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Buy, sell, or hold? A sense-making account of factors influencing trading decisions

Daphne Sobolev^{1*}, Bryan Chan² and Nigel Harvey²

Abstract: We investigated the effects of news valence, the direction of trends in graphically presented price series, and the culture and personality of traders in a financial trading task. Participants were given 12 virtual shares of financial assets and asked to use price graphs and news items to maximize their returns by buying, selling, or holding each one. In making their decisions, they were influenced by properties of both news items and price series but they relied more on the former. Western participants had lower trading latencies and lower return dispersions than Eastern participants. Those with greater openness to experience had lower trading latencies. Participants bought more shares when they forecast that prices would rise but failed to sell more when they forecast that they would fall. These findings are all consistent with the view that people trading assets try to make sense of information by incorporating it within a coherent narrative.

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PUBLIC INTEREST STATEMENT

We investigated the effects of news valence, the direction of trends in graphically presented price series, and the culture and personality of traders in a financial trading task. Participants were given 12 virtual shares of financial assets and asked to use price graphs and news items to maximize their returns by buying, selling, or holding each one. In making their decisions, they were influenced by properties of both news items and price series but they relied more on the former. Western participants had lower trading latencies and lower return dispersions than Eastern participants. Those with greater openness to experience had lower trading latencies. Participants bought more shares when they forecast that prices would rise but failed to sell more when they forecast that they would fall. These findings are all consistent with the view that people trading assets try to make sense of information by incorporating it within a coherent narrative.

1. Introduction

Modern behavioral theories developed to simulate markets typically employ models of agents that exhibit some aspects of human behavior. By so doing, they provide insight into phenomena that are not explained by classical theories. However, the assumptions underlying agents' behavior do not always reflect results of psychological studies. There are a number of examples of this.

Harras and Sornette (2011) constructed a market model, in which agents choose at each time step whether to trade or not. Traders in their model use information from three sources: private information, public information, and the expected decisions of other traders. However, their model does not take into account news valence, even though the importance that people attribute to information depends on its valence (Kahneman & Tversky, 1979) and does not allow for differences in the way people react to verbal news and graphically presented price series (Andreassen, 1990).

Kuzmina's (2010) model consisted of three types of agents: rational investors, noise investors, and emotional investors. The agents differed in the way they reacted to news. Kuzmina assumed that all market participants submit their trades simultaneously. However, Odean (1998) shows that the timing of buy/sell decision is highly variable.

Anufriev and Panchenko (2009) modeled a market with fundamentalists and trend-following agents, assuming that all agents were risk averse. However, though psychological studies have shown that some people are risk seeking rather than risk-averse (Cheung & Mikels, 2011; Nicholson, Soane, Fenton-O'Creevy, & Willman, 2005), Anufriev and Panchenko (2009) did not take such individual differences into account.

To some extent, mismatches between models and data reflect the simplifications necessary to ensure that mathematical manipulation of the equations within the models is tractable (De Grauwe, 2010). Inappropriate assumptions may also reflect lack of communication between those working within behavioral finance and psychology. However, financial modelers could also point out that the psychological literature typically supplies disconnected principles for human behavior that are not always easy to apply to trading environments. Therefore, there is a need to provide those who are developing agent-based simulations of market behavior with behavioral principles that are more specifically relevant to their concerns.

Here we are concerned with three main issues: the way people, who employ technical analysis methods (e.g. a proportion of retail investors), incorporate news and graphically presented price series into their financial decisions, the time they take to make those decisions, and the effect of individual differences on their decisions. These three issues are all relevant to assumptions included, explicitly or implicitly, in behavioral models of the market of the sort described above. They are also germane to assumptions that are included in classical models of market behavior. For example, the efficient market hypothesis (EMH) requires that news is incorporated into asset prices immediately and in an unbiased manner. Incorporation of news should, therefore, be independent of individual differences (Findlay & Williams, 2000).

2. Literature review

2.1. The effect of news on financial decisions

Different versions of the EMH define the scope of the information to be included in prices. This information varies from the previous price series (the weak version) through all publicly available information (the semi-strong version) to all information (the strong version). The semi-strong and strong versions of the EMH therefore assert that news cannot be used by investors in order to make profit (Findlay & Williams, 2000). Nevertheless, it is widely accepted that news has a large effect on investment decisions and price series (Barber & Odean, 2008; Cecchini, Aytug, Koehler, & Pathak, 2010; Engelberg & Parsons, 2011; Hayo & Neuenkirch, 2012; Reeves & Sawicki, 2007; Tetlock, 2007).

How do people respond to news? Caginalp, Porter, and Hao (2010) have produced evidence implying that people underreact to news when valuing asset prices. However, De Bondt and Thaler (1985) argued on the basis of their analysis of winner and loser portfolios that they overreact to news. Moreover, Tuckett (2012) has shown that investors construct narratives in order to give their world meaning and to enable them to function under conditions of extreme uncertainty. Thus, people may attribute high importance to news because news items are the narratives of the financial world: they describe, or at least give the illusion, of causality, whereas price graphs that appear largely random may not offer the same degree of psychological comfort. We therefore hypothesize that, when provided with both types of information, people will choose to base their trading strategy on news more than they do on price graphs (H_1).

Andreassen (1990) used experiments to study the conditions under which overreaction to news occurred, and, in particular, the effect of contradiction between news items and stock price trends on financial decisions. He presented his participants with 60 experimental trials, each consisting of a display of the current price of a stock, the price change from the previous trial, and a news item about the stock. Participants were instructed to “buy shares for less than you sell them” and “sell them before they do down.” There were three experimental conditions. In the first condition, participants saw no news; in the second, they saw “normal” news; in the third, they saw “reversed news.” “Normal” news items were positive when price trend was positive and negative when price trend was negative. The valence of “reversed” news was opposite to the sign of the price series trend. Trends in the series were manipulated as well. The main dependent variable was participants’ “tracking”, measured by the correlation between the number of shares held at the end of each trial and the concurrent price. Andreassen (1990) found that tracking was the highest in the reverse-news and no news conditions, and weakest in the normal news condition.

Oberlechner and Hocking (2004) performed a large-scale survey to examine the views that foreign exchange traders hold on news available to market participants. In line with the results of Andreassen (1990), they found that news items that were consistent with market expectations were considered less important than those that were inconsistent with them. Hence, we hypothesize that participants will track prices more and show more active trading (buying or selling rather than holding their assets) in non-contradicting conditions than in contradicting ones (H_2).

Andreassen (1990) did not examine the effect of each of the four possible combinations of news valence and price trend separately. Considering only contradicting versus non-contradicting results masks any effects of news valence. However, we know that people react to good and bad news in an asymmetric way. For instance, Galati and Ho (2003) found that people tend to ignore good news but react to bad news. Hence, on the basis of their results, we hypothesized that, when short-selling is not possible, people will sell more assets when the news is bad than they will buy when it is good (H_3).

2.2. The timing of financial decisions

The second assumption of the EMH deals with trading latencies of market participants. Nearly all behavioral models have to make some assumptions about agents’ trading latencies (e.g. Kuzmina, 2010).

The psychological basis for the timing of financial decisions has not been subject to intensive investigation. However, Lee and Andrade (2011) found that participants in whom they had induced a sense of fear tended to sell stocks earlier than participants in the control condition. They chose to manipulate fear because it is increased by risk and uncertainty. Their results therefore imply that financial risk and uncertainty reduce trading latency.

