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A Leading Indicator of Economic Activity: International and Spanish Context

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Abstract

This paper reviews international practices in nowcasting and related approaches to the early assessment of macroeconomic conditions in order to provide a comparative and methodological reference for the analysis of short-term macroeconomic statistics within Spain's official statistical framework. Drawing on evidence from national statistical institutes in the United Kingdom, Germany, the Netherlands, Switzerland, and Italy, as well as from Eurostat, the study documents a broad methodological landscape that includes ARIMA and MIDAS models, dynamic factor models, Fourier-based decomposition, neural networks, and signature-based approaches. These methods make increasing use of high-frequency and timely data to generate early signals on broad macroeconomic developments. The Spanish case is examined in depth, with particular attention to the robustness, coherence, and level of disaggregation of the Quarterly National Accounts compiled by the National Statistics Institute (INE), together with the institutional, methodological, and operational requirements associated with preserving consistency within the European System of Accounts. The paper thus offers a structured evidence base for comparative analysis and methodological reflection on the production of short-term macroeconomic statistics.

Keywords

Nowcasting; Leading economic indicators; Official statistics; National accounts; GDP; High-frequency data; Econometric and machine-learning methods.

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Contents

1 Introduction

Gross Domestic Product (GDP) is widely regarded as the most comprehensive indicator of a country's macroeconomic performance. It summarizes the overall level of economic activity and plays a central role in informing public policy decisions, including those related to fiscal and monetary policy, as well as the design and evaluation of social programs. In recent years, the use of GDP has expanded beyond the public sector, becoming increasingly relevant in the private sector for risk assessment, economic forecasting, and strategic planning. This growing reliance on Gross Domestic Product (GDP) as a primary indicator of economic health has significantly intensified the international demand for more timely and high-frequency, or even real-time, estimates. This shift is driven by the need for faster, more accurate data to inform policy decisions, particularly during crises.

However, collecting official basic data and processing them to obtain official short-term indicators is time-consuming and they almost always need additional resources. Consequently, the first calculation of a short-term overall economic indicator will necessarily include some proportion of estimates as not all basic data will be available at that time of release. It is important to highlight that, the earlier such a short-term overall economic indicator is to be calculated, the larger the proportion of data to be estimated will be and therefore the uncertainty associated with the results and, probably, the magnitude of subsequent revisions. The trade-off between the timeliness (speed of release) and reliability (accuracy and precision) of economic statistics is a foundational, and largely unavoidable, challenge in official statistics. To provide actionable data for policymakers and financial markets, statistical agencies must release information quickly, which often means relying on incomplete, partial datasets. This necessitates a ”first estimate” that is subsequently revised multiple times as more comprehensive data becomes available.

An early estimate of an economic key figure can be referred to as forecast, nowcast or flash estimate, depending on when it is produced. An estimate that is produced at a time when few, or no official basic data are available, is generally a forecast. A nowcast (from ”now” and ”forecast”) is a very early estimate produced during or shortly after the end of a reference period. Finally, a flash estimate is typically calculated only some time after the end of a reference period.

In light of this need for earlier but still reliable data, the Spanish Statistical Office, through its annual working plan (Plan de Actuación 2025), has promoted research into innovative methods to produce more timely GDP estimates while preserving the reliability and confidence levels of its publications. Currently, the Spanish Statistical Office, aligned with the majority of national statistical offices in Europe, publishes the GDP in quarterly and annual frequencies. For each quarter, two estimates are released: an initial estimate approximately thirty days after the end of the reference period, followed by a revised estimate around ninety days after the end of the reference period. This article explores both the available techniques and the national and international context, in order to lay the groundwork for making an informed decision about the feasibility and advisability of producing a leading indicator of economic activity, capable of providing a measurement of economic activity closer to the reference period than that currently produced by the Quarterly National Accounts (QNA) while maintaining quality standards.

The techniques for estimating GDP within a short time frame are commonly referenced to as GDP nowcasting, as previously stated. These methods rely on the timely availability of high-frequency indicators to approximate current economic activity. A range of methodological approaches have been used for this task:

- Traditional econometric models, such as linear regression, optimized with regularization techniques such as LASSO and ridge equations to improve variable selection and reduce the dimensionality of the problem. An example of using simple regression can be read in Koenig and Dolomas [8].
- ARIMA (AutoRegressive Integrated Moving Average) models, widely used in time series analysis, which are able to capture autocorrelation patterns and trends in GDP or its components, and can serve either as forecasting tools themselves or as part of more complex nowcasting frameworks. An example of this methodology combined with bottom-up aggregation is presented by Dickopf et al. [5].
- MIDAS (Mixed-Data Sampling) models which allow the use of data sources and indicators with different publication frequencies in a coherent way. An example of applying this methodology for nowcasting is proposed by Kuzin et al. [10].
- Dynamic factor models that aim to reduce the dimensionality of the problem by constructing unobserved factors that capture the common dynamics governing GDP evolution. Giannone et al. [7] present a well-known example of the application of this methodology to GDP nowcasting.
- Machine learning methods, such as random forests, which are able to capture non-linear relationships increasing the complexity of the algorithms. Richardson et al. [22] analysed the performance of this kind of methods (SVM (Support Vector Machine) and neural network) compared with more classical ones for GDP nowcasting.

In addition to these model-based approaches, a complementary form of GDP nowcasting involves applying methodologies similar to those used in the first quarterly GDP estimation, for example the widely used bottom-up aggregation based on other economic aggregates, which may or may not have complete data available at the time of estimation. For these data gaps, the forecasting techniques described above can be applied, allowing the construction of a timely aggregate GDP estimate.

The rest of the article is organized as follows. The second section offers a review of the nowcasting practices used in European countries, highlighting the key methodological frameworks, as well as an overview of the Spanish context regarding the short-term measurement of economic activity by INE, along with the framework in which this measurement is carried out. Finally, the article concludes with a synthesis of the main findings which should serve as a basis for reflection on the current situation and possible future alternatives, taking into account the context in which we find ourselves, both in terms of the standardized evaluation of the different quality dimensions carried out by Eurostat, as well as the limited resources available, the basic information that can be incorporated and, above all, the users' needs.

2 Nowcasting in Official Statistics: International Experience

The need to deliver GDP data more timely and at higher frequencies does not concern only the Spanish Statistical Office, it is shared across all national statistical offices in Europe. For that reason, several national statistical offices have in recent years begun initiatives to explore alternative methodologies for short-term economic monitoring. These efforts have included the development of nowcasting models and, in some cases, the publication of leading economic indicators as experimental statistics.

To gather detailed information on these initiatives within European national statistical offices, a consultation was carried out with the Expert Group in Quarterly National Accounts (EG QNA), group that operates under the coordination of Eurostat. This forum provided an opportunity to exchange experiences and establish direct contact with other national statistical offices, enabling a better understanding of the practices and methodologies which have already been implemented or researched with the aim of GDP nowcasting and higher-frequency publications. Responses and comments were received from Switzerland, the Netherlands, and Germany, as well as Eurostat itself, which also shared its experiences in this area.

This section presents an overview of the experiences shared by European national statistical offices in the EG consultation, together with the cases of the statistical offices of the United Kingdom and Italy, for which the publicly available information has been analyzed. In addition, the experiences of Eurostat and Spain regarding nowcasting techniques and their possibilities are described.

2.1 UK

Among European countries, the United Kingdom stands out for having institutionalized the monthly publication of GDP, a practice that reflects a commitment to improving the availability of GDP data. This monthly GDP publication has been released by the Office for National Statistics (ONS) since 2018, around forty days after the end of the reference month. Due to this publication lag, this methodology cannot be considered as nowcasting but it is considered a good practice for providing valuable early insights into GDP growth trends and turning points. In addition, these estimates are consistent with the quarterly national accounts, despite not following the exact same methodology.

According to its official methodological report [16], the monthly GDP estimate is based exclusively on the output approach (production, services, and construction sectors), as the expenditure and income components are not sufficiently available at this frequency. This first publication relies on approximately 80 % of the source data typically used in quarterly estimations, with the remainder imputed using short-term forecasting models based on historical data. Given the limited availability of data, this first estimation is subject to revisions during the following months as more complete data become available.

In addition to this official monthly publication, the ONS has pursued innovative nowcasting research in collaboration with the Alan Turing Institute (UK's national institute for data science and artificial intelligence). This partnership has focused on the application of advanced mathematical and machine learning techniques to short-term economic forecasting, with a main focus on applying the signature method [3] (a mathematical approach grounded in path theory that represents time series data into a structured algebraic representation). This approach has shown promising results in capturing complex temporal dependencies and nonlinear relationships among economic indicators, enhancing predictive accuracy in high-frequency contexts. The next section describes this work.

2.1.1 Signature Method

The path signature is a property of continuous paths. Formally, a path in $\mathbb{R}^d$ is defined as a continuous function $X : [a, b] \to \mathbb{R}^d$ where each component is a one-dimensional path $X^k : [a, b] \to \mathbb{R}$. The signature is defined through an iterative construction. Let

$$S^1(X^k)_{a,t} \equiv \int_a^t dX_s^k = X_t^k - X_a^k,$$

and define the double iterated integral as

$$S^2(X^k X^l)_{a,t} \equiv \int_a^t S^1(X^k)_{a,s} dX_s^l = \int_a^t \int_a^s dX_r^k dX_s^l.$$

More generally, the n-fold iterated integral is defined by

$$S^n(X^{k_1} X^{k_2} ... X^{k_{n-1}} X^{k_n})_{a,t} \equiv \int_a^t S^{n-1}(X^{k_1} X^{k_2} ... X^{k_{n-1}})_{a,s} dX_s^{k_n}.$$

The superscript n denotes the number of iterated integrals, referred to as "level". Then, the signature of the path is the ordered infinite collection of all such terms

$$S(X)_{a,b} \equiv \left(1, S^1(X^1)_{a,b}, ..., S^1(X^d)_{a,b}, S^2(X^1X^1)_{a,b}, S^2(X^1X^2)_{a,b}, ...\right).$$

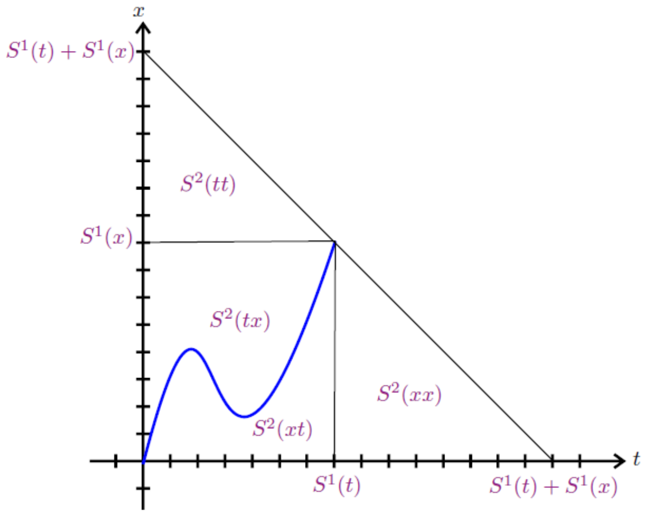


Figure 1: Illustration of the first 2 levels of the signature terms of a two- dimensional path (with variables t and x). *Taken from [3]*

The path signature captures geometric information, such as the order of events. The first level signature terms give the change/increment in each dimension between the start and end of the path. The second level terms are linked to areas bounded by the path. Figure 1 show a visual representation of the intervals and areas represented by the signature terms for a two-dimensional path. When working with real data, the variables are only observed at discrete intervals. So, in practice, it is needed to work with truncated signatures, $S^k(X)_{[0,T]}$. The paper argues, although we will not discuss it here, that the Kalman filter can be equivalently written as a linear regression problem on the signature space, which provides an easy approach to nowcasting, using regression on the signatures of the observations.

Let Y_t be the (low-frequency) target variable and let X_t be the (high-frequency) observed explanatory variables at t. Motivated by the approximation of the Kalman Filter in terms of signatures, it is assumed that for some truncation level k there is a model of the form

$$Y_t = \sum_{k=0}^{k} (\alpha_k + \beta_k Y_{t-}) \psi_{k,t} + \epsilon_t,$$

where

- Y_{t-} is a past observation of the low frequency target variable, available at the time of nowcast. This can correspond to the target variable at the beginning of the lookback window over which the signatures are computed, or the most recent observation;
- ϵ_t is a mean-zero error term which is assumed to be stationary;
- $\psi_{k,t}$ is a sequence (for each value of t) of signature terms at level k, including iterated integrals of t and the different components of the observed process X, calculated over a lookback window ending at the present time;
- α_k, β_k are vectors of regression coefficients (the dimension of which depends on k).

There are a variety of practices for choosing the signature truncation level k, as proposed by [15] through hyperparameter optimisation.

They set out the proposed framework in two algorithms. Algorithm 1 gives the procedures to fit a single signature regression model on a set of cleaned data. The full proposed signature regression method pipeline is as detailed in Algorithm 2.

Algorithm 1: Fit signature regression model.

Input:

- cleaned/pre-processed data available in a wide table, pivot format, which includes the observed data and the target variable;
- target variable name;
- data parameters such as the publication lag in the target variable;
- a set of model parameters associated with the number of signature terms such as the truncation level, lookback window length, whether to use the previous known value of the target variable.

Process:

1. Define the auxiliary dataframe of observations available.
2. Convert the path information of the observations into truncated signatures over the lookback window.
3. Split signatures into training data and test data. The train data can be a proportion of the data available, or it can be the maximum data available (all timepoints where the target is defined).
4. Fit a (regularised) regression model.

Return: Fitted model.

Algorithm 2: Signature regression framework.

```
Input:
  • data available (observation & target) in a wide table, pivot format;
  • target variable name;
  • data parameters, e.g. publication lag in the target variable;
  • model parameters associated with signature regression, e.g. the truncation
    level, lookback window length, whether to use the previous known value
    of the target etc, these may be given as lists to hyperparameter search
    over.
Impute missing values in the dataset by specified method (defaults to forward
fill for all values except those at the beginning which are filled by backward fill).
  for each set of hyperparameters/configurations do
    for each time over the hyperparameter optimisation period do
      1. Fit a signature regression model as outlined in Algorithm 1.
      2. Evaluate the hidden data set with the regression model.
      3. Store predictions and errors.
    end for
  end for
Identify the best set of hyperparameters.
  if Recursive nowcasts then
    for each time that a nowcast is required do
      1. Fit a signature regression model as outlined in Algorithm 1.
      2. Evaluate the test set (only the time for the current nowcast)
         with the regression model for a nowcast value.
    end for
  else
    1. Combine the train and validation set and fit a signature regression
       model as outlined in Algorithm 1.
    2. Evaluate the test set with the above trained regression model.
  end if
  Return: Fitted model.
```

Regarding the experiment setup, a simulation of a state space model is performed and these methods are compared with the Kalman filter obtained from the simulated model (and therefore optimal).

Figure 2 shows the residuals of the Kalman Filter plotted against the residuals of the signature method. The line of best fit in this case has gradient 1.00 and a y-intercept of -0.02. The R^2 of the regression on these residuals is 0.99. The result shows a very good alignment of the errors of the signature method against the ideal filter.

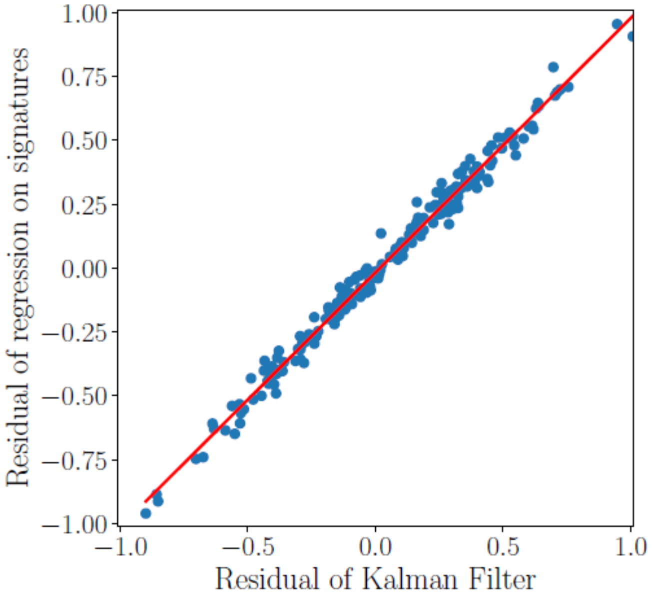


Figure 2: Residuals of the Kalman Filter against the signature method on simulated sampled data. *Taken from [3]*

Figure 3 compares the inferred paths of the Kalman filter and the fitted signature model on one particular simulated path, which shows that the signature method predicts very similarly to the Kalman filter.

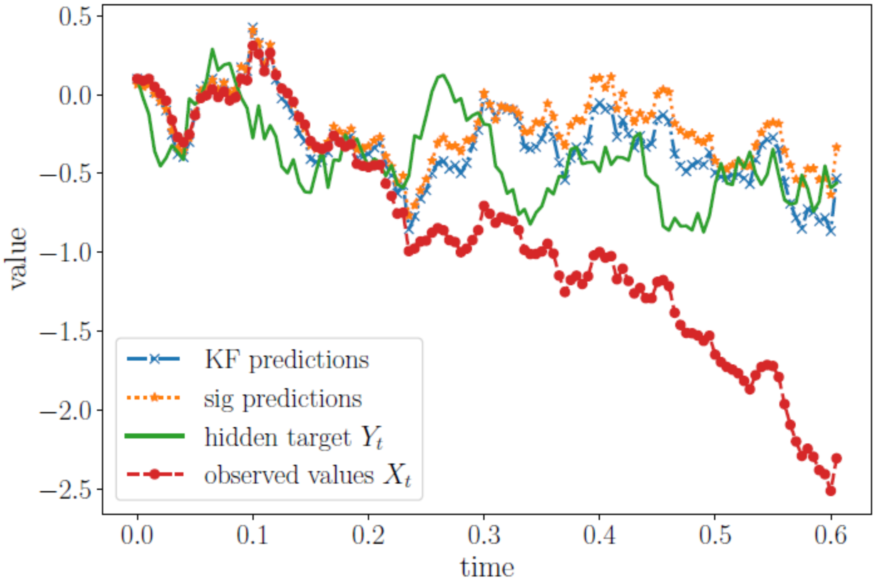


Figure 3: Illustration of one regularly sampled simulated path - the observed values (X_t) along with the true, hidden values that need to be inferred (Y_t). The trajectories inferred from X_t with the Kalman Filter and the signature method are also shown. *Taken from [3]*

A practical application of this technique can be seen in Section 6 of [3], where the authors employ signature-based regression to nowcast U.S. quarterly GDP growth and benchmark its performance against a dynamic factor model (DFM) patterned after the New York Fed Staff Nowcast. Using a comprehensive set of monthly macroeconomic indicators organised into soft, real, labour, and global factor blocks, they generate weekly nowcasts by estimating both a state-space DFM and a signature-based model in which truncated iterated integrals of the factor series serve as regressors within a regularised linear framework. Their results show that the signature method systematically attains lower root-mean-square errors than both the DFM and the published New York Fed nowcast across validation and test samples. Moreover, the precision of the forecast improves further when the signatures are calculated not from the raw factors of the principal - components but from the filtered factor estimates of the DFM, indicating that the signature representation functions both as a competitive stand alone nonlinear estimator - and as an enhancement layer that strengthens the predictive ability of traditional dynamic factor models.

