Handbook of Behavioral Finance

Edited by

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1 Framing effects, selective information and market behavior: an experimental analysis

Erich Kirchler, Boris Maciejovsky and Martin Weber

INTRODUCTION

Communication about asset return distribution is a central issue in finance. Investment advisors are legally obligated to inform clients about potential investment risks, which are usually expressed as the variance or standard deviation of the underlying distribution of the investment's future returns. Investors are implicitly assumed to accurately perceive and interpret statistical information, irrespective of how that information is presented.

In recent years, many new ways of acquiring financial information have become available, with the main source, of course, being the Internet. Yahoo!Finance, for instance, offers free market information, business news and personal finance plans, while BigCharts allows investors to create personalized interactive charts. Market data provider eSignal even assumes a positive relationship between information quantity and investment success by promising 'You'll make more, because you'll know more.'

Evidence suggests that investors generally benefit from the provision of information. Empirical studies, however, indicate that more information does not necessarily lead to more knowledge. In the psychological literature, this is referred to as the illusion of knowledge, and is confirmed empirically for many decision domains. For example, Park (2001) shows that even when news media recipients are socially involved with issues covered in the media, they are prone to the illusion of knowledge. The tendency increases the more recipients use the media.

In the finance domain, Barber and Odean (2001) investigate the performance of investors who switched from phone-based trading to internet trading. While these traders initially beat the market by about 3 percent prior to going online, their performance decreased afterward, resulting in a performance of 2 percent below the market. Similarly, Choi et al. (2002) report evidence of underperformance in the market timing of online traders in 401(k) plans. Access to vast quantities of investment data on the Internet, therefore, does not necessarily imply better performance.

Information plays an important role not only in individual investment decisions, but also in market environments. Market efficiency requires that aggregate market prices will not be affected by either objectively irrelevant information, or by selectively distributed information. For example, if some traders receive a positive signal about an asset's likely returns, and an equal number receive the opposite signal, this information, because it is completely revealed, should not affect aggregate market prices. Thus, while individual investors may be prone to biases like the illusion of knowledge, aggregate market prices are considered unbiased.

This chapter focuses on the communication and the quality of information in the context of a competitive asset market. We investigate the impact of objectively irrelevant information on trading behavior by drawing upon a novel type of framing. Traders are confronted with randomly distributed selective information about the performance of potential investments. The information is provided in either a positive or a negative frame, and is essentially irrelevant to the decision. Since we symmetrically distribute the additional information among traders, aggregate market behavior is expected to remain unaffected. In addition, we also investigate the robustness of the disposition effect in a competitive market environment with available real-time data.

Our results indicate that objectively irrelevant information does influence trading behavior. Moreover, positively and negatively framed information leads to a particular trading pattern, but leaves trading prices and trading volume unaffected. Our findings also support the disposition effect. Participants who experience a gain sell their assets more rapidly than those who experience a loss. This effect is further moderated by framing: positively framed market participants generally sell their assets later than negatively framed participants.

The next section discusses framing effects and the disposition effect. We introduce the experimental design and the procedure in the section that follows it. The third section covers the results, and the final section discusses our findings.

FRAMING EFFECTS

Expected utility theory assumes descriptive invariance, which implies that different representations of the same choice problem should yield the same preference. However, several empirical studies indicate that this axiom is frequently violated in individual decision making. McNeil et al. (1982), for example, show that the same medical statistics, framed either in terms of mortality rates or in terms of survival rates, lead to different preferences. Framing effects are also observed in decisions involving risky lotteries and monetary payoffs (Kahneman and Tversky, 1983; Tversky and Kahneman, 1981). More recently, Statman (1995) and Kahneman and Riepe (1998) have applied the concept of framing to financial decisions, such as dollar-cost averaging.

Weber et al. (2000) investigated the impact of endowment framing on market prices in an experimental asset market. Participants were given either (1) cash plus a certain amount of positively valued risky assets (long position, positive framing), or (2) a larger amount of cash and certain state-contingent liabilities (short position, negative framing). In terms of final wealth, the endowments were identical. In line with the predictions of prospect theory, Weber et al. (2000) found that overpricing[1] was observed more often for negatively framed market participants than for positively framed participants.

In contrast to the Weber et al. (2000) study, where participants' actual initial endowments were altered, we investigate whether framing effects are also robust under weaker conditions, for example, when participants only obtain different and more importantly irrelevant information.

Our experimental procedure differs from the way framing effects were originally studied by Tversky and Kahneman (1981). Their subjects were presented with scenarios in which a hypothetical decision problem was semantically framed in terms of 'gains' or 'losses.' However, the concept of framing in studies emphasizing the role of language in the decision problem lacks conclusive empirical evidence. Kühberger (1995) found that

a variation of missing items of information in the decision problem produced markedly different framing effects. Moreover, with fully described decision problems, no framing effects emerged at all.

However, the results of a meta-analysis of 136 empirical studies indicate that the framing effect is a generally reliable phenomenon (Kühberger, 1998). A further meta-analysis, which focused particularly on Asian disease-like studies, indicates that risk preference depends on the size of the payoff, the probability level, and the type of goods at stake (Kühberger et al., 1999).

