AI-Powered Forecasting in Central Banking: Enhancing GDP and Inflation Predictions with Predictive Algorithms

Author: Natali Dzneladze

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Abstract

Monitoring GDP and inflation statistics as accurately as possible is essential for successful monetary policy and, ultimately, sustainable macroeconomic growth is a key goal for central banks. However, the models we use for measuring GDP and inflation tend to fall behind with the current dynamic complexity of the economic environment we all face today. GDP can be complicated assessment to measure accurately because it results can be delayed and revised, and inflation is provided adjusted or revised, due to changing dynamics often driven by economic shocks. Inflation in the casual context is often driven more rapidly and persistently, based on global supply chains or even behaviors among consumers that are not accounted for in models often relied upon. Moreover, innovative AI and machine learning-based predictive algorithms leveraging high frequency data, like payment systems, internet prices and even sentiment analysis of news provide central banks an unprecedented opportunity to extract correlations to use in the forecasting process. As found in recent studies evaluating alternative methods of forecasting, these new algorithms should not be viewed strictly in opposition to economic theory, but angled toward improving traditional tools of forecasting. This article also presents AI as a public good; timelier and more inclusive policymaking, with predictive technologies, can safeguard households and businesses against the destabilizing effects of economic shocks.

The challenge, however, is not technical but institutional: how to integrate these powerful technologies in ways that complement, rather than replace, human judgment and accountability. This research paper examines three major themes: the structural flaws in existing forecasting methodologies, the potential of AI to increase stability and resilience, and the ethical and governance considerations that must guide its responsible implementation in central banking.

Limitations of Current Forecasting Approaches

For decades, central banks have relied on structural macroeconomic models such as dynamic stochastic general equilibrium (DSGE) frameworks and output-gap–based forecasting systems. These models offer important virtues: they embed economic theory, enable counterfactual scenario analysis, and enforce internal consistency among macro variables. However, they suffer from several critical weaknesses. First, DSGE models are often misspecified with restrictive assumptions (e.g. linear dynamics, representative agents, frictionless markets), limiting their ability to capture nonlinearities, regime shifts, or structural breaks. Second, their reliance on lagged, low-frequency macro data makes them slow to incorporate sudden shocks. Third, they are vulnerable to parameter instability: calibrations or estimations made in "normal times" may become invalid during crises.

As an example, the Bank of England uses a variant of the DSGE-based framework (rooted in its COMPASS model) as one component of its forecasting toolbox. But the Bank itself acknowledges that no single model—DSGE included—can fully capture the complexity of the economy in all states of the world. Moreover, a recent independent review led by Ben Bernanke found significant shortcomings in the Bank's forecasting infrastructure, partly owing to outdated modelling practices and difficulties in adapting to the increased uncertainty of the post-pandemic era. Empirical evaluations of the Bank's forecasts indicate persistent forecast errors: for example, inflation forecasts have sometimes underestimated the pass-through from wage growth, and the model's assumed Phillips-curve relationship appears too flat. These internal results underline the real-world challenge: even well-resourced central banks confront serious limitations when relying primarily on structural models.

Now while these approaches provide theoretical consistency and policy guidance, they face well-known shortcomings:

Time lags and revisions: Accurate real-time assessment of economic conditions is undermined by two interrelated frictions: data publication lags and subsequent data revisions. Official GDP estimates are typically released weeks or even months after a quarter ends, and early estimates are often revised multiple times before converging to a stable value. This lag and revision process create a "moving target" for central banks: policy decisions must be made on incomplete, noisy, and uncertain data. The problem is not just practical, but also empirically significant. For instance, Bernanke & Boivin (2002) show that forecast accuracy is substantially degraded when models rely on vintage, unrevised data rather than final data. In "Real-Time Data, Revisions and the Predictive Ability of DSGE Models", the authors illustrate how forecast error variance increases when data undergo multiple revisions.

