The role of risk in investment behaviour and the manifestation of behavioural biases by individual investors

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Submitted in fulfilment of the requirements of the degree of

Doctor of Philosophy in Accounting and Finance

Adam Smith Business School, College of Social Sciences

University of Glasgow

October 2020

Abstract

I use a novel dataset based on 8,000 retail clients of a large brokerage house over four years to evaluate if individual investors take decisions according to one of the dominating decision-making theories – traditional Expected Utility Theory or behavioural Prospect Theory. Another key question of my research is the role of affect in judgements and its impact on investment results and behaviour.

The thesis includes three related empirical chapters. In the first empirical chapter, I explore how (ir)rational are retail investors and what are the boundaries of their rationality proxied with the relation between realised risk and return. In the second empirical chapter, I examine how the correlation between risk and return for the same group of investors varies in Live trading environment versus virtual Contest environment highlighting the role of emotions in correlation dynamics. In the third empirical chapter, I keep the emphasis on comparing Live and Contest investment settings, but now I evaluate the impact of emotions on profitability and various manifestations of risk behaviour.

My research contributes to the academic literature in the domain of finance and investments that is trying to establish the positioning and the role of emotional account in the judgement and decision-making of economic agents. I provide empirical evidence that feelings have a substantial impact on investment results and risk behaviour of individual traders. The empirical nature of my analysis involving a large group of private investors grants significant support to prior findings that predominantly developed using neuro-physiological, interview-type and experimental methodologies. Besides, I present empirical support for the long-lasting debate concerning traditional and behavioural financial theories. Analysing the relation between risk and return, I manage to validate that investors in my sample manifest

all behavioural patterns implied by Prospect Theory: they are risk-averse in the gains domain, risk-seeking in the losses domain and exposed to the loss aversion bias.

Contents

1.Introduction

The history of the modern theory of decision-making under risk and uncertainty represents 80 years of a nonstop academic debate on the hot topics of human behaviour, rationality, risk attitudes, performance as well as its reasons and implications among the other similarly vital elements of our existence. Over this long historical time frame and beyond, the understanding of the core premises of risky choice has radically evolved several times.

Initially, the theory started from the psychology-grounded explanations by the prominent predecessors from Adam Smith's Theory of Moral Sentiment to John Maynard Keynes's concept of Animal Spirits. Next, it was followed by stringent mathematical rules and rationalisations of the Expected Utility Theory by von Neumann and Morgenstern (1944), widely accepted and adopted in the majority of modern theories and models in Economics and Finance. Finally, it was enriched by the modern psychology-based behavioural Prospect Theory by Kahneman and Tversky (1979) and supplemented by the reinvented emotions-focused 'Risk-as-Feelings' model by Loewenstein et al. (2001) and theories alike that are gaining momentum in the new century. For the outside observer, it may seem that the history of thought has made a full circle as the concept of 'emotions' in economic context has made a journey from the recognition in the work of Adam Smith to almost complete oblivion in the second part of 20th century and back to a growing credit in the contemporary papers frequently appearing in finance academic journals that I review in the literature section. Yet, the real picture is far more challenging than that.

Since the 1970s, when Prospect Theory was formulated (Kahneman and Tversky (1979)), the world of finance has been increasingly living in the way of a dichotomy of behavioural and neoclassic explanations of behaviour. Traditional theory's tenets warrant all widely accepted modern models in finance, for instance, (Modern) Portfolio Theory (Markowitz

(1952, 1959)), asset pricing models (e.g. Sharpe (1964), Fama and French (1992)), Efficient Market Hypothesis (Fama (1965)) and other, which are firmly grounded on the axiom of economic agent's rationality. Behavioural perspective is gaining power along with the mounting evidence of human irrationality in all domains of finance and economics – from unwise behaviour of individuals, e.g. taxi drivers (Camerer et al. (1997)) to the unwise behaviour of financial markets that grow into bubbles and then burst with devastating consequences (Shiller (2016)). Methodologically, Behavioural Economics is still lagging as its primary weapon so far – laboratory or field experiments – is frequently challenged for the issue of scalability (see Al-Ubaydli et al. (2017) for discussion). Nevertheless, updated theoretical agenda is continuously emerging, for instance, the concept of hyperbolic discounting in intertemporal choice (Laibson (1997)), Behavioural Capital Asset Pricing Theory (Shefrin and Statman (1994)) or Behavioural Portfolio Theory (Shefrin and Statman (2000)) to name a few. Still, empirical confirmation of behavioural theories remains a largely unfilled gap of this alternative economic perspective of decision-making.

In my research, I come across considerable heterogeneity of behaviour, which corresponds to other studies in the same area, for example, the empirical research on disposition effect (Dhar and Zhu (2006)) or overall performance of day traders (Barber et al. (2014)). This fact leads to the assumption that there are vital psychological forces behind individual decision-making dynamics. Kahneman and Tversky in their Prospect Theory explained the properties of the S-shaped value function curve in terms of psychophysical processes. However, growing evidence exposes emotions[1] as a robust potential factor that can elucidate many behavioural artefacts that Prospect Theory is unable to embrace. In some life situations that invoke strong feelings, there is evidence that decision-making and behaviour can even be

[1] For simplicity, I use the notions 'affect', 'feelings', 'emotions' interchangeably throughout the thesis following most of finance scholars, although modern psychologists would insist that these terms have unequal meanings (see, for example, Frijda (2007), Scherer (2005)). In Section 2.1, I provide the explanations of the psychological terms I frequently use in my research.

reversed to the predictions of any of the consequentialist theories, which comprise both Expected Utility Theory and Prospect Theory. Preference reversals serve as a good example of this phenomenon of the emotional impact. As Ariely and Loewenstein (2006) show in their study, sexual arousal may provoke multiple self-destructive behaviours, which would not be elicited in the calm state. In the literature review section, I discuss more examples of that category.

In the last twenty years, the effect of emotions on decision making under uncertainty became the area of interest to researchers from several scientific disciplines including Finance, Psychology and Neuroscience. This research has summed up into a series of theoretical conceptualisations known as dual process models of individual decision-making. These theories recognise that individuals in their decisions are impacted to a varying extent by the current or anticipatory degree of internal emotional state. Dominating feelings may change the routine process, whereby the decision is inherently consequentialist, i.e. the decision-maker multiplies the value derived from a value function by the decision weight drawn from the decision weighting function, and both functions evolve predictably and uninterruptedly. Dual process models of behaviour become an alternative framework of judgement and decision-making with 'Risk-as-feelings' hypothesis (Loewenstein et al. (2001)) being one of its most notorious representations. According to this perspective, the processing and outcome of decisions are highly dependent on the degree of affective charge of the environment in which a choice is made. Some factors, for example, the vividness of potential outcomes, the immediacy of an outcome, duration of an emotion-eliciting event, personal characteristics, etc., raise the emotional intensity of choice, which has a distorting effect on the realised behaviour. The theory contends that the higher is the emotional charge of the dominating environment, the stronger the individual's decisions and behaviour depart from thoughtful undertakings. Furthermore, Hsee and Rottenstreich (2004) demonstrate experimentally that feelings tend to aggravate the dynamics of the 'standard' value function contemplated by Prospect Theory. That is, in the more affect-rich environment, concave (gains) part of the function will tend to become even more outwardly curved, and convex (losses) part even more inwardly curved.

To align between Prospect Theory and dual process theory, I construct a theoretical model of portfolio choice following the studies of Vlcek and Hens (2011) and Jakusch et al. (2019) with the aim to test the impact of affect-poor and affect-rich parameters of the value function, probability weighting function and loss aversion on various aspects of individual investor's behaviour. For instance, the relation between an investor's realised risk and performance, disposition bias, risk-taking practice in the domains of gains and losses.

1.1. Introduction to the first empirical chapter. Do individual investors make rational decisions? Prospect Theory view on the negative relation between risk and return.

A critical part of the disagreement between traditional and behavioural frameworks lies in the idea of the rationality of economic agents. In the view of prescriptive Expected Utility Theory (von Neumann and Morgenstern (1944)), a rational person in the pursuit of self-interest should favour a choice that would maximise the expected output per the unit of risk of not achieving the desired level of output, so that the decision value function has a concave form across the whole spectrum. In the application to finance, an investor should strive to maximise expected return per unit of deviation of return. In contrast, Prospect Theory (Kahneman and Tversky (1979) that is a descriptive type of model, suggests that concavity will only be sustained for gambles involving gains. In the losses domain, most individuals would tend to prefer more risk to less risk for the same level of return. This situation will make the decision value function convex for losses, and therefore falling out of the rationality scope. Hence, Prospect Theory's value function has its famous S-shape.

Consequently, this controversy between theories poses a challenge for the empirical observation of individuals: are they indeed demonstrating rational behaviour in real life? I undertake to investigate this question in my first empirical chapter. More specifically, I apply my research question to the empirical study of individual investors and formulate it in the following way:

Do individual investors change their risk behaviour subject to positive or negative trading results?

In my theoretical model in Section 2.10, I draw the prediction that given Prospect Theory-based preferences by an investor and certain other assumptions as formulated in the theoretical models by Barberis and Xiong (2009), Vlcek and Hens (2011) and Jakusch et al. (2019), individuals are inclined to reveal disposition effect, a positive relation between risk and return in the gains domain (relative to the reference point) and a negative relation between risk and return in the losses domain.

To find an answer to the research question and test the predictions of the theoretical model, I explore the database that contains full trading statistics for more than 8,000 individual investors over four years. I aim to focus on the analysis of the correlation between return and risk that I measure as a statistical deviation of return. Intuitively, this variable should be directly related to realised (ir)rational behaviour and is an appropriate candidate for its proxy. Zero correlation between risk and return would mean risk neutrality, positive correlation coefficient should be a sign of risk-averse behaviour, while negative correlation must indicate that an individual is exposed to risk-seeking. I conjecture that the strength of the coefficient should also matter. Even though both theories under consideration hypothesise non-linear relation between return and risk, a larger coefficient should denote a more robust connection, hence more compelling risk-averse or risk-seeking behaviour. Stating that, I must stress that the link between the degree of rationality and investment performance is very far from being clear. Investment results can be impacted by other essential variables, such as skill and mere luck. Therefore, it is possible that an individual trader exhibiting a strong positive correlation between return and risk simultaneously would have negative investment performance. In my study, I devote special attention to exploring this aspect of behaviour.

If Prospect Theory holds and investors' behavioural patterns correspond to the S-shaped value function, the following three empirical outcomes should be observed (Tversky and Kahneman (1992)): investors should demonstrate risk-averse behaviour (positive correlation between risk and return) above the reference point, and risk-seeking behaviour (negative correlation between risk and return) below the reference point. Additionally, loss aversion bias should be demonstrated, i.e. losses should loom larger than gains (negative correlation should be higher than positive in modulus). I identified all these effects in the theoretical model in Section 2.10, and they were statistically significant.

The investigation that I pursue reveals that roughly 72% of the subjects in my selection can be attributed to S-type (i.e. Prospect Theory-guided) behaviour. Only 8% of investors show the evidence of fully risk-averse model that corresponds to the Expected Utility Theory. Another group of traders, an impressive 20%, adhere to convex value function for losses and gains, which indicates risk-seeking behaviour and does not fit any existing theoretical framework. To investigate the assumed link between rationality and performance and pave the way for future research, I split investors into 'Gainers' and 'Losers' according to their overall positive or negative performance. I find that outperforming investors, on average, demonstrate a much clearer tendency towards rationality, i.e. positive relation between risk and return. For example, the share of 'Gainers' that manifest fully risk-averse behaviour is 16% against only 4% of 'Losers'. For the registered cases of entirely risk-seeking behaviour, the proportion is reversed – 7% and 26%, respectively. At the same time, I also manage to conclude that the link between performance and rationality is far from perfect. 41% of 'Gainers' have a negative correlation between risk and return, while 32% of 'Losers' are featured with positive risk/return relation. Even though rational behaviour is capable of predicting trading success, other factors like skill or luck seem to be essential as well.

