

Recasting Economic Measurement: The Promise and Trade-offs of Alternative Data

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Received: 09 March 2026; Revised: 17 June 2026; Accepted: 18 June 2026

Abstract

Central banks today operate in an environment where information needs are rapidly evolving, requiring indicators that are agile, diverse, timely, and capable of providing a comprehensive view of emerging economic developments. The growing availability of non-traditional data sources, coupled with advances in data science, offers significant opportunities to enhance the economic analysis. Developing new indicators from alternative data sources and applying advanced analytics requires careful evaluation to ensure their reliability and efficacy with established macroeconomic measures. Such evaluation is inherently complex, as existing benchmarks may be insufficient or missing, contain coverage gaps, vary in timeliness, and sometimes lack conceptual alignment, thereby undermining the ability to compare indicators accurately. In this context, this paper provides an overview of emerging indicators, explores potential measurement differences, and examines the challenges of integrating non-traditional data with traditional indicators.

Key words: Alternative data; Machine learning; CPI inflation; Sentiment analysis; Remote sensing; Uncertainty; Economic policy; Geospatial modelling; NDVI; EPU; NLP; Online prices; Agriculture.

AMS Subject Classifications: 62K05, 05B05

*This is an extended version of the keynote address delivered at the 28th Annual Conference of the Society of Statistics, Computers and Applications, co-hosted by Savitribai Phule Pune University, on January 5, 2026. Ajit R. Joshi is the Executive Director and Shweta Kumari is Assistant Adviser in the Department of Statistics and Information Management of Reserve Bank of India. The views expressed in this paper are those of the authors and not the institution to which they belong.

1. Background

Measurement of variables is a fundamental aspect of statistical science and the robustness of the methodology employed in measurement determines the utility of any analysis

carried out using the most advanced techniques. As technology is now part of any activity, the transactions and interactions generate a large quantity of data, without any specific data collection efforts. These have come to be categorised as alternative data, as they are often not part of official statistical methodology, at least thus far. But these alternate data sources are becoming mainstream, and all the policy makers and official agencies are embracing them. In this context, I thought it appropriate to place before you some of the observations while using these data for policy analysis.

For a central bank, which plays the roles of data producer and data user, interest in the so-called alternate data sources emanate from both sides. Globally central banks are taking keen interest in these data and the data science techniques to leverage these rich repositories in their own analysis and to enrich the statistical framework.

Developing new indicators from alternative data sources and applying advanced analytics requires careful evaluation to ensure their reliability and the ability to better track the concepts being measured. Such evaluation is inherently complex, as existing benchmarks may be insufficient, missing, contain coverage gaps, or vary in timeliness. The conceptual alignment of the new measures with the standard methodologies also needs to be understood, so as to contextualise the outcome of the new measures and their comparability with the traditional indicators. Therefore, we propose to provide an overview of a few emerging indicators, explore potential measurement differences, and examine the challenges of integrating non-traditional data with traditional indicators. Considering their distinct dynamics, we seek to deliberate on how they could be treated as reliable source of information in a long-term setting, extending beyond one-time research application.

2. Online food prices - why online prices are important

I will begin with an indicator which is probably the most well-known and central to my work in the Reserve Bank. Thanks to the transparent approach of the Ministry of Statistics and Programme Implementation, we all know that the major price indexes are under revision, and we should see the new ones by next month. In the context of the revision exercise, online prices have emerged as a potential data source because they provide high-frequency, real-time information on the movement of prices. Traditional price collection surveys are typically monthly and rely on field visits, whereas online data can be harvested daily from multiple retailers. This enables analysts and policymakers to detect inflationary pressures before availability of the official statistics. In periods of sudden shocks, such as pandemics, supply-chain disruptions, or major policy changes (for example, the recent GST rationalisation), online prices can reveal changes immediately, well before these appear in official inflation measures. Their speed, wide product coverage, and relatively low data collection cost make them an important tool in the price-monitoring ecosystem. For economies with expanding e-commerce, online prices increasingly reflect the prices paid by a large share of consumers. Thus, they are innovative, complementary, and valuable for understanding market dynamics.