In practice, central banks acknowledge the challenge. For example, the Bank of England supplements its core DSGE-derived COMPASS forecasts with a broader model suite and judgment precisely to offset the shortcomings of delayed and revised data.Its staff often refer to the adage "all models are wrong, but some are useful" in interpreting evolving forecasts.recent internal working paper by the BoE found that its inflation forecasts have tended to underestimate the pass-through from wage growth, and that its Phillips-curve is too flat, which suggests systematic mis-specification exacerbated by real-time data uncertainty.

One additional nuance to emphasize is forecast feedback / endogeneity: policy decisions based on early forecasts may themselves influence economic outcomes, thereby complicating retrospective evaluation of forecasts. The recent paper "Forecasting with Feedback" (Lieli & Nieto-Barthaburu, 2023) formalizes this: when forecasts guide policy, the policy response can alter the trajectory of economic variables, meaning forecast errors are not purely exogenous.

In sum, the combination of publication lags, data revisions, limited observability, and feedback effects means that even the most sophisticated structural models struggle to deliver reliable "real-time" forecasts—especially in turbulent periods. This fundamental constraint of current forecasting approaches opens space for AI/ML techniques, which can exploit higher-frequency and alternative data sources to improve real-time detection of turning points.

Difficulty capturing shocks: Traditional forecasting models are built upon the expectation of smooth, predictable associations. They are incapable of capturing the nonlinear impact of shocks, whether the collapse of the financial system in 2008, sudden tariff increases, or the onset of the COVID-19 pandemic. Standard forecasting models could not anticipate the sudden stop in the global movement of people, collapse of industry and commerce providing services to households, outlining balloons of new fiscal and monetary stimulus for a totally uncertain future. When the Federal Reserve first downplayed the persistence of inflationary pressure in 2021 as "transitory", it quickly became a credibility challenge when they ultimately needed to address increasing rates. By the time rate hikes began in earnest in early 2022 inflation had already set into multi-decade high territory. This forced an abrupt tightening campaign, contributing to volatility in financial markets and criticism regarding the Fed's forecasting model.

Data limitations: Conventional forecasting methodologies rely on a relatively narrow range of official statistics (GDP growth, consumer price indexes, labor market reports, and trade balances). These measures are important, though they tend to be slow, lagging, and subject to revision. In the digital economy, however, there is now a huge range of alternative datasets available, from card payment transactions and online retail prices to moving data from mobile phones and satellite data on industrial activity, that can provide real-time signals which can identify turning points much sooner than conventional data releases.

Nevertheless, access to such high-frequency datasets is by no means ubiquitous. Many countries, especially emerging and developing economies, have either not developed the data collection capabilities (infrastructure) to generate these datasets, or have legal and privacy barriers to accessing them. Even in advanced economies, central banks are depending on private companies for access to the data, raising issues of cost, reliability, and continuity. Overall, while there are enormous possibilities for using "big data," most national banks are still working with incomplete datasets, so their forecasts are slower and less sensitive to abrupt changes in the economy.

In conclusion, while models and projections based on theory remain important, their blind spots underscore the importance of considering complementarity.

AI and Predictive Algorithms in Economics

Machine learning thrives where traditional econometrics struggles, namely in high-dimensional, noisy, and complex datasets. Several algorithms are particularly promising for central banks: *random forests* and *gradient boosting*, which are effective at uncovering nonlinear relationships; *neural networks*, suited to capturing dynamic interactions including textual or image-based data; and *sparse-group LASSO,* which can integrate mixed-frequency information and select the most relevant predictors from hundreds of candidates.

Recent research illustrates the potential of these methods. Babii, Ghysels, and Striaukas (2020) applied a sparse-group LASSO approach to nowcast U.S. GDP, incorporating not only standard macroeconomic and financial series but also textual data from news articles to capture shifts in sentiment in real time. At horizons of one to two months, their model outperformed the Federal Reserve Bank of New York's widely used dynamic factor model (DFM), and its performance improved further when augmented with financial indicators such as credit spreads, equity prices, and news attention indices. Importantly, the gains were particularly pronounced during turbulent periods such as the 2008 financial crisis and the European debt crises of the early 2010s. These results are not unique. Both the European Central Bank and the Bank of England have conducted experiments with machine learning for inflation forecasting and nowcasting, with resounding conclusions that data-driven models can add to and even outperform the predictive efficacy of standard structural frameworks. This is important evidence that AI automated systems are not just technological innovations, but practical tools used for clear policymaking relevance. Their specific strength lay in their ability to utilize nontraditional unstructured data, which standard econometric frameworks often do not record, or for which they struggle to integrate.

