Beyond the Numbers: The Role of People and Processes in Central Bank Forecasting

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Abstract:

We complement the previous discussions of Bernanke's review of the Bank of England's forecasting activities and highlight directions for future research that are relevant to central banks and the wider forecasting community. Decisions in central banks, such as monetary policy ones, are hardly algorithmic, often influenced by policy and current soft contextual information, introducing challenges in evaluating and specifying forecasts. The use of alternatives to standard econometric models is highlighted in the Bernanke report and other commentaries in this series. These methodological alternatives require both more research, to be validly applied and evaluated, and a cultural shift for those with forecasting responsibilities in central banks. Critically, uncertainty estimates in central bank forecasts are hardly purely model based. How this is done and how to best communicate it to stakeholders and counterparties are fertile areas for research with potentially important implications for market participants. Finally, while academic research often focuses on large, well-funded central banks, there is a significant opportunity to help smaller, less-resourced institutions.

Introduction

The Bernanke review (Bernanke, 2024) of the Bank of England's (BoE) forecasting activities to support monetary policy has proved controversial, not least because of its overly narrow focus and neglect of an established literature from which to evaluate the BoE's performance. Earlier, Stekler (2007) identified many of the issues in the organizational processes, which have been given too little research and practical attention, but are considered in this set of commentaries. In this last contribution, we offer additional views motivated by our research and experience in forecasting in a range of organizations, including central banks. Our objective is to complement the previous discussions and highlight directions for future research that are relevant to central banks and the wider forecasting community.

In the first part of the commentary, we look at the nature of forecasts in central banks and specifically (i) the implications of how these forecasts are used, where non-algorithmic decisions introduce challenges in evaluating and specifying forecasts; (ii) the unavoidability of bias in central bank forecasts and the need for transparent communication; and highlight (iii) the case for multi-model forecasting, that necessitates an organizational and cultural shift in central bank forecasting. In the second part, we focus on the uncertainty of forecasts, and specifically on the need (i) to incorporate soft contextual information in uncertainty estimates; (ii) for more research in methodological alternatives, such as scenario based forecasts, to reach their potential; and (iii) the critical need to effectively communicate uncertainty to policy and decision makers, who may lack a deep understanding of modelling. Finally, we highlight that academic research, for good reasons, has focused on a small sample of central banks that have extensive resources and data sources. This is not representative of the global reality. Likewise, there are diverse forecasting needs within central banks, both large and small, that could benefit from the broader research agenda examined in the forecasting community (Stekler, 2007).

Forecasts, targets, and policy making

A forecast is an input for decision-making under uncertainty, ideally requiring a complete predictive distribution rather than just a point estimate. In applications like inventory management, there is an algorithmic connection that directly translates forecasts into decisions. This is beneficial because it enables the use of optimal loss functions and performance metrics, facilitates automation, and enables decision-makers to explicitly incorporate their risk preferences (Axsäter, 2006). However, for less structured decisions, particularly those taken over at a tactical or strategic horizon, this algorithmic link is often absent. This ambiguity makes it difficult for decision-makers to standardize how they use forecasts or to articulate their risk preferences. This creates two key challenges. First, it complicates the identification of an appropriate loss function for model specification (Granger & Machina, 2006; Kourentzes et al., 2020). Second, when forecasters and users are separate, forecasts must be robust enough to facilitate diverse and often unstated objectives. In these less-structured environments, organizational culture and politics become influential, shaping how forecasts are specified and evaluated (Ord et al., 2017, Chapter 13). This highlights a critical tension: institutions like central banks must reconcile the academic tradition of generating forecasts in isolation with the reality of how these initial forecasts, as embedded in models and software, are actually used to inform complex, non-algorithmic decisions. This is a common challenge in economic and business forecasting, and is evident in our community as well (Giannone et al., 2019).

