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A SURVEY OF MACROECONOMIC NOWCASTING APPLICATIONS

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ABSTRACT

Nowcasting, broadly understood as the real-time assessment of current and near-term economic conditions, is a framework of growing importance that helps inform both economic policy decision for Governments and Central banks but also shape strategies of private institutions. In this paper, a dataset of macroeconomic nowcasting application papers is compiled and analyzed to identify the main research themes and gaps in the literature. Results find that literature is rather concentrated in nowcasting aggregate economic measures, specifically GDP which appears as the target variable in 74% of the papers examined. In terms of modelling frameworks, even though there is no consensus about the best-performing type of model, Dynamic Factor Models seem to be widely preferred as they were used in 37.5% of the nowcasting applications. However, Machine Learning applications are being increasingly used after the COVID-19 pandemic, coupled by an increased reliance in the use of alternative sources of data, which feature in an average of 51.7% of annual publications between 2020-2026, compared with 18.6% during 2010–2019. Despite advances in the field, important challenges remain, as illustrated not only by the difficulties many nowcasting models faced during periods of economic turbulence but also more recently, by the Atlanta Fed's toolkit's "GDPNow" nowcasting undershoot associated with differences in the classification of gold imports. Further challenges arise from the insufficiently explored limitations and potential biases of alternative data sources, as well as difficulties in acquiring historical data vintages necessary for conducting true real-time nowcasting evaluations. Against this background, future research should focus on: (i) continuing on extending nowcasting applications to underexplored variables and economies, (ii) examining the predictive properties and limitations of alternative data, and (iii) examine the potential usefulness of evaluation frameworks that combine real-time predictor vintages with final revised estimates of target variables to assess predictive performance against their underlying economic movements while avoiding look-ahead bias, so as to avoid misguiding policy makers during periods of substantial data revisions.

Keywords: Dynamic Factor, Forecasting, Macro econometrics, Mixed Frequency, Nowcasting
JEL: C53, C55, C82, E27, E37

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1. Introduction

Defined as "the prediction of the present, the very near future, and the very near past" (Banbura *et al*., 2011), nowcasting is becoming an increasingly essential tool in economic policy analysis. Nowcasting involves the use of high-frequency, timely available variables to estimate the current state of variables that are typically observed with lower frequency and often reported with considerable delays, such as Gross Domestic Product (GDP) or unemployment rate. This real-time perspective gained increasing attention over the past two decades, especially during periods of extremely volatile economic activity, such as the global financial crisis of 2008 and the COVID-19 pandemic. In such contexts, policymakers and analysts urgently require up-to-date information to respond to constantly changing conditions. This is where the appeal of nowcasting lies: in providing the potential to gain more immediate insights into economic trends, thus enabling informed decision-making.

Over the past two decades, a wealth of nowcasting models has been developed, aided by advances in data collection which led to the provision of new alternative data sources, ranging from mobility metrics and online activity to satellite imagery. The timelier manner in which such data are available has led to a renewed interest in nowcasting over the past few years.

Against this background, the aim of this paper is to present a comprehensive literature review of nowcasting applications for macroeconomic variables, exploring dominant approaches, advances over the years, limitations and potential future directions of research. To that end, 343 papers are surveyed from Q1 and Q2 Scopus indexed journals recording types of models used, their estimation and evaluation characteristics along with their scope and the variables used. Key insights arising from this synthesis are the concentration of nowcasting literature on aggregate measures and advanced economies, the inability of models to adapt to changing economic conditions (with impact of the increase in US imports of gold in anticipation of the US tariff hikes being an indicative example), the need for further research on the limitations of alternative data sources and the challenges of designing genuine real-time evaluations, particularly regarding access to historical data vintages and the effects of revisions to nowcasting target variables.

Hence, the remaining of this paper is organized as follows: Section 2 provides the methodology used to construct the dataset; section 3 provides a thematic overview of surveyed literature; section 4 provides quantitative insights from the dataset, while section 5 discusses gaps identified in the literature and suggests potential future directions for nowcasting research. Section 6 concludes.

2. Publications' dataset construction methodology

To ensure adequate coverage the Scopus database was selected to recover papers from (see Norris and Oppenheim, 2007). The search covered the period from 2000 to 2026 (cutoff date: September 8th, 2026). Studies were retrieved using two Boolean queries; one broad, topic-based search and one designed to capture studies associated with methods used in nowcasting. More specifically:

Query 1: Studies were retrieved when terms such as nowcast, now-cast, backcast, current-quarter forecast, or real-time estimate appeared in the title. When these terms appeared in the broader title-abstract-keyword field, they were required to co-occur with terminology establishing a macroeconomic context, including economic activity, economic growth, business cycles, national accounts, labour markets, monetary or fiscal policy, official statistics, or central banks.

Query 2: Studies were retrieved using broader forecasting terminology, including real-time, short-term and current-quarter forecasting, provided that these terms co-occurred with both a macroeconomic term (as in query 1) and at least one recognized nowcasting methodology, such as factor models, MIDAS, bridge equations, VAR/state-space approaches, or machine-learning techniques.

Both queries included English written papers across the subjects of: Economics, Econometrics and Finance, Mathematics, Business, Management and Accounting, Decision Sciences. Query 1 also included Social Sciences whereas query 2 included Computer Science in an attempt to capture machine learning and artificial intelligence applications to nowcasting. Exact queries can be found in Table 1.

Query 1 yielded 853 results, whereas query 2 returned 271. As the aim is to trace the development of macroeconomic nowcasting and document literature direction and omittances, studies were initially screened through their titles and abstracts and were included in the literature body when they contributed evidence on at least one of the following dimensions: (i) the development or application of a nowcasting methodology

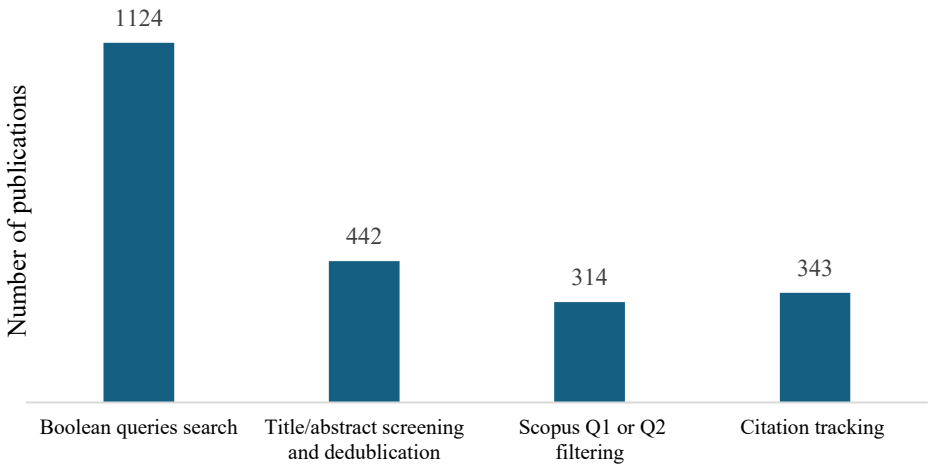
(ii) the comparative forecasting performance of alternative modelling approaches (iii) the usefulness of particular information sets or predictor categories for real-time prediction or (iv) methodological issues specific to macroeconomic nowcasting. This process, along with a deduplication of results, resulted in an amount of 442 studies, with the majority of the discarded studies being related to either meteorological nowcasting or sustainability and urban planning.

