Making Forecasts More Trustworthy

SIMON SPAVOUND AND NIKOLAOS KOURENTZES

PREVIEW *Trustworthy forecasts, the authors argue, have four key components – reliability, stability, intelligibility, and alignment with user needs – and they offer guidance on how organizations can adapt their perspectives and behaviors to achieve more trustworthy forecasts.*

INTRODUCTION

The last decade has seen a dramatic shift in the way organisations produce and consume forecasts.

- The number of forecasts has increased. Decisions are being made at more disaggregated levels, reflecting increasingly customised product and service offerings, as well as a wider reach to more markets. These changes have been accelerated by the COVID-19 pandemic, forcing businesses to investigate multichannel operations. There is also an increased cadence of operational decisions, reflecting greater emphasis on higher-frequency forecasting.
- There has been a conscious shift to develop in-house analytical expertise, either in the form of dedicated teams or in the expansion of demand-planning teams to include data scientists. The latter reflects the maturity of data science and the vast open-source, data-science ecosystem. The impact has expanded the forecasting toolbox to make use of the new expertise and resources.
- There has been growth in in-house computational resources, including cloud services. Advances in machine learning, as demonstrated by recent forecasting competitions, have increased mainstream awareness of the potential for data science to improve forecasting performance – while increasing organisational expectations for improved performance.

BENEFITS AND THREATS

These new forces represent both a benefit and potential threat to organisations. On one hand, forecasting practitioners gain direct access to state-of-the-art algorithms and methods through open-source software. Moreover, the competitive pressure on traditional analytics has pushed commercial software providers to innovate and adopt open-source libraries and ideas. The additional in-house expertise helps organizations customise such tools for a tailored solution.

From a less positive standpoint, we observe a proliferation of poorly conceived solutions, often the result of quick online searches for available libraries. We also observe an ill-considered "horse race" manner of comparing methods, which doesn't adequately take business needs and modeling literacy into account. Too often the selection of methods is based on convenience, rather than using reasonable and reliable benchmarks in evaluation of all available and appropriate methodologies.

Additionally, the methods and implementations can be so complex that they become opaque. Many data scientists are overly focused on easily understood metrics such as forecast accuracy, rather than performance indicators that make business sense. As convincingly reported in this issue's accompanying article by the Target Corp. data- science team forecasts should be directly connected to key performance indicators, rather than the intermediate goals of forecast accuracy.

Aggravating the problem is a lack of ability at the executive level for interpreting analytical outputs. While we believe the onus should be on the producers of forecasts to provide a compelling narrative of their applicability, we believe there is too little focus on considerations such as reliability, stability, and explainability or

Key Points

- The past decade has seen revolutionary changes in how companies are producing and consuming forecasts. The changes reflect the need to offer a wider range of products, to market through multiple channels, and to make operational decisions more frequently.
- The development and maturation of in-house analytical expertise has helped organisations respond to these developments. The forecasting toolbox has been broadened to tap this new expertise; but this is both a benefit and a potential threat to the organisation.
- On one hand, forecasting practitioners gain direct access to state-of-the-art algorithms and methods, often implemented by the authoring teams of the original research. From a less positive standpoint, we observe a proliferation of poorly conceived solutions, frequently the result of a quick online search for available libraries. Poor forecasts not only fail to improve business performance but may leave consumers disillusioned with the forecasting process and so falling back onto simpler methods.
- An emphasis on trustworthiness in forecasting practice is all the more essential. Here, we provide guidance on four areas of focus to achieve trustworthy forecasts: reliability, stability, intelligibility, and alignment with user needs.
- Wider exposure of data-science students to the practical realities of forecasting – including skills in communication with stakeholders and understanding the demands of businesses – would serve to complement the educational emphasis on algorithmic approaches to forecasting.

intelligibility – elements that are the basis of trustworthiness.

There is compelling research that users often adjust forecasts, or outright reject them, in part because of lack of transparency and understanding (Önkal and colleagues, 2012). Moreover, forecast evaluation is still overly focused on point forecasts, ignoring their probabilistic nature, and there is empirical evidence that the performance of inventory decisions relates more closely to forecast bias than accuracy (Kourentzes and colleagues, 2020). Largely ignored is the stability of the model across time, which is a key characteristic for trust (Arrieta and colleagues, 2020).

Forecasting methods have matured to the point that we are able to go beyond convenient solutions and metrics to seek effective support for organisational decisions. Such support puts the user and business needs at the forefront, rather than the conventions of statistical and machine-learning methods. The bottom line is the need to provide trustworthy forecasting systems.

