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Effects on stock investments of information about short versus long price series

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Abstract

Purpose – The purpose of this paper is to investigate whether stock price predictions and investment decisions improve by exposure to increasing price series.

Design/methodology/approach – The authors conducted three laboratory experiments in which undergraduates were asked to role-play being investors buying and selling stock shares. Their task was to predict an unknown closing price from an opening price and to choose the number of stocks to purchase to the opening price (risk aversion) or the closing price (risk taking). In Experiment 1 stock prices differed in volatility for increasing, decreasing or no price trend. Prices were in different conditions provided numerically for 15 trading days, for the last 10 trading days, or for the last five trading days. In Experiment 2 the price series were also visually displayed as scatter plots. In Experiment 3 the stock prices were presented for the preceding 15 days, only for each third day (five days) of the preceding 15 days, or as five prices, each aggregated for three consecutive days of the preceding 15 days. Only numerical price information was provided.

Findings – The results of Experiments 1 and 2 showed that predictions were not markedly worse for shorter than longer price series. Possibly because longer price series increase information processing load, visual information had some influence to reduce prediction errors for the longer price series. The results of Experiment 3 showed that accuracy of predictions increased for less price volatility due to aggregation, whereas again there was no difference between five and 15 trading days. Purchase decisions resulted in better outcomes for the aggregated prices.

Research limitations/implications – Investorś performance in stock markets may not improve by increasing the length of evaluation intervals unless the quality of the information is also increased. The results need to be verified in actual stock markets.

Practical implications – The results have bearings on the design of bonus systems.

Originality/value – The paper shows how stock price predictions and buying and selling decisions depend on amount and quality of information about historical prices.

Keywords Stock markets, Stock prices, Investors, Stock investment, Price series length, Price trend prediction

Paper type Research paper

Introduction

Short-termism has been quoted as causing excessively volatile stock markets (Stiglitz, 1989), pressuring companies to sacrifice prudent environmental and social conduct in favor of short-term earnings (Sparkes, 2002), and contributing toward giving rise to

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financial crises (Dallas, 2012). Short-termism has been defined as a preference for actions in the short term that have detrimental consequences in the long term (Marginson and McAulay, 2008). A potentially contributing factor toward stock market short-termism is the prevalent incentive schemes for professional investors. In banks and fund management companies, stock portfolio managers are generally awarded bonuses conditionally on their investments producing superior returns relative to an index (Hedesström, 2010). These bonuses are often based on annual portfolio performance, although quarterly evaluation is also common (Unzicker, 2008). Even if the time horizon for investments is long term – as is the case in, for example, pension funds – stock portfolio managers may nevertheless be pushed toward shorter-term goals since these are the basis on which their bonuses are calculated (O'Barr *et al.*, 1992). Concerns have long been expressed that bonuses to stock portfolio managers are based on too short time periods, and longer evaluation intervals have been advocated. For instance, Hopkinson (1990) proposed intervals of three or four years. Yet, on the whole the finance sector has been slow to respond to such calls. Furthermore, empirical research on potential implications of prolonged evaluation intervals is largely lacking.

Two factors warrant investigation when considering the effects of prolonging the interval during which stock portfolio managers' performance is evaluated. One concerns the effect of longer evaluation intervals on motivation. The main rationale for offering bonuses is to increase employees' motivation to produce good results. It is therefore important to establish how bonus schemes could be designed such that delayed payouts will be equally motivating as more immediate payouts. This question was addressed by Hedesström *et al.* (2012) who reported two experiments in which participants chose between bonuses paid out either frequently (four short-term bonuses) or infrequently (one long-term bonus). It was assumed that more preferred bonus schemes are more motivating than less preferred bonus schemes. Consistent with research on time discounting (for reviews, see Frederick *et al.*, 2002; Soman *et al.*, 2006), a majority of participants chose the short-term bonuses. In order to be equally attractive the long-term bonus needed to be between 20 and 40 percent higher than the four added short-term bonuses.

The second factor in need of further empirical investigation concerns the focus of this paper, namely the effect of longer evaluation intervals on stock investments. To our knowledge the only previous study exploring this is Baker (1998) that investigated bonus schemes among UK fund management companies showing that average holding periods of stocks (proxy for short-termism) decreased with frequency of performance evaluations. Possibly, this implies that longer evaluation intervals prompt portfolio managers to view stocks' value development in a prolonged time frame, thus making them less susceptible to adjusting trades to noisy short-term price fluctuations. An alternative explanation is that portfolio managers simply become less active when being evaluated less frequently. Baker's (1998) study sheds no light on whether longer evaluation intervals lead to better investment decisions.

We present a series of experiments examining how length of evaluation interval may affect stock investors' performance in two respects, namely ability to predict future stock prices, and ability to make investment decisions maximizing outcomes. The experiments are based on the assumption that stock investors with a short-term performance goal are likely to base forecasts and investment decisions on immediately preceding price movements, while stock investors with a longer-term performance goal are likely to base forecasts and investment decisions on price movements reaching further back in time. Variation in length of evaluation intervals across bonus schemes is thus, in our experiments, operationalized as exposure to stock price series varying in length.

Intuitively, longer data series providing more information should lead to better predictions than shorter data series providing less information. This has been shown in research on forecasting and trend extrapolation. For example, Andreassen and Kraus (1990) found that in order to successfully forecast a trend, people need to be exposed to a series sufficiently long for them to be able to confirm any pattern they believe exists. However, too much information can also lead to information overload and less accurate forecasts (for a review, see Webby and O'Connor, 1996). For example, Lawrence and O'Connor's (1992) experiments on time-series extrapolation showed that forecast accuracy for longer series of 40 information units was significantly worse than for shorter series of 20 information units.