Despite the promising results obtained through this experimental nowcasting approach, it has not been formally implemented yet in the ONS's official publication framework.

2.2 Germany

The German statistical office (Destatis), aligned with other countries in the European Union, currently releases official GDP data on a quarterly basis, with a first estimate available approximately thirty days after the end of the reference quarter. The Department of National Accounts does not publish any leading indicators, nonetheless, Destatis has researched an experimental nowcasting approach [23] capable of producing early GDP estimates as soon as ten days after the end of the reference quarter, which represents a great breakthrough compared to the lag in the standard publication schedule.

According to the technical paper [5], the data sources used for this GDP nowcasting framework combines both official and non-official indicators, which stands in clear contrast to the data used for the current quarterly GDP publication, which relies exclusively on official statistical indicators. On the official side, it includes short-term economic statistics such as industrial production indices, retail trade turnover, balance of payments statistics, and employment data. Complementing these official indicators, there are non-official sources intended to capture more immediate shifts in economic activity, including business and consumer sentiment surveys, high-frequency financial market indicators, and new digital data such as electricity production and weather data. The integration of such heterogeneous inputs allows the model to incorporate early signals of economic change that are not yet visible in traditional statistics, thus enhancing the timeliness and flexibility of GDP estimation.

The GDP nowcasting approach is based on an econometric model combining bottom-up aggregation methodology and ARIMA models, including suitable indicators in the model as external regressors. The estimate is not based on all three GDP approaches, but rather only the production approach and the expenditure approach. Both are computed through bottom-up aggregation, whereby a set of sub-aggregates are estimated based on the data sources described in the previous paragraph, complemented with ARIMA based projections to fill in the timestamps not available yet. Using these sub-aggregates, GDP is calculated independently via the two approaches. For the final GDP estimate, a weighted average of the two results is produced, assigning greater weight to the production approach, given its comparatively higher data coverage and reliability at the early stage of estimation.

The quality of the t+10 GDP nowcast is backtested, that is, assessing the quality of the regression models by means of historical data. Assessing the quality of the t+10 GDP nowcast is based on two common revision or deviation measures: the mean revision (MR) and the mean absolute revision (MAR).

$$MR_{t+n} = \frac{\sum_{t=1}^{T} (y_{t,t+n} - \hat{y}_{t,t+n})}{T}$$

$$MAR_{t+n} = \frac{\sum_{t=1}^{T} |y_{t,t+n} - \hat{y}_{t,t+n}|}{T}$$

Figure 4 shows the estimates of the t+10 GDP nowcast and the t+30 GDP flash, compared with the GDP results released at t+45. The values are GDP change rates on the same quarter of previous year (yoy growth rates).

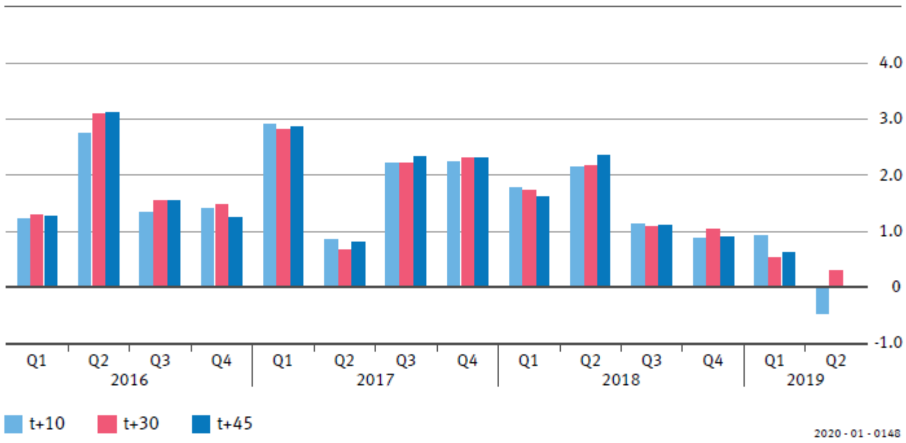


Figure 4: Change rates of the gross domestic product on the same quarter of the previous year. Percentage points. *Taken from [5]*

On the other hand, Figure —5 shows the revisions of the t+10 GDP nowcast and the t+30 GDP flash in relation to the GDP result released at t+45 days for the individual quarters of the period examined. Table 1 shows the revision measures explained before, the standard deviation and the maximum revisions in the test period.

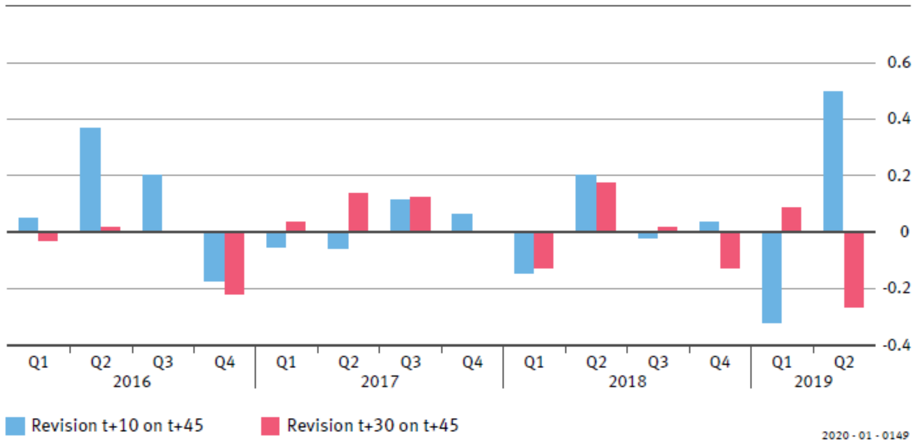
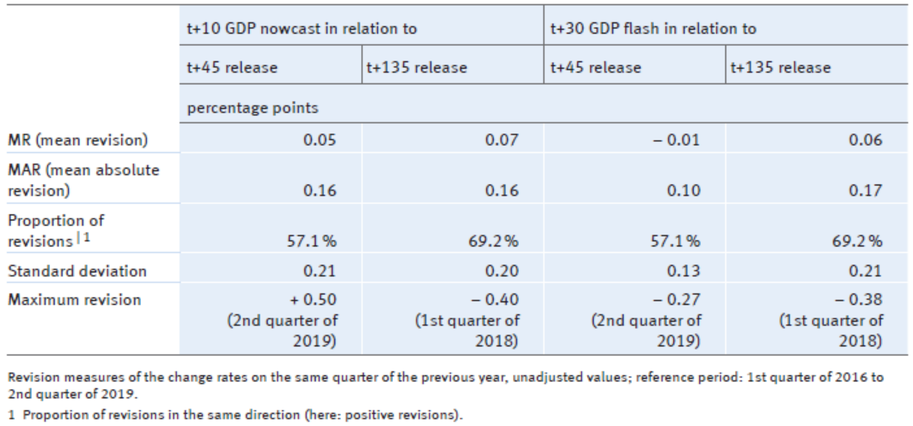


Figure 5: Revisions of the change rates of the gross domestic product. Percentage points. *Taken from [5]*



	t+10 GDP nowcast in relation to		t+30 GDP flash in relation to	
	t+45 release	t+135 release	t+45 release	t+135 release
	percentage points			
MR (mean revision)	0.05	0.07	– 0.01	0.06
MAR (mean absolute revision)	0.16	0.16	0.10	0.17
Proportion of revisions [1]	57.1 %	69.2 %	57.1 %	69.2 %
Standard deviation	0.21	0.20	0.13	0.21
Maximum revision	+ 0.50 (2nd quarter of 2019)	– 0.40 (1st quarter of 2018)	– 0.27 (2nd quarter of 2019)	– 0.38 (1st quarter of 2018)

Revision measures of the change rates on the same quarter of the previous year, unadjusted values; reference period: 1st quarter of 2016 to 2nd quarter of 2019.

1 Proportion of revisions in the same direction (here: positive revisions).

Table 1: Revisions measures of the t+10 GDP nowcast and the t+30 GDP flash. *Taken from [5]*

The report conclude that, although calculations regarding a t+10 GDP nowcast are promising, revision analyses show that the quality of the t+10 GDP nowcast is inferior to that of the t+30 GDP flash, and that early GDP estimation can be further improved, focusing on improvement in optimizing the econometric models and in including additional non-official sentiment and survey indicators and short-term indicators based on new digital data.

2.3 Netherlands

In line with the European statistical framework, Statistics Netherlands (CBS) publishes official GDP estimates on a quarterly basis. The first estimate, known as “flash estimate”, is released approximately 30 days after the end of the reference quarter, and the second one is published with 85 days lag. Although neither a monthly GDP estimate nor an early estimate is officially published, CBS has shown a strong commitment to explore and research advanced methods and the use of high-frequency indicators to improve the timeliness of economic monitoring.

Over the past decade, CBS has published a series of research articles related to producing more timely estimates of the Netherlands’ macroeconomic indicators, including GDP. Firstly, in 2018, an initial report [19] explored the use of linear filters and ARIMA models for nowcasting economic time series. Building on these early results, in 2020 a new study [9] employed dynamic factor models (DFM), combining principal component analysis and Kalman filtering to extract latent economic factors from a broad set of indicators for GDP nowcasting. More recently, this article has been extended to 2025 [20] with the introduction of time series decomposition techniques (trend and seasonal patterns) based on Fourier analysis. On the other hand, in 2024, CBS evaluated the performance of deep learning methods, including neural networks, to improve short-term GDP predictions [17].

Regarding the 2020 article [9], a dynamic factor model is used to nowcast GDP, combining principal component analysis to reduce dimensionality and Kalman filter to handle the different publication lag that each indicator has. In this case, the target variable is GDP itself (or GDP growth rate), and the estimation was based on the expenditure approach, so the selected indicators mainly relate to private consumption, investment, government spending, exports and imports. Additionally, the model incorporated more general economic indicators, such as labor market and unemployment data, as well as expectation indicators. In contrast, the 2025 extension [20] applied a similar DFM methodology, but incorporated a Fourier-based decomposition of time series to separate trend and seasonal components, predicting each effect individually. Here, the target is no longer GDP as a whole but the four macroeconomic aggregates composing the production approach: Agriculture and Industrial Goods, Commercial Services, Non-Commercial Services, and Product Taxes minus Product Subsidies. Consequently, the main indicators used differ from the 2020 approach, focusing on production-related activity.

Although these studies have shown encouraging potential to produce more timely indicators, CBS has not incorporated any of these model-based approaches into its official statistical releases. To date, the institution continues to restrict its GDP releases to official quarterly publications, while the experimental nowcasting models remain at a research stage.

2.3.1 Dynamic Factor Model

The work [9] presents a dynamic factor model to estimate the GDP growth rate. Let Y_t be a N-dimensional vector of monthly indicators. It is assumed that Y_t follows a DFM with r latent factors, which are not observed directly,

$$\begin{aligned} Y_t &= \Lambda F_t + \epsilon_t, \\ F_t &= A F_{t-1} + u_t, \\ \epsilon_t &\sim N(0, \Sigma_t), \\ u_t &\sim N(0, Q_t) \end{aligned}$$

where ϵ_t is a N-dimensional vector and F_t a r-dimensional vector of factors, with $r << N$. The $N \times r$ matrix of factor loadings Λ is assumed to be time-invariant. Its elements λ_{ij} are the correlations between the i-th indicator and the j-th factor. the covariance matrix of the idiosyncratic disturbances Σ_t is assumed to be diagonal, which means that the errors are independent and uncorrelated. The first term on the right of first equation is the common component of Y_t, which captures a large part of the comovements in the data, the joint dynamics. The second term is the idiosyncratic component, which represents the individual specific (stochastic) shock corresponding to each of the N predictors. Both components are orthogonal processes. It is also assumed that the factors follow an AR process. The coefficient matrix A is assumed to be time invariant. The error term u_t is a white noise process independent of the idiosyncratic shocks ϵ_{it} at all lead and lags, such that $E[\epsilon_t u'_{t-j}] = 0$ for all j.

The previous equations form the state space representation. The quarterly GDP estimation procedure essentially follows four steps:

1. Apply Principal Component Analysis (PCA) to estimate the common factors. In order to reduce the dimensionality of the problem, only the first r principal components are used.
2. The second step entails estimating the coefficient matrices A and Λ, by applying a Vector Autoregressive (VAR) model and Ordinary Least Squares (OLS) respectively.
3. Third step is the Kalman filter, to make nowcasts of the factors.
4. The last step involves transforming the nowcasted monthly factors to a nowcast of the GDP growth rate,

   $$Y_t = \beta F_t + \epsilon_t.$$

   Once β is estimated, then $\hat{Y}_t$ can be computed, together with its uncertainty, $Var(\hat{Y}_t)$.

Regarding PCA, for selecting the number of factors a couple of tests were conducted (Acceleration Analysis, Parallel Analysis, Kaiser Rule and Optimal Coordinates method), obtaining the following results:

- The first factor captures the general trend. It exhibits the clear drop during the financial crisis and subsequently the (less severe) drop around the Eurocrisis. It is highly correlated with producer sentiments and vacancy indicators, CLI and the AEX index.
- The second factor is a fairly stable factor. It shows a clear seasonal pattern. Indicators that load heavily on this factor are indicators regarding the production, revenues and prices of raw materials, minerals and energy. In addition, some CPI and governmental series are related to this factor.
- The third factor loads quite heavily on indicators that respond slowly to economic decline, such as unemployment rates, numbers on social benefits and consumption of durable goods. The drop of the crisis also shows a little delay compared to the other factors. In addition, series on the housing market are related with this factor.
- The fourth factor is highly correlated with time series of sentiment indicators. It also contains quite some time series on consumption and is highly correlated with the number of mortgages taken out. It might reflect the consumer and producer sentiment.
- The final factors do not exhibit a clear correlation with a certain group of indicators. They contain for example prices and revenues of industry and raw materials. However, also governmental time series and series on trade are captured in these factors.

Based on the tests, five seems to be the appropriate number of components. These factors together capture 79.27% of the total variance. Figure 6 shows these five factors.

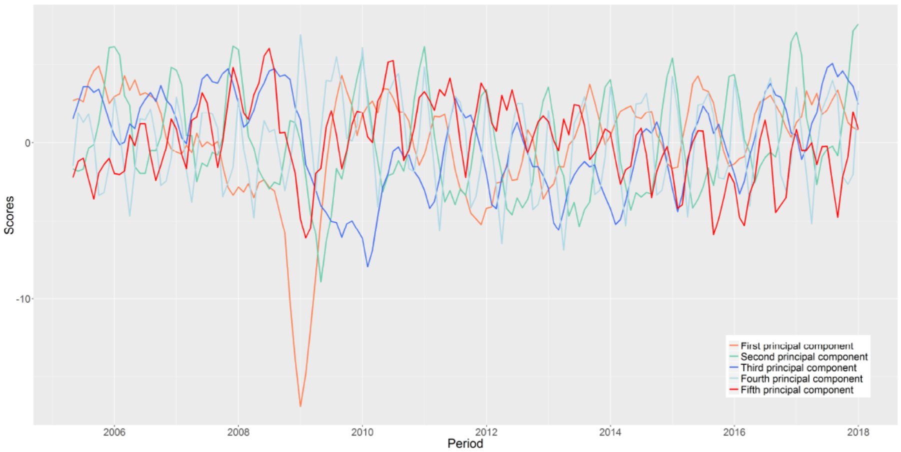


Figure 6: First five principal components. *Taken from [9].*

Concerning the last step in the estimation of GDP growth rate, it is necessary to run a regression to estimate β. The model described above relies on the assumption of having stationary time series. The entire nowcasting procedure is applied to stationary time series (by taking (log) differences), in addition to nonstationary data, to investigate whether this has an effect on the nowcasting performance. The first approach is referred to as the Econometric Approach (EA) and the latter as the Operational Approach (OA). For the EA, the regression is run using the historical GDP growth rates, while for the OA the historical GDP values are used.

As the model assumes a monthly indicator but the GDP is a quarterly series, it is necessary to get quarterly factors to obtain β. Taking monthly differences, two ways to estimate the GDP growth rate are considered:

- **M1**: $\hat{Y}_t^Q = \beta_0 F_t^m + \beta_1 F_{t-1}^m + \beta_2 F_{t-2}^m + \epsilon_t$
- **M2**: $F_t^Q = \frac{1}{3}\left[F_t^m + 2F_{t-1}^m + 3F_{t-2}^m + 2F_{t-3}^m + F_{t-4}^m\right]$

Method **M2** is motivated by the approximation from [13], approximating the sum of the three monthly values by their geometric mean plus a constant. Quarterly value of GDP, z_t^Q, is the sum of the GDP of the corresponding months within that quarter

$$z_t^Q = z_t^m + z_{t-1}^m + z_{t-2}^m.$$

Then, the following expression for the GDP growth rate is obtained

$$\begin{aligned}\hat{Y}_t^Q &= \ln(z_t^Q) - \ln(z_{t-1}^Q) \approx \\ &\approx \frac{1}{3}\left[\ln(z_t^m) + \ln(z_{t-1}^m) + \ln(z_{t-2}^m) - \ln(z_{t-3}^m) - \ln(z_{t-4}^m) - \ln(z_{t-5}^m)\right] = \\ &= \frac{1}{3}\left(\hat{Y}_t^m + 2\hat{Y}_{t-1}^m + 3\hat{Y}_{t-2}^m + 2\hat{Y}_{t-3}^m + \hat{Y}_{t-4}^m\right),\end{aligned}$$

where $\hat{Y}_t^m = \ln(z_t^m) - \ln(z_{t-1}^m)$ denotes the unobserved monthly GDP growth rate.