In the same empirical chapter, I attempt to examine what factors are influencing the degree of rationality represented by the correlation between risk and return. I collect a broad array of personal, trading and risk variables that are regressed on the calculated correlation coefficients for investors. Also, I run several model specifications – one for 'Gainers' group of investors, one for 'Losers' and a model for all investors. I discover that some variables have an unequal impact on outperforming and underperforming subjects. For example, in the set of activity variables, the number of completed trades does not influence 'Gainers', while playing a positive role for 'Losers'. Turnover – the value of all completed trades – also has no impact on 'Gainers', but in this case, the negative effect on underperformers. At the same time, the time duration of an average trade, positive risk (positive semi-deviation of return) and the use (proportion) of stop-loss conditional orders all have a positive influence on the risk/return correlation for each of the groups. The opposite effect is observed for such variables as investor's age and the use (proportion) of take-profit conditional orders.

1.2. Introduction to the second empirical chapter. The role of affect in the degree of rational behaviour

In my second empirical chapter, I examine the expectations of dual process models embodied in 'Risk-as-feelings' hypothesis with application to rationality that I continue to proxy by the correlation between risk and return. I formulate the following research question: "What is the effect of emotions on risk and return relation?" To test it, I explore if investors adjust their degree of rationality when taking standard investment decisions in two environments that are distinct from the affective charge point of view.

To approach such research, it is necessary to identify and analyse two settings that are different in terms of emotional charge and at the same time, show the closest possible similarity in all other aspects. Unsurprisingly, most studies conducted in the area of the influence of feelings are carried out purely in an experimental setting. Rarely these are field experiments. The main problem of such arrangements is the difficulty to induce natural emotions in humans when they know they are under surveillance, not to mention ethical challenges of modulating fear, anger and other strong emotional states. For example, specifying the directions for future research, Rick and Loewenstein ((2008), p. 150) contend that "[There is a] need to study stronger emotions that have generally been examined in the empirical literature. Many vitally important decisions are made "in the heat of the moment", and indeed important economic decisions […] often evoke powerful emotions. But studying the impact of such emotions is difficult – in part because it is difficult if not impossible to manipulate such strong emotional states experimentally and in part because people generally do not like to be studied when they are in heightened emotional states".

I achieve the goal by isolating the two investment environments that encompass a high degree of resemblance in all properties except for the level of emotional charge. For that, I make the selection of the same group of Live investors (i.e. with real money and real risk) as in the first empirical chapter, but now I complement it with another type of data. In addition to providing Live trading accounts, which are funded by investors themselves, the brokerage house that provided the statistics runs a trading Contest, which is basically a trading game that entirely replicates Live trading environment, including the marketplace (electronic platform), orders, fees, execution, etc. It is a serious venture where top performers get high-value real prizes credited on their Live accounts, and that gathers around 1,000 contestants every month for around five years. Further, I match investors having both types of accounts – Live and Contest and obtain 618 such individuals. Effectively, I assume that the only fundamental factor that is different for Live and Contest accounts of the same trader is the degree of emotional intensity or vividness that is comprised in the opening, maintaining and closing a trading position. It represents a natural control for an 'emotional' variable and gives an excellent and rare opportunity to conduct empirical testing of the dual process theories. Consequently, I designate Live environment as 'affect-rich' and Contest environment as 'affect-poor'. As a result, I fulfil both conditions outlined by Rick and Loewenstein with respect to my subjects: I can gauge the behaviour 'in the heat of the moment' and compare it against less emotionally-charged but qualitatively identical decisions, and the subjects do not 'feel' the researcher behind their back when they make these decisions in both types of trading environments.

I reinforce the analytical approach above with the assumptions of the theoretical model that I draw in Section 2.10. In the model, I approximate the affect-rich and affect-poor environments by taking the model parameters from the two sources. First, it is the original Prospect Theory model (Kahneman and Tversky (1992)) that has been worked out in an affect-poor experimental setting. As an affect-rich counterpart, I take the parameters from the model of Jakusch et al. (2019). They conducted their parametrisation based on Live trading results of individual investors (very similar to my dataset). I evaluate the resulting consequences of the two sets of parameters on the relation between risk and return. My model, just as my analytical framework, predicts the statistically significant difference in the correlation coefficients between the two environments. However, in the model, I reveal the significant difference only for the correlation in the losses domain.

In my findings, I discover the presence of noteworthy disparity for the two settings, which makes from 0.20 to 0.25 in correlation terms depending on the measurement method. The difference is significant at the 1% confidence level. Live aggregated correlation coefficient proves to be stronger (more negative) than in Contest. After breaking total risk measure into positive semi-deviation of returns (representing gains domain) and negative semi-deviation of returns (representing losses domain), I find that the shift in correlations between settings is to a large extent derived from the convex (losses) part of the value function, while the change in concave (gains) part is much more reserved. My results confirm the assumptions of 'Risk-as-feelings' models – in the more affect-rich setting (Live) the subjects become more risk-averse in gains domain and more risk-seeking in losses domain that reflects the growing effect of 'valuation by feelings' versus 'valuation by calculation' (Rottenstreich and Hsee (2004)). It is equally valid for underperforming and outperforming investors. These results cannot be explained by either Expected Utility Theory or Prospect Theory. The findings are also in line with the predictions of my theoretical model.

1.3. Introduction to the third empirical chapter. The role of risk and emotional engagement in trading behaviour and the manifestation of behavioural biases by investors

In the third empirical chapter, I continue expanding the investigation of the role that emotions play in risky decision-making beyond the implied rationality of behaviour. Although traditional economic theory treats emotions as a by-product of the decision-making process, there is growing evidence, theoretical, empirical and experimental, promoting an alternative view of a much more extensive function of feelings and its impact on profitability and risk that draw my attention. Furthermore, I use the same dataset of investors possessing two types of trading accounts – Live and Contest – that I exploited in the second empirical chapter. Altogether, 523 individual investors fall under the criteria of the subsequent research.

I break the last empirical chapter into three separate parts, each examining distinct aspects of affective interference with financial behaviour. The first part investigates the differences in performance between Live and Contest trading modes, the second part addresses emotional transformations of risk, and the third part strives to combine return and risk into a single framework using multiple regression analysis.

In Part 1, I assess the following research question:

Does variation in emotional intensity pertaining to the investment decision influences financial performance?

My goal is to examine the assumption derived from the literature (see Loewenstein et al. (2001) for review) advocating the emotional perspective in a way that the difference in emotional charge between Live and Contest would impact the financial decisions of individual subjects, translating into the essential modification of trading behaviour and significant performance disparity. To corroborate the assumption of return inequality between Live and Contest, I undertake to isolate and compare trading returns in both settings.

After the conducted analysis, I discover a substantial shift in performance between the two environments. Surprisingly, against the widely accepted belief of the industry and investors that is spread in the professional internet forums, Live is found to outperform Contest on average, yet it should be noted that Live average performance is statistically indistinguishable from zero, while Contest results are negative. The difference between the two equals 0.022% per average trade and is significant both economically and statistically. Furthermore, I find that the difference in trading results comes along with the altered investment patterns. When in Live, investors become more focused on their trading activity and possibly get more 'myopic' or concentrated on the short term. This can be inferred from the fact that they start relying on market orders much more than they do in Contest – the share of conditional orders drops from 43% in Contest to 23% in Live. Next, in Live, intraday trading practice becomes more popular – the share of intraday trades rises from 65% in Contest to 78% in Live. Another essential effect is the increase in the average number of transactions – from 448 in Contest to almost double 877 in Live, and a corresponding drop in the average duration of a single trade – from 7.82 hours in Contest to only 4.11 hours in Live.

The second part of my study is devoted to the analysis of risk. Unlike the neoclassic model of decision-making, in Prospect Theory framework risk is a multifaceted phenomenon comprising three risk factors: the form of the value function, the form of probability weighting function and loss aversion. I employ several alternative methods to test my hypotheses about each of these manifestations of risk. For the evaluation of the impact of feelings on the value function, I compute the disposition effect (Shefrin and Statman (1985)) and complement it with the comparison of positive and negative semi-deviations in the two environments.

The other two manifestations of risk behaviour – loss aversion bias and the probability weighting function – are hard, if possible, to evaluate using market orders, therefore, I focus on the statistics of realised conditional orders.

Regarding loss aversion, I assume that the bias should motivate investors to place take-profit orders[2] closer to the market price and have them executed swiftly. With stop-loss orders, it is expected to be different, as individuals in the 'risk-seeking mode' should be mentally urged to prevent losses from realising or 'to give it a chance if it goes wrong', hence they would place sell conditional orders further away from the market price. Stop-loss orders should be found to get realised less frequently based on this logic because the market would have to move a longer distance to fill such a conditional order. Therefore, I aim to test for two assumptions: first, that the absolute return of stop-loss orders is higher than the absolute return of take-profit orders; and second, that the number of realised conditional stop-loss orders is smaller than the number of realised take-profit orders.

Further, the form of decision weighting function as a risk variable is examined. In my analysis, I concentrate on the test of two possible alternative scenarios of affective influence: optimism/savouring and pessimism/dread that both alter the elevation of the probability weighting function. I speculate that both emotional states should have an effect on decisions regarding the placement of conditional orders. Specifically, savouring can lead to over appreciation of objective probabilities for gains and undervaluation of objective probabilities for losses in case of more affect-rich environment. Dread might have the opposite effect.

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[2] It is a common practice of traders to place conditional orders together with opening a trading position, therefore, conditional orders serve as a good indicator of investors' plans and emotional experiences at the moment when it is not yet known how the open position will evolve.

Consequently, for empirical evidence of the shift in optimism, the profitability of take-profit orders in Live should exceed the one in Contest, while for stop-loss orders Live should underperform Contest[3], equally because investors in Live will tend to place both types of orders further away from the market price. A contrasting picture should be observed if the sensation of dread prevails. In this scenario, investors would lean towards placing stop-loss and take-profit orders closer to the current market price, hence it is expected that Live stop-loss orders will outpace Contest and Live take-profit orders will generate smaller return than in Contest.

In the study, I find evidence of the impact of emotions in all three facets of risk behaviour. For example, there is a statistically significant disparity in disposition effect in both environments that is accompanied by the shift in realised volatility from Live to Contest. My study demonstrates that only positive semi-deviations in Live and Contest are substantially dissimilar, and Live positive semi-deviation is indeed more concave as hypothesised by 'Risk-as-feelings' hypothesis, i.e. in the gains domain, investors turn more risk-averse in the more affect-rich realm. As for negative standard-deviation, statistical tests fail to reject the null hypothesis about their equality. In the chapter, I discuss the possible explanations and implications of this effect.

I uncover that loss aversion is present in both environments that I explore. Take-profit orders turn out to be significantly more profitable in modulus than stop-loss orders, which is an indication that stop-loss orders are, in general, placed closer to the market price. The frequency of realised conditional orders also confirms this: I reveal that the number of stop-loss orders exceeds take-profit orders by the factor of two. Nevertheless, I fail to find any difference between loss aversion bias in Contest and Live.

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[3] It should be recalled that stop-loss orders reside in the losses domain, therefore, if an investor places such orders closer to the current market price, she cuts her realised loss if the price moves against her and raises her overall profitability compared to more distantly placed orders.

The results that I obtain point to the presence of the dread account in the behaviour of investors. I discover that stop-loss orders in Live outperform Contest, and the opposite effect is observable for take-profit orders. There is a good chance that it is the surge in pessimism in affect-rich environment responsible for the equality of negative semi-deviations in Live and Contest that I discussed above. Grounded on 'Risk-as-Feelings' model, I develop an analytical framework, in which an investor should become substantially more risk-loving when experiencing a loss of real money from the value function perspective, yet the excessive risk-taking is suppressed by the overestimated fearful reaction to the small probability of the disastrous negative outcome. This reaction urges an investor to place stop-loss orders closer to the market price, and they get frequently filled (realised), which curbs negative performance.

