Incentive-Driven Trading: Behavioral Impacts in Financial Markets

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Abstract

Individual risk attitudes vary based on numerous factors, such as the perception of the win-to-loss ratio, current financial situation, and cognitive biases. This study aims to investigate risk-taking and trading behavior under different compensation schemes using a dynamic experimental setting. Utilizing the Zurich Trading Simulator, a gamified trading tool, it is shown that compensation schemes significantly affect trading behavior.

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1 Introduction

Individuals vary in their investment behavior, based on their perception of the win-to-loss ratio, current financial situation, and the stakes size (Rabin, 2000). Personality defined within the framework of Big Five taxonomy also has an impact on both short and long-term investment (Mayfield et al., 2008). This leads to a situation in which people facing an identical expected value of an outcome vary in their decision-making. The impact of one's behavior and biases on utility function is part of a broader study, defined as Behavioral Economics (Ritter, 2003). The author proposes the idea that people are not always rational decision-makers when it comes to money. This irrationality can be observed in the finance industry when different stakeholders have different goals. A threat arises when the portfolio manager's objectives are not aligned with the investor's goals. Professional investors might compare performance with their peers, which leads to increased risk-taking and trading activity (Andraszewicz et al., 2022).

A misalignment occurs when a manager is not financially committed to his fund. Previous research shows that in such a situation he is likely to take on more risk (Ackermann et al., 1999). There is substantial literature supporting the thesis that managerial incentives influence risk-taking behavior, and that performance-related components of the salary encourage fund managers to take excessive risk (Kouwenberg & Ziemba, 2007). Furthermore, evidence points to the fact that incentive schemes with a threshold pose a moral hazard in the hedge fund industry. This is because the managers maximize their expected value of fees (Panageas & Westerfield, 2009). Furthermore, fixed-wage compensations, not aligned with payoffs, encourage minimal effort (Lazear, 2000). Fixed-wage compensation rarely produces positive incentive effects, since effort is not adequately rewarded (Bonner et al., 2000; Flannery & Roberts, 2021).

Measuring the activity of stock trading is important when assessing individual trading behavior. In a 2011 experiment, Jacobs and Weber (2012) focused on measuring the local bias of investors for firms trading on the German stock market. In their methodology, they determined trading activity by the number of buys and sells each day and compared the turnover between groups to look for a local bias. The authors concluded that investors in the German stock market found that local bias significantly impacts trading volume. However, their analysis was lacking in other ways of measuring trading activity. It did not mention individual trading frequency or the relation to risk. Those expansions, combined with risk analysis, could help better explain trading behavior. Conclusions based on a more rounded approach (trading behavior rather than only trading activity) will facilitate making more general predictions, scoping beyond the experimental sample.

The timing of the investment decision (buy/sell) is another component of trading behavior. There is a strong link between investor behavior and the short-term price movements of a stock. This has been shown by observing investment behavior right before and after the earnings announcement (Frieder, 2004). There is no real information that makes the price go up or down at the time of the decision. It is simply investors recognizing that others have a cognitive preconception of what the price will do irrespective of the fair valuation. They bet on other investors perceiving the earnings announcement as positive or negative, rather than based on fundamental analysis. It is another example of individual characteristics impacting trading behavior.

Another factor impacting the risk-taking aspect of trading behavior is the compensation scheme size and structure. Managers look at their decisions through the lens of their incentive scheme. This means that they perceive it as an investment problem, which they then try to solve (Carpenter, 2000). In situations where the firm's leadership compensation structure consists of options, its convexity plays an important role. It makes managers seek payoffs that are "away from the money," and thus lead to an overall risk burden increase. However, the paper has also shown that giving the manager more options makes him seek less risk (Carpenter, 2000).

This is in line with the theory that being heavily invested in the firm correlates with a more risk-averse approach to financial decision-making.

One of the most renowned and commonly referenced ways of measuring risk aversion is using multiple price listings (Holt & Laury, 2002). In such a task, subjects are asked to choose between lottery A or B. The choices vary in size and probability of a payoff. There is a calculation of the expected value of the lotteries, and often subjects choose a less risky one with a smaller EV, indicating risk aversion. The Holt and Laury paper serves as a great tool for identifying cognitive biases. If at price A, some individuals choose to sell, hold, or buy the stock and made different decisions, then it could be evidence of some cognitive bias. However, in a dynamic environment, this method is not the most applicable and thus will not be used in this experiment. The individuals will have to make hundreds of small decisions, which cannot be summarized as a choice difference between decision A and B. The methodology section explains in detail the alternative risk aversion measurement method.

When eliciting risk, there exists a trade-off between predictive power and noise based on the complexity of the method (Dave et al., 2010). This occurs when a trading task gets mathematically complex, and some participants might not fully understand it, thus creating noisy results. In the case of this experiment, the participants are from the fields of finance and economics, so their calculation skills should be adequate. Consequently, the manipulation variable in the experiment (incentive scheme) will have a somewhat complex structure. The reason for this is because the highly expected mathematical skills should help with understanding the experiment and thus limit the noise. Another aspect of eliciting risk preferences is the relationship with time (Andersen et al., 2008). The authors of the above article created a series of choice experiments and asked participants to make choices regarding the payoffs in their timing. The goal was to determine how individuals perceive present and future payoffs. One of the conclusions was that the preferences are not consistent. There are differences between short- and long-term preferences, as well as differences when it comes to the size of the reward. This hints that risk preferences revealed in this experiment might not be consistent with individual risk preferences in other settings.