The second set of estimates takes three-month differences of the indicator series Y_t, to transform all monthly indicators to quarterly equivalents. Then the resulting factors are also quarterly. Every month quarterly estimates of the factors are constructed, so other two ways to estimate the GDP growth rate are considered:

- **Q1**: Takes every third element of the estimated factors.
- **Q2**: Takes the three-month average of the factors.

Additionally, two methods based on the same procedure but then applied to nonstationary data are considered. That is, every third element of the estimated factors, as well as the three-month average will be used to compute F_t^Q.

The six different methods are compared and the different selection of the parameters are explored: the effect of the number of factors (r), the number of lags p in the VAR-regression and the effect of adding lags (ly) of GDP in the regression to estimate β. Figure 7 shows the single model that better works to estimate GDP quarterly growth rate, which is **M2** with parameters $r = 4$, $p = 1$, $ly = 0$.

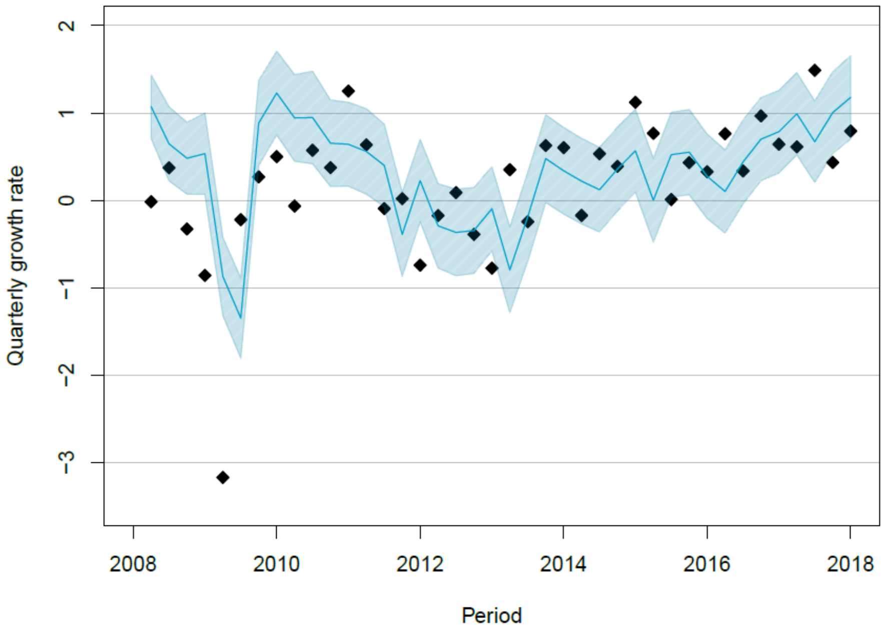


Figure 7: Nowcast Q2 ($r = 4$, $p = 1$, $ly = 0$). The black dots are the realised historical GDP growth rates. The blue line reflects the nowcast. The shaded area represents the corresponding uncertainty, taking one standard error. *Taken from [9].*

The paper also explore the averaging of models instead of use a single model, concluding that the best-performing model uses the model set

$$\{\text{flash}, \mathbf{Q2}_{410}, \mathbf{M2}_{411}, \mathbf{M2}_{412}\}$$

The last section checks whether the model is appropriate to estimate year on year growth rates of the GDP. The time series are made stationary by taking yearly differences or transformed into yearly growth rates. The PCA analysis indicated using around 7 factors and the same techniques to get quarterly factors from the monthly factor are used, that is, taking every third element (**Y1**) and the three-month average (**Y2**). Figure 8 shows the best model for nowcasting year on year growth rates, which is model **Y2** with $r = 6$, $p = 1$ and $ly = 1$.

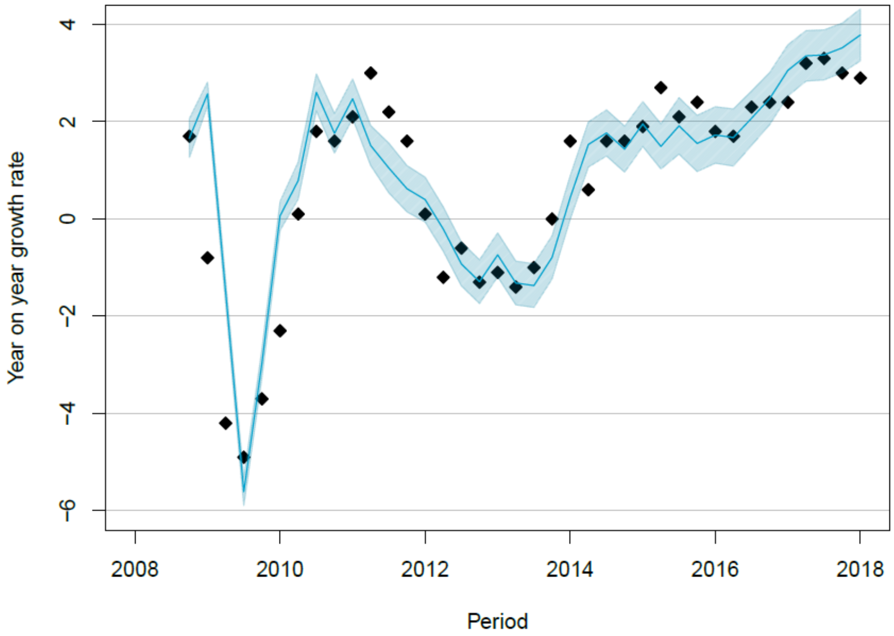


Figure 8: Nowcast Y2 ($r = 6$, $p = 1$, $ly = 1$). The black dots are the realised historical GDP values. The blue line reflects the nowcast. The shaded area represents the corresponding uncertainty, taking one standard error. *Taken from [9].*

2.3.2 Nowcasting of Trend and Seasonal Patterns Based on Fourier Analysis

The work [20] also applies a DFM methodology, using PCA components to reduce the number of factors and the Kalman filter to nowcast the indicators, but in this case the target variables are four macroeconomic aggregates composing the production approach: Agriculture and Industrial Goods, Commercial Services, Non-Commercial Services, and Product Taxes minus Product Subsidies.

In this study, nowcasting is performed by first decomposing the series into trend+noise and seasonal components, to estimate each effect individually. The filter used to decompose the time series suppress all Fourier components with frequencies $f < \frac{1}{\text{year}}$ and also all frequencies $f > f_{N_{yq}} - \frac{1}{\text{year}}$, where $f_{N_{yq}}$ is the Nyquist frequency,

$$f_{N_{yq}} = \frac{1}{2\Delta_t}$$

The filter is the following:

$$R(f) = \begin{cases} 0 & f < \frac{1}{\text{year}} \\ 1 & 1/\text{year} < f < f_{N_{yq}} - \frac{1}{\text{year}} \\ 0 & f_{N_{yq}} - \frac{1}{\text{year}} < f \end{cases}$$

This filter selects all periodic or quasi-periodic variations with periods less than a year, but greater than a period which would be considered stochastic variations. Multiplying instead by $1 - R(f)$ suppresses all such intra-year periodicities. An inverse Fourier transform of $R(f)$ thus yields appropriate weights:

$$w(t) = \frac{4sin(at)}{\pi t} cos\left(\frac{\pi t}{2\Delta_t}\right)$$

where $t = 0$ corresponds to the centre of the window for the moving average, and in which the constant a:

$$a = \pi\left(f_{N_{yq}} - \frac{2}{year}\right)$$

In practice, such a sharp edged filter is impractical because it implies that the window over which to perform the weighted average in the time domain becomes very large or even infinite. It is more practical to modify $R(f)$ so that at the transition frequencies the changeover from 0 to 1 is not discontinuous but it is as steep as feasible. For more details see [18].

As previously stated, the target series compose the national accounts of the production side of the economy. A nowcast of GDP, and the uncertainty interval around its point estimate, can simply be obtained by aggregating respectively the point estimate nowcasts of the individual target series, or their uncertainties.

The target time series are denoted with Y^i_{nt}, with $i \in \tau, \zeta$, for trend+noise and seasonal components, respectively, $n \in 1, ..., N$ and $t \in 1, ..., T$. The common factors are denoted with f^i_{lt}, where $j \in 1, ..., v^i$ runs over the optimal amount of factors r^i plus an extra term s^i, $v^i = r^i + s^i$ with $i \in \tau, \zeta$. For the trend+noise component a linear trend term is added to the set of factors, while an intercept term is added to the set of factors for both the trend+noise and seasonal components. Then $s^\tau = 2$ and $s^\zeta = 1$. Here it is assumed that the target and factor series are all regularly sampled and all at the same instances. Then, the relation can be modelled as:

$$Y^i = F^i \beta^i + \epsilon^i$$

where Y^i is a $(T \times N)$ matrix containing the decomposed target series observations, F^i is a $(T \times v^i)$ matrix of common factors and additional intercept (or intercept and trend) term. The $(v^i \times N)$ matrix β^i relates the factors to the target series and ϵ^i is a $(T \times N)$ matrix of idiosyncratic errors. As in the previous work, once β^i is estimated, the estimation $\hat{Y}^i_{nt}$ and its variance $V(\hat{Y}^i_{nt})$ can be computed. Finally, the estimate of the GDP is obtained by:

$$\hat{Y}_{(N+1)t} = \sum_{n=1}^{N} \hat{Y}^{\tau}_{nt} + \sum_{n=1}^{N} \hat{Y}^{\zeta}_{nt}$$

Initially, before applying the described method, the cubic spline interpolation technique is applied individually on the time series. Each series is resampled from the resulting smooth continuous function at a bi-weekly cadence. Figures 9 and 10 show the nowcast of the GDP after the estimation on the individual aggregates.

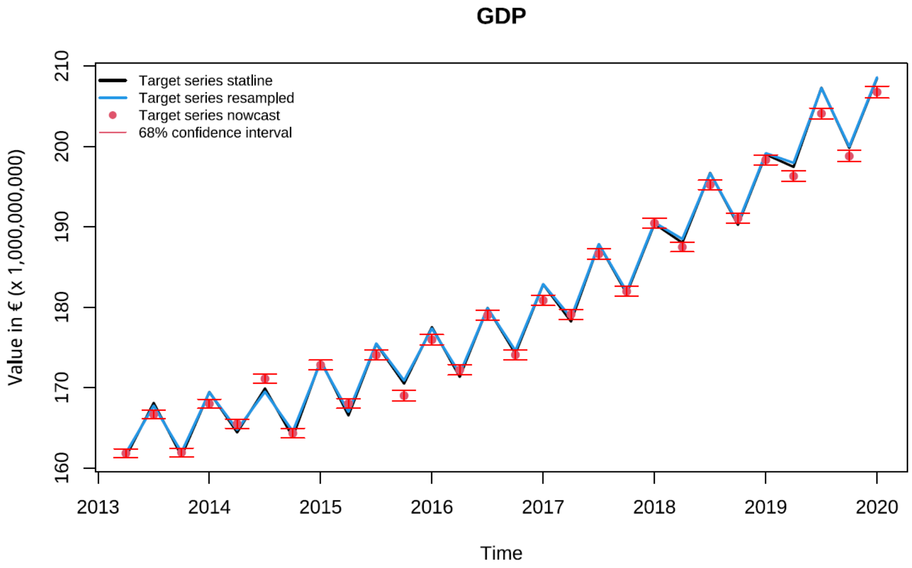


Figure 9: Nowcasts and realized figures of the GDP in unit measurements. *Taken from [20].*

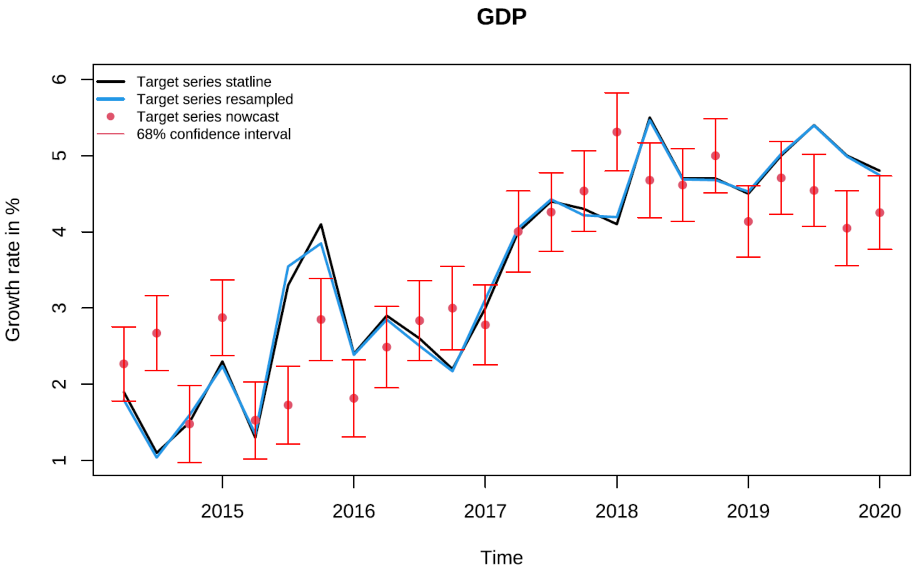


Figure 10: Nowcasts and realized figures of the GDP in growth rates. *Taken from [20].*

2.3.3 Artificial Neural Network

The study [17] explores deep learning techniques, in particular the artificial neural networks (ANN), for nowcasting time series in official statistics, as an alternative to classic time series models.

Let y_t be the target variable at time t, with $t = 1, \ldots, T$, and X_t the auxiliary variables at time t. The matrix X_t consists of m auxiliary variables, all given for $t = 1, \ldots, T$. Any time series model is basically a function of historical observations and auxiliary data and, in a classic time series model, the goal is to find an appropriate form of the relation such that it has good explanatory and predictive value:

$$y_t = f(y_{t-1}, y_{t-2}, ..., y_{t-n}, x_{1,t}, x_{2,t}, ..., x_{m,t}) + \epsilon_t \quad \text{for} \quad t = 1, ..., T$$

In neural networks, the function f is not explicitly defined, and but instead lets the learning algorithm discover for itself which patterns are present in the data. The algorithm only trains the network in order to give good predictions for the output variable, and explanatory value of the model is not explicitly considered. Figure 11 gives an example of the inputs in a feed-forward neural network with a single hidden layer. In practice, the number of hidden layers and the number of neurons in each layer is one of the most important choices to determine. Although guidelines exist, this is largely a matter of trial and error and depends on the application at hand.

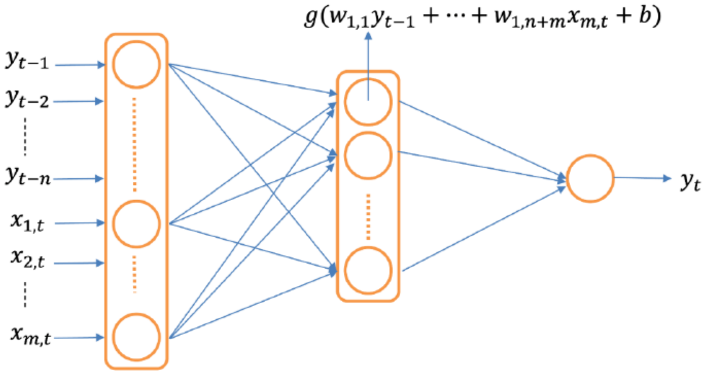


Figure 11: Time series nowcasting model in a feed-forward neural network. *Taken from [17].*

In order to learn a mapping from inputs to output, some inputs should be given lower weights than other inputs. This is done via the neurons in each layer. Each neuron receives a number of inputs from the previous layer, suppose these are $x = x_1, ...x_k$. The neuron then first computes a weighted sum of these inputs:

$$z = wx + b = w_1x_1 + ... + w_kx_k + b$$

After computing this linear combination, an activation function $g(l)$ is applied. The activation function determines the output of the neuron and thus how the network learns the training data. Some of the most important ones are the linear activation function (which is just the weighted sum above), tanh (which results in an output between -1 and 1), the ReLU (rectified linear unit) and the sigmoid function. In this study, the two latter are applied:

$$\text{ReLU:} \quad g(z) = \max(0, z)$$

$$\text{Sigmoid:} \quad g(z) = \frac{1}{1 + e^{-z}}$$

The training set is processed in the model in relatively small portions which are called batches. After a batch is processed, the weights are adjusted. Stochastic gradient descent is an iterative method to optimize the loss of a predictive model for the training set. It uses the first order derivative of the loss function. At each batch, it calculates in which way the weights should be adjusted so that the loss can reach a minimum. The learning rate parameter determines the size of this adjustment step at each iteration. Through backpropagation, which calculates gradients for the weights, the loss is transferred from one layer to another, and the weights are modified depending on the loss. In the application of this study, the 'Adam' optimizer is used to perform this task and vary the learning rate. Processing the entire training set once is called an epoch. The loss-function determines how the difference between output of the model and true value is computed.

A simple approach is to train a model with a predetermined number of epochs. Another possibility is to apply ‘early stopping’, in which after every epoch the model is applied on a validation set (this validation set is not part of the training set and therefore not involved in the estimation of the weights) and compute the validation loss. Then the training can stop when this validation loss does not improve anymore for several epochs, and the weights with the smallest validation loss can be used.

This study uses four types of ANN: Dense neural networks (DNN), Recurrent neural network (RNN), Long short-term memory (LSTM) and Neural Prophet. These models are also compared with ARIMA-models and state space models, also called structural models (STM). In the paper can be found more details about each one of the ANN models. The paper presents the results of simulations and also an empirical study of the performance of deep learning methods.

The quality of the models is evaluated by looking at figures where the predictions are compared with the true values using the following measures:

$$\begin{aligned}
\text{ME} &= \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)\\
\text{MAE} &= \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i|\\
\text{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}\\
\text{MAPE} &= \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i}{x_i} - 1| * 100,
\end{aligned}$$

with n = total numbers of observations, y_i = actual value for the ith observation and x_i = predicted value for the ith observation.

Figure 12 and table 2 compare the results for nowcasting of GDP using DNN and LSTM algorithms, which have shown the best performance through different simulations and the study of empirical variables, and compare with classic time series models. DNN(16,8,3,1) refers to a model with three hidden layers with 16, 8 and 3 neurons respectively.