Nevertheless, challenges do remain. Machine learning models are often nontransparent, prone to overfitting, and require robust governance to ensure predictions are robust and explainable. As such, the lesson for central banks is not that AI should displace standard forecasting frameworks, but that AI should be leveraged as a complement, offering a sharper, more timely, and more flexible outlook on the economy. If used ethically, these tools can also reinforce the social objective of central banking by reducing uncertainty for the disproportionately affected lower-income households and improving inclusiveness for economic stability.

Benefits for Central Banks

Incorporating predictive models into the tools used for economic forecasting will bring central banks capabilities that are far beyond simple incremental improvements.

More accurate and timely forecasts. Algorithms based on machine learning can combine high-frequency indicators such as card transactions, shipping costs or online prices to provide a real-time perspective of GDP and inflation. For all intents and purposes, a properly conducted machine learning study has the ability to detect turning points sooner than traditional approaches that look at lagged quarterly data. In the case of inflation forecasts, algorithms leveraged on datasets of wages, energy prices, global supply chains and sentiment indicators have consistently demonstrated an ability to capture unanticipated changes quicker than standard econometric models. Projects at the ECB and the Bank of England have shown pilot models using machine learning outperform traditional forecasting methods over short horizons and particularly in times of high volatility.

Enhanced evaluation of stress-tests and scenario-analysis. One of the most important features of AI-driven models is scale. Central banks often want to assess how the economy would behave after multiple shocks at the same time—higher oil prices, turmoil in financial markets, or disruptions in trade. Traditional scenario analysis requires weeks of model respecification and runs, and there are strenuous efforts involved in analyzing hypothetical scenarios. In comparison, AI systems will be able assess potential thousands of scenarios in a matter of minutes, and will uncover vulnerabilities that an analysis based on a single shock would miss. An AI Model could test the simultaneous effects of tariff increases and shocks to energy prices providing policymakers a full matrix of vulnerabilities which they may not be aware of. In this way, central banks can prepare playbooks ahead of time as part of planning rather than having to sort these issues during a time of crisis.

Improved monitoring of financial stability. AI can also strengthen supervisory review by detecting early signs of fragility in banking and credit markets. For example, machine learning applications to loan level data, payment networks and market sentiment can identify vulnerabilities preceeding situations of systemic risk. The BIS has spotlighted this ability in its research on "suptech" (supervisory technology) as well as research through this process that demonstrates how these approaches support less reactive, more data informed regulation.

Enhancing communication and transparency. Central banks grapple with the problem of communicating policy decisions in a way that effectively manages expectations. Natural language processing (NLP) facilitates systematic scrutiny of central bank speeches, press releases, and market commentary, providing policymakers with useful readings of the extent to which their messages have been received and clarity is required. Such a feedback loop can make forward guidance more precise and credible, driving improved transmission of policy measures to households and firms.

Overall, these developments illustrate that AI capabilities do not simply add a dimension of technical efficiency, but expand the very domain of central banking practice. They facilitate a shift for institutions from reactive to proactive policymaking - thus reinforcing resilience to shocks, protecting financial stability, and ultimately protecting households and businesses from the economic costs of uncertainty.

In this regard, AI-enabled forecasting is not just a technical improvement but a social safety-net: improving the way policy reaches and protects individuals at most risk of adverse effects of crises.

