Moving towards probability forecasting

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Abstract

This paper proposes an international collaboration between researchers in academia and policymaking institutions to stimulate and coordinate research on probability forecasting in macroeconomics, developing a toolbox for short-term prediction. The toolbox should include time series models, methods for forecast combination, and techniques for probabilistic forecast evaluation in order to reduce the setup costs and risks to both individual researchers and policymaking organizations. A particular emphasis should be placed on replication studies with the toolbox so that central bankers can be sure that they are utilizing best practice techniques to produce probabilistic forecasts of events of interest.

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Introduction

Macroeconomic forecasts are imperfect. If a forecaster provides information about inflation next month, there is considerable inaccuracy implied. The inaccuracy stems (in part) from imprecise real-time measurements, latent variables, model uncertainty, parameter uncertainty, and the inherently unpredictable nature of the macroeconomy. Nevertheless, most central banks provide little information on forecast imprecision. Furthermore, the probabilities of outcomes that are economically substantive, although not the most likely, receive little attention. Put differently, conventional macroeconomic forecasting neglects the assessment of risk, and the probability of extreme events.

The neglect of formal probabilistic forecasts for macroeconomic decision-making before the Global Financial Crisis (GFC) parallels the experience in another applied statistics field in the late 1990s. In December 1999, a storm called Lothar caused extensive damage across Europe; see MacKenzie (2003). Key meteorological institutes failed to offer timely storm warnings. The incident sparked the research and development of systems for producing probability forecasts. Ex post analysis using modern methods has shown that Lothar was highly likely to miss land. Contemporary forecasters were correct, from the perspective of the most likely outcome. There was, however, a significant probability that the storm would strike land, which the forecasters missed. That is, the state-of-the-art weather forecasting systems in the late 1990s—like those used by most macroeconomic policymakers today—did not generate accurate probabilities for extreme events. Even though the meteorological practitioners worked with (highly) non-linear specifications, insufficient attention was paid to probabilistic forecast verification. Moving beyond Gaussian predictive densities enhanced considerably the probability forecasting performance, without compromising point forecasting accuracy, or the theoretical structure of the models.

The 2007 vintage workhorse macroeconomic policy models had little to say about the probability of extreme events. Even today, hardly any institutions produce forecasts for the probability of a recession, or the probability of deflation. Most policymakers limit their analysis to (near) linear Gaussian specifications, and communicate only the "most likely" scenario to the public. This approach masks quantifiable information of use to policymakers for both the formulation and communication of the policy stance from a risk management perspective.

Related literature

The academic work concerned with macroeconomic probability forecasting can be grouped into two distinct programs. The first concerns methods for probabilistic forecast evaluation; the second focuses on techniques for improving the accuracy of probabilistic forecasts.

Although evaluations of probabilistic forecasts are common in applied statistics fields, forecast evaluation exercises published by central banks and other policymaking institutions restrict attention to point forecasting accuracy. Some recent papers considering probabilistic forecast evaluation include Garratt, Lee, Pesaran and Shin (2003), Adolfson, Andersson, Lindé, Villani and Vredin (2007), Lahiri and Wang (2007), Garratt, Koop, Mise and Vahey (2009), Kryshko, Schorfheide and Sill (2010), Berge and Jorda (2011), Clark (2011), Diks, Panchenko and van Dijk (2011), Galbraith and van Norden (2011, 2012), Gneiting and Ranjan (2011), and Mitchell and Wallis (2011). These papers typically use the forecast density relative to the outturn, or gauge performance in terms of predicting discrete events, such as a recession. In meteorology and other applied statistics fields, it is common to link forecast evaluation explicitly to the relevant economic decision. Berrocal, Raftery, Gneiting and Steed (2010) provide a recent example for a road maintenance problem. Granger and Pesaran (2000) propose applications in economics.

The second program focuses on improving forecast accuracy. Most policymaking macroeconomic models are (approximately) linear Gaussian—with features that are difficult to reconcile with the theory and data; see, for example, the discussion by Robertson, Tallman and Whiteman (2005). A long tradition in macro-econometrics has emphasized the importance of non-linearities in macroeconomics. Morley (2009) provides a review of the literature; and recent examples include Paap, Segers and van Dijk (2009), Hamilton (2011), Arora, Little and McSharry (2012), De Livera, Hyndman and Snyder (2011) and Koop, Léon-González and Strachan (2011). Methods for handling fat and asymmetric tails are common in financial econometrics; see, for example, Patton (2006). Copula models are widely exploited in other applied statistics fields as flexible tools to allow for non-linear dependence and non-Gaussian error distributions. Examples include Clayton (1978), Li (2000), Lambert and Vandenhende (2002), and Danaher and Smith (2011).