In our experimental procedure, we use a novel type of framing that is not based on semantic variations of a decision problem. Instead, participants are informed that dividends are randomly determined and drawn from a normal distribution with a commonly known fixed μ and fixed σ, where we assume that μ is the aspirational reference payoff. For a given probability p, p between 0 and 0.5, we let $\underline{Xp}$ and $\overline{Xp}$ denote the $100p$ and $100(1 - p)$ percentiles, respectively. For a given p, subjects are told that dividends will be less than $\underline{Xp}$ with probability p (negative framing), or that dividends will exceed $\overline{Xp}$ with probability p (positive framing). We distinguish between two independent markets, A and B, in which percentile information follows two different probabilities. The framed information on market A deviates more extremely from μ than the framed information on market B ($p_A < p_B$).

Our experimental approach is also related to the 'anchoring and adjustment' bias (Tversky and Kahneman, 1974), a sequential decision situation in which initial information serves as an anchor from which adjustments in the decision process are made insufficiently.[2] In our design, the positively and negatively deviating dividend information represents the initial information, the anchor. If subjects respond to this additional percentile information, we expect trading behavior to be influenced systematically. This is because positive information should increase traders' dividend expectations and negative information should lower them, leading to a particular trading pattern. Positively framed buyers are expected to purchase assets from negatively framed sellers, and negatively framed sellers are expected to sell their assets to positively framed buyers.

If the framed information does have a systematic impact on traders' dividend expectations, we hypothesize that there will be differential trading activity on markets A and B. Because the additional irrelevant information deviates more strongly from the aspirational reference payoff μ on market A, we expect that the more extreme information on this market will create more diverging dividend expectations on the part of the traders. We assume this will increase the likelihood that pairs of participants willing to trade will actually meet on the market.

The experimental design also allows us to investigate whether framing effects vanish if the decision problem is fully described, as suggested by Kühberger (1995). The market possesses complete information in our experiment, as positively and negatively framed information is symmetrically distributed among traders.

One might argue that the percentile information in our approach serves two different roles: an informational role, and a framing role. From a normative perspective, the additional percentile information is logically redundant. Nevertheless, knowledge of the mean and the standard deviation of the normal distribution may be perceived as useful in the decision-making process, for example, to learn about the shape of the distribution.

Assuming that information dissemination takes place,[3] however, rules out the informational role, since the redundant percentile information was symmetrically distributed to market participants with prior statistical training. Any behavioral regularities observed are therefore likely to be due only to the framing role.

DISPOSITION EFFECT

The disposition effect is one implication of prospect theory (Kahneman and Tversky, 1979, Tversky and Kahneman, 1992). In contrast to the utility function implied by expected utility theory, the value function v postulated by prospect theory is defined in terms of gains and losses relative to a reference point, not in terms of absolute levels of final wealth. Prospect theory assumes that the value function is concave for gains and convex for losses. In a financial context, therefore, we expect that winner assets will be sold more readily than loser assets in order to collect the gain and 'repair' the loss, respectively (Shefrin and Statman, 1985).

This hypothesis has been supported empirically for field data (Heisler, 1994; Odean, 1998), and in experimental asset markets (Heilmann et al., 2000; Weber and Camerer, 1998). Odean (1998) analyzed trading records for 10000 accounts at a large discount brokerage house and found that investors held losing stocks for a median of 124 days, while winners were held for only 104 days. Using an experimental call market, Heilmann et al. (2000) showed that the number of assets offered and sold was higher during periods of rising trading prices than during periods of falling trading prices.

In contrast to Heilmann et al. (2000), who used the price of the previous trading period as the reference point, we focus on individual behavior. We define the reference point, as Weber and Camerer (1998) did, as the subject's purchase price. But unlike the experimental procedure of Weber and Camerer (1998), which determined prices by a random process, our market prices are determined solely by the market participants themselves on a computerized experimental asset market.

We contribute to the existing literature by studying the disposition effect in the context of a competitive market environment using available real-time data. We expect that purchase prices that are lower than the previous trading price will imply a gain and lead to more rapid selling, while purchase prices that are higher than the previous trading price will imply a loss and lead to less rapid selling.

THE EXPERIMENT

Participants

Our experiment consisted of eight sessions of an experimental asset market. There were 64 participants, all students at either Vienna University or the Vienna University of Economics and Business Administration. Forty-nine were economics students; the remaining 15 were enrolled in other social science disciplines. All participants had taken at least introductory courses in statistics.

There were 22 females and 42 males, aged 19 to 31 (M = 22.52, SD = 2.90). On

Table 1.1 Positive and negative dividend information for all periods – markets A and B

	Market and (Period)	$\sigma_1 = 20$ $\underline{Xp} - \overline{Xp}$	Market and (Period)	$\sigma_2 = 30$ $\underline{Xp} - \overline{Xp}$	Market and (Period)	$\sigma_3 = 40$ $\underline{Xp} - \overline{Xp}$
$\mu_1 = 95$	*A*(1)	56–134	*A*(2)	36–154	*A*(3)	17–174
	B(9)	92–98	*B*(8)	91–99	*B*(7)	90–100
$\mu_2 = 135$	*A*(4)	96–174	*A*(5)	76–194	*A*(6)	57–214
	B(6)	132–138	*B*(5)	131–139	*B*(4)	130–140
$\mu_3 = 105$	*A*(7)	66–144	*A*(8)	46–164	*A*(9)	27–184
	B(3)	102–108	*B*(2)	101–109	*B*(1)	100–110

average, participants earned €19.14, with a standard deviation of €14.94. The experiment took about 2 hours and 15 minutes.