Central bank forecasts are seldom based solely on quantitative data; they frequently incorporate contextual information and expert judgment from sources, both internal and external. This human element can introduce bias even before the implicit or explicit integration of policy objectives (Fildes & Goodwin, 2007; Bernanke, 2024). Furthermore, as these forecasts are often communicated externally, they can function as a policy tool by making deliberate statements or signals. This distinction is critical: forecasts must be understood not only as objective predictions but also as potentially biased outputs influenced by institutional targets or policy (Blinder et al., 2008). Likewise, limitations of chosen or available modeling approaches, can introduce blind spots and biases, a criticism raised by the Bernanke report (Bernanke, 2024). It is idealistic to assume that forecasts are truly objective. This introduces clear requirements regarding the communication of the initial forecasts: what information is incorporated and how? Is this objective information, expectations, or targets? Users of forecasts may have limited interest in the modelling aspects, but they can gain value from understanding what information and expectations are already incorporated in a forecast and adjust their decisions accordingly. Likewise, this initial forecast can be further revised into a final forecast supporting decisions, or informing external forecasts, where central bank projections are shown to have an influence (Huber, 2015). These further highlight the need for clear communication. In a very different context, both experimental and field data have demonstrated how forecasters mis-weight the information available to them (see e.g. Sroginis et al., 2023): this is a feature we would expect to see in the incorporation of recently released data on the economy. There is far less research on how established practices, cultural norms, and even software choices within an organization affect the quality of forecasts. Addressing this gap is important for central banks and economic forecasting more broadly.

Relying on a single family of models risks introducing systemic biases. A multi-model approach is essential, one that incorporates diverse modeling philosophies and assumptions. These different approaches can fail in distinct ways, revealing limitations in each other's frameworks and prompting forecasters to identify gaps in their own thinking. This diversity can lead to more refined individual models or more robust combined forecasts. Historically, central banks have favored econometric models, influenced by the background of their staff and the expectations of economists. However, the rise of machine learning (ML) and artificial intelligence (AI) offers new capabilities, such as incorporating unstructured data, like text, into forecasts (Zheng et al., 2024). These methods are built on different principles, they often prioritize local approximation over uncovering a true underlying data-generating process, and require a distinct skill set for effective implementation. Two contrasting suggestions are provided by our commentators, agent-based modelling (Kirman, Armstrong and Hynes, 2025) and focused short-term models to deal with rapid shifts (Castle et al., 2025).

Adopting such a multi-model strategy requires not only further research to validate the benefits of these diverse tools but, more importantly, a significant cultural shift within central banks regarding their modeling practices and hiring. This evolution mirrors the one seen in the academic forecasting community, where ML/AI is now a widely accepted and valued tool, as evidenced by the M-competitions (Makridakis et al., 2018, 2022).

Estimation and communication of uncertainty

Forecast errors arise from two primary sources: inherent data randomness and model misspecification. Although it is good practice to communicate forecast uncertainty through an error distribution, standard analytical formulas often simplify this by assuming the model is correct, focusing only on the innovation term (Chatfield, 2013, Chapter 7). In reality, errors from model inadequacies are challenging to quantify and may not follow the same distribution as innovation errors, potentially leading to uncharacteristic outcomes, as illustrated by Castle et al. (2025). This suggests a need to move beyond purely model-based uncertainty estimates, irrespective if these are strictly model-based or a combination of models and empirical estimation methods, and incorporate soft contextual information, which necessarily requires a judgmental element. We are lacking the methodological tools to do this effectively or efficiently, calling for more research.

The Bernanke report calls for the use of scenarios to better communicate the uncertainty in forecasts (Bernanke, 2014). While scenarios can help reveal and quantify uncertainty, they are not without challenges (Goodwin et al., 2019). Scenarios are useful for capturing potential futures not reflected in the model, but their creation and validation lack a well-defined methodology in the forecasting literature. Even more fundamentally, there is no agreed understanding of what a set of scenarios represents (Fildes, 2022). Without such a framework, scenarios risk reinforcing existing narratives or being poorly specified. Given the widespread use of scenarios in long-term and strategic forecasting, this remains a fundamental weakness in Bernanke's recommendations and critical gap in the scenario literature.

Regardless of how uncertainty is estimated, its effective communication to decision-makers remains a hurdle. When a direct, algorithmic connection between forecasts and decisions is absent, uncertainty can be difficult to integrate. Some decision-makers, with limited insight into the modeling process, may find the task daunting and revert to a point forecast, whilst others prefer to incorporate a range to reflect their perceptions of uncertainty, derived in part from that offered to them by the modellers (Du et al., 2011). Therefore, a key area for future research is to investigate effective methods for communicating uncertainty to decision-makers, for instance, those confronting central bank inflation forecasts.

Forecasting in central banks

While the Bank of England and other central banks in developed economies possess extensive forecasting resources, this maturity is not representative of the majority of global institutions. Many central banks (and businesses) face significant limitations in data, software, and computational power. Academic forecasting research, which often focuses on data-rich, technically complex problems, may therefore produce innovations with limited applicability. This calls for complimentary approaches that may be less technically complex, but still scientifically valid, that could have a wider societal impact. This highlights a need for research into resilient solutions that can operate effectively under resource constraints, and in turn, poses the question of whether complex methodologies can degrade robustly.