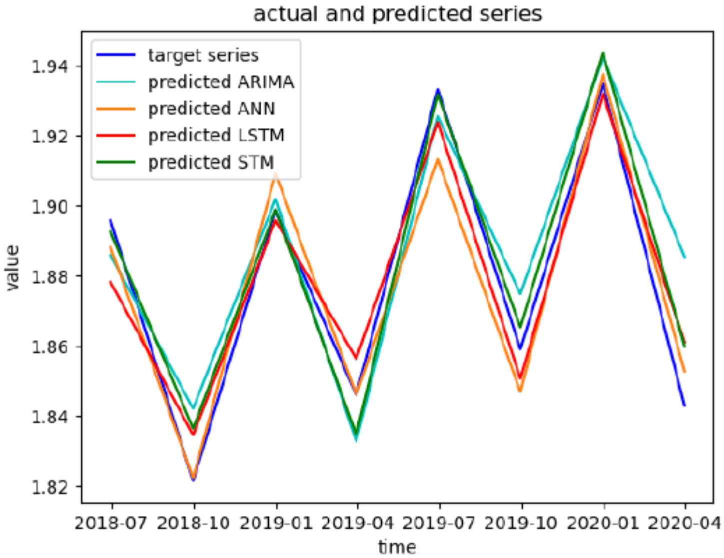
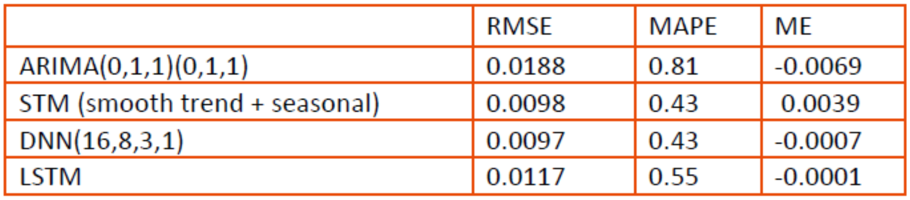


Figure 12: One step ahead nowcasts for DNN, LSTM, ARIMA and STM models. *Taken from [17].*



	RMSE	MAPE	ME
ARIMA(0,1,1)(0,1,1)	0.0188	0.81	-0.0069
STM (smooth trend + seasonal)	0.0098	0.43	0.0039
DNN(16,8,3,1)	0.0097	0.43	-0.0007
LSTM	0.0117	0.55	-0.0001

Table 2: Accuracy measures for the test set of 8 periods. *Taken from [17].*

The main conclusion of the study is that neural network algorithms can produce similar results (i.e., accuracy of predictions/nowcasts) if applied to univariate time series. In order to achieve this, some effort is required in optimizing parameters and further settings of the algorithms, perhaps more than with classic methods. When applied to a more challenging problem with several auxiliary variables and a more volatile series, it is found that the LSTM model, which should be especially suitable for time series data, gave accurate results. This leads to the conclusion that deep learning can perhaps add value compared to classical methods for specific problems.

2.4 Switzerland

The official institution responsible for the publication of GDP in Switzerland is the State Secretariat for Economic Affairs (SECO). In line with the standards adopted by Eurostat and most European national statistical offices, SECO releases official GDP values on a quarterly basis, with a time lag of approximately 45 days after the end of the reference quarter. Although no monthly GDP estimate or early release is distributed, SECO has developed two complementary indicators that allow short-term monitoring of the economy: the Weekly Economic Activity (WEA) indicator and the Swiss Economic Confidence index (SEC).

The Weekly Economic Activity (WEA) indicator [25] is designed as a high-frequency proxy for economic activity. It is constructed from nine series, with weekly or in some cases daily availability, each of them adjusted using ARIMA models to account for seasonality and short-term dynamics. These series cover almost every major dimension of the economy, including private consumption, exports, imports, production activity, financial market indicators, and unemployment data. The adjusted indicators are then combined through a Dynamic Factor Model (DFM), which extracts a latent factor related to the year-on-year growth rate of weekly economic activity, that is, comparing the current week with the same week of the previous year. Empirical evaluations show that this indicator exhibits a strong correlation with actual year-on-year GDP growth.

The Swiss Economic Confidence Index (SEC) [26], by contrast, is a monthly sentiment-based indicator that captures perceptions of the state of the economy. It is calculated based on a selection of public and private surveys, released with relatively low publication lags, and covering a wide range of economic dimensions. These surveys can be divided into two categories: those reflecting assessments of the current economic situation, and those reflecting expectations about the future. Once the relevant surveys and indicators are selected, the SEC index is computed in a simple way as an unweighted arithmetic average. This indicator has been shown to provide valuable information on confidence trends and turning points ahead of official GDP releases.

In both technical reports, the potential of these indicators for nowcasting and forecasting GDP growth rates is assessed. The results indicate a satisfactory performance, since both the WEA and the SEC index show a strong correlation with actual GDP values, thus providing useful measures to anticipate short-term economic fluctuations.

2.4.1 Weekly Economic Activity

The econometric methodology is to use a Dynamic Factor Model (DFM) to explain the information contained in a vector of observable time series by a small number of unobserved (latent) series.

The idea of the model is to decompose a vector of observed time series X_t of dimension n into two orthogonal components: common components, also called latent factors, denoted by f_t, which capture the co-movements among the observed variables in X_t, and an idiosyncratic component, $u_{t,i}$, $\forall i = 1, ..., n$.

The vector of time series X_t consists of nine weekly series (Air pollution, Card transactions, Cash withdrawals, Electricity consumption, Goods exports, Goods imports, Net tonne kilometers, Sight deposits and Registered unemployment). All individual series in X_t are given by year-on-year growth rates and are standardized. The DFM is specified $\forall t = 1, ..., T$ by the following system of equations:

$$\begin{aligned} X_t &= \gamma \ \cdot f_t + u_t, \\ (1 - \phi_f(L)) \cdot f_t &= v_t^f, \\ (1 - \phi_{u,i}(L)) \cdot u_{t,i} &= v_{t,i} \quad \forall i = 1, ..., n \\ \begin{pmatrix} v_t^f \\ v_t \end{pmatrix} &\sim NID \left(0, \begin{pmatrix} \sigma_f^2 & 0 \\ 0 & \Sigma_v \end{pmatrix} \right). \end{aligned}$$

In the first equation, the idiosyncratic component is given by $u_t = (u_{t,1}, ..., u_{t,n})'$. The vector of factor loadings γ captures the relation between the common factor f_t – the object of interest – and the observed variables in X_t. Second and third equations are the transition equations, where $v_t = (v_{t,1}, ..., v_{t,n})'$. $\phi_f(L)$ and $\phi_{u,i}(L)$ are lag-polynomials. The common component f_t is identified based on both the historical cross-correlations of the vector of variables x_t and its own historical auto-correlations. Identification is achieved only up to scale, as initial conditions for the parameters — $\gamma, \phi_f(L), \phi_{u,i}(L)$ and Σ_v, respectively — are necessary to complete the model. The two primary methods for estimating the model are by principal components and state space methods.

Once the model has been estimated, the index of weekly economic activity is derived from the common factor f_t. As the common factor is not anchored to any measure of economic activity, its values are not directly interpretable. To convert the common factor into meaningful units, the f_t are re-scaled to the quarterly year-on-year GDP growth rates, following [12]. The scaling and shift coefficients are estimated using the regression

$$\Delta^4 \text{GDP}_{t_q} = \beta_1 + \beta_2 \cdot f_{t_q} + e_{t_{q'}}$$

where $\Delta^4\text{GDP}_{t_q}$ is the quarterly year-on-year growth rate of GDP, f_{t_q} is the common component on a quarterly frequency t_q. Then, the WEA index is computed as:

$$\text{WEA}_{t_q} = \hat{\beta}_1 + \hat{\beta}_2 \cdot f_{t_q}$$

Figure 13 shows the resulting weekly economic activity index starting in 2005. It captures the economic development indicated by GDP growth over a long period of time. The index has a correlation of 0.9 with the GDP growth rate at a quarterly level and, for the period between the major crises in 2009 and 2020, the correlation is almost 0.6

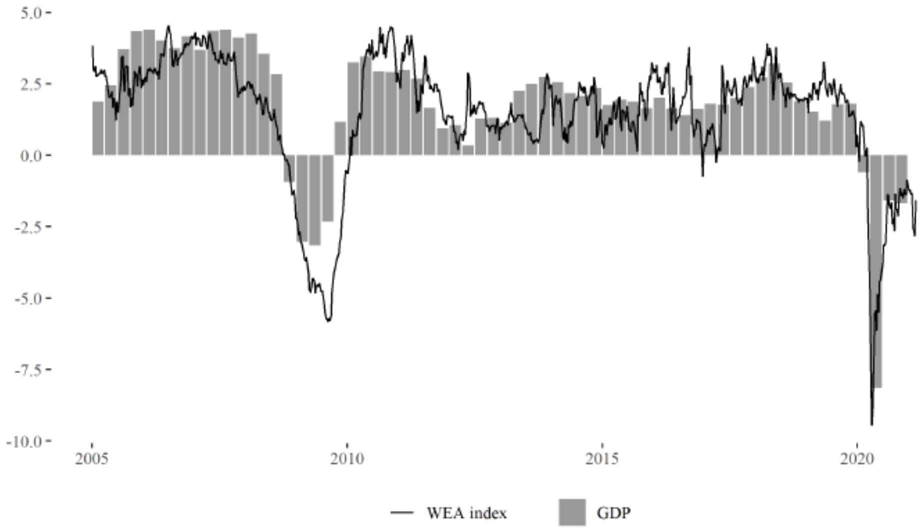


Figure 13: Swiss weekly economic activity (WEA) index. *Taken from [25].*

The marginal contribution of variable $x_{i,t} \in X_t$ to the factor f_t is given by $\Delta f_t / \Delta x_{i,t} = \gamma_i$. Then, the contribution of variable $x_{i,t}$ for the change in the factor can then be computed by $\Delta f_t = \gamma_i \Delta x_{i,t}$. Figure 14 shows the contribution of the variables to the weekly index, which let to use the WEA index to assess the extent to which different sectors and/or markets shape the overall economic dynamics.

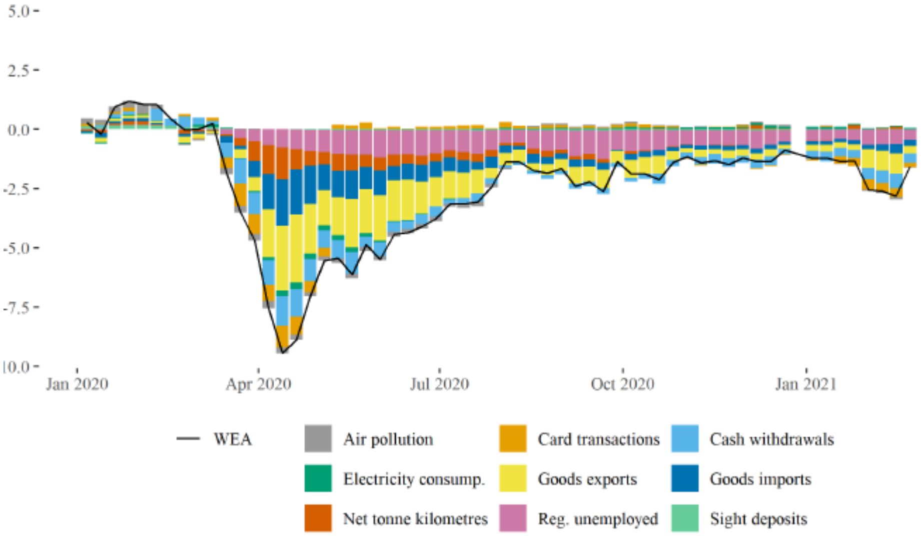


Figure 14: Contribution of the variables to the weekly index. *Taken from [25].*

2.4.2 Swiss Economic Confidence Index

The SEC indicator is computed as the arithmetic, unweighted average in each quarter from the selected indicators. The resulting indicator is shown in Figure 15.

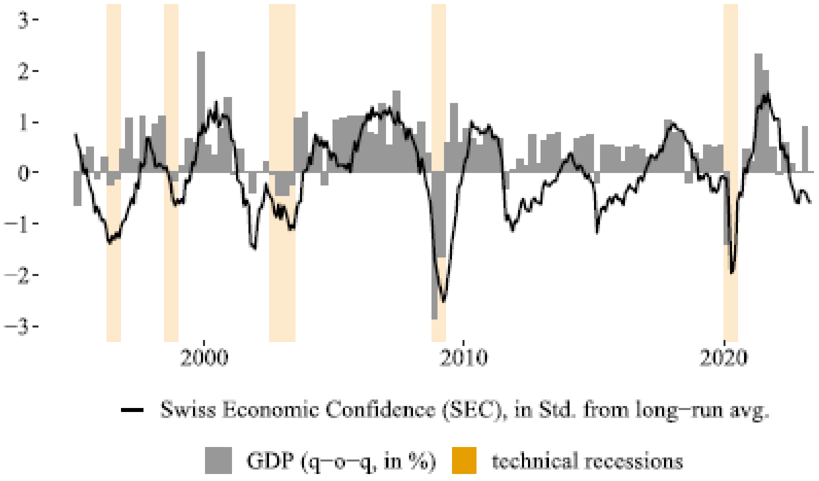


Figure 15: Swiss economic confidence — SEC. *Taken from [26].*

To select an indicator it has to meet the following three selection criteria, which give a total of 40 indicators:

1. It exhibits at least five years of observations, in order to avoid spurious correlations.
2. Indicators at quarterly frequency should have a publication delay of at most 30 days after the end of the respective quarter.
3. Based on the robust $\tilde{t}_{xy,k}$ statistic, its contemporaneous correlation with GDP is significant at the 5% level and at least 0.35 in absolute terms.

The $\tilde{t}_{xy,k}$ is the robust estimator proposed by [4] to test the significance of the pairwise correlations.

To analyse the relation between SEC and GDP, two linear regressions are computed. The first one regresses the quarter-over-quarter GDP growth on the quarterly average SEC index, following

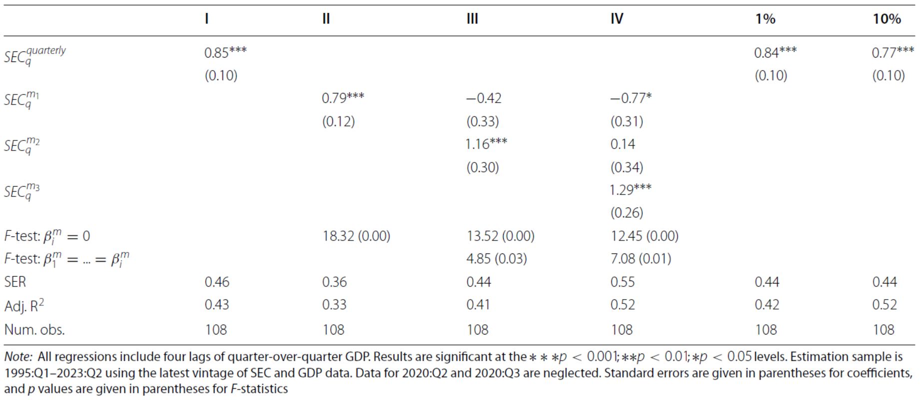
$$\Delta \text{GDP}_q = c + \beta \text{SEC}_q^{\text{quarterly}} + \sum_{s=1}^{4} \delta_s \Delta \text{GDP}_{q-s} + e_q$$

where ΔGDP_q is the quarter-over-quarter real GDP growth in quarter q and $\text{SEC}_q^{\text{quarterly}}$ is the quarterly average SEC index. The results in column (I) of Table 3 show that the quarterly SEC is a significant predictor of GDP growth, with 46% of variation explained (31% without lagged GDP growth), roughly 45 days before the release.

The second regression is the quarter-over-quarter growth rate on the flow of information from the SEC, starting with the SEC for just the first month of the quarter, and so on, following

$$\Delta \text{GDP}_q = c^m + \sum_{i=1}^{m} \beta_i^m \text{SEC}_q^{m_i} + \sum_{s=1}^{4} \delta_s^m \Delta \text{GDP}_{q-s} + e_q^m, \qquad m = 1, 2, 3$$

where $\text{SEC}_q^{m_i}$ is the monthly SEC index for the i-th month of quarter q. Columns (II–IV) report the results. The most recent month's SEC is a significant positive predictor of growth, with the adjusted R^2 rising from 0.36 to 0.55, which means that every additional data point adds information for the current quarter. The robustness of the results with respect to the selection criteria is also tested. Lowering the significance threshold to the 10% level yields a wider set of selected indicators (around 45). Raising instead the significance level to 1% lowers the amount of selected indicators further (around 20). Columns 5 and 6 of the table show that the relationship between the resulting indices and GDP is qualitatively similar, especially for the index constructed with a 1% threshold.