Experimental Design

The experiment was conducted in a 2 × 2 factorial design in order to study the interaction of differently framed participants within one market. The independent variables were (1) the framing of dividend information (positively versus negatively) as a between-subjects factor, and (2) the probability of the framed information as a within-subjects factor (low versus high probability; $p_A = 0.05$ and $p_B = 0.45$). Participants were randomly assigned to one of the two framing conditions. All were informed that dividends would be randomly drawn from a normal distribution with a μ of 95, 105 or 135 and a σ of 20, 30 or 40. See Table 1.1 for the combination and sequence of μ and σ. In order to keep subjects' attention levels high, we balanced μ and σ across trading periods.

Prior to the trading periods, participants were given the actual μ and σ as well as additional irrelevant percentile information, $\underline{Xp}$ (negative framing) and $\overline{Xp}$ (positive framing). Figure 1.1 shows what information was available to subjects at the beginning of the trading periods.

Experimental Procedure

The experiment consisted of four phases:

1. We measured subjective propensity toward risk by using certainty equivalents and binary lottery choices to control for possible differences in individual risk attitude.
2. We opened the experimental asset market and assets were traded.
3. Participants were asked to complete a short questionnaire.
4. We repeated the procedure to control for risk attitude. The exact sequence of events in the experiment is shown in Figure 1.2.

Phase 1

After brief instructions, participants were asked to reveal their certainty equivalent for a lottery that offers a payoff of 100 experimental currency units (ECUs)[4] with a probability of $p = 0.50$ and zero otherwise. They were also asked to make seven decisions

In this period, dividends are randomly drawn from a normal distribution with a mean of 95 ECU and a standard deviation of 20 ECU.

With a probability of 5 percent the next dividend will be larger (smaller) or equal to 134 ECU (56 ECU). This means that on average in five out of 100 cases the observed dividend will be larger (smaller) or equal to 134 ECU (56 ECU).

Note: The information provided to subjects in the negative framing condition is displayed in parentheses.

Figure 1.1 Available information at the beginning of the first trading period of market A for positively and negatively framed subjects

among risky lotteries.[5] The payoffs of the lotteries are listed in Table 1.2. As a control for position effects, the lotteries were systematically varied with respect to $a1$ (the highest possible payoff), $a2$ (the lowest possible payoff), A (certain payoff), and the sequence of $a1/a2$ (risky payoff).

The certainty equivalent allows us to infer participants' attitudes toward risk. More precisely, it allows us to discriminate between risk aversion, risk neutrality and risk-seeking behavior. A certainty equivalent that is lower than the expected value of the lottery, which is 50 ECUs, indicates risk aversion; a certainty equivalent equal to 50 ECUs indicates risk neutrality; and a certainty equivalent above 50 ECUs indicates risk-seeking behavior.

The seven lottery decisions can also be used to infer risk attitude. However, since each lottery has the same expected value, we can discriminate only between risk aversion (if the certain payoff is chosen) and risk neutrality (if the risky payoff is chosen).

We randomly selected one of the seven decisions to determine the individual payoff. This payoff from the lotteries was then added to the total payoff from the market. Phase 1 took 15 to 20 minutes.

Phase 2

After receiving instructions about the experimental asset market[6] and a short questionnaire to check their understanding of the instructions, subjects participated in two trial periods of six minutes each to become familiar with the market's selling and buying procedures. After the trial periods, we opened the asset market. Overall, we ran eight sessions with eight subjects each on a computerized asset market using the software z-Tree (the Zurich Toolbox for Readymade Economic Experiments, Fischbacher, 2007).

The computer screen for the auction is shown in Figure 1.3. Each market participant was entitled to (1) submit bids and asks, (2) accept standing bids and asks, where only better offers, i.e. higher bids and lower asks, were allowed, or (3) remain passive. Bids and asks were automatically ranked to indicate the most favorable offer. Information about the trading history, provided as a chronological list of contracts, was displayed throughout the trading periods.

The market was performed as a continuous anonymous double auction. Participants were endowed with 1000 ECUs (100 ECUs equals €0.18), plus five risky assets A and five risky assets B (these assets were traded separately on markets A and B). To ensure comparability, the sequence of the two markets was chosen in advance and applied to all