There is also existent research on people's ability to identify trends from time-series data that have bearing on our research. Foremost, a general tendency of underestimating trends, negative as well as positive, has been firmly established (Bolger and Harvey, 1993; Eggleton, 1982; Lawrence and Makridakis, 1989; Sanders, 1992). This so-called trend-damping bias has been explained by the use of the anchor-and-adjustment heuristic (Tversky and Kahneman, 1974). It is posit that that forecasts are made by first anchoring on the last data point, then making an (typically insufficient) adjustment away from it to take the trend into account (Bolger and Harvey, 1993; Eggleton, 1982). Trend damping has been found to increase with data variance (Eggleton, 1982; Harvey and Bolger, 1996; Sanders, 1992), which has been attributed to larger trend ambiguity providing a better scope for top-down imposition of beliefs about the future (Harvey and Bolger, 1996). Trend damping has furthermore been demonstrated to be less pronounced for negative trends than for positive trends, possibly reflecting a general optimism bias (Reimers and Harvey, 2011; Weinstein, 1989).

Another robust finding is the over-forecasting bias (e.g. Eggleton, 1982; Lawrence and Makridakis, 1989), that is the tendency to predict too high estimates for un-trended data series. This bias is hypothesized to stem from over-optimism (Reimers and Harvey, 2011) or from the fact that people more frequently encounter increasing data series than decreasing data series (Harvey and Bolger, 1996).

We report three laboratory experiments in which accuracy of predictions of a price trend and investment performance are assessed. First, we investigate participants' predictions of a future stock price for a linear positive, linear negative, or no trend over time. Second, we investigate whether participants on the basis of their accurate predictions make investment decisions that maximize returns and hence bonus payments. The experiments are designed to make possible investigating the hypothesis that information about shorter compared to longer price series have detrimental effects on predictions of future stock prices and, as a consequence, on investment decisions. We have not recruited professional investors for the experiments but undergraduates who in general are less knowledgeable about stock markets. In the concluding part of the paper, we will note how this may limit generalizability of the results. We have also made other changes that make the experimental conditions differ from an actual stock market. The evaluation intervals (5, 10, and 15 trading days) are much shorter than would normally be the case. On the other hand, the price series are simplified by only consisting of either a positive linear, negative linear, or no trend (a constant) to which random numbers are added by independent sampling from a normal distribution. The simplification of the information about the price series justifies that they are shorter. Also, more realistic price series would have been beneficial to professional investors and therefore providing a more realistic assessment of their performance, whereas naïve investors are not likely to benefit to the same extent or at all.

Experiment 1 investigates whether and how the number of previous trading days for which a stock price is presented impacts on predictions of stock prices and decisions to purchase stocks. Since the results of Experiment 1 suggest that longer price series are no better than shorter price series, possibly due to information overload, two additional experiments are performed. In Experiment 2 the price series is also visually displayed. Experiment 3 disentangles the effects on predictions and investment decisions of amount and reliability of stock price information. The results of both these experiments indicate that information load plays a role.

Experiment 1

In Experiment 1 we conjecture that more information (longer price series) vs less information (shorter price series) about a negative, positive, or no price trend would lead to more accurate predictions of a future stock price and as a consequence better investment decisions. In the following we develop a set of more specific hypotheses.

Price predictions

We expect (*H1a*) prediction accuracy to increase with price-series length. Since price trends are likely to be harder to identify when price volatility (variance) is high, we expect (*H1b*) price-series length to have a more pronounced effect on predictions when price volatility is high than when price volatility is low. On the basis of the previous research reviewed above, we expect (*H1c*) prices to be under-predicted for positive and over-predicted for negative price trends, and that (*H1d*) this trend-damping bias is more pronounced for negative than for positive price trend. In accordance with the over-forecasting bias, we furthermore hypothesize (*H1e*) that price predictions are too high when there is no trend.

Investments

The experiment is designed so that participants for each stock can make either a risk-taking (buying at an unknown closing price) or a risk-averse (buying at the known opening price) investment decision. In order to maximize outcomes, risk-taking is optimal for negative price trend (decreasing prices), whereas risk aversion is optimal for positive price trend (increasing prices). We expect (*H2a*) that participants' investment decisions will reflect this to a greater extent when being exposed to longer than shorter price series, and (*H2b*) that when price volatility is higher, longer price series will have a more pronounced beneficial effect on investment decisions than shorter price series.

Method

Participants. Participants were 36 undergraduates (22 women) enrolled in different study programs at University of Gothenburg, Sweden, recruited through sign-up sheets and e-mails. Their mean age was 27.4 years (SD = 7.6).

Experimental design. Equal numbers of participants were randomly assigned to two groups in a mixed factorial experimental design consisting of one (price volatility: low vs high) between-groups factor and two (3 (price-series length: 5 vs 10 vs 15 trading days) by 3 (price trend: no vs positive vs negative)) within-groups factors.

Procedure. When arriving to the laboratory participants were seated in separate cubicles and given a booklet to fill out at their own pace. An experimenter was present to supervise them. A session lasted for approximately 30 minutes.

Participants were asked to role-play being an investor employed by a company. They were presented nine different number series. Each number series represented how the price of a particular fictitious stock (a different stock for each of the nine number series) had changed over the preceding trading days. The stocks varied with respect to how much information was disclosed about previous prices. In one condition opening and closing prices were shown for the last five trading days, in a second condition for the same last five trading days and the five preceding trading days, and in a third condition for the same last ten trading days and the five preceding trading days. Thus, in the first condition the information about the previous stock prices consisted of the opening and closing prices for 5 previous trading days, in the second condition for 10 previous trading days, and in the third condition for 15 previous trading days. Each page in the booklet presented the information about one of the stocks. Participants were shown a table with each line disclosing the stock price in the beginning (opening price) of each trading day and on the same line the closing price the same trading day. From the second day the opening price was the same as the closing price the preceding day.