1.4. Contribution of the thesis

To the best of my knowledge, my study represents one of the first attempts to conduct the empirical examination of rationality and emotions perspectives attributable to individual investors in the context of a real market environment. I use this setting to test the degree of rationality pertinent to individual economic agents as well as the role that feelings play in the decision-making process.

Both topics – rational behaviour and emotional account in decision-making – receive close attention in the academic literature. However, the principal instruments in the research of these areas are traditionally grounded on experimental methodology. The latter is frequently criticised for small and concentrated samples, intricate research designs, lack of authenticity, etc. The natural validity of the experimental environment is a particularly acute problem for the study of feelings. Strong emotions are hard to invoke, regulate and guide into the direction demanded for the purpose of the research, simultaneously remaining within the moral and ethical boundaries. Besides, the subjects, when they know they are observed, tend to behave unnaturally. In this regard, my real market data set that permits to proxy the degree of rationality and to control for the factor of affect, grants the opportunity to corroborate the validity of several important economic models of individual behaviour.

In the first chapter, I manage to demonstrate empirically that the majority of investors follow the decision-making mechanism of Prospect Theory (Kahneman and Tversky (1979)) rather than Expected Utility Theory (von Neumann and Morgenstern (1944)), which follows from the observed sequence of investment decisions. In the second and third chapters, I conclude that stronger emotional charge of investors results in a significant change in risk/return relation, behavioural patterns, profitability and risk behaviour. These findings confirm the assumptions and predictions of 'Risk-as-feelings' model (Loewenstein et al. (2001)). The implications of my research can foster further investigation of the impact of affect on financial decision-making testing some of my findings with new data and research design. The emergence of novel data sets in investments, payments, loans and other retail financial domains should largely assist the academic progress in this area.

Another contribution that is attributed to my first empirical chapter is the established empirical link between rationality and performance. Unfortunately, this question is not properly covered by the existing literature. I reveal that both properties are positively related. Outperforming investors tend to exhibit a higher degree of rationality than underperforming investors. Moreover, for gaining individuals, the correlation between risk and return is on average above zero, while for losing traders, the coefficient is negative. At the same time, my findings show that the level of rationality is only one of the set of variables that have an influence on profitability. There are gaining investors with a negative correlation between return and risk and underperformers, who proved a high degree of rationality as measured by the methodological approach adopted in my analysis. The aspect of the interaction between rationality and investment results should be further examined with the help of additional methods and data, but my study and findings provide the initial platform for such an investigation.

Further, I contribute to the extant literature on behavioural biases, especially the hypothesis of their affective roots. In the second and third chapters of the thesis, I explore loss aversion and disposition effect. My results suggest that loss aversion is deeply ingrained into investors' behaviour and is so psychologically robust that the change from affect-poor to the affect-rich environment does not have a significant effect on it. My subjects were prone to overweighting losses over gains, even with the mere paper risk involved. Besides, I offer a new methodology to assess loss aversion that is based on the analysis of conditional orders. The approach is founded on the assumption that loss-averse individuals should tend to place stop-loss conditional orders significantly closer to the current market price of a financial instrument than take-profit orders. Fearing losses more than savouring gains, investors will try to play with the conditional orders to ensure the psychological comfort from the trading activity. The alleged scenario must lead to more frequent execution of stop-loss orders compared to take-profit orders considering that the market value follows a random walk pattern. Using the method, I find the evidence that stop-loss orders get realised two times more often than take-profit orders. Studying the disposition effect, I confirm that the bias is statistically significantly different in affect-rich and affect-poor settings. It contributes to the literature that identified the emotional explanations behind the disposition effect using an experimental methodology (Richards et al. (2018), Summers and Duxbury (2012)).

1.5. Thesis structure

The thesis is organised as follows. Section 1 starts with the general introduction into the research. After that, each of the three empirical chapters is introduced in separate sub-sections, followed by the description of their academic contribution.

Section 2 outlines the relevant literature on consequential decision-making theories that include traditional models like Expected Utility Theory and Prospect Theory. The difference between them is described and analysed. The remainder of the literature review is devoted to the non-consequentialist perspective and how it can impact performance and diverse manifestations of risk behaviour. Further, I provide the mathematical description of Prospect Theory model and develop my own model of investment choice for the investors with Prospect Theory-based preferences. The purpose of the model is to explore the predictions regarding the relation between risk and return for the modelled decision-maker. The section is continued with data set description and the overview of the methodology used throughout the thesis.

Section 3 introduces the first empirical chapter that is focused on the analysis of the rationality of individual investors. The degree of rationality is proxied via the correlation between realised risk and profitability. Correlations are computed and evaluated at two levels – individual-investor level and pooled-data level.

Section 4 covers the second empirical chapter that examines and compares the correlation between risk and return on two types of accounts – real money account that is dubbed ‘Live’ environment, and paper money account that is called ‘Contest’ environment.

Section 5 describes the third empirical chapter that expands the comparison of investors’ behaviour in ‘Live’ and ‘Contest’ and the evaluation of the role of emotions in other important domains – profitability, the form of the value function, the form of probability weighting function and loss aversion bias.

Section 6 summarises conclusions of the empirical chapters and provides a discussion of the results. Also, implications and limitations of the research are examined, followed by considerations for future research.

2. Literature Review

I start the literature review with the introduction to the terminology used in the economic and financial papers dealing with the role of affect and emotions on decision-making. I focus on several critical affective notions that I frequently use in the thesis. Further, in this section, I revise two related frameworks of decision-making. The first framework is the traditional consequentialist perspective that implicitly treats the process of risky choice as a genuinely conscious, cognitive activity. The second framework claims a better descriptive power of human behaviour, introducing an important adjustment that integrates affect into the judgement routine. Both standpoints contend that individuals make decisions by combining the value function with the probability weighting function. However, the compelling factor of feelings in the non-consequentialist perspective is believed to guide and alter individual behaviour under risk for many real-life judgements. After examining the relevant literature, I discover the gap in the empirical testing of the non-consequentialist model in the financial domain and the role of feelings in financial decision-making. The literature review sections are structured as follows. In Section 2.3., I present two main consequentialist theories of decision making – Expected Utility Theory and Prospect Theory, highlighting similarities and differences between them. Next, in Section 2.4. I describe the evolution and principles behind the non-consequentialist framework. In the same section, I review the papers that explore the influence of emotions on the performance of individual decision-makers. Finally, I look at the research examining the role of emotions in various facets of risk behaviour.

At the end of Chapter 2, I provide the detailed mathematical description of Prospect Theory (Kahneman and Tversky (1979,1992)) and develop a theoretical model of portfolio choice by the investor with Prospect Theory preferences.

2.1. Psychological terminology in economic research

Throughout my thesis, I frequently use psychological terminology. Psychological research makes a clear distinction (certainly not without exceptions) between such phenomena as emotions, feelings, affect, mood, sentiment (Elster (1998), Frijda (2007), Fairchild (2014)). However, it is almost impossible to define clear boundaries between them, just as there are no clear boundaries for emotions centres in the brain (Barrett (2006)). The empirical dataset that I use in the current research does not provide for the chance to control for the specific sensations expressed by the subjects. Usually, to introduce such controls, it is required to apply different research methods, for instance, using various forms of experimental designs (I describe them in more detail in Section 2.5). Nevertheless, it is customary for behavioural economic science that makes use of psychological principles and concepts in economics and finance, to apply specific terms interchangeably, especially, emotions, feelings, affect and visceral factors. Although I generally follow this tradition in my study, I find it essential to provide an overview of different classes of the sensations and explore their application in academic research during the last few decades.

2.1.1. Affect

In economic research, affect is frequently used as a collective concept of emotions (for example, Loewenstein and Lerner (2003). Loewenstein and O'Donoghue (2004) follow this practice, and implicitly include emotions (anger) and visceral factors (fear, hunger, sexual desire) into the concept of affect. Several papers (Rottestreich and Hsee (2001), Pachur et al. (2013)) use the term affect to distinguish between affect-rich and affect-poor prospects and highlight the presence of 'affect gap' in behaviour and decision-making. However, such application is conceptually very close to emotion.

2.1.2. Visceral factors

Visceral factors, also known as visceral influences, have a closer connection to physiological states than psychology (Loewenstein (1996)). The typical examples of such conditions include the drive states like hunger, thirst, physical pain, fear, cravings, etc. Loewenstein (1996) identifies two defining characteristics of visceral influences. First, a usually negative direct hedonic impact, which is featured with immediate attention switching to the developing inner state. Second, a direct effect on the preferences of particular goods and actions. Visceral states frequently lead to sharp changes in behaviour. Humans describe such situations as being 'Out-of-control'. Because of their mostly negative nature, the described psychological/physiological conditions produce the behaviour that is detrimental to an individual's self-interest. For example, Ariely and Loewenstein (2006) find that sexual arousal can generate deeply anti-social motivations and actions.

Visceral factors are substantially different from tastes or preferences – two notions frequently used in traditional economic studies. Unlike tastes, visceral factors are mostly influenced by unexpected external stimulations or deprivations and hence are far more volatile.

2.1.3. Emotions

The term 'emotions' is the one that is the most frequently used in the economic literature to refer to psychological sensations of individual decision-makers. Elster (1998), Scherer (2005) and Frijda (2007) give their classification of emotions' attributes to distinguish them from other affective phenomena. These classifications substantially overlap, hence I will provide only one of the views provided by Scherer (p. 699-702, (2005)).

1. Emotions are event focused – there should be a cognitive antecedent to elicit the sequence of the emotional reaction of the organism. The events can be prompted by other people or external circumstances or by an individual's own actions or thoughts. Notably, the event must have a meaning for the person to cause the emotional reaction.
2. Emotions are appraisal driven – the emotion-generating event must be relevant for an individual's concerns. A person should care about the event itself or the changes to the environment that the event brings about.
3. Emotions produce response synchronisation – response preparation is a complex process in the organism that requires the combination and synchronisation of multiple physiological and psychological processes.
4. Emotions are transient, rapidly adapting states – events and their appraisal of relevance occur frequently and change quickly. Emotional reactions are usually unstable and naturally adjust to the ongoing appraisal process and modification of circumstances.

5. Emotions are featured with high intensity – comparing to other states, for instance, moods, emotions usually are intense enough to refocus the attention of an individual to the ongoing psychological process so that a person can cognitively experience the inner sensation.
6. Emotions have a relatively short duration – emotions engender the mobilisation of many processes in the organism. Very long emotional experience can be harmful to a person's physiological or psychological state. In terms of duration, emotions can be positioned between more intense (and more destructive) visceral factors and less intense moods.

2.1.4. Feelings

The term 'feelings' is the most frequently interchanged with 'emotions'. However, Scherer (2005) defines feelings as only one of the components of emotions that helps to regulate the organism-environment function. Scherer (p.699, (2005)) contends that "using the term feeling, a single component denoting the subjective experience process, as a synonym for emotion, the total multi-modal component process, produces serious confusions and hampers our understanding of the phenomenon."

2.1.5. Mood

Scherer (2005) defines mood as a dispersed affective state that is characterised by durable subjective sensations that can last for hours or even days. Unlike emotions, mood can arise without any specific reason that can be clearly connected to a straightforward appraisal. Other features of mood include a low level of arousal and little tendency to respond with action.

2.2. How to measure emotions?

The measurement of emotions is a long-debated topic. Possible tools for such measurement have offered across all the three principal research methodologies of emotions: neurophysiological, experimental and empirical.

One of the top researchers of emotions, Scherer (2005) explains that emotion is a collective phenomenon made of five organismic components (p.697-698): "The components of an emotion episode are the respective states of the five subsystems and the process consists of the coordinated changes over time". The components are – evaluation of objects and events, system regulation, preparation and direction of action, communication of reaction and behavioural intention and monitoring of internal state and organism-environment interaction. Some of the components can be cognitively evaluated, interpreted and measured, e.g. evaluation of objects and events. Such assessment and measurement take place through the interview or self-reporting questionnaire that contains the questions like:

- How pleasant or unpleasant is the event or object in general, independent of the current satiation?

