Assessing risk in graphically presented financial series

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ABSTRACT

Mandelbrot and Hudson (2004) argued that traders use their natural sensitivity to the fractal properties of price graphs to assess risk and that they are better able to do this when given price change as well as price level information. Their arguments imply that risk assessments should be higher when the Hurst exponents are lower, that this relationship should be stronger in the presence of price change information and that risk assessment should depend more strongly on the Hurst exponent than on the standard deviation of the series.

Participants were asked to decide which of two assets was riskier by inspecting graphs of their price series. Graphs with lower Hurst exponents were selected only by those who were less emotionally stable and hence more sensitive to risk. However, when both price series and price change series were presented, the assets with lower Hurst exponents were selected by all participants.

In a second experiment, participants were given both price level and price change series for a number of assets and rated the risk of trading in each one. Ratings depended more strongly on Hurst exponents than on other measures of volatility. They also depended on indicators of potential loss.

Human risk assessment deviates from the way that risk is measured in modern finance theory: it requires integration of information relevant to both uncertainty and loss aversion, thereby imposing high attentional demands on traders. These demands may impair risk assessment but they can be eased by adding displays of price change information.

Key words: Risk; fractal series; Hurst exponent; time series; financial risk.

1. INTRODUCTION

Risk assessment is one of the most important tasks financial analysts perform. In particular, it is used for portfolio optimisation (Holton, 2004). A large number of techniques designed to help practitioners deal with financial risk have, therefore, been developed. For instance, the Black-Scholes formula provides investors with a hedging strategy, which should, theoretically, yield a risk-free portfolio (Black and Scholes, 1973).

The approach to risk assessment used by most analysts relies on strong theoretical assumptions. For example, financial price change series are assumed to follow a random walk: they must be independent, normally distributed, and show statistical stationarity (i.e. the process generating them must remain constant over time). Furthermore, the risk associated with trading or investing is assumed to be measured by series variance (Fraser-Sampson, 2014)[1].

Evidence has now accumulated showing that these assumptions are not realistic. Real financial series are not independent (Fama and French, 1988), are platykurtic rather than normal (Schoutens, 2003), and are non-stationary (Mandelbrot, 1997). As a result, variance measures have severely underestimated levels of financial risk (Mandelbrot and Hudson, 2004).

Many of those working in finance recognize that there are problems associated with the orthodox (normative) approach. Investment analysts have argued that alternative measures of financial risk should be adopted (Fraser-Sampson, 2014) and Haug and Taleb (2011, p 98) have pointed out that traders do not actually evaluate risk using the normative approach: 'Option traders do not "buy theories", particularly speculative general equilibrium ones, which they find too risky for them and extremely lacking in standards of reliability. A normative theory is, simply, not good for decision-making under uncertainty (particularly if it is in chronic disagreement with empirical evidence)'. Mandelbrot and Hudson (2004, p 231) concur with Haug and Taleb (2011): "Real investors know better than economists. They instinctively realize that the market is very, very risky, riskier than the standard [normative] models say".

Thus critics of the normative approach argue that assessments of financial risk are based on intuition. In both the professional and retail sectors, investors and traders typically use commercially available platforms to display graphical representations of price series and base their intuitive assessments of financial risk on particular features of those series. Our aim here is to discover which features they use. To meet this aim, we simulated series so that we knew exactly what features they contained. To ensure the fidelity of these simulations, they were structured in the way that real financial series are structured rather than in the way that orthodox finance theory assumes that they are structured.

Financial price series have been shown to exhibit a fractal structure (Mandelbrot, 1997). A large body of evidence now supports this (e.g., Parthasarathy, 2013; Malavoglia, Gaio, Júnior and Lima, 2012; Sun, Rachev and Fabozzi, 2007; In and Kim, 2006). Hence, in what follows, we use fractal series (fractional Brownian motion) to model price series.

Fractional Brownian motion (fBm) series can be considered as a generalisation of the random walk model favoured by modern financial theory. The characteristics of an FBm series depend on its Hurst exponent (H). This is a measure of the roughness of the series: series with Hurst exponents close to zero are rough whereas those with Hurst exponents close to one are smooth (Peitgen and Saupe, 1988). Figure 1 shows examples of fBm series with nine different H exponents ranging from 0.1 to 0.9.

Mathematically, fractional Brownian motion with a Hurst exponent, H, satisfies the condition that the variance of the differences between the series values (X) at times t_1 and t_2 is proportional to the difference between those times to the power 2H:

(1) $\text{var}\big(X(t_2) - X(t_1)\big) \propto |t_2 - t_1|^{2H}$, where $0 < H < 1$.

For a random walk, the differences $(X(t_2) - X(t_1))$ have a Gaussian distribution and satisfy (1) with H = 0.5. When H is above 0.5, series are persistent: they change their direction less frequently than they do in a random walk. When H is below 0.5, series are anti-persistent: they reverse their direction more frequently than they do in a random walk. The term fractional Gaussian noise (fGn) refers to the

sequences of differences between consecutive elements of fBm series. Examples of fBm series and their corresponding fGn series are presented in Figure 2.

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Figures 1 and 2 about here

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The value of H in many financial series lies between 0.3 and 0.7. For instance, Sang, Ma and Wang (2001) examined the Hurst exponent of the daily stock returns of different companies for 3500 trading days starting from January 2, 1970: for Caterpillar, it was 0.3290; for General Electric, it was 0.5008; for Coca Cola, it was 0.6499.

To be able to intuit that the degree of risk in financial series is greater than that derived from financial models, people would need to be sensitive to the features of fractal series. Indeed, there is already some evidence that they are able to discriminate between fBm series with different Hurst exponents (Gilden, Schmuckler and Clayton, 1993; Westheimer 1991).

In fact, Mandelbrot and Hudson (2004) went further: they suggested that people are more sensitive to geometrical properties of fGn price change series than to their corresponding fBm price level series. Their arguments were based on an informal demonstration: they presented the readers with sets of price level and price change graphs, and wrote: "All fairly similar, many readers will say [about the price level graphs]. Indeed, stripped of legends, axis labels, and other clues to context, most price "fever charts," as they are called in the financial press, look much the same. But pictures can deceive better than words. For the truth, look at the next set of charts. These show, rather than the prices themselves, the change in price from moment to moment. Now, a pattern emerges, and the eye is smarter than we normally give it credit for - especially at perceiving how things change" (Mandelbrot and Hudson, 2004, pages 17-18).