Table 1: Scopus Queries

Query title	Query text
Query 1	(TITLE (nowcast* OR "now-cast*" OR backcast* OR "current-quarter forecast*" OR "current quarter forecast*" OR "real-time estimate*" OR "real time estimate*") OR TITLE-ABS-KEY ((nowcast* OR "now-cast*" OR backcast* OR "current-quarter forecast*" OR "current quarter forecast*" OR "real-time estimate*" OR "real time estimate*") AND (macroeconom* OR "economic activity" OR "economic indicator*" OR "economic condition*" OR "economic growth" OR "business cycle*" OR "national account*" OR "official statistic*" OR "monetary policy" OR fiscal* OR "labour market*" OR "labor market*" OR "central bank*"))) AND PUBYEAR > 1999 AND PUBYEAR < 2027 AND (LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "MATH") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "DECI")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))
Query 2	TITLE-ABS-KEY((nowcast* OR "now-cast*" OR backcast* OR "real-time forecast*" OR "real time forecast*" OR "real-time monitor*" OR "real time monitor*" OR "short-term forecast*" OR "short term forecast*" OR "current-quarter forecast*" OR "current quarter forecast*") AND (macroeconom* OR "economic activity" OR "business cycle*" OR "national account*" OR "central bank*") AND ("dynamic factor*" OR "factor model*" OR "diffusion index*" OR "principal component*" OR MIDAS OR "mixed-frequency*" OR "mixed frequency*" OR "bridge equation*" OR "mixed-frequency VAR*" OR "mixed frequency VAR*" OR "Bayesian VAR*" OR "state-space model*" OR "state space model*" OR "Kalman filter*" OR "machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network*" OR "random forest*" OR "gradient boost*" OR XGBoost OR "support vector machine*" OR LASSO OR "elastic net" OR regularization OR regularisation OR shrinkage OR "high-dimensional" OR "high dimensional" OR ensemble*)) AND PUBYEAR > 1999 AND PUBYEAR < 2027 AND (LIMIT-TO (DOCTYPE,"ar"))) AND (LIMIT-TO (SUBJAREA,"ECON") OR LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"MATH") OR LIMIT-TO (SUBJAREA,"COMP") OR LIMIT-TO (SUBJAREA,"DECI")) AND (LIMIT-TO (LANGUAGE,"English"))

The resulting study corpus was further filtered to only include publications in outlets ranked in the top two Scopus quartiles (Q1 and Q2) to reduce the risk of less established or weakly reviewed publications influencing the results, bringing the corpus further down to 314 studies. In an attempt to include papers not captured by the Boolean queries, either because they used alternative terminology or were published before the terminology of nowcasting became widely established, the study database was complemented by papers resulting from backwards and forward citation tracking, with all the papers retrieved from this process were added to the study corpus if they adhered to all the above-mentioned criteria. 29 additional papers were retrieved from this process, bringing the final study database to 343 papers. Figure 1 provides an overview of the steps followed.

Figure 1: Study corpus construction steps



Source: Author's calculations

For each paper included in the dataset, in addition to the dimensions to which it contributed evidence, the following information was recorded: authors, publication outlet, year of publication, modelling approaches employed (type of models used, aggregated or disaggregated approach), target variable, and country of study. For papers comparing the nowcasting accuracy of different model types, the best-performing model or approach was also identified. Furthermore, in the dataset is also documented whether alternative data were used and, if so, their type, as well as how ragged-edge data were handled. Lastly, given the importance of accounting for the real-time flow of information when evaluating forecasting performance (Evans, 2005), the evaluation design employed in each paper was recorded and classified into one of the following four categories:

True real-time: Nowcasts are evaluated using historical data vintages containing only the information actually available at each forecast date.

Pseudo real-time: Nowcasts are generated by reconstructing historical datasets according to actual or assumed publication schedules and depending on data availability. Typically, most recent revised data are used rather than data vintages.

Out of sample with latest vintage data: Nowcasts are generated based on latest data vintages, without taking into account the historical publication calendar.

In sample evaluation / methodological illustration: Nowcasts or models are assessed using data included in their estimation or are demonstrated through

methodological examples, simulations, or fitted-value analysis, without any type of nowcasting evaluation.

3. Thematic analysis

With the goal of highlighting common findings, contradictions and methodological developments, the papers included in the surveyed literature are categorized across following themes: Nowcasting model architectures, information sets and predictor suitability, real-time data flow and revisions, utilization of alternative data, machine learning methods, non-linearities and structural changes, and forecast combinations and uncertainties. While many papers could fit in more than one thematic, categorization was made by taking into account each paper's primary contribution and how the inclusion in a specific category helps highlight aspects of literature.

3.1. Nowcasting model architecture

Nowcasting literature is largely focused on models that can accommodate the usage of a large number of variables across mixed frequencies and of asynchronous release dates. Such models include Bridge equation models, Mixed Data Sampling models or MIDAS (Ghysels *et al.*, 2006), Mixed Frequency Vector Autoregressions, or MF-VARs (Foroni *et al.*, 2013) and the Dynamic Factor models (DFMs)[1]. While these specifications dominate the literature, they are not the only approaches employed. Other, less frequently used methods documented in the literature include stock-flow identities (Barnichon and Nekarda, 2012), Structural models (Červená and Schneider, 2014; Eftimoski, 2019; Yau and Hueng, 2019), usage of higher order stochastic cycles and phase shifts (Chen and Mills, 2012), models with time varying weights on variables of different frequencies (Knotek and Zaman, 2017), spectrum analysis (de Carvalho and Rua, 2017), Bayesian methods (Koop *et al*., 2024), Mixed frequency cointegrating regressions (Miller, 2014) or simple tracking of data changes (Lacey King *et al.,* 2022). Furthermore, some nowcasting applications seek not to know the value of an economic variable but rather construct a real-time measure or indicator of economic activity or other macroeconomic variable based on high frequency inputs (Albu, 2008; Funke *et al.*, 2015; Bhadury *et al.*, 2021; Di Giacinto *et al*., 2021; Eraslan and Götz, 2021;

[1] For a more detailed presentation of model specifications, you are referred to the Appendix.

Fuleky, 2022; Kwon, 2022; Zhang *et al.*, 2022; Wegmüller *et al.* 2023; Siliverstovs, 2024; Huang *et al.* 2026).

Focusing on DFMs, which are based on the works of Stock and Watson (2002a; 2002b) on forecasting using factors and indices that summarize information from larger datasets in a suitable way (Artis *et al.*, 2005; Radovan and Masten, 2025), their application for GDP nowcasting is found to be the most extensive across a variety of settings from advanced economies (Rünstler *et al.*, 2009; Urasawa, 2014; Hindrayanto *et al.*, 2016; Chernis & Sekkel, 2017; Hayashi & Tachi, 2023; Cascaldi-Garcia *et al.*, 2024) to emerging and more data-constrained ones (Liu *et al.*, 2012; Camacho *et al.*, 2015; Luciani *et al.*, 2018; González-Astudillo & Baquero, 2019; Alkhareif & Barnett, 2022; Kaustubh & Ranjan, 2025; Qureshi *et al.*, 2026), as they make effective use of timely monthly information (Jansen et al. 2016). Their usage for nowcasting is not limited to GDP but extends to provincial and regional economic activity (Chernis *et al.*, 2020; Barbaglia *et al.*, 2026), industrial production (Bulligan *et al.*, 2010), the output gap (Aastveit & Trovik, 2014), domestic demand (Egan, 2023), international services trade (Jaax *et al.*, 2024), and personal consumption of services (Chen & Hood, 2025). The widespread use of DFMs has also motivated research on methodological improvements: (i) on their estimation DFMs and factor extraction via Bayesian shrinkage (De Mol *et al.,* 2008), principal components and Kalman filtering (Doz *et al.,* 2011), target-weighted likelihood (Blasques *et al.,* 2016), through partial least squares (Rauhala, 2026), Sparce Principal Components (Cepni & Guney, 2019; Chikamatsu *et al.*, 2021) or via collapsed dynamic factor analysis (Bräuning & Koopman, 2014), (ii) on relaxing constraints such as the non-stationarity of common factors (Peña and Poncela, 2004) and temporal and cross sectional aggregation constraints (Proietti, 2011) and (iii) on incorporating Bayesian approaches to account for the uncertainty surrounding the estimated factors and the model parameters (Zhang *et al.*, 2018; Zhang *et al.*, 2022). Further methodological research on DFMs has focused on the appropriate number of factors (Barhoumi *et al*., 2013; Luo and Yu, 2021) and aspects of factors' specification (Schumacher, 2007; Heij *et al.*, 2008; Dahl *et al.*, 2009; den Reijer, 2013). As far as forecast effectiveness is concerned literature hints towards the fact that it is conditional on the overall setting. More specifically, Foroni and Marcellino (2014) find that factor augmented methods yield substantial nowcasting benefits for certain GDP components, while Kočenda and Poghosyan (2020) report limited evidence of

statistically significant gains relative to benchmark for EU countries, irrespective of their GDP volatility. Additionally, Charles and Darné (2022) state that DFMs have a hard time backcasting world trade during turbulent times while Marcellino and Sivec (2021) report that DFMs remain resilient when nowcasting a small economy's GDP during crises.