- How different is the event from what the person expected at this moment?

Other components – system regulation, preparation of action – can be measured through neurophysiological study. Such studies can include heart rate measurement following an emotional event, speed of breathing, dilating pupils, changes in facial expression, brain reaction, etc. I review some of the featured neurophysiological papers in Section 2.3.2.1.

Some of the studies – primarily experimental in design – offer a different way of measuring emotions. In effect, they propose to identify a so-called affective gap by modulating the subjects into affect-rich and affect-poor internal states and evaluating any difference in behaviour and parameters of subjects' decision, for example, performance. Featured examples of such studies are Rottenstreich and Hsee (2001), Hsee and Rottenstreich (2004), Pachur et al. (2014). Loewenstein et al. (2001) contend that the feelings-induced reaction to an event in the affect-rich environment (that engenders changes in behaviour) reflects the subjective sense of risk in individuals, rather than cognitively processed algebraic multiplication of severity and probability of outcomes of the same event. I extensively use the concept of affective gaps and the idea expressed by 'Risk-as-Feelings' hypothesis (Loewenstein et al. (2001)) throughout my thesis. Unfortunately, these concepts, just as my dataset, do not allow precise measurement of emotions. However, I manage to compare two real-life financial decision-making environments that are different only by the degree of affect-richness. It enables me to identify changes in risk behaviour, performance, and the relation between them and attribute these changes to emotions.

2.3. Consequentialist view on decision making and the role of emotions

In this section, I briefly review two fundamental theories of decision-making under risk, Expected Utility Theory and Prospect Theory. Even though the two models have critical dissimilarities in certain aspects, they are alike in the way of constructing the decision as the elicitation of maximum utility from consequential algebraic multiplication of each anticipated choice’s value (severity) by its subjective probability (likelihood).

The classic framework of decision-making, risk and return is outlined in the Expected Utility Theory (Neumann and Morgenstern (1944)). The theory implies that individuals make choices based on the maximisation of the concave utility function. The Expected Utility Theory is grounded on the set of baseline rational behaviour assumptions about an individual: focus on the realised preference, dominant risk aversion, the ability to make unbiased, optimal, wealth-maximising choice between all available prospects, unlimited processing capacity, exclusively financial character of objectives formulation, disposition to act in own best interests. The conjectured knowledge about future outcomes by a decision-maker along with other assumptions allows the treatment of risk perception as an objective, parametric measure, which can be estimated using such statistical variables as standard deviation, skewness and kurtosis. In the Expected Utility Theory perspective, the perceived return is the average value of all outcomes weighted by the respective likelihood.

Concerning the view of risk, traditional finance uses the concept of attitude to risk, which comprises the notions of risk tolerance and degree of risk aversion. The notion of risk aversion has been extended from the Expected Utility Theory to another notorious classical financial theory – Modern Portfolio Theory (MPT) (Markowitz (1952, 1959)). Modern Portfolio Theory introduced an integrated risk-return framework, in which higher investment risk should be remunerated with a higher return, implying a positive correlation between the two, and both risk and return can be statistically measured. An investor can find an optimal risky portfolio by maximising the utility function, which, in turn, is a function of investment risk, the investment return and investor's attitude to risk (degree of risk aversion).

The behavioural economics' approach to risk and benefit can be traced from its critical component, the (Cumulative) Prospect Theory by Kahneman and Tversky (1974, 1979, 1992). The researchers contend that the normative Expected Utility Theory is psychologically unfeasible in its core axiomatic assumption of invariance and dominance, or representation of outcomes in terms of total wealth. Prospect Theory introduces several conceptual modifications to the classic theory appropriated for better alignment with the actual behaviour of individuals. Their summary is presented in Table 2.1.

Table 2.1. Distinctions between the main attributes of Expected Utility Theory and Prospect Theory. Adapted from Tversky and Kahneman ((1992), p. 316).

Category	Expected Utility Theory	Prospect Theory
Objects of choice	Probability distributions over wealth	Prospects framed in terms of gains and losses
Valuation rule	Expected utility	Two-part (losses/gains) cumulative functional
Characteristics of valuation function	Utility is a concave function of wealth	S-shaped value function and inverse S-shaped weighting function

Also, in contrast to the Expected Utility Theory, the authors of Prospect Theory distinguish between the two types of evaluation of outcome attractiveness by the decision-maker: experience value – the psychological degree of attractiveness or disliking actually experienced from an outcome, and decision value – the objective expected impact of an outcome in a choice[4]. The transformation, or mapping, of experienced subjective values to objective states is conducted by what Kahneman and Tversky (1984) called 'hedonic psychophysics'. Kahneman and Tversky separate the value function from weighting function by recognising two categories of psychophysical processes: a) the psychophysics of value that predefines distinctive value functions for outcomes framed as reference-dependent changes in wealth (i.e. gains and losses with zero as status quo, or a reference point), rather than a single value function for absolute total wealth (as in Expected Utility Theory); and b) the psychophysics of chance representing a nonlinear function of subjective probabilities used to evaluate prospects[5]. When the two nonlinear psychophysics-shaped functions are combined, the result is the 'fourfold pattern of risk attitudes'. Tversky and Kahneman explain ((1992), p.306): "[…] the shapes of the value and the weighting functions

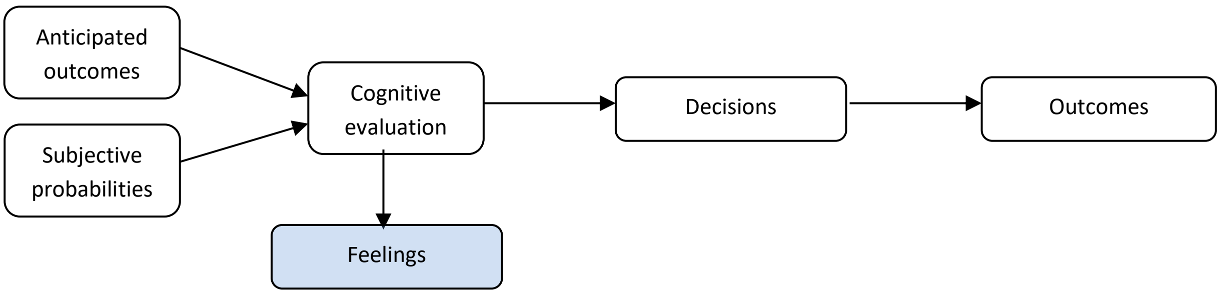
[4] According to Kahneman and Tversky (1984), traditional theory of decision-making does not differentiate between the two because it is implicitly assumed that they are coherent, which is in agreement with the concept of rationality.

[5] Tversky and Kahneman ((1992), p. 303) explain the psychophysical nonlinearity of both functions – value and weighting (probability), with the principle of diminishing sensitivity: "In the evaluation of outcomes [value function], the reference point serves as a boundary that distinguishes gains from losses. In the evaluation of uncertainty [probability weighting function], there are two natural boundaries – certainty and impossibility – that correspond to the endpoints of the certainty scale. Diminishing sensitivity entails that the impact of a given change in probability diminishes with its distance from the boundary. […] For uncertain prospects, this principle yields subadditivity for very unlikely events and superadditivity near certainty."

imply risk-averse and risk-seeking preferences, respectively, for gains and for losses of moderate or high probability. Furthermore, the shape of the weighting functions favours risk-seeking for small probabilities of gains and risk aversion for small probabilities of loss, provided the outcomes are not extreme."

Considering the impact of affect on the performance and risk of decisions in the consequentialist framework, both EUT and PT share a coherent view. As demonstrated in Figure 2.1, the models imply that humans make decisions by careful cognitive analysis of the consequences of the choices they have (Loewenstein et al. (2001), p. 267). Emotions, affects, feelings are epiphenomenal in these theories, meaning they cannot and do not impact the desirability of choice outcomes.

Figure 2.1 The perspective of consequentialist theories, Expected Utility Theory and Prospect Theory, on decision making. Adapted from Loewenstein et al. (2001)



The Expected Utility Theory sees risk attitude as a form of the value (utility) function, which is always concave, reflecting the inherent risk aversion of individuals. That is, when given two choices with the same expected outcome, a less volatile option will and should always be selected by a rational decision-maker. It implies the correlation between risk and return to remain positive across the whole spectrum of the utility function. In Expected Utility Theory world risk is a statistical parameter that can (and should) be measured when making a choice. Expected Utility Theory prescribes a compulsory algebraic account of the decision-making process. Prospect Theory view on how decisions are made under risk is more flexible, reflecting the descriptive nature of the model. Kahneman and Tversky claim that the core principle of Expected Utility Theory that only final wealth is of value for people implies too long-term oriented thinking, which is psychologically unrealistic. In real life, humans take a short-term perspective on important (and not that important) decisions in their lives. In the boundaries of short-term thinking, absolute final wealth loses its grip, giving way to changes in wealth that become more significant. Changes in wealth imply the existence of a reference point, around which wealth fluctuates. In this framework, risk is not only the curvature of the value function (concave in the gains domain, and convex in the losses domain), but also the loss aversion – perceived dominance of losses over gains, and decisional weighting function – overweighting choices with extreme probability versus more probable choices. The correlation between risk and return also undergoes imminent transformation under Prospect Theory. The correlation remains positive only in the domain of gains backed by the concave form of the value function. In losses domain, risk-seeking behaviour entails correlation to drop below zero and turn negative. Besides, loss aversion bias leads to the expectation that negative correlation must be stronger in modulus than a positive one for the equivalent degree of outcome’s severity. I test these assumptions in my theoretical model in Section 2.10 and the first chapter of my empirical research.

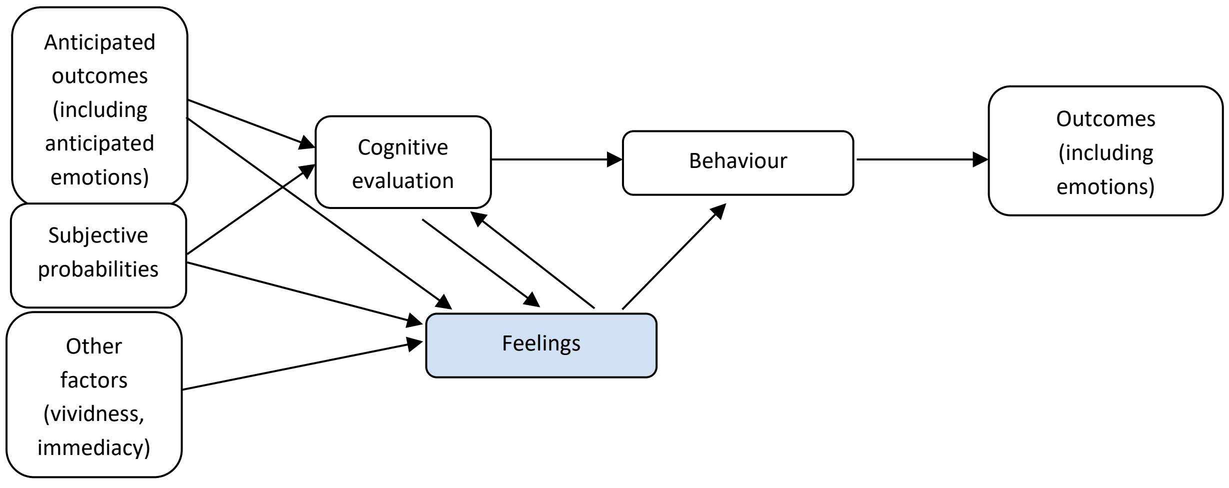
2.4. Dual-process theories of decision making, risk and return

In this section, I describe the models that strive to make a better approximation to real-life human behaviour by integrating emotions into decision processing. I also cover and review the literature that accumulated considerable evidence of the role that feelings play in the formation of decision outcomes, decision performance, and risky behaviour inherent into decisions. These studies claim that ignoring emotions largely deteriorates the predictive power and reliability of traditional models.