Another aspect of decision making in experimental settings is risk aversion and expected utility theory (Rabin, 2000). Risk aversion refers to a preference for avoiding risk, especially in the case of potential losses. Expected utility is represented by a model explaining subjective utility expectations coming from potential outcomes. Both phenomena will potentially be observed in the following experiment. On one hand, in the pre-study, individual risk preferences will be measured, and given a large sample, some individuals should show high risk aversion. This means that, regardless of the experimental treatment, they will prefer safer outcomes. On the other hand, everyone will have their utility curve. This implies that the financial outcomes of the experiment are not the only sources of happiness for the participants. This will thus be taken into account in terms of this paper's limitations.

One of the most influential theories regarding the influence of price patterns on behavior is the Prospect Theory by Tversky and Kahneman (1974). The theory introduces the idea that people are more sensitive to losses than gains. Presentencing or "framing" can impact people's choices (Tversky & Kahneman, 1981). Loss aversion, which refers to the fact that people tend to feel more strongly about losses than they do about gains of the same size, can be observed in many situations. It implies that in a compensation scheme with a threshold, people will behave differently below and above it. For instance, if the reward for reaching a threshold is 5 CHF, then reaching it means a lot of additional utility. However, losing the "earned" 5 CHF would cause people to suffer a larger utility loss compared to the gain from the same value. This indicates that individual risk preferences are not transitive throughout the whole price pattern. Other drivers for behavior under uncertainty are representative heuristics (Tversky & Kahneman, 1974). It is the tendency to expect certain outcomes with a probability based on how similar it is to a stereotype. In the case of risk behavior in an experimental setting, it will be affected by participation in other experiments with risk measurement, as well as individual expectations of price development. Despite the price being fully randomized, participants will have a preexisting bias towards overestimating the likelihood of their expected price development.

Despite random sequences, some participants will interpret them as patterns. To minimize the probability of selection bias, the experimental stock price was randomized. This also ensures that the prices in the experiment are representative of a larger sample and not influenced by the experiment designer's bias (Thaler & Sunstein, 2003). Furthermore, the generalizability of the findings can be used to draw conclusions that extend beyond just the sample population.

The above serves as a starting point for the research question. However, experiments based on historical data and primary lab research are not the same. To answer the research question (discussed in more detail in the Design section): To what extent do incentive schemes impact trading behavior? one more publication needs attention. It serves as a leeway between the theoretical framework and already existing experimental evidence. The article creates an overview of already existing literature on the relationship between monetary incentives and effort/task performance. In addition to the literature review on the topic, the authors suggest that the meta-analysis provides mixed results (Bonner et al., 2000). This means that the methodology for comparing risk and incentive schemes should be individually tailored to the experiment. They develop a framework that should guide experiment designers. In the framework, monetary incentives impact effort, which in turn impacts task performance. However, many other variables affect both perception of monetary incentives and task performance. These variables include person variables, task variables, environmental variables, and incentive scheme variables. To fully understand the risk-reward relationship, all the above-mentioned factors should be taken into consideration. In my experiment, effort will be a proxy for trading activity, since that is the only action participants will be able to take. However, as explained in the methodology section, effort should not be judged identically for all participants, since each compensation scheme has its own goal based on the payoff scheme. Moreover, since risk preferences share the structure of major psychological traits, individual characteristics will play a big role in this experiment (Frey et al., 2017). One such example is that risk preferences have a similar psychometric structure to intelligence. However, Frey emphasizes the risk measurement method. In other words, understanding individuals' risk preferences and being able to affect them can have implications beyond Behavioral Economics.

1.1 Pilot Study

Additionally, to the previously mentioned literature, the experiments from a Master's student conducting prior research with the Zurich Trading Simulator will be used as a point of reference for setting up the incentive schemes (Dousolier, 2021). The primary finding suggests that risk-taking varies based on participant compensation. More specifically, in contrast to people working as fund managers trading their fund's money, individuals trading with their "own" money seem to be more risk-averse. Individuals whose compensation is based on the threshold they must reach to get a bonus seem to take on more risk than the average across participants, especially if the threshold is difficult to achieve (i.e., a high threshold). Moreover, they trade more frequently and with higher volume, which—given the existence of transaction fees—can be suboptimal.

The issue with the above research is that threshold manipulation was not set up optimally. In the experiment, the bonus was set up as a non-monetary value: it was a credit incentive for students, which they required to obtain their degree at the University of Basel. This can be seen as a limitation, since non-monetary and monetary incentives do not necessarily work in the same way.

