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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, only 50 data points were presented in each time series to the participants whereas financial data are abundant and complex. Furthermore, both moving average filters and scaling are offered commonly as options in financial data analysis programs. For instance, Yahoo! Finance (http://finance.yahoo.com/) enables users to choose the time scale on which data are to be presented and which technical indicators are to be displayed including moving window averages. Moving window averaging filters are applied to smooth graphs. Investors and traders use these options frequently (Glezakos & Mylonas, 2003). However, the experimental settings used by Reimers and Harvey (2011) did not allow participants either to change the scale of the data presented or to smooth it. Finally, market participants and trading tasks are heterogeneous (Müller et al., 1993). In particular, forecasting tasks may involve different trading horizons and multi-period forecast densities.

I suggest that the correlated response model holds in situations which simulate financial situations, in addition to the scenarios studied previously. I conjecture that when people are asked to make forecasts from graphically presented price series, the dispersion and variability of the forecasts are correlated with the variability of the data series. Thus, I suggest the following hypotheses:

$H_1$: Point forecast dispersion is positively correlated with the local steepness and the oscillation of the data graphs.

$H_2$: The local steepness and the oscillation of multi-period forecasts are positively correlated with the corresponding variability measures of the data graphs.

Experiment 1 tests Hypothesis $H_1$. In particular, I examine its robustness across a wide range of data series and forecast horizons, and also when participants are given the option of scaling the provided data. Experiment 2 then tests Hypothesis $H_2$. I investigate its robustness across a wide range of data series and forecast densities, and also when participants are given the option of applying moving average filters on the series presented.

Experiments 1 and 2 are described in Sections 2 and 3, respectively. The general discussion is presented in Section 4.

## 2. Experiment 1

In Experiment 1, participants were presented with sequences of graphs representing price series, the time interval of which they could control using a slider. Similar scaling options are available in financial data analysis programs. Participants were then asked to choose the time interval that they considered the most appropriate for making financial forecasts and decisions, and to make such forecasts and decisions based on the time-scaled graph. Two variables were manipulated: the variability of the original data graphs and the forecast horizon required. Fig. 1 depicts the task window of Experiment 1.

### 2.1. Method

#### 2.1.1. Participants

Thirty-four people (15 men and 19 women), with an average age of 23.29 years, acted as participants. Participants' fees were determined based on their decisions: they were each paid a flat fee of £3.00, but received a further £1.00 if their financial decisions were more than 65% correct. Correctness was determined by participant's performance with respect to the graphs generated. For instance, if the prices on the required forecast day were more than 5% lower than those on day 200, a 'buy' decision was considered correct and both 'sell' and 'hold' decisions were considered wrong.

#### 2.1.2. Stimulus materials

The time series presented to the participants were fractional Brownian motions (fBm). Many researchers consider fractal graphs to be adequate for modeling price series, as the probabilities they attribute to financial crises are more realistic than those produced by the random walk model (In & Kim, 2006; Malavoglia, Gaio, Júnior, & Lima, 2012; Mandelbrot & Hudson, 2004; Mihajlovsky, 2013; Panas & Ninni, 2010; Parthasarathy, 2013; Sun, Rachev, & Fabozzi, 2007). This is due to the 'fat tails' of many fBm series. Fat tails assign higher probabilities to rare events than those attributed by the normal distribution (Mandelbrot & Hudson, 2004).

Fractional Brownian motions depend on a constant termed the Hurst exponent ($H$). The range of the Hurst exponent of time series is [0,1], where a value of $H = 0.5$ corresponds to the random walk model (Peitgen & Saupe, 1988). In this sense, the fractal model can be considered a generalization of the random walk model. However, it has been shown that many stocks have a Hurst exponent in the interval [0.3,0.7] (Sang, Ma, & Wang, 2001).

Examples of fBm series are presented in Fig. 2, which shows that time series with low Hurst exponent values look noisier and more volatile than those with high Hurst exponents. Indeed, the Hurst exponent is negatively correlated with variability measures of the series, including the local steepness, oscillation, and standard deviation (provided that the series were generated by the same algorithm). Gilden, Schmuckler, and Clayton (1993) and Kumar, Zhou, and Glaser (1993) showed that people are highly sensitive to the Hurst exponent of fBm graphs.

In line with the results of Sang et al. (2001), stimulus graphs comprised five sets of three time series with Hurst exponents of $H = 0.3, 0.5$, and 0.7. Time series were produced using the spectral method described by Saupe (Peitgen & Saupe, 1988), with all series including 62 831 ($\sim 1000 \cdot 2\pi$) points. This large number of points was chosen so as to enable scaling and an examination of the forecast quality. However, participants were not presented with all data points. The series were presented to the participants as asset price graphs, with a constant added to ensure that they were positive. They were also multiplied by 100 in order to increase the measurement precision by encouraging participants to make forecasts using more than one significant digit.