	I	II	III	IV	1%	10%
$SEC_q^{quarterly}$	0.85***				0.84***	0.77***
	(0.10)				(0.10)	(0.10)
$SEC_q^{m_1}$		0.79***	−0.42	−0.77*		
		(0.12)	(0.33)	(0.31)		
$SEC_q^{m_2}$			1.16***	0.14		
			(0.30)	(0.34)		
$SEC_q^{m_3}$				1.29***		
				(0.26)		
F-test: $\beta_i^m = 0$		18.32 (0.00)	13.52 (0.00)	12.45 (0.00)		
F-test: $\beta_1^m = ... = \beta_i^m$			4.85 (0.03)	7.08 (0.01)		
SER	0.46	0.36	0.44	0.55	0.44	0.44
Adj. R^2	0.43	0.33	0.41	0.52	0.42	0.52
Num. obs.	108	108	108	108	108	108

Note: All regressions include four lags of quarter-over-quarter GDP. Results are significant at the $***p < 0.001$; $**p < 0.01$; $*p < 0.05$ levels. Estimation sample is 1995:Q1–2023:Q2 using the latest vintage of SEC and GDP data. Data for 2020:Q2 and 2020:Q3 are neglected. Standard errors are given in parentheses for coefficients, and *p* values are given in parentheses for *F*-statistics

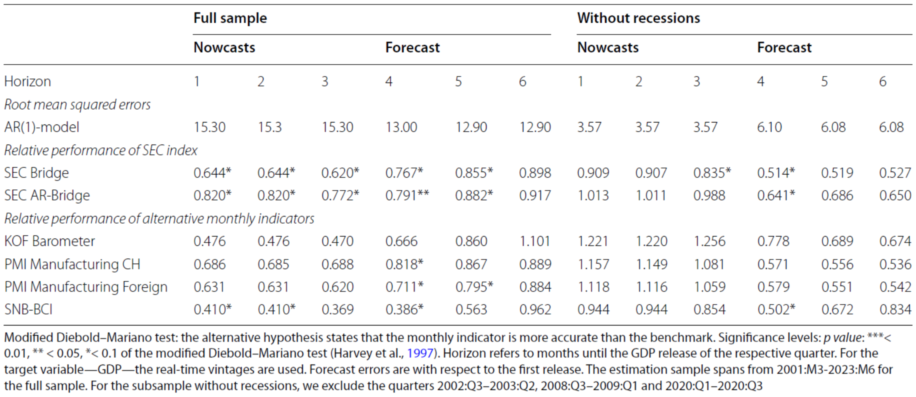
Table 3: Regressing GDP on SEC index. *Taken from [26].*

Finally, bridge equations are used to predict GDP with the SEC indicator. The univariate bridge equation is given by:

$$y_{t_q} = \alpha + \gamma y_{t_q - 1} + \beta(L) x_{t_q} + u_{t_q},$$

where y_{t_q} is the quarterly GDP growth. The bridge equation contains a constant, α, and potentially an autoregressive term, $\gamma y t_q - 1$. The lag polynomial is given by $\beta(L) = \sum_{i=0}^{p} \beta_{i+1} L^i$, with $L x_{t_q} = x_{t_q - 1}$. The predictor x_{t_q} is the monthly SEC index $x_{t_{[m]}}$ aggregated to the quarterly frequency. Two distinct econometric models are considered: (i) bridge equations and (ii) bridge equations with auto-regressive elements (AR-Bridge), where the lag order is determined by BIC.

The relative root-mean-squared error (RMSE) is computed to measure the predictive accuracy, which is shown in Table 4. The table also reports the RMSE of the benchmark univariate AR(1)-model as well as other well-established monthly business cycle indicators for the Swiss economy.



	Full sample						**Without recessions**					
	Nowcasts			**Forecast**			**Nowcasts**			**Forecast**		
Horizon	1	2	3	4	5	6	1	2	3	4	5	6
Root mean squared errors												
AR(1)-model	15.30	15.3	15.30	13.00	12.90	12.90	3.57	3.57	3.57	6.10	6.08	6.08
Relative performance of SEC index												
SEC Bridge	0.644*	0.644*	0.620*	0.767*	0.855*	0.898	0.909	0.907	0.835*	0.514*	0.519	0.527
SEC AR-Bridge	0.820*	0.820*	0.772*	0.791**	0.882*	0.917	1.013	1.011	0.988	0.641*	0.686	0.650
Relative performance of alternative monthly indicators												
KOF Barometer	0.476	0.476	0.470	0.666	0.860	1.101	1.221	1.220	1.256	0.778	0.689	0.674
PMI Manufacturing CH	0.686	0.685	0.688	0.818*	0.867	0.889	1.157	1.149	1.081	0.571	0.556	0.536
PMI Manufacturing Foreign	0.631	0.631	0.620	0.711*	0.795*	0.884	1.118	1.116	1.059	0.579	0.551	0.542
SNB-BCI	0.410*	0.410*	0.369	0.386*	0.563	0.962	0.944	0.944	0.854	0.502*	0.672	0.834

Modified Diebold–Mariano test: the alternative hypothesis states that the monthly indicator is more accurate than the benchmark. Significance levels: *p value*: ***< 0.01, ** < 0.05, *< 0.1 of the modified Diebold–Mariano test (Harvey et al., 1997). Horizon refers to months until the GDP release of the respective quarter. For the target variable—GDP—the real-time vintages are used. Forecast errors are with respect to the first release. The estimation sample spans from 2001:M3-2023:M6 for the full sample. For the subsample without recessions, we exclude the quarters 2002:Q3–2003:Q2, 2008:Q3–2009:Q1 and 2020:Q1–2020:Q3

Table 4: Predictive accuracy. *Taken from [26].*

2.5 Italy

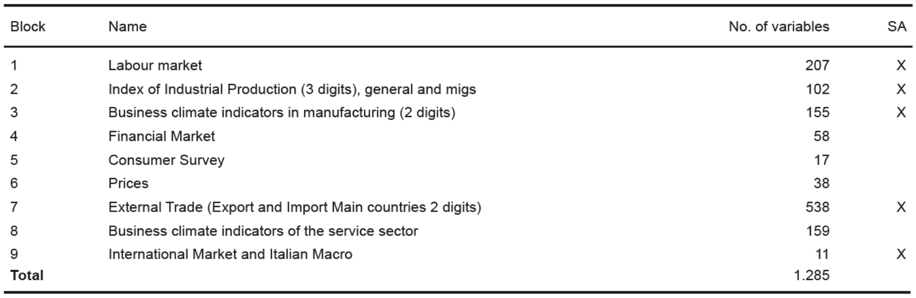
The Italian National Institute of Statistics (ISTAT) releases official GDP values on a quarterly basis, in line with the Eurostat framework. The first estimate is usually published about 30 days after the end of the reference quarter, followed by a more detailed release at a later stage. Although ISTAT does not produce monthly GDP estimates or explicit nowcasting exercises, it has placed particular emphasis on improving the timeliness of its outputs and providing an up-to-date picture of economic conditions. A great example of this commitment is the publication of the Note on Italian Economy every two months, approximately two weeks after the end of the reference period, which offers an assessment of the "current" state of the Italian economy by analysing the most recent releases of key macroeconomic indicators. Beyond this monitoring activity, ISTAT has also developed the RAT-ITA (Real-time Assessment of the Italian Economy) framework [1] to nowcast the current quarterly-on-quarterly GDP growth sign in each month.

Regarding this RAT-Ita framework [1], it is important to highlight that the objective of this tool is not to estimate the exact level of GDP, but rather to predict the sign of GDP growth. The estimation is carried out on a monthly basis, which requires the use of a very large dataset consisting of more than one thousand monthly indicators. These series cover almost all dimensions of the economy (such as industrial production, retail sales, foreign trade, and labor market data) complemented by survey-based measures of business and consumer confidence. Methodologically, this framework relies on a dynamic factor model to identify the most relevant factors, from this extensive dataset, to assess the direction of GDP growth. Each selected factor is then transformed into a binary variable depending on whether its evolution points to an expansion or a contraction in GDP. Finally, the prediction is derived from the aggregation of the different factors, for which four alternative strategies are evaluated: arithmetic mean, geometric mean, logarithmic opinion pooling, and beta-transformed linear opinion pool.

Despite the research and implementation of the RAT-Ita framework [1], ISTAT does not release any official publication directly associated with it. Nevertheless, the availability of this experimental tool, together with the bi-monthly Note on Italian Economy, demonstrates ISTAT's clear commitment to enhancing the timeliness of its economic assessments and to providing instruments that allow a near real-time evaluation of Italy's economic conditions.

2.5.1 RAT-Ita Index

The aim of this work is to nowcast the binary event represented by the sign of the quarter on quarter (q-o-q) GDP growth rate (i.e. the direction of change in GDP), using a total of 1285 indicators, which can be classified in nine different blocks (Table 5)



Block	Name	No. of variables	SA
1	Labour market	207	X
2	Index of Industrial Production (3 digits), general and migs	102	X
3	Business climate indicators in manufacturing (2 digits)	155	X
4	Financial Market	58	
5	Consumer Survey	17	
6	Prices	38	
7	External Trade (Export and Import Main countries 2 digits)	538	X
8	Business climate indicators of the service sector	159	
9	International Market and Italian Macro	11	X
Total		1.285	

Table 5: The indicators' block coverage. *Taken from [1].*

The methodology is carried out by a three-step procedure:

1. Selection of a time-varying subset of monthly series which picks the most suitable indicators to track the signs of GDP directional changes up to the latest available quarter;
2. Estimation of the signal coming from each selected-indicator to nowcast the GDP sign;
3. Aggregation of the signal on the GDP sign provided by each selected indicator.

The procedure runs each quarter, after the new GDP figure is released, providing the update of the selected indicators' list.

The selection step uses different techniques: the Directional Accuracy test (DAC), the Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC) and one based on the spectral coherence between the quarterly growth rate of GDP and of each indicator. The full list of the selected monthly indicators is obtained by merging the single lists coming from the three techniques. The selection process is run each quarter, after a GDP update is released, while the selection is left unchanged for the following months until a new GDP release occurs.

Once the indicators have been selected, the sign of the current-quarter GDP growth is estimated using two different approaches:

- The probability prediction, which estimates the conditional probability of occurrence of a negative sign for the target;
- The binary point prediction, which transforms the selected indicator in a binary variable, delivering the positive/negative classification of the target ([11]).

Each approach used to nowcast the GDP sign is characterised by 4 different aggregation methods, leading to 8 different values for the nowcasting of the GDP sign.

To compute the probability prediction, a logit model is used, regressing each of the n selected time series against the GDP, expressed in terms of 0 (positive quarterly growth rate) and 1 (negative quarterly growth rate):

$$GDP_{01} = \Lambda(c + x_i\beta_i) \qquad i = 1, ..., n$$

where Λ is the logistic function and x_i is the $i-th$ indicator. Each regression returns the estimated probability $\hat{p}_i$ for the event GDP_1. Then, the probability values are aggregated in four different ways:

- Aritmetic mean (**Amean**):

$$\hat{p}_A = \frac{\sum_{i=1}^{n} \hat{p}_i}{n}.$$

- Geometric mean (**Gmean**):

$$\hat{p}_G = \frac{\left[\prod_{i=1}^{n}\left(\frac{\hat{p}_i}{1-\hat{p}_i}\right)^{1/n}\right]^a}{1 + \left[\prod_{i=1}^{n}\left(\frac{\hat{p}_i}{1-\hat{p}_i}\right)^{1/n}\right]^a}$$

  where $a \geq 1$ is an unknown parameter to correct the systematic bias in the forecast probability, which is estimated as ([24])

$$\hat{a} = arg\,min_a \sum_{t=1}^{T} \left(\hat{p}_{G,t}(a) - GDP_{01,t}\right)^2.$$

- Logarithmic opinion pooling (**Elop**):

$$\hat{p}_L = \frac{\prod_{i=1}^{n} \hat{p}_i^{w_i}}{\prod_{i=1}^{n} \hat{p}_i^{w_i} + \prod_{i=1}^{n}(1 - \hat{p}_i^{w_i})}$$

  where $w_i = 1/n$.

- Beta-transformed linear opinion pool (**Beta**):

$$\hat{p}_B(\alpha, \beta) = H_{\alpha,\beta}\left(\sum_{i=1}^{N} p_i w_i\right)$$

  where $H_{\alpha,\beta}$ is the cumulative distribution function of the Beta distribution. As in the previous case, $w_i = 1/n$. In line with [24], the overfitting is controlled using $\alpha = \beta \geq 1$. The parameter $\alpha = \beta$ is estimated following [21]:

$$\hat{\alpha} = arg\,max_{\alpha} \sum_{t=1}^{T} GDP_{01,t} \log\left[H_{\alpha,\alpha}\left(\frac{1}{n}\sum_{i=1}^{N}\hat{p}_{it}\right)\right] + \\ + \sum_{t=1}^{T}(1 - GDP_{01,t}) \log\left[1 - H_{\alpha,\alpha}\left(\frac{1}{n}\sum_{i=1}^{N}\hat{p}_{it}\right)\right].$$

The binary point prediction uses diffusion indexes, transforming each time series in a binary variable, then the proportion of classifications equal to 1 is measured. When the proportion is above the threshold 0.5, the GDP growth rate can be interpreted to be negative and positive when below 0.5. Again, four methods of classification are used:

- The benchmarking method (**Bench**): each time series is classified as 0 or 1 when the growth rate is respectively positive or negative.

- Another method is to define a threshold c_i (for each $i = 1, ..., n$) which maximises the indicator's ability to meet the evolution of the target GDP_{01}. Then, c_i is compared with the last value of the indicator: if c_i is lower, the GDP_{01} is classified as 1 (or 0 is higher). Different methods can be used to define c_i:

  - Criterion based on Youden's Index [27] (**Youden**):

$$\max\left(\text{Sensitivity}(c_i) + \text{Specificity}(c_i)\right)$$

  - Criterion based on the minimum p-value relative to the Chi-squared test [14] (**Chi.sq**), which measures the association between the sign of q-o-q GDP growth rate and the binary results obtained using different thresholds.

- Criterion called *closest.topleft* (**CTL**):

  $$min((1 - \text{Sensitivity}(c_i))^2 + r \cdot (1 - \text{Specificity}(c_i))^2)$$

  where r = (1-prevalence)/(cost x prevalence), cost is the relative cost of a false negative classification (as compared with a false positive classification) and prevalence, or the proportion of cases in the population, is the mean of the GDP growth rate sign up to the previous quarter.

Figures 16 and 17 show the different monthly composite indicators obtained according to either the 4 aggregations of probability prediction and binary point prediction, respectively.

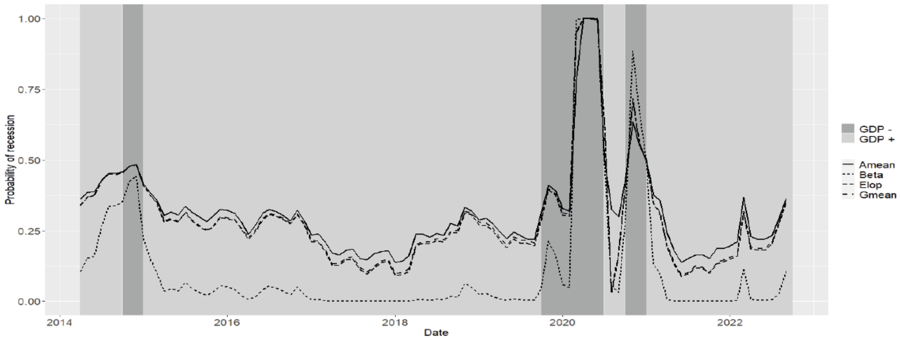


Figure 16: RAT-ITA using probability prediction approach. *Taken from [1].*

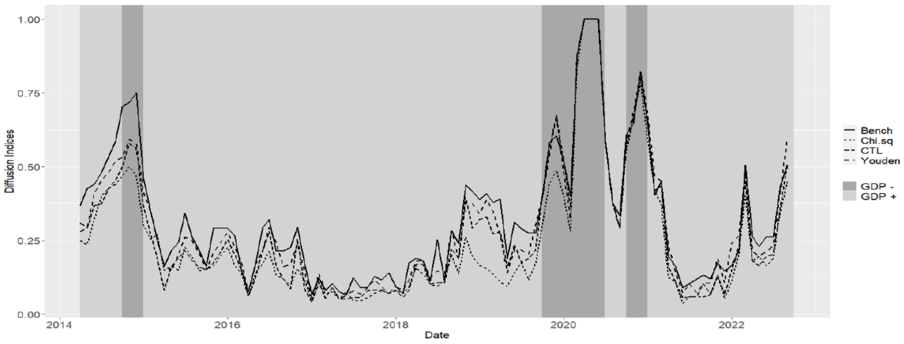


Figure 17: RAT-ITA using diffusion index approach. *Taken from [1].*

The performance of the different aggregation methods has been evaluated using the set of statistics proposed in [11], together with the correlation and the

AUC-ROC between the GDP_{01} and the composite indicator, obtaining that the **CTL** indicator gives the best results and this is the proposed RAT-Ita indicator, shown in Figure 18.

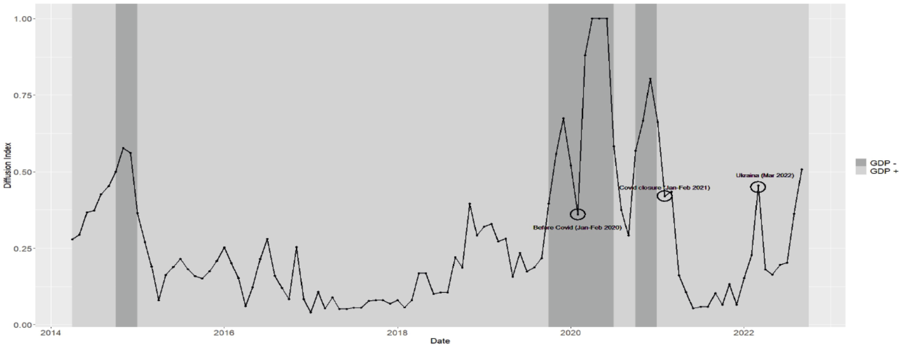


Figure 18: Best diffusion index. *Taken from [1].*

Finally, Table 6 compares the RAT-Ita indicator against other models using the following statistics:

- Accuracy: the proportion of correctly classified cases out of the total number of cases;
- Precision: the proportion of negative growth rates correctly ranked out of the number of times the growth rate was predicted to be negative;
- Specificity: the proportion of correctly classified positive growth rates out of the total positive growth rates;
- Sensitivity: the proportion of correctly classified negative growth rates out of the total negative growth rates.
- DAC p-values and AUC-ROC statistics

	ARIMA	**Bridge**	**Midas**	**RAT-Ita**
Accuracy	0.45	0.55	0.51	**0.96**
Precision	0.16	0.16	0.20	**0.87**
Specificity	0.43	0.56	0.48	**0.98**
Sensitivity	0.6	0.47	0.73	**0.87**
DAC *p*-value	0.97	0.74	0.38	**0.00**
AUC	0.7	0.44	0.59	**0.98**

Table 6: The Performance RAT-ITA against other models. *Taken from [1].*

2.6 Eurostat

Eurostat has evaluated the nowcasting ability of various models for the GDP of Euro Area (EA) and six major EU economies from 2021 to 2024 ([6]). The six economies under consideration include: BE, DE, ES, FR, IT and NL.

