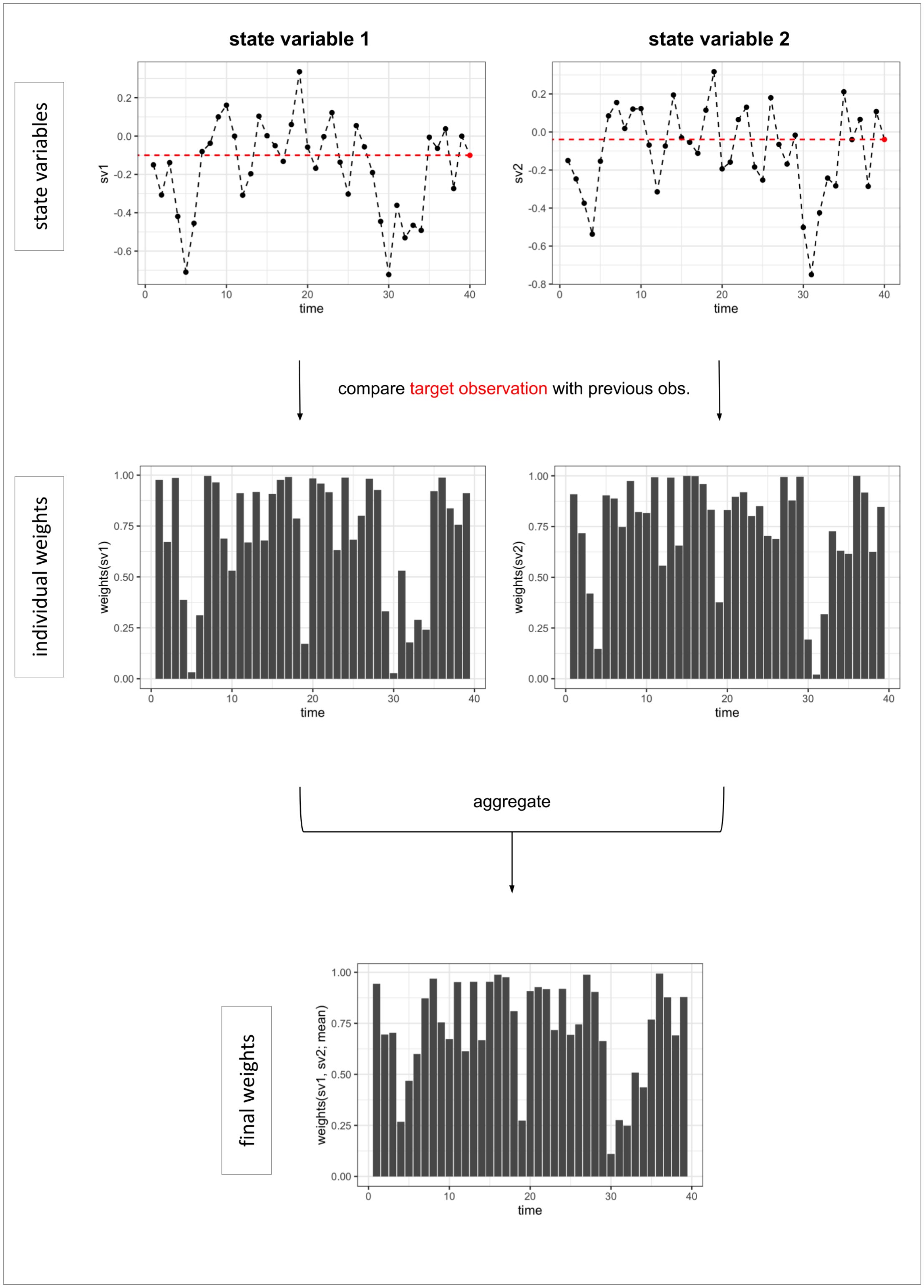

Figure 1: An example of how two state variables are combined into final weights.

3 Data

We apply our methodology to nowcasting quarterly GDP growth in Belgium.[1] The quarter on quarter GDP growth rate is shown in Figure 2. Our sample contains four crisis periods: the dot-com bubble, the financial crisis, the European debt crisis and the COVID-19 crisis. We define these as periods that have at least two consecutive quarters of negative growth. We start from the quarter following the peak, so the first negative quarter, and include the quarters up until the GDP level is higher than the initial level before the crisis period. We thus include both the recession and the recovery.[2]

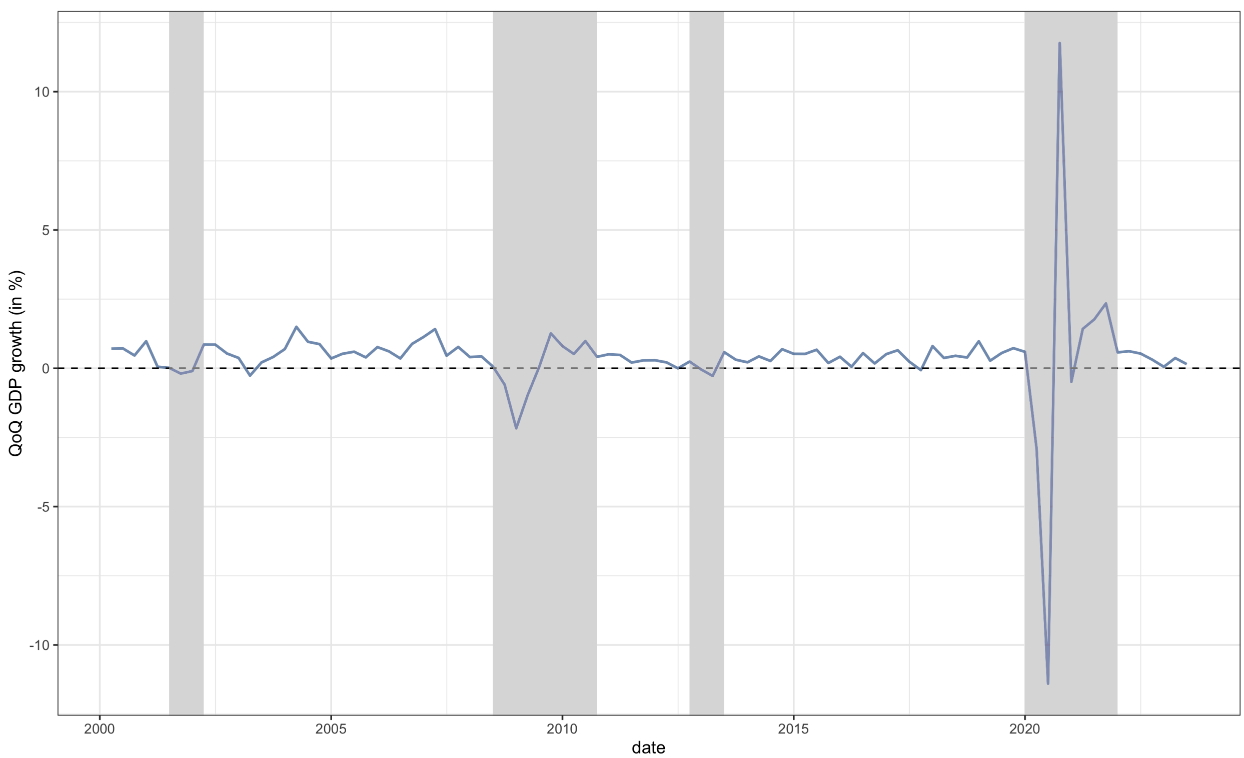

Figure 2: Belgian quarterly GDP growth, with crisis periods marked by the grey areas. The crisis periods we include are: (i) the dot-com bubble, (ii) the financial crisis, (iii) the European debt crisis and (iv) the COVID-19 crisis.[3]

[1] Our sample starts in January 2000 until June 2023.

[2] We get the following crisis periods: (i) dot-com bubble from Q3 2001 until Q1 2002, (ii) financial crisis from Q3 2008 until Q3 2010, (iii) European debt crisis from Q4 2012 until Q2 2013, (iv) COVID-19 crisis from Q1 2020 until Q3 2021.

The model combines data at different frequencies, requiring a synchronisation of time stamps. We exploit the timeliness of the state variables by aggregating them on the weekly frequency, instead of the monthly frequency, as the predictors in the model. We follow Lourenço and Rua (2021) by defining weeks such that the first three weeks of every month consists of seven days and the last week consist of the remaining days of the month. The last week can consist of up to ten days. This way, we have four fixed weeks a month, and 12 weeks a quarter as presented in Table 1.

Quarter:	Quarter											
Month:	Month 1				Month 2				Month 3			
Week:	1	2	3	4	5	6	7	8	9	10	11	12

Table 1: The alignment of the weeks, months and a quarter within a nowcasting mixed–frequency setting with the weeks defined as in Lourenço and Rua (2021).

3.1 Standard predictors

The standard predictors in the Belgian nowcasting setting consist of two main sets: macroeconomic and financial variables (see Appendix D for an extensive list). The macroeconomic variables can be broken down into soft, early hard, and hard indicators. The hard indicators include the reported VAT of Belgian companies, industry-specific indicators such as building permits and number of new cars registered and indicators related to external developments. In general, these indicators are only available with a two-month delay. The early hard indicators have only a one-month delay and are related to the labour market in Belgium. The soft indicators are derived from the answers to the consumer and business surveys conducted by the National Bank of Belgium. The business survey focuses on four major industries: construction, manufacturing, trade and business-related services. They are all available monthly, without any delay. In total, there are 86 macroeconomic indica-

[3] These are defined as periods that have at least two consecutive quarters of negative growth. We start from the quarter following the peak, so the first negative quarter, and include the quarters up until the GDP level is higher than the initial level before the crisis period. We thus include both the recession and the recovery.

tors taken into account in this analysis. The selection of financial variables consists of 8 predictors, which are available without a publication lag. It consists of the ten-year Belgian government bond yield, oil and gold prices, a Belgian and European stock market index and a price index for both energy raw materials and other commodities.

All the macroeconomic indicators are seasonally adjusted. The full set of indicators are log-transformed when positive valued, and a first difference is taken if a unit root is detected by the Augmented Dickey-Fuller test (Dickey and Fuller, 1979). The series have differing availability but starting from 2000, they are all available.

3.2 News data

Our corpus contains over 20 million media news articles from Belgian newspapers, ranging from January 2000 until June 2023. Belgium consists of a Dutch- and a French-speaking region, hence the corpus contains newspapers in both Dutch and in French. We obtained the news articles from the national Belgian News Agency (Belga). It includes eight Dutch newspapers (De Morgen, De Standaard, De Tijd, Gazet van Antwerpen, Het Belang van Limburg, Het Laatste Nieuws and Het Nieuwsblad) and five French newspapers (L'Avenir, La Dernière Heure, La Libre Belgique, L'Echo and Le Soir).

Newspaper	Number of economic articles	Proportion of economic articles	Weekly average	Type	Language
De Tijd	92,666	0.16	82	Elite	Dutch
De Standaard	86,902	0.09	77	Elite	Dutch
De Morgen	57,617	0.08	51	Elite	Dutch
Het Belang van Limburg	38,989	0.03	35	Popular	Dutch
Gazet van Antwerpen	63,044	0.03	56	Popular	Dutch
Het Nieuwsblad	69,758	0.02	62	Popular	Dutch
Het Laatste Nieuws	77,660	0.01	69	Popular	Dutch
L'Echo	102,689	0.18	91	Elite	French
Le Soir	94,000	0.08	88	Elite	French
La Libre Belgique	79,020	0.07	76	Elite	French
La Dernière Heure	53,203	0.03	50	Popular	French
L'Avenir	76,066	0.02	72	Popular	French

Table 2: Descriptive statistics of the Belgian economic news corpus per newspaper from 2000 until 2023. The newspapers above the dashed line are published in Dutch, the ones below are published in French.