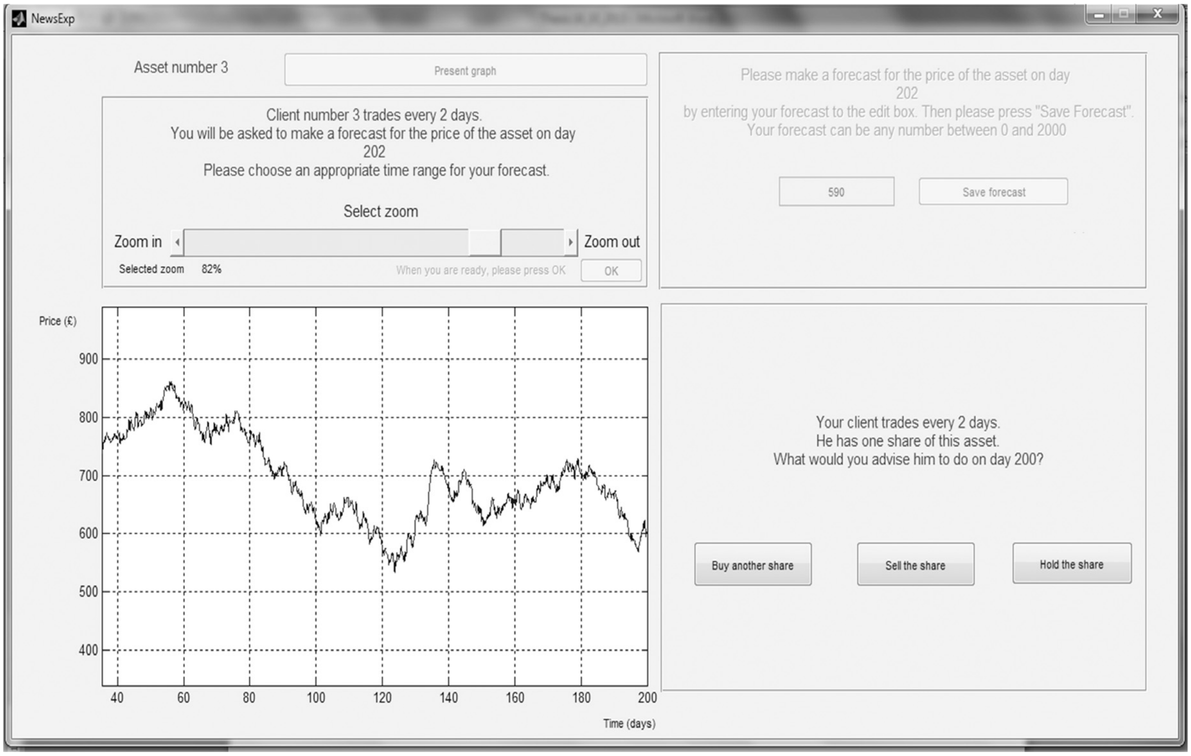


**Fig. 1.** The task window of Experiment 1.

*2.1.3. Stimulus presentation and control*

Stimulus graphs were presented using a Matlab program that enabled the participants to scale the data along the time axis, make forecasts for a specified horizon, and express their financial decisions (see Fig. 1). Examples of scaled fBm graphs are presented in Fig. 2.

Time scaling was accomplished using a slider. At the beginning of each trial, each graph was presented on the time interval [100, 200]. The range of the scaling slider varied from a time interval of four days at the maximum zoom of the slider (presenting price data from days 196 to 200) to 200 days at the minimum zoom (presenting price data from days 0 to 200). Thus, participants could scale the graphs by a factor of 50 (i.e., 200/4).

Participants made single point forecasts by entering numbers into text boxes. The forecast horizon was set to 2, 15, or 100 days, making the factor by which horizons varied (i.e., 100/2) identical to that by which scaling could vary (i.e., 200/4).

Participants then made a financial decision to buy another share of the asset being presented, sell their share, or do neither. On each trial, they could adjust the time interval shown on the graph until they clicked the button "When you are ready, please press OK". They could then edit their forecasts until they clicked the button "Save forecast".

*2.1.4. Design*

Each participant was presented with 48 graphs: three familiarization graphs and 45 experimental graphs. Only the experimental graphs were included in the analysis. Each graph required three responses: first, the choice of time interval; second, a forecast of the asset's future price; and third, a financial decision.

Each participant saw all 15 generated graphs. Each graph was presented three times in different contexts that varied depending on the required forecast horizon (2, 15, and 100 days). The orders of the graphs and the required forecast horizons were chosen randomly. This combination produced a three (forecast horizons) by three (Hurst exponent values) by five (instances of time series with the same Hurst exponent values) within-participants design.

*2.1.5. Procedure*

Participants were instructed to assume that the experiment day was day 200, and to read the following instructions:

> "In the following experiment, you are asked to imagine that you are a financial analyst. You have 45 clients. Each of your clients has one share of a single asset. Clients differ in their trading frequency: some clients trade every two days, some trade every 15 days, and some every 100 days. Your aim should be to increase the total value of their portfolios as your fees will depend on your performance".
>
> "In order to make your decisions, you will be presented with the price graphs of each of these assets. You will be able to control the time range of each graph by changing its zoom".

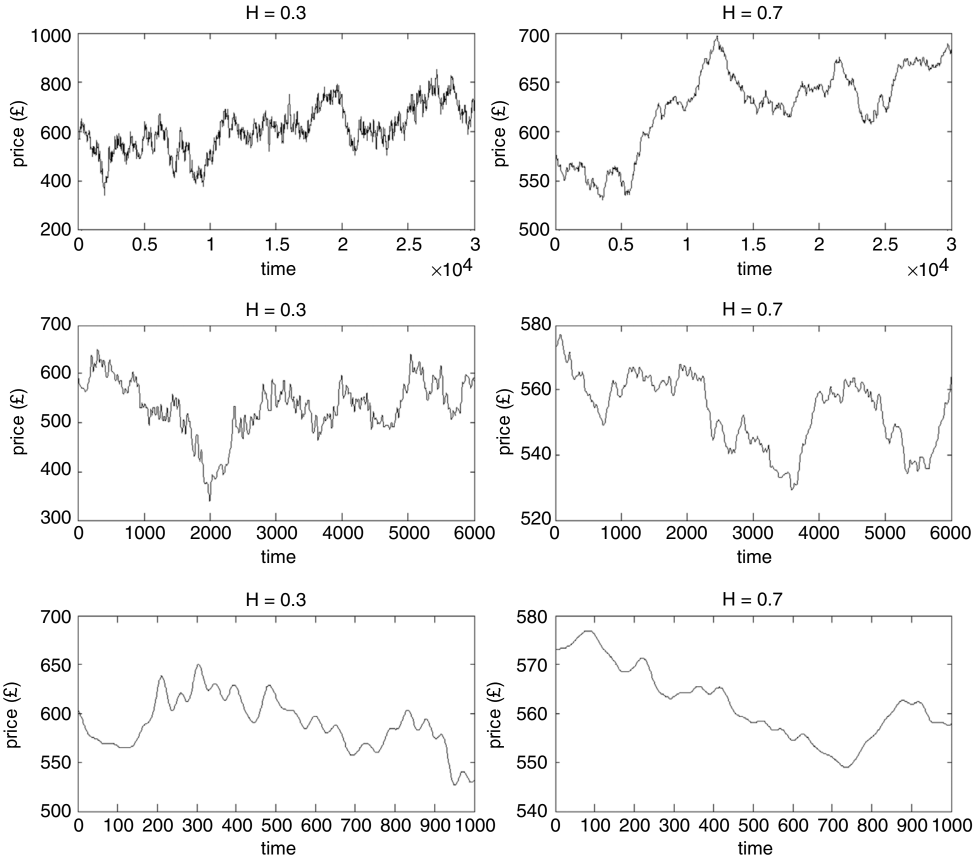


**Fig. 2.** Examples of fBm series with $H = 0.3$ (left panels) and $H = 0.7$ (right panels). The scales of the graphs are different. The data presented refer to 30,000 s (first row), 6000 s (second row) and 1000 s (third row).