In our task, trading latency was defined as the number of data points that participants saw before they made a buy/sell decision. In those cases in which participants chose to hold their shares until the end of the series, trading latency was defined as the maximum number of series points.¹ On the basis

of Lee and Andrade's (2011) findings, we hypothesize that trading latency will be shorter when uncertainty is higher, that is, when there is an inconsistency between news valence and price trends (H_4). Also, if we are correct in hypothesizing that people rely more on news than on price trend data when making financial decisions, then we would expect that the effect of news on trading latencies will be stronger than that of the price trend, and that trading latency will be shorter when news is bad (H_5).

2.3. Individual differences: Effects of culture

The EMH assumption that traders are rational requires homogeneous trader groups. However, this assumption does not hold. Ackert, Church, and Zhang (2002) conducted experimental markets in the US, Canada, and China in order to examine the effect of imperfect private information on information dissemination. In their markets, traders were given information about period-end dividend. The researchers manipulated the accuracy level of the information given to traders. They defined degree of information dissemination as the movement in transaction price towards the price given to well-informed agents. They found that degree of information dissemination depended on the accuracy of the given information and on participants' nationality. When accuracy of information was 90%, news dissemination was greater in the USA and Canada than in China. However, when information accuracy was 75%, it was higher in China than in Canada and similar to that observed in the USA.

Inaccurate or misleading information can be represented by a mismatch between news items and price graph trend. In line with the findings of Ackert et al. (2002), we hypothesize that participants from Western culture will react to news more than participants from Eastern countries in consistent conditions (good news with positive price trend or bad news with negative trend) but that participants from Eastern Asian countries will react to news more than participants from Western countries in inconsistent conditions (good news with negative trend or bad news with positive trend) (H_6).

Nisbett (2003) has carried out a program of work that indicates that people in Eastern cultures think more holistically and less analytically than those in Western ones. They make greater attempts to pull all available evidence into a single holistic framework. Consequently, we should expect them to require more time to produce a narrative that meets their adequacy criteria. If trading requires development of such narratives, they should exhibit longer trading latencies (H_{7a}) that would, in turn, result in higher degrees of dispersion in their returns (H_{7b}).

2.4. Individual differences: Effects of personality

Only Durand, Newby, and Sanghani (2008) and Durand, Newby, Peggs, and Siekierka (2013) have systematically studied how trading decisions are affected by the big five personality traits (McCrae & Costa, 1987; Norman, 1963). These traits comprise extraversion; negative emotion, such as anxiety; openness to experience; agreeableness; conscientiousness. Based on results from their investor survey, Durand et al. (2008) argued that people with different personalities are attracted to different types of security: for example, those who were more extraverted had a greater preference for innovation. Based on results from their trading experiment, Durand et al. (2013) went on to argue that personality influences not only what people trade in but also how they trade. For example, people more open to experience developed more diversified portfolios.

Our trading task is simpler than the one used by Durand et al. (2013). Participants were not required to form portfolios of investments. They merely had to decide whether to sell, hold, or buy a series of 12 assets. We ask whether personality influences performance even in this basic trading task. From our sense-making perspective, we expected that it will do.

We know that people more open to experience have shorter reaction times in a variety of (non-financial) tasks (Fiori & Antonakis, 2012). This is probably because those who are more open to experience have a great need for cognition (Sadowski & Cogburn, 1997). People with higher need for cognition put more cognitive effort into tasks and hence process the information they are given more selectively and effectively (Cacioppo, Petty, & Morris, 1983). This implies that people more open

to experience will put more effort into making sense of trading-related information and succeed in doing so sooner. As a result, they will have shorter trading latencies (H_8). Faster trading may, in turn, influence share buying and resulting returns.

3. Experiment 1

To address our two main aims, we designed Experiment 1 to determine the effects that news valence and trend have on financial decisions and trading latencies in participants from different cultures and with different personalities. As we have seen, all these factors have a role in various behavioral models of the market and are relevant to the assumptions underlying many behavioral models. Furthermore, presenting participants with both price graphs and news items can yield direct evidence about the validity of the assumptions of the EMH.

To test hypotheses H_1 to H_8 , we presented participants with a sequence of 12 graphs of real financial asset prices. Participants were told that they would be initially endowed with one share of each of the assets and a virtual sum of money large enough to buy one additional share of each of those assets.

Graphs of each asset were updated gradually so that a new point was added to the graphs every 0.02 seconds. There were 10 blocks of 20 points. After each block, participants were asked to decide whether to buy, sell, or hold their asset. After every other block (i.e. after the 40th point, the 80th point, and so on), participants were presented with a news item. The direction of the trends in the price graphs and valence of news were manipulated to form a two (positive versus negative trend) by two (good versus bad news) within-participant design. U-shaped and inverse U-shaped graphs were added as fillers to mask the rationale of the experiment.

We recorded the number of shares participants had in each of the experimental conditions after deciding to buy another share of each asset, sell their share, or hold their share. We refer to this variable as the *final share number*. We also recorded the number of points that were displayed before decisions to buy or sell were made. We refer to this as *decision latency*.

3.1. Method

3.1.1. Participants

Sixty people (28 men and 32 women) acted as participants. Number of participants was selected according to Maxwell's (2004) advice to ensure that the sample size was adequate to achieve acceptable statistical power. All of them were recruited through a participant recruitment website at University College London. University College London is a highly international university. For instance, according to the University's student and registry services (<https://www.ucl.ac.uk/srs/statistics>), in 2013–2014, there was a total of 601 Chinese students, as well as 10,400 students classified as "white." This demographical composition enabled us to recruit participants of both Eastern and Western origins.

The majority of the participants had an undergraduate degree or above and came from a wide range of occupational backgrounds. We were interested in examining the behavior of lay people because the Internet has greatly facilitated non-professional trading (Barber & Odean, 2008; Muradoğlu & Harvey, 2012). In addition, studies contrasting the financial behavior of lay people and experts have rarely found differences between them (Muradoğlu & Önköl, 1994; Zaleskiewicz, 2011). Participants' average age was 25.11 years (SD: 10.02). Participants from Western and Eastern cultures were recruited separately to ensure that there were equal numbers in the two groups.

The Western group comprised thirty people (17 men and 13 women) with an average age of 28.89 years. Among their countries of origin were: USA, UK, Romania, Italy, Lithuania, and Russia. Twenty-one of the Western participants were undergraduate or postgraduate students.

The Eastern group comprised thirty people (11 men and 19 women) with an average age of 21.47 years. Among their countries of origin were: Hong Kong, China, and Singapore. Twenty-six of the Eastern participants were undergraduate or postgraduate students.

All participants had spent most of their lives in their country of origin and none were of mixed parentage.

All participants were paid a fixed fee of £2. An additional £2 was available as performance-related pay: if the value of a participant's portfolio at the end of the experiment was at least £15 more than its initial value, an additional £1 was paid; if the value of that portfolio was at least £30 more than its initial value, an additional £2 was paid.