2.1. Why online prices may not match official inflation numbers

Even though online prices are useful in tracking emerging trends, the indices compiled using them may often diverge from official inflation rates. This can occur due to several structural differences, as the online and offline retail markets are not identical. There can

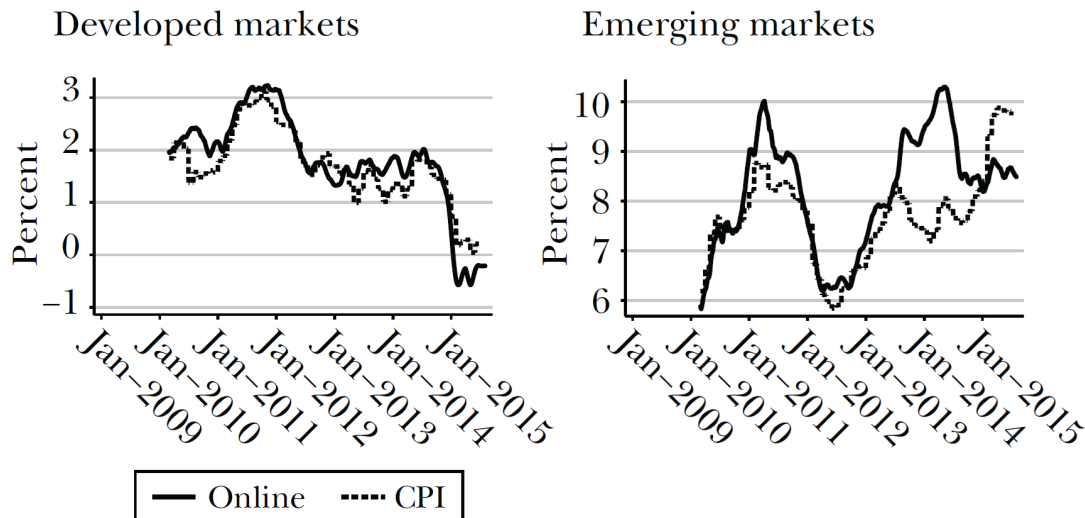


Figure 1: Online v/s CPI - annual inflation rates

Source: Cavallo and Rigobon (2016)

be differences in the coverage of items, the types of commodities sold, and regional price variations. In many places, especially smaller cities and semi-urban areas, a large share of essential daily consumption items is still purchased offline, meaning online prices capture only a partial view. Both offline and online measures seek to capture inflation as a concept, and any divergence between them stems from measurement differences, and should not be treated as an error.

In their Billion Prices Project, Cavallo and Rigobon (2016) find that while the dynamics of online prices is distinct in many aspects from offline sources, the carefully curated online index is able to anticipate movements in the corresponding official consumer price index in many countries. Further, the coherence between the two price indices appears to be more in developed countries, as compared to emerging market economies (Figure 1). While these insights reflect trends observed between 2009 and 2015, current patterns may have evolved significantly after a decade.

2.2. Why we should not target to match with offline prices - but still value them

Given these structural differences, online inflation indices should not be expected to precisely match official CPI estimates. They are designed to track fast-moving price trends, rather than measurement of cost-of-living changes. Their underlying market dynamics, such as the degree of price stickiness, can differ substantially from offline retail markets, leading to different patterns of price adjustments. For example, online competition may lead to frequent changes in prices, as Cavallo (2018) found in the case of US for large multichannel retailers. Price setting can further be influenced by automated or algorithmic pricing mechanisms used by online retailers, as noted by Brown and MacKay (2023), unlike offline retail prices, which are typically revised at discrete and infrequent intervals. In contrast, the official CPI adheres to international statistical standards, reflect representative household expenditure weights,

and follow consistent long-term methodology - requirements that online datasets may not meet. This distinction, however, reinforces rather than diminishes the value of online price data. Their strength lies in offering an additional perspective on price dynamics, which is useful for early detection of market conditions, stress, or structural shifts.

As examined by Mahajan and Tomar (2021) in the Indian context, supply-chain disruptions triggered by pandemic lockdowns resulted in reduced product availability in both online grocery portal and offline markets (mandis). However, the magnitude of decline was found to be lower in online market for select food categories.