"For each asset you will be asked to:

1. Notice the trading frequency of your client and the day you will be asked to make financial forecast for. Look at the price graph of the asset carefully.
2. Choose for each graph a time range which you consider the most appropriate for the purpose of making a financial forecast.
3. Write your forecast for the price of the asset on the required day.
4. Advise to your clients whether to buy another share of the asset, sell their share, or hold it".

Participants could choose the time range of the data graphs by dragging a slider. A forecast was made by entering a number into a text box, and clients could be advised whether to buy, sell, or hold their shares by clicking one of three buttons. All tasks had to be completed before a participant could continue on to the next graph.

## 2.2. Results

I excluded from the analysis any participants whose mean choices of the time scaling factor were more than three standard deviations greater than that of the average of the rest of the group, as well as any whose forecasts differed from the mean of the group by more than two standard deviations. This reduced the sample from 34 to 30 participants, leaving a total of 1350 graphs for analysis.

The variables of primary interest were the dispersion of participants' forecasts and the local steepness and oscillation of the original graphs. In addition, the chosen time scaling factor and the local steepness and oscillation of the scaled graphs were extracted in order to assess both the extent to which participants used the scaling option and the effect of the scaling on the graphs.

### 2.2.1. Forecast dispersion

Participants were presented with five different graphs (instances) for each combination of the Hurst exponent value and forecast horizon. This was taken into account when calculating the forecast dispersion by incorporating different reference levels.

Denote the Hurst exponents of the presented graphs by $H = [0.3, 0.5, 0.7]$, the graph set labels (all graphs in each set had the same Hurst exponent value) by $Instance = [1, 2, 3, 4, 5]$, and the required forecast horizons by $Horizon = [2, 15, 100]$. $F_{i,j,k,l}$ denotes participant $i$'s forecast in the condition in which the Hurst exponent of the graph was $H_j$, the graph was chosen from set $Instance_k$ and the participant was asked to make a forecast for horizon $Horizon_l$. The ranges of these indices are: $i = 1, \ldots, 30$, $j = 1, 2, 3, k = 1, \ldots, 5$, and $l = 1, 2, 3$.

**Table 1**
The standard deviations of the measures $D1$ $D2$ and $D3$, and the length of a 95% prediction interval of a linear regression in each of the experimental conditions ($PI$).

| Measure | Forecast horizon | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2 days | | | 15 days | | | 100 days | | |
| | Hurst exponent | | | | | | | | |
| | 0.3 | 0.5 | 0.7 | 0.3 | 0.5 | 0.7 | 0.3 | 0.5 | 0.7 |
| $std(D1)$ | 38.10 | 42.91 | 39.56 | 65.22 | 45.55 | 36.75 | 133.25 | 83.72 | 130.84 |
| $std(D2)$ | 174.46 | 134.67 | 122.97 | 194.48 | 164.44 | 155.69 | 221.84 | 156.64 | 179.36 |
| $std(D3)$ | 212.67 | 185.18 | 175.86 | 193.23 | 164.66 | 154.23 | 225.14 | 161.85 | 181.13 |
| $2 \cdot 1.96 \cdot std(D1)$ | 149.35 | 168.21 | 155.08 | 255.66 | 178.56 | 144.06 | 522.34 | 328.18 | 512.89 |
| $PI$ | 49.53 | 24.97 | 17.07 | 49.54 | 24.97 | 17.07 | 49.57 | 24.99 | 17.09 |

Note: The standard deviation of $D1$, multiplied by the factor $2 \cdot 1.96$, is presented to allow a comparison of $PI$ to participants' forecast dispersion.

**Table 2**
Correlations between forecast dispersion measures and the local steepness and oscillation of graphs.

| Forecast dispersion measure | Original graphs | | Time-scaled graphs | |
|---|---|---|---|---|
| | Local steepness | Oscillation | Local steepness | Oscillation |
| $FD1$ | $r = 0.12$<br>$p < 0.01$ | $r = 0.22$<br>$p < 0.01$ | $r = 0.29$<br>$p < 0.01$ | $r = 0.44$<br>$p < 0.01$ |
| $FD2$ | $r = 0.13$<br>$p < 0.01$ | $r = 0.23$<br>$p < 0.001$ | $r = 0.31$<br>$p < 0.01$ | $r = 0.45$<br>$p < 0.01$ |
| $FD3$ | $r = 0.17$<br>$p < 0.01$ | $r = 0.15$<br>$p < 0.01$ | $r = 0.34$<br>$p < 0.01$ | $r = 0.46$<br>$p < 0.01$ |

Denote the last point of the data series with $H = H_j$ from set $k$ which participants were presented with (the value of the series on day 200) by $SeriesValue\ onDay200_{j,k}$, and the value of the simulated series on the required forecast day by $SeriesValueOnForecastDay_{j,k,l}$. When an index is omitted, the measure is averaged over the corresponding variable. The following variables were extracted:

1. $D1_{i,j,k,l} = F_{i,j,k,l} - F_{j,k,l}$.$D1$ was used to calculate the forecast dispersion with respect to the mean of the forecasts.
2. $D2_{i,j,k,l} = F_{i,j,k,l} - SeriesValueonDay200_{j,k}$.$D2$ was used to calculate the forecast dispersion with respect to the current price of each asset.
3. $D3_{i,j,k,l} = F_{i,j,k,l} - SeriesValueOnForecastDay_{j,k,l}$.$D3$ was used to calculate participants' forecast errors with respect to the time series produced.

Direct forecast dispersion measures are given by the standard deviations of $D1, D2,$ and $D3$. The standard deviation of each of these measures in each of the experimental conditions is given in Table 1. As the table shows, the standard deviation of $D1$ decreased as the Hurst exponent increased for a forecast horizon of 15 days. Similar patterns were found for $D2$ and $D3$ at forecast horizons of two and 15 days.

When examining Hypothesis $H_1$, $FD1 = |D1|$, $FD2 = |D2|$ and $FD3 = |D3|$ served as forecast dispersion measures. In addition, the local steepness and oscillation of the original graphs (before scaling) were calculated. I measured the perceived local steepness of a scaled time series by extracting the average of the absolute value of the gradient at each point, then multiplying this value by the ratio of the observed time interval and the numbers of pixels along the time axes of the graph (600) (the local steepness measures for the data series after participants' scaling were calculated similarly). The oscillation of each graph was the difference between the graph's minimum and maximum.