3.1.2. Stimulus materials

Eighteen price series of financial assets were downloaded from Yahoo! Finance (<http://finance.yahoo.com/>). Financial assets consisted of stocks of well-known companies, including Ford, Walt Disney, and IBM. Each series consisted of 2,500 close prices of financial assets. To avoid confounding variables, we chose six time series with a Hurst exponent that was close to a constant and in the interval [0.500, 0.556]². (The Hurst exponent of time series is correlated with variables such as the series oscillation, variance and autocorrelation). We then chose 40 subsets of 220 consecutive elements from the original series. Each group of 10 subsets had a positive average trend, a negative average trend, a U-shape, or an inverse U-shape. The criterion for selection as a U-shape or inverse U-shape subsets was that the first and last points were not different by more than half a point. We then reflected subsets with negative and positive average trends about day 110 to create 10 more subsets of positive and negative trends, respectively. U-shaped and inverse U-shaped subsets were reflected about the time axis. Finally, all 80 resultant series were normalized to fit the same price range of [£2, £10]. This procedure for the construction of the series ensured that the average trend of the graphs in the positive and negative trend sets was the same.

Presented news items were based on real items, published on BBC (<http://www.bbc.co.uk/news/>) and Yahoo! Finance (<http://finance.yahoo.com/>). News was of two types, good and bad. Each news item was formulated as a single sentence that referred to a single company. A total of 30 news items evaluated as good were downloaded. Evaluation of the news items' valence was based on the potential of the news to increase the company's value. Bad news was generated from the good news by inverting its meaning. For instance, in order to generate a bad news item from the good news item "Company awarded \$115 Million in Patent-Infringement lawsuit," we transformed it into "Company asked to pay \$115 Million in Patent-Infringement lawsuit." Appendix A provides additional examples of news items that we used.

Participants' personality traits were assessed using the Ten Item Personality Inventory (TIPI), a standardized personality questionnaire (Gosling, Rentfrow, & Swann, 2003). The TIPI measures the Big-Five personality traits: Extraversion, Agreeableness, Conscientiousness, Emotional stability, and Openness to experience. Each personality trait is assessed according to the extent to which participants agree with two statements. For instance, Emotional stability is measured using the statements "I see myself as anxious, easily upset" and "I see myself as calm, emotionally stable." Openness to experience is assessed using the statements "I see myself as open to new experiences, complex" and "I see myself as conventional, uncreative."

3.1.3. Design

Twelve graphs were chosen at random for each participant, four from the positive trend group, four from the negative trend group, two from the U-shaped group, and two from the inverse U-shaped group. Five news items, which were either all good or all bad, were chosen and randomly assigned to each graph to appear after points 40, 80, 120, 160, and 200. News items were sampled without repetition, so that each news item was viewed by each participant only once. Two of the graphs with the positive trend were assigned to good news sets and two of them to bad news sets. Similar

choices were made for the graphs with the negative trend, resulting in a two (positive or negative trend) by two (good or bad news valence) design. Every condition was tested using two graphs per participant.

The purpose of the U-shaped series and inverse U-shaped series was to mask the manipulations, and so participants' results in these conditions were not analyzed. However, each of them was also paired with either good or bad news group. The graphs were not labeled with asset names to ensure that the participants could not use prior knowledge about the assets.

Graphs and news were presented using a graphic user interface program written in Matlab. Figure 1 shows a typical task window from the experiment.

3.1.4. Procedure

The experiment comprised three stages. First, in a familiarization task, participants were asked to make financial decisions with respect to three practice graphs. Results of familiarization task were not included in the analysis. Second, they were asked to make financial decisions with respect to the randomly chosen 12 experimental graphs. Third, they were asked to complete the TIPI questionnaire (Gosling et al., 2003).

Participants were endowed with a virtual sum of money and one share of each of the 12 different assets. They were instructed to increase the total value of their portfolio above its initial value as much as possible. Participants were also told that they would be presented with the price graphs of each of these assets, one at a time. Prices were updated at a rate of one point per 0.2 seconds. The total value of the portfolio and each of the assets was updated after every point as well. These values were presented to the participants in a table. Additional instructions informed them that, after every 20 points, they would be asked to decide whether to (1) buy another share of the asset, resulting in them having another share of the stock but less money to buy more stocks, (2) sell their share of the asset, resulting in them having no shares in it but more money, or (3) hold their share of the asset. Short selling was not an available option in the setting of the experiment. They were informed that, if they decided to buy or sell, they would then move on to consider the next asset. However, if they decided to hold, the price graph of the current asset would continue to be updated in real time until they were asked to make another decision about it at the next decision point. The final contribution of each of the assets to the portfolio was determined according to its price when participants made a buy or sell decision, or the price at day 200 if participants decided to hold the asset on day 200.

After every 40 price points, participants were presented with a piece of news that was related to the current asset, together with a message emphasizing that they should read it carefully.

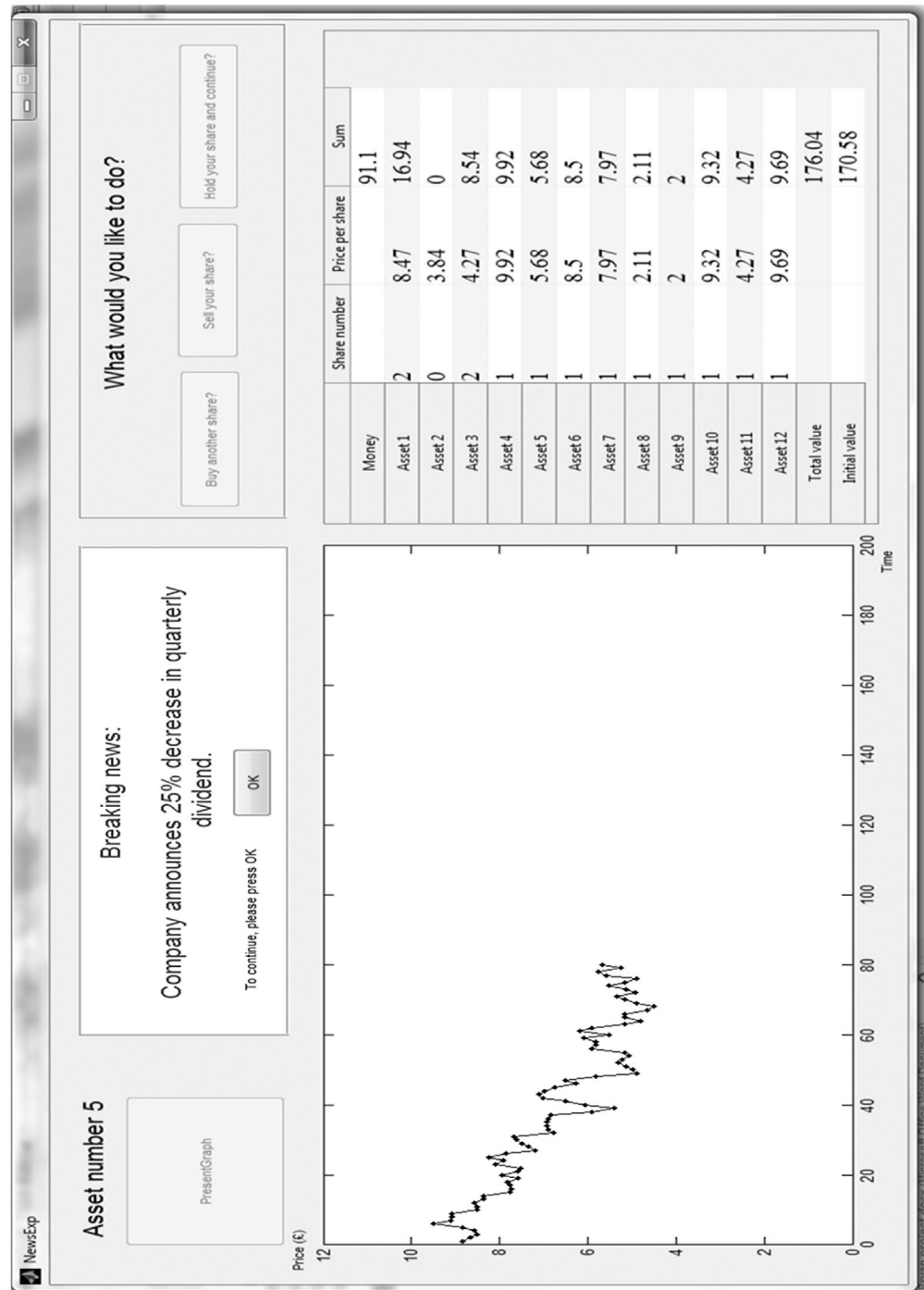
Participants were also told that there might be a "Possible additional investment task" and that the experimenter may ask them to use their portfolio (money and assets left from the second stage of the experiment) for another investment task. The reason for this was that performing any action—buying, selling, or holding an asset—did not change the total value of the portfolio. The total value of participants' portfolio changed only as asset prices changed. Possible future use of assets chosen to be held or bought endowed these actions with financial meaning.