ERROR METRICS AND KPIs

Modellers can be heavily influenced by their technical upbringing, focusing on the mathematical properties of forecasting performance metrics rather than important practical realities. Often overlooked are the specifics of the decisions that the forecasts are designed in the first place to support. Forecasts are shaped not just by models but by contextual information on organisational strategy and internal politics. We do not wish to blur the lines between targets and forecasts, but rather assert that supported decisions do not necessarily seek to maximise forecast accuracy.

Ultimately, decisions derive from the organisation's short and long-term mission and objectives. In for-profit companies, this may be a positive financial outcome and the longevity of the organisation. For nonprofits, this can have a multitude of facets, such as availability of critical resources, such as medicines in poor areas and war zones.

The implicit assumption that accurate forecasts correlate well with these objectives is not always supported by the evidence. For example, Fildes and Kingsman (2011) show that, for material-requirement planning decisions, higher-accuracy forecasts do not always suggest better business outcomes, although there are cases where they do. An inventory management simulation reported that the best-performing forecasts for inventory are sometimes the least accurate considered (Kourentzes and colleagues, 2020). At Target, the data-science team reported that "our partners naturally show more interest in improving operational metrics than forecast accuracy per se. We still find it challenging to draw a correspondence between a delta in an accuracy metric and a delta in operational metrics."

While these are application-specific findings, they demonstrate there is a lack of understanding of how improvements in forecasts can benefit supported decisions (such as how better accuracy translates into inventory savings).

Manary and colleagues (2019) describe the journey of more than a decade at Intel Corp. to improve inventory and forecasting. They lay out the importance of understanding the links connecting inventory policies to the quality of forecasts, as well as gaining trust and buy-in to the policies and solutions.

Interestingly, they identified bias, not accuracy, as the key driver of improved inventory performance (similar to the conclusions of Kourentzes and colleagues, 2020). In over 10 years of work, a small proof of concept developed into an automated inventory planning process, where forecast bias is treated automatically. Supply planners were shown evidence on how the improved forecasting and inventory management enabled gains over their ad hoc approaches. Their understanding of the improvements led to a 99.5% acceptance of the system's prescriptions without further expert intervention (that is, only 0.5% of system forecasts were manually adjusted).

Forecasts within organisations are rarely based solely on a model prediction or even a single organisational function. Rather, processes such as Sales & Operations Planning are used to enrich model-based forecasts with additional information available from across the company, including in supply and production constraints. In the COVID-19 pandemic, many manufacturers opted to reduce the diversity of their product lines to alleviate supply-chain pressures due to the uncertainties, disruptions and restrictions imposed worldwide.

ELEMENTS OF TRUSTWORTHY FORECASTING

We well know that forecasts and plans can be unduly influenced by silo behaviors and other elements of organisational politics. These can undermine trust in the forecasts. A fundamental consideration is that if users do not trust the forecasting process, they are unlikely to follow its recommendations. This results in suboptimal outcomes for organisations, wasted time and effort (and money), and general dissatisfaction with the forecasting process.

We identify four characteristics that promote trust in and use of the forecasts:

- **Reliability** Large errors harm trust (Dietvorst and colleagues, 2015), so checks must be in place to minimize the likelihood of extreme errors. Metrics that measure average forecast errors can hide extremes so that attention must be paid to the distribution of forecast errors (De Kok, 2017; Kourentzes and Athanasopoulos, 2019). A method with a low MAPE that carries risks of outlying errors may be less reliable than one with a higher average error but lower error variance.

  A practical example comes from hierarchical forecasting, where the methods most accurate on average also produce rather volatile errors – extreme, in some cases. In contrast, approaches such as structural or variance scaling perform more consistently over time (Pritularga and colleagues, 2021), even though the metrics show higher errors on average.

- **Stability** Stability over time is another way to reinforce trust in forecasts. Forecasts should not vary wildly from one time period to another, unless there is a fundamental factor or new information that justifies the change. Stable forecasts ease stresses in planning and decision making and avoid the high set-up costs of major changes in production scheduling.

One of the major takeaways from the modeling of temporal hierarchies (Kourentzes and Athanasopoulos, 2019) is that the reconciliation of forecasts based on different time buckets (e.g., weekly, monthly, and yearly) creates "coherency," in that the short-term forecasts cannot fluctuate widely because they are tethered to the longer-term forecasts.