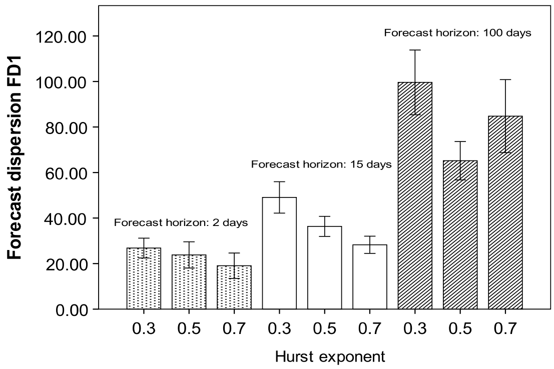


**Fig. 3.** Forecast dispersion measure $FD1$ against the Hurst exponent.

The correlations between $FD1$, $FD2$ and $FD3$ and the local steepness and oscillation of the original and scaled graphs were significant. This supports Hypothesis $H_1$. The correlations are summarized in Table 2. Fig. 3 depicts the means of $FD1_{j,k} = \left|D1_{j,k}\right|$ for the different experimental conditions.

In addition, I carried out a three-way repeated measures ANOVA for each of the dispersion measures, using the variables horizon, Hurst exponent, and 'instance' as within-participant variables. I only report the results of the analysis of $FD1$ here as those for $FD2$ and $FD3$ were similar.

For $FD1$, the sphericity assumption was violated for all variables except for the Hurst exponent and the 'instance'. The analysis revealed that $FD1$ was larger when the Hurst exponent was smaller ($F(2, 58) = 10.32; p < 0.001$; partial $\eta^2 = 0.26$), supporting Hypothesis $H_1$ (the Hurst exponent is correlated negatively with variability measures). Likewise, $FD1$ was larger when the forecast horizon was longer ($F(1.39, 40.42) = 84.67; p < 0.001$;

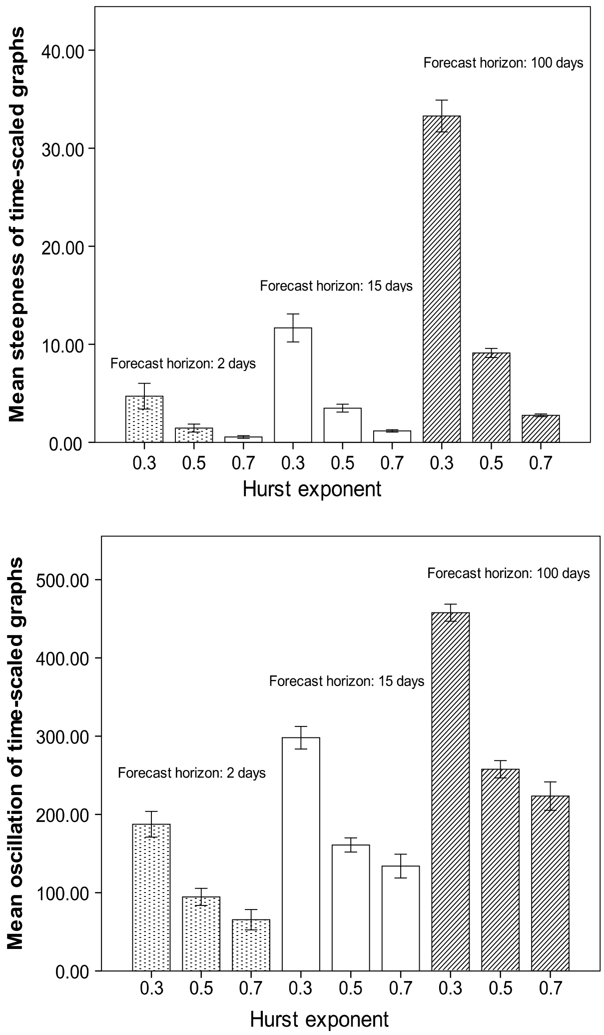


**Fig. 4.** Mean local steepness (upper panel) and oscillation (lower panel) of time-scaled graphs in Experiment 1 against the Hurst exponents of the data graphs.

partial $\eta^2 = 0.75$). There was also a significant effect of 'instance' on the forecast dispersion, indicating that participants reacted to graph characteristics other than the Hurst exponent as well ($F(4, 116) = 16.91$; $p < 0.001$; partial $\eta^2 = 0.37$).

All possible interactions between these variables were significant, with $F > 5.44$($p \leq 0.002$; partial $\eta^2 > 0.16$). I report the results of the interactions and the corresponding simple tests in Table A.1 in the Appendix. None of these interactions contradicted $H_1$.

### 2.2.2. *Choice of time-scaling factor and properties of the scaled graphs*

I examined participants' use of the scaling option and the effect of the scaling on the graphs by analyzing the time scaling factors that participants chose, as well as the local steepness and oscillation of the scaled graphs.

I refer to the location on the scaling-slider that participants chose for each graph as the *time-scaling factor*. This measurement can vary between 0, corresponding to four days, and 1, corresponding to 200 days (the transformation used to translate these time-scaling factors to the actual day number presented on the graphs was: day number = 196 * (time-scaling factor) + 4). The mean time-scaling that participants chose was 0.40, with a standard deviation of 0.37.

The results of $t$-tests performed on participants' choices of the scaling factor showed that the mean value was significantly different from 0.5 (the initial setting): $t(1349) = 9.74$, $p < 0.001$; from 0.0 (maximum zoom): $t(1349) = 40.05$, $p < 0.001$; and from 1.0 (using information from the longest available time-interval): $t(1349) = 59.53$, $p < 0.001$. Therefore, it can be concluded that participants used the scaling option.

The local steepness of the scaled graphs was significantly correlated with the local steepness of the original graphs ($r = 0.58$; $p < 0.01$). Similarly, the oscillation of the scaled graphs was significantly correlated with that of the original graphs ($r = 0.58$; $p < 0.01$). These results show that the participants scaled the graphs in a way that preserved their original variability.