Participants were informed how their fees depended on their performance. However, they were not provided with any trading strategy of the type Andreassen (1990) used to instruct his participants.

At the end of the experiment, participants completed the TIPI questionnaire and were asked whether they identified any patterns in the data.

Figure 1. A typical task window from Experiment 1.

Note: The figure shows the non-conflicting condition with bad news and a negative trend.



3.2. Results

Results are shown in Tables 1 and 2. Primary dependent variables were trading latency and final share number. Trading latency was measured by the number of data points participants saw before making the decision to buy or sell each asset, or the maximum number of presented points (200) if participants made their decision to buy, sell, or hold their asset after all point series had been presented on the graph. A final share number of zero indicated that participants had sold their share, one meant that participants chose to hold their share, and two showed that participants had chosen

Table 1. Results of Experiment 1

			Trend	
			Positive	Negative
<i>Panel A : Western group, N = 30</i>				
Trading latency	News valence	Good	48.33 (48.89)	60.00 (61.84)
		Bad	45.67 (38.28)	36.67 (24.75)
Share number	News valence	Good	1.35 (0.92)	0.83 (0.96)
		Bad	1.03 (1.01)	0.4 (0.81)
Returns	News valence	Good	3.14 (2.00)	-3.31 (2.22)
		Bad	2.12 (1.38)	-2.68 (1.16)
<i>Panel B: Eastern group, N = 30</i>				
Trading latency	News valence	Good	92.33 (71.98)	106.34 (70.78)
		Bad	66.00 (55.27)	73.66 (61.45)
Share number	News valence	Good	1.13 (0.96)	1.15 (0.917)
		Bad	0.72 (0.96)	0.60 (0.87)
Returns	News valence	Good	4.24 (2.25)	-4.35 (2.25)
		Bad	2.94 (1.89)	-3.44 (2.02)

Notes: Panel A shows the results of the Western participant group, and Panel B shows the results of the Eastern participant group in Experiment 1. Data presented consists of trading latency (the number of data points that participants saw before they made a buy/sell decision, or the maximal number of points), Share number (the average number of shares participants had after making their decisions), and returns (the difference between the asset price at decision time and at the time of initial presentation of the series). The results are presented for each of the four experimental conditions separately.

to buy an additional share. We also analyzed participant returns (defined as the difference between the asset price at decision time and at the time of initial presentation of the series).

3.2.1. The effect of news on financial decisions

To examine hypothesis H_1 , we carried out a four-way analysis of variance (ANOVA) on final share number using culture (Western or Eastern) as a between-participant variable and trend (positive or negative), news valence (good or bad), and instance (first or second presentation of series in each condition) as within-participant variables. This revealed that final share number was larger when news was good ($F(1, 29) = 29.35$; $p < 0.001$; partial $\eta^2 = 0.50$) and when trend was positive ($F(1, 29) = 7.56$; $p = 0.01$; partial $\eta^2 = 0.21$). The size of effect of news valence was larger than that of the trend in the graphs, a finding that is consistent with hypothesis H_1 . There was also an interaction between group and trend ($F(1, 29) = 5.40$; $p = 0.027$; partial $\eta^2 = 0.157$). Tests of simple effects showed that in Western participants, final share number was higher when the trend was positive ($F(1, 29) = 11.27$; $p = 0.002$; partial $\eta^2 = 0.28$).

To examine hypothesis H_2 , we put participants' results into two groups: the conflicting conditions (good news, negative trend and bad news, positive trend) and the non-conflicting conditions (good news, positive trend and bad news, negative trend). For each group, we extracted the deviation of the final share number from 1 (the "hold" option). ANOVA failed to yield a significant difference in this variable between the conflicting and non-conflicting conditions ($p > 0.05$). Next, following Andreassen (1990), we calculated participants' price tracking (the correlation between the price of an asset at decision time with the final share number) for the conflicting and non-conflicting sets of results. An ANOVA showed neither an effect of culture nor of conflict between trend type and news type ($p > 0.05$). Hence, we failed to replicate Andreassen's (1990) results: our data are not consistent with hypothesis H_2 .

Table 2. Hypotheses and results of Experiment 1

Hypothesis	Variables in statistical analysis		Results and conclusions
	Dependent variable	Independent variable	
H_1 : When provided with both types of information, people base their trading strategy on news more than they do on price graphs	Final Share number	Culture, trend, news valence, instance	The effect of news valence on final share number ($F(1, 29) = 29.35$; $p < 0.001$; partial $\eta^2 = 0.50$) was larger than that of the trend ($F(1, 29) = 7.56$; $p = 0.01$; partial $\eta^2 = 0.21$) We accepted H_1
H_2 : People track prices more and show more active trading (buying or selling rather than holding their assets) in non-contradicting conditions than in contradicting ones	Deviation of final share number from 1, price tracking	Condition type (contradicting or non-contradicting)	NS We rejected H_2
H_3 : People sell more assets when the news is bad than they buy when it is good when short-selling is not possible	The difference between final share number and 1	News valence	When news was good people bought fewer shares than they sold when news was bad ($F(1, 479) = 5.16$; $p = 0.024$) We accepted H_3
H_4 : Trading latency is shorter when uncertainty is higher, that is, when there is an inconsistency between news valence and price trends	Trading latencies	Condition type	NS We rejected H_4
H_5 : The effect of news on trading latencies is stronger than that of the price trend, and trading latency is shorter when news is bad	Trading latency	Culture, trend, news valence, instance	Trading latency was longer when news was good ($F(1, 29) = 29.05$; $p < 0.01$; partial $\eta^2 = 0.50$) but the effect of trend was insignificant We accepted H_5
H_6 : Participants from Eastern Asian countries react to news more than participants from Western countries in inconsistent conditions	Number of shares, trading latency and returns	Culture, condition type	NS We rejected H_6
H_{7a} : People from Eastern culture exhibit longer trading latencies	Trading latency	Culture, trend, news valence, instance	Trading latency was shorter for Western participants ($F(1, 29) = 17.23$; $p < 0.01$; partial $\eta^2 = 0.37$) We accepted H_{7a}
H_{7b} : Trading decisions of people from eastern countries result in higher degrees of dispersion in their returns	Return dispersion	Culture	Return dispersion in the Eastern group was larger than that of Western group ($t(239) = 5.60$; ($p < 0.001$) We accepted H_{7b}
H_8 : People who are more open to experience have shorter trading latencies	Trading latencies	Self rating of openness to experience	Participants with greater openness to experience had lower trading latencies We accepted H_8

Notes: This table summarizes the hypotheses examined in Experiment 1 and their results. NS represents insignificant results. The variable condition type had two values: contradiction condition or non-contradicting condition.