Turning to other methods of nowcasting, Bridge equations were one of early applications of handling mixed frequency data, and while relatively simpler, they remain a useful now-casting tool, when correctly specified. Baffigi *et al.* (2004), for instance, find that aggregating country-level bridge forecasts produces more accurate euro-area GDP nowcasts than direct area-wide bridge equations and several competing approaches. Other applications, such as those of Antipa *et al.* (2012) and Abdić *et al.* (2020) outperform factor models under certain conditions and for certain horizons. MIDAS models on the other hand, can assign different weights to different high frequency lags and are found to be a flexible tool in nowcasting. Specifically, Kuzin *et al.* (2011) find MIDAS models to be useful for forecasting over short horizons relative to MF-VARs, while Schumacher (2016) finds their performance comparable to that of bridge equation for given sets of predictor groups, with Naser (2015) and Ferrare and Marsilli (2019) finding that factor-augmented MIDAS is the best performing model in nowcasting Bahrain's GDP and global economic growth respectively. Foroni *et al.* (2015) expanded MIDAS flexibility by introducing an unrestricted model specification (U-MIDAS), noting that frequency, lag length, sample size are factors that impact the usefulness of unrestricted weights. MIDAS models are also highlighted by other modifications made such as time-varying coefficients (Chan *et al.*, 2025) or heterogeneous cross-country coefficients (Fosten and Nandi, 2023). Furthermore, Galvao and Lopresto (2020) and Degiannakis (2023) have built a layered models for nowcasting UK and Greek GDP respectively based on MIDAS regressions, while other MIDAS applications include US federal government (Ghysels and Ozkan, 2015) and Baden-Württemberg's economic activity (Kuck & Schweikert, 2021). MF-VARs have been used to a similar extent with Schorfheide and Song (2015) developing the first application and documenting the gains of quarterly forecasts as the quarter progresses with Cimadomo *et al.* (2022) further developing a framework for estimating and nowcasting with mix-frequency Bayesian VARs. The usefulness of this approach is documented in various applications of economic activity nowcasting (Poghosyan,

2016; Madhou *et al.*, 2017; Brave *et al.*, 2019, Hou *et al.* 2023), demonstrating at the same time relative resilience in nowcasting during times of increased uncertainty (Ramadani *et al.*, 2021). Other mix frequency VAR applications include nowcasting regional economic activity (Koop *et al.* 2020a; 2020b), output gap (Berger *et al.*, 2023), the EU labor market (Consolo *et al.*, 2023) and deriving US monthly GDP estimates (Koop *et al.* 2023).

Despite the advances outlined in the literature above, it is evident that there is still not a universally superior nowcasting approach, as there are instances where DFMs fail to outperform even regression models (Brunhes-Lesage and Darné, 2012). All in all, forecasting performance does not necessarily improve as model complexity increases. Furthermore, modelling choices such as aggregation of individual forecasts (Marcellino, 2003), or of target variable subcomponents (Duarte and Rua, 2007; Proietti *et al.*, 2021) can materially improve nowcasting performance.

3.2. Information sets & predictor selection

Predictor selection has been a recurring theme in nowcasting literature, especially for DFMs as by construction they can handle large dimensional datasets. Indeed, larger data panel size is not found to improve factor extraction (Boivin and Ng, 2006) or forecasting performance (Alvarez *et al.* 2016). Predictor variable screening and selection however is found to do so (Schumacher, 2010; Bulligan, 2015; Girardi *et al.*, 2017, Jardet and Meunier, 2022), To that end, several methods have been proposed for selecting a suitable set of predictors for nowcasting: Bai and Ng (2008) developed a method of selecting "targeted predictors" based on the LARS-LASSO-EN algorithm; Banerjee and Marcellino. (2006) utilized past forecasting records; More recent approaches include Bayesian methods (Giannone *et al.*, 2021) and target aware screening (Franjic and Schweikert, 2025).

Focusing on the utilization of specific variable categories, real activity such as labor market data (Berger *et al.* 2022; Kugler and Sheldon, 2023), construction data (Baghestani, 2023), industrial production (de Bondt and Kosekova, 2018), vehicle registrations (Gragera *et al.*, 2026) and leading indicators (Clements and Galvão, 2009; Heij *et al.,* 2011; Kuntze, 2026) are dominant predictors. Prior to the release of such data for a given period, survey data are found to be among the most useful ones due to

their timeliness relative to the reference period and because they bear information directly from the economic agents. Indeed, when nowcasting early in the reference period, soft data derived information such as surveys dominates the nowcast (Giannone *et al.,* 2009; Camacho and Martinez-Martin, 2014; Girardi *et al.*, 2016). The effectiveness of survey information however is conditional on the nowcasted variable (Kaufmann and Scheufele, 2017; Bai *et al.*, 2022) and on whether the nowcasted is conducted on a period of increased uncertainty (Kurz-Kim, 2019). Specific categories of surveys are found to be more informative than others (Lahiri and Monokroussos, 2013; Smets *et al.,* 2014; Wegmueller and Glocker, 2024).

Financial variables are also a useful source of information for nowcasting models, as such data are available at high frequency and are not revised (Andreou *et al.*, 2013, Knotek and Zaman, 2019). Indeed, financial variables are found useful in predicting the state of the economy and recessions (Camacho and Garcia Serrador, 2014; Ntantanis and Pohlman, 2020; Ceci and Silvestrini, 2023; Dubbert and Kempa, 2024; Bakry, 2026). More specifically, commodity prices are found to be useful predictors of small open economies (Aastveit and Trovik, 2012) and global economic activity in general (Matsumoto et al, 2023), carbon emission trading is found to be a useful predictor of Chinese economic activity (Chen *et al.*, 2021) whereas stock market returns contain useful information for nowcasting Gross Fixed Capital Formation (Degiannakis, 2022). Although less explored than financial data, monetary data are also found to be useful predictors in a series of applications (Barnett and Tang, 2016; Tang *et al.*, 2020; El-Shagi and Tochkov, 2022; Barnett *et al.*, 2024).

Global and international variables can also be useful predictors (Baumeister and Guérin, 2021), especially in open economies (Bragoli and Modugno, 2017; Caruso, 2018) or emerging and data constrained ones (Bragoli and Fosten, 2018; Cepni *et al.,* 2019; 2020). A similar principle seems to apply when nowcasting at a subnational level where national, regional or provincial data from other regions can be found informative (Claudio *et al.,* 2020; Cariou *et al.,* 2024) and vice-versa (Owyang *et al.*, 2015). Yet, there is not an-one-size-fits-all approach in including variables from foreign countries, with Andreini *et al.* (2023) providing an informative example where in nowcasting German GDP EU data provide additional predictive ability, whereas US data do not.

Three deductions can be made from the literature presented above. Firstly, a larger dataset does not necessarily lead to more informative nowcasts. Secondly the value of

each data category is time-varying and depends on how far in the reference period the nowcast is conducted. Lastly, predictor usefulness is conditional and depends on the structure of the economy, the target variable and overall economic conditions.