Such findings provide deeper insights into how crisis episodes alter supply-side mechanism, price-setting behaviour, and market dynamics, extending beyond the usual focus of co-movement between online and offline prices. Importantly, such nuances are difficult to detect using conventional offline price data alone, and underscore the value of online prices data further, where prices and availability are recorded at high frequency and responses are faster.

Online prices, therefore, function as a complementary information stream that enhances situational awareness and supports research. Their purpose is not to be a substitute or completely mirror CPI, but to provide insights that enrich monitoring and analysis.

3. Remote sensing - policy perspective

Climatic factors have emerged as an important risk area, drawing heightened attention across global policy forums in recent years. While climate risk is a very broad domain, the inter-linkages with macro-economy and the financial sector are important for the Reserve Bank. Here we focus only on the impact of the weather events on crop conditions and resultant effect on the production. We are attempting evaluation of the supply-side situation using the real time data on weather conditions, and satellite imagery which provide early signals on crop growth conditions and identify the significant stress factors.

3.1. Agricultural data challenge

Data on crop production comes with considerable delay and there are gaps in crop area and production estimates, particularly at disaggregated regional levels. This task is inherently complex considering the vast landscape of our country, diversity of crops, and varying production cycles. The traditional system relies on field surveys and reporting cycles, which limits the availability of timely updates during the crop season. Crop production estimates are also revised subsequently, and the revision is often significant, constraining real-time assessment of evolving supply conditions. The intricacies of agricultural ecosystems get further amplified by frequently changing climatic conditions. As a policy institution, we need information as of yesterday and that is where we started looking up the sky to see whether the satellite data can help us.

3.2. What makes remote sensing a powerful data source?

Remote sensing offers a distinct advantage in agricultural monitoring by enabling regular, large-area observations of crop lands in a consistent and systematic manner (Donaldson

and Storeygard, 2016). Satellite-based measurements facilitate objective assessment of crop health across regions and seasons, reducing dependence on field observations. Importantly, remote sensing captures in-season crop dynamics - such as sowing progress, phenological stages, vegetative growth, and emerging stress - thereby generating timely signals on evolving crop conditions, often well before their full impact is reflected in traditional data (Gumma *et al.*, 2022; Johnson, 2014). This capability is particularly valuable for India, where spatial and temporal variability in climatic condition is substantial.

Geospatial capabilities and change-detection frameworks based on satellite imagery enable early assessment of crop stress and damage arising from droughts, floods, heatwaves, and other extreme weather events. Such “pixels to plots” insights strengthen early warning systems, bridging critical information gaps during the crop season. From sowing to harvesting, remote sensing allows for periodic updates, and production nowcasts well ahead of traditional agricultural statistics.

A recent study by Kumari (2024) provides a scalable framework for integrating remote sensing data for regular crop monitoring and production assessment. Figure 2 illustrates how such data capture spatio-temporal variation in vegetation conditions for Tur and Gram - two major pulses in India - across comparable fortnights in key growing regions. The 2016-17 crop season, which recorded a strong Tur harvest, exhibits higher vegetation levels as early as August 2016, relative to August 2015. Similarly, for Gram, which is a Rabi crop, improved conditions are reflected in November 2021 compared to November 2015.

Importantly, the vegetation index adds substantial value by enhancing both the accuracy and timeliness of production assessment, enabling real-time nowcasts, with estimates getting progressively refined and finalised near harvest phase. The study shows that model-based predictions closely track both upturns and downturns in actual production data.

Further, vegetation conditions are a rich source of advance information for assessing agricultural commodity arrivals in mandis, which, in turn, can influence the future trends in wholesale and retail prices. In the Indian context, Kumari and Kuruganti (2022) combine remote sensing data with ground-based indicators to predict mandi arrivals, demonstrating the usefulness of such information.

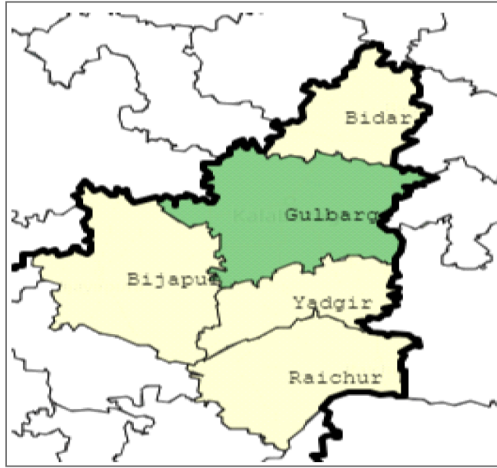
This study also captures spatial heterogeneity in vegetation-arrival relationship across mandis, using geographically weighted regression (GWR) model (Figure 3). This aspect is difficult to identify using traditional data sources, but it is possible by leveraging the spatial granularity of remote sensing data through explicit incorporation of geolocations.