We do not include all news articles in our analysis. Only the articles covering the economy of Belgium are selected. An article is selected if it contains certain economic keywords. The selection of keywords is based on Barbaglia et al. (2023b), de Winter and van Dijk (2023) and expert knowledge. The set of keywords covers different aspects of the economy: general terms, investments, consumption, employment and trade (see Appendix A for the extensive list). The keywords are chosen so that similar articles are selected for Dutch and French. We want articles that cover the economy, but we also want articles that cover Belgium. A filter of geographical keywords is applied to only select articles covering Belgium. It consists of the main regions Flanders and Wallonia and major Belgian cities (this list can be found in Appendix A). Between January 2000 and June 2023, we select around 850,000 articles after applying all the filters. The size of the coverage depends on the newspaper, as can be seen in Table 2. Note that the newspapers are diverse with respect to coverage of the economy. For our analysis later, we divide the newspapers up into two groups, depending on their proportion of economic articles. We use the names *elite* and *popular*, as in Hartley (2009).

3.3 State variables

We explore the use of three types of state variables as drivers of the weights assigned to past observations: (i) survey-based variables, (ii) financial variables, and (iii) news-based variables. For the survey-based and financial variables, we can use readily available variables, while the news-based variables need to be constructed. The construction of the latter will be discussed in subsection 3.4. Many other state variables exist. Following Lenza and Primiceri (2022), one can for instance create a state variable explicitly giving zero weights to the COVID-19 observations.

For the survey based variables, we focus on the business and consumer confidence surveys. In the bottom panel of Figure 3 we see a clear co-movement between both variables, where the business confidence is more stable and consumer confidence displays more variability.

Compared to the other state variables, their major drawback is the lack of timeliness. The surveys are only conducted once a month, and they are published with a delay of at least one week (Algaba et al., 2023).

For the financial variables, we focus on the stock market implied volatility index and the composite indicator of systemic stress. Diebold and Yilmaz (2008) have shown a clear association between the stock market implied volatility and macroeconomic volatility, more specifically volatility in GDP growth. Since our application focuses on Belgium, we will use the Euro Stoxx 50 implied volatility (VSTOXX) index. Previous research has shown its usefulness in predicting the business cycle during crisis periods (Islami and Kurz-Kim, 2014). Additionally, we will use the Belgian Composite Indicator for Systemic Stress (CISS) composed by the ECB. It is an aggregation of indicators in a broad range of financial market segments capturing financial stress. The CISS has been proven useful in the literature to forecast tail risks to GDP growth in the Euro area (Figueres and Jarociński, 2020; De Santis and Van der Veken, 2020). The fourth panel in Figure 3 shows a clear co-movement during major crisis periods between the two indicators. However, during other events such as the dot-com bubble or post COVID-19, the indicators show different behaviour. Compared to survey variables, the advantage of financial variables is their timeliness: they are available every single day.

3.4 News-based state variables

Digitalization of news media has rapidly increased the number of available news articles useful as input for economic decision-making. News is made available every single day and reports constantly on our economy. In order to extract relevant state variables for the economy, we filter the articles by economic and geographical relevance, as explained in the previous section. The next step is to transform these economic news articles into insightful numbers. Text is a high-dimensional data source. The two main approaches are count based indicators such as the Recession index by The Economist (2001) and economic sentiment

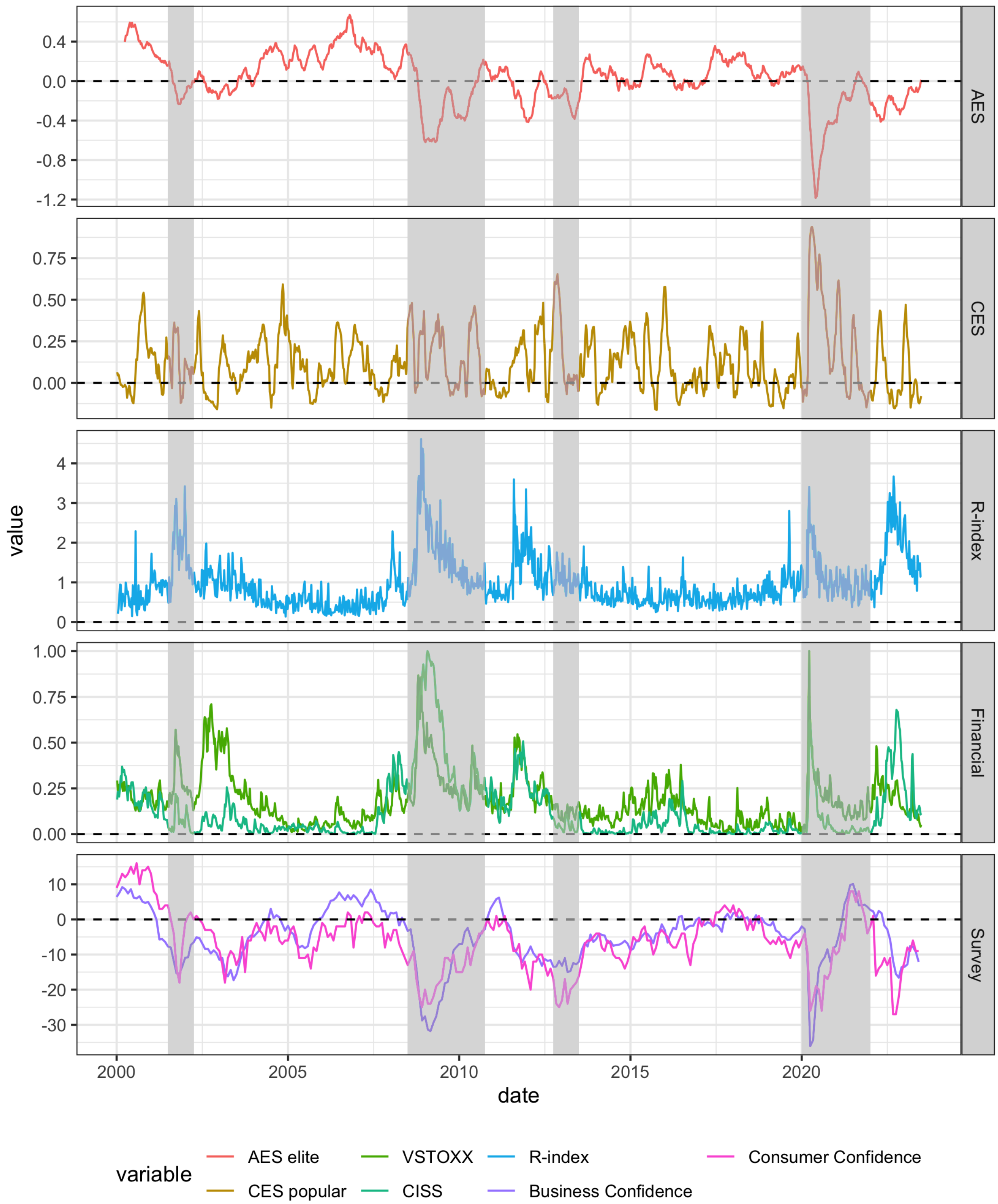

Figure 3: State variables from top to bottom: (i) the Average Economic Sentiment (ii) the Correlation between Economic Sentiment (iii) the Recession index (iv) the Euro Stoxx 50 implied volatility and the Belgian Composite Indicator for Systemic Stress (v) Belgian business and consumer confidence survey. Crisis periods are marked by the grey areas: (i) the dot-com bubble, (ii) the financial crisis, (iii) the European debt crisis and (iv) the COVID-19 crisis.

indicators (Kalamara et al., 2022). The calculation of economic sentiment per newspaper is discussed in Appendix C.

3.4.1 Attention to recession: the R-index

Measuring the onset and duration of economic recessions in real-time is a complex problem, but if possible, a very useful state variable. A simple but effective way to track recessions is to look at the attention given to recessions in the news. We make use of a slightly modified version of the Recession index of *The Economist* (The Economist, 2001). The idea is simple: they count the word *recession* in the US newspapers *Wall Street Journal* and *Financial Times* and track its evolution over time to try to capture upcoming recessions in real time. They divide the number of *recession*-articles by the total number of articles. We however, divide by the economic articles only, to have higher consistency over time.[4] Next, the proportion of selected articles $p_{t,k}$ is rescaled per newspaper, in order to have unit variance for all newspapers. Let K be the number of newspapers, such that $p_{t,k}$ is the rescaled proportion for newspaper k at time t. The R-index at time t is then given by the average of the proportions over the newspapers:

$$R_t = \frac{1}{K} \sum_{k=1}^{K} p_{t,k}. \tag{7}$$

We choose to compute our R-index every week. First, we compute the R-index daily as in Equation 7. Second, we aggregate to the weekly level, as discussed in section 3.

In the third panel of Figure 3 the R-index clearly indicates the dot-com bubble, the financial crisis and the COVID-19 crisis. It also spikes for the European debt crisis, at the time a recession was expected, before the actual recession took place. In December 2011, the National Bank of Belgium foresaw an economic stagnation or even a minor recession at the end of 2011 and the beginning of 2012 (National Bank of Belgium, 2011). In reality, the recession occurred at the end of 2012 and the beginning of 2013.

[4] See Appendix B for an elaborate explanation.

3.4.2 General tendency in news sentiment: the Average Economic Sentiment indicator

The newspapers have a common economic sentiment factor that we can capture based on the simple average of economic news sentiment of the various newspapers. It informs about how positive or negative newspaper are in their coverage of the economy. It is a rough aggregate, since different sources cover different news items. We can expect the dominant news item to be the same in case of a critically important event. This prediction is central in the model of Nimark and Pitschner (2019). Following this argument, it is expected that the average economic sentiment will give a clear signal during economic crisis periods, while being noisier during other periods. Additionally, we expect the elite newspapers to produce a better state variable, since they cover economic topics more consistently over time. The Average Economic Sentiment (AES) for time t is given by:

$$AES_t = \frac{1}{K}\sum_{k=1}^{K} s_{t,k}, \tag{8}$$

with K the number of newspapers and $s_{t,k}$ the weekly sentiment per newspaper k, as defined in Appendix C. More specifically, we create the sentiment index on a weekly frequency, by taking the following steps. We first compute a daily sentiment score so that every day gets an equal weight in the weekly score, independent of the number of daily articles. Since the majority of newspapers considered do not publish on a Sunday, this day is removed for consistency. We take the weekly average of the daily sentiment scores per newspaper, where a week is defined as in section 3. We then take the mean of the newspaper series for the two regions. The Belgian index is obtained by taking the average over the two regions, so both regions are equally represented in the Belgian index. The Average Economic Sentiment (AES) series for elite newspapers is shown in the top panel in Figure 3, clearly signalling the four crisis periods.