3.3. Real-time data flow and revisions

As nowcasting deals with high frequency asynchronous data releases, the impact of each additional data point on the nowcast and nowcast uncertainty is of particular importance. Indeed, timeliness is a determining factor of the value of information contained in each data point (Bańbura and Rünstler, 2011). To that end, several applications document explicitly the effect of the marginal data points (Beber et al, 2015; Modugno *et al.,* 2016; Rusnak, 2016; Dahlhaus *et al.*, 2017) and have constructed applications available to handle the sequential arrival of information while calculating their role in forming the nowcast estimate and in reducing its surrounding uncertainty (Giannone *et al.*, 2008; Bok *et al.*, 2018). While most applications find that as more data become available, nowcast accuracy improves, this improvement is not always guaranteed (Liu *et al.*, 2023)

Another consequence arising from the lack of synchronicity characterizing the real time data flow, is the "ragged edge" problem, i.e. the situation in which a time-series panel has different ending dates across variables, as they are released at different dates and with different publication lags. Early applications handled the "ragged edge" using Dempster *et al.'s* (1977) Expectation Maximization algorithm (e.g. Schumacher and Breitung, 2008), while other applications resort to forecasting predictors (Castle *et al.,* 2009; Bessec, 2013), estimating them (Ferrara *et al.,* 2010), re-aligning the dataset (Marcellino and Schumacher, 2010) or allowing missing values to be handled in within the state space framework (Nunes, 2005; Hepenstrick and Marcellino, 2019; Ankargren and Jonéus, 2021). Most recent applications suggest "masking" data during model estimation in a way that mimics the ragged edge structure at the time of conducting the nowcast (den Reijer, 2026). Koop *et al.*'s (2024) application stands out as a method to deal with ragged edges at both ends of a dataset.

Other methodological aspects regarding the real time dataflow include the impact and handling of data revisions within a nowcasting framework (Clements and Galvão, 2012; Lamprou, 2016; Galvao, 2017; Mogliani *et al.*, 2017; Burlon and D'Imperio,

2020; Brave *et al.*, 2021; Hayashi and Tachi, 2021; Anesti *et al.*, 2022; Sayag *et al.,* 2022; Lehmann, 2024, Berger and Ochsner, 2026; Booth *et al.*, 2026) and nowcasting evaluations in the presence of such revisions (Diron, 2008; Mitchell 2009; Liebermann, 2014; Smith, 2015; Kim and Swanson, 2018; Fosten and Gutknecht; 2020; Jowik *et al.,* 2026), highlighting the importance of making such evaluations as realistic as possible.

3.4. Alternative data

Given the need for timely available data to assess the current state of aspects of the economy, nowcasting literature increasingly incorporates data other than those included in the official statistics, as they can reflect economic developments sooner, especially during times of great uncertainty. Web search queries are a principal alternative data source with wide applications in nowcasting economic activity (Chen *et al.*, 2015; Monokroussos and Zhao, 2020; Aoki *et al.*, 2023; Bantis *et al.*, 2023; Ferrara and Simoni, 2023; Kohns and Bhattacharjee, 2023; Woloszko 2024), unemployment (Fondeur and Karame, 2013; Vicente *et al.*, 2015; Smith, 2016; Naccarato *et al.*, 2018; Dimpfl and Langen, 2019; Nagao *et al.*, 2019; Schiavoni *et al.*, 2021; Grybauskas *et al.*, 2023), other real activity variables (Vosen and Schmidt, 2012; Carrière-Swallow and Labbé, 2013; Coble and Pincheira, 2021; Heikkinen and Heimonen, 2024; Lind and Ramesh, 2025). Other applications using web queries include nowcasting tourism demand (Liu *et al.*, 2021; Zhang *et al.*, 2026), consumer price indices and policy rates (Nakavachara and Lekfuangfu, 2018; Niesert *et al.*, 2020). Web query data are found useful, especially when combined with conventional ones. On the other hand, expanding query sets is not always informative for deriving predictions, while there are instances where the predictive contribution of specific query terms is found to be unstable.

Another alternative data sources, include deriving news sentiment from texts for GDP nowcasting (Iselin and Siliverstovs, 2016; Thorsrud, 2020; Mishra *et al.*, 2021; Zheng *et al.*, 2024), inflation (Goshima *et al.*, 2021), unemployment (Choi, 2026) and the financial cycle (Li *et al.*, 2024). Text derived sentiment data are found to provide early warning signal for economic activity in some applications (Aguilar *et al.*, 2021; Iselin and Siliverstovs, 2013; Algaba *et al.*, 2023; Jiang *et al.*, 2025). On the other hand, other applications highlight the need for simplicity in text extraction, as topic diversification matters more the richer texts (Burri, 2026), whereas other applications

find varying accuracy gains depending on the evaluation period (de Bondt and Sun, 2026), or no gains at all for specific nowcasted target variables (Lukauskas *et al.*, 2022; Xiao *et al.*, 2025).

Transactions and firm turnover submission data can also be a timely indicator of economic activity. More specifically, such transaction and administrative data are used as predictors for GDP (Ermişoğlu *et al.*, 2013; Conesa *et al.*, 2015; Fornaro, 2016; Galbraith and Tkacz, 2018; Fornaro and Luomaranta, 2020; Abdalla *et al.*, 2021; Kapetanios and Papailias, 2022; Barlas et al, 2024), consumption (Duarte et al., 2017; Fourné and Lehmann, 2026), and retail sales (Brinke *et al.,* 2023; Chapman and Desai, 2023).

Other types of alternative data include electricity consumption and prices (Galdi *et al.*, 2023; Stundziene *et al.*, 2023; Lehmann and Möhrle, 2024), satellite derived data (Bolivar, 2024; d'Aspremont *et al.*, 2025; Spelta *et al.*, 2026; Xue *et al.*, 2026), online prices (Macias *et al.*, 2023; Szafranek *et al.*, 2025), mobility data (Askitas and Zimmermann, 2013; Matsumura *et al.*, 2024; Ren, 2025 Kim *et al.,* 2026; Yanotti *et al.,* 2026), lubricant oils consumption (Fruzzetti and Ropele, 2026), carbon emissions (Fu *et al.,* 2022), weather deviations (Schreiber, 2026), and seismic activity (Pezzoli and Tosetti, 2022), while Kapetanios and Papailias (2024) utilize alternative data published from the UK statistics office.

All in all, literature points to the conclusion that the timeliness of alternative data can complement traditional variables in nowcasting, especially during turbulent times, such as the COVID-19 pandemic (Barbaglia *et al.*, 2023; Eckert *et al.,* 2025).

3.5. Machine learning methods, non-linearities and structural changes

Machine learning methods have been increasingly utilized in nowcasting applications. Such applications include LASSO, ridge regressions and other more or less sophisticated methods for variable selection in econometric nowcasting models (Stock and Watson, 2012; Han and Tsay, 2020; Lima *et al.*, 2021; Babii *et al.*, 2022; Aliaj et al, 2023; Alakkari *et al.*, 2024; Kohns and Potjagailo, 2025; Wei and Zhang, 2025; Beyhum and Striaukas, 2026; Bolivar, 2026; Chinn *et al.*, 2026; Constantinescu, 2026). ML methods offer a flexible alternative for nowcasting in the presence of structural breaks too. Specifically, although econometric approaches addressing

structural instability have been developed, primarily through regime-switching specifications, such as univariate Markov-switching models (Guerin and Marcellino, 2013; Barsoum and Stankiewicz, 2015; Aastveit et al., 2016; Stankevich, 2025; Hlouskova and Fortin, 2026), multivariate Markov-switching models (Camacho and Martinez-Martin, 2015; Foroni et al., 2015; Carstensen et al., 2020; Glocker and Wegmueller, 2020; Leiva-Leon et al., 2024), or other threshold-based approaches (Kovacs et al., 2017), these methods typically rely on explicitly specified mechanisms. In contrast, ML methods can detect nonlinear relationships and complex interactions directly from the data, potentially allowing for greater flexibility in capturing changes in economic dynamics without necessarily imposing predefined functional forms. Such applications include: Tree based nowcasting (Soybilgen and Yazgan, 2021; Mourougane *et al.*, 2025; Qureshi *et al.*, 2026), neural network methods (Wang *et al.*, 2022; Borup *et al.*, 2023; Lin and Michailidis, 2024; Guo *et al.*, 2026; Németh and Hadházi, 2026), Supervised Vector Quantization (Giusto and Piger, 2017), ML generated non-linear autoregression with exogenous variables (Cicceri *et al.*, 2020), Variational autoencoders (Ueda *et al.*, 2026) or, more recently, foundation AI models (Wong and Yu, 2026). Indeed, ML methods can outperform econometric ones (Richardson, 2021; Hopp, 2024; Kant *et al.*, 2025; Jönsson, 2026; Chaouch and Ben Sassi; 2026), with the results however depending on the available data and the evaluation period. Indeed, complex non-linear ML methods are not always found to be the most accurate in terms of nowcasting performance (Zhang *et al.*, 2023). Furthermore, ML superiority in nowcasting should be taken with a pinch a salt, as they are usually benchmarked against conventional econometric models, while there is literature suggesting that break adjustments, geographic event timing and data weighting among other methods can make econometric models more robust to the extreme observations and improve nowcasting performance (Castle and Hendry, 2010; Kristensen, 2014; Barnett *et al.*, 2016; Gagliardini *et al.*, 2017; Koop *et al.*, 2021; Lahiri and Yang, 2022; Larson and Sinclair, 2022; Huber *et al.*, 2023). ML methods and econometric models can also be used complementarily, providing nowcasting gains during crises (Furukawa, 2024).