This claim that people are more sensitive to the riskiness of investments when price change information is presented in addition to price level information is relevant to commonly used financial data displays. Nowadays, many financial data providers enable the display price change series in

addition to price level series. For instance, Bloomberg charts

(http://www.bloomberg.com/professional/tools-analytics/charts/) and Yahoo! Finance

(http://finance.yahoo.com) do so. Some have presented change graphs as default (e.g., Yahoo!

Finance).

Mandelbrot and Hudson's (2004) informal demonstration, their views about the information that

influences financial risk assessment, and the characteristics of displays used in finance are all factors

that imply that risk assessment will depend more strongly on the properties of financial series when

price change series are presented together with price level series than when price level series are

presented alone (Hypothesis H_1). What will be the nature of any such dependence? As prices become

more volatile as the Hurst exponent decreases (Figure 2), people deciding which of two assets poses

the greater risk should select the one with the lower Hurst exponent (Hypothesis H_2).

A further prediction arises from Mandelbrot and Hudson's (2004) position. People whose risk

perception is particularly astute should be more sensitive to the increase in risk that occurs as the

Hurst exponent decreases. In fact, little is known about the types of personality that are associated

with enhanced risk perception. This is because most studies of the effects of personality on risk

processing have been concerned with risk taking rather than risk assessment. For example, a classic

study by Nicholson, Soane, Fenton-O'Creevy and Willman (2005) showed that propensity to take

risks was associated with all of the Big Five personality traits. In particular, it increased with

extraversion and openness to experience and decreased with neuroticism, agreeableness and

conscientiousness.

Although the present study is not concerned with risk taking, Nicholson et al's (2005) study still has

implications for how we should investigate the possibility of individual differences in risk assessment.

As Fox and Tannenbaum (2011) point out, individual differences in risk taking may arise from

individual differences in risk assessment. For example, suppose that extraverts prefer assets with

lower Hurst exponents than introverts. This would show that they prefer to take higher financial risks.

However, this effect could arise because they assess assets with a given Hurst exponent to be of lower

risk than introverts do. As a result, there may be no difference in the level of *assessed* risk that extraverts and introverts are willing to take.

This means that Nicholson et al's (2005) results can be interpreted as showing that all Big Five personality traits affect risk assessment, risk taking, or both these processes. This implies that we should search for a relation between each of the Big Five traits and the strength of the relation between changes in the Hurst exponent and changes in the level of assessed risk. If Nicholson et al's (2005) findings relate to risk assessment rather than (or in addition to) risk taking, we should expect the strength of this relation to decrease with extraversion and openness to experience but to increase with neuroticism, agreeableness and conscientiousness.

In fact, there is some limited research into personality and risk assessment that allows us to generate more specific hypotheses. For example, in non-financial domains, it has been found that risks tend to be assessed as higher by people who are more anxious, more prone to generalized worry, more neurotic, or more emotionally unstable: there is a moderate but consistent correlation between people's scores on these traits and their risk assessments (Källmén, 2000; Sjöberg, 2003). Thus, more neurotic people tend to assess risks as greater. Consequently, as the Hurst exponent decreases from 1.0 (low risk) towards 0.0 (high risk), the increase in risk assessment should be greater for more emotionally unstable people. In other words, they should be more sensitive to the increase in risk that accompanies a decrease in the Hurst exponent (Hypothesis H_{3a}).

Extraverts are venturesome (Eysenck and Eysenck, 1978, 1980) and so, when compared with others, they are likely to be less sensitive to risk (but more sensitive to return). Thus, as the Hurst exponent decreases from 1.0 towards 0.0, the increase in risk assessment should be less for more extraverted people. In other words, they should be less sensitive to the increase in risk that accompanies a decrease in the Hurst exponent (Hypothesis H_{3b}). Note that both this hypothesis and the previous one (H_{3a}) are consistent with what we would expect if Nicholson et al's (2005) findings reflected, at least in part, differences in risk *assessment*.

2. EXPERIMENT 1

On each trial, participants were presented with financial data pertaining to two assets and asked to perform a risk discrimination task. In addition, they also performed a randomness discrimination task on series with the same characteristics. There were two reasons for this. First, randomness discrimination served as a control for assessing participants' sensitivity to the Hurst exponents of the graphs. Second, knowing about randomness discrimination could further our understanding of the way people assess financial risk. Greater randomness in price series increases their unpredictability and, thereby, elevates risk. Hence, randomness perception may be seen as a component of risk assessment.

To investigate possible effects of personality on risk assessment, we followed Sjöberg's (2003) approach and measured the Big Five personality traits (emotional stability, extraversion, openness to experience, agreeableness, conscientiousness). We then correlated people's scores on these traits with indices of sensitivity to risk derived from signal detection theory.

2.1. Method

Both the experiments in this study were performed on the internet. Online experiments reduce experimenter effects and volunteer bias while increasing access to demographically and culturally diverse participant groups (Reips, 2002). In addition, they have similar internal and external validity as those of laboratory or field experiments (Horton, Rand and Zeckhauser, 2011).

2.1.1. Materials

Stimulus materials consisted of six sets of price level graphs with Hurst coefficients $H = 0.1, 0.2, 0.3,$ ...,0.9 (group 1comprising 54 graphs), six sets with Hurst exponents $H = 0.35, 0.4, 0.45, ...,0.75$ (group 2 comprising 54 graphs), six sets with Hurst exponents $H = 0.4, 0.425, 0.45, ...,0.6$ (group 3 comprising 54 graphs), together with 162 price change graphs corresponding to these 162 price level graphs.

All the price level series and their corresponding price change series were produced using the spectral algorithm of Saupe (Peitgen and Saupe, 1988). To avoid confounding of the difference between the first and last data points with the Hurst exponent of the graphs, all graphs depicted one period of the produced fractals. Therefore, the first and last points in each of the graphs were identical. Similarly, to avoid confounding of the graphs' ranges with their Hurst exponents, we normalised all graphs to ensure that they had the same range, the interval [1, 10]. (Normalisation of graph pairs for which the Hurst exponent differs by not more than 0.1 changes the differences between their Hurst exponents only very slightly).

Each series comprised 6284 points. The graphs were saved in jpg format. These jpg images (1366 x 768 pixels) extended over a third of a 15-inch computer screen. In this way, participants saw the whole series from start to finish but it was contracted uniformly into approximately 500 pixels. Though resolution was reduced somewhat, it was still high and series characteristics were unaffected.