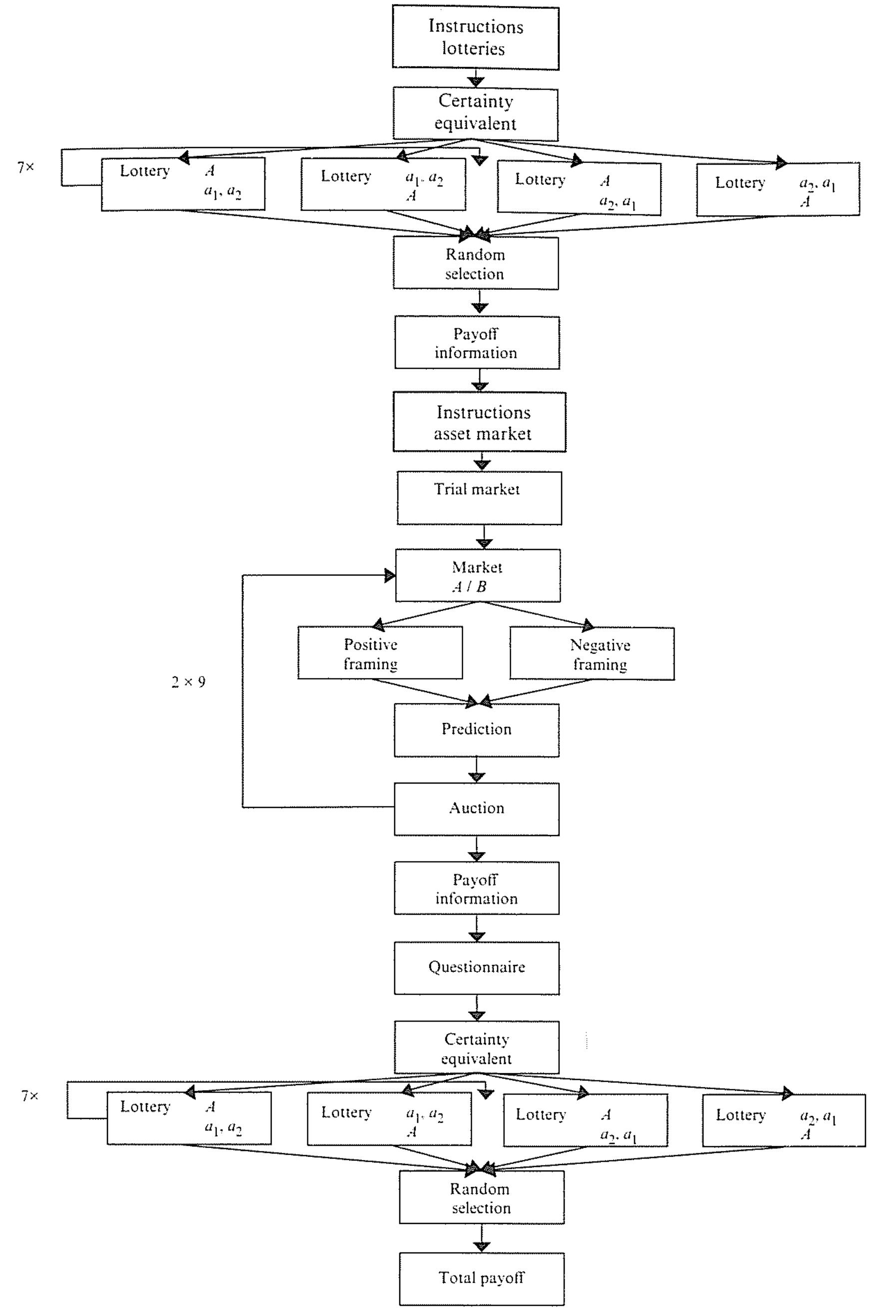

Figure 1.2 Sequence of events in the experiments

Table 1.2 Lottery payoffs in experimental currency units

Lottery		Payoff	p	Expected value
1	$a1$	160	0.20	88
	$a2$	70	0.80	
	A	88	1.00	88
2	$a1$	150	0.32	99
	$a2$	75	0.68	
	A	99	1.00	99
3	$a1$	178	0.28	106
	$a2$	78	0.72	
	A	106	1.00	106
4	$a1$	140	0.35	101
	$a2$	80	0.65	
	A	101	1.00	101
5	$a1$	135	0.40	105
	$a2$	85	0.60	
	A	105	1.00	105
6	$a1$	188	0.25	98
	$a2$	68	0.75	
	A	98	1.00	98
7	$a1$	130	0.30	102
	$a2$	90	0.70	
	A	102	1.00	102

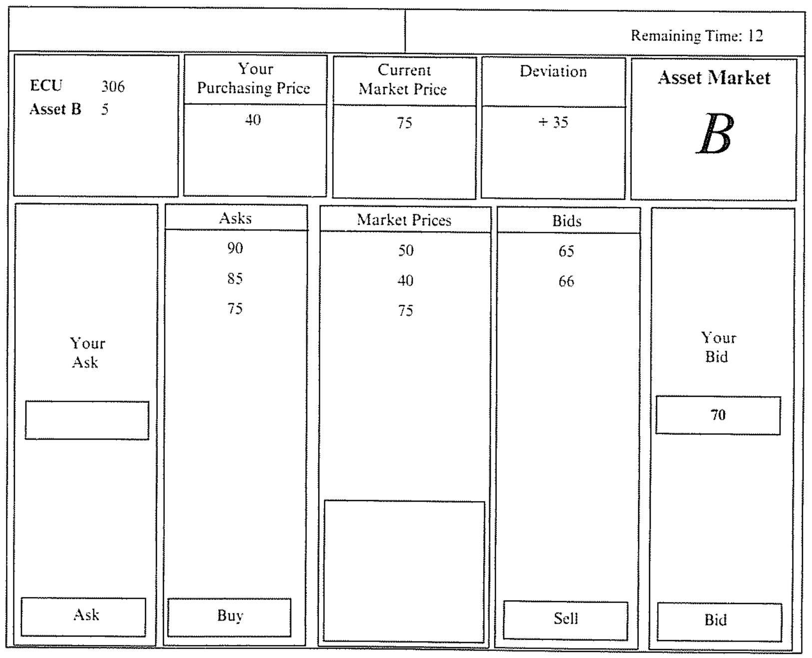

Figure 1.3 Auction computer screen

eight sessions. Dividends were randomly determined and drawn from a normal distribution (see Table 1.1).

We informed participants that the markets would be open for at least eight periods, and at most 12 periods. The probability that the markets would end after the eighth, ninth, tenth, or eleventh period was 25 percent. At the end of the final market period, the liquidation value of the asset would be zero. Again to ensure comparability, we randomly chose the last market period once for all eight sessions. According to this random selection, we determined that each market ended after the ninth period. Each trading period lasted for 180 seconds.