3.4.3 Agreement in news sentiment: the Correlation of Economic Sentiment indicator

A news event can only become a news story if the journalist selects the event as relevant news. According to Nimark and Pitschner (2019), the diversity in news coverage across news sources is state-dependent. Normally, news outlets cover a whole spectrum of different economic topics, but major events shift the overall news focus and make the news coverage more focused on a small set of topics. Kuhlen and Preston (2023) confirms this topic concentration during eventful periods using topic probability vectors for the Wall Street Journal. Our empirical approach considers sentiment correlation to capture the increased homogeneity in both topic selection and polarity across multiple news outlets. Specifically, following Nimark and Pitschner (2019), we expect that in eventful periods the correlation between sentiment of news outlets increases. We expect this increase to be the most pronounced for the correlation between popular newspapers. They generally focus less on economic topics (Hartley, 2009), so the economic sentiment is expected to be a lot more diffuse during normal times, in contrast with the occurrence of major economic news events.

We propose to exploit this state-dependence to infer the economic state from the observed correlation between economic sentiment of different newspapers. The construction of our indicator consists of two steps. First, a pairwise rolling correlation between all individual newspaper sentiment series is computed. We will look at a 12–week or quarterly rolling correlation in order to pick up signals timely. Second, the mean of the correlations at each point in time is taken to get the Correlation between Economic Sentiment indicator (CES):

$$CES_t = \frac{2}{(K)(K-1)} \sum_{i=1}^{K-1} \sum_{j=i+1}^{K} \rho_L \left(s_{t,i}, s_{t,j} \right), \tag{9}$$

with $\rho_L(\cdot,\cdot)$ the Pearson correlation computed on a rolling window of L observations.

Figure 3 shows the correlation between economic sentiment for popular newspapers. The correlation peaks reasonably during crisis periods, except for the dot-com bubble. The index spikes significantly in 2004 as well. During this period, the Belgian quarterly GDP growth exceeded 1% on average. These are the highest growth numbers recorded in our sample, without the recoveries after crises taken into account. This indicates that the correlation indices do not solely spike during crisis periods, but during expansion periods as well. This can be useful for nowcasting since predictors can be informative both during expansion periods and during recession periods. If the state variable can identify the strong expansion periods, this can only help us in future nowcasts. Other indices, such as the R-index, only identify the recession periods. In that case, we possibly lose information of strong expansion periods.

3.5 Quarterly aggregation of state variables

Our goal is to use these weekly and monthly state variables to construct quarterly state variables for nowcasting the quarterly real activity of the ongoing quarter. For past quarters, we compute quarterly state variables by taking the average value per quarter, denoted z_t. For the ongoing quarter, we use a mixed-frequency prediction model. Specifically, let $t, \frac{t-1}{k}, \frac{t-2}{k}, \ldots, \frac{t-(k-1)}{k}$ be the k equispaced observation within quarter t. We then predict the quarterly average state variable using the following restricted MIDAS model (Ghysels et al., 2007)[5]:

$$z_t = \alpha + \beta_1 \sum_{i=1}^{l} b(i;\gamma) z^f_{t-1+\frac{i}{k}} + \epsilon_t \tag{10}$$

with z_t the quarterly average, z^f_t the weekly or monthly state variable, k the number of high-frequency periods aligning with a quarter, l the number of already observed periods in the quarter and $b(i;\gamma)$ the weighting function. The latter is decided in a data-driven way using the midasr R package (Ghysels et al., 2016). In the application to nowcasting GDP growth for Belgium, we allow the algorithm to use an exponential Almon lag, a beta density, a log-Cauchy density or a Nakagami density weighting function.

[5] An alternative approach is the expanding mean as in Ashwin et al. (2023). The quarterly estimate is then the simple mean of the available observations for the current quarter.

4 State–based weights

The obtained state variables for the Belgian economy are mapped to weights as in Equation 4. They play a crucial role in our proposed state-based weighted methodology. The boxplots in Figure 4 illustrate how the weights vary during the three out-of-sample crisis periods.[6] The rows show these three crisis periods: the financial crisis, the European debt crisis and the COVID-19 crisis. The columns show four stages for each crisis period: before the crisis, at the onset, during and after the crisis. For each of these stages, this links to a specific month for every crisis period, which is shown in the top right corner of the graph. At this specific month, the weights are computed with respect to the state of that month. The state variables used are the CES popular, the R-index and the VSTOXX.[7] Subsequently, the weights are split up in two groups: the weights from historical crisis periods, and the weights from non-crisis periods.

A consistent pattern is visible across all crisis periods. Before a crisis, weights for non-crisis periods are typically higher than those for preceding crisis periods. As a crisis unfolds, there is a notable shift, with the median weight of crisis periods becoming higher than the median of non-crisis weights. This difference persists or even increases during the crisis. After the crisis, there is a reversal, and non-crisis periods regain higher weights. We thus find that the state variables accurately indicate the state of the economy, by overweighting previous crisis periods during a new crisis.

There is variation present in the weights between the different crisis periods. The European debt crisis is the mildest crisis. We can also see this in the weights in Figure 4. Before the crisis, the weights are very similar between the crisis and non-crisis periods. At the beginning of the crisis, there is only a minor shift between the crisis and non-crisis weights distribution. In contrast, for the COVID-19 and financial crises, the shift from pre-crisis to the beginning of the crisis is more clear. Pre-crisis, the weights for the crisis periods are sig-

[6] In section 5, we explain that the out-of-sample analysis starts in 2008. So we do not compute nowcasts during the dot-com bubble, hence these weights are not shown here.

[7] We show in section 6 that these are the best performing state variables.

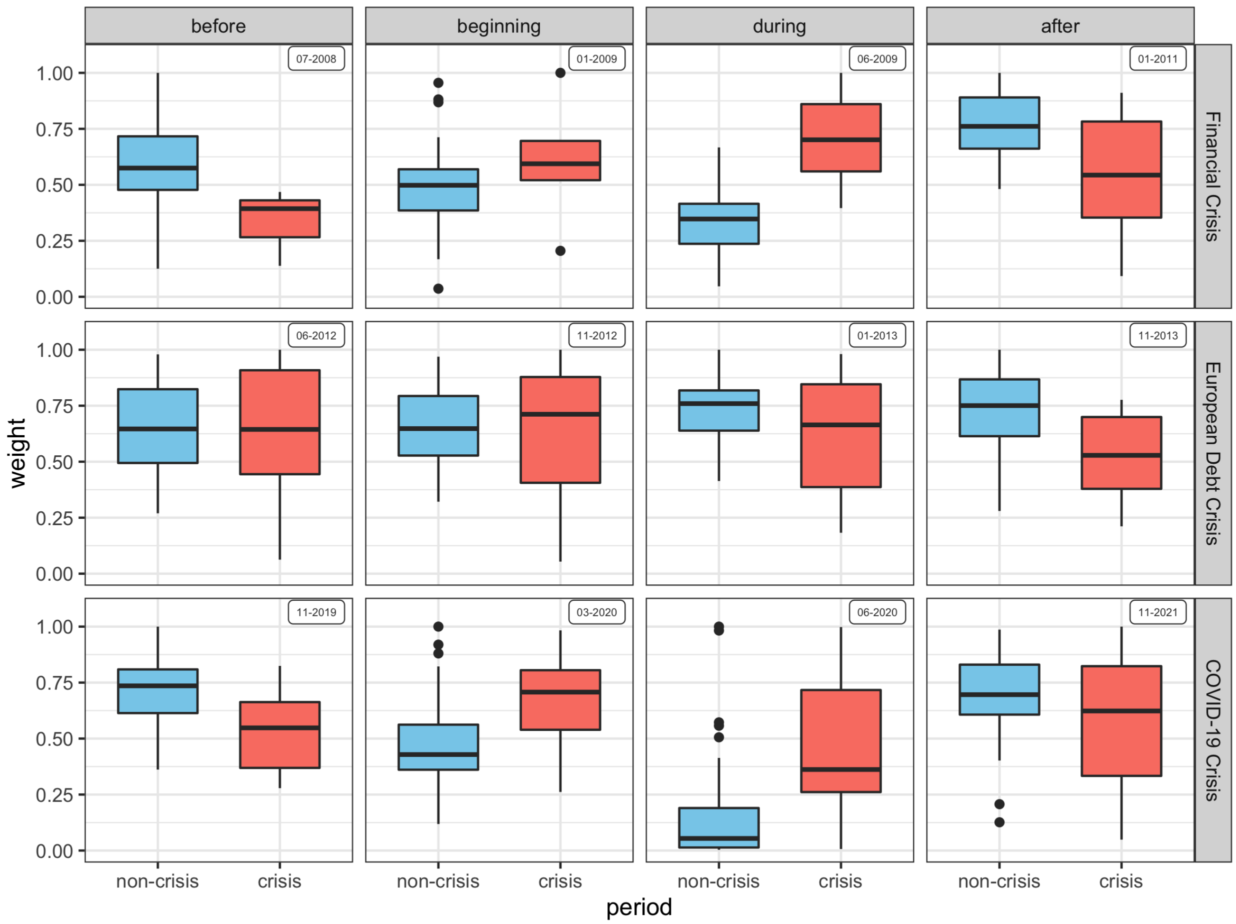

Figure 4: Boxplots of the weights based on the combination of the state variables CES popular, R-index and VSTOXX, divided into two groups: crisis and non-crisis periods. The rows indicate the out-of-sample crisis periods. The columns indicate four stages for each crisis period. The specific month for each stage-crisis combination is shown in the top-right corner. At this specific month, the historical weights are calculated, and split up into the two shown groups: crisis and non-crisis periods.

nificantly lower than the non-crisis weights, while at the beginning of these crises, the crisis period weights shift upwards, and the non-crisis weights downwards. Also note that at the beginning of these crises, a substantial number of non-crisis observations still receive high weights. This diminishes significantly during the crisis. Importantly, the figure indicates very few instances where observations receive zero weights.

This analysis suggests that during a crisis period, previous crisis periods generally receive higher weights than non-crisis periods. However, non-crisis periods still receive non-zero weights as well. The weights essentially determine how to balance the information between these two types of observations for each nowcast. In the next sections, we study the gains in nowcasting accuracy when using these dynamically adjusted weights. We first consider a simple model with only a constant term. The resulting estimator is the state-based weighted mean. We then study the case of nowcasting GDP growth using the BREL framework, which is currently used by the National Bank of Belgium for nowcasting GDP growth.

5 Nowcasting with the state–based weighted mean

The simplest prediction model is the model with constant term and no predictors. Under this model, the least squares estimate is the mean growth rate over the estimation sample. This model leads to time-varying nowcasts of GDP growth as the estimation window expands over time. Introducing state variable weights leads to using the weighted mean estimator. In this section, we evaluate first the gains under this simple model. In the next section, we consider the use of the state-of-the-art BREL nowcasting approach of Piette (2016) used by the National Bank of Belgium for nowcasting GDP growth. After evaluating both nowcasting approaches with the single state variables, we consider combining state variables and compare the weighted with the unweighted predictor selection.

5.1 The nowcasting setup and evaluation

The goal in this nowcasting exercise is to nowcast quarterly GDP growth in Belgium. The estimation sample starts in Q1 2000, and the out-of-sample analysis starts from Q1 2008 until Q2 2023 with an expanding estimation window. This way, both the financial crisis, the European debt crisis and the COVID-19 crisis are included in the out-of-sample results. The dot-com bubble crisis is only included in the training sample, but not in the out-of-sample results. We perform a pseudo real-time analysis by replicating the real-time ragged edges data availability. Herein, we use the final vintages for both GDP and the macroeconomic data. For consistency, we also use the final vintages for the macroeconomic data.