2.4.1. History and main principles of non-consequentialist perspective

The development and evolution of so-called dual-process theories have been associated with an augmented understanding of the role of affect in decision making over the last two decades. The cognitive-only view on choice and psychological biases was updated and, gradually, a more balanced view was taken. For instance, Kahneman (2003) revisits prior approach by granting equal position to cognition and affect, which he calls 'a more integrated view of the role of affect in intuitive judgment'[6]. The sample of the dual-process framework is graphically represented in Figure 2.2.

Figure 2.2. The evolution of perspectives of the role of affect in judgment and decision making. Adapted from Loewenstein et al. (2001)



[6] Kahneman ((2003), p.710) comments that "in terms of the scope of responses that it governs, the natural assessment of affect should join representativeness and availability in the list of general-purpose heuristic attributes. The failure to identify the affect heuristic much earlier and its enthusiastic acceptance in recent years reflect significant changes in the general climate of psychological opinion."

Generally, for all dual-process models, behaviour is the result of the interaction between cognitive and emotional processing. Several important conclusions follow from Figure 2.2. First, feelings can directly surface from anticipated outcomes and probabilities without the intermediation of cognition. Second, cognition and feelings may have different determining factors. The factors that are essential for the emotional charge at the moment of choice, such as vividness or immediacy of an outcome, have a minor impact on cognitive processing. Third, behaviour can be predominantly mediated by feelings, which can generate decisions that are reversed from what is predicted by consequentialist models.

The starting point for models integrating affect can be attributed to Epstein (1994) and Sloman (1996) who formulate a dual-process theory[7] of thinking and knowing grounded on prior psychological research (e.g. Brewer (1988), Bargh (1989), Fazio (1990)). As the researchers suggest, humans process information and make decisions based on two systems, experiential (feelings) and rational (cognition), accordingly, System 1 and System 2 as labelled by Kahneman (2011), or analytic and intuitive (Epstein ((1994), p.710): "There is no dearth of evidence in everyday life that people apprehend reality in two fundamentally different ways, one variously labelled intuitive, automatic, natural, non-verbal, narrative, and experiential, and the other analytical, deliberative, verbal, and rational. […] Embedded in common language is evidence that people are intuitively aware of two fundamentally diverse ways of knowing, one associated with feelings and experience, and the other with intellect."[8]

[7] The latest review and debate about the dual-process theories can be found in Evans (2008) and Evans and Stanovich (2013).

[8] Sloman (1996) labels the two systems of mental processing as associative and rule-based. He does not explicitly relate associative system to emotions, affect or feelings (these words even do not appear in the paper), nevertheless, when describing the associative system, he uses such affect-related notions as imagination, fantasy, or intuition. Sloman ((1996), p. 6) focuses on approaches to problem solving and reasoning when he claims that "two systems, two algorithms are designed to achieve different computational goals. One is associative, and it seems to operate reflexively. It draws inferences from a kind of statistical description of its environment by making use of the similarity between problem elements, interpreted using such aspects of general knowledge as images and stereotypes. The other is rule based and tries to describe the world by capturing different kinds of structure, structure that is logical, hierarchical, and causal-mechanical."

Researchers demonstrate how the distinction between the two systems is explicitly manifested through common behavioural patterns and biases, such as irrational fears, superstitious thinking, religion, etc. This is how Slovic et al. ((2004), p. 313) illustrate how experiential and analytic systems coexist: "It was the experiential system, after all, that enabled human beings to survive during their extended period of evolution. Long before there was probability theory, risk assessment, and decision analysis, there were intuition, instinct, and gut feeling to tell us whether an animal was safe to approach or the water was safe to drink. As life became more complex and humans gained more control over their environment, analytic tools were invented to 'boost' the rationality of our experiential thinking. Subsequently, analytic thinking was placed on a pedestal and portrayed as the epitome of rationality."

Table 2.2. Two modes of thinking and deciding: System 1 versus System 2. Adapted from Slovic et al. ((2004), p. 313)

System 1 – Experiential	System 2 – Analytic
1. Holistic	Analytic
2. Affective: pleasure-pain oriented	Logical: reason oriented (what is sensible)
3. Behaviour mediated by 'vibes' from past experiences	Behaviour mediated by conscious appraisal of events
4. Encodes reality in concrete images, metaphors, and narratives	Encodes reality in abstract symbols, words, and numbers
5. More rapid processing: oriented toward immediate action	Slower processing: oriented toward delayed action
6. Associationistic connections	Logical connections
7. Self-evidently valid: "experiencing is believing"	Requires justification via logic and evidence

Another version of behavioural dichotomy is offered by Loewenstein and O'Donoghue (2004). In their two-system model of behaviour, individual's motivations and decisions are placed between the extremes of 'affective optimum' and 'deliberative (cognitive) optimum'. Some stimuli can activate only a single system, while others can trigger two systems simultaneously. Most of the time, both systems will work in unison, bolstering and reinforcing each other. Nevertheless, occasionally, they may turn contradictory[9]. In such a case, the degree to which one system will prevail over the other concerning a concrete decision largely depends on stimuli specifications. According to the researchers, a salient parameter defining the primacy of one of the systems is stimulus proximity to the decision-maker in one of the relevant dimensions, e.g. temporal, visual, or physical[10]. Generally, though, affective system will dominate over deliberative, but humans are empowered with willpower to control and overrule affective reactions.

2.4.2. ‘Risk-as-Feelings’ model of decision-making

The synthesis of dual-process conceptualisation and its key predictions are highlighted in the ‘Risk-as-Feelings hypothesis’ by Loewenstein et al. (2001). The authors dispute the historical view on feelings as a mere product of the judgment process as regarded by classic theories. Further, they argue that the introduction of a group of regret/disappointment theories that embrace emotional reactions does not significantly modify the existing consequentialist conception in the way how a decision-maker forms his behaviour. Loewenstein et al. (p. 267-268) name this type of emotions ‘anticipated’, which make part of a cognitive process and can be described as “a component of the expected consequences of the decision [and] emotions that are expected to occur when outcomes are experienced, rather than emotions that are experienced at the time of decision”. In contrast to the classic perspective, the researchers outline their own framework of the function of affect in

[9] Loewenstein and O’Donoghue ((2004), p.9) gave an example with food as a stimulus. The complementing activation of two systems may occur when the sight of food evokes the (affective) feeling of hunger together with a (cognitively processed) thought of the need to have a meal. In contrast, the contradictory activation of affective and deliberative systems may happen if in response to having a feeling of hunger a person remembers being on a diet, which demands self-rationing.

[10] The proximity parameter and its impact on behaviour is highly correlated with the intensity variable explained in Loewenstein (1996). High degree of proximity and intensity lead to more explicit activation of affective system and impulsive behaviour.

judgment. In this framework, the behaviour is tuned by anticipatory emotions rather than anticipated. According to Loewenstein et al. (p.267-268), anticipatory emotions are "immediate [unexpected] visceral reactions (e.g. fear, anxiety, dread) to risks and uncertainties". The new perspective establishes two new meaningful and contradictory interactions, grounded on the prior studies of emotions.

First, feelings reciprocally impact and inform cognitive reactions. The fact that cognition shapes emotional states has been known for a long time. For example, appraisal theories (see Forgas (2008) for review) argue that representations about past, current and future affective reactions are preceded by cognitive mechanisms. However, the role of feelings in informing cognitive processes is a relatively new domain of explorations. Nevertheless, a substantial amount of evidence posits that emotions and cognition complement each other to produce decisions and behaviour. As Loewenstein et al. (p.271) summarise: "affect typically […] provides inputs into decision making that help people to [cognitively] evaluate alternative courses of action, albeit not always in normative fashion".

Second, emotions can directly tune behaviour without (or at little) cognitive mediation[11]. Based on the alternative line of literature, affective reactions frequently depart from purely cognitively processed maximisation of wealth. In such cases, feelings commonly dictate behaviour. For example, Zuckerman (1994, 2007) put forth a theory according to which people engage in financial, social, legal, etc. risky behaviour for the sake of (Zuckerman (1994), p. 27) "seeking of varied, novel, complex, and intense sensations"[12]. Often, such sensation-seeking behaviour is wealth-destructive from a purely cognitive perspective, for instance, in the financial domain, several papers (Dorn and Sengmueller (2009), Dorn et al.

[11] Loewenstein et al. ((2001), p. 270) explained that "feeling states are postulated to respond to factors, such as the immediacy of risk, that do not enter into cognitive evaluation of the risk and also respond to probabilities and outcome values in a fashion that is different from the way in which these variables enter into cognitive evaluations. Because their determinants are different, emotional reactions to risks can diverge from cognitive evaluations of the same risks".
[12] Sensation seeking has a clearly established link to human neurophysiology, as it directly correlates with androgen exposure and dopaminergic reward (e.g. Campbell et al. (2010)).

(2014)) provide evidence that trading by individual investors is substantially motivated by the search of new sensations, which generally leads to excessive trading and losses. Further support of emotional dominance over cognition can be found in the gambling literature (see Johansson et al. (2009), Binde (2009), Spurrier and Blaszczynski (2014) for review), where the destruction of wealth by gambling is mostly driven by affective motivations (e.g. dreams of the jackpot, seeking of new emotions or inducing the change of mood)[13].

In their model, Loewenstein at al. propose an approach to integrate the two competing instances – the complementary role of emotions in cognitive decision making, and discordant effect of anticipatory feelings – into a theory that attempts (Loewenstein et al. (2001), p.270) "to explain when and why emotional reactions diverge from cognitive evaluations of risk and to explain how these responses interact to determine behaviour". The authors associate the divergence with two aspects – discrepancy in response to purely traditional consequentialist models' inputs – probabilities and outcomes; and anticipatory emotions-specific factors that classic models do not consider, such as affective vividness of a decision, or time lag between decision and outcome.

2.5. The impact of feelings on performance

2.5.1. Predictions under consequentialist and dual-process perspectives

As discussed in the previous sections, there are two alternative (and largely complementary) views on how emotions influence behaviour, and subsequently performance. According to the consequentialist-type models, we should not observe any meaningful impact: feelings do

[13] Accordingly, pathological gambling is closely related to dysfunctional impulsivity.

not influence outcomes, or at least, they can be envisaged in advance and dealt with accordingly.

For ‘Risk-as-Feelings’ hypothesis and similar theories, the relation between affect and outcomes is more intricate. As was outlined, emotions can be classified as anticipated (expected) and anticipatory (immediate). Expected emotions are, by definition, the product of cognitive processes that take place when an individual analyses the impact of decisions and actions on her future emotional state. Anticipatory emotions are felt immediately (and usually unpredictably) at the moment of a decision. Very often they are processed subconsciously and may generate impulsive behaviour that is causing actions against one’s realised cognitively-processed self-interest. Underlining this peculiarity, Rick and Loewenstein ((2008), p. 150) note that human actions under the effect of emotions are very much distinct from the thoughtful and rational multiplication of costs and benefits. In contrast, it is a far more chaotic process that “often drives behaviour in exactly the opposite direction from that suggested by a weighting of costs and benefits”.

Non-consequentialist framework predicts that even under otherwise identical circumstances, performance may deviate in response to the change in immediate emotional intensity. Most of the time and for the most of decisions, these deviations will not be dramatic, and will keep the decision-making process generally within the boundaries of consequentialist model’s predictions. However, in rare cases, the more vigorous emotional intensity may bring about more massive departure from the standard expectations. It should be understood, though, that the power of the non-consequentialist framework is most efficiently elicited not for overturning the predictions of Prospect Theory but for correcting its precision.