- **Intelligibility** The key elements of a forecast should be explainable if the forecast is to be trusted by its users. Users may show little interest in the algorithmic intricacies of the forecast model but demand to know what information went into the model, as well as the logic of how this information was used. Intelligibility can reduce the incentives for wasteful interventions (e.g., judgmentally adjusting for information already accounted for), and also increase trust in the model (Arrieta and colleagues, 2020).

This does not rule out use of "black box" models, which are often unfairly criticised. Users do not require a detailed understanding of the technicalities of the model, but rather a functional understanding. This requires describing the inputs to the model, how they are transformed into forecasts, and what circumstances could cause the model to break down. Target agrees:

> *Our users really do care about how the forecasts are generated, what the main drivers are, what features are the most important, and by how much. In short, they want the forecasts to be intuitive and explainable because that is how they can relate the forecasts to the operational metrics and objectives that they are ultimately interested in.*

Most of us do not have an engineering understanding of the inner workings of a car, yet are quite confident in the safety of driving the vehicle. Forecasting models should be presented to users in the same way, with an emphasis on the benefits and how they outweigh the potential risks. The responsibility also falls on the software developer and their design of the software interface (Fildes and colleagues, 2020).

Most of us do not have an engineering understanding of the inner workings of a car, yet are quite confident in the safety of driving the vehicle. Forecasting models should be presented to users in the same way, with an emphasis on the benefits and how they outweigh the potential risks.

Target is one company that has chosen to make explainability a criterion for model selection.

> *We have found it more expedient to invest in a framework of models that are more transparent than large-scale, off-the-shelf pure ML or deep-learning models. Our models decompose demand (and forecasts) into a set of constituent submodels and components. The explanatory power offered by this framework as well as the ability to adapt our models to different use cases is critical for our business processes.*

- **Alignment** To be trusted by users, a forecast must align with user objectives. Forecast models should be built and evaluated on the basis of metrics that correlate well with the decision outcome. This may not always be straightforward. For example, sustainability is increasingly becoming a corporate objective, yet it is not obvious how to connect forecasts explicitly to the achievement of this objective. On the other hand, forecasts for inventory management can readily be aligned with appropriate inventory performance indicators.

Trustworthiness is an increasingly important consideration, particularly in applications of artificial intelligence, as evidenced by the 2019 European Commission's report on ethics guidelines for trustworthy AI.
(***https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai***)

Trustworthiness demands that we place human decision makers at centre stage and that models operate in step with them. Sanders and Wood (2021) refer to this collaboration in organizations as the *humachine*.

THE EDUCATION AND TRAINING ELEMENT

University courses can tend towards the theoretical aspects of things at the expense of the practical. The focus of education in data science has been on providing graduates an algorithmic skill set. But this focus is potentially at the expense of problem-structuring skills and business understanding, critical elements in establishing trustworthiness.

Wider exposure of data-science students to the practical realities of forecasting – including skills in communication with stakeholders and understanding the demands of the business world – would serve students well to complement the algorithmic approaches to forecasting. To this end, we would like to see closer interaction between universities and companies in curriculum development and research.

REFERENCES

Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R. & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI, *Information Fusion*, 58, 82-115.

De Kok, S., (2017). The Quest for a Better Forecast Error Metric: Measuring More than the Average Error, *Foresight*, Issue 46 (Summer), 36-45.

Dietvorst, B.J., Simmons, J.P. & Massey, C. (2015). Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err, *Journal of Experimental Psychology: General*, 144(1), 114.

Fildes, R. & Kingsman, B. (2011). Incorporating Demand Uncertainty and Forecast Error in Supply Chain Planning Models, *Journal of the Operational Research Society*, 62(3), 483-500.

Fildes, R., Goodwin, P. & Önkal, D. (2019). Use and Misuse of Information in Supply Chain Forecasting of Promotion Effects, *International Journal of Forecasting*, 35(1), 144-156.

Kourentzes, N. & Athanasopoulos, G. (2019). Cross-temporal Coherent Forecasts for Australian Tourism, *Annals of Tourism Research*, 75, 393-409.

Kourentzes, N., Trapero, J.R. & Barrow, D.K. (2020). Optimising Forecasting Models for Inventory Planning, *International Journal of Production Economics*, 225, 107597.

Makridakis, S., Wheelwright, S.C. & Hyndman, R.J. (2008). *Forecasting Methods and Applications*, John Wiley & Sons.

Manary, M.P., Wieland, B., Willems, S.P. & Kempf, K.G. (2019). Analytics Makes Inventory Planning a Lights-Out Activity at Intel Corporation, INFORMS *Journal on Applied Analytics*, 49 (1), 52-63.