This challenge is relevant not only to high-level strategic forecasts but also to the multitude of operational forecasts central banks require. By engaging with the wider business forecasting community, central banks can leverage existing expertise, applying it to their operational challenges, with a direct impact on their core mission. Both points underscore a broader research gap regarding the organizational aspects of forecasting, including the impact of software, culture, and process. Central banks, with their high skill base and research orientation, are a particularly amenable subject for investigating these challenges, which are common to economic and business forecasting more generally,

Concluding remarks

Our objective with this commentary was to revisit some of the ideas in the Bernanke report and the other commentaries, and to identify various fruitful directions of research. This series of commentaries was inspired by the review of forecasting at the BoE, to elicit discussion and further research in the journal. In this commentary, we reflect the various BoE review discussion points from the wider perspective of the extensive forecasting literature, to highlight gaps in the research either with a central bank focus or more widely. If anything, the Bernanke review has highlighted that high-stake forecasting, requires us to tackle research questions that are potentially riskier and go beyond our modelling comfort zones. Additional research in the various areas we discussed is very welcome. But to end on a pessimistic note, the various related issues identified by Stekler (2007) have not met with much of a response and the organizational aspects of forecasting still remain a neglected topic (Fildes & Goodwin, 2021). Somewhat more optimistically, our arguments point to a significant research gap when it comes to the organizational aspects of forecasting that is fertile ground for future work.

References

Axsäter, S. (2006). *Inventory control*. Boston, MA: Springer US.

Armstrong, J. S. (2001). *Principles of Forecasting: A Handbook for Researchers and Practitioners*. Springer Science & Business Media.

Bernanke, B. (2024). Forecasting for monetary policy making and communication at the Bank of England: a review. *Bank of England Independent Evaluation Office*, *12*.

Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D. J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature*, *46*(4), 910-945.

Chatfield, C. (2013). *The analysis of time series: theory and practice*. Springer.

Du, N., Budescu, D. V., Shelly, M. K., & Omer, T. C. (2011). The appeal of vague financial forecasts. *Organizational Behavior and Human Decision Processes, 114*, 179-189.

Fildes, R. (2022). "Scenarios, strategic conversations, and forecasting: A commentary on Rowland and Spaniol (2021)." *Futures & Foresight Science* **4**(1): e112.

Fildes, R., & Goodwin, P. (2007). Against your better judgment? How organizations can improve their use of management judgment in forecasting. *Interfaces*, *37*(6), 570-576.

Fildes, R., & Goodwin, P. (2021). Engaging research with practice—An invited editorial. *International Journal of Forecasting*, *37*(3), 1047-1048.

Giannone, D., Kapetanios, G., & McCraken, M. W. (2019). Editorial: Central bank forecasting. *International Journal of Forecasting,* 35(4), 1561-1563.

Goodwin, P., Gönül, M. S., & Önkal, D. (2019). When providing optimistic and pessimistic scenarios can be detrimental to judgmental demand forecasts and production decisions. *European Journal of Operational Research*, *273*(3), 992-1004.

Granger, C. W., & Machina, M. J. (2006). Forecasting and decision theory. *Handbook of Economic Forecasting*, *1*, 81-98.

Hubert, P. (2015). Do central bank forecasts influence private agents? Forecasting performance versus signals. *Journal of Money, Credit and Banking*, *47*(4), 771-789.

Kirman, A., Armstrong, A., & Hynes, W. (2025). Forecasting and policy when "we simply do not know". *International Journal of Forecasting*.

Kourentzes, N., Trapero, J. R., & Barrow, D. K. (2020). Optimising forecasting models for inventory planning. *International Journal of Production Economics*, *225*, 107597.

Ord, K., Fildes, R. & Kourentzes, N. (2017). *Principles of Business Forecasting (2nd ed.)*. Wessex Press Publishing Co.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). The M4 Competition: Results, findings, conclusion and way forward. *International Journal of forecasting*, *34*(4), 802-808.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. *International Journal of Forecasting*, *38*(4), 1346-1364.

Sroginis, A., Fildes, R., & Kourentzes, N. (2023). Use of contextual and model-based information in adjusting promotional forecasts. *European Journal of Operational Research*, *307*(3), 1177-1191.

Zheng, T., Fan, X., Jin, W., & Fang, K. (2024). Words or numbers? Macroeconomic nowcasting with textual and macroeconomic data. *International Journal of Forecasting*, *40*(2), 746-761.