2.1.2 Psychometric instrument

Participants' personalities were assessed using the standardized Ten-Item Personality Inventory (TIPI) developed by Gosling, Rentfrow, and Swann (2003) to score people on the Big Five traits. This instrument was developed "for situations where very short measures are needed, personality is not the primary topic of interest, or researchers can tolerate the somewhat diminished psychometric properties associated with very brief measures" (Gosling et al, 2003, p 504). All three of these conditions held for our study.

First, web-based studies should be of short duration (Birnbaum, 2002) and, because the experimental section of our study comprised 100 trials, we needed a brief measure of personality to ensure completion. The TIPI can be completed in two or three minutes whereas Costa and McCrae's (1992) 240-item NEO-PI-R, the gold-standard for measuring the Big Five personality traits, requires about 45 minutes. Källmén (2000, p 118) emphasized the severity of the non-completion problem when he reported that, even with just 129 items, "only 39% of the questionnaires were returned, resulting in less external validity".

Second, personality is not our primary topic of interest in our study: we are using it purely to test one of the three hypotheses arising from Mandelbrot and Hudson's (2004) claims.

Third, recent studies have shown that the TIPI exhibits "reasonably acceptable psychometric properties for measuring the Big Five in terms of test-retest reliability, self-other agreement, factor structure, convergence with the NOE-PI-R and correlations with relevant criteria (Romero, Villar, Gómez-Fraguela and López-Romero, 2012, p 289) and that results are "favorable in terms of the factor structure and convergent validity of the TIPI" (Ehrhart, Ehrhart, Roesch, Chung-Herrera, Nadler and Bradshaw, 2009, p 900)[2]. These findings suggest any decrease in psychometric properties arising from use of the TIPI rather than the NEO-PI-R would be tolerable and more than offset by higher completion rates and the resulting greater external validity.

2.1.3 Design

Two groups of participants saw pairs of graphs of computer-generated fractal series. Those in the first group were presented with price level series; those in the second group saw both the price level series and the price change series derived from them.

The difference in the Hurst exponents between the graphs in each pair was manipulated. Participants performed risk discrimination and randomness discrimination tasks in random order. Finally, they completed the personality questionnaire.

Two sets of 50 price level graph pairs were randomly chosen for each participant from the 18 sets of nine price level graphs, with a constraint upon the size of the difference in their Hurst exponents (ΔH). Thus, each set of fifty graph pairs included 15 pairs with $\Delta H = 0.100$ chosen from the six sets of group 1, 15 pairs with $\Delta H = 0.050$ chosen from the six sets of group 2, and 20 pairs with $\Delta H = 0.025$ chosen from the six sets of group 3.

Each graph pair was determined through four randomization processes. Firstly, two graph sets were chosen randomly from one of the groups. Second, one graph was chosen randomly from one of the selected sets. Denote the value of the Hurst exponent of this graph by H_1. Thirdly, the program determined randomly whether the Hurst exponent of the second graph would be $H_2 = H_1 + \Delta H$ or $H_2 = $

$H_1 - \Delta H$, where ΔH was 0.1 for pairs from group 1, 0.05 for pairs from group 2, and 0.025 for pairs from group 3. A graph with H_2 was selected accordingly from the second graph set. (When the first graph had the maximal or minimal Hurst exponent value in its set, the second graph had lower or higher value of the Hurst exponent, respectively). Finally, the order of presentation the graphs in each pair was randomized.

The whole process producing these two sets of 50 pairs of graphs was carried out separately for each participant. One set seen by the participant was used for the risk discrimination task and the other set was used for the randomness discrimination task.

In the risk discrimination task, participants were asked to decide which of the assets represented by the two graphs in the pair would be the riskier one in which to trade. In the randomness discrimination task, they were asked to decide which of the assets represented by the two graphs in the pair had prices that behaved more randomly. The order of the tasks was randomly chosen for each participant. Figure 3 shows typical task windows for risk discrimination in the first condition (upper panel) and for randomness discrimination in the second condition (lower panel).

These manipulations resulted in a two (price levels only versus price levels and changes) by two (risk versus randomness discrimination) by three ($\Delta H = 0.1,\ 0.05,\ 0.025$) design.

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Figure 3 about here

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2.1.4 Participants

Participants were solicited from financial analyst and economist groups on LinkedIn. A prize draw encouraged participation. The prize consisted of three memory sticks.

Over a period of one month, 77 people participated in the first condition (price levels only). Only those who completed all tasks (21 men and 20 women, average age: 45.3) were included in the analysis. All but one had academic degrees or were students. Twelve participants had a PhD, nine had an MSc, 14 had a BSc/BA, and five were students.

Over a period of one month, 81 people participated in the second condition (both price levels and changes). Of these, 47 people (16 women, 31 men, average age: 46.1) completed all tasks and were included in the analysis. Apart from three of them, all had academic degrees or were students. Four participants had a PhD, 19 had an MSc, and 21 had a BA/BSc.

Participants included people from Australia, New Zealand, Malaysia, India, Philippines, Canada, USA, Argentina, UK, the Netherlands, Norway, France, Luxembourg, Italy, Greece, Israel, Poland, and Ukraine.

Participants were asked whether they were financial analysts. In the first condition, seven participants answered positively. In the second condition, ten answered positively.

2.1.5 Procedure

The experiment consisted of three tasks. In the risk task, participants were presented with 50 pairs of graphs. They were asked to determine which of the graphs presented in each pair represented the asset in which it was riskier to trade. The randomness task was similar to the risk task, except that participants were asked to determine which of the two graphs represented an asset in which prices behaved more randomly. Order of completing these tasks was randomly chosen for each participant. After performing them, participants completed the TIPI questionnaire as their third task.

2.2. Results

In risk task, we extracted, for each participant, the percentage of trials in which they selected the graph with the lower Hurst exponent as the riskier asset (Risk%). In the randomness task, we extracted, for each participant, the percentage of trials in which they selected the graph with the lower Hurst exponent as the one in which the series behaved more randomly (Randomness%). We excluded participants for whom the mean values of Risk% or Randomness% were more than two standard deviations larger than the group mean. This resulted in four participants being discarded from the second group. In addition, to ensure that our tests of H_3 were not distorted by outlying data points with large residuals or high leverage, we discarded participants for whom Cook's distance (Cook,

1977) was more than two standard deviations greater than the group mean[3]. This resulted in exclusion of one participant in each group. Thus the analyses were performed on 40 participants in the first group and 42 participants in the second one.

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Tables I and II about here

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Table I shows means and standard deviations for both types of comparison for each level of ΔH in the two groups. When participants were presented only with price level information, the percentage of trials in which the series with the lower H value was selected as more risky did not differ significantly from chance for any value of ΔH. However, in all other cases, t-tests showed that series with the lower H value were selected as riskier (group presented with both price level and change information) and more random (both groups).