For each price-series length there were three price-trend conditions: no price trend, a linearly increasing price trend, and a linearly decreasing price trend. In order to generate the stock prices, SEK 500 was used as an initial value to which numbers were added randomly sampled from a normal distribution, in a low price-volatility condition ($M = 0$; SD = SEK 25) and in a high price-volatility condition ($M = 0$; SD = SEK 75). The increasing price trend was obtained by adding a number that increased linearly with the trial number (1-15), and the decreasing price trend by subtracting the same numbers. In order to make the price level vary for the different stocks, constants were added or subtracted resulting in the means of SEK 300, SEK 350, SEK 400, SEK 450, SEK 500, SEK 550, SEK 600, SEK 650, and SEK 700 for the nine different stocks.

Participants' task was to purchase 100 shares of each of the nine stocks. At the bottom of the page with the prices for the preceding trading days, only the opening price was shown for the (6th, 11th, or 16th) trading day when participants were asked to purchase the stock. Before making a purchase decision, participants were asked to write their predicted closing price in the space provided on the same line as the opening price was shown. They were told that the closing price would be more likely to be higher than the opening price if the stock price showed an increasing trend, more likely to be lower if the stock price showed a decreasing trend, and equally likely to be higher or lower if the stock price showed no trend. After that they indicated how many stock shares (from 0 to 100) they would purchase at the unknown closing price (and by default the remaining shares purchased at the known opening price). The instructions read (translated from the Swedish): "The opening price today is SEK X. What do you think the closing price will be? Please write down what you think in the space provided. Then indicate how many stock shares (0-100) you would purchase at the closing price."

Participants earned a bonus of SEK 0.45 (approximately 0.06 USD) per share calculated for one randomly determined stock if they purchased shares at the known opening price. If they instead purchased shares at the unknown closing price, they earned a bonus three times as high (SEK 1.35 per share) if the closing price was lower than the opening price, otherwise they would receive no bonus for the shares purchased at the closing price.

A Latin Square was used to first counterbalance across participants the order in which the different price-series lengths were presented, then within each price series another Latin Square to counterbalance across participants the order in which the different price trends were presented. The different mean levels of the stock prices were across participants assigned equally often to each combination of price-series length and price trend.

The participants were finally debriefed and paid a flat sum of SEK 50 in addition to the bonus calculated for a randomly chosen stock. The average bonus was SEK 96.80.

Results

Price predictions. Table I presents mean predictions of the stocks' closing prices as well as signed and unsigned prediction errors, computed by subtracting with or without sign the correct closing price from the predicted closing price. As may be seen, at high price-volatility prediction errors tend to be larger for 5 and 10 trading days than for 15 trading days. No significant effects of price-series length were, however, revealed at $p < 0.05$ in parallel 2 (price volatility: low vs high) by 3 (price-series length: 5 vs 10 vs 15 trading days) by 3 (price trend: no vs positive vs negative) analyses of variance (ANOVAs) with repeated measures on the last two factors.

Some other significant effects were observed. The main effect of price trend was significant on price predictions, $F(2, 68) = 68.07$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.79$. Predictions were highest for positive, lowest for negative, and in between for no price trend ($M_{\text{positive price trend}} = 579.6$ vs $M_{\text{negative price trend}} = 445.5$ vs $M_{\text{no price trend}} = 518.7$).

On signed prediction errors the ANOVA yielded a significant main effect of price trend, $F(2, 68) = 8.44$, $p = 0.001$, $\omega^2_{\text{partial}} = 0.29$, due to under-prediction for positive

Measure	Price volatility	Price trend	Price-series length: 5 trading days *M* (SD)	10 trading days *M* (SD)	15 trading days *M* (SD)
Prediction	Low	No	512.7 (86.8)	515.3 (86.0)	505.3 (112.3)
		Positive	570.7 (89.0)	572.7 (105.0)	570.8 (97.7)
		Negative	442.2 (97.1)	443.0 (116.3)	446.6 (100.4)
	High	No	547.7 (153.3)	535.3 (134.7)	495.8 (131.8)
		Positive	621.72 (135.8)	562.4 (118.8)	579.1 (123.7)
		Negative	426.2 (113.8)	464.4 (119.9)	450.7 (111.6)
Signed errors	Low	No	12.7 (44.5)	15.3 (60.0)	5.3 (43.9)
		Positive	−13.2 (34.8)	−12.3 (52.1)	−14.2 (41.7)
		Negative	27.2 (42.9)	28.0 (44.5)	31.6 (55.4)
	High	No	47.7 (92.7)	35.2 (79.3)	−4.2 (66.9)
		Positive	37.8 (83.9)	−22.6 (71.5)	−5.9 (80.8)
		Negative	11.2 (113.1)	49.4 (95.8)	35.7 (70.8)
Unsigned errors	Low	No	33.2 (31.3)	38.4 (47.8)	31.6 (30.0)
		Positive	30.7 (19.9)	38.3 (36.3)	33.8 (27.2)
		Negative	41.7 (28.0)	42.6 (29.9)	51.2 (36.9)
	High	No	79.4 (65.8)	59.6 (61.9)	52.2 (40.1)
		Positive	73.1 (53.9)	60.3 (42.4)	62.3 (49.6)
		Negative	65.7 (91.5)	87.0 (61.2)	56.0 (55.2)

Table I.
Mean predicted closing prices, signed prediction errors, and unsigned prediction errors related to price-series length (number of trading days with price information), price trend, and price volatility (Experiment 1)

trend and over-prediction for negative and no price trend ($M_{\text{positive price trend}} = -5.1$ vs $M_{\text{negative price trend}} = 30.5$ vs $M_{\text{no price trend}} = 18.7$). The interaction between price-series length and price trend did not reach significance, $F(4, 136) = 1.75$, $p = 0.147$, $\omega^2_{\text{partial}} = 0.08$, but a tendency of over-prediction for all price trends was revealed in the five trading-days condition ($M_{\text{5 trading days, positive price trend}} = 12.3$ vs $M_{\text{5 trading days, negative price trend}} = 19.2$ vs $M_{\text{5 trading days, no price trend}} = 30.2$), whereas in the ten and 15 trading-days conditions prices tended to be under-predicted for positive and over-predicted for negative and no price trend ($M_{\text{10 trading days, positive price trend}} = -17.4$ vs $M_{\text{10 trading days, negative price trend}} = 38.7$ vs $M_{\text{10 trading days, no price trend}} = 25.3$ vs $M_{\text{15 trading days, positive price trend}} = -10.1$ vs $M_{\text{15 trading days, negative price trend}} = 33.7$ vs $M_{\text{15 trading days, no price trend}} = 0.6$).