3.6. Forecast combinations and uncertainty

While usually in literature only a model or a few competing models are examined, in reality practitioners obtain forecasts from multiple models and either average them,

poll them together or use their judgement. This pooling of nowcasts is found to result to more stable nowcasts in certain occasions (Drechsel and Maurin, 2011; Soybilgen and Yazgan, 2018; den Reijer and Johansson, 2019; Proietti and Giovannelli, 2021; Zhemkov, 2021; Assunção and Fernandes, 2022; Zhang *et al.*, 2025). Yet, results are not universal as models built by pooling information can be found to outperform forecast combinations (Bec and Mogliani, 2015). Other applications of forecast averaging include combinations of density nowcasts (Aastveit *et al.*, 2014; Mazzi *et al.*, 2014; Aastveit *et al.*, 2018; Knotek and Zaman, 2023) or weight model outputs in a dynamic way (Berge, 2015; Onorante and Raftery, 2016; Guerin and Leiva-Leon, 2017; Krüger *et al.*, 2017; McAlinn, 2021 Eraslan and Schröder, 2023).

Density nowcasts are also a useful complementary tool to point nowcasting as they can capture information the latter miss: uncertainty, skewness or data revision impact (Garratt *et al.*, 2008; Carriero *et al.*, 2015; Javed *et al.*, 2022; Labonne, 2025). Surveys are found to be particularly informative in deriving such nowcasts (Ferrara, 2007; Marcellino *et al.*, 2016; Tallman *et al.*, 2020), yet during Covid their gains are found to diminish (Çakmaklı and Demircan, 2023; Antolín-Díaz *et al.*, 2024).

A last aspect of nowcasting literature concerns the evaluation of the magnitude of downside risks rather the providing point or density nowcasts. To that end, Branch (2014) demonstrated the relevance of nowcasting uncertainty in conducting monetary policies under asymmetric losses, Garrat *et al.* (2014) quantified the uncertainty surrounding alternative output-gap estimates, while Schreiber & Soldatenkova's (2016) framework estimates probabilities of business cycle turning points in real time. Siliverstovs (2020) demonstrated the risks associated with relying on aggregate forecasting accuracy measures when evaluating nowcasting models. Ferrara *et al.* (2022) and Chuliá *et al.* (2024) modified the growth-at-risk framework (Busch *et al.*, 2022), allowing downside risks to be evaluated in real-time. Seo *et al.* (2026) on the other hand, assess downside risks via forecast combinations from heterogeneous models.

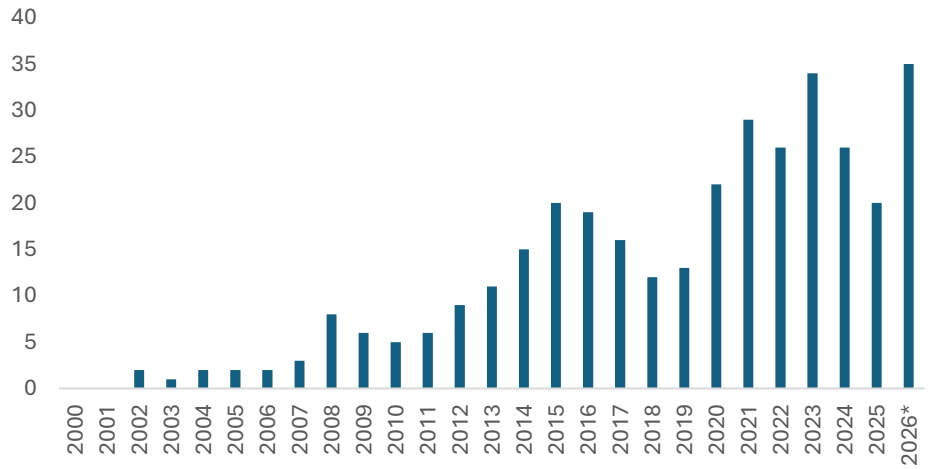
4. Dataset descriptive analysis

The dataset consists of papers written by 662 unique authors and co-authors, spanning across 90 journals. 42% of the surveyed papers' contributions regard

development of nowcasting methodologies or investigation of related challenges; 30% explore the suitability of particular variables or datasets as predictors; 16% of papers focus on comparing nowcasting of alternative models, with the remaining 12% presenting specific model applications to a country or target variable.

Interest in conducting nowcasting research seems to follow an upward trend throughout the sample period (2000-2026), with publications per year displaying significant acceleration after both the financial-EU debt crisis and the COVID-19 pandemic. More specifically, between 2000 and 2008 c.2 papers were published per annum, whereas in the period ranging from 2009 to 2019 this number increased to 12. After 2020 the average annual number of nowcasting related publications has further grown to 27. In 2026, even though only papers published up to September 8th are included, 35 nowcasting papers have been published, thus being the year with the most publications, hinting that the field continues to draw research interest. Figure 2 displays analytically nowcasting publications per annum:

Figure 2: Number of nowcasting related publications per year



**Papers published up to September 8th, 2026*
Source: Authors' calculations

Regarding the economies targeted by nowcasting research, the United States has attracted the greatest attention, accounting for approximately one-third of the surveyed literature (117 papers), followed by Germany (47) and the Euro Area (38). France, Italy, the United Kingdom, China, and Spain have also received considerable attention, each featuring in 20–30 studies. Japan, Canada, the Netherlands, Brazil, India, and Switzerland have been studied to a lesser extent, with 10-20 papers focusing on each economy. Table 2 provides a detailed breakdown of nowcasting applications by target economy.

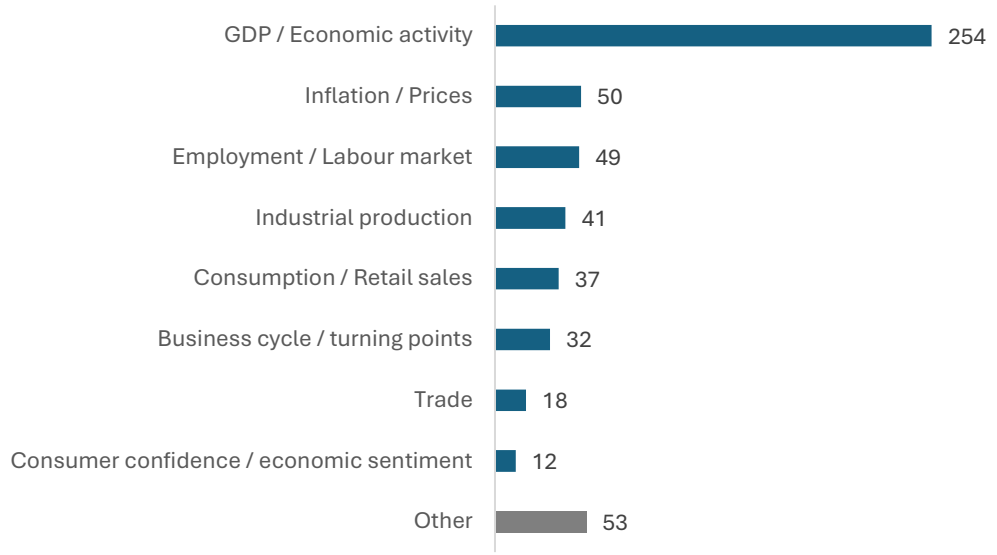
Table 2: Surveyed nowcasting literature by target economy

