Forecasters and Rationality- a comment on Fritsch et al., Forecasting the Brazilian Real and Mexican Peso: Asymmetric loss, forecast rationality and forecaster herding

Abstract

In this commentary stimulated by Fritsch et al. (2014) paper on" Forecasting the Brazilian Real and Mexican Peso" and the implications for forecast rationality, I first survey the literature on forecaster behaviour concluding that in any particular application, organisational factors and psychological factors heavily influence the characteristics of the forecasters' errors. Econometric models can never decompose the error into these potential sources due to the reliance on non-experimental data. An interdisciplinary research strategy of triangulation is needed if we are to improve both our understanding of forecaster behaviour and the value of such forecasts.

Keywords: forecaster behaviour; loss functions; rationality; interdisciplinary research

Introduction

In the paper I comment on here, Fritsch et al. use the example of the Brazilian Real and the Mexican Peso to discuss the interesting and potentially important issues of forecasters' behaviour; in particular they examine the question of whether an implicit loss function can be inferred for these exchange rate forecasters with which their forecast can be viewed as 'rational'. The authors' careful analysis leads to an ambivalent conclusion as to the form of the loss functions apparently adopted by the individual forecasters; for some the function may be symmetric, for others asymmetric. Where their tests lead to rejection of rationality they suggest that this may be due to the assumptions of the test rather than reflecting the reality of their forecasters behaviour. While there are a number of technical issues that could be explored[1], in this note I suggest the lack of a clear resolution to the questions posed by Fritsch and colleagues is an inevitable result of the methodology they have adopted.

The assumption that statistical or econometric models necessarily offer a more appropriate choice when forecasting for any problem situation has never been shared by practising forecasters. Surveys of forecasting practice regularly lead to the conclusion that judgment is at the heart of the forecasting process in many if not most applications (McCarthy, Davis, Golicic, & Mentzer, 2006). However, the early research on judgmental forecasting was focussed on the question of whether judgmental based

[1] Peel (Lancaster) noted in correspondence the paper would benefit for greater clarity on: a. how the overlapping errors in 3 month ahead forecasts have been handled.
b. More on precise dating of forecasts and outcomes. Irregular interval changes due to data collection from the forecasters can change results.
c. The instrument set appears to contain non-stationary variables with unclear implications.

forecasts could outperform statistical model-based forecasts. Hogarth and Makridakis (1981) reached the unequivocal conclusion that quantitative methods outperform judgmental forecasts Even at the time this contrasted with the conclusions coming out of the accounting earnings forecasting literature where analysts forecasts, primarily judgmental, were proving more accurate than time series methods (Armstrong, 1983; Brown, Hagerman, Griffin, & Zmijewski, 1987)). Nor were such organisationally based judgmental forecasts executed in a vacuum – they were often based on a statistical forecast where judgment adjusted (or even overrode) the statistical forecast. Understanding judgmental forecasts and their characteristics became a core research question both for the microeconomic foundations of economics and finance as well as practical concerns focussed on improving business forecasting. In this commentary we briefly review the research evidence on forecaster behaviour across a number of business and economic applications concluding that reliance on a single paradigm to understand the issues (such as rationality, efficiency, herding etc.) is inadequate. What is needed is an interdisciplinary approach that combines methodologies; it is the only research route forward that can answer the important questions as to what influences organizational forecasts and how they might be made more valuable to their users.

Bias and Efficiency

The debate on the relative accuracy of judgmental forecasts quickly became more nuanced beyond forecast comparisons with first the accounting researchers followed by macroeconomists focusing on the question of bias, efficiency and rationality, and the availability of information. Recent examples include Kwag and Shrieves (2006) examining earnings forecasts, stock price forecasts (Aretz, Bartram, & Pope, 2011), macroeconomic forecasts (Dovern & Weisser, 2011) and sports forecasting (Smith & Williams, 2010). Most of these studies have found apparent inefficiencies, adding further confirmation to the earlier research. In one of the less researched areas where judgment is undoubtedly most prevalent, company sales forecasting, both Fildes et al. (2009) and Franses and Legerstee (2009) also found their forecasters to be biased and overly optimistic. In general then we may conclude that forecasters are biased but both the amount of bias and even the direction of bias depends on the organizational context.