The ANOVA on unsigned prediction errors yielded a significant main effect of price volatility, $F(1, 34) = 21.29$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.36$, due to smaller errors for low volatility than for high price-volatility ($M_{\text{low price volatility}} = 37.9$ vs $M_{\text{high price volatility}} = 66.2$).

Investments. Mean numbers of stocks purchased at the unknown closing price are given in Table II. No significant effects of price-series length were revealed in a 2 (price volatility: low vs high) by 3 (price-series length: 5 vs 10 vs 15 trading days) by 3 (price trend: no vs positive vs negative) ANOVA with repeated measures on the last two factors. A significant main effect of price trend, $F(2, 68) = 5.08$, $p = 0.009$, $\omega^2_{\text{partial}} = 0.18$, was due to more stocks being purchased at the unknown closing price for positive and no price trend than for negative price trend ($M_{\text{positive price trend}} = 56.8$ vs $M_{\text{no price trend}} = 54.4$ vs $M_{\text{negative price trend}} = 40.9$).

Discussion

Price-series length affected neither price predictions nor investment decisions significantly. *H1a*, *H1b*, *H2a*, and *H2b* were hence not confirmed. However, marginal support was obtained for *H1a* and *H1b* since prediction errors tended to be higher for 5 and 10 trading days than for 15 trading days in the high price-volatility condition. Confirming *H1c*, showing a trend-damping bias signed prediction errors revealed prices to be under-predicted for positive and over-predicted for negative price trend. Furthermore, in accordance with *H1d*, trend damping tended to be more pronounced for negative than for positive price trend. Finally, confirming *H1e*, signed prediction errors showed that prices were over-predicted when there was no price trend. Further evidence of an over-forecasting bias was obtained as a tendency of price over-prediction for all price trends in the condition with the shortest price series (five trading

		Price-series length		
Price volatility	Price trend	5 trading days *M* (SD)	10 trading days *M* (SD)	15 trading days *M* (SD)
Low	No	48.6 (36.7)	51.1 (37.2)	56.7 (40.1)
	Positive	56.1 (41.3)	47.8 (38.4)	64.7 (35.4)
	Negative	50.0 (40.4)	34.4 (38.1)	34.4 (36.9)
High	No	49.2 (44.9)	61.4 (41.7)	59.7 (38.3)
	Positive	43.1 (38.7)	71.3 (37.7)	57.8 (42.4)
	Negative	47.3 (44.5)	47.4 (40.2)	31.7 (38.8)

Table II. Mean numbers of stocks (0-100) purchased at unknown closing price related to price-series length (number of trading days with price information), price trend, and price volatility (Experiment 1) days, where trend ambiguity was likely to be highest). *H2a* and *H2b* were not supported, since no effect of price-series length on investment decisions was observed.

Experiment 2

A high information-processing load imposed by longer price series (Webby and O'Connor, 1996) may possibly account for that price-series length yielded no significant effects in Experiment 1. In Experiment 2 an attempt is made to reduce information-processing load by adding to the tabular stock-price information graphs displaying the stock prices plotted against trading days. Forecasting research has shown that presenting trended time-series data in scatter plots tend to result in better predictions compared to tabular presentation (for review, see Harvey and Bolger, 1996). Harvey and Bolger (1996, p. 131) state that "(t)aking trended data out of a graph and putting them in a table may be cognitively equivalent to increasing their variability." Hence, Experiment 2 rests on the assumption that visually displaying the data will make price trends appear more salient, thereby potentiating effects of price-series length on predictions and investments.

The hypotheses for Experiment 2 are the same as to those for Experiment 1.

Method

Participants. Participants were another 36 undergraduates (22 women) enrolled in different study programs at University of Gothenburg recruited through sign-up sheets and e-mails. Their mean age was 28.9 years (SD = 12.3).

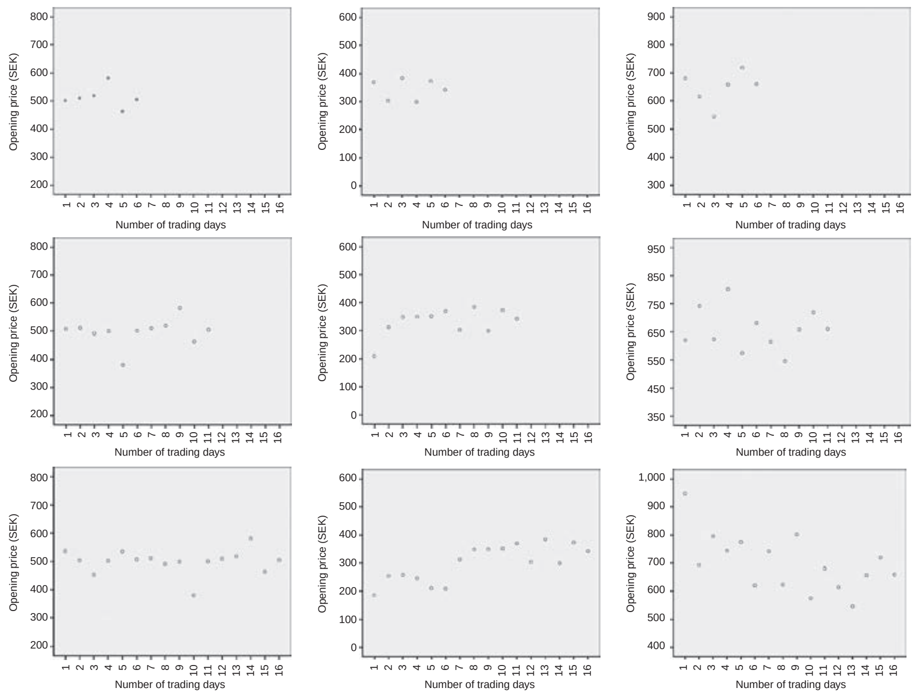
Experimental design and procedure. The experimental design and procedure was the same as in Experiment 1. The only difference was that on each page of the booklet a scatter plot was added to the table with numerical stock price information. Examples of scatter plots for 5, 10, and 15 trading days are displayed in Figure 1 for no and for positive price trend in the low price-volatility condition, and for negative price trend in the high price-volatility condition. As in Experiment 1, the mean price varied across stocks. In the graphs the origin was chosen such that the mean of each price sequence was placed at the mid-point of the price-axis.

