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The effect of price volatility on judgmental forecasts: The correlated response model

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ABSTRACT

Traders often employ judgmental methods when making financial forecasts. To characterize judgmental forecasts from graphically-presented time series, I propose the correlated response model, according to which the properties of judgmental forecasts are correlated with those of the forecasted series. In two experiments, participants were presented with graphs depicting synthetic price series. In Experiment 1, participants were asked to make point forecasts for different time horizons. Participants could control the graphs' time scales. In Experiment 2, participants made multi-period forecasts, and could apply moving average filters to the graphs. The dispersion of point forecasts between participants (the standard deviation of participants' point forecasts) and the variability of individual participant's multi-period forecasts (local steepness and oscillation) were extracted. Both forecast measures were found to be significantly correlated with variability measures of the original, scaled, and smoothed data graphs. Thus, the results supported the correlated response model and provided insights into the forecasting process.

1. Introduction

A high percentage of market participants base their trades on methods which involve extrapolation and pattern recognition of graphically presented financial time series (Batchelor, 2013; Batchelor & Kwan, 2007; Cheung & Chinn, 2001; Taylor & Allen, 1992). Furthermore, it has been found that the majority of FX dealers (Gehrig & Menkhoff, 2006) and fund managers (Menkhoff, 2010) incorporate technical analysis techniques in their decision-making processes. Nevertheless, the dependence of forecasts from graphically-displayed price series on the properties of the data series has not been studied within Finance and has been understudied within Judgmental Forecasting. In particular, there has not been any exploration of the way in which properties of data graphs affect forecast dispersion (the extent to which forecasters disagree about their forecasts) and forecast variability (the local steepness and oscillation of individual forecaster's multi-period forecasts).

This paper aims at understanding the way in which properties of graphically-presented time series affect forecast variability and dispersion. I suggest that the variability of the given time series is correlated with the forecast dispersion of point forecasts and the variability of multi-period forecasts. Moreover, this effect is robust across different time series, forecast horizons or multi-period forecast densities, and when the forecasters are given the option to scale or smooth the graphs. I provide a theoretical justification for this relationship by proposing the correlated response model, described in Section 1.1. The experimental hypotheses are described in Section 1.2.

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1.1. The correlated response model: background and definition

A large body of research about the way in which people produce forecasts from graphically presented time series has accumulated over the past twenty years. Harvey (1995) showed that, when making multi-period forecasts from graphically-presented time series, people tend to imitate the noise component of the time series. This tendency resulted in a correlation between the noise level of the forecasts and the noise level of the data. Bolger and Harvey (1993) hypothesized that people imitated the noise in order to make their forecasts representative of the data series. Furthermore, Harvey, Ewart, and West (1997) showed that participants had a strong tendency to imitate the noise component of the data. In one of their experiments, the following instructions were given (p. 126): "Put six crosses on the graph to show us your forecasts. Obviously you cannot be certain where these future points will be, but try to ensure that your forecasts show the *most likely* positions for them. For example, if you feel that a particular point could lie within a range of values, put your cross in the centre of that range if you feel that this is the most likely position for the true point within the range. Your aim is to maximize the probability that your forecasts will be correct". Nevertheless, participants in their experiment imitated the noise of the data series.

Lawrence and Makridakis (1989) showed that, though people tend to damp trends, judgmental forecasts correspond to the slope of the given data. Similar results were obtained in other studies (e.g., that of Bolger & Harvey, 1993). A comprehensive survey of the influence of data characteristics on forecasts was provided by Lawrence, Goodwin, O'Connor, and Önkal (2006).

The topic of forecast dispersion has not been studied much in judgmental forecasting. However, Reimers and Harvey (2011) examined the effect of random noise on judgmental forecasts and mentioned that their experiment "shows that the participants were more variable in their responses when the noise was higher" (see Reimers & Harvey, 2011, p. 1202). The same result was found in their second experiment. Similar relationships between data variability and forecast dispersion were observed in the case of inflation forecasts by Cukierman and Wachtel (1979, 1982). This may be because noisy data are characterized by high levels of variability and uncertainty, and are therefore likely to enable the expression of individual differences more than data with low variability levels. Indeed, in a different context Caspi and Moffitt (1993) suggested that "individual differences are most likely to be accentuated by unpredictability, when there is a press to behave but no information about how to behave adaptively. Such transition situations are revealing because during these periods [...] individuals must summon their resources". Drawing on this work, Yang (2012) contended that "individual differences are accentuated when individuals face ambiguous and uncertain events with insufficient information to allow adaptive behaviour". As highly variable data emphasize individual differences more than data that are characterized by low variability, they are, in particular, more likely to highlight individual differences in forecasting. However, the latter is expected to result in larger group forecast dispersion. Thus, differences in the expression of individual characteristics in forecasting may explain the relationship between the variability of the given data and forecast dispersion. This explanation is in line with the work of Cukierman and Wachtel (1979), who suggested that differences in the interpretation of volatile data affect forecast dispersion.

Each of the experimental forecasting papers mentioned above examined a highly specialized aspect of forecasting, and, thus, contributed to our understanding of forecast biases and errors. However, their results have not been united into a single model. In addition to identifying biases, these papers show that, to different levels of accuracy, judgmental forecasts from graphically presented series preserve properties of the given data series. A possible explanation for this preservation may be that imitation is one of the most powerful human learning processes (Bandura & Barab, 1971). In other contexts, it has been shown that people have an innate tendency to imitate stimuli (Heyes, 2011).

Uniting the results of the experimental papers mentioned above and generalizing them further, I suggest the correlated response model, formulated below.

The correlated response model. In judgmental forecasting tasks, which involve forecasts from graphically-presented time series, people's responses are correlated with the properties of the given series. In particular:

1. The trend of the data series and the trend of the forecast are positively correlated (Bolger & Harvey, 1993; Lawrence & Makridakis, 1989).
2. The variability of multi-period forecasts and that of the data series are positively correlated (Bolger & Harvey, 1993; Harvey, 1995; Harvey et al., 1997).
3. The forecast dispersion of single point forecasts is correlated with the variability of the data (Reimers & Harvey, 2011).

The main measure of forecast dispersion of single point forecasts in this study is the standard deviation of the point forecasts made by independent forecasters (though two other measures of forecast dispersion are also examined, as is described in Section 2.2.1). Two main data variability measures are used: local steepness and oscillation. The local steepness of a graph is defined as the average of the absolute value of the gradients of the graph. The graph's oscillation is defined as the difference between the maximum and minimum values of the graph over a given interval (Trench, 2002).

As this paper aims to obtain an understanding of the ways in which properties of graphically-presented time series affect forecast variability measures, I concentrate on parts 2 and 3 of the correlated response model.

1.2. Hypotheses

The tasks in the experimental studies described in Section 1.1 were not designed to simulate financial situations. For instance, Reimers and Harvey's (2011) experimental tasks were in the contexts of sales (Experiment 1) and profit (Experiments 2 and 3) forecasts. In addition,