A large suite of nowcasting models have been developed to be evaluated in real-time combining a set of estimating methodologies and different ways to deal with the issue of mixed- frequency. Let y_t, $t = 1 \dots T$, be the target variable and $x_t = (x_{1t}, \dots, x_{Nt})$ be a set of potential predictors, with N being very large. The aim is to provide estimates for current values of y_t. Two different approaches are used:

- **Dimensionality Reduction**: Principal Components Analysis (PCA), Dynamic Factor Analysis (DFA) and Partial Least Squares (PLS).
- **Sparse Regression**: Ridge Regression, LASSO Regression and Elastic Net (EN)

  These methods use different penalty functions in order to effectively estimate the β_i parameters. While LASSO and, in some cases, Elastic Net can shrink some coefficients exactly to zero—thereby performing variable selection— Ridge regression only shrinks coefficients toward zero but never eliminates variables entirely.

All predictors are expressed in monthly frequency whereas the GDP growth rate is expressed in quarterly frequency. To deal with mixed-frequency two different approaches are considered:

- Bridge models:

  $$y_{t_q} = \alpha + \sum_{i=1}^{j} \beta_i(L) x_{it_q} + u_{t_q},$$

  where $\beta_i(L)$ is a lag polynomial and x_{it_q} are the monthly indicators aggregated at quarterly frequency.
- Unrestricted MIDAS (UMIDAS):

  $$c(L^m)w(L)y_{t_m} = \delta_1(L)x_{1t_m} + ... + \delta_N(L)x_{Nt_m} + \epsilon_{t_m},$$

  where $c(L^m) = (1 - c_1 L^m - ... - c_c L^{mc})$, $\delta_j(L) = (\delta_{j,0} + \delta_{j,1} L + ... + \delta_{j,v} L^v)$, $j = 1, \dots, N$ and the aggregation scheme $w(L)$ is supposed known.

To ensure consistency across all cases, a dataset of corresponding indicators for all economies is organized. These include hard data (production, retail sales, unemployment, interest rates, equity, volatility, etc.) as well as soft data (surveys etc.).

The GDP nowcasting is executed at three estimation time points attempting to exploit the different information available across time. These estimation points are: (i) about a month prior to the reference date, $T - 30$, (ii) on the reference date, T and (iii) two weeks after the reference date, $T + 15$.

Combining the different types of indicators (HARD, SOFT, HARD+SOFT), the different methodologies (PCA, DFA, PLS, Ridge Regression, LASSO and EN) and the different mixed-frequency settings (Bridge models and UMIDAS), a set of 70 models can be evaluated over 12 quarters: from 2021Q4 to 2024Q3 at estimation points $T - 30$, T and $T + 15$.

In the evaluation of the models a double-sorted filter is used:

1. Filter the individual models choosing those which have a $CONC > 80\%$.
2. Rank them according to their MAE.

The above statistics are defined as follows:

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |y_t - \hat{y}_t|$$

$$CONC = \frac{1}{T} \sum_{t=1}^{T} I[\text{sgn}(y_t) - \text{sgn}(\hat{y}_t)],$$

where $\text{sgn}(\cdot)$ denotes the sign function and $I[\cdot]$ is an indicator variable taking 1 when the sign of the estimate, $\hat{y}_t$, is equal to the sign of the observed value, y_t.

The individual models are complemented by using model averages, considering the following types of model averages:

- Static Model Averages: assigning equal weight to all models of the same methodology.
- Dynamic Model Averages (MAE): assigning equal weights to the Top 5, Top 10, Top 20 and Top 50 models ranked according to their MAE over the past 4 quarters
- Dynamic Model Averages (CONC): assigning equal weights to the Top 5, Top 10, Top 20 and Top 50 models ranked first according to their CONC and then according to their MAE over the past 4 quarters.

The paper shows the results for all models and the comparisons between them, concluding that there is some heterogeneity across the various cases, however there is evidence that penalized regression methods work better for EA, BE, DE, ES and FR, whereas factor models seem to work better for IT and NL.

2.7 Spain

The Spanish National Statistics Institute (INE) currently publishes, one month after the end of the quarter (t+30 days, where t is the reference quarter), a preliminary estimate of the results of Spain's Quarterly National Accounts: Main Aggregates (QNA). At this point, not only a preliminary estimate of the GDP generated in the economy during quarter t is provided, **but also an estimate of each of its components**, from three perspectives: supply, demand, and income (both in terms of volume and at current prices for the first two, and at current prices for the income perspective).

A measurement of employment trends is also provided in terms of employed persons, jobs, full-time equivalent jobs, and hours worked.

All estimates are presented in both non-adjusted and seasonally and calendar-adjusted form. As mentioned above, this is a preliminary estimate based on all available information for the reference quarter.

It is worth highlighting that Spain is among the very few countries that provide the same level of disaggregation in their t+30 estimates as in their t+90 releases. This high degree of detail serves, first, as a valuable analytical tool, enabling a thorough assessment of the drivers behind GDP growth or contraction. Second, it enhances transparency by clearly identifying the sources of revisions in subsequent publications following the preliminary estimate.

The results for each quarter are revised around t+90 days after the reference period, incorporating all available information since the preliminary estimate and including updated results from previous quarters of the current year (T) This publication not only incorporates information from baseline statistics (or information from administrative records) that was not available in the advance publication, but also incorporates the updates to the results that occur in these statistics and administrative records.These updates occur in both current period results and those relating to prior periods, and all must be included to accurately reflect growth rates.

Furthermore, for the second quarter of each year, revised results from the first quarter of year (T-3) are published, consistent with the updated results of Spain's Annual National Accounts. At least every five years, extraordinary revisions of the complete series of results must be carried out to ensure the updating of statistical sources and estimation methods, as well as their alignment with the recommendations issued by relevant international forums.

Regarding the measurement of economic activity provided by the quarterly accounts published by the INE (National Statistics Institute), it is important to note that:

- Unlike other indicators developed to measure the evolution of economic activity without forming part of an integrated system, the quarterly accounts constitute a subsystem of Spain's National Accounts, **fully integrated both methodologically and numerically**. This implies, in particular, that the principles, definitions, accounting rules, and structure used in the quarterly accounts are the same as those used in the annual accounts and are established in Regulation (EU) 549/2013 on the European System of National and Regional Accounts 2010 [1].It also implies that the quarterly estimates provided within the framework of the Spanish National Accounts (QNA and QNFSA [2]) are fully consistent with each other and with the annual estimates.

Any advance measurement of the evolution of economic activity developed and published by INE within the framework of national accounts must satisfy this consistency. This would imply that its value should be updated each time the results produced on a longer timescale are published. Thus, a monthly or weekly publication would be revised once the corresponding quarterly data is available, and similarly when the annual estimate is published. It is important to consider this aspect both from the perspective of communication with users and the necessary technical and human resources.

- In complete consistency with what has been described in the Eurostat's Handbook on quarterly national accounts [3] and with international practice, the compilation process for the Spanish QNA includes the integration of direct results from other operations, in some cases compiled by other organizations, within the Spanish national accounts system:
  - The account for external trade in goods and services from the Rest of the World Accounts (consistent with the results of the Trade Balance of the Balance of Payments and International Investment Position, published by the Bank of Spain) and compiled primarily from foreign trade statistics from the Customs and Excise Department of the Spanish State Tax Administration Agency (AEAT), the International Trade in Services Survey (ITSS) [4], and the Tourism Expenditure Survey (EGATUR), produced by the Spanish National Statistics Institute (INE).

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[1] Amended by Regulation (EU) 2023/734 of the European Parliament and of the Council of 15 March 2023

[2] Quarterly non-financial accounts for the institutional sectors

[3] `https://ec.europa.eu/eurostat/documents/3859598/5936013/KS-GQ-13-004-EN.PDF/3544793c-0bde-4381-a7ad-a5cfe5d8c8d0`

[4] The INE has stopped publishing this statistical operation, although it continues to compile it to serve as input for the Balance of Payments and National Accounts statistics of the Spanish economy, as well as for the two new annual statistics that began to be published, replacing the ITSS, from 2024: International Trade in Services by Company Characteristics (STEC) and International Trade in Services by Mode of Service Supply (MoS).

  - Quarterly Non-Financial Accounts of Public Administrations, the monthly series of non-financial operations carried out by the aggregate of the Central Government, Regional Government, and Social Security Funds subsectors [5], and the monthly series of taxes and social security contributions [6], all prepared by the Audit Office (IGAE).
  - Accounts of the institutional sector of Financial Institutions, prepared primarily from accounting information provided by the supervisory bodies (Bank of Spain, National Securities Market Commission, and Directorate General of Insurance and Pension Funds of the Ministry of Economy, Trade, and Business).

  In other areas, indirect methods are used that make use of all current available quantitative information on the evolution of an aggregate (or part of it) during the period.

  Any advance measurement of the evolution of economic activity developed and published within the framework of national accounts by the INE should incorporate information from these sources as much as possible. Therefore, their availability date must be taken into account.

- The data transmission schedule to Eurostat must be taken into account, in relation to how the development of a new leading indicator of economic activity might interact with data already published and transmitted by the INE. Regulation (EU) 2023/734 of the European Parliament and of the Council of 15 March 2023 amending Regulation (EU) No 549/2013 on the European System of National and Regional Accounts in the European Union and repealing eleven legal acts in the field of national accounts includes this data transmission program. Annex B states that Member States shall transmit to the Commission (Eurostat) the accounts defined in the data tables of that annex. Each data table specifies the voluntary and mandatory variables to be transmitted, the reference periods required, and the transmission deadlines.

  Two tables are transmitted to Eurostat regarding the measurement of short term evolution of the economy within the framework of the National Accounts, and therefore, two national publications are carried out in each quarter.

  - Table 1F corresponds to the preliminary (also known as Flash) estimates of GDP and employment (voluntary quarterly transmissions). As set out in the regulation, the Commission (Eurostat) and the

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[5] `https://www.igae.pap.hacienda.gob.es/sitios/igae/es-ES/Contabilidad/ContabilidadNacional/Publicaciones/Paginas/DatosConsolidados.aspx`

[6] `https://www.igae.pap.hacienda.gob.es/sitios/igae/es-ES/Contabilidad/ContabilidadNacional/Publicaciones/Paginas/iaimpuestosycotizaciones.aspx`

Member States agree among themselves on the voluntary transmission of advance estimates of GDP growth and employment in order to ensure coordinated and periodic publication of the relevant European aggregate estimates approximately 30 or 45 days after the reference period. Member States transmitting these estimates to the Commission (Eurostat) shall send them each quarter at least one working day before the agreed publication date, clearly indicating whether the estimates can be published (preferred option).

Spain currently reports, at t+30, with the same level of disaggregation as that offered in the t+90 publication. This level of detail is highly valued by Eurostat, which frequently encourages countries to work on the possibility of offering greater detail in their t+30 estimates. **This effectively means bringing forward the transmission of Table 1Q, described in the following section, by about 30 days**, as can be seen in the following figure taken from the latest edition of the Quality report on national and regional accounts (prepared and disseminated by Eurostat) in its 2025 edition and referring to the 2024 transmissions.

Figure 51

Release containing components of GDP, transmission of data for 2024Q3

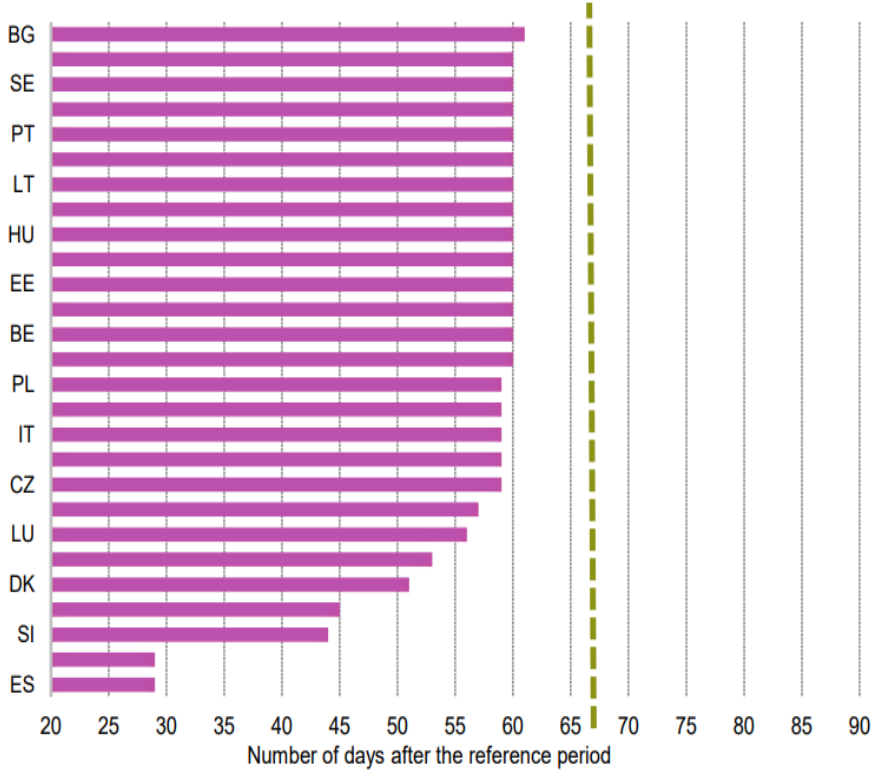

Figure 19: Days after the reference period of submission of data for the reference fourth quarter of 2024 by the different countries

Not only is the short delay with which the information is sent important, but above all, the level of detail with which it is provided. As already indicated, Spain transmits to Eurostat (and publishes nationally) the same level of detail at (t+30) as at (t+90). As can be seen in the following figure taken, again, from the latest edition of the Quality report on national and regional accounts, Spain provides at (t+30), i.e., around 30 days before the legal deadline for data submission, which is at (t+60), complete information on the GDP estimate by supply (T0101Q); by demand (T0102Q); and by income (T0103Q).

In addition, Population and total employment data is also transmitted, distinguishing between employees and self-employed workers

(T0110Q), as well as employment by sector of activity (T0111Q) and household final consumption expenditure by durability (T0117Q). Although the geographical disaggregation of exports (T0120Q) and imports (T0121Q) was previously sent in (T+60), this information is now transmitted in an integrated manner with the rest of the estimates in (T+30).