After finishing, participants were debriefed and paid a flat sum of SEK 50 in addition to the bonus calculated for a randomly chosen stock. The average bonus paid out was SEK 96.80.

Results

Price predictions. The same three dependent variables as in Experiment 1 were analysed, that is price predictions, signed prediction errors, and unsigned prediction errors. Means are given in Table III. Parallel 2 (price volatility: low vs high) by 3 (price-series length: 5 vs 10 vs 15 trading days) by 3 (price trend: no vs positive vs negative) ANOVAs with repeated measures on the last two factors were performed.

Price predictions were highest for positive, lowest for negative, and in between for no price trend ($M_{\text{positive price trend}} = 572.1$ vs $M_{\text{negative price trend}} = 436.4$ vs $M_{\text{no price trend}} = 525.1$), $F(2, 68) = 51.63$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.74$. Predictions were furthermore higher for high than for low price volatility ($M_{\text{high volatility}} = 521.2$ vs $M_{\text{low volatility}} = 501.2$), $F(1, 34) = 6.48$, $p = 0.016$, $\omega^2_{\text{partial}} = 0.13$. The effect of price-series length on price predictions was not significant, $F < 1$, but the means showed that in the 5 trading-days condition higher predictions were made than in the 10 and 15 trading-days conditions ($M_{\text{5 trading days}} = 572.1$ vs $M_{\text{10 trading days}} = 436.4$ vs $M_{\text{15 trading days}} = 525.1$).



Note: The graphs with no and positive price trends represent the low price-volatility condition, the graphs with negative price trend the high price-volatility condition

Figure 1. Examples of visual presentations of stock prices in Experiment 2 for 5 (upper graphs), 10 (middle graphs), and 15 trading days (lower graphs) corresponding to no (left graphs), positive (middle graphs), and negative price trend (right graphs)

On the signed prediction errors, effect of price-series length approached significance due to larger price over-predictions in the 5 than in the 10 and 15 trading-days conditions ($M_{5\ \mathrm{trading\ days}} = 24.8$ vs $M_{10\ \mathrm{trading\ days}} = 2.4$ vs $M_{15\ \mathrm{trading\ days}} = 7.2$), $F(2, 68) = 2.56$, $p = 0.085$, $\omega^2_{\mathrm{partial}} = 0.08$. A significant effect of price trend, $F(2, 68) = 7.34$, $p = 0.001$, $\omega^2_{\mathrm{partial}} = 0.25$, substantiated that there was price under-prediction for positive and price over-prediction for negative and no price trend ($M_{\mathrm{positive\ price\ trend}} = -12.6$ vs $M_{\mathrm{negative\ price\ trend}} = 19.5$ vs $M_{\mathrm{no\ price\ trend}} = 27.4$). A significant main effect of price volatility was due to larger price over-prediction for high than for low price volatility ($M_{\mathrm{high\ price\ volatility}} = 21.5$ vs $M_{\mathrm{low\ price\ volatility}} = 1.5$), $F(1, 34) = 6.38$, $p = 0.016$, $\omega^2_{\mathrm{partial}} = 0.13$.

A significant main effect of price-series length on unsigned prediction errors was due to larger errors in the 5 than in the 10 and 15 trading-days conditions ($M_{5\ \mathrm{trading\ days}} = 70.5$ vs $M_{10\ \mathrm{trading\ days}} = 55.5$ vs $M_{15\ \mathrm{trading\ days}} = 49.7$), $F(2, 68) = 5.69$, $p = 0.005$, $\omega^2_{\mathrm{partial}} = 0.21$. Significantly smaller unsigned errors were observed for low than for high price-volatility ($M_{\mathrm{low\ volatility}} = 33.5$ vs $M_{\mathrm{high\ volatility}} = 83.6$), $F(1, 34) = 31.88$, $p < 0.001$, $\omega^2_{\mathrm{partial}} = 0.46$.

Investments. Mean numbers of stocks purchased at the unknown closing price are shown in Table IV. An ANOVA yielded no significant effects.

Discussion

Significantly smaller unsigned (and near-significantly smaller signed) price-prediction errors were observed for the longer price series (10 and 15 trading days) than for the

Table III. mean predicted closing prices, signed prediction errors, and unsigned prediction errors related to price-series length (number of trading days with price information), price trend, and price volatility (Experiment 2)

Measure	Price volatility	Price trend	Price-series length 5 trading days M (SD)	10 trading days M (SD)	15 trading days M (SD)
Prediction	Low	No	533.3 (140.7)	503.5 (152.8)	505.1 (137.1)
		Positive	561.8 (151.8)	557.6 (153.1)	576.1 (127.1)
		Negative	431.2 (128.3)	419.9 (141.0)	422.6 (141.8)
	High	No	569.3 (190.5)	499.3 (163.0)	540.2 (166.0)
		Positive	581.3 (220.2)	598.3 (174.6)	557.9 (157.3)
		Negative	484.2 (139.8)	430.0 (164.8)	430.2 (147.1)
Signed errors	Low	No	33.3 (74.2)	3.5 (38.6)	5.1 (24.5)
		Positive	−21.0 (55.5)	−27.4 (44.4)	−8.9 (49.9)
		Negative	16.2 (37.2)	4.9 (30.5)	7.6 (30.5)
	High	No	58.2 (108.4)	13.2 (88.8)	51.3 (90.0)
		Positive	1.3 (118.3)	10.5 (116.0)	−29.9 (95.1)
		Negative	60.9 (96.8)	9.4 (104.1)	18.0 (91.0)
Unsigned errors	Low	No	40.2 (70.5)	31.8 (20.8)	17.8 (17.1)
		Positive	50.7 (28.8)	40.3 (32.4)	39.2 (30.8)
		Negative	32.0 (24.1)	27.1 (13.4)	22.6 (21.3)
	High	No	107.3 (56.1)	69.9 (53.8)	73.3 (72.1)
		Positive	99.4 (59.4)	84.2 (78.0)	75.2 (63.2)
		Negative	93.4 (63.7)	79.6 (65.0)	70.1 (58.4)