A number of recent papers in macroeconomics have proposed using mixtures or forecast density combinations to enhance performance by approximating non-linear and non-Gaussian processes. Key contributions with forecast density combinations include (among others) Geweke and Amisano (2011), Jore, Mitchell and Vahey (2010), Gneiting and Thorarinsdottir (2010), Waggoner and Zha (2010), Billio, Casarin, Ravazzolo and van Dijk (2011), Bjørnland, Gerdrup, Jore, Smith and Thorsrud (2011), and Garratt, Mitchell, Vahey and Wakerly (2011). These papers build on earlier macroeconomic research on forecast combinations by, for example, Hendry and Clements (2004), Wallis (2005), Mitchell and Hall (2005) and Kapetanios, Labhard and Price (2008). Timmermann (2006) provides a review of forecast combination; and Clements and Harvey (2011) discuss combining probabilistic forecasts. Aastveit, Gerdrup, Jore and Thorsrud (2011) consider intra-month probability forecasts, generalizing the more traditional point forecasting approach of, for example, Giannone, Reichlin and Small (2008), Lombadi and Maier (2011) and Kuzin, Marcellino and Schumacher (2011). Faust and Wright (2011) and Kozicki and Tinsley (2012) discuss the scope for survey evidence to improve timely forecasting. Giordani, Kohn and van Dijk (2007) and Maheu and Gordon (2008) provide examples based on mixtures.

Probabilistic forecasting in practice at central banks

Despite the extant body of literature devoted to probability macroeconomic forecasting, only a handful of central banks have pursued the approach, including the Bank of England. Norges Bank has a short-term forecasting system based on probability forecasting; see Bjørnland, Gerdrup, Jore, Smith and Thorsrud (2011). Furthermore, finance ministries, independent fiscal watchdogs and data agencies pay little attention to probabilities (with the UK's Office for Budget Responsibility a notable exception).

Uptake has been slow for three main reasons. First, given the techniques for probability forecasting and evaluation are relatively new to economists, very little exposure occurs at the graduate or undergraduate level. This leaves practitioners to learn unfamiliar techniques on-the-job by replicating papers after they appear in journals. Inefficiencies arise because the methods are computationally burdensome, with the code sometimes idiosyncratic or unobtainable.

Second, with the research frontier of macroeconomic forecasting constantly shifting, it is risky for a policy-oriented organization to invest in the new technology. Recently developed techniques for probability forecasting and evaluation are often based on long runs of US data, and in some cases, performance is less impressive with other datasets.

Third, the existing macroeconomic literature says little about extreme event predictability, despite the recent financial crisis. The default policymakers' modeling framework, grounded on assumptions of linear dependence and Gaussian errors, hinders progress in this regard.

A proposal

These challenges slowing the uptake by central banks and other policymaking institutions could be considerably eased by the existence of a probability forecasting toolbox. Such a toolbox might include macro-econometric models, data, methods for forecast combination and probabilistic forecast evaluation tools suitable for short-term macroeconomic prediction. International collaboration between researchers in academia and central banks could stimulate and coordinate research on probability forecasting around such a toolbox. The toolbox itself could substantially reduce the setup costs and risks faced by both individual researchers and central banks in adopting probability forecasting techniques, not least by greatly facilitating replication analysis.

Conclusion

In this short paper, we have argued that central bankers should switch to probability forecasting. The recent financial crisis has changed the nature of macroeconomic forecasting. It no longer suffices to claim that a forecasting system is adequate if it matches the point forecasting accuracy of a simple autoregressive benchmark. To close the gap between the extant academic literature and policymaking practice, and to foster further research in probability forecasting, requires a bold collaborative step. Our proposal to accelerate research into probability forecasting methods and practice involves pooling knowledge and resources across central banks and academia through the construction of a toolbox for short-term macroeconomic prediction. Such a step would spread the cost and risk of developing the new technology amongst many.

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