It is learnt that remote sensing-based inputs are increasingly used internally to inform official crop estimates (Ministry of Agriculture and Farmers Welfare (MoA&FW), 2025; Navalgund and Ray, 2019); however, their specific role and quantitative contribution are not published separately.

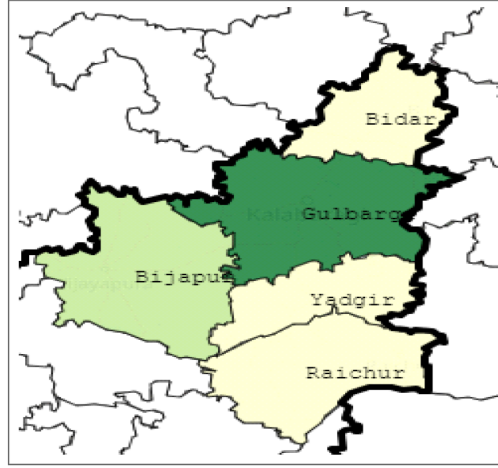
3.3. Why the difference

While remote sensing offers high-frequency, real-time spatial observations, and its ability to track actual crop production is well-established in various research studies, its estimates can sometimes differ from traditional crop statistics because of structural and

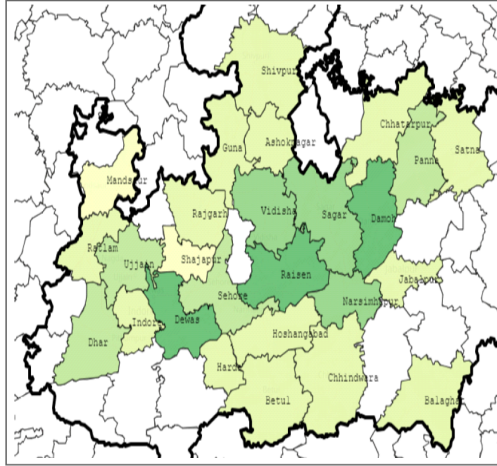
Tur - select districts in Karnataka
Aug-2015 2nd ft.



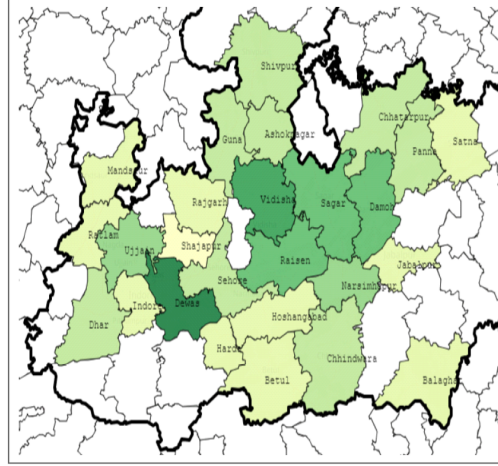
Aug-2016 2nd ft



Gram - select districts in Madhya Pradesh
Nov-2015 2nd ft.



Nov-2021 2nd ft



Note: Yellow to Green gradient scale represents lower to higher vegetation value.

Figure 2: Geospatial variation of vegetation

Source: Kumari (2024)

measurement differences. The indicators - such as vegetation indices, soil moisture, photosynthetically active radiation (PAR) - are biophysical proxies, rather than direct measures of crop yield or production. Differences also arise from scale and granularity. Satellite data record information at the pixel level and can cover heterogeneous plots, capturing fine spatial variation that is often missed in aggregated data. Because official statistics are aggregated at broad administrative levels, downscaling granular satellite data to these levels can reduce its informational richness and contribute to divergence.