Before the market opened, participants were told which market (A or B) and which trading period (1 to 9) were open, and the last average market price and closing price of the asset traded. They were also given either positively or negatively framed dividend information, and asked to predict the next average trading price of the assets. Phase 2 took about 80 to 90 minutes.

Phase 3

Participants were asked to fill out a computerized post-experimental questionnaire with items designed to measure how well they had understood the experiment and how much effort they had put into arriving at accurate decisions. Phase 3 took about 15 to 20 minutes.

Phase 4

Participants again had to reveal their certainty equivalent for a lottery offering a payoff of 100 ECUs with a probability of $p = 0.50$ and zero otherwise, and to make seven decisions among lotteries (100 ECUs equals €0.73). The payoffs were identical to those used in phase 1 (see Table 1.2). Phase 4 took about 15 to 20 minutes.

EXPERIMENTAL RESULTS

Data Analysis

Over the eight sessions, with two times nine trading periods each, participants submitted 6983 offers, of which 3168 contracts were concluded. Thus the participants concluded an average of 22 contracts per period (SD = 9.19), ranging from a minimum of four to a maximum of 68 contracts. The average market price was 368.15 ECUs (SD = 390.71).

Figures 1.4 and 1.5 indicate that, over the trading periods, the number of concluded contracts decreased in both markets, A ($\chi^2(1) = 112.91$, $p < 0.001$) and B ($\chi^2(1) = 73.83$, $p < 0.001$), while the number of offers not accepted increased in both markets, A ($\chi^2(1) = 75.02$, $p < 0.001$) and B ($\chi^2(1) = 20.16$, $p < 0.05$). We posit that prices may have increased over trading periods, and this conjecture was confirmed. Average trading prices were statistically significantly higher in the last period of both markets, A ($M_{A,9} = 235.77$, $SD_{A,9} = 216.29$) and B ($M_{B,9} = 354.34$, $SD_{B,9} = 425.30$), compared to the first period ($M_{A,1} = 150.06$, $SD_{A,1} = 83.73$; $F(1; 649) = 40.52$, $p < 0.001$; $M_{B,1} = 163.94$, $SD_{B,1} = 82.45$; $F(1; 625) = 50.74$, $p < 0.001$).

However, Figure 1.6 indicates that average trading prices on both markets sharply

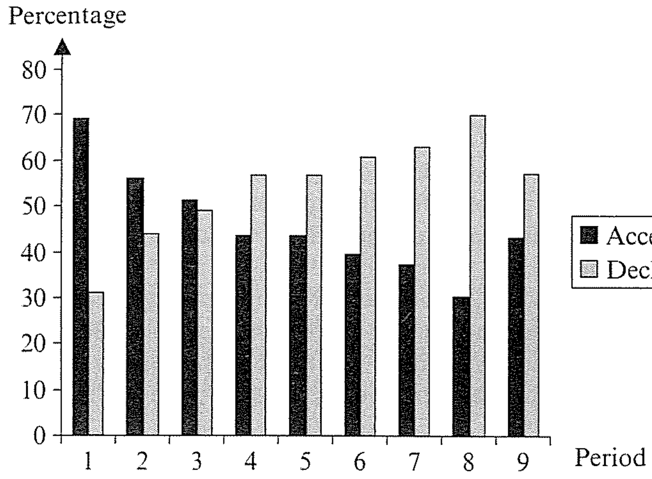

Figure 1.4 Percentage of accepted and declined offers for market A

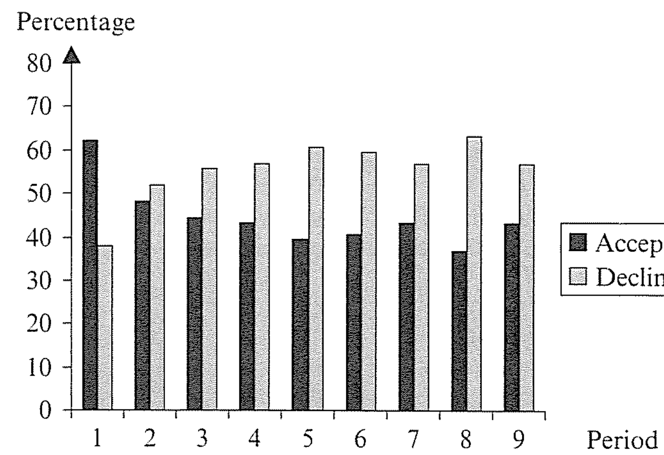

Figure 1.5 Percentage of accepted and declined offers for market B

declined in late trading periods, when uncertainty about market duration was important. This uncertainty about market termination depressed average trading prices, although they were still higher in the last period than in the first. Figure 1.6 also indicates that during highly uncertain times, especially in late trading periods, the variance of market prices increased.

To control for possible differences in individual risk attitude, we investigated whether risk attitude differed between sessions and between experimental conditions, with respect to elicited certainty equivalents and binary lottery decisions. The average certainty equivalent revealed by the subjects was 44.23 (SD = 31.20), indicating a slight degree of risk aversion. Certainty equivalents did not differ significantly between the eight sessions ($F(7; 56) = 0.48$, $p = 0.84$).