Table IV. Mean number of stocks (0-100) purchased at unknown closing price related to price-series length (number of trading days with price information), price trend, and price volatility (Experiment 2)

Price volatility	Price trend	Price-series length 5 trading days M (SD)	10 trading days M (SD)	15 trading days M (SD)
Low	No	39.2 (37.7)	49.7 (26.8)	40.2 (30.6)
	Positive	49.4 (38.1)	48.6 (32.8)	52.2 (40.3)
	Negative	56.7 (34.3)	55.3 (32.9)	43.6 (32.9)
High	No	47.0 (32.9)	37.8 (38.7)	49.4 (36.5)
	Positive	40.8 (32.1)	52.2 (38.4)	58.7 (39.8)
	Negative	44.4 (35.4)	44.5 (40.2)	47.7 (41.0)

shorter five-day price series. *H1a* was thus weakly supported. In other aspects, the results of Experiment 1 were largely replicated. No support for *H1b* was obtained, since the effect of price-series length on prediction accuracy was not significantly affected by price volatility. Confirming *H1c*, signed prediction errors showed that stock prices were under-predicted for positive and over-predicted for negative price trend. In accordance with *H1d*, Table III indicates more pronounced trend damping for negative price trend than for positive price trend. *H1e* was confirmed by stock prices being over-predicted when there was no price trend, and further supported by the tendency of price over-prediction for all price trends in the condition with the shortest price series (five trading days). *H2a* and *H2b* were not supported, since no effect of price-series length on investments was observed.

Experiment 3

The results of Experiment 2 suggest that high information-processing load caused the lack of effects of price-series length in Experiment 1. However, while presenting data graphically made stock-price predictions improve with price-series length, no such effect was shown on investment decisions. In Experiment 3 we investigate whether price predictions and investment decisions would improve if the number of presented stock prices is reduced without at the same time reducing the time span (and restricting the range). We also seek to further disentangle the role of price volatility.

Three price-presentation formats are compared. In the 15 trading-days condition, stock prices for all 15 trading days are presented (as in Experiments 1 and 2), in the five trading-days condition only stock prices for every third of the 15 trading days are presented, while in the five aggregated-prices condition stock prices are presented as a series of five averages, each calculated based on the prices in three consecutive trading days. We expect information-processing load to be less pronounced in the two latter conditions with only five data points. However, due to higher variance, trend ambiguity is likely to be increased in the five trading-days condition, which may eliminate any beneficial effects of decreased information-processing load on price predictions and investment decisions compared to the 15 trading-days condition. In contrast, we expect the five aggregated-prices condition to decrease both processing load and price volatility and hence trend ambiguity compared to the 15 trading-days condition.

Price predictions

Based on the above, we expect (*H1a*) to observe more accurate price predictions in the five aggregated-prices condition than in the 5 and 15 trading-days conditions. As a consequence of the more accurate price predictions, we expect (*H1b*) less trend damping and (*H1c*) less over-prediction in the five aggregated-prices condition than in the 5 and 15 trading-days conditions.

Investments

As in the previous experiments, participants can for each stock make either a risk-taking (buying at an unknown closing price) or a risk-averse (buying at the known opening price) investment decision. In order to maximize outcomes, risk-taking is optimal for negative price trend (decreasing prices), whereas risk aversion is optimal for positive price trend (increasing prices). We expect (*H2*) participants' investment decisions to reflect this to a greater extent in the five aggregated-prices than in the 5 and 15 trading-days conditions.

Method

Participants. Participants were another 36 undergraduates (26 women) enrolled in different study programs at University of Gothenburg recruited through sign-up sheets and e-mails. Their mean age was 27.5 years (SD = 9.4).

Experimental design. The experimental design consisted of two (3 (price presentation format: five aggregated prices vs 5 trading days vs 15 trading days) by 3 (price trend: no vs positive vs negative)) within-group factors.

Procedure. The procedure was the same as in the high price-volatility condition in Experiment 1. Examples of the presented prices are given in Table V. A bonus was paid according to the same system as in the preceding experiments. The average bonus paid out was SEK 91.60.

Table V.
Stock-price information with no price trend presented in Experiment 3 for 15 trading days, five trading days (in italics), and five aggregated prices (M)

Trading day	Opening price (SEK)	Closing price (SEK)
1	505	533
2	*533* $M = 517$	*514* $M = 533$
3	514	553
4	553	583
5	*583* $M = 536$	*473* $M = 500$
6	473	443
7	443	496
8	*496* $M = 474$	*437* $M = 485$
9	437	522
10	522	462
11	*462* $M = 469$	*424* $M = 460$
12	424	494
13	494	580
14	*580* $M = 522$	*491* $M = 516$
15	491	478

Note: Participants were exposed to all three price-presentation formats for prices varying in average and trend

Results

Table VI shows mean predictions of the stocks' closing price, mean signed prediction errors, mean unsigned prediction errors, and mean numbers of stocks purchased at the unknown closing price.