Fig. 4 depicts the mean local steepness and oscillation of the time-scaled graphs for the different conditions of

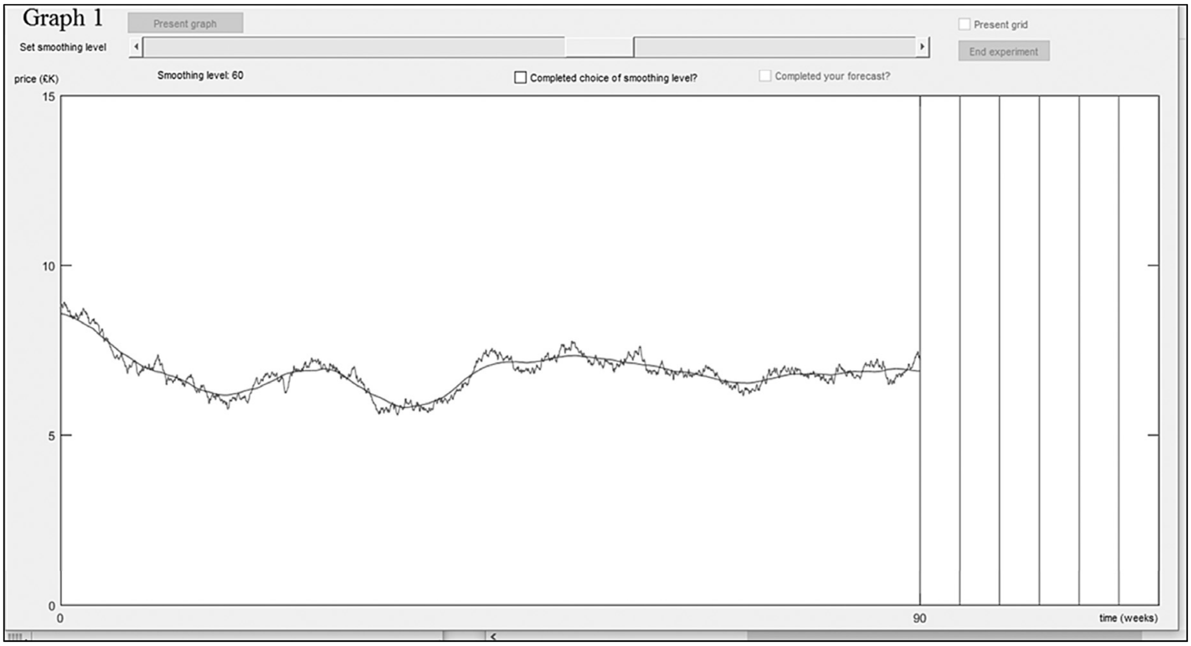


**Fig. 5.** The task window of Experiment 2: a price graph and the corresponding smoothed graph.

the Hurst exponent and forecast horizon. To conclude, variability measures of the scaled graphs were correlated with the corresponding variability measures of the data graphs.

*2.2.3. Additional analysis: a comparison between human forecast dispersion and linear regression prediction intervals for an individual value*

The 95% prediction interval for an individual value of a linear regression (*PI*) was calculated as a benchmark for the assessment of the dispersion of participants' forecasts. The length of a 95% *PI* of a linear regression is given by

$$PI = 2 \cdot 1.96 S_e \sqrt{1 + \frac{1}{N} + \frac{(x - \bar{x})^2}{(N-1)\, S_x^2}},$$

where $N$ is the number of data series points, $\bar{x}$ is the mean of these points, $S_x$ is their standard deviation, and $x$ is the forecast point (taking into account the forecast horizon). $S_e$ is given by $S_e = \sqrt{\frac{1}{N-2} \sum_{i=1}^{N} e_i^2}$, where $e_i$ is the regression line error, calculated for all data series points (Hyndman & Athanasopoulos, 2014). Here, *PI* was calculated with respect to the time interval that participants were initially presented with (the period between days 100 and 200), taking into account $N = 15,000$ points. The prediction interval lengths, averaged over all graphs presented in each condition, are presented in Table 1.

The dispersion of participants' forecasts can be compared with *PI* by multiplying the standard deviation of $D1$ by a factor of $2 \cdot 1.96$, since, assuming normality, the measure $2 \cdot 1.96 \cdot std(D1)$ represents a 95% confidence interval for $D1$. The values of $2 \cdot 1.96 \cdot std(D1)$ are presented in Table 1. A comparison of *PI* and $2 \cdot 1.96 \cdot std(D1)$ reveals that the 95% prediction interval for an individual value of a linear regression is smaller than the human dispersion measure $2 \cdot 1.96 \cdot std(D1)$ (the same holds also for $2 \cdot 1.96 \cdot std(D2)$ and $2 \cdot 1.96 \cdot std(D3)$). Thus, the dispersion of participants' forecasts is larger than the linear regression prediction intervals for an individual value. Hence, human forecast dispersion is not statistically optimal, as could be expected to be the case for rational forecasters.

## 3. Experiment 2

In Experiment 2, participants were presented with a sequence of time series. Each sequence was shown on a separate trial. At the beginning of each trial, two identical copies of the same time series were presented on the same axes. Both copies remained visible for the duration of each trial. However, the task window enabled participants to smooth one of the graphs, while the other remained fixed. That made it possible for the participants to smooth each price data graph while still seeing the original data. Participants were asked to choose the smoothness level they considered the most appropriate for making financial decisions, and then to make forecasts based on the smoothed graph. Two variables were manipulated: the Hurst exponent of the original data graphs (and thus also their local steepness and oscillation), and the number of forecast points required, or, equivalently, the forecast density. Fig. 5 depicts the task window of Experiment 2. It shows a graph of the original data and the corresponding smoothed graph (on the same axes).

### 3.1. Method

*3.1.1. Participants*

Thirty-four people (15 men and 19 women) acted as participants. Their average age was 26.4 years. They were each paid a flat fee of £3.00.