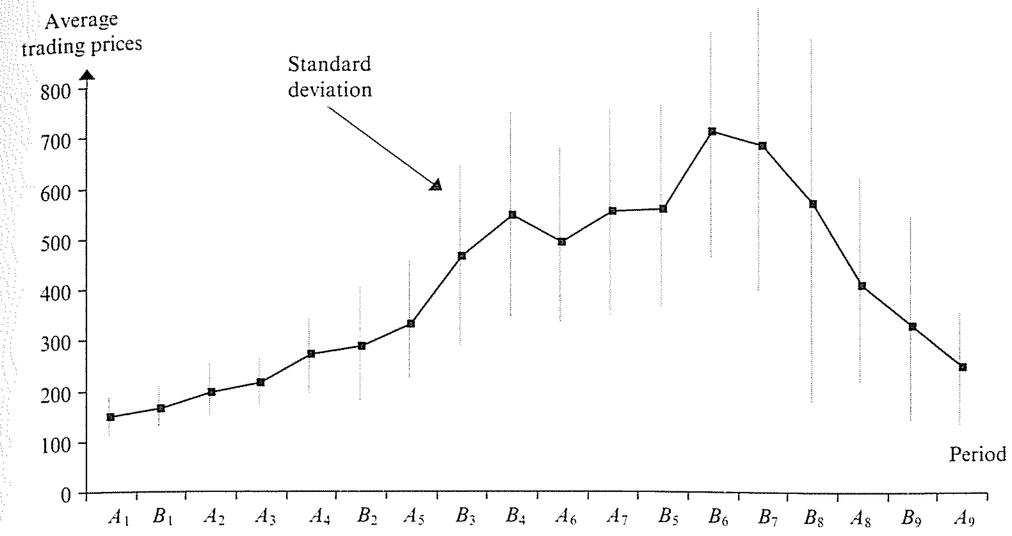

Figure 1.6 Average trading prices and standard deviations for markets A *and* B *across periods*

We computed a risk attitude index from the seven decisions among lotteries ranging from 0 = risk neutrality to 7 = risk aversion. The average risk attitude was 3.66 (SD = 2.15). Again, we observed no statistically significant difference between the eight sessions ($F(7; 56) = 0.95$, $p = 0.47$). Nor was there any statistically significant difference between positively and negatively framed subjects with respect to the certainty equivalent ($F(1; 62) = 0.09$, $p = 0.76$) and the lottery decisions ($F(1; 62) = 0.05$, $p = 0.82$). Thus any differences in observed behavior between experimental conditions are not likely to be caused by different underlying risk attitudes. There was also no difference in risk attitude between the first measurement (before the market was performed) and the second measurement for either the certainty equivalents ($M_I = 44.23$, $SD_I = 31.20$; $M_{II} = 45.58$, $SD_{II} = 31.91$; $F(1; 62) = 0.15$, $p = 0.70$) or the lottery decisions ($M_I = 3.34$, $SD_I = 2.10$; $M_{II} = 3.67$, $SD_{II} = 2.44$; $F(1; 62) = 1.22$, $p = 0.27$). The results indicate that market behavior did not have a recursive impact on individual risk attitude.

The results from the questionnaire reveal that the instructions were clear and easy to understand (M = 7.16, SD = 2.00), and confirmed that the participants carefully considered their buying orders (M = 6.13, SD = 1.91) and selling orders (M = 6.09, SD = 2.08). Subjects also emphasized that they had tried to maximize their earnings (M = 6.83, SD = 1.94). All questions were formulated as statements that subjects could disagree or agree with (ranging from 1 = do not agree to 9 = fully agree).

Framing Effects

The results confirm our hypothesis that positively framed buyers purchase assets from negatively rather than from positively framed sellers ($\chi^2(1) = 6.61$, $p < 0.01$), and that negatively framed sellers sell their assets to positively rather than to negatively framed

Table 1.3 Observed and expected trading volume between positively framed buyers and positively and negatively framed sellers

	Positively framed buyers	
	Observed trading volume	Expected trading volume
Positively framed sellers	634	683.6
Negatively framed sellers	870	820.4
	1504	

Table 1.4 Observed and expected trading volume between negatively framed sellers and positively and negatively framed buyers

	Negatively framed sellers	
	Observed trading volume	Expected trading volume
Positively framed buyers	905	839.5
Negatively framed buyers	634	699.5
	1539	

buyers ($\chi^2(1) = 11.26, p < 0.001$). Tables 1.3 and 1.4 show the observed and the expected trading volume between positively and negatively framed subjects.

We also expected that varying the probabilities of the framed information would shape individual price expectations. Since the framed dividend information on market *A* was more extreme than on market *B*, we expected trading volume on market *A* to be higher due to more diverging dividend expectations.

The results at least weakly support our conjecture. The total number of concluded contracts was higher on market *A* (1636) than on market *B* (1532) ($\chi^2(1) = 3.41, p = 0.07$). However, the total number of offers not accepted did not differ between the two ($\chi^2(1) = 0.12, p = 0.73$). On market *A*, the number was 1918; on market *B* it was 1897.

Figure 1.6 indicates that participants did not seem to distinguish between the two asset markets, so the observed higher trading volume on market *A* may be attributable to the unbalanced sequence of periods of the two markets. Figure 1.6 indicates that prices followed an upward trend on both markets up to the sixth period of market *B*, and then sharply decreased in later trading periods. Note that at the beginning of the experiment, when participants were still highly inexperienced, market *A* was opened more often than market *B*, while in later trading periods this pattern was reversed. Thus the higher number of concluded contracts may be a result of this sequence of trading periods.