The results are evaluated on the full sample and several subsamples, since the extreme observations of the COVID-19 crisis dominate the other periods in the full sample. We analyse four subsamples: the financial crisis, the European debt crisis, the COVID-19 crisis and the full sample excluding the previously mentioned crisis periods[8].

The predictors that are fed into BREL are available monthly. We perform the nowcast three times every quarter: once after the first month, once after two months and once when the whole quarter has been observed. These three different nowcasting time points are denoted as M1, M2 and M3.

In this nowcasting application, we focus on the following media-news based state variables: the 12-week rolling Correlation between Economic Sentiment index for popular newspapers (CES popular), the Average Economic Sentiment index for elite newspapers (AES elite) and the R-index. As financial variables, we will use the Euro Stoxx 50 implied volatility index (VSTOXX) and the composite indicator of systemic stress (CISS). We also include survey based indicators as state variables. Both the Belgian business confidence indicator (BC survey) and consumer confidence indicator (CC survey), published by the National Bank of Belgium, are included in the results. Since the surveys are only performed once a month, they are only available on the monthly frequency, while all other state variables are available on the weekly frequency.

We use the root mean squared forecasting errors to evaluate the nowcasting performance:

$$RMSFE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2},$$

with y the Belgian quarterly GDP growth. We perform a Diebold-Mariano test to evaluate whether the non-nested state-based weighted approaches outperform the benchmark

[8]We define these as periods that have at least two consecutive quarters of negative growth. We start from the quarter following the peak of the GDP level, so the first negative quarter. We include all the quarters up until the GDP level is higher than the initial level before the crisis period. We get the following crisis periods as subsamples: (i) financial crisis from Q3 2008 until Q3 2010, (ii) European debt crisis from Q4 2012 until Q2 2013, (iii) COVID-19 crisis from Q1 2020 until Q3 2021.

approaches significantly. The grey cells indicate the approaches for which the state-based weighted approach outperforms the respective benchmark. The symbols *, **, *** indicate that the weighted approach outperforms the benchmark significantly respectively on the 10%, 5% and 1% significance level according to the Diebold-Mariano test (Diebold and Mariano, 1995). We perform the test twice, with two different standard errors. For the first estimate of the standard error, we use the full sample. However, since the full sample includes the COVID-19 period, which are clear outliers, we also compute the standard error on the subsample before 2020. We denote both results in the tables, separated by a forward slash, with the results with the full sample standard error shown first.

5.2 Single state variables

Table 3 shows the root mean squared forecasting error when using a model with only a constant term. The resulting nowcast is the expanding window based historical mean estimate when no weights are used, and the weighted historical mean otherwise.

First, notice that the results for the unweighted mean, because of a lack of GDP updates, remains constant throughout the quarter. However, the state variables, and thus the weights, do change throughout the quarter. This results in different nowcasts for the state-based weighted mean for every month of the quarter. Additionally, notice that the RMSFE generally decreases throughout the quarter for the state-based weighted mean. This decline is expected as the longer the quarter has been observed, the more information there is available, and the better the state variables will assess the state of the current quarter.

Using a simple approach, like the historical mean, allows us to clearly link the results in Table 3 with the graphs in Figure 3.

Indeed, note first that for the CES popular, we expect the weighted approach to perform well for the European debt crisis and the COVID-19 crisis, but less accurate for the financial crisis period due to a less distinct spike for the state variable in Figure 3. The AES elite weighted mean drops during all three crisis periods quite well, so we find it to perform

Sample		State Variable	Month of the quarter		
			M1	M2	M3
Full Sample	News	CES popular	2.19/***	2.19/***	2.18/***
		AES elite	2.12/***	2.10/***	2.10/***
		R-index	2.18/*	2.17/**	2.18/**
	Financial	VSTOXX	2.19*/***	2.19*/***	2.19*/***
		CISS	2.21	2.21	2.20
	Survey	BC survey	2.28	2.41	2.13/***
		CC survey	2.27	2.33	2.26
		unweighted mean	2.22	2.22	2.22
Financial Crisis	News	CES popular	1.15	1.15	1.15
		AES elite	1.07/***	1.03/***	1.03/***
		R-index	0.89***/***	0.87***/***	0.88***/***
	Financial	VSTOXX	1.05***/***	1.06**/***	1.03**/***
		CISS	1.20	1.17	1.18
	Survey	BC survey	1.32	1.32	1.21
		CC survey	1.20	1.20	0.96/***
		unweighted mean	1.15	1.15	1.15
European Debt Crisis	News	CES popular	0.48/*	0.48/*	0.48/*
		AES elite	0.48	0.45	0.43
		R-index	0.49	0.52	0.51
	Financial	VSTOXX	0.59	0.59	0.60
		CISS	0.58	0.56	0.57
	Survey	BC survey	0.47	0.46	0.43
		CC survey	0.68	0.57	0.47
		unweighted mean	0.49	0.49	0.49
COVID-19 Crisis	News	CES popular	6.34***/***	6.35***/***	6.33***/***
		AES elite	6.15***/***	6.09***/***	6.09***/***
		R-index	6.34***/***	6.31***/***	6.32***/***
	Financial	VSTOXX	6.37***/***	6.36***/***	6.35***/***
		CISS	6.40***/***	6.39***/***	6.37***/***
	Survey	BC survey	6.58	6.97	6.15***/***
		CC survey	6.58	6.75	6.60
		unweighted mean	6.44	6.44	6.44
Excluding Crisis Periods	News	CES popular	0.24	0.24	0.24
		AES elite	0.26	0.26	0.26
		R-index	0.40	0.39	0.40
	Financial	VSTOXX	0.28	0.28	0.28
		CISS	0.27	0.27	0.27
	Survey	BC survey	0.27	0.27	0.26
		CC survey	0.28	0.26	0.25
		unweighted mean	0.24	0.24	0.24

Table 3: Root mean squared forecasting error for the state-based weighted mean with individual state variables and the unweighted mean for different subsamples.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which the state-based weighted mean outperforms the unweighted mean. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for the state-based weighted mean being superior to the unweighted mean. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

well for all the crisis periods. In Figure 3, the R-index surprisingly spikes just before the European debt crisis. This surprising result aligns with the anticipation of a recession by the National Bank of Belgium in December 2011, preceding the actual recession in late 2012 and early 2013 (National Bank of Belgium, 2011). Consequently, the R-index weighted mean outperforms the unweighted mean only for the financial and COVID-19 crises.

Similarly, for the nowcasts of the VSTOXX and CISS weighted mean, no improvement is observed during the European debt crisis, as they do not exhibit spikes during this period. VSTOXX concentrates on European financial markets rather than solely on Belgium. While CISS focuses on Belgium, it is heavily influenced by the European system, making it dependent on European stability. The severity of the European debt crisis in Europe was evident in 2011 and early 2012, aligning with spikes in both indicators. However, the impact on Belgian GDP occurred later, from Q4 2012 until Q2 2013. Surprisingly, the CISS weighted mean also shows no improvement during the financial crisis. Examining the weights reveals that they remain too scarce for too long due to the extended plateau for the CISS state variable during this crisis. It appears more effective when state variables spike briefly and then gradually return to their normal level.

Similar to the R-index, for the VSTOXX and CISS weighted mean, no improvement is observed for the European debt crisis, as they do not spike during this period. VSTOXX concentrates on European financial markets rather than solely on Belgium. While CISS focuses on Belgium, it is heavily influenced by the European system, making it dependent on European stability. The severity of the European debt crisis in Europe was in 2011 and early 2012, aligning with spikes in both indicators. However, the impact on Belgian GDP occurred later, from Q4 2012 until Q2 2013. Surprisingly, the CISS weighted mean also shows no improvement during the financial crisis. Examining the weights reveals that they remain too scarce for too long due to the high plateau for the CISS state variable during this period. It appears more effective when state variables spike briefly at the beginning of a crisis and then gradually return to their normal level.

For weighted mean using the survey variables, we find no clear overall improvements, except for the last month of the quarter (M3). This can be attributed to the less timely nature of these state variables. They are published monthly and with a publication lag, compared to the weekly and immediately available nature of other state variables.

In the subsample that excludes crisis periods, there are no clear improvements of the state-based weighted mean over the simple unweighted mean. The state-based weighted mean assigns lower weights to crisis periods and assigns higher weights to periods with higher growth. As a result, there is a slight overestimation of GDP growth.

This simple model highlights the value of weighting observations. While the unweighted mean performs well during normal periods, its performance diminishes during crisis periods. It is then that weights improve the accuracy. The next section introduces the BREL nowcasting approach, which leverages additional data to improve accuracy.

6 Nowcasting with state–based weighted BREL

In this section, we examine the accuracy gains of our proposed methodology applied to the BREL nowcasting approach of Piette (2016), used by the National Bank of Belgium for estimating current GDP growth. First, we introduce the standard BREL framework. Afterwards, we discuss the accuracy gains from including weights in BREL using a single state variable. Next, we look at the BREL nowcasting performance when using a combination of state variables. In the last part, we discuss the time-variation in the predictor selection.

6.1 The BREL nowcasting approach

BREL combines elastic net, to make a selection of the predictors, with a bridge equation, to handle the mixed-frequency problem (Piette, 2016). The bridge equation relates the quarterly GDP growth y_t, to monthly predictors aggregated to the quarterly frequency, $x_{j,t}$.

The final nowcasting model to be estimated at time T is given by:

$$y_t = \theta_{0,T} + \sum_{j=1}^{n_T} \theta_{j,T} x_{(j),t} + \epsilon_t, \tag{11}$$

where $\theta_{j,T}$ are the time-varying parameters and n_T the time-varying number of predictors included in the model. The predictors $x_{(j),t}$ are ranked based on their predictive power for y_t, such that $x_{(j),t}$ is more predictive than $x_{(j+1),t}$ for y_t.

The predictive power ranking relies on the elastic net estimation of a large-scale autoregressive distributed lag (ADL) model with 94 predictors, along with five lags for each predictor.[9] The penalty parameter λ is gradually decreased to find the $n = 10$ most relevant predictors. The number n_T, with $1 \leq n_T \leq n$, is the model size that minimises the Bayesian Information Criterion.

We include the state-based weights in each step where estimation is needed, namely the elastic net, the BIC, and the final model estimation.

6.2 Single state variables

Table 4 shows the root mean squared forecasting error for state-based weighted BREL and for unweighted BREL for different subsamples of the nowcasting exercise. The results in Table 4 show that the state-based weighted method can improve unweighted BREL for the full sample. The nowcasting gains can be large, up to 20% for the R-index, compared to the state-of-the-art unweighted BREL approach.

For the majority of the state variables, state-based weighted BREL outperforms unweighted BREL in the last month of the quarter during crisis periods, and in the second month for the major crises, the financial and COVID-19 crisis. However, in quarters excluding crisis periods, we find an opposite pattern. At the beginning of the quarter, although not significantly, for most of the variables, weighted BREL outperforms unweighted BREL.

[9] See Appendix D for the full list of predictors.