Consequently, it follows from the literature that the necessary adjustments to Prospect Theory are dependent on the ability to comprehend and identify the degree of emotional intensity attributed to the event. For this purpose, I explore the variables that are known to mediate the level of the dominating intensity of affect. There are several factors described in the literature, for instance, the duration of the emotion-eliciting event, the time interval between decision and realisation of an outcome, nature of emotion, or personal characteristics of an emotion-experiencing person. Yet, one of the widely accepted key elements that shape human emotional reactions to stimuli is the vividness with which we mentally perceive the expected consequences possibly produced by interaction with these stimuli (Loewenstein et al. (2001)). However, vividness is a complex construct consisting of several constituents, which should be analysed because of their importance for the research question. Frijda (1986, 2007) and Sonnemans and Frijda (1994, 1995) mention concern strength, concern relevance and appraisal.

Concern is defined as an integral of "motives, goals, both acute and latent, and preferences or aversions for particular classes of stimuli" (Sonnemans and Frijda (1995), p.485). Concerns may vary in terms of their significance to the subject, i.e. have a different degree of strength. The second dimension of concern is its relevance to the stimuli under consideration. Generally, the higher the strength of concern and the magnitude of stimulus value to a person, the more intense emotion should be expected. With respect to financial trading, a number of concerns have been discussed in the literature. Apart from classical explanations for trading, such as material welfare, liquidity management, retirement savings (Hoffman (2007)), some more extravagant concerns have been discovered: entertainment (Dorn and Sengmueller (2009)), sensation seeking (Grinblatt and Keloharju (2008)), rise in self-esteem (Barberis and Xiong (2008)), aspiration for riches (Kumar (2009)).

Appraisal is a vital variable in the emotional intensity function. In addition to the appraisal of the relevance of the event or stimulus for the subject, there is a second dimension of the concept – contextual appraisal. It relates to the attributes of the event that are involved in emotional processing. Notably, one of the attributes is "how real the event is felt to be, i.e. whether or not it actually occurred, or whether or not it actually does have the implications it might seem to have" (Sonnemans and Frijda (1995), p.486). Basically, it can be referred to as 'a sense of reality'. Sonnemans and Frijda (1995) find that sense of reality is particularly well correlated with the emotion of fear[14]. They also encounter that the feeling of anger is boosted if there is someone else to blame for the situation. As is known from both popular and academic literature (e.g. Oberlechner (2004)), fear and anger are perpetual companions of financial trader.

In Section 2.10, I develop a theoretical model to compare the predictions regarding some aspects of behaviour made under the affect-poor perspective (proxied by the parameters from the original Prospect Theory model) and the affect-rich perspective (represented by the parameters from the model of Jakusch et al. (2019).

2.5.2. Extant literature on the influence of emotions on performance, methodologies and main findings

The testing of the interplay between affect, behaviour and performance so far has been conducted along with the three methodologies that dominate existing literature: neurophysiological analysis, experimental analysis, and interview-type studies. Although the principal place in this domain of literature is devoted to a general workplace context, a limited number of papers discuss and examine the job and activity of (mostly professional) financial traders or lay people taking a broader set of financial decisions. Because of the scarcity of relevant empirical data sets, and the inability to properly manipulate feelings in the empirical settings, there is a clear gap in terms of empirical investigations of the impact of emotions on performance.

[14] They also found that when self-esteem is hurt by the event, the feeling of fear is reinforced.

2.5.2.1. Neurophysiological studies

The standard approach under neurophysiological methodology is to gauge and establish a relation between a specific neurophysiological variable and trading performance. Examples of variables that were used in the literature include second-to-fourth digit length ratio (Coates at al. (2009)), the level of testosterone (Coates and Herbert (2008)), and heart rate variability (Fenton O'Creevy et al. (2012)). Typically, the studies focus on a small group of professional traders as subjects, primarily because of limited possibility to reach out larger professional and lay traders populations. The papers using this type of research methods generate mixed results on the role of affect in trading results. For instance, Coates et al. (2008) find that second-to-fourth digit ratio (that is known to be dependent on the prenatal exposure to androgenic steroids and postnatal sensitivity to testosterone circulation – a recognised factor in the emotional regulation of risk-taking) is positively correlated with performance. Traders with higher ratio demonstrate better adaptation to financial markers if measured by the long-term results and survival criterion. Another evidence of the positive influence of emotions comes from the study of Coates and Herbert (2008). The authors demonstrate that traders with higher testosterone (associated with positive affect) morning level have significantly better performance during the day. In contrast, Fenton-O'Creevy et al. (2012) show that higher level of affect (measured by the heart rate variability) has a moderate negative correlation with performance (proxied by traders' annual remuneration).

Fairchild et al. (2016) combine a neurophysiological design with the experimental setting of a simulated stock market game using a group of students as subjects. The authors collect and study the relationship between many individual variables: level of risk aversion, risk-seeking, loss aversion, self-reported emotions, actual emotions measured with the help of GSR equipment that is combined with the results of a trading game (return and behaviour). The focus in this paper and the design of the simulated trading is made specifically on the bear market. The intriguing results reported in the paper demonstrate several performance-related findings—subjects with a higher degree of risk aversion exhibit lower performance, higher realised volatility and lower Sharpe ratio. The authors explain such a counter-intuitive result by suggesting that in a bear market, it does not pay off to be risk-averse. They also assume that the reason for the identified phenomenon can be psychological/emotion-based: higher risk-aversion together with a larger proportion of risky assets investment may produce anxiety and emotional paralysis.

2.5.2.2. Experimental studies

The experimental branch of literature is based on the two-step approach. Initially, researchers extract subjects' emotions-related attitudes and other variables through a questionnaire or a survey. After that, this data is matched against a set of tailored decision-making exercises. Again, as in the studies following neurophysiological methodologies, the conclusions regarding the positive or negative role of feelings in performance turn out to be mixed. For example, Seo and Barrett (2007) break down the affect variable into two dimensions: affective intensity (reactivity) and affective influence regulation (management). In the experimental stock trading game setting, they explore how the dimensions interact with the trading performance. The researchers discover that the personal trait of experiencing more intense emotions is positively related to individual trading results. The same conclusion is reached regarding better emotions regulation skills. Interestingly, the two dimensions are found to impact performance in the additive fashion and not interactive. The contrasting result is demonstrated in the papers of Schunk and Betsch (2006) and Lo et al. (2005). The first co-authors, using an experimental lottery design, construct subjects' personal utility function that is matched against the result of the questionnaire on individual decision-making style (intuition or deliberation). They find that individuals with a more elaborate analytical approach have more linear utility functions, hence smaller exposure to emotional biases (and closer proximity to expected return maximisation). However, it comes at the cost of longer average time spent on a decision. Lo et al. (2005) match paper and real trading performance of a group of financial day traders against their responses to the personality test and regular survey of current mood (using Mood Adjective Checklist inventory). The evidence they obtain suggests that traders with more intense affective reactions to both losses and gains tend to have worse returns than subjects manifesting weaker emotional reactivity.

2.5.2.3. Interview-type studies

Finally, the interview-type analysis technique implies obtaining affective variables from interviews with the subjects further comparing the variables to performance statistics. A featured example of such study is the paper of Fenton-O'Creevy et al. (2011), in which the authors interview a group of professional traders with an attempt to elicit the role of feelings in the daily work and decision-making of a trader, the use of intuition and its effect on performance. These qualitative data are used together with performance statistics measured by total remuneration of traders. It is identified that the changes in mood resulting from prior good or bad trades harm the following results overall. Also, high performing traders have markedly distinct emotion regulation strategies compared to low performing traders. Specifically, high performers apply more cautious strategies regulating the impact of intuition on their decisions.

2.5.2.4. Conclusion of the studies review

The studies reviewed above use creative approaches to provide some interesting findings regarding the impact of feelings on decision performance. However, they clearly do not extend to establishing whether more emotions are generally good or bad for a large population of people in the natural environment making, for instance, a sequence of standard financial decisions. Essentially, it is indicated that feelings' effect is strongly heterogeneous and can play both positive and negative role in behaviour and performance depending on the angle of view and the defined methodology, scenario or conditions of the study. This fact corresponds to the bifurcation of a broader research perspective (see Loewenstein et al. (2001) and Seo and Barrett (2007) for the more detailed review), in which emotions are considered as either negative because they induce various biases that hurt decision-makers or positive because they operate as decision facilitators that power and enable the whole decision-making mechanics.

Fenton-O'Creevy et al. (2012) also discuss the possible reasons behind the duality of findings concerning the impact of emotions on performance. They argue that both positive and negative effect revealed in the literature may be due to the distinction between the incidental and integral emotions. Incidental emotions are the class of experiences that are unrelated to the decision itself. For example, that can be the impact of a depressed feeling after a family conflict on the investment decision made later that day. Incidental emotions are generally considered in the literature to deteriorate the rational processing of information and produce biased decisions. Their role is mostly found to be harmful to performance.

In contrast, integral emotions represent the type of experiences that are relevant to processed decisions. They are often unconscious and involve both past and current experience of the decision-maker specific for the judgement made. The papers that target integral emotions often find a positive impact on performance. Fenton-O'Creevy et al. (2012) argue that the two perspectives may not be in contradiction but rather complement one another. The authors also suggest that for successful decision-making, one should engage in emotion regulation such that the role of incidental emotions is cut short, while the experience-based integral emotions are duly capitalised upon.

As concluding remarks, it is essential to mention that the papers mentioned above and, more generally, methodologies share several vital issues. First, because of time, financial, data protection and other types of restrictions, researchers can hire a very limited number of subjects, usually few dozens, and focus only on the most professional traders from trading floors of major banks. Second, subjects are aware that they are being observed and evaluated during the experiment, which may be a strong behaviour changing factor and a stimulus by itself, producing noise in feelings elicitation and distorting research results. Third, to a large extent, the non-empirical techniques are reliant on what subjects say, rather than their actual behaviour. There is extensive evidence that these two instances can differ. A more natural domain of empirical analysis can potentially control for these disturbances.

2.6. The impact of emotions on risk behaviour

An essential conclusion stemming from the papers considered in the previous section is that performance most of the times is strongly dependent and mediated by risk preferences and risk behaviour in the episodes of judgments under uncertainty involving emotions. Therefore, in this section, I examine studies that focus specifically on the interactions between feelings and risky choices. In the non-consequentialist framework, emotions are predicted to have a direct impact on behaviour under risk and uncertainty. However, as it is explained in Kahneman and Tversky conceptualisation (1979, 1992), the risk is a multi-dimensional construct that is based on three main components – the form of the outcome valuation function, the form of the probability weighting function, and loss aversion. In the subsequent sections, I describe the risk components one by one.

2.6.1. Emotions and the form of the value function

The valuation function has been found in Prospect Theory framework to have an S-shaped form, which Kahneman and Tversky explained by “psychophysics of value” principle. In accordance with it, the psychological perception of the magnitude of change in value decreases as the change happens further away from the status quo. As a result, individuals will face a concave valuation function in the domain of gains, and convex function in the domain of losses. In other words, they will tend to be risk-averse for gains and risk-seeking for losses. Later, Kahneman et al. (1999) and Hsee and Rottenstreich (2004) expanded and largely modified the psychophysics explanation originating a framework of ‘affective valuation’ or ‘valuation by feelings’. This principle or method of valuation has become the cornerstone of the dual-process theory that has been referred to in the prior discussion. The theory contends that individuals are naturally equipped or utilise two classes of thinking and deciding, one based on cognitive apparatus, and another on emotional processing. Both are substantially different from the stimulus valuation standpoint. Cognitive analysis recognises the continuity of the valuation function, i.e. the value function evolves gradually from the reference point, while emotional analysis has a propensity towards binary-like structure, i.e. everything/nothing, or gains/losses. Most of the psychological value is derived from the mere appearance of stimuli themselves and tend to ignore the pertaining degree of scope, i.e. are insensitive to severity[15].