To examine hypothesis H_3 , we grouped all participants' results together, and extracted two new variables. The first one was the difference between final share number and 1 share (the result of a "hold" choice) when news was good. The second variable was the difference between 1 share and final share number when news was bad. These variables indicate the signed choice deviation from a "hold" decision. ANOVA revealed that when news was good people bought fewer shares (mean: 0.12; SD: 0.95) than they sold when news was bad (mean: 0.31; SD: 0.95). This difference ($F(1, 479) = 5.16$; $p = 0.024$) is consistent with hypothesis H_3 .

3.2.2. *The timing of financial decisions*

To examine hypothesis H_4 , we performed a t-test to compare trading latencies in the conflicting and non-conflicting conditions. No difference was found ($p > 0.05$): our data are not consistent with hypothesis H_4 .

To examine hypothesis H_5 , we carried out a four-way ANOVA on trading latency with culture (Western or Eastern) as a between-participant variable and trend (positive or negative), news valence (good or bad), and instance (first or second presentation of series in each condition) as within-participant variables. This showed that trading latency was longer when news was good ($F(1, 29) = 29.05$; $p < 0.01$; partial $\eta^2 = 0.50$) but that the effect of trend was insignificant. This pattern of results is consistent with hypothesis H_5 .

3.2.3. *Effects of culture*

To investigate Hypothesis H_6 , we performed three separate two-way ANOVAs on number of shares, trading latency and returns, each with culture (Western or Eastern) as a between-participant variable and condition (non-conflicting or conflicting) as a within-participant variable. The ANOVAs revealed that in no case was an interaction effect between culture and condition found ($p > 0.05$). We therefore reject hypothesis H_6 .

To examine hypothesis H_{7a} , we carried out a four-way ANOVA on trading latency with culture as a between-participant variable and trend, news valence, and instance as within-participant variables. This showed that trading latency was shorter for Western participants ($F(1, 29) = 17.23$; $p < 0.01$; partial $\eta^2 = 0.37$), a finding that is consistent with hypothesis H_{7a} .

We performed a four-way analysis of variance (ANOVA) on returns using the same variables as before. As expected, returns were larger when trends were positive ($F(1, 29) = 417.32$, $p < 0.001$; partial $\eta^2 = 0.94$). Table 1 shows that return variances of participants from the Eastern group were higher than those of participants from the Western group. To compare these, we defined return dispersion as the absolute value of the difference between the return of each asset of each participant and the mean return in participant's group. A t-test revealed that return dispersion in the Eastern group was larger than that of Western group ($t(239) = 5.60$; $p < 0.001$). These results are consistent with hypothesis H_{7a} .

In addition, 18 of the Eastern participants gave a positive answer to the question "Did you find any pattern associated with the news?" and 12 of the Western participants did so. This difference was not significant ($\chi^2(1) = 1.20$; NS).

3.2.4. *Effects of personality*

For each of the participants and for each of the experimental conditions (good or bad news, positive or negative trend), we extracted the mean trading latency, mean final share number and mean returns. Participants with greater openness to experience had lower trading latencies ($r = -0.28$; $p = 0.033$ when news was good and the trend was positive; $r = -0.32$; $p = 0.014$ when news was good and the trend was negative; $r = -0.368$; $p = 0.004$ when news was bad and the trend was positive; $r = -0.331$; $p = 0.011$ when news was bad and the trend was negative). They also bought more shares but only when bad news was combined with a positive trend in the price data ($r = 0.36$; $p = 0.005$). Finally, their returns were higher when the trend in the price data was negative ($r = 0.34$; $p = 0.008$ for good news; $r = 0.31$; $p = 0.016$ for bad news) but lower when it was positive and the news was bad ($r = -0.27$; $p = 0.038$). These results are consistent with hypothesis H_8 . Correlations between remaining four personality traits and the task variables were not statistically significant.

3.2.5. *Effects of possible confounding variables*

We did not match the age or gender of participants in the Western and Eastern groups precisely. However, these variables had no significant effects on trading latency or return dispersion and so cannot provide an alternative account for the differences observed between the two groups. Furthermore, analyses showed that there were no learning (or fatigue) effects.

3.3. Discussion

Participants made faster decisions (H_2) and bought fewer shares when news was bad than when it was good. They also sold more shares when the news was bad than they bought when it was good (H_3). In addition, participants bought more shares when the trend in the price data was positive but this effect was weaker than that of the news valence (H_1).

Why was the effect of news valence on share number stronger than that of the trend in the price graphs? Though participants were instructed to pay attention to the news items, their presentation was no more visually salient than that of the trend in the price series (Figure 1). Furthermore, portfolio values were continuously updated in a manner that matched the price changes in the graph. Participants could, therefore, see that their losses (or gains) corresponded directly to changes in the price series rather than to the news items. Hence, we interpret the greater influence of news on trading in light of Tuckett's (2012) arguments that people need to find meaning in their environment. News offers narratives and therefore people tend to focus on it.

None of the hypotheses (H_2 , H_4 , H_6) based on putative effects of a conflict between news and price data were supported. Although share buying was affected both by news and by price trend, effects of these variables did not interact in the manner expected on the basis of conflict effects.

Participants in the Eastern group made their trades much later than those in the Western one, and, as a result, their return dispersions were larger (H_7). This finding is consistent with the notion that they developed more complex narratives that pulled together the different pieces of information they had encountered into a more holistic framework (Nisbett, 2003).

Our finding that participants with greater openness to experience had shorter trading latencies is consistent with results obtained by Fiori and Antonakis (2012) in a variety of non-financial tasks. However, from a risk taking perspective, it is perhaps surprising. Nicholson et al. (2005) found that propensity to take risks was greater in extraverts and in those who are more open to experience. As shorter trading latencies indicate lower risk propensity, their findings would lead us to expect longer rather than shorter decision latencies in those with high levels of openness to experience. Hence, it appears unlikely that the relation between trading latency and openness to experience was mediated by risk propensity. Instead, it is more likely that people open to experience put more cognitive effort into their task and thereby made more effective use of the information they received. As a result, they were able to produce a satisfactory narrative for it sooner.

4. Experiment 2

Experiment 2 was designed to further our understanding of the processes that guide trading decisions. In their survey, Oberlechner and Hocking (2004) found that foreign exchange traders attributed high relevance to news items which were perceived as being able to influence the market. Thus, in our task, we expect a positive correlation between views about the extent to which an event would affect prices and final share number (H_8).

Despite a large literature on judgmental forecasting (Lawrence, Goodwin, O'Connor, & Önköl, 2006), Harvey's (2010) study appears to be the only one that has established a connection between financial forecasts and decisions—and those were managerial rather than financial decisions. Andreassen (1990) merely conjectured that forecasts mediate between data and decisions. Given that Experiment 1 demonstrated that decisions are influenced both by news and by price data, such mediation implies that forecasts should also be affected by these variables. In particular, the difference between a participant's forecast and the last data point should depend on the news valence and the direction of the trend in the price data (H_{10}). Furthermore, there should be a positive correlation between that difference and final share number (H_{11}).