Regions/Countries	Number of papers	Regions/Countries	Number of papers
United States	117	Hungary	4
Germany	47	Luxembourg	4
Euro Area	38	Slovakia	4
France	30	Taiwan	4
Italy	30	Chile	3
United Kingdom	29	Czechia	3
China	25	Israel	3
Spain	22	New Zealand	3
Japan	19	Hong Kong SAR (China)	3
Canada	15	OECD	2
Netherlands	13	Bolivia	2
Brazil	12	Colombia	2
India	12	Cyprus	2
Switzerland	12	Ecuador	2
Mexico	10	Malta	2
Portugal	10	North Macedonia	2
South Africa	10	Oman	2
Belgium	9	Pakistan	2
Greece	9	Peru	2
Türkiye	9	Romania	2
Global / World	8	Saudi Arabia	2
Australia	8	Thailand	2
Austria	8	Ukraine	2
Finland	8	G7	1
Korea, South	7	Armenia	1
Lithuania	7	Bahrain	1
Poland	7	Bosnia and Herzegovina	1
Russia	7	Bulgaria	1
Indonesia	6	Costa Rica	1
Norway	6	Dominica	1
Slovenia	6	Dominican Republic	1
Ireland	5	Iceland	1
Latvia	5	Mauritius	1
Sweden	5	Syria	1
Argentina	4	Uruguay	1
Denmark	4	Venezuela	1
Estonia	4	Not applicable	2

Papers do not sum up to 343, as there are papers that study more than one economy. Source: Authors' calculations

Turning to target variables, GDP and aggregate economic activity have attracted the greatest attention, featuring in 254 papers (74% of the reviewed literature). Inflation and labor market variables have also been extensively studied, appearing as target variables in 50 and 49 papers, respectively. The literature has additionally examined variables commonly used as predictors as target variables themselves, albeit to a comparatively limited extent: industrial production (41 papers), consumption and retail sales (37 papers), trade-related variables (18 papers), and consumer confidence or sentiment indicators (12 papers). Furthermore, 32 studies focus on assessing business cycle conditions in real time, while 53 papers examine other, less explored, target variables, primarily alongside those mentioned above (e.g. tourism demand, housing starts, or tax revenues).

Figure 3: Target variables in nowcasting



Papers do not sum up to 343, as there are studies which examine more than one target variables.
Source: Authors' calculations

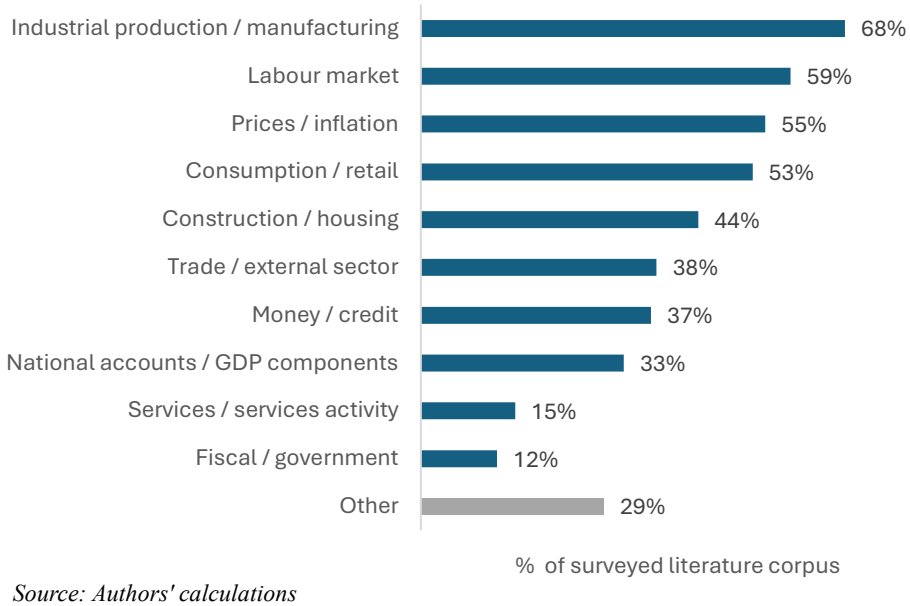
As far as methods and nowcasting application design are concerned, Dynamic factor models are the most preferred approach, featuring in 37.9% of the surveyed literature, followed by Machine Learning (ML) and Mixed Frequency Data Sampling (MIDAS) model applications, which appear in 27% and 26.7% of the literature surveyed, followed by Bridge equations (18%) and mixed frequency and Bayesian vector autoregression (MF-VAR/BVAR) methods (15%). 21% of the papers included in the database used only other approaches.

Interestingly, ML methods have gained traction after the COVID-19 pandemic, as 86% of papers employing such methods appear between 2020 and 2026 (41.7% of

total publications over the same period). A similar dynamic appears when models are categorized based on whether they use linear or non-linear specifications (such as Markov-Switching or regime-dependent methods for econometric applications and Tree based or Neural network approaches for ML applications). Specifically, 76% of the 89 papers using non-linear approaches, appear after 2020, possibly hinting towards the need for developing models that could address the extreme economic fluctuations witnessed during the COVID-19 pandemic and the lockdown period.

Focusing on variables used as predictors to derive nowcasting predictions, macroeconomic variables appear in 89.5% of the surveyed literature corpus with industrial production and similar variables appearing in 68% of papers, Labor market variables appear in 59.3% of surveyed literature, followed by prices/inflation data (55.2%), consumption/retail sales data (53.1%), construction variables (44.5%), with other variables appearing less frequently (see Figure 4).

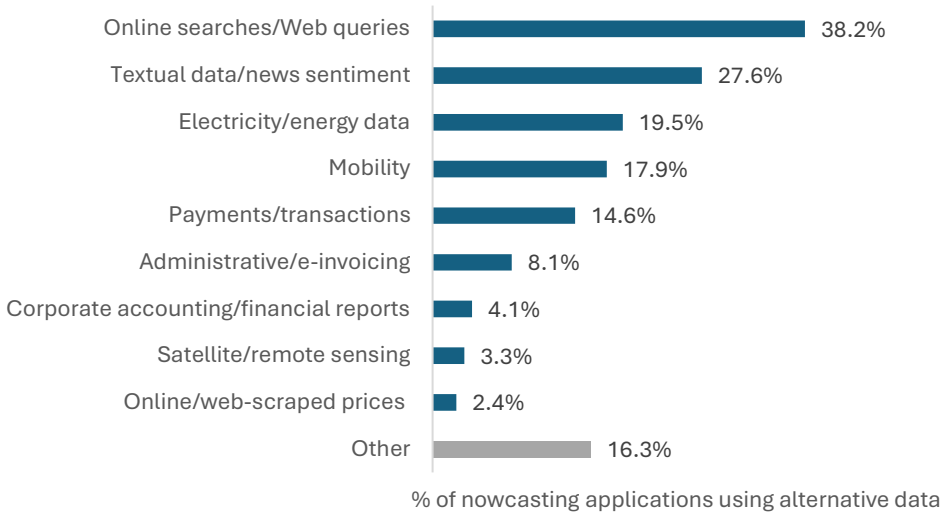
Figure 4: Macroeconomic variable categories used as predictors in nowcasting



Source: Authors' calculations

Beyond macroeconomic variables, surveys and financial variables are also widely used, as they are utilized in 66.3% and 65.6% of applications respectively. Variables from countries other than the target country (such as neighboring or significant trade partner countries) are used in 31.4% of papers. Alternative data are present as predictors in 35.7% of papers; Figure 5 shows the different types of alternative data found in the surveyed corpus.

Figure 5: Alternative data in nowcasting applications



Source: Authors' calculations

Alternative data utilization is not evenly distributed across publications, as 81.3% of papers containing such data are published after 2020. Indicatively, papers including alternative data amount on average to 51.7% of annual publications after 2020 vs just 18.6% between 2019 and 2010, with no paper published prior to that period using any such data. Combined with the rise of ML methods and non-linear specifications discussed above, this potentially further points to research efforts focusing on addressing the difficulties models prior to 2020 faced in nowcasting during the pandemic.