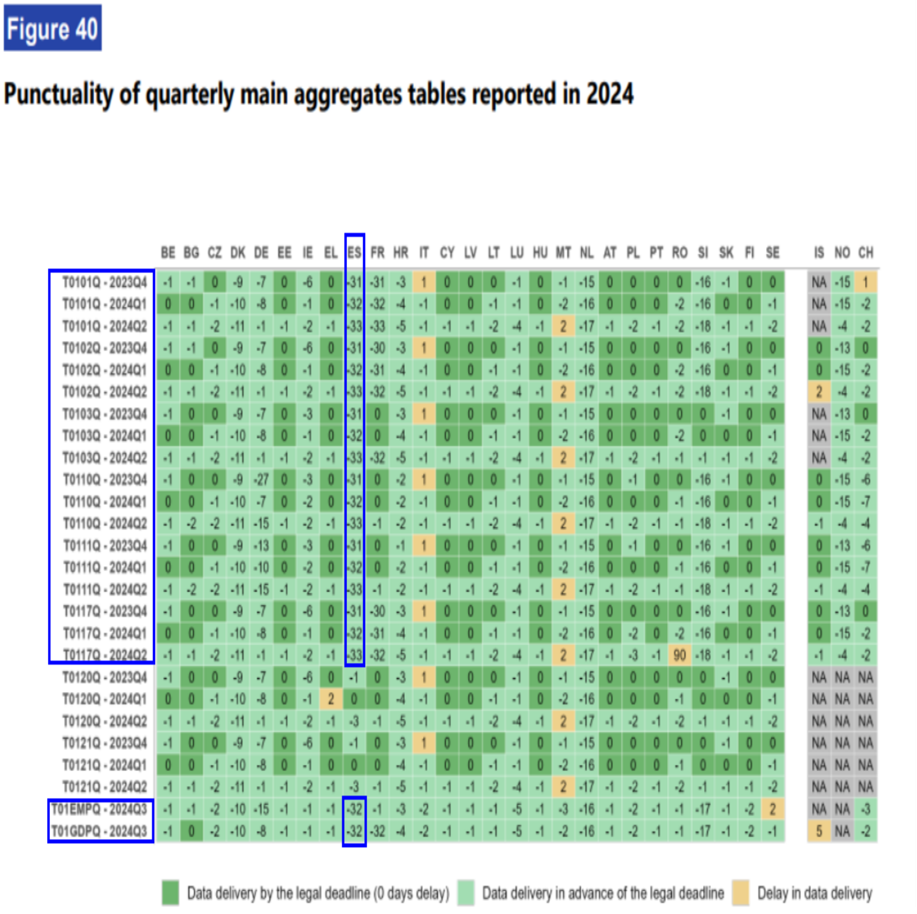

Figure 40

Punctuality of quarterly main aggregates tables reported in 2024

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	IS	NO	CH
T0101Q - 2023Q4	-1	-1	0	-9	-7	0	-6	0	-31	-31	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	-16	-1	0	0	NA	-15	1
T0101Q - 2024Q1	0	0	-1	-10	-8	0	-1	0	-32	-32	-4	-1	0	0	-1	-1	0	-2	-16	0	0	0	-2	-16	0	0	-1	NA	-15	-2
T0101Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-33	-33	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-2	-18	-1	-1	-2	NA	-4	-2
T0102Q - 2023Q4	-1	-1	0	-9	-7	0	-6	0	-31	-30	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	-16	-1	0	0	0	-13	0
T0102Q - 2024Q1	0	0	-1	-10	-8	0	-1	0	-32	-31	-4	-1	0	0	-1	-1	0	-2	-16	0	0	0	-2	-16	0	0	-1	0	-15	-2
T0102Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-33	-32	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-2	-18	-1	-1	-2	2	-4	-2
T0103Q - 2023Q4	-1	0	0	-9	-7	0	-3	0	-31	0	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	0	-1	0	0	NA	-13	0
T0103Q - 2024Q1	0	0	-1	-10	-8	0	-1	0	-32	0	-4	-1	0	0	-1	-1	0	-2	-16	0	0	0	-2	0	0	0	-1	NA	-15	-2
T0103Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-33	-32	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-1	-1	-1	-1	-2	NA	-4	-2
T0110Q - 2023Q4	-1	0	0	-9	-27	0	-3	0	-31	0	-2	1	0	0	0	-1	0	-1	-15	0	-1	0	0	-16	-1	0	0	0	-15	-6
T0110Q - 2024Q1	0	0	-1	-10	-7	0	-2	0	-32	0	-2	-1	0	0	-1	-1	0	-2	-16	0	0	0	-1	-16	0	0	-1	0	-15	-7
T0110Q - 2024Q2	-1	-2	-2	-11	-15	-1	-2	-1	-33	-1	-2	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-1	-18	-1	-1	-2	-1	-4	-4
T0111Q - 2023Q4	-1	0	0	-9	-13	0	-3	0	-31	0	-1	1	0	0	0	-1	0	-1	-15	0	-1	0	0	-16	-1	0	0	0	-13	-6
T0111Q - 2024Q1	0	0	-1	-10	-10	0	-2	0	-32	0	-2	-1	0	0	-1	-1	0	-2	-16	0	0	0	-1	-16	0	0	-1	0	-15	-7
T0111Q - 2024Q2	-1	-2	-2	-11	-15	-1	-2	-1	-33	-1	-2	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-1	-18	-1	-1	-2	-1	-4	-4
T0117Q - 2023Q4	-1	0	0	-9	-7	0	-6	0	-31	-30	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	-16	-1	0	0	0	-13	0
T0117Q - 2024Q1	0	0	-1	-10	-8	0	-1	0	-32	-31	-4	-1	0	0	-1	-1	0	-2	-16	0	-2	0	-2	-16	0	0	-1	0	-15	-2
T0117Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-33	-32	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-3	-1	90	-18	-1	-1	-2	-1	-4	-2
T0120Q - 2023Q4	-1	0	0	-9	-7	0	-6	0	-1	0	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	0	-1	0	0	NA	NA	NA
T0120Q - 2024Q1	0	0	-1	-10	-8	0	-1	2	0	0	-4	-1	0	0	-1	-1	0	-2	-16	0	0	0	-1	0	0	0	-1	NA	NA	NA
T0120Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-3	-1	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-2	-1	-1	-1	-2	NA	NA	NA
T0121Q - 2023Q4	-1	0	0	-9	-7	0	-6	0	-1	0	-3	1	0	0	0	-1	0	-1	-15	0	0	0	0	0	-1	0	0	NA	NA	NA
T0121Q - 2024Q1	0	0	-1	-10	-8	0	-1	0	0	0	-4	-1	0	0	-1	-1	0	-2	-16	0	0	0	-1	0	0	0	-1	NA	NA	NA
T0121Q - 2024Q2	-1	-1	-2	-11	-1	-1	-2	-1	-3	-1	-5	-1	-1	-1	-2	-4	-1	2	-17	-1	-2	-1	-2	-1	-1	-1	-2	NA	NA	NA
T01EMPQ - 2024Q3	-1	-1	-2	-10	-15	-1	-1	-1	-32	-1	-3	-2	-1	-1	-1	-5	-1	-3	-16	-1	-2	-1	-1	-17	-1	-2	2	NA	NA	-3
T01GDPQ - 2024Q3	-1	0	-2	-10	-8	-1	-1	-1	-32	-32	-4	-2	-1	-1	-1	-5	-1	-2	-16	-1	-2	-1	-1	-17	-1	-2	-1	5	NA	-2

🟩 Data delivery by the legal deadline (0 days delay) 🟩 Data delivery in advance of the legal deadline 🟨 Delay in data delivery

Figure 20: Details of the quarterly information available in (t+30)

In this context, it would be difficult to justify both a reduction in the amount of information transmitted at t+30 or a delay in its transmission. This must be taken into account from the point of view of the resources needed for the implementation of a new statistical operation, but also from the conceptual point of view and the reconciliation of the need for earlier information and the desired level of detail.

- Table 1Q corresponds to Main aggregates of the quarterly national accounts (annual aggregates in the case of T1A). The data in Table 1A must be reported at t + 2 months and t + 9 months after the reference period, and those in Table 1Q at t + 2 months after that period. If a Member State transmits a complete dataset at t + 2 months, it will not be necessary to transmit the data at t + 3 months. Table 1Q will be consistent with Table 1A at t + 9 months.

  Since the transmission of table 1Q in t+2 months is already covered by the complete transmission of t+30, Spain does not carry out a separate transmission until t+85, at which time the direct information mentioned above is incorporated and thus ensuring consistency with the information published by the Balance of Payments prepared by the Bank of Spain, the Accounts of the Public Administrations prepared by the IGAE and the Quarterly Non-Financial Accounts of the Institutional Sectors prepared by the INE itself.

This schema for compiling results, submitting data to Eurostat to comply with regulatory obligations, and disseminating them nationally, is the result of a comprehensive analysis carried out in 2017, which included a SWOT analysis (Strengths, Weaknesses (internal factors), Opportunities, Threats (external factors)). The current system offers the main advantages of providing users with comprehensive information very close to the reference period, while maintaining consistency with other closely related operations, such as the Balance of Payments and the General Government Accounts, and with a level of revision in line with that of our European partners.

Regarding revisions (and other quality dimensions), it is important to remember that Eurostat conducts an annual comparative analysis (cited in the previous point) of the different quality dimensions of statistics (specifically National Accounts estimates). The quality measures are standardized across all countries, were agreed upon years ago after an analysis of various alternatives, and are calculated and reported by Eurostat. The results are published in the Quality Report on National and Regional Accounts[7], the latest version of which was released in November. It should be noted that the latest results include both ordinary and extraordinary revisions.

Figure 21, taken from the aforementioned report, shows the annual revisions as shown by the average relative mean absolute revisions, in which it can be seen that Spain is at levels of revisions similar to Germany, Belgium, Sweden or Italy.

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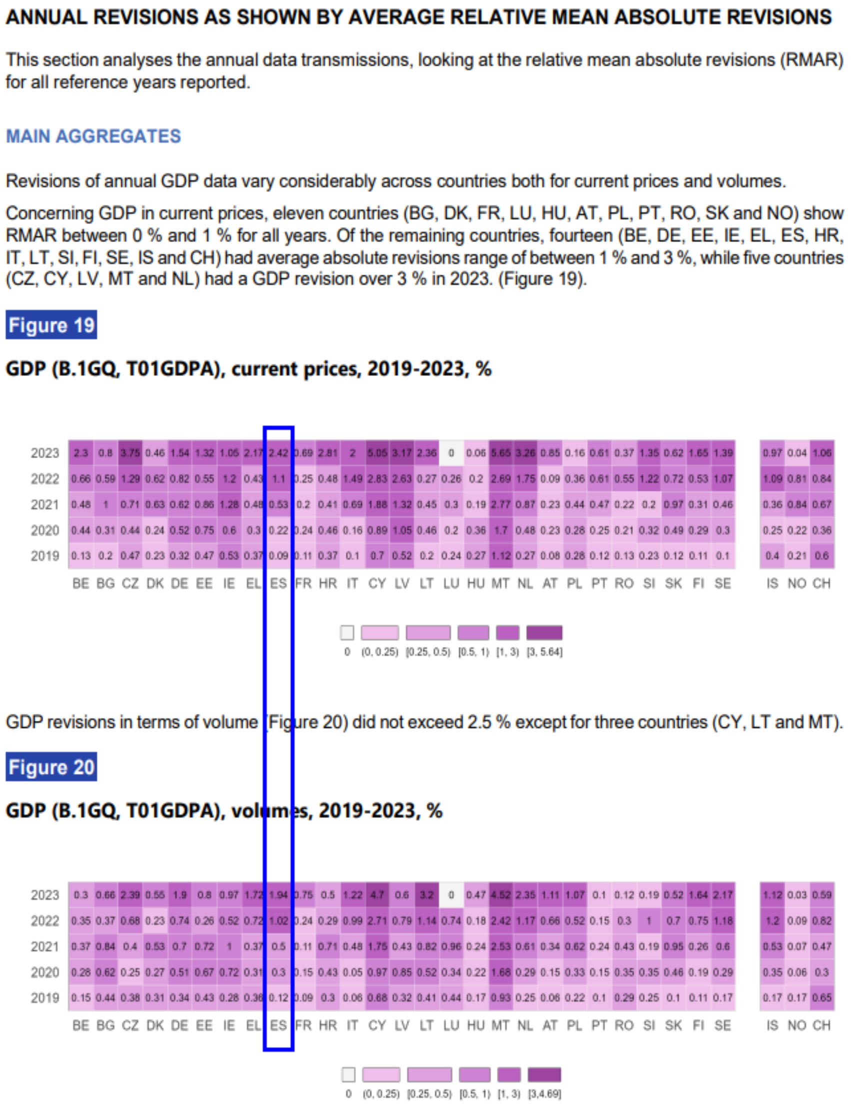
[7] `https://ec.europa.eu/eurostat/en/web/products-statistical-reports/w/ks-01-25-052`



ANNUAL REVISIONS AS SHOWN BY AVERAGE RELATIVE MEAN ABSOLUTE REVISIONS

This section analyses the annual data transmissions, looking at the relative mean absolute revisions (RMAR) for all reference years reported.

MAIN AGGREGATES

Revisions of annual GDP data vary considerably across countries both for current prices and volumes.

Concerning GDP in current prices, eleven countries (BG, DK, FR, LU, HU, AT, PL, PT, RO, SK and NO) show RMAR between 0 % and 1 % for all years. Of the remaining countries, fourteen (BE, DE, EE, IE, EL, ES, HR, IT, LT, SI, FI, SE, IS and CH) had average absolute revisions range of between 1 % and 3 %, while five countries (CZ, CY, LV, MT and NL) had a GDP revision over 3 % in 2023. (Figure 19).

Figure 19

GDP (B.1GQ, T01GDPA), current prices, 2019-2023, %

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	IS	NO	CH
2023	2.3	0.8	3.75	0.46	1.54	1.32	1.05	2.17	2.42	0.69	2.81	2	5.05	3.17	2.36	0	0.06	5.65	3.26	0.85	0.16	0.61	0.37	1.35	0.62	1.65	1.39	0.97	0.04	1.06
2022	0.66	0.59	1.29	0.62	0.82	0.55	1.2	0.43	1.1	0.25	0.48	1.49	2.83	2.63	0.27	0.26	0.2	2.69	1.75	0.09	0.36	0.61	0.55	1.22	0.72	0.53	1.07	1.09	0.81	0.84
2021	0.48	1	0.71	0.63	0.62	0.86	1.28	0.48	0.53	0.2	0.41	0.69	1.88	1.32	0.45	0.3	0.19	2.77	0.87	0.23	0.44	0.47	0.22	0.2	0.97	0.31	0.46	0.36	0.84	0.67
2020	0.44	0.31	0.44	0.24	0.52	0.75	0.6	0.3	0.22	0.24	0.46	0.16	0.89	1.05	0.46	0.2	0.36	1.7	0.48	0.23	0.28	0.25	0.21	0.32	0.49	0.29	0.3	0.25	0.22	0.36
2019	0.13	0.2	0.47	0.23	0.32	0.47	0.53	0.37	0.09	0.11	0.37	0.1	0.7	0.52	0.2	0.24	0.27	1.12	0.27	0.08	0.28	0.12	0.13	0.23	0.12	0.11	0.1	0.4	0.21	0.6

0 (0, 0.25) [0.25, 0.5) [0.5, 1) [1, 3) [3, 5.64]

GDP revisions in terms of volume (Figure 20) did not exceed 2.5 % except for three countries (CY, LT and MT).

Figure 20

GDP (B.1GQ, T01GDPA), volumes, 2019-2023, %

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	IS	NO	CH
2023	0.3	0.66	2.39	0.55	1.9	0.8	0.97	1.72	1.94	0.75	0.5	1.22	4.7	0.6	3.2	0	0.47	4.52	2.35	1.11	1.07	0.1	0.12	0.19	0.52	1.64	2.17	1.12	0.03	0.59
2022	0.35	0.37	0.68	0.23	0.74	0.26	0.52	0.72	1.02	0.24	0.29	0.99	2.71	0.79	1.14	0.74	0.18	2.42	1.17	0.66	0.52	0.15	0.3	1	0.7	0.75	1.18	1.2	0.09	0.82
2021	0.37	0.84	0.4	0.53	0.7	0.72	1	0.37	0.5	0.11	0.71	0.48	1.75	0.43	0.82	0.96	0.24	2.53	0.61	0.34	0.62	0.24	0.43	0.19	0.95	0.26	0.6	0.53	0.07	0.47
2020	0.28	0.62	0.25	0.27	0.51	0.67	0.72	0.31	0.3	0.15	0.43	0.05	0.97	0.85	0.52	0.34	0.22	1.68	0.29	0.15	0.33	0.15	0.35	0.35	0.46	0.19	0.29	0.35	0.06	0.3
2019	0.15	0.44	0.38	0.31	0.34	0.43	0.28	0.36	0.12	0.09	0.3	0.06	0.68	0.32	0.41	0.44	0.17	0.93	0.25	0.06	0.22	0.1	0.29	0.25	0.1	0.11	0.17	0.17	0.17	0.65

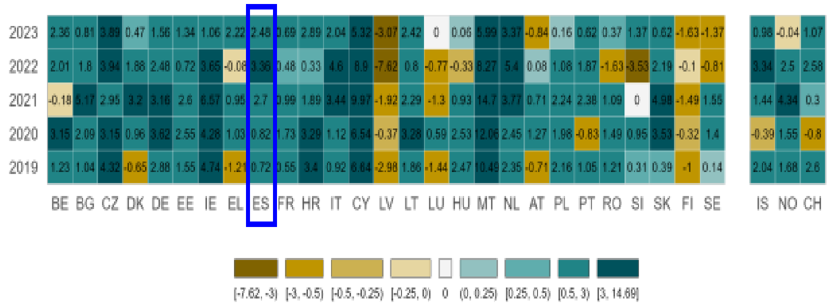
0 (0, 0.25) [0.25, 0.5) [0.5, 1) [1, 3) [3,4.69]

Figure 21: Annual revisions as shown by average relative mean absolute revisions.

A similar picture emerges from the analysis of revisions in terms of the latest published value of the year-on-year growth rate versus the value initially anticipated as an aggregation of QNA, as can be seen in Figure 22.

Figure 74

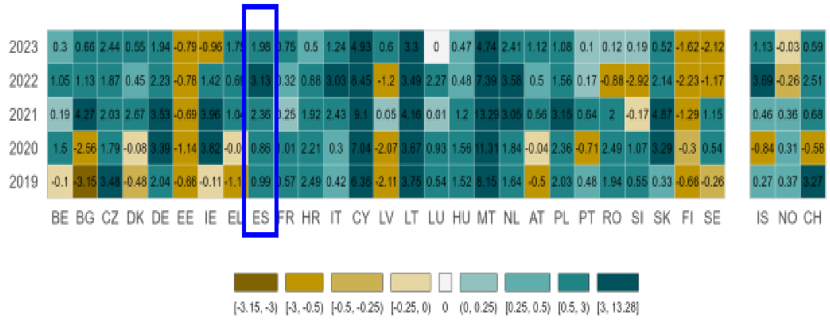
Latest minus first growth rate for annual data of gross domestic product (B.1GQ, T01GDPA), current prices, %



	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	IS	NO	CH
2023	2.36	0.81	3.89	0.47	1.56	1.34	1.06	2.22	2.48	0.69	2.89	2.04	5.32	-3.07	2.42	0	0.06	5.99	3.37	-0.84	0.16	0.62	0.37	1.37	0.62	-1.63	-1.37	0.98	-0.04	1.07
2022	2.01	1.8	3.94	1.88	2.48	0.72	3.65	-0.08	3.36	0.48	0.33	4.6	8.9	-7.62	0.8	-0.77	-0.33	8.27	5.4	0.08	1.08	1.87	-1.63	-3.53	2.19	-0.1	-0.81	3.34	2.5	2.58
2021	-0.18	5.17	2.95	3.2	3.16	2.6	6.57	0.95	2.7	0.99	1.89	3.44	9.97	-1.92	2.29	-1.3	0.93	14.7	3.77	0.71	2.24	2.38	1.09	0	4.98	-1.49	1.55	1.44	4.34	0.3
2020	3.15	2.09	3.15	0.96	3.62	2.55	4.28	1.03	0.82	1.73	3.29	1.12	6.54	-0.37	3.28	0.59	2.53	12.06	2.45	1.27	1.98	-0.83	1.49	0.95	3.53	-0.32	1.4	-0.39	1.55	-0.8
2019	1.23	1.04	4.32	-0.65	2.88	1.55	4.74	-1.21	0.72	0.55	3.4	0.92	6.64	-2.98	1.86	-1.44	2.47	10.49	2.35	-0.71	2.16	1.05	1.21	0.31	0.39	-1	0.14	2.04	1.68	2.6

Figure 75

Latest minus first growth rate for annual data of gross domestic product (B.1GQ, T01GDPA), volumes, %



	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	IS	NO	CH
2023	0.3	0.66	2.44	0.55	1.94	-0.79	-0.96	1.7	1.98	0.75	0.5	1.24	4.93	0.6	3.3	0	0.47	4.74	2.41	1.12	1.08	0.1	0.12	0.19	0.52	-1.62	-2.12	1.13	-0.03	0.59
2022	1.05	1.13	1.87	0.45	2.23	-0.78	1.42	0.6	3.13	0.32	0.88	3.03	8.45	-1.2	3.49	2.27	0.48	7.39	3.58	0.5	1.56	0.17	-0.88	-2.92	2.14	-2.23	-1.17	3.69	-0.26	2.51
2021	0.19	4.27	2.03	2.67	3.53	-0.69	3.96	1.04	2.36	0.25	1.92	2.43	9.1	0.05	4.16	0.01	1.2	13.29	3.05	0.56	3.15	0.64	2	-0.17	4.87	-1.29	1.15	0.46	0.36	0.68
2020	1.5	-2.56	1.79	-0.08	3.39	-1.14	3.82	-0.0	0.86	1.01	2.21	0.3	7.04	-2.07	3.67	0.93	1.56	11.31	1.84	-0.04	2.36	-0.71	2.49	1.07	3.29	-0.3	0.54	-0.84	0.31	-0.58
2019	-0.1	-3.15	3.48	-0.48	2.04	-0.86	-0.11	-1.1	0.99	0.57	2.49	0.42	6.36	-2.11	3.75	0.54	1.52	8.15	1.64	-0.5	2.03	0.48	1.94	0.55	0.33	-0.66	-0.26	0.27	0.37	3.27

Figure 22: Annual revisions comparing the latest revision with the initial value expressed in percentage

Any alteration to the current schedule, whether through bringing forward the information currently published in t+30 or developing new products, must be subject to a detailed analysis to ensure that current strengths are not diminished.