Price predictions. A 3 (price-presentation format: 5 aggregated prices vs 5 trading days vs 15 trading days) by 3 (price trend: no vs positive vs negative) repeated-measures ANOVA revealed a significant effect of price trend on price predictions, $F(2, 70) = 35.32$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.66$. Predictions were highest for positive, lowest for negative, and in between for no price trend ($M_{\text{positive price trend}} = 558.6$ vs $M_{\text{negative price trend}} = 438.4$ vs $M_{\text{no price trend}} = 501.4$).

A parallel ANOVA on the signed prediction errors yielded a significant main effect of price trend, $F(2, 70) = 10.95$, $p < 0.001$, $\eta^2_{\text{partial}} = 0.24$, due to price under-prediction for

Table VI.
Mean predicted closing prices, mean signed and unsigned prediction errors, and mean number of stocks (0-100) purchased at unknown closing price related to price trend and price-presentation format (Experiment 3)

		Price-presentation format		
Measure	Price trend	15 trading days M (SD)	5 trading days M (SD)	5 aggregated prices M (SD)
Prediction	No	469.6 (139.4)	511.1 (144.4)	496.6 (143.4)
	Positive	549.7 (160.5)	541.9 (161.8)	584.4 (145.0)
	Negative	450.3 (146.4)	444.9 (133.8)	420.2 (144.6)
Signed errors	No	−3.4 (66.0)	11.1 (57.6)	−3.4 (30.2)
	Positive	−35.3 (54.7)	−43.1 (123.0)	1.6 (44.9)
	Negative	35.3 (70.6)	29.9 (58.1)	5.2 (47.2)
Unsigned errors	No	55.1 (35.4)	47.4 (33.7)	22.1 (20.6)
	Positive	50.5 (40.6)	68.5 (110.6)	31.9 (31.1)
	Negative	61.9 (48.2)	48.9 (42.9)	35.9 (30.5)
Purchased stocks	No	45.4 (37.6)	48.6 (40.3)	47.6 (36.5)
	Positive	57.5 (38.4)	49.3 (40.3)	27.2 (35.1)
	Negative	35.0 (41.3)	51.7 (44.0)	61.8 (37.3)

positive, price over-prediction for negative, and accurate price prediction for no price trend ($M_{\text{positive price trend}} = -25.6$ vs $M_{\text{negative price trend}} = 23.4$ vs $M_{\text{no price trend}} = 1.4$). Furthermore, the interaction between price-presentation format and price trend, $F(4, 140) = 3.89$, $p = 0.005$, $\omega^2_{\text{partial}} = 0.24$, reached significance. In the five aggregated-prices condition signed prediction errors differed marginally due to price trend ($M_{\text{5 aggregated prices, positive price trend}} = 1.6$ vs $M_{\text{5 aggregated prices, negative price trend}} = 5.2$ vs $M_{\text{5 aggregated prices, no price trend}} = -3.4$). In the five and 15 trading-days conditions price under-prediction was observed for positive ($M_{\text{5 selected trading days, positive price trend}} = -43.1$ vs $M_{\text{15 trading days, positive price trend}} = -35.3$), price over-prediction for negative ($M_{\text{5 selected trading days, negative price trend}} = 29.9$ vs $M_{\text{15 trading days, negative price trend}} = 35.3$), and accurate price prediction for no price trend ($M_{\text{5 selected trading days, no price trend}} = 11.1$ vs $M_{\text{15 trading days, no price trend}} = -3.4$).

The unsigned prediction errors submitted to a parallel ANOVA yielded a significant main effect of price-presentation format, $F(2, 70) = 12.15$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.38$, due to larger errors in the 5 and 15 trading-days than in the five aggregated-prices condition ($M_{\text{5 aggregated prices}} = 30.0$ vs $M_{\text{5 selected trading days}} = 54.9$ vs $M_{\text{15 trading days}} = 55.8$).

Investments. A parallel ANOVA on the number of stocks purchased at the unknown closing price revealed a significant interaction between price-presentation format and price trend, $F(4, 140) = 5.93$, $p < 0.001$, $\omega^2_{\text{partial}} = 0.35$. In the five aggregated-prices condition, fewer stocks were purchased to the unknown closing price for positive and more stocks for negative than for no price trend ($M_{\text{5 aggregated prices, positive price trend}} = 27.2$ vs $M_{\text{5 aggregated prices, negative price trend}} = 61.8$ vs $M_{\text{5 aggregated prices, no price trend}} = 47.6$). In the 15 trading-days condition more stocks were purchased to the unknown closing price for a positive price trend, whereas fewer stocks were purchased for negative or no price trend ($M_{\text{15 trading days, positive price trend}} = 57.5$ vs $M_{\text{15 trading days, negative price trend}} = 35.0$ vs $M_{\text{15 trading days, no price trend}} = 45.4$). In the five trading-days condition there were marginal differences due to price trend ($M_{\text{5 selected prices, positive price trend}} = 49.3$ vs $M_{\text{5 selected prices, negative price trend}} = 51.7$ vs $M_{\text{5 selected prices, no price trend}} = 48.6$).

Discussion

As hypothesized, performance in the five aggregated-prices condition exceeded performance in the 5 and 15 trading-days conditions. Confirming *H1a*, unsigned price prediction errors were smaller in the five aggregated-prices condition than in the other conditions. In accordance with *H1b*, trend damping was observed in the 5 and 15 trading-days conditions but not in the five aggregated-prices condition. *H1c* was not supported, since the over-forecasting bias was not observed in any of the conditions. *H2* was confirmed, since in the five aggregated-prices condition risk-taking (purchases at the unknown closing price) was more prevalent for negative and less prevalent for positive than for no price trend. Investment decisions were worst in the 15 trading-days condition, where risk-taking was, conversely, more prevalent for positive and less prevalent for negative than for no price trend. In the five trading-days condition, risk-taking differed only marginally across price trend conditions.