We also investigated whether the observed matching of unequally informed subjects led to different trading prices. For this analysis we distinguished between: (1) trades with negatively framed sellers and buyers, (2) trades with positively framed sellers and buyers, and (3) trades with mixed pairs of sellers and buyers. We ran a repeated ANOVA (analysis of variance) with the trading pattern as a between-subjects factor and the market (*A* or *B*) as a within-subjects factor. We aggregated the data by replacing the nine periods of the two markets by the overall mean of each market. The

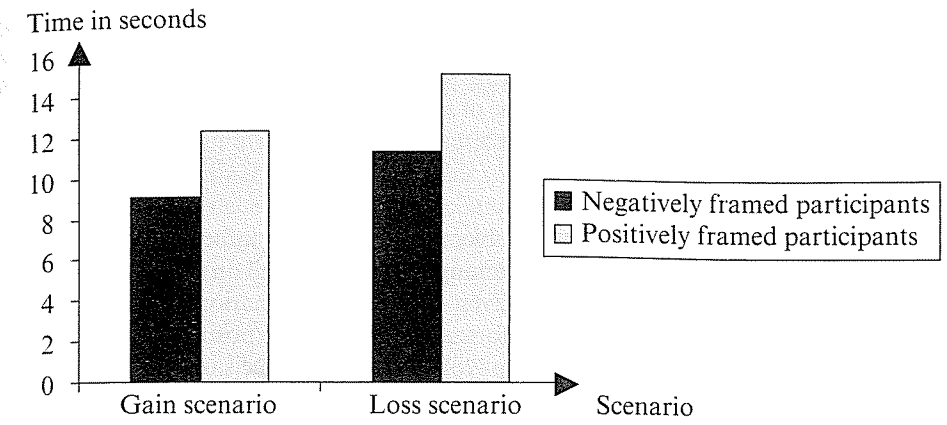

Figure 1.7 Average time difference between buying action and the next selling action for positively and negatively framed participants in gain and loss scenarios

results indicate that trading prices were not statistically significantly different between trading patterns ($F(2; 21) = 0.07, p = 0.93$), but did differ across the two markets ($F(2; 21) = 28.71, p < 0.001$).

Our findings indicate that objectively irrelevant information influences trading behavior: positively framed buyers purchase assets from negatively rather than from positively framed sellers, and negatively framed sellers sell their assets to positively rather than to negatively framed buyers. The matching of unequally informed subjects, however, does not lead to different trading prices. We also find that a probability variation of the framed information impacts trading volume. We believe that this is attributable primarily to the unbalanced sequence of trading periods across markets.

Disposition Effect

Based on the predictions of prospect theory, we expect that a purchase price lower than the previous market price implies a gain situation that leads to more rapid selling. In turn, a purchase price higher than the previous trading price implies a loss situation that leads to less rapid selling.

To test this conjecture, we defined two scenarios, one for a gain where the purchase price is below the previous market price, and the other for a loss, where the purchase price is higher than the previous market price. The software z-Tree used in the experiment (Fischbacher, 2007) enabled us to calculate the exact time in seconds between a subject's buying and selling, so we are able to show that market participants who experienced a gain sold their assets significantly earlier ($M_G = 10.12, SD_G = 23.30$) than market participants who experienced a loss ($M_L = 13.66, SD_L = 26.90; F(2; 1306) = 3.01, p < 0.05$).

This effect was moderated by framing (see Figure 1.7). Positively framed market participants generally sold their assets later than negatively framed market participants ($M_P = 13.90, SD_P = 27.62; M_N = 10.32, SD_N = 23.72; F(1; 1307) = 6.34, p < 0.05$). Thus we assume that framing shapes individual expectations, and thereby influences market behavior. Positively framed participants seemed to be more optimistic about the likely performance and profit of their assets. They were thus also more patient, in both gain and in loss situations.

CONCLUSIONS

This chapter investigates the impact of objectively irrelevant information on trading behavior. We draw upon a novel type of framing that is not based on semantic variations of a decision problem. Participants are given complete information about a distribution, and receive additional percentile information that either positively or negatively deviates from an aspirational reference payoff. Normative decision theories such as expected utility theory require that this additional information be neglected in the decision process, so it is not expected to influence behavior in a market environment. From a behavioral perspective, however, we expect that the additional information will serve as an anchor in the decision process, and systematically influence individual behavior even in market environments.

We also investigated the impact of a probability variation of the framed information and the robustness of the disposition effect in a competitive market environment with real-time data. Our results indicate:

1. Objectively irrelevant information does influence individual trading behavior. Moreover, positively and negatively framed information leads to a particular trading pattern: positively framed buyers purchase assets from negatively framed sellers, and negatively framed sellers sell their assets to positively framed buyers. The observed matching of unequally informed subjects, however, does not lead to different trading prices.
2. There is weak support for the conjecture that a probability variation of the framed information impacts trading volume. However, we believe that this effect is attributable to the unbalanced sequence of trading periods in the two asset markets, not to the available information.
3. The disposition effect was confirmed. Participants sold their assets more readily in gain situations than in loss situations. The effect was further moderated by framing: positively framed market participants generally sold their assets later than negatively framed participants. The framing of dividend information influenced individual expectations, and therefore market behavior as well.