We performed a signal detection analysis on participants' choices[4]. We used this approach because it allowed us to separate out the degree to which participants interpret differences in H as differences in risk or randomness (sensitivity, d') from any response biases (β) arising from a greater tendency to label either the first or second graph as the riskier or more random one. A 'hit' was defined as a case in which the first graph was chosen when the Hurst exponent of that graph was the smaller one, a 'miss' was defined as a case in which the second graph was chosen when the Hurst exponent of the first graph was the smaller one, a 'false alarm' was defined as a case in which the first graph was chosen when the Hurst exponent of the second graph was the smaller one, and a 'correct rejection' was defined as a case in which the second graph was chosen when the Hurst exponent of that graph was the smaller one. For each participant, we calculated d' (sensitivity) and β (bias) indices (Macmillan and Creelman, 2005). To avoid a case in which d' is infinite (perfect accuracy), we converted proportions of 0 and 1 into $1/(2N)$ and $1 - 1/(2N)$ (as suggested in Macmillan and Creelman, 2005, page 8).

The d' index is usually referred to as a sensitivity measure. In the current setting, it can be regarded as reflecting participants' understanding of the notions of risk and randomness. For instance, participant

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with hit rate of 1 and false-alarm rate of 0 in the randomness rating task could be considered perfectly sensitive to the randomness in the series. However, such results are better regarded as revealing that the participant's definition of randomness coincided with the notion that series with lower Hurst exponents are more random.

Descriptive statistics for d' and β are presented in Table II. As can be seen from the table, all d' values were significantly different from zero, apart from those for the risk assessment in the price-level-only condition. Most β values were not significantly different from 1.0, indicating an absence of response bias. (Where there was a response bias, it represented a greater tendency to identify the second graph as the riskier one.)

A three-way ANOVA on the d' index, using condition (price-level-only versus price-level-and-change) as a between-participants variable and assessment type and ΔH as within-participant variables, revealed greater sensitivity in the price-level-and-change than in the price-level-only condition (F (1, 39) = 41.80; p < .01; partial η^2 = .52), in the randomness task than in the risk task (F (1, 39) = 23.11; p < .01; partial η^2 = .37), and when ΔH was larger (F (2, 78) = 64.48; p < .01, partial η^2 = .62). These results support hypotheses H₁ and H₂: the analysis failed to show any effect of the Hurst exponent on risk assessment in the price-level-only condition. However, there was a significant effect of the Hurst exponent on risk assessment when price change graphs were presented alongside the corresponding price series.

The interaction of condition and assessment type was significant (F (1, 39) = 5.83; p = .02, partial η^2 = .13), indicating that there was a larger difference between the two conditions in the risk task than in the randomness task. There were also significant interactions between condition and ΔH (F (2, 78) = 8.49; p < .01, partial η^2 = .18) and between task type and ΔH (F (2, 78) = 3.31; p = .042, partial η^2 = .08). These arose because ΔH had no effect on sensitivity when participants in the price-level-only condition made risk discriminations but did have effects on sensitivity when participants in that condition made randomness discriminations and when those in the price-level-and-change condition made both types of discrimination.

A three-way ANOVA on the β index using the same variables as before revealed no significant effects.

For each task and for each level of ΔH, we extracted correlations between scores on the five personality traits and d'. For the condition in which people saw price levels only, d' for the risk task correlated with emotional stability when ΔH was large (r = -.32; p = .04) and medium (r = -.33; p = .04). In this task, d' also correlated with agreeableness when ΔH was large (r = .37; p = .02) and medium (r = .33; p = .04). These results are interesting because, as we have seen, d' levels for the risk task in the price level only condition were not significantly different from zero when calculated across all the participants in that condition. To investigate this apparent paradox, we used median splits to divide those in this condition first into low emotionally stable and high emotionally stable sub-groups and then into low agreeableness and high agreeableness sub-groups. We found that, for the low emotionally stable sub-group, the d' value of 0.59 was significantly different from 0.0 (t (19) = 2.31; p < .05). (No such difference was found for the high emotionally stable group.) However, the d' value for the high agreeableness sub-group (0.54) was not significantly different from 0.0. These results provide support for H_{3a} and show that some people are able to extract risk information from price level graphs even in the absence of their corresponding price change graphs[5].

For those who saw price changes as well as price levels, d' for the risk task correlated with extraversion when ΔH was high (r = -.50; p < .01), medium (r = -.48; p < .01) and low (r = -.34; p = .03). Extraverts were less sensitive to risk. This result provides support for H_{3b}. There was also a correlation between β and extraversion when ΔH was high (r = -.46; p < .01). There were no other significant correlations between personality traits and d' or β in either task.

One-way analyses of variance on the d' and β indices using degree of expertise (financial analysts versus others) as a between participants variable showed no significant effects on either task when only price levels were graphed. However, when price changes as well as price levels were shown, the d' indices of experts in the randomness task (but not in the risk task) were higher (F (1, 40) = 8.70; p < .01): experts were more sensitive to differences in the Hurst exponents of the graphs but did not use

that information in their risk discrimination and so did not gain any advantage over non-experts in that task.

2.3. Discussion

Participants had difficulty in making risk discriminations between assets that had different Hurst exponents on the basis of their price levels alone. However, there was clear evidence that, when provided with the same information, participants could make randomness discriminations between assets that had different Hurst exponents with relative ease. This implies that the results with risk discrimination did not reflect people's difficulty in seeing differences between graphs. Instead, people did not interpret the differences that they saw in terms of differences in riskiness of trading in the assets.

When price change graphs corresponding to the price level graphs were added to the display, participants selected the asset with the lower Hurst exponent as the riskier one. Adding the price change graphs enabled people to interpret the differences between series with different Hurst exponents in terms of differences in riskiness. Results from the randomness task with prices level only showed that they could already see differences between the graphs but it was only when the price change series were added that these differences were interpreted as differences in riskiness. Specifically, participants saw the series with the lower Hurst exponent as the more risky one. Taken together, these results are consistent with hypotheses H_1 and H_2.

It is possible that the presence of price change information merely highlighted the role that randomness has in determining risk. If so, priming people with the concept of randomness may have a similar effect. However, an additional analysis of the results from the risk task that compared performance of individuals in the price level only group who completed the randomness task first with that of those in the same group who completed the randomness task second showed no differences in either d' or β. Thus price change information seems to have done more than just alert people to the role that randomness has in determining levels of risk: it facilitated the extraction of information about different levels of risk from the series with different Hurst exponents.