General discussion

We investigated whether exposure to longer vs shorter series of previous stock prices improves predictions of future stock prices and, as a consequence, investment decisions. If so, this would strengthen the case for prolonged evaluation intervals in performance-based bonus schemes to stock portfolio managers. Experiment 1 did, however, not show any beneficial effects of longer price series on either predictions or investment decisions. A possible interpretation is that there exists an optimal length of the price series due to the trade-off of amount against reliability of information. In order to enable detection of a price trend, a price series must therefore be long enough to provide sufficiently reliable information at the same times as being short enough not to impose too high information-processing load. We claim that the results of Experiment 2 partially support this interpretation since visually displaying the price series – which compared to tabular presentation may be cognitively equivalent to decreasing variance (Harvey and Bolger, 1996) and thereby processing load – resulted in price predictions improving with price-series length. An even stronger support we claim was obtained in Experiment 3 where both price predictions and investment decisions improved when the length and the volatility (variance) of the price series were simultaneously decreased.

An explanation of the present results is that people in general are myopic (Benartzi and Thaler, 1995; Thaler *et al.*, 1997) when processing stock prices sequentially, thus placing too much weight on unsystematic short-term price variation and failing to perceive underlying price trends. Graphs as those presented in Experiment 2 may counteract the myopic tendency by defocussing attention from unsystematic local variation, thereby potentiating effects of price-series length on prediction performance. In viewing a scatter plot people are free to compare any price values, for instance the beginning of the sequence to the end of the sequence and thus both construct and test trend hypotheses (Andreassen and Kraus, 1990). Furthermore, the visual perception system has evolved to extract information about positions, length, and orientation, which may make people generally better equipped to process graphical than tabular data (Harvey and Bolger, 1996). A possible caveat of Experiment 2 is that the tabular information that was simultaneously available continued to influence information processing. However, we find it plausible that the participants chose to largely ignore the tables in favor of the more readily digestible graphs, thus resulting in decreased information processing load compared to Experiment 1. Yet, as the results suggested, large unsystematic price variation may still have had an influence.

The results were stronger in Experiment 3 comparing three price presentation formats, all covering the same period of 15 preceding trading days. Accuracy of price predictions and investment decisions increased in the condition where consecutive averages were computed such that both number of information units and unsystematic local variation were reduced. When participants in another condition (being exposed to prices for all 15 trading days as in Experiments 1 and 2) encountered the price information necessary to calculate the same consecutive averages, they apparently failed to do these calculations themselves, resulting in much worse predictions and investment decisions. Indicating that this performance difference was due to a difference not only in the number of information units, but also in variance, a third condition, where only the number of information units was reduced, resulted in worse investment decisions than in the former condition but better than in the latter. Reduction in the number of information units and reduction in variance are both factors likely to reduce information-processing load. While reduction in variance improved accuracy of price predictions in Experiments 1-3, presumably as consequence of decreased trend ambiguity, Experiment 3 showed that reduction in the number of information improved predictions only in combination with reduction in variance.

A caveat needs, however, be noted concerning the interpretation of the results of Experiment 3. In this experiment the prices for five trading days were selected within the full, wider price range, thus reducing overlap among the prices. The consequence would be that the price trend becomes less ambiguous. Reducing the overlap was, however, still not sufficient as can be determined by comparing the results of Experiment 3 to the results of Experiments 1 and 2 for the same number of prices (5 and 15). Yet, it cannot be ruled out that both averaging (reducing price volatility) and reducing overlap account for the improved performance compared to Experiments 1 and 2 in which only price volatility was reduced.

A key to understanding why directionally accurate price trend predictions observed in all experiments did not improve investment decisions is perhaps that confidence in the price predictions remained low except in Experiment 3 when the price trends became less ambiguous by the presentation of consecutive averages. The unsigned prediction errors that express variability in the predictions may be interpreted as approximate assessments of confidence. In Experiment 1 only price volatility had an impact on the unsigned prediction errors, in Experiment 2 price-series length, and in Experiment 3 price volatility.

It is noteworthy that in none of the experiments did the participants make random predictions of the price trends but the results were consistent with the generally observed phenomenon of trend damping, that is overprediction of negative and underprediction of positive price trends (e.g. Bolger and Harvey, 1993; Eggleton, 1982). This is also consistent with a judgmental regression effect or response contraction bias (Jou *et al.*, 2004; Stevens and Greenbaum, 1966).

Some limitations need to be addressed. First, participants in the experiments were undergraduates with in general limited knowledge of stock market investments. While not claiming without further evidence that the present results directly generalize to professional investors, we believe that our replication of typical prediction errors observed in previous research under realistic conditions (Harvey and Bolger, 1996; Webby and O'Connor, 1996) suggests that even other aspects of the results may generalize. Even if professional investors possess expert knowledge, they may frequently act under time pressure and other constraints preventing them from using their full knowledge in making judgments and decisions (MacGregor *et al.*, 2000; Nofsinger, 2005).

Second, in the experiments the participants had no other information than the stocks' previous price movements on which to base their stock price predictions and investment decisions. While price trend is considered also in a real-life stock market investment context (and plausibly constituting the basis of most stock investment decisions), stock purchase decisions ought to be based primarily on fundamental factors impacting the stock's prospects such as stock companies' cash flow, return on assets, and capital management. Reducing information on which to base price predictions and investment decisions to previous price movements alone was, however, deemed necessary in order to be able to test our experimental hypotheses. Yet, external validity had to be compromised.

Bearing these limitations in mind, the presented series of experiments gave little support to the suggestion that exposure to longer price series improve predictions of future stock prices and therefore investment decisions. Rather, a balance needs to be struck between amount of information and reliability of information. Although the present results, by implication, suggest the existence of some optimal evaluation interval for rewarding investors, this should not be taken to imply that short-term evaluations do not generally have negative effects on investment performance. In other experiments (Andersson *et al.*, 2012), we have shown that when price information is presented sequentially (across trading days) and investors themselves decide when to purchase the stocks, they do this earlier than what is optimal, a finding potentiated by a short-term bonus. Impatience (Hedesström *et al.*, 2012) may here play a role it did not do in the present experiments.

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Further reading

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