Timing is another factor, satellites provide continuous in-season insights, whereas field surveys are periodic and may lag by weeks or months. At high-frequency or local levels, corresponding official data is not available, as national statistics typically provide a single estimate for the whole crop year (which gets updated subsequently). By the time state or district level estimates are published (often 1-2 years lag), timely comparison becomes

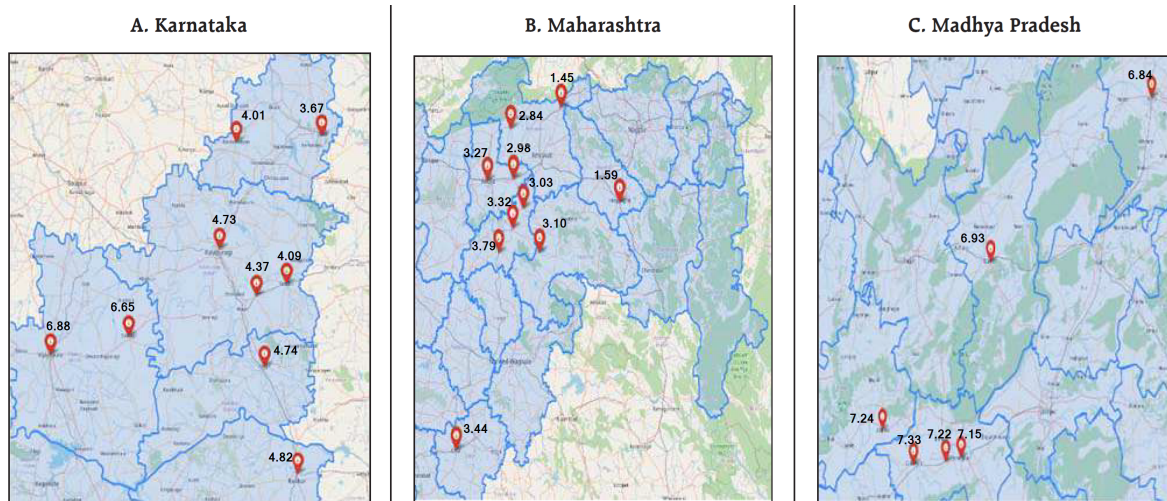


Figure 3: Vegetation coefficient at mandi level - GWR model

Source: Kumari and Kuruganti (2022)

impossible. Methodological variations - including crop classification and phenological models, area selection frameworks, weighting patterns, and data calibration techniques - further influence the assessment.

3.4. Way forward

The differences in the two sets of estimates are to be expected. Understanding them helps interpret remote sensing outputs appropriately and leverage the rich dataset. While ground surveys remain useful for validating yields, satellite-based monitoring adds a dynamic, high-resolution complementary perspective. In this way, both these techniques can help the other data collection efforts more comprehensive and provide opportunity for mutual learning. As analytical and geospatial techniques advance and data integration improves, the value of remote sensing for agriculture is expected to grow further. There should be no expectation for remote sensing data to perfectly match traditional statistics. Instead, by combining 'boots on the ground' with 'eyes in the sky,' a more nuanced and holistic view of agricultural conditions can be obtained. This integrated perspective would go a long way in providing actionable intelligence to manage climate risks and their impacts on macro-economy.

4. Soft data – why we need more than just hard data

Monitoring the economy requires going beyond conventional statistical indicators *viz.* inflation, growth, production, trade or employment. While these “hard numbers” remain indispensable, they capture only the observable outcomes of economic activity, and do not fully reflect different types and levels of disaggregation, evolving expectations, and behavioural responses that significantly influence economic dynamics. Soft data, comprising media reports, expert analysis, sector-specific studies, and corporate communication, helps capture these dimensions.

4.1. Media as a bridge

Media acts as a crucial communication bridge between households, markets and policymakers by reporting and reflecting the perceptions and expectations of economic agents. Even in periods when official statistics or surveys face constraints, as seen during the COVID-19 pandemic, such soft information remains accessible, offering timely insights into economic conditions.

4.2. Early signals

A major strength of news-based information is its timeliness. Many macroeconomic indicators are released with lag, revised later, or available only at low frequency. Media reports, on the other hand, often pick up emerging pressures or on-ground reality much earlier. Coverage of rising input costs, supply chain disruptions, shifts in consumer demand, rural distress, trade bottlenecks, or early signs of recovery provide valuable real-time signals well before these are captured by the official statistics. In this sense, soft data serves as an important source for an early-warning system.