Complementing rather than replacing traditional models

By themselves, AI forecasts are not enough. While AI excels at finding correlations or exploiting nonlinearities, they are not explanations of why the economy works the way it does. The role of structural models such as DSGEs or FPAS are still essential, as they provide the framework for understanding causation, transmission mechanisms, and policy trade-offs. In practice, AI should be regarded as a powerful “second opinion”: if machine learning models predict that inflation rises faster than a core structural forecast indicates, policymakers must re-assess their assumptions. If they do not agree, confidence can be drawn from the degree to which both approaches support a forecast of the same direction. This hybrid approach of using AI as an early warning system while using traditional models to anchor decision-making is increasingly accepted as the most credible route forward.

Risks and Challenges

Although there is power in the promise of AI, there also comes deep institutional and ethical risks that central banks will need to confront. Central banks as institutions that have the responsibility to safeguard economic and financial stability cannot deploy predictive algorithms without addressing underlying risks:

Opacity and accountability. Many of the machine learning models we develop are "black boxes" and if those forecasts inform policy choices that cannot be clearly articulated, there is a challenge to the credibility and accountability. The IMF (2021) notes that explainability is a key component to receptivity and public trust.

Data quality and bias. The "garbage in, garbage out" principle has strength in AI. Biased or incomplete datasets can produce misleading forecasts, thus causing disproportionate harm to disadvantaged groups.

Overfitting and robustness. Often, ML models will capture historical noise rather than historical signals - therefore forecasts may fail in out-of-sample periods. This is especially dangerous in crisis situations when conditions deviate sharply from past experience.

Reliance on technologies. Relying on external vendors, cloud providers, or closed-source algorithms introduces concerns about data security and technological sovereignty, as has been noted (BIS, 2019)

The ethical design should ensure that the AI systems used for predictive technologies promote fairness and transparency, in the spirit of the work pursued to advance by types of initiatives like Algoritmi + Inclusivi ,that Luca Trevisan circulated to marry algorithmic development with the principles of inclusion.

Possibilities related to ethical and reputation risk. AI systems have the potential to replicate hidden bias and equity issues. A forecasting system that is not working adequately could result in a policy that is damaging on multiple levels, including economically and in terms of the central bank's legitimacy.

These issues foreshadow that the conversation should not be if central banks can adopt AI, but how organizations can responsibly do so. Responsible adoption requires careful governance processes, strategic ways of informing stakeholders of future developments (i.e. transparency), and investing in developing internal skills so that AI enables, rather than undermines, monetary policy credibility and independence.

Policy Implications and Next Steps

How should central banks move forward? The most recent reports from BIS and IMF conclude that integrating AI must adhere to specific key principles. First, governance matters: institutions need to set out rules for data quality, privacy, and explainability to promote responsible use of AI. Second, complementarity: AI-based forecasts should be seen as complementary to, not a replacement for, theory-based models. A hybrid approach allows policymakers to harness some of AI's strength in forecasting, while retaining policymakers' ability to understand the model and provide accountability. Third, a phase of experimentation: central banks can start with small pilot projects, like nowcasting GDP, before expanding to full-scale AI adoption. Fourth, collaboration: collaborating with academic researchers, private-sector firms, and colleagues from other central banks is essential to do more and innovate, but to avoid dependence on one vendor. Finally, transparency: talking to the public clearly about how and why AI is being used will ensure that the use of AI generally strengthens, rather than undermines, the legitimacy and credibility of monetary policy. Finally, algorithm governance must be human-centred: transparency, representation within the design teams, and explainability of the model ensure that algorithmic-led decision-making serves society equitably.

Conclusion

Artificial intelligence will not supersede the intellectual underpinnings of central banking, but it may change how policymakers respond to uncertainty. Artificial intelligence provides a new predictive algorithm into the forecasting toolbox, allowing central banks to identify turning points sooner, stress test policies over thousands of scenarios and monitor risks in greater depth than before. The challenge here is not simply technical, but institutional, to ensure AI can be a tool for resilience, inclusion and trust. If used responsibly, AI could not only improve the efficiency and credibility of monetary policy, but also lead to greater equity by protecting households and businesses from the destabilizing effects of crises. In this sense AI for central banking is not just about greater efficiency but a contribution towards the wider mission of AI for Good: using technology to create a more stable and inclusive economy.

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