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It is unlikely that price change information had this effect at a purely perceptual level: this is because the results from the randomness task showed that participants were able to discriminate between series on the basis of price level alone. Instead, it appears that the presence of price change information made it easier to assign graphs with different Hurst exponents to different levels of risk. The connection between volatility in the graphs and risk was made more salient. We can ask whether this increased salience made the connection conceptually explicit at a conscious level or whether it remained implicit at a non-conscious level (despite being made stronger).

Our participants could record their comments after each comparison they made (Figure 3). These comments show that, for at least some participants who received the price change information, the connection was conceptually explicit. For example, participant 42 (price level and price change group) said: "Riskier would mean that with greatest daily variance to me, as I could decide to buy or sell with greater confidence if I knew roughly the limits of the risk." In contrast, participant 5 (price level only group) said: "I start thinking I do not understand what "risky" means... Is it bigger gains and losses? More unpredictable behaviour?" Though we cannot attribute these views directly to our experimental manipulations, they are consistent with the notion that price change information rendered the connection between volatility of the series and risk clearer and that this increased clarity was conceptually explicit.

We have seen that interpreting perceptible differences between assets with different Hurst exponents in terms of risk was difficult when only price level graphs were displayed. Only those people who were low on emotional stability and, hence, highly sensitive to risk information, were able to do so. Adding price change information to price level information makes it much easier to interpret perceptible differences between assets with different Hurst exponents in terms of risk. However, those who were extraverted and, hence, less sensitive to risk, still found this task relatively difficult.

3. EXPERIMENT 2

Risk assessment may depend on statistical properties of series other than their Hurst exponents. The standard deviation of the series is likely to influence risk assessment because it represents the

volatility of the asset, an important measure in financial theories (Amilon, 2003; Hendricks, 1996; Kala and Pandey, 2012). However, the dependence of risk assessment on the standard deviation of the series is not well-understood. Klos, Weber and Weber (2005) found that risk assessment was only weakly correlated with estimates of the standard deviation of price series. On the other hand, Sachse, Jungermann and Belting (2012) and Weber, Siebenmorgen, and Weber (2005) found high correlations between risk and volatility. These inconsistencies may be partially explained by differences in the stimulus materials used in the studies. For example, only Weber et al (2005) presented people with a time series data. However, no studies have examined the determinants of assessed riskiness when price change graphs are presented in addition to price level graphs: given the results of our first experiment, we thought it important to do so.

We examined a variety of statistical factors which could affect risk assessment. We included the Hurst exponent and, given its recognized importance, the standard deviation of the series. We also examined the graph's oscillation (the difference between its maximum and minimum values) and the absolute difference between the values of the last and first points of the series because these could be used as easily extracted proxy measures for a graph's volatility. In addition, we included a number of other measures because previous work has indicated they may have an important influence on financial risk assessment. First, because Raghubir and Das (2010) found that risk assessments are correlated with the run lengths in price graphs, we included mean run length. Second, because Duxbury and Summers (2004) found that traders are more loss averse than variance averse, we included two measures that could be easily extracted as proxy measures of the amount of money that could be lost: the difference between the values of the last and first points of the series and the difference between the first point in the series point and the minimum point in the series.

When fractal graphs are produced by a single algorithm, their Hurst exponent is correlated with their standard deviation. However, Mandelbrot and Hudson (2004) and Haug and Taleb (2011) argue that people do not assess risk according to normative measures such as the standard deviation of the series and that they are sensitive to the occurrence of rare event. The probability of rare events is assessed more accurately by the Hurst exponent of the series than by its standard deviation. We, therefore,

hypothesise that the effect of the Hurst exponent on risk assessment will be stronger than that of the standard deviation (Hypothesis H_4).

3.1. Method

The experiment was similar to the second condition of the previous one. Thus, price level graphs were presented with their corresponding price change graphs. However, instead of presenting participants with two assets on each trial and asking them to determine the riskier one, we presented them with a single asset and asked them to rate the risk of trading in it.

3.1.1. Materials

Six sets of target series were generated using the spectral algorithm described by Saupe (Peitgen and Saupe, 1988). Each set comprised nine series, each with a different Hurst exponent that ranged from 0.1 to 0.9 in steps of 0.1. Each one had 6284 points and consisted of one period. The target graphs consisted of a quarter of a period (1571 points). Hence, the differences between the values of the first and last presented points were random. No scaling was performed on the stimulus series. For each of these price level graphs, a corresponding price change graph was calculated in the same way as before.

3.1.2 Design

For each participant, two sets of nine graphs with H = 0.1, 0.2, ... 0.9 were randomly chosen from six sets of price level graphs, giving a set of 18 graphs for each person. This manipulation resulted in a two (graph instance) by nine (Hurst exponent) design.

3.1.3 Participants

Forty-two people (29 men and 13 women, average age: 35.8 years) acted as participants. They were recruited through professional groups of financial analysts and economists on LinkedIn, and via the local departmental pool of participants. All participants were offered participation in a prize draw of

four USB sticks, and information about the experiment. Students from the participant pool were offered, in addition, 0.25 academic credit points.

Participants were asked whether they were financial analysts. Thirteen participants gave a positive answer to this question.

3.1.4 Procedure

Each participant was presented with 18 computer-generated price level graphs and their corresponding price change series. They were asked to look at each graph carefully and to assess the risk of trading in the asset, expressed as a number between 0 and 100, where 0 meant: "not risky at all" and 100 meant "extremely risky". The task window is presented in Figure 4. As this indicates, participants were given the option of explaining the guidelines that they used in making their assessments. (This was not made compulsory because the task was already time-consuming and we recognized that people may not have had insight into the basis of their decisions.)

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Figure 4 about here

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3.2. Results

We examined the relations between participants' risk assessments and the following characteristics of the series they assessed: Hurst exponent (H), standard deviation (Std), the series mean run length (MeanRun), the series oscillation – the difference between its maximum and minimum points (Osc), the difference between the values of the last and first points of the series (Diff), the absolute value of the difference between the values of the last and first points of the series (AbsDiff), and the difference between the first series point and its minimum (FirstMinDiff). Inter-correlations between H, Std, MeanRun and FirstMeanDiff were fairly high (Table 3).