Turning to another aspect of nowcasting applications, that of the asynchronous publication of data (the "ragged edge" problem), it is found in the surveyed literature that, in 39.5% of publications this non-synchronicity is dealt within the model, with the vast majority of those applications (95.5%) being the Kalman filter's ability to handle missing values. Other frequently encountered ways to handle the ragged edge problem include forecasting of predictors via satellite models (24.7%), estimation with other methods such as the Expectation Maximization algorithm, used in 17.7% of the examined papers, or truncation of the dataset panel so it is balanced, something applied in 6.4% of papers. 18.6% of papers used other methods depending on the context, whereas 6.1% of papers did not need to address the ragged edge problem as their focus was on methodological illustrations[2].

[2] Percentages do not sum up to 100% as there are papers which apply more than one approach.

For evaluating model nowcasting performance, apart from the 6.1% of paper presents methods without conducting an out of sample evaluation, 18.9% conducted a simple out of sample evaluation using the latest data vintages, 42.7% performed a pseudo real-time evaluation, whereas only 29.7% did a true real-time evaluation. Pseudo real-time evaluation is conducted more frequently compared to true real time evaluation both before and after 2020. 2.6% of papers could not be classified in one of the abovementioned categories. Turning to the results of those evaluations, out of the 195 papers performing evaluation among different models, DFMs and factor methods are found to be the best performing models in 21% of them, followed by machine learning methods (17%) and forecast combinations of different models (12%). MIDAS models, Bridge equations and VARs are found to be best performing in 6%, 4% and 3% respectively. 12% of the papers had miscellaneous other winners, whereas 24% of the papers reported no clear winner. Of course, results vary depending on the evaluation design, data availability at the target country and the nowcasted variable.

5. Literature gaps and future directions

Despite the growing body of literature, nowcasting is far from an accomplished science. The relatively recent inability of Atlanta FED's "GDPNow" (Higgins, 2014) model to nowcast Real GDP growth is a prominent example of that. More specifically, days prior to the preliminary data release for 2025:Q1 U.S. Real GDP growth, GDPNow's nowcasted value was between -2.7 and -2.8%, with other forecasting sources, such us the survey of professional forecasters and the Blue-Chip survey, ranging between 0.4% and 2.5%. The divergence between these estimates and the initially announced preliminary figure of −0.3% was largely attributed to differences in the classification of gold imports as monetary or non-monetary between GDP estimates compiled by the Bureau of Economic Analysis and balance-of-payments statistics, as well as to other trade distortions arising from anticipated tariff hikes[3]. This incident highlights the need to expand the scope of economic activity from which nowcasts are extracted and the importance of building models flexible enough to be able adapt to

[3]For a more detailed analysis of this incident one could consult Atlanta FED's Policy Hub: Macroblog: "The Switch: The Changing Conditions Behind the New GDPNow Model." (Higgins, 2025)

such changes in the economy (a point somewhat parallel to that of the Lucas, 1776, critique).

Up until now, most applications have primarily focused on nowcasting aggregate measures, particularly GDP. This is because insofar most nowcasting applications seem to have been developed for central banking policy decision-making. This is, however, a notable limitation, as GDP subcomponents especially from the output side, which are examined by relatively few papers, citing data unavailability for specific sectors as a limiting factor (in contrast with expenditure and income approaches) could provide early warning signals for sector-specific shocks, hidden under overall GDP growth. For example, a sharp decline in agricultural Gross Value Added, due to an extreme weather event, can go "unnoticed" due to the small contribution the sector may have on overall GVA. Furthermore, such applications could be useful in private sector institutions, i.e. a retail bank whose loan portfolio's sectoral shares are different than those of GDP. Similarly, variables such as industrial production and services turnover, which are not only used as predictors in nowcasting models but have also policy importance on their own merit, have been underexplored as target variables (usually in the context of model evaluations). Having the capacity to identify surprises in those and other real activity variables early on could help improve GDP nowcasting accuracy in a layered model context, as current methods of dealing with unbalanced datasets either estimate missing observations in the context of the model or ignore them altogether.

Another reason for the dominance of aggregate measures as nowcasting target variables has been the limited scope of timely available variables that would be suitable as predictors for each for these more specific variables. However, the increasing availability of alternative data could be useful in that regard. Indeed, some alternative data have already been proven to improve nowcasting performance, especially when combined with conventional indicators. However, the limitations of such variables should not be underestimated but further explored. Web search queries, being the most used and studied alternative variable provides an insightful example in that regard: The failure of Google to monitor flu epidemics in real time using relevant online search data resulted in biased and ultimately uninformative predictions (Cook *et al*., 2011 and Katsikopoulos *et al*., 2022). Knowing about such sources of uncertainty in other types of alternative variables can help mitigate them and thus constitute a potential direction for future research. For example, Woloszko (2024), who built a neural network model

to track weekly GDP based solely on Google Trends data, accounted for the above-mentioned issue by including search queries related to multiple and different aspects of economic activity. Another limitation of alternative data is that they are usually constituted of short time series, thus limiting their usefulness in econometric models, for example IMF's Portwatch satellite data on export and import volumes and vessel movements are available from 2019 and onwards.

Apart from aggregate measure focus, nowcasting literature is heavily skewed toward nowcasting in advanced economies. This is to be expected as advanced economies have the institutional and statistical capacity to produce a wider range of indicators at a timelier basis. However, given the policy relevance of this issue, research has already focused in covering this gap: Domenico Giannone's partnership for example, with the John Hopkins University[4] to help develop nowcasting tools for data-constrained low-income countries is starting to bear fruit, as the first relevant working papers starting to get published, with a recent early-stage publication on nowcasting Kenya's GDP being an indicative example (Danov *et al.*, 2026).

A last methodological limitation regards nowcasting evaluation designs and is the difficulty in acquisition of vintages to conduct true real-time evaluations, as using latest available vintages of predictor variables introduces look-ahead bias. The same is not necessarily true when it comes to target variables, as benchmarking a model against final vintages of target variables can reveal how it predicts its true underlying values and reduce the probability of misguiding policymakers, especially at times when revisions end up being of significant magnitude, such as during COVID-19 recovery (Giannone and Primiceri, 2026). To that end, a "hybrid" design for forecast evaluations may be worth exploring.

6. Conclusions

In the analysis presented above, 343 nowcasting applications were surveyed to identify prevailing methodological approaches, developments in the literature and potential future research directions. The review revealed that the literature is heavily concentrated on GDP and aggregate economic activity nowcasting and particularly

[4] See Johns Hopkins University's announcement on the matter: "Economic forecasting expert Domenico Giannone joins Johns Hopkins", July, 2025.

focused on advanced economies. In terms of modelling approaches, Dynamic Factor Models appear to be the most widely used, followed by Machine Learning and MIDAS methods, with no consensus emerging about a best-performing approach.

An important finding of the surveyed literature is that nowcasting performance remains conditional on the economic setting, the target variable and the information available at the time of prediction. Periods of heightened uncertainty and abrupt economic changes, such as the COVID-19 pandemic, have highlighted the limitations of certain nowcasting approaches, although some applications demonstrate relative resilience. Against this background, after 2020 research seems to increasingly shift towards Machine Learning methods and non-linear specifications, combined with increased usage of alternative data sources.

Regarding literature gaps and potential future research directions, the development of nowcasting models for variables important from both policy and nowcasting perspectives, such as industrial production, services output and sectoral GVA is proposed, potentially by exploiting the newly available alternative data sources. Such sources, despite their growing use, remain insufficiently explored in terms of their statistical properties, predictive reliability and potential biases. Furthermore, extending nowcasting applications beyond advanced economies could improve the geographical coverage of the literature. Finally, given the biased nowcasts relative to final data vintages witnessed during the pandemic recovery, greater attention should be devoted to nowcasting evaluation designs, potentially combining real-time vintages of predictor variables with final vintages of target variables, in order to assess the predictive performance of the nowcasting models relative to the true evolution of the target variables, thus isolating the impact of data revisions.