2.7.1 Industrial Turnover Index

INE of Spain has proposed an early estimation of the Industrial Turnover Index (ITI), which is a monthly Short-Term Business Statistics produced by National Statistics Institutes (NSIs) in the European Statistical System (ESS) ([2]). This early estimation of the ITI improves the timeliness of this statistic using only the traditional survey data while also providing an accuracy measure.

The proposal reduces the ITI provision delay by using statistical learning algorithms on the available data at times $m + \Delta_i < m + \Delta_{\text{release}}$, $i = 1, 2, 3$, to reconstruct the values of the whole sample. Two fundamental ideas underlie this approach:

1. It is a bottom-up approach so that early estimates of the ITI are produced through the imputation of those missing values at each early time $m+\Delta_i$ at the statistical unit level. No prediction method is applied to any aggregate or index. Aggregates and indices emerge from the imputed sample, as in their final validated released versions.
2. Only aggregate regressors of the reference time period are used together with regressors from past reference time periods at the statistical unit level.

The indices computed in the ITI survey follow a fixed-base Laspeyres formula in two steps:

1. Computation of the elementary indices: The sample of units is partitioned into strata determined by their NUTS2 (Nomenclature of territorial units for statistics; basic regions) geographical variable and some groupings of CNAE-2009 economy activity codes. The elementary index for stratum U_d at reference month m of year y with base year y_B is denoted as

$$_{yB}I^{my}_{U_d}.$$

2. Computation of composite indices: After computing the weight w_d^{yB} of each stratum U_d, for the base period y_B, using data from the Structural Business Statistics (Industrial Sector), the composite index for a functional aggregate $U_A = \cup_{d\in A} U_d$ as

$$_{yB}I^{my}_{U_A} = \sum_{d\in A} w_d^{y_B} \times {}_{yB}I^{my}_{U_d}.$$

Let s_d^{my} denote the sample for the stratum U_d at reference month m of year y and z_k^{my} the target variable value of establishment k at reference month m of year y (the total turnover of the industrial establishment). The core computation in the series of indices is the total population of the industrial turnover

$Z_{U_d}^{my} = \sum_{k \in s_d} z_k^{my}$. Editing tasks are carried out from the data collection activity itself to the final estimation phase. Then, as a consequence of these editing tasks (recontacts and follow-ups), the value z_k^{my} can change several times during this editing phase. Let $z_k^{my,\mathrm{val}}$ be the final validated value of variable z for unit k entering into the computation of the first official release of the ITI for reference month m and year y. Similarly, let $z_k^{my,\mathrm{ed}}(t)$ denote the value of variable z for unit k at the time t of the editing strategy for the reference month m and year y. If t_{release} is the number of days after the reference month ends, under this notation, then $z_k^{my,\mathrm{ed}}(t_{\mathrm{release}}) = z_k^{my,\mathrm{val}}$.

In the traditional production process the estimation of the population total $Z_{U_d}^{my}$ is

$$\hat{Z}_{U_d} = \sum_{k \in s_d} z_k^{val},$$

where the reference time period dependence has been dropped for ease of notation. This can be decomposed at any time t as

$$Z_{s_d} = \sum_{k \in r_d(t)} z_k^{val} + \sum_{k \in s_d - r_d(t)} z_k^{val},$$

where $r_d(t) \subset s_d(t)$ represents the concrete subsample of respondents who has provided their responses at time t.

This decomposition can only be computed after finishing the collection and editing phase, since the final validated values z_k^{val} are needed. The goal is not to wait until all data collection and all data editing are both concluded to produce an early estimation of the ITI with the ongoing collected and edited information. Taking into account the values which are already known and predicting what are not known yet, this estimate can be decomposed as follows:

$$Z_{s_d} = \sum_{k \in r_d(t)} \left[z_k^{\mathrm{ed}}(t) - e_k^{\mathrm{meas}}(t) \right] + \sum_{k \in s_d - r_d(t)} \left[\hat{z}_k^{\mathrm{val}}(t) - e_k^{\mathrm{pred}}(t) \right],$$

where $e_k^{\mathrm{meas}}(t) = z_k^{\mathrm{ed}}(t) - z_k^{\mathrm{val}}$ denotes the measurement error and $e_k^{\mathrm{pred}}(t) = \hat{z}_k^{\mathrm{val}}(t) - z_k^{\mathrm{val}}$ denotes the prediction error.

The estimator for the population total $Z_{U_d}(t)$ with data collected up to time t is given by

$$\hat{Z}_{U_d}(t) = \sum_{k \in r_d(t)} z_k^{\mathrm{ed}}(t) + \sum_{k \in s_d - r_d(t)} \hat{Z}_k^{\mathrm{val},\xi_p}(t),$$

where $\hat{Z}_k^{\mathrm{val},\xi_p}(t)$ is the random variable representing the prediction for value $\hat{z}_k^{\mathrm{val}}(t)$ according to prediction model ξ_p. This estimator, when applied at time t, produces estimates of the form

$$z_{U_d}(t) = \sum_{k \in r_d(t)} z_k^{\mathrm{ed}}(t) + \sum_{k \in s_d - r_d(t)} \hat{z}_k^{\mathrm{val},\xi_p}(t).$$

This estimator amounts to neglecting measurement errors $e_k^{\text{meas}}(t)$ and considering $e_k^{\text{pred}}(t) \approx 0$. In this way, it is necessary to build only one prediction model ξ_p. A second estimator is proposed, for which three models are needed: ξ_p, ξ_m (measurement error model) and ξ_e (model for the prediction error). For simplicity, only the first option is explored in the work.

The construction of each regressor x_k, used in the prediction model ξ_p, is detailed in [2]. All these regressors $\left\{x_k^{(p)}\right\}_{p=1,2,\ldots,P}$ have been constructed using survey microdata and/or paradata from the ITI survey itself, with the exception of some aggregates from the Industrial Price Index and Industrial Production Index surveys. Neither administrative data nor a new digital data source has been used at all.

The selected model to compute the predictions is a gradient boosting algorithm. To predict turnover values at times t_i in reference month m and year y, validated values from the preceding reference month $m-1$ need to be already available at these time instants. Thus, every month m the following procedure is carried out:

- Train the model for a set of multiple alternative hyperparameter h (more details in [2]) with data up to reference month $m-2$.
- Apply each trained model to the data set with corresponding reference month $m-1$ obtaining, thus, the predicted values $\hat{z}_k^{m-1y}(t)$ for each unit k.
- Compute for each trained model ξ_h the absolute error of the total turnover $AE_h = \left|\sum_{k \in s_d^{my}} \hat{z}_k^{m-1y,\xi_h}(t) - z_k^{m-1y,\text{val}}(t)\right|$. The model with the optimal value of AE_h, m_{h^*} it is selected.
- Train again the same model with data up to reference month $m-1$ with hyperparameters h^*.
- Apply the trained model to data collected up to time t of reference month m and year y. Thus, the predicted values $\hat{z}_k^{my,\xi_{h^*}}(t)$ are obtained to be plugged in the estimator.

The whole process from the collection of the data to the final dissemination of the aggregates is completely modular. It consists of the following steps:

- 00. Collect and Validate Data
- 01. Build Regressors
- 02. Build and Evaluate Model
  - 02.01. Train Model

  - 02.11. Predict
  - 02.21. Evaluate Predictions (mean squared errors of predicted values are estimated)
- 03. Compute Aggregates
- 04. Visualize Output (through a dashboard developed in Shiny)

The main results of this pilot study comprise the series of early estimates of the ITI brokendown according to usual production conditions as well as their corresponding yearly and monthly variation rates for the three batches processed by the survey managers ($t + 20$, $t + 27$, $t + 38$). These quantities are computed together with their respective root mean squared error. To assess the quality of these results, these series are also computed for the prediction of the ITI without regressors from the current reference time period and for the true released value at $m + 51$.

The series comprise 60 consecutive months from May 2016 to April 2021. For each reference month five values are computed, namely the initial prediction without current data, the early estimates for the three batches, and the final validated value. The early estimates are computed together with their conditional root mean squared error.

Figure 23 represents an example comprising the three index versions (initial, batches, final) from January 2020 to April 2021. Figure 24 represents the corresponding annual variation rates for these same time periods. The complete analysis of the results can be found in [2].

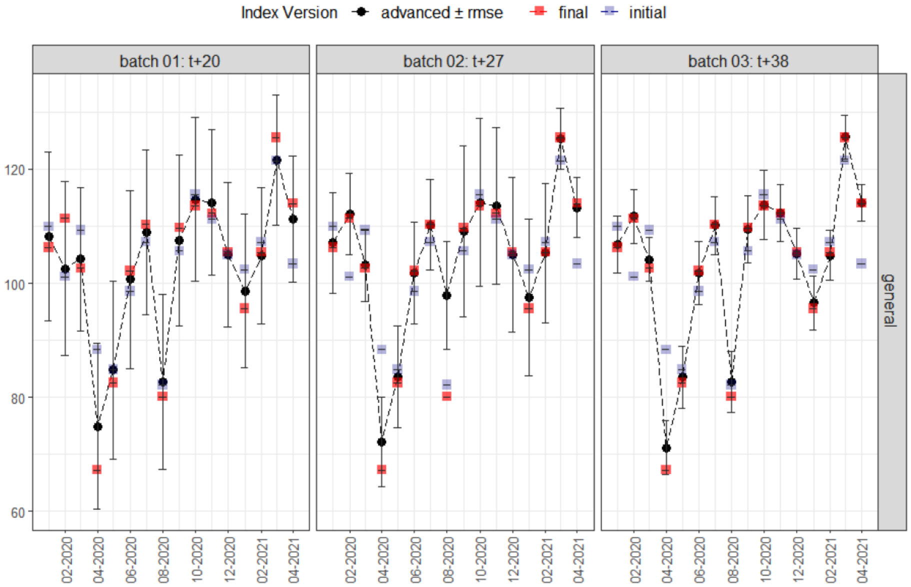


Figure 23: General Index Series from Jan, 2020 to April, 2021. *Taken from [2].*

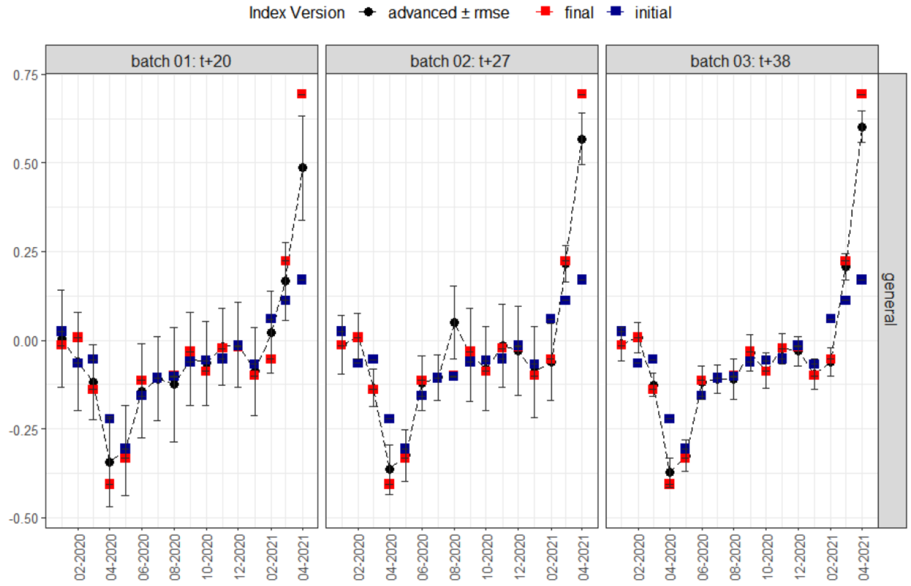


Figure 24: Annual Variation Rates Series from Jan, 2020 to April, 2021. *Taken from [2].*

This new way of producing early estimates of the indices enables the option to have reliable information in a shorter period of time. The timeliness can be reduced in about 30 days keeping under control the accuracy assessment. The method produces accurate early estimates together with uncertainty intervals assessing their reliability. Besides, the fact that this methodology uses only data sources already collected by Statistics Spain (INE) itself, provides autonomy and independence and makes it possible to compute both the predictions and the accuracy indicators with traditional survey data. No new data source needs to be accessed and integrated.

3 Conclusions

Throughout this document, we have reviewed international experiences in nowcasting and development of leading economic indicators to assess not only the feasibility, but also, the necessity and advisability of implementing a leading indicator of economic activity in Spain within the official statistical system.

The practices of several European statistical institutes and Eurostat have been synthesized, highlighting the methodological diversity—from ARIMA and MIDAS models to dynamic factor models, Fourier-based decompositions, machine learning algorithms, and signature methods—and their use of high-frequency and timely data to generate leading estimates of macroeconomic series.

The study also examines the Spanish context, highlighting the minimal lag with which estimates are provided, the high quality, consistency, and level of detail of the Quarterly National Accounts compiled by the INE (National Statistics Institute), as well as the operational, methodological, and regulatory implications of introducing a leading indicator that maintains its coherence with the national accounts framework.

By contrasting international practice with Spain's current system, the document provides an evidence-based framework for evaluating the various alternatives that, looking ahead, are opening up for the future evolution of QNA estimates.

References

[1] Bacchini, F., Golinelli, R., Iannaccone, R., & Zurlo, D. (2023). A new hybrid framework to monitor business cycle: the RAT-Ita approach. *Istat working papers* 5 / 2023.

[2] Barragán S., Barreñada L., Calatrava, J.F., Gálvez Sáenz de Cueto, J.C., Martín del Moral, J.M., Rosa-Pérez, E. & Salgado, D. (2022). Early Estimates of the Industrial Turnover Index using Statistical Learning Algorithms. *INE - Working papers* 03/2022.

[3] Cohen, S., Lui, S., Malpass, W., Mantoan, G., Nesheim, L., De Paula, A., Reeves, A., Scott, C., Small, E., & Yang, L. (2023). Nowcasting with signature methods. `https://arxiv.org/abs/2305.10256`

[4] Dalla, V., Giraitis, L., & Phillips, P. C. B. (2022) Robust tests for white noise and cross-correlation *Econometric Theory, 38(5)* 38(5), 913–941.

[5] Dickopf, X., Janz, C., & Mucha, T. (2019). Moving from GDP flash estimates to GDP nowcasts: First results of a feasibility study to further accelerate early GDP estimation. *WISTA - Scientific Journal* 6-2019, p.47 et seq.

[6] Eurostat: Statistical Working Papers (2025). GDP nowcasting for the euro area and member countries `https://ec.europa.eu/eurostat/web/products-statistical-working-papers/w/ks-01-25-042`.

[7] Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, Volume 55(4), pages 665-676.

[8] Koenig, Evan F., & Dolomas, S. (1997). Real-Time GDP Growth Forecasts. *Federal Reserve Bank of Dallas Working Paper* 97-10.

[9] Kuiper & Pijpers (2020). Nowcasting GDP growth rate: a potential substitute for the current flash estimate. *CBS - Discussion paper* May 2020.

[10] Kuzin, V., Marcellino, M., & Schumacher, C. (2011). MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the euro area. *International Journal of Forecasting* Volume 27 (2), pages 529-542.

[11] Lahiri, K., & L. Yang. (2013) Forecasting Binary Outcomes *In Elliott, G., and A. Timmermann (Eds.). Handbook of Economic Forecasting* Volume 2, Part B, Chapter 19: 1025-1106. Amsterdam, The Netherlands: Elsevier.

[12] Lewis, D., Mertens, K., Stock, J., & Trivedi, M. (2020). Measuring real activity using a weekly economic index *Staff Reports 920, Federal Reserve Bank of New York* 04/2020.

[13] Mariano, R., & Y. Murasawa (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics* 18(4), 427–443.

[14] Miller, R., & Siegmund, D. (1982) Maximally Selected Chi Square Statistics *Biometrics* Volume 38, N. 4: 1011-1016

[15] Morrill, J., Salvi, C., Kidger, P., Foster, J., and Lyons, T. (2021). Neural rough differential equations for long time series. International Conference on Machine Learning.

[16] Office for National Statistics (ONS) (2022). Gross domestic product (GDP) QMI. `https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/grossdomesticproductgdpqmi`

[17] Ouwehand, P., Krieg, S., & Willems, R. (2024). Deep learning for time series forecasting and nowcasting. *CBS - Discussion paper* August 2024.

[18] Perrucci, E., & Pijpers, F. (2017). Filtering in the Fourier domain: a new set of filters for seasonal adjustment of time series and its evaluation. *Tech. rep. The Hague: Statistics Netherlands.* `https://www.cbs.nl/nl-nl/achtergrond/2017/25/filtering-inthe-fourier-domain`.

[19] Pijpers, F. (2018). Nowcasting using linear time series filters. *CBS - Discussion paper* March 2018.

[20] Pijpers, F., Harlaar, L., van den Brakel, J., & Ouwehand, P. (2025). Simultaneous Nowcasting of Netherlands' Macroeconomic Trends and Seasonal Patterns Based on Fourier Analysis. *CBS - Discussion paper* May 2025.

[21] Ranjan, R., & Gneiting., T. (2010) Combining Probability Forecasts *Journal of the Royal Statistical Society, Series B (Statistical Methodology)* Volume 72, N. 1: 71-91.

[22] Richardson, A., van Florenstein Mulder, T., & Vehbi, T. (2021). Nowcasting GDP using machine-learning algorithms: A real-time assessment. *International Journal of Forecasting* Volume 37 (2), pages 941-948.

[23] Statistisches Bundesamt (Destatis) (2019). Nowcast of the overall economic development. `https://www.destatis.de/EN/Service/EXSTAT/Datensaetze/early-indicator-economic-development.html`

[24] Satopää, V.A., Baron, J., Foster, D.P., Mellers, B.A., Tetlock, P.E., & Ungar., L.H. (2014) Combining multiple probability predictions using a simple logit model *International Journal of Forecasting* Volume 30, Issue 2: 344-356.

[25] Wegmüller, P., Glocker, C., & Guggia, V. (2023). Weekly economic activity: Measurement and informational content. *International Journal of Forecasting* Volume 39 (1), pages 228-243.

[26] Wegmüller, P., & Glocker, C. (2024). Capturing Swiss economic confidence. *Swiss J Economics Statistics* Volume 160 (3).

[27] Youden, W.J. (1950) Index for rating diagnostic tests *Cancer* Volume 3, Issue 1: 32-35.