Relationship of news-based sentiment indicators with economic activity, either alone or in combination with other economic indicators, has been examined on a range of variables in many countries and is increasingly being used in forecasting frameworks. Shapiro *et al.* (2017) construct monthly news sentiment index for US from a wide range of economic and financial news articles for a long period from 1980 to 2015, and find a strong correlation with key economic variables. Further, their predictive power is also evaluated and found to be significant in current and near-future term.

Another study in the context of US by Ardia *et al.* (2019) develops a comprehensive design for optimisation of news-based sentiment. Use of sentiment is found to provide valuable gains for forecasting economic growth, relative to forecasts obtained using only the economic and financial indicators (hard data).

Kalamara *et al.* (2020) extract signal from UK newspapers and find that it significantly improves the forecast of key macroeconomic variables such as GDP, inflation, and unemployment, as compared to benchmark model, emphasising the valuable information content.

Various empirical studies indicate that soft information offers key insights, and are particularly useful during periods of stress or economic uncertainty (Aguilar *et al.*, 2021; Buckman *et al.*, 2020). In the Indian context, Kumari and Giddi (2020) derive sentiment from news using machine learning model (Support Vector Machines classifier) and find strong linkage and causality between the sentiment index and retail inflation.

Further, Giddi *et al.* (2022) construct news based sentiment indices for a variety of macroeconomic variables using a fine-grained aspect based sentiment methodology. They find that pessimism was reflected in news narratives much before the impact was recorded in hard data, whose values significantly deviated from historical trends, especially during the first phase of Covid-19. The sentiment indices capture the changing patterns in various sectors of Indian economy and have significant predictive value.

These findings suggest that a high-frequency sentiment index can be a useful com-

plementary indicator to provide early signals on economic conditions. However, considering that textual reports could be noisy, it is important to process the soft information carefully in order to capture the underlying nuances and extract useful signals. Corporate news is another crucial component, particularly for large firms which often act as market makers in pricing, investment, production and employment, and influence wider economic outcomes. Analysing corporate reports, such as earnings calls, management commentary or interviews, and analysts' reports help quick assessment of potential turning points in business cycles.

While analysts often review multiple information sources manually, they often put their analysis out in the public domain or share with policy makers. An automated pipeline can systematically collate and analyse narratives, extract sentiment and key insights, and present the emerging trends in a structured manner. Using NLP and ML techniques, the tasks can be suitably streamlined in a step-wise manner from input data source to the desired output formats, enabling policymakers to quickly decipher the perspectives, enhancing the overall efficiency and consistency, while reducing the time and effort required for manual review of large textual documents.

4.3. Explaining the “Why” behind economic movements

Soft information adds analytical depth by helping explain the “why” behind movements in macroeconomic variables. While hard data may show inflation rising or industrial output slowing, news coverage helps identify the underlying reasons - such as supply constraints, global demand shifts, policy uncertainty, financial conditions, or changes in business and consumer sentiment. These data provide the contexts which are not captured in hard data, and enable analysts to interpret emerging trends more accurately, going beyond quantitative measures in isolation.

4.4. Why uncertainty matters

Uncertainty often shapes the decisions of economic agents (how companies invest, how households spend or save, how markets behave) and influences how policymakers respond, creating a feedback loop that further affects economic outcomes. While the idea of uncertainty is well recognised, its measurement is far from straightforward. Uncertainty is an intangible, multi-dimensional concept, and unlike inflation or growth, it does not have a directly observable counterpart.