Kahneman et al. ((1999), p.212) explain scope insensitivity in the following way: “the quantitative attribute has little weight in the valuation, which is determined mainly by the affective response to a prototypical instance of the good”. Kahneman and his colleagues also argue that at the heart of valuation process is not the revelation of genuine and fundamental

[15] As Hsee and Rottenstreich ((2004), p. 24) assert: “feelings yield marked sensitivity to the presence or absence of a stimulus (i.e., the change from 0 to some scope) but yield little sensitivity to subsequent increments of scope. In contrast, calculations yield relatively constant sensitivity throughout the entire range.”

economic preferences but rather the expression of the momentary attitude of liking or disliking towards the stimulus (p. 204), which has an authentic affective origin. This view very closely overlaps with the models of Affect heuristic (Finucane et al. (2000), Slovic et al. (2004)) and 'Risk as feelings' hypothesis (Loewenstein et al. (2001)), which claim that valuation of risky decisions is mostly a process of approaching choices one likes and avoiding choices one dislikes. That is, affective valuation determines the sign – positive or negative – and intensity of a stimulus. The more intense it is, the more binary, i.e. tending to extremes, the realised attitude (or choice preference) is going to be. Also, the more bipolar is the choice, the more insensitive it is to the scope of a stimulus.

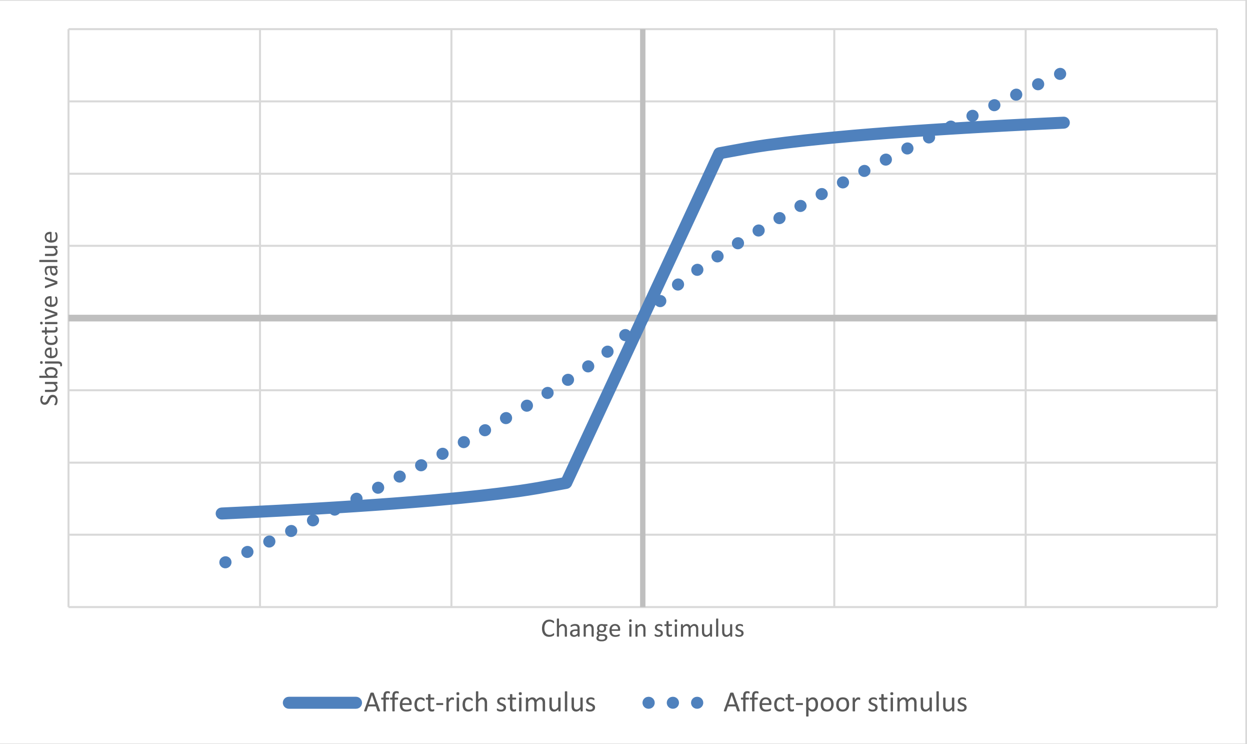
Variation in insensitivity to the scope is demonstrated in the series of smart experiments by Hsee and Rottenstreich (2004). In the first study, the authors show that subjects initially primed to calculations or affect, evince apparent proclivity to more (when primed to calculations) or less (when primed to feelings) sensitivity to scope in the subsequent analysis. In the second study, subjects prove to be more consistent (sensitive to scope) when deciding on the effort spent to earn cash remuneration (a proxy for affect-poor stimulus) than in the case of equivalently priced music book (a proxy for affect-rich stimulus). The third experiment manipulates the visual representation of the stimulus (saving pandas). As it turns out, subjects who see cute pictures of pandas are much less sensitive to the number of animals they are saving with their donation in comparison when pandas are depicted schematically as mere dots. Based on the experiments' proceeds, Hsee and Rottenstreich ((2004, p. 28-29) offer a model equivalent to Cobb-Douglas utility function that would reflect shifts in the curvature of the value function caused by emotional implications of appraised stimuli:

$$V = A^{\alpha} S^{1-\alpha} \qquad \text{(Formula 2.1)}$$

where V stands for the subjective value derived from a stimulus, A denotes the emotional intensity of a stimulus, S stimulus's scope, and α is a coefficient of emotional focus. As noted by Hsee and Rottenstreich, A and α are presumed to be correlated, i.e. more affective stimuli attract more attention from the decision-maker[16].

It is assumed that α is larger for higher A value due to the positive correlation between the two. The resulting function is schematically depicted in Figure 2.3. As presumed, affect-rich stimuli elicit the most of psychological value already at low rates of inducement. Subsequently, the degree of scope sensitivity remains muted. In contrast, affect-poor targets produce high sensitivity to increments in scope.

Figure 2.3 Subjective value function for affect-rich vs. affect-poor stimuli.



Note: The affect-poor prospect value function is constructed using a curvature coefficient from the original study by Tversky and Kahneman (1992), which is 0.88. For affect-rich prospects, the curvature coefficient is arbitrarily lowered to 0.2. Subsequently, the sensitivity to small changes in outcomes becomes disproportionally more acute than to larger changes. The psychological evaluation of an outcome approximates a more binary-like process of 'will occur/will not occur', where the extent is less important.

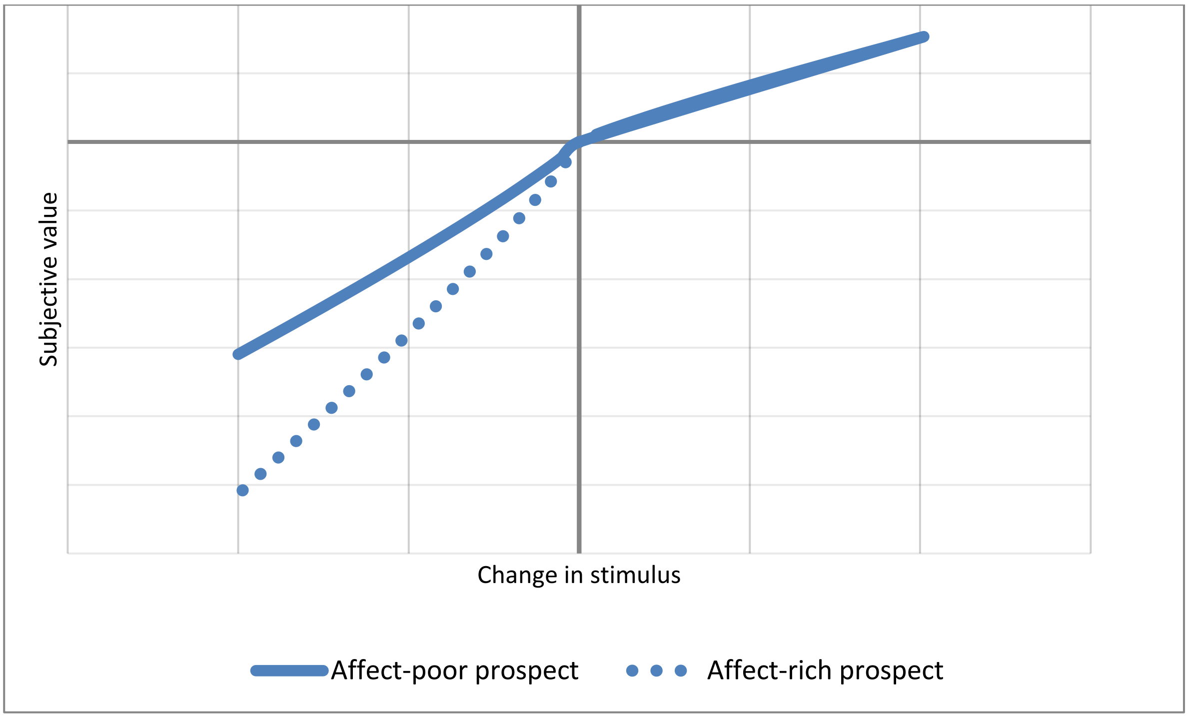
[16] For the sake of focusing on the curvature of the value function, I deliberately ignore the loss aversion factor that is commonly used in specifications of similar models (starting from Kahneman and Tversky (1979)). In what follows, I devote a separate section to the discussion of the possible role of feelings on the loss aversion.

The model outlined above implies consequences that are qualitatively and quantitatively different from what is inferred by consequentialist models. The affect-rich function is progressively more concave in the positive domain and convex in the negative domain for more feelings-eliciting stimuli. Considering that feelings are not integrated into the decision processing under the traditional or Prospect Theory frameworks, both models cannot predict or incorporate the fact that the level of affect pertaining to the prospects may change the form of the value function. Nevertheless, such a change will have a direct influence on the risk behaviour and correlation between risk and return. The shift in the psychological value of a similar type of outcomes should lead to different lines of behaviour depending on the dominating level of emotional charge.

2.6.2. Emotions and loss aversion

The impact of emotions on the second dimension of risk behaviour – loss aversion is explored to a much lesser extent. Most of the research in this area is represented by experimental (Dhar and Wertenbroch (2000), Harinck et al. (2007)) and neurophysiological (De Martino et al. (2010), Weller et al. (2007)) studies. Camerer summarises the literature and expresses his viewpoint on the interaction between loss aversion and feelings in the following way (Camerer (2005), p. 9): “My intuition is that loss-aversion is often an exaggerated emotional fear reaction, an adapted response to the prospect of genuine damaging survival-threatening loss, which overreacts to small losses in our (evolutionarily-new) long lives that are not truly life-threatening. Many of the losses people fear most are not life-threatening, but there is no telling that to an emotional system over-adapted to conveying fear signals. People hate losing jobs, ending relationships, and delaying delivery of rewards, though they rarely die from those “losses” or broken hearts”. It should be kept in mind that loss aversion is normally elicited when both positive and negative choices are part of the same evaluation prospects (so-called mixed choices). That is why loss aversion is qualitatively diverse from risk-averse/risk-seeking analytical framework because the latter typically involves prospects with the same sign (all losses or all gains), Effectively, as is stipulated in the literature of affective loss aversion, in case of more affect-rich stimuli the - λ (loss aversion) coefficient applied to losses section of valuation function in Kahneman-Tversky Prospect Theory framework, is expected to be larger. As a result, affect-richer stimuli must generate a higher degree of overall risk aversion. Graphically, it can be represented in the following way:

Figure 2.4. Loss aversion effect on subjective value function for affect-rich and affect-poor stimuli.



Note: The affect-poor prospect value function is constructed using curvature and loss aversion coefficients from the original study by Tversky and Kahneman (1992), which are 0.88 and 2.25, respectively. For affect-rich prospects, the loss aversion coefficient is arbitrarily raised to 4.