Sample		State Variable	Month of the quarter		
			M1	M2	M3
Full Sample	News	CES popular	2.24	2.04	1.26/***
		AES elite	2.64	3.19	2.65
		R-index	2.34	1.99/**	1.19/***
	Financial	VSTOXX	2.14	1.72/***	1.39/**
		CISS	2.31	2.23	1.36/*
	Survey	BC survey	2.79	3.35	2.08
		CC survey	2.45	2.65	2.76
		unweighted BREL	2.06	2.05	1.47
Financial Crisis	News	CES popular	0.97	0.78/***	0.82/***
		AES elite	0.94	1.13	0.69/***
		R-index	1.28	0.69/***	0.97
	Financial	VSTOXX	1.18	0.87/***	0.70*/***
		CISS	1.44	3.73	1.41
	Survey	BC survey	3.08	1.13	0.82/***
		CC survey	1.34	0.74/***	0.82/***
		unweighted BREL	0.81	1.01	0.92
European Debt Crisis	News	CES popular	0.42	0.46	0.39/*
		AES elite	0.32	0.49	0.44
		R-index	0.39	0.45	0.31
	Financial	VSTOXX	0.39	0.57	0.47
		CISS	0.55	0.70	0.36
	Survey	BC survey	0.44	0.49	0.45
		CC survey	0.49	0.39	0.49
		unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	News	CES popular	6.52	5.90/**	3.46***/***
		AES elite	7.71	9.37	7.78
		R-index	6.75	5.75**/***	3.07***/***
	Financial	VSTOXX	6.10	4.92***/***	3.93***/***
		CISS	6.57	5.03***/***	3.61***/***
	Survey	BC survey	7.47	9.82	6.03
		CC survey	7.06	7.76	8.09
		unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	News	CES popular	0.33/**	0.45	0.43
		AES elite	0.38	0.38	0.35
		R-index	0.37	0.44	0.55
	Financial	VSTOXX	0.46	0.38	0.40
		CISS	0.47	0.35	0.34
	Survey	BC survey	0.41	0.44	0.41
		CC survey	0.38	0.44	0.41
		unweighted BREL	0.47	0.41	0.34

Table 4: Root mean squared forecasting error for state-based weighted BREL with individual state variables and for unweighted BREL for different subsamples of the nowcasting exercise.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which state-based weighted BREL outperforms unweighted BREL. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for state-based weighted BREL being superior to unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

Towards the end of the quarter, unweighted BREL clearly outperforms state-based weighted BREL.

This twofold finding can be explained by the inherent nature of the periods. During crisis periods, the state changes rapidly, making it harder to immediately estimate the state. In the beginning of a quarter, the weights will not carry enough information. However, as the quarter progresses, the estimation of the state will be more accurate, and the weights will become more informative. However, during economically more stable periods, the initial state estimate in the first month, will already be a good estimate of the final state. We see this clearly in the subsample excluding crisis periods, and partly in the European debt crisis, which was a minor crisis. As the quarter progresses, it seems like the information gain of the predictors makes the weights abundant.

When examining the individual results, note the significant impact of the COVID-19 crisis on the full sample results. The relative results are almost identical for both samples, given the considerably errors observed during the COVID-19 period compared to other subsamples. Given the unprecedented nature of this period, nowcasting during this period yields substantial errors.

There is no clear best performing state variable to weight the observations in BREL. However, among the news-based variables, the CES popular and R-index are the top-performing state variables for weighted BREL. The AES weighted BREL shows the most significant improvement over BREL in less extreme samples, but deteriorates substantially over unweighted BREL during the biggest crisis period, COVID-19. Over all subsamples, the CES popular weighted BREL significantly outperforms unweighted BREL the most. It is important to highlight that, unlike the CES popular weighted mean, the CES popular weighted BREL does outperform the benchmark – the unweighted BREL in this case – during the financial crisis. This can be explained by the fact that using the CES popular as a state variable during nowcasting in a crisis, high weights are assigned to both crisis periods and strong expansion periods. For the weighted mean, this leads to the negative growth from crisis periods cancelling out the positive growth from expansion periods, resulting in similar estimates as the unweighted mean. However, BREL contains extra predictors, and can learn the dynamics from both these extreme periods. State-based weighted BREL subsequently uses these learned dynamics to improve nowcasting during crisis times.

Regarding the financial variables, VSTOXX generally outperforms the CISS as state variable for nowcasting GDP growth. The overall performance of the CISS weighted BREL is severely impacted by the financial crisis errors. Similar to the news-based weighted BREL, VSTOXX weighted BREL outperforms unweighted BREL significantly on the full sample and the two major crisis periods.

In contrast, survey variables weighted BREL, similar to the mean results, generally perform worse than news-based and financial weighted BREL. They outperform BREL irregularly on some samples and months of the quarter. Again, this can be explained due to the timeliness: these indicators are published only once a month and with a publication lag.

Overall, the top-performing state variables are the CES popular, the R-index and VSTOXX, which all outperform BREL on the second and third month of the quarter for the full sample. These results suggest that weighting observations according to the economic state can yield both statistical and economic significant nowcasting gains.

6.3 State variable selection: the oracle and state variable combinations

The remaining question is which state variables to choose when nowcasting. We present the oracle model, which assumes one knows the best-performing state variable at each time of nowcasting. Essentially, this model reflects the state-based weighted BREL nowcast closest to the final GDP growth number at every nowcasting time point. The oracle can be seen as the best possible state-based weighted BREL model.

In practice, one cannot know which state variable to choose. Consequently, we show the results for composite weighted BREL, where we combine the three best performing state

Sample	Method	Month of the quarter		
		M1	M2	M3
Full Sample	oracle weighted BREL	$1.92^{*/***}$	$1.38^{/***}$	$0.98^{/***}$
	composite weighted BREL	2.35	$1.80^{/***}$	$1.28^{/***}$
	unweighted mean	2.22	2.22	2.22
	composite weighted mean	2.19	2.19	2.19
	unweighted AR(1)	4.15	4.15	4.15
	composite weighted AR(1)	4.05	3.96	4.13
	unweighted BREL	2.06	2.05	1.47
Financial Crisis	oracle weighted BREL	$0.64^{/***}$	$0.34^{/***}$	$0.17^{/***}$
	composite weighted BREL	1.03	$0.77^{/***}$	$0.80^{/***}$
	unweighted mean	1.15	1.15	1.15
	composite weighted mean	1.12	1.13	1.13
	unweighted AR(1)	0.94	$0.94^{/**}$	0.94
	composite weighted AR(1)	0.92	0.98	0.95
	unweighted BREL	0.81	1.01	0.92
European Debt Crisis	oracle weighted BREL	$0.20^{/**}$	0.30	0.25
	composite weighted BREL	0.41	0.53	$0.37^{/*}$
	unweighted mean	0.49	0.49	0.49
	composite weighted mean	0.52	0.52	0.52
	unweighted AR(1)	0.47	0.47	0.47
	composite weighted AR(1)	0.47	0.48	0.47
	unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	oracle weighted BREL	$5.64^{***/***}$	$4.06^{***/***}$	$2.85^{***/***}$
	composite weighted BREL	6.82	$5.17^{***/***}$	$3.57^{***/***}$
	unweighted mean	6.44	6.44	6.44
	composite weighted mean	6.36	6.35	6.35
	unweighted AR(1)	12.28	12.28	12.28
	composite weighted AR(1)	11.99	11.72	12.21
	unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	oracle weighted BREL	$0.14^{/***}$	$0.14^{/*}$	0.21
	composite weighted BREL	$0.37^{/*}$	0.44	0.38
	unweighted mean	$0.24^{/*}$	$0.24^{/*}$	0.24
	composite weighted mean	$0.24^{/*}$	$0.25^{/*}$	0.25
	unweighted AR(1)	$0.29^{/***}$	$0.29^{/*}$	0.29
	composite weighted AR(1)	$0.28^{/***}$	$0.29^{/*}$	0.29
	unweighted BREL	0.47	0.41	0.34

Table 5: Root mean squared forecasting error of the oracle weighted BREL, composite weighted BREL, the unweighted and composite weighted mean, the unweighted and composite weighted AR(1), and the unweighted BREL for different subsamples of the nowcasting exercise. The composite models combine the following state variables: CES popular, R-index, VSTOXX.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which the model outperforms unweighted BREL. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for the model being superior to unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

variables: CES popular, R-index, and VSTOXX. We do this by aggregating the individual weights over the three different state variables as in Equation 4 using the arithmetic mean for $g(\cdot)$[11]. We will only show the combination of the three all combined.[12] The major advantage of combining state variables, is preventing overfitting. Some state variables have plenty of almost zero weights during some periods. This causes only a few observations being over influential, and thus overfitting and high uncertainty being present. We will refer to this triple weighted approach further on in short as *(composite) weighted BREL*.

Additionally, we include results for the composite weighted and unweighted AR(1) model and the composite weighted and unweighted mean, for reference.[13] The unweighted BREL serves as benchmark. The results are presented in Table 5.

First notice that the oracle weighted BREL significantly outperforms unweighted BREL in most instances. Even for M1, where no single state-based weighted approach outperformed BREL before, the oracle weighted BREL now does.

Examining the composite weighted BREL, we find a significant improvement over unweighted BREL for the last month of the quarter for all crisis periods, and for the second month of the quarter for major crisis periods. Comparing the results from composite weighted BREL in Table 5 with the single state variable weighted BREL results in Table 4 we find that there is always a single state variable that outperforms the composite weighted BREL. However, the composite BREL outperforms unweighted BREL more consistently across the different subsamples.

The AR(1) models and historical means never outperform BREL, except for the subsample excluding crisis periods. During stable economic conditions, it appears that simplicity is key. The composite weighted AR(1) even slightly improves upon the unweighted AR(1).

From these findings, we recommend to choose the weighted or unweighted mean for nowcasting during non-crisis periods and choose the composite weighted BREL for nowcasting

[11] We got similar results using the maximum function for $g(\cdot)$ (see Table F3 in Appendix F).
[12] Table F2 in Appendix F shows the combinations of state variables of lower order.
[13] The weighted AR(1) weighted with the single state variables can be found in Table F1 in Appendix F.

economic growth during crisis periods. The outperformance of the historical mean over more advanced nowcasting models during expansion periods was also found by Siliverstovs (2021a,b) and Siliverstovs and Wochner (2021) for EU and US nowcasting applications.

6.4 Time variation in selected predictors

It can be expected that the importance of predictors in BREL depends on the state of the economy, and the selected predictors thus change over time. When estimating a model during an economic shock, an unweighted approach gives equal weights to all observations, which can result in less informative predictors being chosen. However, a weighted approach that emphasises historically similar periods can lead to a faster changing selection of variables over time. We compare unweighted BREL with the composite weighted BREL of the CES popular, R-index and VSTOXX.

Figure 5: Selection of categories of variables over time for unweighted BREL and composite weighted BREL using the CES popular, R-index and VSTOXX as state variables. See Appendix D for the predictors belonging to each category.

Given that BREL includes 94 possible predictors, we group them for visual clarity. In Figure 5 we group according to the type of predictor, as listed in Appendix D. In Figure 6, we group every type of predictor on a higher level according to the time of release. Soft, early hard, and hard indicators have a publication lag of respectively zero, one and two months. All survey variables are soft indicators. The external indicators regarding confidence are also soft. For simplicity of the figure, we add the financial variables to the soft variables as well, since they are available instantly. The three unemployment indicators are early hard indicators. The rest of the predictors are hard indicators. An overview of publication lag for every predictor can be found in Appendix D.

Figure 5 and Figure 6 show the proportion of the groups of selected predictors over time, separately for the different nowcasting months of the quarter (M1, M2, M3). This proportion allows for a comparison of the selected predictors both over time and between approaches, given that the number of selected predictors may change over time.