Onkal, D., Gonul, M.S. & Goodwin, P. (2012). Why Should I Trust Your Forecasts?, *Foresight*, Issue 27 (Fall), 5-9.

Pritularga, K.F., Svetunkov, I. & Kourentzes, N. (2021). Stochastic Coherency in Forecast Reconciliation, *International Journal of Production Economics*, 240, 108221.

Sanders, N. & Wood, J. (2021). Combining Humans and Machines in an Emerging Form of Enterprise: The Humachine, *Foresight*, Issue 61 (Q2), 28-35.

Yousefi, M., Faulkenberg, S. & Subramanian, L. (2022). The Demand Forecasting Project at Target: Improving Collaboration and Adoption, *Foresight*, Issue 66 (Q3).

Simon Spavound is a Data-Science Team Lead at Peak, a Decision Intelligence company. His work focuses on solving business problems primarily utilizing forecasting and optimization techniques. He has a PhD in Economics from Lancaster University.

simon.spavound@peak.ai

Nikolaos Kourentzes is a Professor of Predictive Analytics at the Skovde Artificial Intelligence Lab, Sweden. His research interests are in modeling, ways to mitigate uncertainty, and behavioral and organizational aspects of the forecasting process.

nikolaos.kourentzes@his.se

Commentary on "Making Forecasts More Trustworthy"

PAUL GOODWIN, M. SINAN GÖNÜL, AND DILEK ÖNKAL

Forty years ago, two analysts at British Gas, a major utility supplier in the UK, wrote a paper describing their experiences in implementing a complex forecasting method (Taylor and Thomas, 1982). They had designed a process to forecast the daily consumer demand for natural gas based on factors such as the day of the week, the previous day's demand, and the following day's temperature forecast. On most days, it proved to be highly accurate. Yet the operational personnel – the intended users of the model – were unconvinced that it was performing well. The occasional large error lurked in their memories while they tended to forget the model's routine accuracy.

Intended users of a forecast model which proved highly accurate most of the time were unconvinced that it was performing well. The occasional large error loomed large in their memories while they tended to forget the model's routine accuracy.

This case study demonstrates the importance of three of the attributes that Simon Spavound and Nikolaos Kourentzes identify in their insightful article as crucial in determining whether a forecasting method is trusted or not.

- First, the model was not intelligible to its intended users.
- Second, its reliability was not apparent to them.
- Third, the model did not align with their objectives: large errors were expensive, so avoiding these was more important to them than achieving modest reductions in smaller errors.

The British Gas model did at least meet the fourth criterion of stability. But the effects of instability on trust can be seen elsewhere; for example, in reports that U.S. president Jimmy Carter repeatedly complained about the inconsistency of forecasts by his economic advisors. President Carter hinted that he'd be better off using a fortune-teller at the Georgia State Fair (Nordhaus, 1987).

ARE FORECASTS BECOMING MORE OR LESS TRUSTWORTHY?

These many decades later, the evidence provided by Spavound and Kourentzes suggests that trust in forecasting has not improved and, indeed, might even have declined. Algorithm aversion and skepticism have now become major issues (Dietvorst and colleagues, 2015, 2018). Managers in some companies override over 90 per cent of their statistical forecasts (e.g., Fildes and colleagues, 2009). In the media and elsewhere, macroeconomic and political forecasts are regularly attacked and even lampooned (Goodwin, 2017, p.4).

Worse still, trust is often misplaced. In one experiment, participants were prepared to pay for predictions of whether a coin toss would result in heads or tails (Powdthavee and Riyanto, 2015). Soi-disant experts can often convince people, without evidence, that they have special powers of foresight (Armstrong, 1980; Önkal and colleagues, 2017). In some cases, the salience of a single lucky, highly accurate prediction is sufficient to confer credibility on a person's forecasts, despite a general record of inaccuracy (Goodwin, 2017, p.149).

WHAT CAN BE DONE?

So, what can we do to foster trust where it is merited? How can intelligibility, alignment, reliability, and stability be achieved and demonstrated?

Intelligibility is becoming more challenging as increased computing power permits the application of highly complex and opaque forecasting methods. At minimum, forecasters need to make their assumptions transparent and declare the information they are using. But additionally, it is often possible to create a nontechnical account of how the model assumptions and variables are turned into forecasts. As the Target team shows in this issue of *Foresight*, people's trust can be gained by favoring explainable models over black-box methods. The resulting trust can often be more valuable than incremental improvements in accuracy that might emanate from approaches that are incomprehensible to forecast users.