Implementing the same outlier exclusion criteria as were used for the first experiment reduced the number of participants by four, resulting in a sample of 38 people. An analysis of variance on participants' risk assessments, using Hurst exponent (0.1, 0.2, ..., 0.9) and Instance (first or second

presentation) as within-participant variables showed only that risk assessments were higher when the Hurst exponent was smaller (F (5.38, 199.21) = 32.44; p < .01; partial η^2 = .47)[6]. This effect is shown in Figure 5. Further analyses within the Hurst exponent range that bounds most real assets [0.3, 0.7] revealed that risk estimates for [0.3, 0.4] were higher than those for [0.6, 0.7] (t (159) = 8.70; p < .01). In addition, risk estimates for [0.1, 0.3] were higher than those for [0.4, 0.6] (t (239) = 0.15; p < .01) and those for [0.4, 0.6] were higher than those for [0.7, 0.9] (t (239) = 6.00; p < .01). These results show that the findings from Experiment 1 that supported H_2 generalize to the rating paradigm used here.

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Figure 5 and Tables III and IV about here

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The correlations between risk ratings and the seven predictor variables are shown in the first row of Table 4. Those between risk ratings and H, Std, Osc and FirstMinDiff were the highest, with absolute values were in the range [0.46, 0.49]. The similarity of the correlations for these predictors is to be expected because, as we have seen, their inter-correlations were fairly high (Table III). The second row of Table 4 shows the partial correlations between risk assessments and each of the seven predictor variables controlling for the effect of the other six predictors. The partial correlation with the Hurst exponent (r = 0.16) is second only to the correlation with Diff (r = -22). The partial correlation with Std (r = -0.05) was not significant.

A regression of risk rating on to these seven variables yielded $R^2 = 0.31$ (F (7, 683) = 45.38; p < .01). The beta values (β) corresponding to each of the variables are shown in the third row of Table IV. The absolute value of the β of the Hurst exponent (0.67; p < .01) was the highest one whereas the β value of Std was insignificant. However, given the high levels of multicollinearity, we calculated the squared semi-partial correlations for each predictor variable. These provide estimates of the unique variance in a judgment that can be attributed to a cue (Cohen and Cohen, 1983; Cooksey, 1996) and are also known as usefulness indices (Darlington, 1968). They are calculated by taking the difference between the R^2 values of the full regression model containing all predictors and the R^2

values of a reduced regression model containing all seven variables except for the predictor of interest. An index of relative weight for a predictor can be extracted by dividing the usefulness index for that predictor by the sum of the usefulness indices of all predictors. This describes the proportion of the total amount of uniquely explained variance in the risk assessments attributable to a particular predictor.

Usefulness indices for each predictor are shown in the fourth row of Table IV. Usefulness index for Diff was the largest with an index of relative weight of 0.42 but the usefulness index for H was the next largest with an index of relative weight of 0.21. The usefulness index for Std was the smallest with a relative weight of .01. Thus the Hurst exponents of the series were more than twenty times more predictive of people's risk assessments than their standard deviations. This result is consistent with Hypothesis H4.

Fifteen participants chose to outline their decision guidelines for at least one of the series. While these data are insufficient to analyse systematically, they included comments consistent with the view that, when making their risk assessments, participants attempted to take into account both the overall change in price (Diff) and the series volatility (e.g., H). Thus, participant 8 said: "Consider trending always, wild fluctuations implies a lot of risk but as long as the general trend is up then this can to some degree mitigate"; participant 20 said: "Erratic price change is more risky than static price change. Overall downward trend in price is more risky than overall upward trend"; participant 24 said: "Constant (or almost constant) increase with hardly any decline points in the process - not risky" and participant 41 said "General trend up tended to get lower risk than general trend down, with large price fluctuation increasing risk".

3.3. Discussion

This experiment used a risk rating task rather than a risk discrimination task. Despite the change in paradigm, the results again indicate that the Hurst exponent influences risk judgements when price change graphs are presented along with price level graphs: the lower the Hurst exponent, the higher the assessed risk. Support for H_2 is therefore strengthened.

The dependence of risk assessment on the Hurst exponent was much stronger than on the standard deviation of the graphs, a measure used to estimate the historical volatility in normative financial models (Hendricks, 1996). This finding supports Mandelbrot and Hudson's (2004) views about people's reaction to fractal characteristics of price series and Hypothesis H_4.

There was one other strong predictor of people's risk ratings. This was the difference between the first and last elements of the presented series, a measure of the amount of money which is likely to be lost when trading in an asset. Thus our results confirm Duxbury and Summers' (2004) findings that assessments of risk reflect loss aversion more than variance aversion.

Raghubir and Das (2010) found that people assess series with longer run lengths as riskier. Our experiments demonstrated an opposite effect: the correlation between the graphs' mean run length and risk ratings was negative (Table 4). This difference between the two studies may reflect the difference in the type of time series used: ours were fractal whereas theirs were not. Alternatively, it may reflect the idiosyncrasies in the single time series that Raghubir and Das (2010) used for each run length. For example, the single series in the condition with the longest run length of eight comprised a short upward section, followed by a long downward section, followed by a medium length upward section. The middle downward section is highly salient and may have led to the relatively high risk assessments for that condition (due to loss aversion of the sort mentioned in the previous paragraph). A series with the same run length but comprising a short downward section, followed by a long upward section, and terminating in a medium length downward section may well have produced much lower risk assessments.

4. GENERAL DISCUSSION

There is increasing acceptance that price series of financial assets have fractal structure. This may be because, in contrast to the random walk assumption adopted by modern financial theory, evidence for the fractal structure of these series is accumulating (e.g., Parthasarathy, 2013; Malavoglia, Gaio, Júnior and Lima, 2012; Sun, Rachev and Fabozzi, 2007; In and Kim, 2006).

The likelihood of extreme events in fractal series is different from that in the random walk series on which modern finance theory is based. Mandelbrot and Hudson (2004) argue that people are sensitive to fractal structure and, hence, to the fact that financial risks are higher than those calculated on the basis of that theory. They point out that this can explain a number of financial anomalies, such as the equity premium puzzle (Mehra and Prescott, 1985, 2003).

Discriminating which of two assets was associated with higher risk was difficult when price series alone were presented (Experiment 1). Under this condition, people were able to discriminate which of two series was more random but could not discriminate which was riskier. The only exceptions occurred in less emotionally stable people, who are known to be more risk-sensitive. Therefore, in general, it appears that people had some difficulty in using randomness information to assess risk.

Findings from Experiment 2 suggest a possible source of this difficulty. Results from that study indicated that uncertainty/randomness/variance aversion (reflected by the Hurst exponent) and loss aversion (reflected by downward price trends) make relatively large but independent contributions to people's ratings of risk. Thus extraction of risk estimates from randomness information is not a simple transformation but involves incorporating information about potential loss. Combination of these two types of information is likely to be cognitively demanding as it requires people to mentally integrate their estimate of a global change in the series corresponding to loss (e.g., the overall difference between the first and last points) with their estimate of the average local change corresponding to randomness (e.g., mean level of consecutive fluctuations). These cognitive demands were met more readily by those particularly concerned with risk (i.e., people who were emotionally less stable).