Experiment 2 was similar to Experiment 1. However, to examine Hypothesis H_9 , participants were asked to rate the plausibility that presented news could affect the price of each asset. Additionally, to investigate Hypotheses H_{10} – H_{11} , they were asked to make forecasts after every 20-point block.

Experiment 2 also provided an opportunity for confirming our conclusions pertaining to hypotheses H_1 – H_5 .

4.1. Method

In addition to making trading decisions, this experiment required participants to make forecasts and to assess how plausible it was that each news event would affect asset prices.

4.1.1. Participants

Thirty people (11 men and 19 women) recruited in the same way as before acted as participants. Again, number of participants was selected according to Maxwell's (2004) advice to ensure that the sample size was appropriate for achieving acceptable statistical power. All participants were from Western culture (among their countries of origin were: USA, Canada, Finland, Italy, UK, Ireland, Germany, and Spain) and their average age was 25.23 years (SD: 6.99). Twenty-eight of them were undergraduate or postgraduate students. They were paid a fixed fee of £2. Up to an additional £2 was paid according to their performance in the same way as in Experiment 1.

4.1.2. Materials and design

These were the same as in Experiment 1. In particular, we used the price graphs of financial assets and news items as described in Section 3.1.2 Each participant was presented with 12 graphs, chosen at random as described in Section 3.1.3.

4.1.3. Procedure

The procedure was similar to Experiment 1, except that participants were presented with a news item every 40 points starting from point 20 (rather than every 40 points starting from point 40). This was to ensure that all participants, including those who decided to buy or sell their assets after 20 points, saw at least one news item.

In addition, after every 20 points, participants were asked, before making their decision, to make a single forecast for the point that was 20 points ahead of the current one. Forecasts were made by clicking the mouse on a vertical line designating the required forecast date. Until participants pressed the button “save forecast,” they could edit their forecast by clicking the mouse again on the line. Moreover, whenever a news item was presented, participants were asked to rate how plausible it was that such a news event would affect asset prices. Plausibility ratings were performed using a slider and they ranged between zero and 100, where 0 meant “not plausible at all,” and 100 meant “extremely plausible.” Figure 2 presents a typical task window in Experiment 2.

4.2. Results

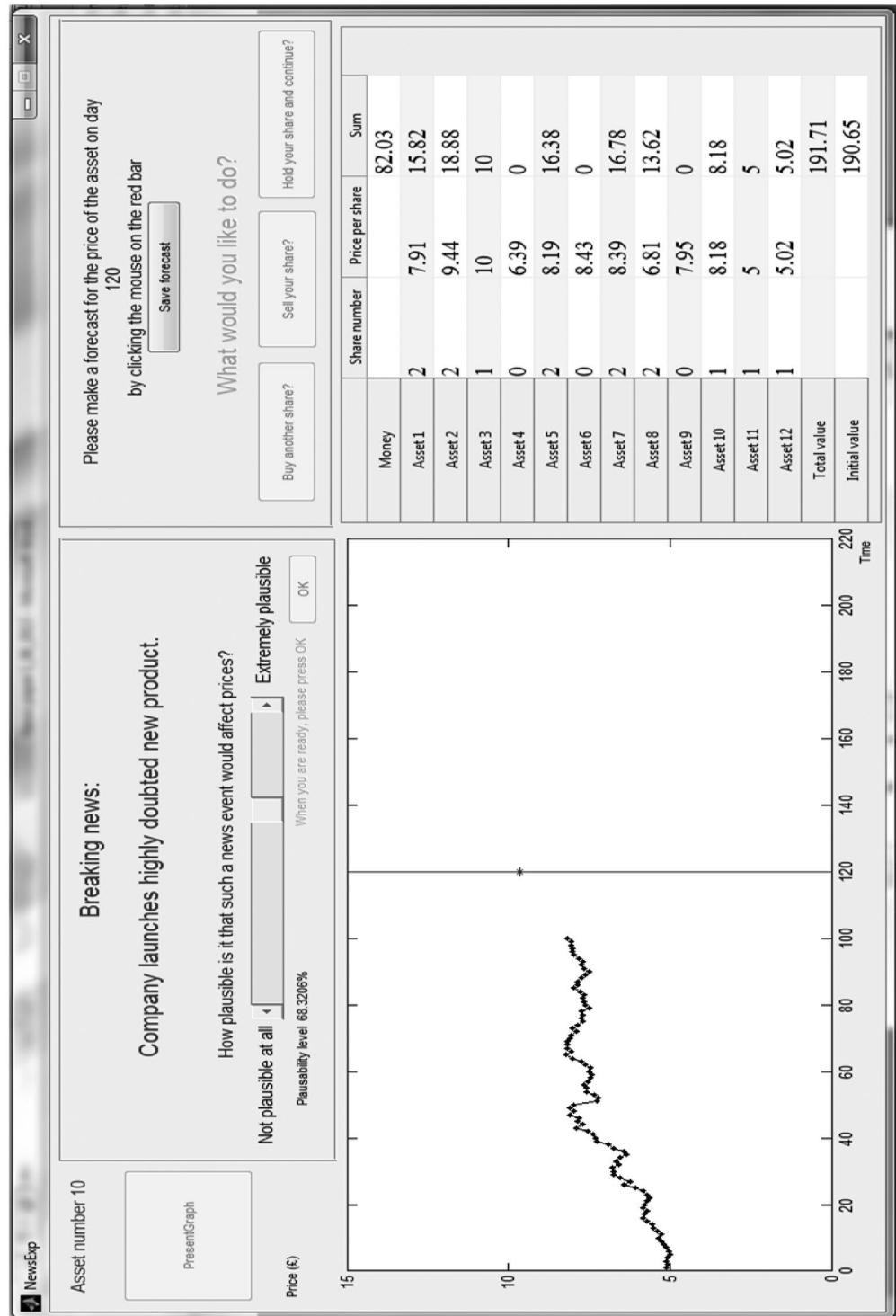
Results are shown in Tables 3 and 4. In addition to analyzing the data as before, we extracted participants' plausibility ratings and forecasts. (One forecast of one of the participants in the condition bad news, negative average trend was removed because it was more than four standard deviations from the mean of the forecasts in that condition).

4.2.1. The effect of news on financial decisions

A three-way ANOVA, using trend (positive or negative), news valence (good or bad), and instance (first or second presentation of series in each condition) as within-participant variables, showed that final share number was higher when news was good ($F(1, 29) = 11.47$; $p = 0.002$; partial $\eta^2 = 0.28$) and when price graphs had a positive trend ($F(1, 29) = 4.54$; $p = 0.042$; partial $\eta^2 = 0.14$). These results are consistent with hypothesis H_1 and replicate those obtained in Experiment 1.

Figure 2. A typical task window from Experiment 2.

Note: The figure shows the conflicting condition with bad news and a positive trend.



As before, we classified trials into those in which the news valence and price trend were conflicting and non-conflicting. ANOVAs comparing the final number of shares and the deviation of final number of shares from 1 (“hold” decision) failed to find any significant effect of conflict ($p > 0.05$). Thus, as in Experiment I, we reject Hypothesis H_2 .