Providing a narrative alongside the forecasts can be helpful as well. Gönül and colleagues (2006) have found that explanations accompanying forecasts can lead to lower subsequent adjustments and a higher acceptance of those predictions. As Spavound and Kourentzes point out, an intuitive understanding of how things work is sufficient for us to trust many technical devices, so why not forecasts?

Alignment means that, in some cases, complexity is not justified anyway. Decisions linked to forecasts don't always require high accuracy, so a simpler and more understandable approach will suffice. A key element of alignment is the perception of goodwill on the part of the forecast provider: a feeling that they share and understand the user's objectives (Gönül and colleagues, 2012).

Alignment implies the need for close collaboration between forecasters and their clients, a point well recognised by the Target team.

Our experience in delivering a large-scale demand-forecasting application with multiple customers and a diverse set of objectives has taught us that active engagement with our stakeholders is the key to achieving enterprise adoption and success. Any misalignment between those who generate forecasts and those who consume them is often the main reason behind hesitancy to adopt new forecasting methods.

Providers of forecasts who act to protect their own interests, such as in herding or politically influenced forecasts, can compromise trust.

Forecasts should be regarded as honest expressions of what is expected to happen in the future – nothing more, nothing less. While they need to be aligned with decisions, they should also be regarded as distinct from decisions. For example, a forecast of the demand for a product is different from a decision on how much stock to hold to achieve a given customer-service level. Conflating the two, which sometimes happens (Fildes and colleagues, 2009), can lead to confusion and an erosion of trust.

Yet even when the distinction is clear, there's often a lack of understanding of the transformation of forecasts into organizational decisions. A set of generated predictions might be highly accurate, but if they don't translate to good decisions and outcomes, the quality of those forecasts is one of the first things to be blamed. Meticulous attempts should be made in organizations to establish and disseminate a clear connection between forecasts and the decisions that depend on them. The Target team show how this can be achieved.

Reliability is often regarded as being synonymous with accuracy measurement. But, as Spavound and Kourentzes indicate, accuracy metrics can hide the occurrence of rare but impactful large errors. Additionally, they can ignore the need to avoid bias. Many decision analysts

The disclosure of the forecast process to forecast users is more likely to engender trust in the reliability of forecasts than an abstruse accuracy metric, which might be out-of-date anyway if underlying conditions have changed.

argue that we should judge the quality of a decision by the process that produced it, not its outcome. A good outcome does not necessarily imply a good decision and vice versa, because decision outcomes can be subject to luck.

The same perspective can be embraced when assessing the reliability of a forecast. Were appropriate and cost-effective data employed? Was there an underlying rationale for the method? Were the needs of the decision maker addressed? Were the underlying assumptions plausible, and did they survive challenges? Was the process free of political interference?

The disclosure of the forecast process to forecast users is more likely to engender trust in the reliability of forecasts than an abstruse accuracy metric, which might be out-of-date anyway if underlying conditions have changed.

Trust based on reliability also requires an acceptance of uncertainty on the part of users. Some factors are inherently unpredictable, so forecast errors are inevitable, but some senior managers, in particular,

Behavioural factors lie at the very core of achieving trust in forecasting. While educational focus has been on developing the algorithmic and analytical knowledge, training to enhance behavioural insights appears to have been largely neglected.

are known to be intolerant of forecasts that miss the mark. While forecasts expressed as prediction intervals do indicate uncertainty, managers may discount them if the intervals are too wide, even when they accurately reflect the true level of uncertainty. It has even been suggested that forecasters should artificially narrow intervals to increase the likelihood that managers will accept that at least some uncertainty is present – though, in the long run, such dishonesty is unlikely to engender trust! Education appears to be the way forward here.

Achieving **stability** can require a careful balancing act from forecasters. A German study found that economic forecasters were unwilling to alter their forecasts even when new information suggested they needed to be changed (Kirchgässner and Müller, 2006). They feared that people would see such changes as a sign of incompetence and their reputation would suffer. Other studies have suggested that people are too eager to make changes (Van den Broeke and colleagues, 2019). Again, transparency of the underlying process is likely to be the answer. The reasons for any changes can be subject to scrutiny and, where they appear to be justified, they are more likely to be trusted.