4.5. Relevance of text-based indices

Beyond financial market volatility indicators and business-survey-based measures, recent years have seen the emergence of soft-data based measures of uncertainty. In this context, text-based uncertainty indices such as the Economic Policy Uncertainty (EPU) Index, Geopolitical Risk Index (GRI) and Trade Policy Uncertainty (TPU) have gained remarkable traction (Baker *et al.*, 2016; Caldara and Iacoviello, 2022; Caldara *et al.*, 2020). By covering a broad spectrum of issues from fiscal and monetary policy developments to geopolitical tensions, trade disputes and tariff actions, they offer a comprehensive view of evolving risks, many of which may not immediately appear in traditional macro variables. These indices provide timely, nuanced, and quantitative signals of uncertainty by tracking emerging media narratives on economic policies, trade, and geopolitical risks. These text-

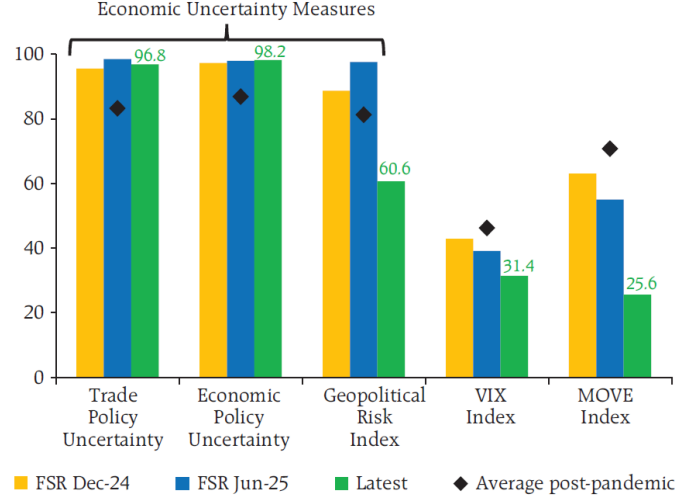


Figure 4: Disconnect between uncertainty and financial market volatility (percentile)

Source: For details, please refer to Financial Stability Report (FSR) Dec 2025, RBI

based uncertainty indicators are often analysed jointly with financial market indicators (*e.g.* VIX, MOVE index) for a comprehensive assessment of evolving economic conditions (Ahir *et al.*, 2025; Baker *et al.*, 2020).

This is particularly relevant for a dynamic and fast-growing economy like India, where policy decisions and evolving developments (including potential external shocks) can quickly influence expectations and market confidence. Their high-frequency nature makes them particularly valuable during fast-moving episodes such as tariff tantrums, geopolitical escalations, or major policy shifts. Their standardised methodology also enables meaningful cross-country comparison, supporting analysis of global uncertainty dynamics and potential spillovers, which are significant for EMEs. It is, therefore, important to monitor a range of indicators on a regular basis to detect any signs of emerging stress and vulnerabilities (Economic Survey 2025-26; FSR 2025; WEO 2026). These indicators should, however, be used with caution, as different indicators may not always converge and convey the same degree of uncertainty, as seen during recent times (Figure 4).

4.6. Benchmarking

Evaluating the effectiveness of these uncertainty indicators is inherently challenging because there is no single “true” economic indicator against which they can be directly benchmarked. There is also a natural difference in the way these are constructed and interpreted. While heightened uncertainty generally tends to dampen investment and productivity, such relationships typically manifest over the business and financial cycle, rather than in short-term, although the magnitude and persistence of such effects vary across countries (Castelnuovo, 2023).

In addition, causality is difficult to isolate, as uncertainty itself may be both a driver and a reflection of economic stress. News-based indices may also be influenced by reporting

intensity, narrative framing or country-specific contexts. Therefore, while they may not always have a direct, contemporaneous, or mechanical link to real economy, these indicators remain valuable as narrative and complementary tools that enrich economic understanding and policy assessment.

5. Concluding observations

The increasing complexity and digitalisation of economic activity have opened a treasure trove of information for the public policy institutions. This has not only enabled the development of completely new indicators but also created opportunities to complement and enrich conventional statistical measures with more timely, granular, and near real-time insights, which is becoming increasingly necessary. As alternative indicators become more widely used, there is a natural tendency to assess them by how closely they align with traditional measures. However, this framing can be limiting, as it places undue emphasis on correspondence rather than informational value.

The more relevant question is how these indicators help improve understanding of evolving economic dynamics and whether they add insights that are not readily available from existing data sources. The utility of such indicators is therefore best evaluated by examining how they contribute to decision-making within structural and forecasting frameworks. Ignoring the relevant indicators could expose policy analysis to model and data-quality risks. As the saying goes, “the proof of the pudding is in eating”; similarly, the value of new-age indicators will ultimately be established through their performance in practical analytical applications.