Table 3. Results of Experiment 2

Western participants (N = 30)			Trend	
			Positive	Negative
Trading latency	News valence	Good	75.00 (58.87)	69.00 (60.78)
		Bad	67.33 (55.11)	45.00 (38.90)
Share number	News valence	Good	1.15 (0.97)	0.85 (0.95)
		Bad	0.55 (0.87)	0.31 (0.72)
Plausibility	News valence	Good	0.67 (0.16)	0.65 (0.17)
		Bad	0.65 (0.18)	0.68 (0.17)
Forecasts	News valence	Good	0.76 (0.66)	0.69 (1.05)
		Bad	-0.08 (0.94)	-0.49 (1.07)
Returns	News valence	Good	2.20 (1.29)	-2.23 (1.36)
		Bad	1.57 (1.23)	-1.59 (0.91)

Notes: This table shows averages of the results of Experiment 2. Data presented consists of trading latency (the number of data points that participants saw before they made a buy/sell decision, or the maximal number of points), Share number (the average number of shares participants had after making their decisions), Plausibility ratings (participants' rating of the plausibility that presented news could affect the price of each asset), forecasts (the difference between participants' forecasts and the last data point), and returns (the difference between the asset price at decision time and at the time of initial presentation of the series). The results are presented for each of the four experimental conditions separately.

To test hypothesis H_3 , we proceeded in the same way as before. The ANOVA revealed an asymmetry in final share number with respect to news and trend ($F(1, 119) = 11.62; p = 0.001$). Participants sold more shares when news was bad and the trend in the price data negative than they bought when news was good and the trend in the price data was positive. Similar results were obtained when we compared deviation from “hold” option for good news and bad news ($F(1, 239) = 24.20; p < 0.001$). As in Experiment I, our results are consistent with hypothesis H_3 .

4.2.2. The timing of financial decisions

An ANOVA comparing differences between trading latencies in conflicting and non-conflicting conditions failed to reveal any effects of conflict ($p > 0.05$). Thus, as in Experiment I, our data do not support hypothesis H_4 .

A three-way ANOVA using trend, news valence, and instance as within-participant variables showed that trading latency was longer when the news was good ($F(1, 29) = 8.23; p = 0.008$; partial $\eta^2 = 0.22$). As no main effect of trend was obtained, our results are again consistent with hypothesis H_5 .

There was an interaction between news and trend ($F(1, 29) = 5.68; p = 0.024$; partial $\eta^2 = 0.16$). Tests of simple effects showed that, when the trend was negative, trading latency was longer in the good news condition ($F(1, 29) = 14.27; p = 0.001$; partial $\eta^2 = 0.33$) and that, when the news was bad, trading latency was longer when the trend was positive ($F(1, 29) = 11.44; p = 0.002$; partial $\eta^2 = 0.28$). Further analysis showed that trading latency was longer when the news was good and the trend positive than when the news was bad and the trend negative ($t(59) = 3.43; p = 0.001$).

4.2.3. Plausibility ratings

A three-way ANOVA on plausibility estimates using the same three variables as before failed to find any significant effects ($p > 0.05$). Thus, our data failed to support Hypothesis H_6 .

4.2.4. Dependence of forecasts on news valence and trends in price data

Participants could produce up to 10 forecasts for each asset. For each time, t , at which participants made a decision regarding an asset, we extracted the differences between their forecasts for the price of the asset at time $t + 20$ and the price of the asset at time t . We then averaged these differences for each graph. An ANOVA, using the variables trend (positive or negative), news valence

Table 4. Hypotheses and results of Experiment 2

Hypothesis	Variables in statistical analysis		Results and conclusions
	Dependent variable	Independent variable	
H_1 : When provided with both types of information, people base their trading strategy on news more than they do on price graphs	Final Share number	Trend, news valence, instance	The effect of news on final share number ($F(1, 29) = 11.47$; $p = 0.002$; partial $\eta^2 = 0.28$) was larger than the effect of trend ($F(1, 29) = 4.54$; $p = 0.042$; partial $\eta^2 = 0.14$) We accepted H_1
H_2 : People track prices more and show more active trading (buying or selling rather than holding their assets) in non-contradicting conditions than in contradicting ones	Deviation of final share number from 1, final number of shares	Condition type (contradicting or non-contradicting)	NS We rejected H_2
H_3 : People sell more assets when the news is bad than they buy when it is good when short-selling is not possible	The difference between final share number and 1	News valence	Participants sold more shares when news was bad and the trend in the price data negative than they bought when news was good and the trend in the price data was positive ($F(1, 239) = 24.20$; $p < 0.001$) We accepted H_3 .
H_4 : Trading latency is shorter when uncertainty is higher, that is, when there is an inconsistency between news valence and price trends	Trading latencies	Condition type	NS We rejected H_4
H_5 : The effect of news on trading latencies is stronger than that of the price trend, and trading latency is shorter when news is bad	Trading latency	Trend, news valence, instance	Trading latency was longer when the news was good ($F(1, 29) = 8.23$; $p = 0.008$; partial $\eta^2 = 0.22$). No main effect of trend was obtained We accepted H_5
H_6 : There is a positive correlation between views about the extent to which an event would affect prices and final share number	Plausibility estimates	Trend, news valence, instance	NS We rejected H_6
H_{10} : The difference between a participant's forecast and the last data point depends on the news valence and the direction of the trend in the price data	The difference between forecasts and asset prices	Trend, news valence, instance	The difference between forecasts and asset prices was higher when news was good ($F(1, 29) = 38.93$; $p < 0.001$; partial $\eta^2 = 0.57$), and when the trend was positive ($F(1, 29) = 14.76$; $p = 0.001$; partial $\eta^2 = 0.34$) We accepted H_{10}
H_{11} : There is a positive correlation between the difference between a participant's forecast and the last data point, and the final share number	Final share number	The difference between a participant's forecast and the last data point	There were positive correlations when the trends were positive, whether the news items were good ($r = 0.53$; $p < 0.001$) or bad ($r = 0.48$; $p < 0.001$) We accepted H_{11}

Notes: This table summarizes the hypotheses examined in Experiment 2 and their results. NS represents insignificant results. The variable condition type had two values: contradiction condition or non-contradicting condition.

(good or bad), and instance (first or second presentation of series in each condition), showed that the difference between forecasts and asset prices was higher when news was good ($F(1, 29) = 38.93$; $p < 0.001$; partial $\eta^2 = 0.57$), and when the trend was positive ($F(1, 29) = 14.76$; $p = 0.001$; partial $\eta^2 = 0.34$). These results provide support hypothesis H_{10} .

4.2.5. Correlation between forecasts and financial decisions

To examine Hypothesis H_{11} , we calculated the correlation of the number of shares participants had at the end of each trial with the difference between participants' forecasts at the time of their final

trading decisions and the value of the last price they saw. A positive correlation between these two variables shows that participants tended to buy more shares when they thought that the prices would rise. Calculated for each condition separately, we found positive correlations when the trends were positive, whether the news items were good ($r = 0.53$; $p < 0.001$) or bad ($r = 0.48$; $p < 0.001$). No significant correlations were obtained for conditions with negative trends ($p > 0.05$). These results suggest that forecasts mediated between the data and trading decisions only when prices were rising. Thus, our results partially support hypothesis H_{11} .

4.2.6. Effects of possible confounding variables

Analysis showed that participants' gender had no significant effects on trading latency, returns or forecasts.

4.3. Discussion

Just as in Experiment 1, results were consistent with hypotheses H_1 , H_3 , and H_5 but not with H_2 and H_4 . Thus, our findings here give us additional confidence in the conclusions that we drew from that earlier experiment.