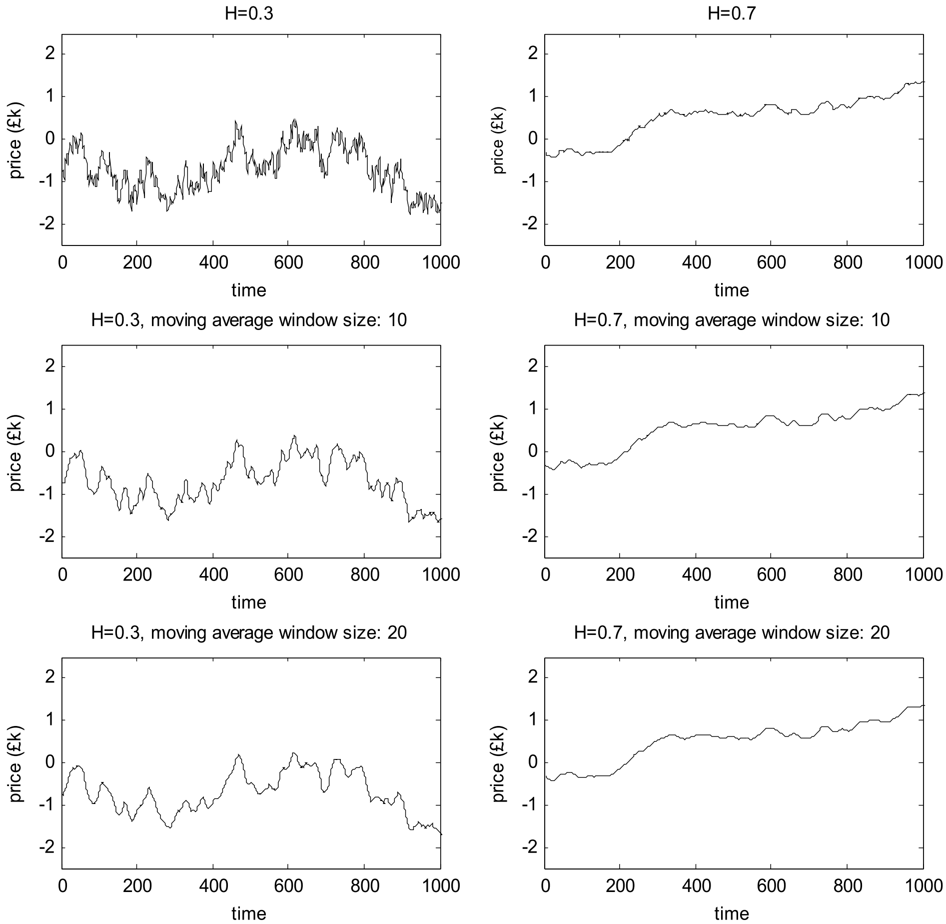


**Fig. 6.** Examples of fBm series with $H = 0.3$ (left panel, first row) and $H = 0.7$ (right panel, first row). The graphs in the second and third rows were obtained from the graphs in the first row by applying moving average filters with window sizes of 10 and 20 points, respectively.

#### *3.1.2. Stimulus materials and the presentation program*

The stimulus graphs included six sets of five fBm time series with Hurst exponents of $H = 0.3$, 0.4, 0.5, 0.6, and 0.7. As with Experiment 1, the time series were produced using the spectral method described by Saupe (Peitgen & Saupe, 1988). All of the time series included 3600 points, and were presented to the participants as asset price graphs.

The stimulus graphs were presented using a Matlab program. The experimental program enabled the participants to apply an averaging filter to the price graphs while viewing the original price graphs, and to make forecasts on pre-specified dates (see Fig. 5). Examples of smoothed fBm series are presented in Fig. 6.

The averaging filter was applied using a slider. The filter's range was from an averaging window of size 2 (averaging over every two adjacent elements of the series) to averaging over the whole series, the latter resulting in a constant line. The slider was exponentially calibrated so as to enable participants to both express fine details at the lower end of the scale and reach the maximum averaging.

The experimental program required the participants to make forecasts on various dates, designated by vertical lines. There were 6, 12, 24, or 36 lines per graph. In each task, participants could continue to adjust the smoothing level until they ticked the box "Completed choice of smoothing level?". They could then edit their forecasts as desired by clicking the mouse again on any bar, until they ticked the box "Completed your forecast?".

#### *3.1.3. Design*

Each participant was presented with 23 graphs: three familiarization graphs and 20 experimental graphs. Only the experimental graphs were taken into account during the analysis stage. Each graph required two responses: first, the choice of the smoothing level; second, forecasts of the asset's future prices.

For each participant, four graphs were chosen randomly from the stimulus sets for each value of Hurst exponent ($H = 0.3$, 0.4, 0.5, 0.6, 0.7). The density of the required forecast was manipulated for each value of the Hurst exponent, and was set to a value of 6, 12, 24, or 36 forecasts within a three-year period. This gave rise to a five (Hurst exponent) by four (forecast density) design. The ordering of the trials with different Hurst exponents and forecast densities was random.

#### 3.1.4. Procedure

Participants were asked to read the following instructions:

"In the following task, you are asked to imagine that you are a financial analyst working at an investment company. Your clients ask you to give them a three year forecast. Each client asks for a forecast of a different resolution: some clients need a monthly forecast (a total of 36 points), some require a forecast point every 6 months (a total of 6 points), and some are interested in an intermediate number of forecast points (a total of 12 points or 24 points)".

"You will be presented with a series of 3 practice graphs and 20 experiment graphs representing prices of different assets. The program will enable you to set the smoothness level of the data graphs. You are asked:

1. to look at the graphs carefully,
2. *for each of the graphs, to determine the smoothness level you consider the most appropriate for making financial decisions from it,*
3. to predict the prices on a series of time points *based on the smoothened graph*. The number of forecasts will be 6, 12, 24, or 36 points according to the request obtained from each of your clients".

Participants chose the smoothness level of their data graphs by dragging a slider. The smoothed graph was presented in red, while the original graph was presented in blue.

Forecasts were made by clicking a mouse at an appropriate point on each vertical line, indicating a specific date. Participants had to place forecasts on all vertical lines (dates) for a given graph before they could continue to the next graph.

### 3.2. Results

Any participant whose mean smoothing level choices were more than two standard deviations greater than the average of the rest of the group was excluded from the analysis. This reduced the sample from 34 to 32 participants. Three additional extreme measurements (out of the original $20 * 34 = 680$ measurements), in which participants chose smoothing levels that were more than four standard deviations greater than the mean of the experimental condition, were removed as well. Thus, 637 graphs were used for the analysis.

The variables of primary interest here were the local steepness and oscillation of the forecasts and the original data graphs. The standard deviation of participants' forecasts was extracted in order to provide an additional variability measure as a basis for comparing the results. As in Experiment 1, the local steepness and oscillation of smoothed graphs were calculated. The chosen smoothing factors were extracted too, as they could indicate the window sizes of the moving average filters that the participants applied to the data. The local steepness and oscillation of the smoothed graphs were used to assess the similarities between the original and smoothed data.