Presenting price change information in addition to price level information made the task of integrating different sources of information relevant to risk assessment much easier. As a result, it was successfully performed not just by emotionally less stable people who are highly sensitive to risk but also by those with a much wider range of personality characteristics. Only extraverts showed a relatively low sensitivity to differences in the Hurst exponent under these conditions. This finding is attributable to their greater tendency to be venturesome (Eysenck and Eysenck, 1978, 1980) and,

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hence, to a reduced concern with risk. Generally, though, people's greater sensitivity to differences in the Hurst exponent when price change information is displayed suggests that provision of that information by financial data providers represents an effective strategy for facilitating the assessment of risk.

Our focus has been on how people use price series information to assess risk. We accept that other factors also influence risk assessments. These include news and implied or actual information about fundamental properties that are likely to affect the success of companies. For example, Weber et al (2005) showed that risk assessment is affected by providing participants with company names independently of the provision of other data types.

We have suggested that using price series to assess risk is a cognitively demanding task that can be eased by adding price change information. Conversely, we would expect it to be made more difficult by factors that increase attentional demands. For example, prices in the experiments reported here were not updated in real time; participants were viewed static price graphs. While many investors view price information in this format, active traders are faced with a constant stream of prices updated in real time. This will impose higher cognitive demands and, hence, might impair their risk assessment. Extending the approach used here to dynamical settings would be needed to ascertain whether this is so.

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Footnotes

1. Theoretically, risk is defined in terms of the variance of returns but, in short-term trading, where return is the sell price minus the buy price, variance of the price series is what matters.

2. Mean value of Cronbach's Alpha was 0.6. According to the commonly used guidelines, this is classified as 'questionable' (George and Mallery, 2003). However, psychometric authorities (Kline, 2000; Wood and Hampson, 2005) have pointed out that alphas are misleading when calculated on scales with very small numbers of items.

3. Cook's distance assesses the effect of deleting an observation (X). The predictions for the full regression model are calculated for each observation except X. Then they are re-calculated for the reduced model that excludes X. The difference between the predictions for each observation derived from the two models is squared, the squared differences are summed, and the result is divided by the number of fitted parameters and the mean squared error of the model. Our measures of Cook's distance were derived from regressions of A% and B% on to the TIPI personality scores when $\Delta H = 0.1$.

4. Analysis of variance on A% and B% led to similar conclusions to those produced by the signal detection analyses that we report.

5. In this group, agreeableness was also correlated with d' for the randomness task with medium ΔH ($r = .34$; $p = .03$) and with β of the randomness task with low ΔH ($r = .32$; $p = .047$).

6. The Hurst exponent violated Mauchly's test of sphericity and so here we report the results of a Huynh-Feldt test.

Table I. Experiment 1: Mean values and standard deviations of A% and B% at each level of ΔH in the two groups.

Group	Task	ΔH	Mean	Standard deviation
1. Price level only	Risk comparison (A%)	0.1	0.55	0.21
		0.05	0.54	0.19
		0.025	0.51	0.17
	Randomness comparison (B%)	0.1	0.76*	0.19
		0.05	0.67*	0.16
		0.025	0.59*	0.12
2. Both price level and price change	Risk comparison (A%)	0.1	0.82*	0.21
		0.05	0.70*	0.20
		0.025	0.61*	0.12
	Randomness comparison (B%)	0.1	0.87*	0.14
		0.05	0.77*	0.16
		0.025	0.65*	0.14

Note: * indicates that a t-test shows that the mean value is different from chance level (0.5) at $p < 0.5$.

Table II. Experiment 1: Mean values and standard deviations of the d' and β indices for the two tasks at each level of ΔH in the two groups.

Group	Task	ΔH	d'		β	
			Mean	Std	Mean	Std
1. Price	Risk	0.1	0.29	1.24	1.08	0.42
level only	comparison	0.05	0.22	1.12	1.07	0.51
		0.025	0.08	0.97	1.10	0.41
	Randomness	0.1	1.53*	1.15	0.96	0.32
	comparison	0.05	0.91*	0.90	1.24†	0.68
		0.025	0.49*	0.68	1.25	0.81

Group	Task	ΔH	d'		β	
			Mean	Std	Mean	Std
2. Both	Risk	0.1	1.88*	1.18	1.24†	0.48
price level	comparison	0.05	1.16*	1.16	1.11	0.49
and		0.025	0.63*	0.75	1.19†	0.54
change	Randomness	0.1	2.18*	0.83	1.18	0.67
	comparison	0.05	1.55*	0.94	1.25†	0.62
		0.025	0.88*	0.78	1.11	0.41

Note: * indicates that a t-test shows that the mean value is different from 0.0 at $p < 0.1$.

† indicates that a t-test shows that the mean value is different from 1.0 at $p < .05$.

Table III. Experiment 2: Correlations between the variables characterizing series

	H	Std	MeanRun	Osc	Diff	AbsDiff	FirstMinDiff
H		r = -.78*,	r = .92*,	r = -.86*,	r = -.08*,	r = -.32*,	r = -.63*,
		p < .01	p < .01	p < .01	p = .04	p < .01	p < .01
Std			r = -.67*,	r = .95*,	r = -.10*,	r = .55*,	r = .73*,
			p < .01	p < .01	p = .01	p < .01	p < .01
MeanRun				r = -.70*,	r = -.08*,	r = -.29*,	r = -.49*,
				p < .01	p = .04	p < .01	p < .01
Osc					r = -.03,	r = .45*,	r = .75*,
					p = .48	p < .01	p < .01
Diff						r = -.003,	r = -.60*,
						p = .95	p < .01
AbsDiff							r = .33*,
							p < .01

Table IV. Experiment 2: Correlations and partial correlations between risk ratings and variables characterizing series, together with beta values and squared semi-partial correlations (usefulness indices) from the multiple regression of risk assessment on to the variables characterizing series.