In Figure 5, the predictor selection is overall quite stable after a shift during the financial crisis. Starting in 2020 another notable shift is observed. Both approaches show an increased importance of turnover and external indicators during this period. For the turnover, it is especially the turnover in hotels and restaurants that becomes increasingly important, reflecting the severe impact experienced by this sector due to forced closures. However, weighted BREL temporarily picks up industrial and more 'other' indicators at the onset of the COVID-19 crisis. The 'other' variables consist of an indicator that was very informative during COVID-19, namely 'nights spent in hotels'. After the onset of the crisis, the weighted approach allows the approach to quickly deselect the turnover and industrial indicators.

When comparing the approaches overall, note that the predictor selection of BREL is the most stable over time. The estimation sample is expanding over time, so for BREL, every new observation has only a marginal influence. For state-based weighted BREL however, with every new observation, the state, and thus the weights, can change. As a result, the predictor selection for these approaches show more variability over time. This is particularly evident when comparing the period between 2010 and 2019 for the two approaches.

In Figure 6 we present the proportional predictor selection, grouped by their publication

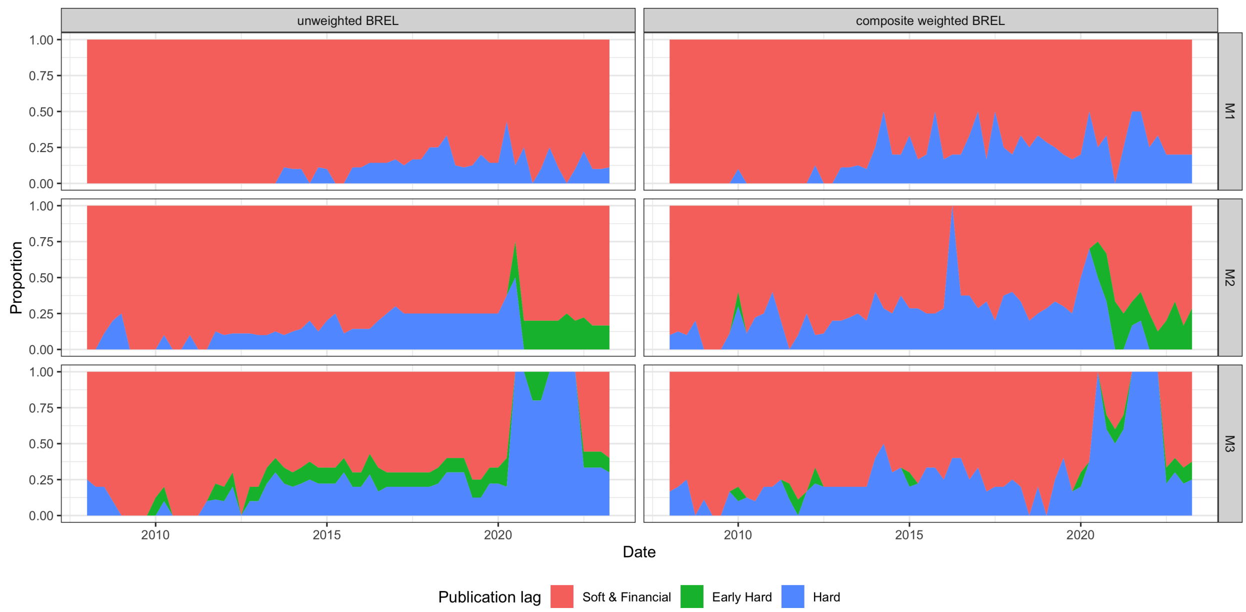

Figure 6: Selection of the predictors grouped according to their availability during the quarter (soft and financial: no publication lag; early hard: one month publication lag; hard: two months publication lag) for unweighted BREL and composite weighted BREL using the CES popular, R-index and VSTOXX as state variables. See Appendix D for the list of predictors belonging to each group.

lag, for unweighted and composite weighted BREL. The variability in the selection over time is again very clear between both approaches, as in Figure 5. We also find that hard indicators are more selected early in the quarter by the composite weighted BREL.

The soft indicators are most important for both approaches in the first month of the quarter (M1). They become less important, however still very important, toward the end of the quarter. During COVID-19, it is the clearest that hard predictors become more important towards the end of the quarter. It is only in month M3 that the hard indicators have information on the current quarter, since they are published with a lag of two months. These results are in line with the literature (Bessec, 2013; Piette, 2016).

Overall, our findings suggest that the selection of predictors is state-dependent and is subject to changes over time. The weighted approach enables us to capture these changes more effectively than the unweighted approach.

7 Conclusion

Economic nowcasting methods project observed data into predictions. We propose an estimation approach that weights observations based on the state in which the data was observed. At the time of nowcasting, these weights reflect the similarity of historical observations to the current state. We operationalise this using single and composite state variables constructed using news-based and macro-financial variables. The highest accuracy gains are expected in extreme economic states, for which differentiating across observations from normal versus extreme periods matters most.

We test the predictive power of our state-based weighting estimation for nowcasting the Belgian GDP growth over the period January 2000 to June 2023. During crisis periods, we find that the state-based weighting improves the nowcasting performance significantly in the second and third month of the quarter. The potential application of the state-based weighting methodology goes beyond the covered models and target variable.

A challenging question is to select the adequate state variable. We recommend using a combination of media news-based and financial variables. To capture economic crisis periods in which a small number of news events dominate, we build a state variable based on the correlation between economic sentiment of popular newspapers. We also use a news-based Recession-index, and the implied volatility of the Euro Stoxx 50. The oracle approach of selecting the best state variable in each nowcasting period leads to accuracy gains of over 50% in the second and third month of the quarter. In case of a full data-driven approach, we recommend using a combination of state variables to capture the similarity of past data with the current nowcasting period.

The weights are not only important to obtain the nowcast, but also to explain the nowcast. They serve as support for the narrative that explains the obtained nowcast number. Building the narrative and choosing the state variable are in practice clearly related. This is why the analysis with the oracle choice of the state variable is not a pure theoretic abstraction. It reflects the current practice of augmenting models with judgement. Specifically, at the

National Bank of Belgium, judgements are based on extensive business surveys and expert knowledge. The weighted least squares approach provides a structured approach to combine the judgement with the data by choosing the state variable that reflects best which historical data is informative for current economic conditions.

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A Keywords for economic article selection

The following tables consist of the keywords we use to select an article as economic and covering Belgium. An article must contain at least one keyword from each table. The list of keywords in Table A1 is used to classify an article as economic. The list of keywords in Table A2 is used to classify an article as covering Belgium.

	Dutch	**French**
Economy	Economie, Ekonomie	Économie
	Economisch, Ekonomisch, Economische, Ekonomische	Économique
	Bbp	Pib
	Bruto binnenlands product, Bruto nationaal produkt	Produit intérieur brut
	Bnp	Pnb
	Bruto nationaal product, Bruto binnenlands produkt	Produit national brut
Investment	Investeringsgroei	Croissance
	Bedrijfsinvesteringen	
	Concurrentiekracht, Konkurrentiekracht	Compétitivité
	Concurrentievermogen	
	Konkurrentievermogen	
	Conjunctuur, Konkjunktuur	Cycle économique
	Conjuncturele, Konjunturele	Conjoncturel
	welvaart	Prospérité
	Recessie	Récession
Consumption	Bestedingen	
	Consumentenbestedingen	Dépenses des consommateurs
	Konsumentenbestedingen	Consommation des ménages
	Consumptiegroei	
	Konsumptiegroei	
Labour	Arbeidsmarkt	Marché du travail, Marché de l'emploi
	Werklozen	Chômeurs
	Werkloosheid	Taux de chômage
		Chômage des jeunes
	Jobs, arbeidsplaatsen	Emplois
	Werkgelegenheid	Création d'emplois
		Destruction d'emplois
	Werkzoekenden	Demandeurs d'emploi
	Tewerkstelling	Taux d'activité, Taux d'emploi
Trade	Buitenlandse handel	Commerce international
	Import	Importation
	Export	Exportation

Table A1: Keywords in Dutch and French to select economic articles, subdivided by economic topic.

	Dutch	**French**
General	België	Belgique
	Vlaanderen	Flandre
	Wallonië	Wallonie
Flanders	Antwerpen	Anvers
	Brugge	Bruges
	Brussel	Bruxelles
	Gent	Gand
	Genk	Genk
	Hasselt	Hasselt
	Kortrijk	Coutrai
	Leuven	Louvain
	Mechelen	Malines
	Oostende	Ostende
Wallonia	Bergen	Mons
	Charleroi	Charleroi
	La Louvière	La Louvière
	Luik	Liège
	Namen	Namur
	Seraing	Seraing

Table A2: The geographic keywords to select articles that cover Belgium. Additionally, derivations of these names are used, but excluded from this list for clarity reasons.

B Design of the R-index

We discuss here the difference between the article selection of the R-index presented in this paper and the R-index from The Economist (2001). The original R-index by The Economist (2001) divides the R-articles by the total number of articles. We divide by the number of economic articles. Our approach yields a R-index that is more robust to changes in economic news coverage. Consider the following decomposition:

$$\frac{\#\text{ articles mentioning recession}}{\#\text{ total articles}} = \frac{\#\text{ articles mentioning recession}}{\#\text{ economic articles}} \times \frac{\#\text{ economic articles}}{\#\text{ total articles}}$$
$$= p_{t,k} \times \frac{\#\text{ economic articles}}{\#\text{ total articles}}.$$

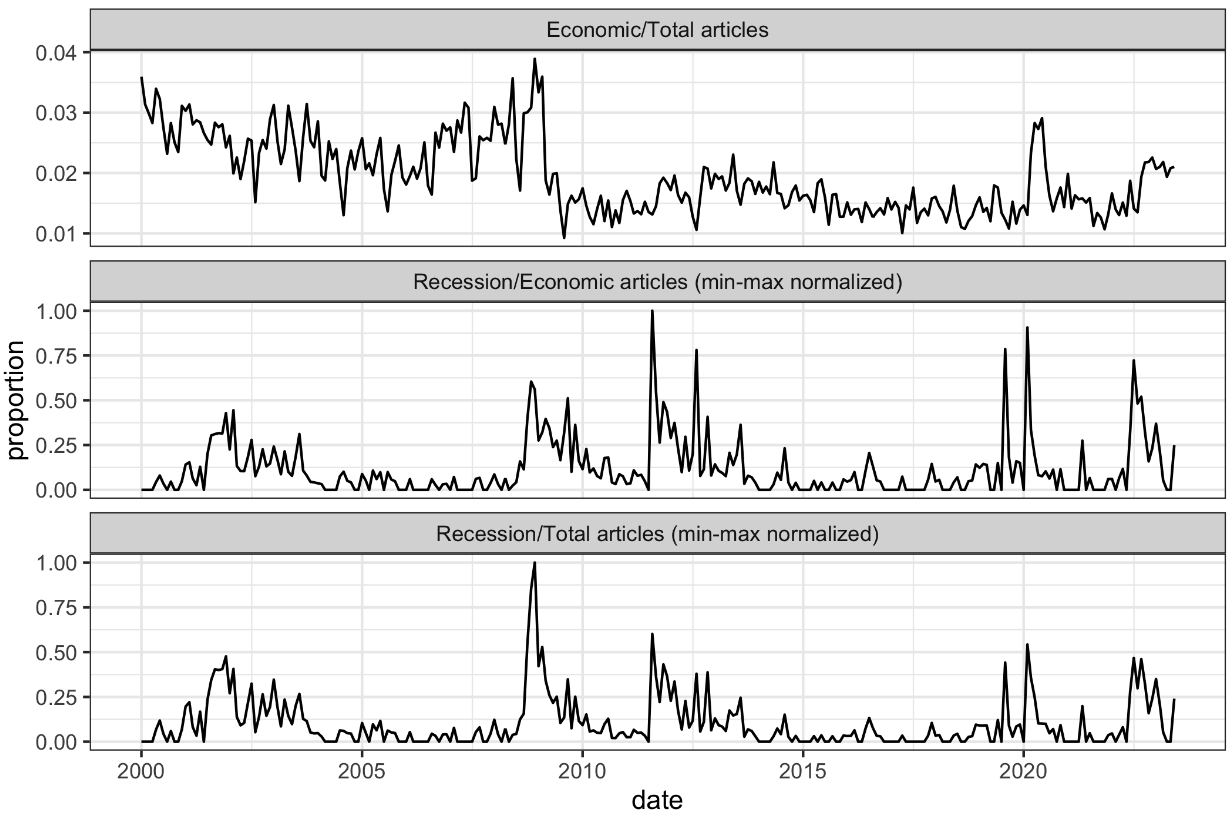

Figure B1: We show for the newspaper Het Nieuwsblad: the number of economic articles over Total number of articles (top), the number of R-articles over the number of economic articles or $p_{t,k}$ (middle), and the number of R-articles over the number of Total articles (bottom). The last two panels are min-max normalized.