However, overall, the results are in line with literature concerning risk-taking for different types of hedge funds. Incentive fees reduce managers' implicit level of loss aversion. On the other hand, if a manager's own stake in the fund is more than 30%, risk-taking is reduced (Kouwenberg & Ziemba, 2007). The last conclusion from the pilot studies is that there seems to be no dominant strategy for the control and treatment groups. No group seemed to choose a trading strategy that would provide a statistically significant higher return on investment than the average across all participants. The pilot results have been promising; however, the incentive schemes selected have not been optimal for reflecting real-life behavior. The reason for this is that only the linear compensation mirrors a potential scenario for an individual investor.

1.2 Research Question and Hypotheses

The literature review, combined with the pilot study, led to the development of the following research question:

To what extent do incentive schemes impact trading behavior?

The following hypotheses will help answer the research question above:

- **Hypothesis 1a** – The more aligned a compensation scheme, the fewer the number of transactions.
- **Hypothesis 1b** – The more aligned a compensation scheme, the smaller the average size of transactions.
- **Hypothesis 1c** – The more aligned a compensation scheme, the smaller volume of shares traded.
- **Hypothesis 2a** – There is a negative effect of aligning the incentive schemes on risk.
- **Hypothesis 2b** – There exists a strong correlation between self-reported risk and in-game risk.
- **Hypothesis 3a** – In compensation with a fixed bonus, individuals will suspend all risk-taking and trading activity after reaching the threshold.

- **Hypothesis 3b** – Participants in experimental conditions with a threshold will behave more risk-seeking under the threshold and less risk-seeking just above the threshold.

Hypotheses 1a, 1b, and 1c are based largely on previous findings indicating that misaligning incentive schemes leads to higher risk-taking (Ackermann et al., 1999). Moreover, being disconnected from the monetary outcome does not promote risk aversion (Holt & Laury, 2002). The risk-taking in this experiment can be partially observed via trading activity. Trading more often, with higher frequency, and with higher volume implies higher risk-taking behavior.

Hypothesis 2a is based on the same principle but focuses on looking at risk as a share of the risky asset of the whole portfolio, rather than through trading activity. The hypothesized effect on risk has an additional noise component created by individual biases of the expected future price movement (Frieder, 2004). **Hypothesis 2b** adds the component of self-reported risk. Questionnaires are a common way to measure risk (Charness et al., 2013). If individuals answer honestly, their self-reported risk and in-game risk should be correlated.

Hypotheses 3a and **3b** focus on common compensation types, namely performance-based compensation. On one hand, fixed compensations invite minimal effort (Lazear, 2000). In the Zurich Trading Simulator setting, this indicates that when reaching the performance threshold, participants should no longer be interested in making any more trades or putting in any more effort. This is the expected outcome for **Hypothesis 3a**. If participants in the experiment behave like real-world managers, they will look at the structure of their compensation as an investment problem (Carpenter, 2000). They will adjust their behavior according to their individual solution to that problem. Threshold conditions by design incentivize reaching the threshold; thus, participants will aggressively try to reach it and then limit their exposure to stay above it. This is in line with Prospect Theory by Tversky and Kahneman (1979), which states that people have different utility curves depending on whether they have a positive or negative monetary outcome. The expected outcome in **Hypothesis 3b** is higher risk-taking behavior below the threshold and lower risk-taking behavior above the threshold.

2 Methodology

This study employs the Zurich Trading Simulator to simulate various compensation schemes.

3 Results

The results of the experiment indicate that compensation schemes significantly impact trading behavior. Schemes incorporating performance-related components tended to increase risk-taking behaviors, while fixed compensation resulted in more conservative trading strategies.

4 Conclusion

The results of this study suggest that the trading behavior of individuals is impacted by compensation schemes. The trading behavior was analyzed in three different dimensions. The first dimension relates to the size, transaction value, and frequency of trades. When comparing the three experimental groups, it was found that the linear compensation scheme resulted in significantly different behavior in terms of the average size of transactions and the average transaction share value, compared to the fixed and watermark schemes. However, there was no statistically significant difference in the number of trades between the groups.

The second dimension relates to risk-taking. On one hand, the experiment showed that self-reported risk and elicited risk are not correlated. This has significant implications for the insurance and banking sectors when trying to assess potential risk profiles purely based on survey data. On the other hand, looking at aggregated risk across the experimental conditions, the statistics were not significant, implying no difference between the groups. However, a visual analysis of the risk behavior concerning the price path implied differences at certain time points.

The last dimension of analysis is related to threshold behavior. There were significant differences in the experimental condition both below and above the threshold. This implies that the experimental manipulation was successful, and participants attempted to optimize their payoffs according to the compensation scheme.

In terms of expanding the current behavioral finance experimental research relating to compensation schemes, this experiment brings value by examining behavior in a dynamic setting. Differences in risk preferences have been shown in other experiments, but most of them focused on choosing between A and B and analyzing utility curves. The dynamic setting using the Zurich Trading Simulator (ZTS), combined with price randomization, allows for more generalized conclusions. It also provides more insight into relatively under-researched variables, such as the frequency of trades, average trade size, trade value, as well as dynamic threshold behavior.

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