Broadening the statistical information base and remaining open to new indicators, while exercising appropriate due diligence, can significantly strengthen the analytical foundations, improve our understanding of economic reality, and bring policy thinking closer to it.

References

- Aguilar, P., Ghirelli, C., Pacce, M. and Urtasun, A. (2021). Can news help measure economic sentiment? An application in COVID-19 times. *Economic Letters*, **199**, 109730.
- Ahir, H., Bloom, N., and Furceri, D. (2025). Uncertainty about uncertainty. *Finance and Development Magazine*, International Monetary Fund.
- Ardia, D., Bluteau, K. and Boudt, K. (2019). Questioning the news about economic growth: Sparse forecasting using thousands of news-based sentiment values. *International Journal of Forecasting*, **35**, 1370–1386.
- Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, **131**, 1593–1636.
- Baker, S. R., Bloom, N., Davis, S. J., and Terry, S. J. (2020). COVID-induced economic uncertainty (No. w26983). National Bureau of Economic Research.
- Brown, Z. Y., and MacKay, A. (2023). Competition in pricing algorithms. *American Economic Journal: Microeconomics*, **15**, 109–156.
- Buckman, S. R., Shapiro, A. H., Sudhof, M. and Wilson, D. J. (2020). News sentiment in the time of COVID-19. *FRBSF Economic Letter*, **08**, 5–10.

- Caldara, D., and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, **112**, 1194–1225.
- Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., and Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, **109**, 38–59.
- Castelnuovo, E. (2023). Uncertainty before and during COVID-19: A survey. *Journal of Economic Surveys*, **37**, 821–864.
- Cavallo, A. (2018). More Amazon effects: Online competition and pricing behaviors. National Bureau of Economic Research, Working Paper No. 25138.
- Cavallo, A. and Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, **30**, 151–178.
- Donaldson, D. and Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, **30**, 171–198.
- Economic Survey 2025-26. Government of India, Ministry of Finance.
- FSR (Financial Stability Report) (June and December 2025). Reserve Bank of India.
- Gumma, M. K., Kadiyala, M. D. M., Panjala, P., Ray, S. S., Akuraju, V. R., Dubey, S., Smith, A. P., Das, R., and Whitbread, A. M. (2022). Assimilation of remote sensing data into crop growth model for yield estimation: A case study from India. *Journal of the Indian Society of Remote Sensing*, **50**.
- Giddi, G., Kumari, S. and Maiti, S. S. (2022). When a news story is more than just text: evidence from Indian economy. RBI Bulletin.
- Johnson, D. M. (2014). An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States. *Remote Sensing of Environment*, **141**.
- Kalamara, E., Turrell, A., Redl, C., Kapetanios, G. and Kapadia, S. (2020). Making text count: Economic forecasting using newspaper text. Bank of England Staff Working Paper No. 865.
- Kumari, S. (2024). From pixels to plots: Synthesizing remote sensing into crop production estimation. *Journal of Income and Wealth*, **46**, 113–123.
- Kumari, S. and Kuruganti, S. (2022). Remote sensing applications for policy: An assessment of agricultural commodity arrivals. RBI Bulletin, July.
- Kumari, S. and Giddi, G. (2020). Inflation decoded through power of words, RBI Bulletin.
- Lobell, D. B., Azzari, G., Burke, M., Gourlay, S., Jin, Z., Kilic, T., and Murray, S. (2019). Eyes in the sky, boots on the ground: Assessing satellite- and ground-based approaches to crop yield measurement and analysis. *American Journal of Agricultural Economics*, **102**, 202–219.
- Mahajan, K., and Tomar, S. (2021). COVID-19 and supply chain disruption: Evidence from food markets in India. *American Journal of Agricultural Economics*, **103**, 35–52.
- Ministry of Agriculture and Farmers Welfare (2025). Assessment of crop losses through satellite. Press release dated February 11, 2025 by PIB Delhi.
- Navalgund, R. R., and Ray, S. S. (2019). Application of space technology in agriculture: An overview. Smart Agri Post.
- Shapiro, A. H., Sudhof, M. and Wilson, D. (2017). Measuring news sentiment. Federal Reserve Bank of San Francisco Working Paper 2017-01.
- World Economic Outlook (WEO) update (2026). International Monetary Fund. January.