In the last equation, the second factor is prone to strategic editorial decisions. This may result in an inconsistent number of economic articles over time. Possible reasons for such decisions are a shift of the reader's population or other strategic decisions. Additionally, on the short term this can also be influenced by for example weekend editions. This can shift the number of economic articles severely downward, since the topics covered in weekend editions are less focused on economics.

We show the impact of this choice through Figure B1. The top panel shows the proportion of economic articles over the total number of articles. There is a clear drop before 2010, where after the proportion of economic articles stays on this new level. The proportion goes from 0.03 to 0.15 on average. This kind of regime switch, we do not want to capture with our R-index, hence we divide by the number of economic instead of all articles.

From the bottom two panels of Figure B1, the impact is clear. The peaks after 2010 in the bottom panel – Recession-articles divided by the total number of articles – are much lower compared to the middle panel. This follows from the top panel. If there are less economic articles written, subsequently, there will be fewer articles written containing the word 'recession'.

To avoid these effects and have a more consistent R-index over time, we choose to divide by the number of economic articles instead of all articles.

C Calculation of weekly sentiment per newspaper

For each newspaper, we use a lexicon-based approach to transform news articles into sentiment scores. The Sentometrics Economic Sentiment lexicon covers finance and business in both Dutch and French and has proven very effective in previous research in a now and forecasting context (Algaba et al., 2023; Ardia et al., 2019). Figure C1 shows a sample of the most frequent positive and negative lexicon words.

Figure C1: Word cloud of most common positive (left) and negative (right) lexicon words (translated to English) in our corpus.

We also take into account valence shifters, from the sentometrics R package (Ardia et al., 2021). These are words in the neighbourhood of the polarised word that either alter the size of the polarity – *amplifiers* increase the size of the polarity while *deamplifiers* decrease it – or that alter the polarity itself – so-called *negators*. A neighbourhood of a polarised word is defined as the four words in front and two words behind the word.

We obtain the sentiment on the article-level by aggregating the individual word polarities (possibly shifted by valence shifters) across the article. Let us denote the sentiment of the jth polarised word in article i in newspaper k at time t as $s_{t,k,i,j}$ and the corresponding valence shifter as $v_{t,k,i,j}$ (this equals 1 if there are none in the neighbourhood). We weigh every sentiment word by one over the number of polarised words in article i: $\frac{1}{n_{t,k,i}}$. The sentiment score $s_{t,k,i}$ for an article i in newspaper k at time t can furthermore be computed as:

$$s_{t,k,i} = \frac{1}{n_{t,k,i}} \sum_{j=1}^{n_{t,k,i}} v_{t,k,i,j} s_{t,k,i,j}.$$

We get one sentiment score per newspaper k at time t by averaging over all I_t articles:

$$s_{t,k} = \frac{1}{I_t} \sum_{i=1}^{I_t} s_{t,k,i}.$$

D List of candidate predictors in BREL

The extensive list of predictors used in the nowcasting exercise in section 6 are given in Table D1 and Table D2. The soft indicators and financial variables are published with no delay, the early hard indicators with one month, and the hard indicators with two months of delay.

Variable	Category	Publication lag
Construction - assessment of order book	Business Survey	Soft
Construction - demand expectations	Business Survey	Soft
Construction - employment expectations	Business Survey	Soft
Construction - price expectations	Business Survey	Soft
Construction - trend in activity	Business Survey	Soft
Construction - trend in employment	Business Survey	Soft
Construction - trend in equipment	Business Survey	Soft
Construction - trend in orders	Business Survey	Soft
Construction - trend in prices	Business Survey	Soft
Civil engineering and roadworks - assessment of order book	Business Survey	Soft
Civil engineering and roadworks - demand expectations	Business Survey	Soft
Civil engineering and roadworks - employment expectations	Business Survey	Soft
Civil engineering and roadworks - price expectations	Business Survey	Soft
Civil engineering and roadworks - trend in activity	Business Survey	Soft
Civil engineering and roadworks - trend in number of contracts concluded	Business Survey	Soft
Civil engineering and roadworks - trend in prices	Business Survey	Soft
Civil engineering and roadworks - trend in number of tenders	Business Survey	Soft
Civil engineering and roadworks - trend in amount of work to be done	Business Survey	Soft
Manufacturing - assessment of export order book	Business Survey	Soft
Manufacturing - assessment of the level of stocks of finished products	Business Survey	Soft
Manufacturing - assessment of total order book	Business Survey	Soft
Manufacturing - demand expectations	Business Survey	Soft
Manufacturing - employment expectations	Business Survey	Soft
Manufacturing - price expectations	Business Survey	Soft
Manufacturing - trend in orders from the domestic market	Business Survey	Soft
Manufacturing - trend in export orders	Business Survey	Soft
Manufacturing - trend in prices	Business Survey	Soft
Manufacturing - trend in the production rate	Business Survey	Soft
Business-related services - assessment of activity	Business Survey	Soft
Business-related services - activity expectations	Business Survey	Soft
Business-related services - general demand expectations	Business Survey	Soft
Business-related services - employment expectations	Business Survey	Soft
Business-related services - price expectations	Business Survey	Soft
Business-related services - trend in activity	Business Survey	Soft
Business-related services - trend in employment	Business Survey	Soft
Business-related services - trend in prices	Business Survey	Soft
Retail trade - assessment of the level of stocks	Business Survey	Soft
Retail trade - assessment of sales	Business Survey	Soft
Retail trade - demand expectations	Business Survey	Soft
Retail trade - employment expectations	Business Survey	Soft
Retail trade - intentions of placing orders	Business Survey	Soft
Retail trade - price expectations	Business Survey	Soft
Retail trade - trend in prices	Business Survey	Soft
Retail trade - trend in sales	Business Survey	Soft

Table D1: BREL predictors: Business survey indicators. Soft indicators: no publication lag.

Description	Category	Publication lag
Consumer survey - Economic situation in Belgium (forecasts for the next 12 months)	Consumer survey	Soft
Consumer survey - Financial situation of households (forecasts for the next 12 months)	Consumer survey	Soft
Consumer survey - Saving of households (forecasts of saving for "next" 12 months)	Consumer survey	Soft
Consumer survey - Unemployment in Belgium (forecasts for the next 12 months)	Consumer survey	Soft
Consumer survey - current assessment of financial situation	Consumer survey	Soft
Consumer survey - expectations for major purchases (next 12 months)	Consumer survey	Soft
Total turnover	Turnover	Hard
Turnover in construction	Turnover	Hard
Turnover in business services	Turnover	Hard
Turnover in hotels and restaurants	Turnover	Hard
Turnover in manufacturing	Turnover	Hard
Turnover in retail trade	Turnover	Hard
Turnover in services	Turnover	Hard
Permits for new residential buildings (in m2)	Other	Hard
Permits for new non-residential buildings (in m2)	Other	Hard
Nights spent in hotels or similar accommodation by non-residents	Other	Hard
Work volume of temporary workers	Employment	Early Hard
Unemployed jobseekers	Employment	Early Hard
Adjusted harmonised unemployment rate	Employment	Early Hard
Industrial production, excluding construction	Industrial	Hard
Production of capital goods	Industrial	Hard
Production in construction	Industrial	Hard
Production of durable consumer goods	Industrial	Hard
Production of intermediate goods	Industrial	Hard
Production in manufacturing	Industrial	Hard
Production of non-durable consumer goods	Industrial	Hard
Industrial production in the advanced economies	External	Hard
Industrial production in the emerging economies	External	Hard
Trade in goods in the euro area	External	Hard
Trade in goods in the advanced economies	External	Hard
Trade in goods in the emerging economies	External	Hard
Industrial confidence in the euro area	External	Soft
Industrial confidence in Germany	External	Soft
Industrial confidence in France	External	Soft
Industrial confidence in the Netherlands	External	Soft
Consumer confidence in the euro area	External	Soft
Consumer confidence in Germany	External	Soft
Consumer confidence in France	External	Soft
Consumer confidence in the Netherlands	External	Soft
Industrial production in the euro area	External	Hard
Industrial production in Germany	External	Hard
Industrial production in France	External	Hard
Ten-year Belgian government bond yield	Financial	Financial
Euro Stoxx Broad Index	Financial	Financial
Brussels All Shares Index	Financial	Financial
Crude Oil-Brent Dated Free on Board	Financial	Financial
Import prices of energy raw materials in international market	Financial	Financial
Commodity import prices in international market, excluding energy	Financial	Financial
Spot price of gold (Standard & Poors GSCI)	Financial	Financial
Spreads on ten-year Belgian government bonds compared to the German Bund	Financial	Financial

Table D2: BREL predictors: Consumer survey, VAT, labour market and external development indicators and financial variables. Soft and financial indicators: no publication lag; early hard indicators: one month publication lag; hard indicators: two months publication lag.

E Design of news sentiment indices: elite vs popular vs all newspapers

In this appendix we discuss the results for the nowcasting exercise for CES and AES state variables for the following subsets of newspapers: all newspapers, only elite and only popular. In the original results, we only showed the CES popular and AES elite.