With rational agents at the core of important microeconomic models of market efficiency as well as models of the economy, research moved on from the question of bias to the question of the efficiency of the forecasters in their use of information. Assuming the primary goal of the forecaster is to produce the most accurate forecasts achievable, as measured by mean squared error, then a forecaster is said to be efficient with regard to an information set X_{t-1} know at period *(t-1)* if in the regression:

$$Y_t - \widehat{Y}_{t-1}(1) = e_t = \beta_0 + \beta_1 X_{t-1} + \nu_t$$

where $\widehat{Y}_{t-1}(1)$ is the one-period ahead forecast made at period *t-1* for period *t*, $\beta_0=\beta_1=0$ with ν_t independent.. The information set may include past forecasts and past actuals. Crucially, it may include unobservables and also β_1 may be time varying.

The interpretation is straightforward: if $\beta_1 \neq 0$, then knowledge of *X* could be used to improve the forecaster's accuracy.

In *Accounting earnings forecasting* research on this question of efficiency in earnings forecasting has been particularly vigorous with Ramnath, Rock, & Shane (2008) offering a structured bibliography. But the research has not stopped with the question of mean squared error efficiency. It has concerned itself with a variety of interesting and important questions as to why earnings forecasts might be inefficient. The reasons can be split into organisational, institutional and psychological although the boundary between these categories is often unclear

Organisational and institutional reasons for inefficiency include employer characteristics such as firm size, the number of firms the forecaster follows (Clement, Michael B., 1999) and differences in accounting regulations across countries (see Ramnath et al., 2008, Table 5).

Individual forecaster characteristics also prove important determinants of accuracy with optimism an often observed phenomenon. For example, Easterwood and Nutt (1999) examined the effects of positive and negative information on earnings forecasts finding overreaction to positive information, underreaction to negative information and as a consequence, the forecasts are systematically optimistic. Other authors have followed up this question with no conclusive result (see Ramnath, Table 4). Organisational and linked career concerns also affect accuracy (Hong & Kubik, 2003). In addition, analyst forecasts are also affected by such factors as pressure to conform to the prevailing consensus or even Seasonal Affective Disorder (Dolvin, Pyles, & Wu, 2009)). Whether such pressures are psychological factors or the forecaster's reaction to organisational incentives, many forecasters tend to 'herd', that is their released forecast is influenced by the prevailing consensus. Contrarian 'bold' forecasts prove more accurate (Bernhardt, Campello, & Kutsoati, 2006; Clement, M. B. & Tse, 2005).

In addition the accounting literature has concerned itself with the question of how users (in this case investors) respond to the forecasts and investors' preferences for different types of analyst: there is no necessary match between the two.

Economic forecasting also supplies us with examples where again both organisational, institutional and behavioural factors affect accuracy. For example, anti-herding bold forecasts are observed with exchange rate and oil price forecasters, (Pierdzioch, Ruelke, & Stadtmann, 2010; Pierdzioch &

Stadtmann, 2010). Personal anecdote offers a contrasting account of how an oil price forecaster aimed to fall "half way between Esso and Shell". In analyses of individual forecasters, bias is common although inefficiencies where publicly available information is neglected are rarer. In fact as Franses, Kranendonk, & Lanser (2011) point out at least with regard to their Dutch macroeconomic forecasters, the judgments they made tended to remove bias arising from the base line econometric model. In contrast, at the industry level Fildes (1991) showed how macroeconomic forecasts were inefficiently interpreted as to their effects on construction output forecasts, despite the construction forecasts being unbiased. Forecast accuracy is partially explained by the forecaster's ideology as well as their chosen primary technique (Batchelor & Dua, 1990)). But the personal characteristics, in this case the age of the macroeconomic forecasters also affects accuracy: the older forecasters, eager to benefit from a reputational effect led them to make overly bold forecasts with the bold forecasters proved less accurate (Lamont, 2002).

Sales forecasting of detailed SKU-level products is perhaps the most common area of business forecasting activity, applying to suppliers, manufacturers and retailers. Here however there has been less research on forecaster behaviour. Surveys have repeatedly highlighted the role of judgment (Fildes & Goodwin, 2007; McCarthy et al., 2006) but there has been limited examination of the judgmental forecasts themselves. Various studies by Diamantopoulos and Mathews (for example Mathews & Diamantopoulos, 1986, 1989) showed bias in simple statistical forecasting being removed by the judgmental adjustment process and they also argued that accuracy was improved. But the analysis of these forecasts are fraught with difficult statistical issues of magnitude and non-normality. Only recently have researchers returned to the problem (Fildes et al., 2009; Franses & Legerstee, 2009; Franses & Legerstee, 2010; Franses & Legerstee, 2011). To summarise this recent forecasting literature, the judgmental forecasts are biased, inefficient and there is evidence of optimism bias with too many forecasts being overly adjusted positively. It would seem that different forecasters (faced with different products in different countries) enjoy unsurprisingly different levels of forecasting accuracy. There is also an effect on manufacturer forecasting accuracy depending on which retail company is purchasing. The adjustments (and their accuracy) depend in part on the past forecast errors themselves, the baseline statistical forecast as well as external events.