Experiment 2 supported Andreassen's (1990) claim that forecasts mediate between data and decisions. Forecasts depended strongly on news valence. Their dependence on the trends in the price series was weaker. Yet many experiments have shown that, in the absence of any news, forecasts depend strongly on the trends in data series (e.g. Harvey & Reimers, 2013; Lawrence et al., 2006). It appears that the presence of news dominates information relating to the trend in the price series: as we argued above, the appeal of the narrative structure of news is so strong that people prefer to act on it rather than on the trend cues.³

However, once forecasts had been made, their influence on trading was affected by the trend in the price series. When that trend was positive, forecasts were taken into account when making decisions to buy or sell.

5. General discussion

During the past few years, a large body of research on agent-based market models has accumulated. However, many market behavioral models include assumptions which are not based on psychological findings. Our study has supplied data relevant to these models and cast new light on the way people react to financial data in trading tasks. Specifically, we chose to examine three factors that are relevant to EMH and frequently involved in modern financial models: the effect of news on financial decisions, trading latency, and individual differences between investors. Superficially, these three factors may appear to be diverse and unconnected. However, the effects related to them can all be accommodated within a single coherent approach.

Though our results are consistent with previous work on the inadequacy of the EMH (e.g. Findlay & Williams, 2000), they are best understood within a framework for understanding and modeling trader behavior that takes into account the natural, human search for meaning.

First, though participants in our experiments could always see that the value of their portfolio changed according to the trend of the presented price graphs, most of them still chose to base their decisions on news items rather than on the price series. (If participants had insight into the experimental manipulation, they would have based their decisions on the price graph more than on the news items). Trading latencies also depended on news rather than on the trend in price series. News provides narratives for those searching for meaning more easily than price trends do. In fact, news items may allow people to make sense of the price trends by supplying "cognitively comforting" causal interpretations of them in the way that Tuckett (2012) suggests. Causal interpretations within a narrative also underlie fundamental analysis and so this may also help to explain why many analysts prefer it over technical analysis.

Second, openness to experience is correlated with need for cognition (Sadowski & Cogburn, 1997). Cacioppo et al. (1983) have shown that those with higher need for cognition put more cognitive effort into tasks and, as a result, are better able to focus their attention on the most relevant information. This implies that people in our task who were more open to experience put more cognitive effort into selectively processing and integrating the information they received. As a result, they produced adequate narratives more quickly and were able to act on them sooner: they had shorter trading latencies.

Third, trading latencies of participants from Eastern cultures were much longer than those of Western participants. This difference resulted in a significantly higher dispersion of returns in the Eastern group. We know from the work of Nisbett and his colleagues (e.g. Nisbett, 2003; Nisbett, Peng, Choi, & Norenzayan, 2001) that those in Eastern cultures think more holistically and less analytically than those in Western ones. They make greater attempts to pull all available evidence into a single holistic framework. Narratives provide the primary means for bringing evidence into a coherent framework (Pennington & Hastie, 1993). Finding more coherent narratives requires additional processing. According to this line of reasoning, our Eastern participants had higher trading latencies because they spent more time make sensing of the evidence by generating more coherent narratives to explain it.

Fourth, forecasts may provide some insight into how participants selectively incorporated price trend information into their narratives. Forecasts were indeed higher when news was good and price trend was positive. Thus, even though forecasts were not optimal, they were in the right direction, a finding consistent with previous work (Harvey & Reimers, 2013). However, these forecasts influenced trading only when price trends were positive. Even though participants had forecast a drop in price when the price trend was down, they tended not to sell (c.f. Odean, 1998). One interpretation, derived from one originally proposed by Lawrence and Makridakis (1989), is that people had contrasting narratives for up trends and down trends. If prices were increasing, no agency would intervene to stop them from increasing and, hence, trades could be consistent with forecasts. However, if prices were forecast to decrease, there would be at least a possibility that some agency (e.g. the company owned by the shareholders) would intervene in an attempt to prevent any further decrease. As a consequence, it would be sensible not to act on or to delay acting on the forecast.

In summary, our findings shed light on previously reported, but not entirely understood, phenomena. For instance, Odean (1998) found that traders tend to hold losing assets too long and sell them too early. He explained his result through tax considerations but we suggest that search for meaning may account for it. Traders attempt to make sense of information by incorporating it within a narrative that provides a causal interpretation of events. Given research in other domains (Pennington & Hastie, 1993), it is likely that people select between different possible narratives by choosing the one that has the greatest degree of coherence. Other approaches, such as the EMH or behavioral models that incorporate a number of disconnected cognitive biases, do not appear to be capable of providing a satisfactory explanation for our findings.

5.1. Limitations

Participants in our experiments were not professional traders. We were interested in obtaining results from lay people as it has been shown that, over the last few years, a large number of lay people have started trading (Barber & Odean, 2008). In addition, it has been found that in many financial tasks, experts exhibit similar behavior to that of lay people (Muradoğlu & Önkal, 1994; Zaleskiewicz, 2011). Furthermore, the present results are consistent with those obtained from studies of professional traders (e.g. Odean, 1998). However, it would still be valuable to replicate them on populations of professional traders, retail investors and other market participants who use technical analysis methods.

We focused on one characteristic of news and price graphs: their valence or sign. However, both news and price graphs have other features that could be important (Nelson, Bloomfield, Hales, & Libby, 2001). For example, the degree of relevance of the news to the asset may affect financial decisions and the volatility of price graphs may influence trading latency.

In all of our experiments, participants were exposed to both graphical and verbal data. In future work, these could be studied separately. This would allow examination of the way that people perform in situations that require “pure” technical or “pure” fundamental analysis.

5.2. Summary

Our findings are not consistent with the assumptions underlying classical (EMH) or behavioral models of the market: news valence matters, timing of trading decisions is highly variable, and individual differences related to culture and personality affect the way that traders respond to news. However, our results are broadly consistent with a story model of trading that emphasizes investors’ search for meaning (e.g. Tuckett, 2012). In particular, they emphasize the importance of including realistic assumptions about the effects of news on decisions, latency times, and individual differences in financial models.

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Notes

1. The graphs that participants saw showed asset price as a function of time. Hence, trading latency represented the date on which participants made their financial decision in the virtual trading task rather than the actual duration of each trial.
2. This interval ensured that successive price changes were independent, thereby making series consistent with the random walk behavior expected from the EMH. This allows our results to be compared with predictions derived from that approach.
3. Our inclusion of filler series with U-shaped and inverted U-shaped trends may have acted to reduce the weight that participants put on price trend data when making their trading decisions. However, inclusion of filler series ensured high external validity of the experiments: clearly, in real life, not all trends are easy to identify.

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Appendix A

Participants were presented with news items based on real news published on BBC (<http://www.bbc.co.uk/news/>) and Yahoo! Finance (<http://finance.yahoo.com/>). News items used in the experiments were classified as “good” if they could increase the value of the company. Examples of good news items included:

- (1) The company hits a 2-year high after new product release.
- (2) The company’s new product sales exceed predictions.
- (3) Analyst: “The company is in a good position.”
- (4) Company generates 4,000 new jobs.
- (5) Company enters Top 100 companies list.
- (6) Company announces 25% increase in quarterly dividend.

Bad news items were generated by changing the valence of the good news. The bad news items corresponding to the examples of good news items presented above were as follows:

- (1) The company hits a 2-year low after new product release.
- (2) The company’s new product sales failed to meet predictions.
- (3) Analyst: “The company is in a tough position.”
- (4) Company forced to cut 4,000 jobs.
- (5) Company loses place in Top 100 companies list.
- (6) Company announces 25% decrease in quarterly dividend.



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