THE BEHAVIOURAL ELEMENT

All these dimensions point to how behavioural factors lie at the very core of achieving trust in forecasting. As also noted by Spavound and Kourentzes, while educational focus has been on developing the algorithmic and analytical knowledge, training to enhance behavioural insights appears to have been largely neglected.

At precisely the time when human-AI interactions are taking center stage in forecasting and decision making, we need to develop the behavioural forecasting toolbox to achieve trustworthy predictions that translate to winning decisions (Önkal and colleagues, 2019).

In conclusion, Simon Spavound and Nikolaos Kourentzes's article is timely. There is a danger that recent improvements in forecasting methods, particularly those based on algorithms, will not be implemented because they are misunderstood and distrusted by users. By identifying the key attributes underlying trust, their discussion provides a set of valuable indications of how we might avoid this danger.

REFERENCES

Armstrong, J.S. (1980). The Seer-Sucker Theory: The Value of Experts in Forecasting, *Technology Review*, June/July, 16-24.

Dietvorst, B.J., Simmons, J.P. & Massey, C. (2015). Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err, *Journal of Experimental Psychology: General*, 144(1), 114-126.

Dietvorst, B.J., Simmons, J.P. & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them, *Management Science*, 64(3), 1155-1170.

Fildes, R., Goodwin, P., Lawrence, M. & Nikolopoulos, K. (2009). Effective Forecasting and Judgmental Adjustments: An Empirical Evaluation and Strategies for Improvement in Supply-Chain Planning, *International Journal of Forecasting*, 25, 3-23.

Gönül, M.S., Önkal, D. & Goodwin, P. (2012). Why Should I Trust Your Forecasts? *Foresight*, Issue 27, 5-9.

Gönül, M.S., Önkal, D. & Lawrence, M. (2006). The Effects of Structural Characteristics of Explanations on Use of a DSS, *Decision Support Systems*, 42(3), 1481-1493.

Goodwin, P. (2017). *Forewarned: A Sceptic's Guide to Prediction*, London: Biteback Publications.

Kirchgässner, G. & Müller, U.K. (2006). Are Forecasters Reluctant to Revise Their Predictions? Some German Evidence, *Journal of Forecasting*, 25, 401–413.

Nordhaus, W.D. (1987). Forecasting Efficiency: Concepts and Applications, *The Review of Economics and Statistics*, November, 667–674.

Önkal, D., Gönül, M.S., Goodwin, P., Thomson, M. & Öz, E. (2017). Evaluating Expert Advice in Forecasting: Users' Reactions to Presumed vs. Experienced Credibility, *International Journal of Forecasting*, 33, 280-297.

Önkal, D., Gönül, M.S. & DeBaets, S. (2019). Trusting Forecasts, *Futures & Foresight Science*, 1, 3-4, 10 p., e19.

Powdthavee, N. & Riyanto, Y.E. (2015). Would You Pay for Transparently Useless Advice? A Test of Boundaries of Beliefs in the Folly of Predictions, *Review of Economics and Statistics*, 97, 257–272.

Taylor, P.F. & Thomas, M.E. (1982). Short-Term Forecasting: Horses for Courses, *Journal of the Operational Research Society*, 33, 685-694.

Van den Broeke, M., De Baets, S., Vereecke, A., Baecke, P. & Vanderheyden, K. (2019). Judgmental Forecast Adjustments over Different Time Horizons, *Omega*, 87, 34-45.

Paul Goodwin is an Emeritus Professor at the University of Bath, UK, author of numerous books and articles on the use of judgment in forecasting, and *Foresight*'s Editor for Hot New Research. Paul, M. Sinan Gönül, and Dilek Önkal have collaborated on numerous research projects on the subject of achieving trust in the forecasting process. Their 2012 *Foresight* article "Why hould I Trust Your Forecasts?" was one of six awardees to the *Foresight* Hall of Fame for articles printed in the journal through 2017.

p.goodwin@bath.ac.uk

M. Sinan Gönül is an Associate Professor of Business Analytics and a Director of Education at the Newcastle Business School, Northumbria University. His research focuses on judgmental forecasting, judgment & decision-making, decision and forecasting support systems and behavioural operational research/ operations management.

Sinan.Gonul@northumbria.ac.uk

Dilek Önkal is Professor of Business Information Systems & Analytics and Head of the Analytics Subject Group at the Newcastle Business School, Northumbria University. Her research focuses on judgmental forecasting, judgment and decision making, forecasting/decision support systems, risk perception and risk communication with a strong emphasis on multi-disciplinary interactions.

Dilek.Onkal@Northumbria.Ac.Uk