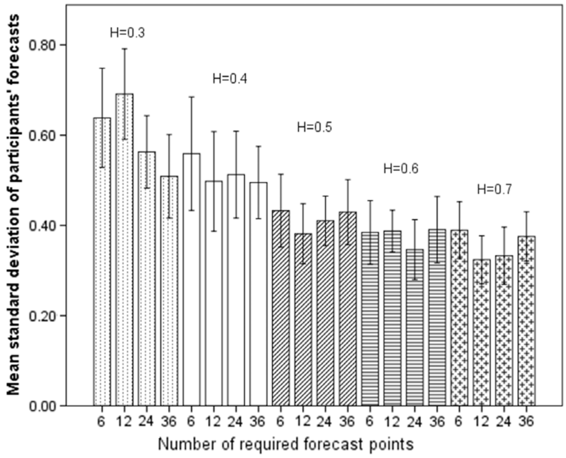


**Fig. 7.** The mean standard deviation of participants' forecasts from graphs with different Hurst exponent values against the required number of forecast points.

#### 3.2.1. Properties of the participants' forecasts

I examined Hypothesis $H_2$ by extracting the local steepness and oscillation of the forecasts and the original data graphs. Significant correlations were found between the local steepness of the forecasts and the local steepness of the data before and after smoothing ($r = 0.39$; $p < 0.01$, and $r = 0.33$; $p < 0.01$ respectively). Similarly significant correlations were found between the oscillation of the forecasts and the oscillation of the data both before and after smoothing ($r = 0.43$; $p < 0.01$, and $r = 0.40$; $p < 0.01$ respectively). Positive correlations were also found between the standard deviation of the forecasts and the local steepness and oscillation of the data graphs before smoothing ($r = 0.375$; $p < 0.01$, and $r = 0.443$; $p < 0.01$ respectively). These results support Hypotheses $H_2$, and suggest that participants imitate the properties of the data when making judgmental forecasts from graphs, hence providing further support for the correlated response model. In addition, they are in line with Harvey's (1995) finding that people tend to add noise to their forecasts. This tendency is irrational in the sense that trend-line statistical forecasts are characterized by superior accuracy (Harvey et al., 1997).

I obtained further support for $H_2$ by carrying out a two-way repeated measures ANOVA on the standard deviation of participants' forecasts, with the Hurst exponent and the forecast density as within-participant variables. The Huynh-Feldt test showed that the standard deviation of participants' forecasts was larger when the Hurst exponent of the data graphs was smaller ($F(3.58, 110.97) = 32.95$; $p < 0.01$; partial $\eta^2 = 0.52$). (The effect of the forecast density on forecast dispersion was insignificant, $p = 0.057$). Fig. 7 depicts the standard deviation of participants' forecasts against the required forecast density for the given values of the Hurst exponent.

#### 3.2.2. Choice of the smoothness level and properties of the smoothed data graphs

The mean smoothness level that participants chose was 59.09, and the standard deviation was larger than the

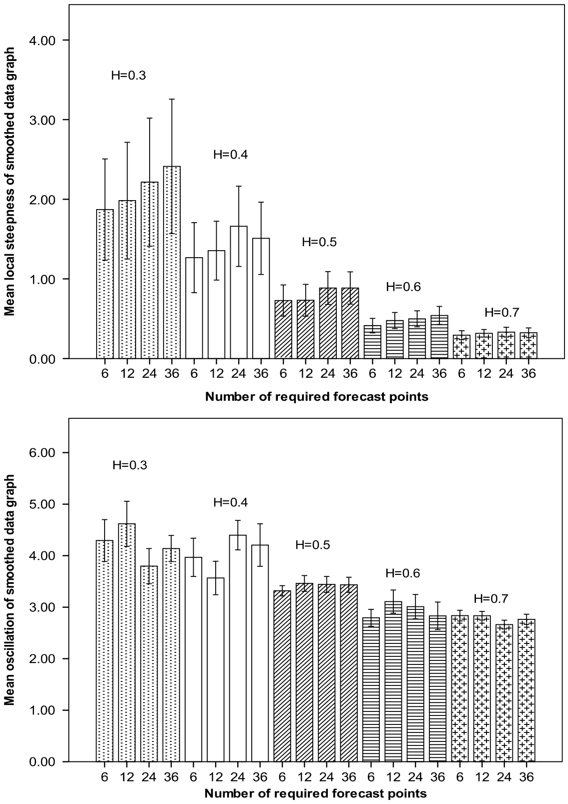


**Fig. 8.** The mean local steepness (upper panel) and oscillation (lower panel) of smoothed data graphs.

mean, at 82.61. A $t$-test performed on participants' choices of smoothness levels showed that it was significantly larger than 1 (a trivial filter): $t(636) = 17.76$ ($p < 0.01$).

The correlation between the oscillations of the smoothed and original data graphs was $r = 0.88$; $p < 0.01$. This suggests that the participants smoothed the graphs in a way that maintained a correlation between the variability measures of the smoothed and original graphs.

Fig. 8 depicts the local steepness and mean oscillation of the smoothed data graph for the different values of the Hurst exponent and the different numbers of forecast points required.

## 4. General discussion

In the book "An engine, not a camera: how financial models shape markets", MacKenzie (2006, p. 12) wrote: "Financial economics, I argue, did more than analyze markets; it altered them. It was an 'engine' [...]: an active force transforming its environment, not a camera passively recording it". I suggest that a central component of the engine of the market – the way in which people perceive financial data and make forecasts from it – is not as passive as a camera, but still preserves important properties of the data.

This study has examined the way in which people perceive graphically presented price series by considering their choices of scaling and moving window averaging. Both techniques are highly popular among both investors and traders (Batchelor, 2013; Batchelor & Kwan, 2007; Cheung & Chinn, 2001; Gehrig & Menkhoff, 2006; Menkhoff, 2010; Taylor & Allen, 1992). The results of this study indicate that, although there is considerable variability among people in their choice of the scaling and moving window averaging parameters, there are significant correlations between the local steepness and oscillation of the transformed data graphs, and the local steepness and oscillation of the original price graphs.