Sample	State Variable	Month of the quarter		
		M1	M2	M3
Full Sample	CES all	2.14	2.46	2.18
	CES elite	2.04	2.18	1.28/***
	CES popular	2.24	2.04	1.26/***
	unweighted BREL	2.06	2.05	1.47
Financial Crisis	CES all	1.12	0.92/***	1.28
	CES elite	1.00	0.94/**	0.57/***
	CES popular	0.97	0.78/***	0.82/***
	unweighted BREL	0.81	1.01	0.92
European Debt Crisis	CES all	0.32	0.49	0.44
	CES elite	0.36	0.56	0.41
	CES popular	0.42	0.46	0.39/*
	unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	CES all	6.19	7.19	6.26
	CES elite	5.91***/***	6.32	3.64***/***
	CES popular	6.52	5.90/**	3.46***/***
	unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	CES all	0.33/*	0.39	0.33
	CES elite	0.34/*	0.40	0.35
	CES popular	0.33/**	0.45	0.43
	unweighted BREL	0.47	0.41	0.34

Table E1: Root mean squared forecasting error of state-based weighted BREL focusing on the subgroups (all, only elite, only popular newspapers) of the Correlation between Economic Sentiment (CES) index and compare with unweighted BREL.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which weighted BREL outperforms unweighted BREL. The *, **, *** indicate respectively $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ and $p \leq 0.01$ for the weighted BREL being superior to the unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

In the main results, we focused on the AES and CES for respectively elite and popular newspapers. In this section, we compare their performance to the other subsets that we could have considered. These include: all newspapers, only the elite newspapers, or only the popular newspapers. The tables shown in this section are an extension of Table 4 in section 6. Table E1 shows that the popular CES is indeed the best performing for the majority of samples and months of the quarter. The CES for popular newspapers outperforms all other

Sample	State Variable	Month of the quarter		
		M1	M2	M3
Full Sample	AES all	2.35	3.22	2.93
	AES elite	2.64	3.19	2.65
	AES popular	2.32	2.95	2.17
	unweighted BREL	2.06	2.05	1.47
Financial Crisis	AES all	1.07	$0.72^{/***}$	$0.59^{/***}$
	AES elite	0.94	1.13	$0.69^{/***}$
	AES popular	1.02	$0.72^{/**}$	0.95
	unweighted BREL	0.81	1.01	0.92
European Debt Crisis	AES all	0.43	0.49	0.39
	AES elite	0.32	0.49	0.44
	AES popular	0.41	0.52	0.44
	unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	AES all	6.65	9.49	8.63
	AES elite	7.71	9.37	7.78
	AES popular	6.65	8.61	6.28
	unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	AES all	0.71	0.41	0.37
	AES elite	0.38	0.38	0.35
	AES popular	0.61	0.61	0.37
	unweighted BREL	0.47	0.41	0.34

Table E2: Root mean squared forecasting error of state-based weighted BREL focusing on the subgroups (all, only elite, only popular newspapers) of the Average Economic Sentiment (AES) index and compare with unweighted BREL.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which weighted BREL outperforms unweighted BREL. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for the weighted BREL being superior to the unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

state variables for the majority of M2 and M3 for most of the samples. For scenario M1, the performance varies across different newspaper groups.

In Table E2 we show the performance for the three AES indices, together with unweighted BREL. First, it is important to note that all of these state variables barely outperform unweighted BREL. This could be explained by the noise in the indices in between crisis periods. The AES index with elite newspapers outperforms unweighted BREL the most. But when also comparing the samples and months of the quarter when the state-based weighted BREL approaches do not outperform unweighted BREL, AES popular seems to outperform the elite version more.

F Further nowcasting results

F.1 AR(1) model: single state variables

Sample	State Variable		Month of the quarter		
			M1	M2	M3
Full Sample	News	CES popular	2.98/***	3.10/***	3.19/***
		AES elite	3.08/***	3.01/***	3.02/***
		R-index	4.41	3.49/***	3.53/***
	Financial	VSTOXX	4.11/***	3.89/***	4.02/***
		CISS	3.03/***	2.91/***	2.89/***
	Survey	BC survey	5.03	5.96	3.02/***
		CC survey	4.81	5.23	5.19
		unweighted AR(1)	4.15	4.15	4.15
Financial Crisis	News	CES popular	0.95	0.95	0.95
		AES elite	1.31	1.81	1.81
		R-index	2.41	2.13	1.56
	Financial	VSTOXX	0.87/***	1.12	1.03
		CISS	1.97	1.96	1.96
	Survey	BC survey	3.14	3.13	3.28
		CC survey	1.86	1.85	1.78
		unweighted AR(1)	0.94	0.94	0.94
European Debt Crisis	News	CES popular	0.47	0.46	0.46
		AES elite	0.49	0.48	0.45
		R-index	0.48	0.47	0.47
	Financial	VSTOXX	0.50	0.50	0.50
		CISS	0.50	0.48	0.49
	Survey	BC survey	0.51	0.50	0.48
		CC survey	0.60	0.54	0.46
		unweighted AR(1)	0.47	0.47	0.47
COVID-19 Crisis	News	CES popular	8.77***/***	9.12***/***	9.40***/***
		AES elite	9.00***/***	8.70***/***	8.72***/***
		R-index	12.80	10.06***/***	10.33***/***
	Financial	VSTOXX	12.16***/***	11.47***/***	11.87***/***
		CISS	8.70***/***	8.32***/***	8.27***/***
	Survey	BC survey	14.51	17.36	8.16***/***
		CC survey	14.10	15.38	15.30
		unweighted AR(1)	12.29	12.29	12.29
Excluding Crisis Periods	News	CES popular	0.27	0.27	0.27
		AES elite	0.28	0.29	0.30
		R-index	0.31	0.31	0.29
	Financial	VSTOXX	0.31	0.32	0.32
		CISS	0.31	0.30	0.30
	Survey	BC survey	0.28	0.29	0.27
		CC survey	0.48	0.34	0.31
		unweighted AR(1)	0.29	0.29	0.29

Table F1: Root mean squared forecasting error for state-based weighted AR(1) models and for the unweighted AR(1) model for different subsamples of the nowcasting exercise.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which the state-based weighted models outperform the unweighted AR(1) model. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for the state-based weighted model being superior to the unweighted AR(1) model. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

F.2 Composite state-based weighted BREL: further results

F.2.1 Composite state-based weighted BREL: all combinations

In this section, we extend the results on the composite weighted BREL shown in Table 5, where we only show the combination of all three. Here we add the pairs as well.

Sample	State Variables	Month of the quarter		
		M1	M2	M3
Full Sample	CES popular, R-index	2.54	1.90$^{/***}$	1.14$^{/***}$
	CES popular, VSTOXX	2.35	1.74$^{/***}$	1.36$^{/***}$
	R-index, VSTOXX	2.33	1.76$^{/***}$	1.28$^{/***}$
	CES popular, R-index, VSTOXX	2.35	1.80$^{/***}$	1.28$^{/***}$
	unweighted BREL	2.06	2.05	1.47
Financial Crisis	CES popular, R-index	0.99	0.77$^{/***}$	0.80$^{/***}$
	CES popular, VSTOXX	1.03	0.78$^{/***}$	0.82$^{/***}$
	R-index, VSTOXX	1.37	0.76$^{/***}$	0.99
	CES popular, R-index, VSTOXX	1.03	0.77$^{/***}$	0.80$^{/***}$
	unweighted BREL	0.81	1.01	0.92
European Debt Crisis	CES popular, R-index	0.47	0.58	0.45
	CES popular, VSTOXX	0.45	0.56	0.36$^{/**}$
	R-index, VSTOXX	0.31	0.41	0.49
	CES popular, R-index, VSTOXX	0.41	0.53	0.37$^{/*}$
	unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	CES popular, R-index	7.40	5.51$^{***/***}$	3.14$^{***/***}$
	CES popular, VSTOXX	6.82	4.96$^{***/***}$	3.83$^{***/***}$
	R-index, VSTOXX	6.68	5.05$^{***/***}$	3.47$^{***/***}$
	CES popular, R-index, VSTOXX	6.82	5.17$^{***/***}$	3.57$^{***/***}$
	unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	CES popular, R-index	0.42	0.35	0.36
	CES popular, VSTOXX	0.39	0.47	0.37
	R-index, VSTOXX	0.42	0.43	0.42
	CES popular, R-index, VSTOXX	0.37$^{/*}$	0.44	0.38
	unweighted BREL	0.47	0.41	0.34

Table F2: Root mean squared forecasting error of composite state-based weighted BREL using the arithmetic mean as aggregating function and for unweighted BREL for different subsamples of the nowcasting exercise.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which state-based weighted BREL outperforms unweighted BREL. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for state-based weighted BREL being superior unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

F.2.2 Composite weights using the maximum as aggregation

In this section, we perform a robustness check, on the choice of aggregation function when combining state variables. The results in Table F3 differ from Table F2 by using the maximum as aggregation function.

Sample	State Variables	Month of the quarter		
		M1	M2	M3
Full Sample	CES popular, R-index	2.56	$1.94^{/***}$	$1.15^{/***}$
	CES popular, VSTOXX	2.31	$1.72^{/***}$	$1.37^{/***}$
	R-index, VSTOXX	2.32	$1.71^{/***}$	$1.34^{/***}$
	CES popular, R-index, VSTOXX	2.32	$1.72^{/***}$	$1.35^{/***}$
	unweighted BREL	2.06	2.05	1.47
Financial Crisis	CES popular, R-index	0.97	$0.82^{/***}$	$0.81^{/***}$
	CES popular, VSTOXX	0.98	$0.87^{/***}$	$0.85^{/***}$
	R-index, VSTOXX	1.30	$0.84^{/***}$	$0.74^{/**}$
	CES popular, R-index, VSTOXX	0.94	$0.82^{/***}$	$0.83^{/***}$
	unweighted BREL	0.81	1.01	0.92
European Debt Crisis	CES popular, R-index	0.32	0.44	0.46
	CES popular, VSTOXX	$0.33^{/*}$	0.53	$0.35^{/**}$
	R-index, VSTOXX	0.43	0.52	0.45
	CES popular, R-index, VSTOXX	0.35	0.53	$0.32^{/**}$
	unweighted BREL	0.46	0.44	0.47
COVID-19 Crisis	CES popular, R-index	7.41	$5.63^{***/***}$	$3.14^{***/***}$
	CES popular, VSTOXX	6.71	$4.91^{***/***}$	$3.84^{***/***}$
	R-index, VSTOXX	6.66	$4.89^{***/***}$	$3.77^{***/***}$
	CES popular, R-index, VSTOXX	6.74	$4.91^{***/***}$	$3.81^{***/***}$
	unweighted BREL	5.95	5.91	4.15
Excluding Crisis Periods	CES popular, R-index	0.51	0.32	0.36
	CES popular, VSTOXX	0.4	0.43	0.38
	R-index, VSTOXX	0.39	0.42	0.40
	CES popular, R-index, VSTOXX	0.42	0.42	0.35
	unweighted BREL	0.47	0.41	0.34

Table F3: Root mean squared forecasting error of combined state-based weighted BREL using the maximum as aggregation function and for the unweighted BREL for different subsamples of the nowcasting exercise.

*Note: M1, M2 and M3 depict the end of the first, second and third month of the nowcasting quarter respectively. The full out-of-sample period is from Q1 2008 to Q2 2023 (62 observations). The financial crisis period is from Q3 2008 to Q3 2010 (10 observations). The European debt crisis is from Q4 2012 to Q2 2013 (3 observations). The COVID-19 crisis is from Q1 2020 to Q3 2021 (7 observations). Grey cells highlight the months of the quarter for which state-based weighted BREL outperforms unweighted BREL. The *, **, *** indicate respectively* $0.05 < p \leq 0.1, 0.01 < p \leq 0.05,$ *and* $p \leq 0.01$ *for state-based weighted BREL being superior to unweighted BREL. The test is performed twice, with different standard errors: once with COVID-19 in the sample and once cutting off the sample before. This is indicated respectively before and after the /. Testing is based on the Diebold and Mariano (1995) test statistic implemented with the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of Andrews (1991) and Andrews and Monahan (1992).*

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