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Appendix: Nowcasting Models

i. Bridge equation models

Let $Y_{q,t}$ be the target variable to be nowcasted observed at time t and published at a quarterly frequency (hence the q in the subscript). In a similar fashion, predictor variables are denoted by $X_{f,t,}$ where f denotes either monthly (m) or quarterly (q) frequency. Then, the bridge equation model can be defined as follows:

$$Y_{q,t} = b_0 + \sum_{i=1}^{k} b_i(L)X_{i,q,t} + \varepsilon_{q,t},\ i = 1, \dots, k, \qquad (1)$$
$$\varepsilon_{q,t} \sim N(0, \sigma^2),$$

where $b_i(L) = b_{i.1} + \cdots + b_{i,s}L^s$, denoting a lag polynomial of length s. The $X_{q,t}$ variables enter the equation directly. For the $X_{m,t}$ variables, on the other hand, the process is as follows:

1. Variables are projected for the remainder of the quarter in question via an auxiliary model (for example, an autoregression or a VAR model).
2. Variables are then properly aggregated (via summation or averaging, depending on the context) and are thus transformed into quarterly frequency variables that can be inserted in equation (1), which in its turn can then be estimated by OLS.

ii. Dynamic Factor Models

For a target variable Y_t and a set of predictor variables $X_{i,t}$, $i=1\dots,k$, a dynamic factor model is defined as follows:

$$X_{i,t} = \sum_{j=1}^{k} \lambda_j f_{j,t} + e_{i,t},\ \ e_{i.t} \sim N(0, \sigma_i^2) \qquad (2)$$

where:

$$f_{j,t} = \sum_{p=1}^{q} a_p\, f_{j,t-p} + u_{j,t},\ \ u_{j.t} \sim N\left(0, \sigma_j^2\right). \qquad (3)$$

Eq. 2 is called the measurement equation and Eq. 3 is called the state equation. In Eq. 2, f_j represents the j common factors driving the predictor variables, and λ_j are the loadings that link factors to variables; $e_{j,t}$ is the idiosyncratic component of each predictor variable.

Factors are usually assumed to follow an autoregressive process, as described in Eq. 3, but can also follow a VAR process, as seen in the two-step estimator proposed by Doz *et al.* (2011). Upon specification, the model can be estimated using state-space methods, such as the Kalman filter.

Once the factor has been estimated it can be used to nowcast the target variable:

$$Y_t = b_0 + \sum_{i=1}^{j} b_i f_{i,t} + b_{j+1}Y_{t-1} + \varepsilon_t. \qquad (4)$$

Should the variables at hand be of mixed frequencies, then the nowcast in a dynamic factor model context can be obtain either by using a bridge model to bridge the high frequency factors to the lower frequency target variable (the so-called

"bridging with factors" approach) or by modeling the relationship directly using a MIDAS approach (see next section). Alternatively, lower frequency predictor variable can be estimated in the context of the DFM as an unobserved higher frequency process in the state vector. For example, Mariano and Murasawa (2003) estimate the unobserved monthly GDP growth by considering the quarterly values as its geometric mean:

$$y_{q,t} = \frac{1}{3}y_{m,t} + \frac{2}{3}y_{m,t-1} + y_{m,t-2} + \frac{2}{3}y_{m,t-3} + \frac{1}{3}y_{m,t-4}, \quad (5)$$

(with lowercase letters denoted natural logarithms of the variable $Y_{q,t}$).

iii. Mixed Data Sampling (MIDAS) models

MIDAS models allow relating directly high-frequency variables to lower frequency ones through a parsimonious non-equal weighting scheme. For example, for quarterly and monthly variables:

$$Y_{q,t} = b_0 + \sum_{i=1}^{h} b_i X_{i,q,t} + f\left(\{X_{i,m,t}\}, \theta, \lambda\right) + \varepsilon_{q,t}, \quad (6)$$

where f is a function describing the relationship between quarterly and monthly variables, through a polynomial weighting scheme, with θ and λ being parameters to be estimated (depending on the polynomial chosen). In the case of Almon lag weighting, which is among the most common specifications, the model is formulated as follows:

$$Y_{q,t} = b_0 + \sum_{i=1}^{h} b_i X_{i,q,t} + \sum_{\tau=0}^{k-1} X_{i,m,t-\tau}\left(\sum_{j=0}^{p} \tau^j \theta_j\right) + \varepsilon_{q,t}, \quad (7)$$

where k denotes the number of high frequency lags in the model, τ denotes the number of high frequency periods up to time t, and p is the polynomial lag order.

The model can then be estimated using Non-linear Least Squares. Given that in the Almon lag weighting scheme, θ depends on the lag order and not the lags of the higher frequency variables, it makes MIDAS a parsimonious specification.

iv. Mixed-Frequency VAR

When modelling mixed frequency variables in a VAR context, there two approaches one can follow: either model the lower frequency variables as an unobserved high frequency process or rely solely on observable data. in the former case the model is specified as follows:

$$\boldsymbol{Y}_t = \boldsymbol{A} + \boldsymbol{B}_1\boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{B}_k\boldsymbol{Y}_{t-k} + \boldsymbol{\varepsilon}_t,\ \boldsymbol{\varepsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{8}$$

where $\boldsymbol{Y}_t$ denotes the total sample of fully observable and partially observable data (denoted $\boldsymbol{X}_t$ and $\boldsymbol{Z}_t$ respectively). The model is then partitioned as follows:

$$\begin{bmatrix}\boldsymbol{X}_t\\ \boldsymbol{Z}_t\end{bmatrix} = \begin{bmatrix}\boldsymbol{A}_X\\ \boldsymbol{A}_Z\end{bmatrix} + \begin{bmatrix}\boldsymbol{B}_{1,xx} & \boldsymbol{B}_{1,xz}\\ \boldsymbol{B}_{1,zx} & \boldsymbol{B}_{1,zz}\end{bmatrix}\begin{bmatrix}\boldsymbol{X}_{t-1}\\ \boldsymbol{Z}_{t-1}\end{bmatrix} + \cdots + \begin{bmatrix}\boldsymbol{B}_{k,xx} & \boldsymbol{B}_{k,xz}\\ \boldsymbol{B}_{k,zx} & \boldsymbol{B}_{k,zz}\end{bmatrix}\begin{bmatrix}\boldsymbol{X}_{t-k}\\ \boldsymbol{Z}_{t-k}\end{bmatrix} + \begin{bmatrix}\boldsymbol{\varepsilon}_{x,t}\\ \boldsymbol{\varepsilon}_{z,t}\end{bmatrix}, \tag{9}$$

where

$$\begin{bmatrix}\boldsymbol{\varepsilon}_{x,t}\\ \boldsymbol{\varepsilon}_{z,t}\end{bmatrix} \sim N\left(\begin{bmatrix}\boldsymbol{0}\\ \boldsymbol{0}\end{bmatrix}, \begin{bmatrix}\boldsymbol{\Sigma}_{xx} & \boldsymbol{\Sigma}_{xz}\\ \boldsymbol{\Sigma}_{zx} & \boldsymbol{\Sigma}_{zz}\end{bmatrix}\right).$$

The model can then be estimated by using the Gibbs sampler, the Kalman filter or other state-space methods. A detailed presentation of this approach is found at Eraker *et al.* (2015).

In the alternative specification, the model is estimated via an unrestricted MIDAS (U-MIDAS) approach after stacking high and low frequency variables:

$$\begin{bmatrix}X_{H(t,1)}\\ \vdots\\ X_{H(t,m)}\\ X_{L(t)}\end{bmatrix} = \boldsymbol{A}_0 + \sum_{j=1}^{p}\boldsymbol{A}_j\begin{bmatrix}X_{H(t-j,1)}\\ \vdots\\ X_{H(t-j,m)}\\ X_{L(t-j)}\end{bmatrix} + \varepsilon_t, \tag{10}$$

with ε_t being a white noise process. In the above *p*-lag VAR representation, X_L denotes low frequency variables sampled at time *t*, divided at *m* intervals, in which high frequency variables X_H are observed.

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