	H	Std	MeanRun	Osc	Diff	AbsDiff	FirstMinDiff
Correlation with risk rating	r = −.47, p < .01	r = .46, p < .01	r = −.39, p < .01	r = .49, p < .01	r = −.19, p < .01	r = .24, p < .01	r = .46, p < .01
Partial correlation with risk rating	r = −.16, p < .01	r = −.05, p = .168	r = .09, p = .01	r = .10, p < .01	r = −.22, p < .01	r = .11, p < .01	r = −.12, p < .01
Beta values in full regression	β = −.67 p < .01	β = −.19 p = .17	β = .27 p = .01	β = .49 p < .01	β = −.45 p < .01	β = .11 p < .01	β = −.37 p < .01
Usefulness indices	0.017	0.001	0.006	0.006	0.034	0.007	0.01

Figure captions

Figure 1. Examples of fBm series with Hurst exponents ranging from 0.1 (anti-persistent) through 0.5 (random walk) to 0.9 (persistent) in 0.1 increments.

Figure 2. fBm series with H = 0.3, 0.5, 0.7 (left column) and their corresponding fGn series (right column).

Figure 3 Task windows from Experiment 1: Risk discrimination task in price level only condition (upper panel); randomness discrimination task in price level and price change condition (lower panel).

Figure 4. A task window from Experiment 2.

Figure 5. Experiment 2: Mean risk assessment plotted against the Hurst exponents of the presented graphs.
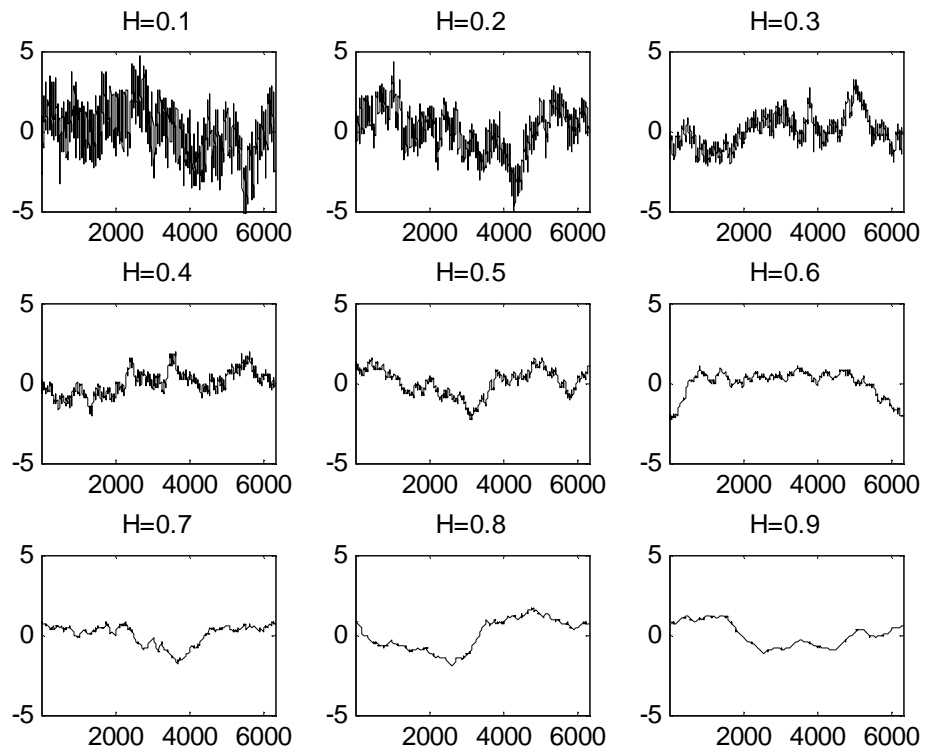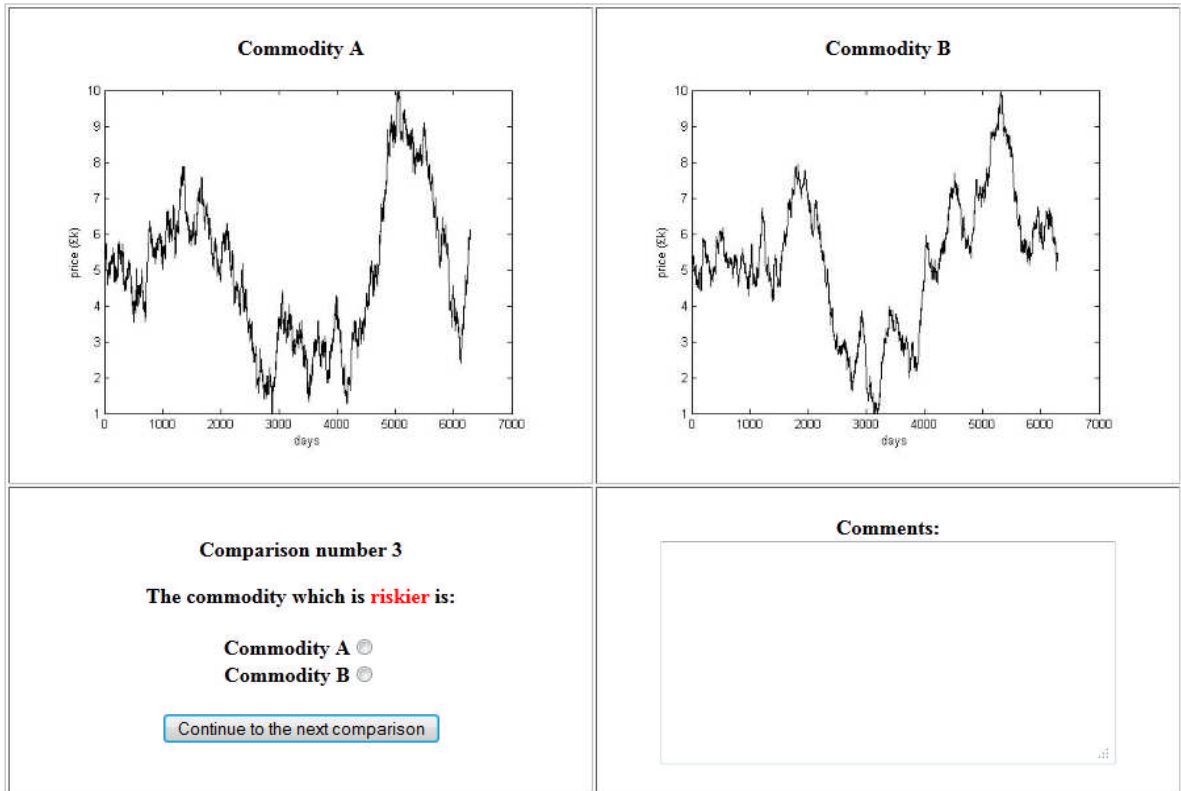
Figure 1.

Figure 2.

Figure 3.

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Figure 4.

Figure 5.