Two properties of forecasts were examined: the forecast variability and forecast dispersion. Significant correlations were found between both of these measures and the local steepness and oscillation of the original price graphs. Furthermore, the Hurst exponent had a significant effect on participants' forecast variability and dispersion. These results are in line with previously reported findings (Bolger & Harvey, 1993; Harvey, 1995; Harvey et al., 1997; Reimers & Harvey, 2011), and were robust across a wide range of data series, different tasks (point and multi-period forecasts) and when participants could scale or smooth the data. The robustness of these findings with respect to scaling and smoothing can be explained in part by the correlations between the variability measures of the scaled and smoothed graphs and the original data graphs.

### 4.1. Contributions

This paper has made contributions to two fields: finance and judgmental forecasting. As forecast dispersion has been shown to be a predictor of important financial variables (Athanassakos & Kalimipalli, 2003; Li & Wu, 2014), many studies have focused on the determinants of the forecast dispersion (e.g., Kwon, 2002; Platikanova & Mattei, 2016). However, the effect of the properties of the data on forecast dispersion has been overlooked. Given that a large percentage of market participants incorporate financial graph analysis into the decision making process (Gehrig & Menkhoff, 2006; Menkhoff, 2010), it is important to examine the effects of price graph properties on forecast dispersion. The results presented here indicate that the forecast dispersion is significantly correlated with historical price variability measures.

Research on judgmental forecasting has tended to focus on the identification of specific biases and the estimation of forecast errors. Uniting the results of a few classical papers (Bolger & Harvey, 1993; Harvey, 1995; Harvey et al., 1997; Reimers & Harvey, 2011), I have suggested the correlated response model, according to which people who are performing judgmental forecasting tasks from graphically presented time series tend to imitate the given data. This tendency may be perceived as irrational, in the sense that participants are including noise in their forecasts. In addition, human point forecast dispersions were larger than the 95% prediction intervals of linear regressions.

Furthermore, the experiments described in this study have explored the effects of a few factors that had not been studied previously, including the scaling and smoothing of data graphs. Aiming at a high external validity, complex time series resembling financial price series were utilized as stimuli (Mandelbrot & Hudson, 2004).

**Table A.1**
Interactions and tests of simple effects in Experiment 1.

| Repeated measures ANOVA | | Interaction | Results of tests of simple effects |
|---|---|---|---|
| Dependent variable | Independent variables | | |
| *FD*1 | Horizon, Hurst exponent, and instance | Hurst exponent and horizon ($F(3.09, 89.73) = 5.44$; $p = 0.002$; partial $\eta^2 = 0.16$) | For each $H$ value, FD1 was larger when the forecast horizon was longer (for $H = 0.3$, $F(2, 28) = 33.00$; $p < 0.001$; partial $\eta^2 = 0.70$, for $H = 0.5$, $F(2, 28) = 24.68$; $p < 0.001$; partial $\eta^2 = 0.64$, and for $H = 0.7$, $F(2, 28) = 31.75$; $p < 0.001$; partial $\eta^2 = 0.69$). For forecast horizons of 15 and 100 days, FD1 was larger when the Hurst exponent was smaller (for a forecast horizon of 15 days $F(2, 28) = 11.16$; $p < 0.001$; partial $\eta^2 = 0.44$; for a forecast horizon of 100 days $F(2, 28) = 6.68$; $p = 0.004$; partial $\eta^2 = 0.32$). |
| | | Hurst exponent and instance ($F(6.79, 196.97) = 7.67$; $p = 0.002$; partial $\eta^2 = 0.21$), | For small and medium $H$ values, the effects of instance on FD1 were smaller than those obtained for large $H$ values (for $H = 0.3$, $F(4, 26) = 5.41$; $p = 0.003$; partial $\eta^2 = 0.45$, and for $H = 0.5$, $F(4, 26) = 5.73$; $p = 0.002$; partial $\eta^2 = 0.47$, for $H = 0.7$, $F(4, 26) = 12.55$; $p < 0.001$; partial $\eta^2 = 0.66$). |
| | | Horizon and instance ($F(4.41, 127.89) = 18.28$; $p = 0.002$; partial $\eta^2 = 0.39$) | For small and medium forecast horizon, the effect of instance on FD1 was insignificant. However, for a forecast horizon of 100 days, a strong effect of instance on FD1 was obtained ($F(4, 26) = 14.93$; $p < 0.001$; partial $\eta^2 = 0.70$). |

### 4.2. Limitations and further researc

Although price series volatility changes dynamically, it is approximated many times by a slowly varying function (Zhu & Chen, 2011) or a piecewise constant function (Lu, 2010). The results presented here show that the forecast dispersion is correlated with past volatility measures. However, forecast dispersion is likely to be correlated with the volatility of future returns as well (Athanassakos & Kalimipalli, 2003; Lobo & Tung, 2000). Thus, judgmental forecasts may serve as a mechanism which helps to stabilize price series volatility. A field study exploring this conjecture could yield important insights into the nature of volatility.

Participants in my two experiments were lay people. Research comparing financial forecasts produced by lay people and practitioners has typically found only small differences between the two groups (Muradoğlu & Önkal, 1994; Zaleskiewicz, 2011). Bodnaruk and Simonov (2015) recently showed that investment decisions of financial experts (fund managers) are no better than those of other investors. Furthermore over the last few years, the internet has made trading easier for both lay people (Muradoglu & Harvey, 2012) and inexperienced investors (Barber & Odean, 2001). Nevertheless, the lack of expertise in my sample could limit the generality of the results. Thus, I consider that a study of the effects of expertise on performances in the tasks employed here would be worthwhile.

The stimulus graphs utilized in this study displayed synthetic fractal series. The choice of fractals aimed at a high external validity: while previous studies in judgmental forecasting have usually utilized less complex series as experimental stimuli, many financial studies have employed fractals, especially those which have dealt with trading horizons (e.g., Kristoufek, 2012). However, it is important to note that some researchers do not accept the fractal market hypothesis (Onali & Goddard, 2011). Therefore it is important to replicate the experiments performed here using real-life price series. It could be also beneficial to examine the effect of the graphical interface on participants' responses, as the graphical interfaces developed for the experiments may limit the generality of the results.

Moreover the graphs that participants were presented with did not depict special financial situations, such as financial crises and bubbles. I consider it essential to explore participants' behaviors in such cases.

Finally, Experiment 1 treated the trading horizon and the Hurst exponents of the graphs as independent variables. However, this assumption may not hold in all conditions (Vácha & Vošvrda, 2005).

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## Appendix. Interactions and tests of simple effects

See Table A.1.

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