Forecaster's loss functions – the key research issues

For want of anything better economists have committed themselves to the notion that forecasts and forecasters are rational, that is to say unbiased and efficient. While some of the studies of aggregate forecaster behaviour in earnings forecasting and economic forecasting have suggested rationality, micro studies of individual forecasters and many consensus forecasts have fallen at these hurdles. How then to resurrect rationality? While the variety of loss functions that may apply in different forecasting situations has long been recognized (Granger, 1969) the attempts to identify the loss functions of forecasters are more recent: for example, in the earnings literature Clatworth et al. (2012), in economic forecasting (Christodoulakis & Mamatzakis, 2008; Elliott, Timmermann, & Komunjer, 2008; Sinclair, Joutz, & Stekler, 2010) and in government revenue forecasting Krol (2013). Fritsche et al. (this issue) consider the case of exchange rate forecasters in the emerging markets of the Brazilian Real and the Mexican Peso, their objective being to identify the likely form of the asymmetric loss and any deviations from rationality. Unsurprisingly given the flexibility provided by a wide range of alternative loss functions, this strand of research has claimed to rehabilitate the efficiency and rationality of individual forecasters.. But even within this framework the model does not always hold (Capistran & Timmermann, 2009) due to a shift (for many of the forecasters) over time in the sign of the bias.

A laboratory experiment of sales forecasting Lawrence (Lawrence & O'Connor, 2005) has also provided evidence to support the notion of asymmetric loss. However, survey evidence Fildes and Goodwin (2007) showed accuracy (measured by MAPE, almost symmetric ove plausible ranges) as the primary objective of a large group of industry forecasters. Other objectives also emerge in discussion with forecasters, including the need for smoothing and transparency.

In non-experimental data there is an obvious confounding between the rationality of the forecasts and the imputed loss function, that is to say forecasters can be regarded as irrational with one loss function and rational as evaluated with another. Even if rationality is assumed according to some unobserved loss function, the aim being to identify the loss function, there remain problems of identification (Lieli & Stinchcombe, 2013). The study by Fritsche et al. (this issue) adds further evidence on the question of individual forecaster's loss functions, concluding that even allowing for general asymmetric loss some forecasters are still apparently irrational.

Conclusions

Fritsche et al.'s conclusion that "forecast accuracy is not the only argument in forecasters loss functions", from the literature described here, is clearly correct in many application areas. But why would we expect it to be? – a forecaster has to make a living and may be rewarded by forecast users from a variety of motives. The final question I therefore I wish to raise here , stimulated by Fritsche al.'s study of exchange rates, is whether their chosen research strategy of examining the ex post realisations of a forecasting process is sufficiently rich to lead to an understanding of the drivers behind individual forecasting accuracy. We know from the literature cited that many forecasters are biased, inefficient (in a MSE sense), herd (or don't), seek reputational effects (or don't), are motivated towards accuracy (or not) and are affected by all the various psychological ailments that may lead to forecast error. We have less knowledge of the forecaster's (usually implicit) predictive density function which lies behind the point prediction. What are the important research questions that remain?

An individual forecaster's loss function cannot be identified by non-experimental data on point predictions alone. What is needed is a research strategy of methodological triangulation whereby field data, survey and interview are combined, with further insights gained from behavioural experiments. The questions that need to be addressed do not stop with the identification of a loss function but the circumstances which engender it. And more particularly, how the biases and inefficiencies can be removed as far as the forecast users are concerned as there is potentially a serious mismatch between the users' objectives and the forecasters'. The user does not want a forecast 'tainted' by the adoption of an unknown loss function. If improvements in the decision being faced are to be made, they need to be made first in the forecasts and separately in the conditional decisions. To make this point concrete in the context of sales forecasting, can software be designed to ensure that information is used efficiently by a company's forecasters and the various organisational biases mitigated against so that the final forecast is as accurate as possible (given the company's metrics)? Here the aim must be to support the forecaster in producing a well-calibrated predictive density so that users facing decisions incurring different losses can decide for themselves. As yet little or no progress has been made on this question, either through research or in practice (where prediction intervals are rarely meaningful or monitored). Too much of the research carried out uses only one tool rather than an interdisciplinary approach to answering the range of interesting questions, both academic and practical as to how to improve the organisational effectiveness of forecasters.

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