Since objectively irrelevant information influenced market behavior, our findings violate expected utility theory and the invariance axiom. They are also inconsistent with refinements of the expected utility theory that do not account for framing effects, such as rank-dependent utility theories (Quiggin, 1982). Such theories are similar to cumulative prospect theory (see, e.g., Weber and Camerer, 1987 for a more in-depth discussion). The results reported in this chapter stress the importance of the subjective perception of information, which is not captured by expected utility theory or by rank-dependent utility theories because they focus on the processing of objective, and thus invariant, information.

Our results may have important implications for financial decision making. A huge amount of investment information is available to an increasing number of investors all around the world. Standard finance theory assumes that markets filter out irrelevant information, allowing individuals to arrive at unbiased decisions. In particular, it assumes that even if irrelevant information helps nothing, it does not harm anything either. But our findings cast doubt on this assertion. Additional irrelevant information does not leave the decision problem unchanged. It can systematically influence trading behavior even in competitive market environments.

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NOTES

1. Overpricing refers to market prices that exceed the total value of the lotteries traded (Rietz, 1993).
2. Tversky and Kahneman (1974) asked subjects to estimate the percentage of African countries in the United Nations after a number between 0 and 100 had been drawn by spinning a wheel of fortune. Estimates were dependent on the initially drawn number. The authors found that when a high number was drawn, the subjects tended to estimate a higher median percentage of countries than when a low number was drawn.
3. There is indeed strong experimental evidence that asset markets are highly informationally efficient (for a survey on the literature, see Sunder, 1995).
4. One hundred ECUs equal €0.73.
5. Correspondence between the two measures of certainty equivalents and lottery choices is investigated by, e.g., El-Sehity et al. (2002) and Fellner and Maciejovsky (2007).
6. See the appendix for an English translation of the instructions.

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APPENDIX

Instructions about the Market

Thank you for participating in our experiment. The experiment will last for about 2 hours and 15 minutes. You will trade assets on a market, and your payoff will be contingent on your decisions.

The following explains the trading mechanism in detail. You will learn how to place buy and sell offers and how to accept offers by other market participants. When you have read the instructions, there will be time to ask questions. Afterwards there will be

a short test to check whether you have understood the trading rules. The experiment will not begin until all participants have correctly answered all the questions in the test. You will then participate in a trial market lasting two periods, where you will have the opportunity to try out the buying and selling procedures without affecting your payoffs. The two trial periods will last for six minutes each. After the trial market, the real asset market will be opened.

Let us now explain how the asset market works. Generally, there are two ways to buy and two ways to sell assets.

Let us start with buying. You can either (1) submit a bid to the market, or (2) accept a standing ask made by another market participant. If you want to submit a bid, you must type your maximum buying price in the input box marked 'your bid,' and press the button marked 'bid.' If you want to accept a standing ask made by another market participant, simply press the button 'buy.' Standing asks for the assets are ranked according to prices and listed in columns. Of course, the best offer for you, and all other potential buyers, is the lowest ask, which is listed at the bottom of the column.

Let us now explain selling. You can either (1) submit an ask to the market, or (2) accept a standing bid made by another market participant. To submit an ask, type your minimum selling price in the input box marked 'your ask,' and press the button marked 'ask.' To accept a standing bid made by another market participant, press the button marked 'sell.' Standing bids for the assets are ranked according to prices and listed in columns. Of course, the best offer for you, and all other potential sellers, is the highest bid, again listed at the bottom of the column.

Note that you can engage simultaneously in buying and selling. However, you cannot buy more assets than your cash holdings allow, and you cannot sell more assets than you own. If you have submitted a bid to the market, your available money for further activities is reduced by this amount. If you have submitted an ask to the market, your available asset holdings are reduced by this one offer. We do not grant any credit or allow short-selling.

Only improving offers, i.e., higher bids and lower asks, are allowed on the market. During a trading period, you can buy assets, sell assets, or remain passive.

You can also engage in more than one activity at all times. In fact, you can simultaneously submit buy offers, submit sell offers, and accept standing offers made by other market participants.

You will be informed about the remaining trading time, the current period number, and the previous trades and their trading prices. All trades are chronologically listed in the column marked 'previous trades.'

You will now have the opportunity to try out the buying and selling procedures without affecting your payoffs. The trial market will consist of two periods, each lasting for six minutes.

Now the 'real' markets will be opened. You will trade assets on two separate markets, *A* and *B*. At the beginning of each trading period, you will be reminded whether market *A* or *B* is being opened. The sequence of the market was determined randomly. Each trading period lasts for 180 seconds.

At the beginning of the market, you will be endowed with 1000 experimental currency units (100 ECUs equals E0.18), plus five assets on market *A* and five assets on market *B*. Note that the monetary endowment is carried forward on both markets, but type *A* assets can only be traded on market A and type B assets can only be traded on market B.

The minimum number of trading periods for each of the two markets is eight; the maximum is 12. The probability that the market will end after the eighth, ninth, tenth, or eleventh period is 25 percent. This means there is a 75 percent probability that the market will continue after period 8. Similarly, once each period has been reached, there is an equal chance that the market will continue. Only when period 12 is reached is it certain that this will be the final market period.

Dividends are randomly drawn from a normal distribution with a certain mean and standard deviation. At the beginning of each period, you will be informed about the mean and the standard deviation of the distribution. At the end of the final market period, the liquidation value of the asset is zero. This means that once the final market period is reached, the assets carry no intrinsic value; they will be worth zero ECUs.