2.6.3. Emotions and the form of the probability weighting function

The last facet of risk behaviour is the probability weighting function. Fehr-Duda and Epper ((2012), p. 589 comment: "Probability dependence is the more fundamental of the two [if to compare loss aversion and non-linear probability weighting] because it is observed for all types of prospects: pure gain prospects as well as pure loss and mixed prospects. In contrast, loss aversion is effective for mixed prospects only. It is our impression that probability-dependent risk preferences have not received as much attention as loss aversion has, however". This view is confirmed by a minimal number of studies investigating the emotional nature and affective impact on the weighting function.

There are three components or dimensions of the transformation of probability weighting function that must be encompassed to understand the influence of affect on probability weights: the curvature of the probability weighting function, elevation of the probability weighting function, and asymmetric transformation of the weighting function for gains and losses.

I begin with the first dimension – concavity and convexity parameters of the nonlinear probability function. As was initially outlined in the Prospect Theory framework (Kahneman and Tversky (1979)), for probability weighting function two reference points are naturally identified – zero probability (impossibility) of an event to occur, and 100% probability (certainty) that an event will take place. It has been discovered that humans tend to systematically overweight chances closer to 0% and underestimate objective probabilities closer to 100%. It leads to the inverse S-shaped functional form of the decision weights. There are several explanations of this phenomenon in the literature. Tversky and Kahneman in their Prospect Theory maintain that this is the result of the psychophysical process ('psychophysics of chance') of larger sensitivity to more salient probabilities near to certainty and impossibility, and then diminishing sensitivity to intermediate probabilities. Other researchers (e.g. Rottenstreich and Hsee (2001)) believe that this is in the first place the consequence of emotional implications, primarily the feelings of fear and hope, but also dread and savouring that shape the weighting function. Moreover, in contrast to the standard condition of source independence, probabilities estimation is not separated from the stimulus itself, meaning that the perception of equal probabilities for more affect-rich prospect and the less affect-rich prospect will differ.

In fact, abundant evidence is found indicating that affect-rich and affect-poor probabilities are treated by people in a strikingly different way (see Rick and Loewenstein (2008), Suter et al. (2016) for review of relevant literature)[17]. There are two alternative views on how feelings transform probability weighting of a risky choice. First, individuals may neglect probabilities (beliefs) whatsoever when placed into an affect-rich set-up. In this scenario, the choice is essentially shaped by vivid representation (mental imagery) of possible extreme outcomes – worst- and best-case scenarios leading to the engagement of minimax rule (i.e. changes in probabilities close to reference points elicit most – close to all – of psychological impact). This way of rationing can be found in Pachur et al. (2014). In the alternative construct, the affect-rich setting does not block probability function completely but only distorts it in comparison to an affect-poor set-up. In this conceptualisation, put forth by, e.g. Rottenstreich and Hsee (2001), the risky choice is best fitted by the probability weighting function described in Cumulative Prospect Theory (CPT) (Tversky and Kahneman (1992)). Suter et al. (2016) investigate which of the two models – CPT or minimax rule – can better explain the ‘affective gaps’. They conduct their experiments on an individual decision-maker level and discover that individual preferences in risky choice are best described by the so-called dual-system model (DSM) that combines both constructs administered by a linear

[17] Practically, it allows rejecting probability-outcome independence, which is one of the core assumptions in the consequentialist theories (e.g. Expected Utility Theory and Prospect Theory).

weighting function[18]. The study comprises an important conclusion that the weight for minimax rule (that ignores probabilities) rises two-fold from 20% in affect-poor set-up to 44% in the affect-rich set-up.

The second dimension of affective influence on the probability function reflected in the literature is its elevation. Fehr-Duda and Epper (2012) refer to the elevation factor as the affect-charged degree of optimism or pessimism pertaining to the decision-maker. The formal treatment of this effect is proposed by Goldstein and Einhorn (1987) and Prelec (1998)[19] and used in the featured studies of Tversky and Fox (1995), Wu and Gonzalez (1996), Gonzalez and Wu (1999). According to Goldstein and Einhorn (1987), the probability weighting function is described as (see Dhami ((2016), p. 123) for more details):

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} \qquad \text{(Formula 2.3)}$$

where γ is the parameter of the curvature of probability function, and δ is responsible for elevation of the function. A lower value of γ and higher value of δ produce more pronounced curvature and higher elevation of the probability function (i.e. higher degree of nonlinearity) above the objective probabilities linear function used in the Expected Utility Theory, for which $w(p) = p$.

Several papers investigate the elevation parameter (e.g. Gonzalez and Wu (1999), Fehr-Duda et al. (2010)) and find that models incorporating elevation better explain the experimental

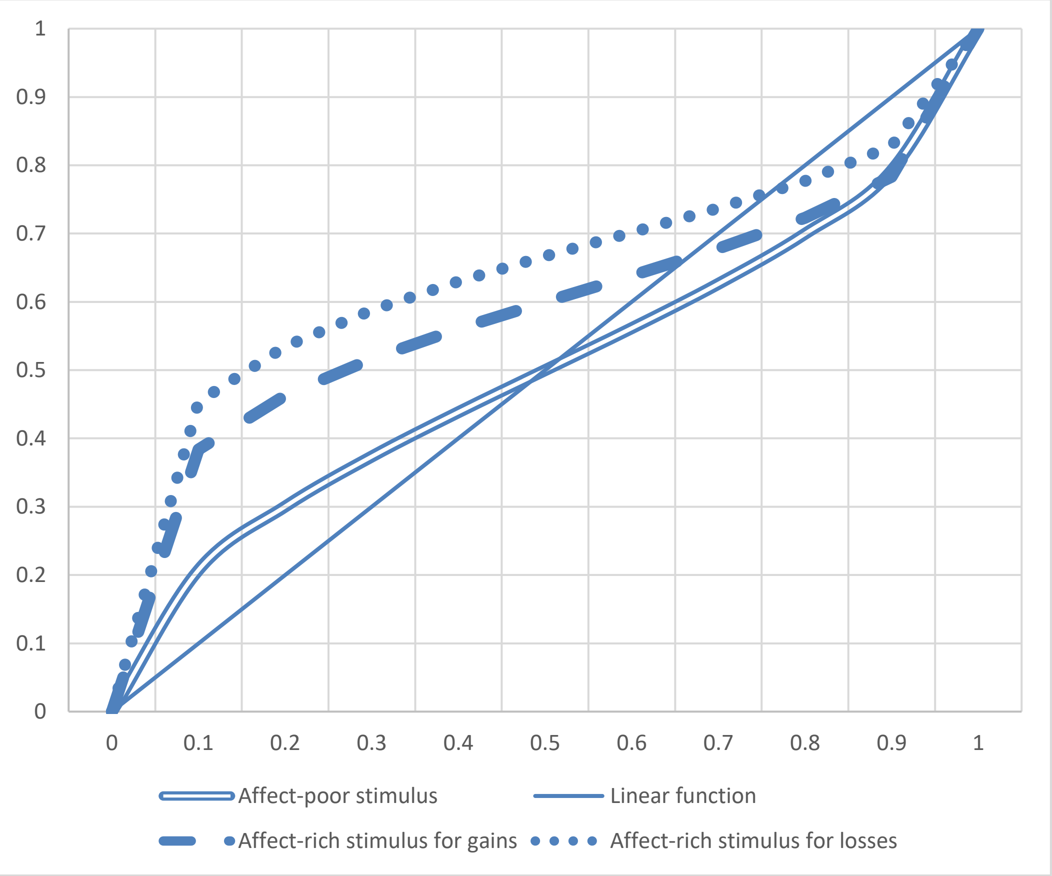
[18] Suter et al (2016) base their analysis on the formal dual-system model (DSM) developed by Mukherjee (2010). The concept is very much alike dual process models that I described in the prior sections of literature review (Epstein (1994), Sloman (1996), Kahneman (2003)). Suter et al. (p.444) explicate the DSM: „This hybrid modelling framework assumes that risky choices stem from a confluence of two qualitatively different systems, whose relative influence can vary continuously: a) a deliberate, expectation-based system that is sensitive to both outcome and probability information; and b) an affective system that is influenced by the decision maker's mood and how she feels about a specific prospect and that considers only the value of an outcome and whether it is possible or impossible (thus ignoring probability)."

[19] Gonzalez and Wu (1999) demonstrate that both functions were equally appropriate for their experimental data.

data. In practice, higher elevation may result in consistent overestimation of objective probabilities across the whole probability function causing extreme over-optimism in gains domain, and over pessimism in the losses domain engendering excessive risk-seeking or risk aversion.

Finally, the third dimension of the role of emotions in the evolution of the weighting function is asymmetric dynamics of curvature and elevation for gains and losses domains. Here, I refer to the experimental studies of Abdellaoui (2000), and Abdellaoui et al. (2005), who discover that decisions weights in the loss domain exhibit more elevation than in the gains domain. It results in relatively higher risk aversion for losses. Combining all three aspects of the decision weighting function, the graphical representation of affect-rich versus affect-poor stimuli may look in the following way:

Figure 2.5. Probability weighting function for affect-rich and affect-poor stimuli comprising gains and losses domains.



Note: The linear function denotes an objective probability, whereby the subjective (vertical axes) and objective evaluation (horizontal axes) of probabilities match. The affect-poor weighting function is constructed using the curvature coefficient of 0.69 (Kahneman and Tversky (1992). Affect-rich weighting function for gains is constructed using the curvature coefficient of 0.4 and elevation coefficient of 1.5. Finally, affect-rich weighting function for losses employs the same curvature coefficient of 0.4, but the elevation coefficient is raised to 2.

2.7. The impact of emotions on the correlation between risk and return

In the sections above, I have reviewed the extant research on the role of feelings in performance and risky choices of individuals. As a logical continuation of this discussion, it might be natural to assume that the interaction between these two variables also should have deserved some attention. Correlation between risk and return historically has taken a prominent place in financial theory. For example, it plays a central role in most of the asset pricing or valuation models. In all these theories, which are grounded on the inviolable principle of rationality, any escalation of risk must be compensated by higher return. The only question is how this risk factor or factors should be calculated. Further, it must be noted that empirical evidence that started to mount from the papers of French et al. (1987) and Campbell (1987) exploring international stock markets' risk and return has up to now provided mixed results on the positive or negative nature of risk-return trade-off. Nevertheless, stock prices are not readily convertible to the risk-return choices of identifiable individuals, therefore, they are out of the scope of the current research.

A bit more relevant studies on the risk-return correlation of individual decision-makers can be found in the empirical research on organisation theory. First pioneered by Bowman (1980), who has discovered the negative relation between the volatility and average return on equity (ROE) of US firms, similar studies have repeatedly unearthed this phenomenon, known as 'Bowman paradox', across various countries and industries. Later, researchers have associated this effect with Prospect Theory (Fiegenbaum and Thomas (1988), Fiegenbaum (1990), Chou et al. (2009)) demonstrating that outperforming firms exhibit positive relation between profitability and its variance while underperforming firms manifest the opposite behaviour. Clear evidence of loss aversion bias has also been identified. Considering that business decisions directly influencing corporate performance and volatility are taken by the managers, i.e. identifiable individuals, this is the best evidence so far demonstrating potential traces of irrational behaviour in risk-return correlation research.

To the best of my knowledge, there were no other attempts to approach this topic in the past, especially with application to the role of emotions in the correlation dynamics, which indicates a gap in the literature worth investigating. In Section 2.10, I analyse the relation between risk and return in the framework of the theoretical model, whereby an individual investor is making portfolio selection choice having Prospect Theory-like preferences. I compare and make predictions on how the risk-return correlation may change depending on the more/less affect-infused environment of decision-making.

2.8. Summary of the reviewed literature and identified research gaps

The analysis of the literature covering the decision making under risk and uncertainty demonstrates that in the past two decades the non-consequentialist perspective introduced a new set of hypotheses striving to explain human judgements through the prism of the more enhanced impact of feelings on performance, behaviour and the relation between the two. Nevertheless, my examination shows that these hypotheses so far have been insufficiently tested: for some of them, the results still are very scarce. Furthermore, it is important to note that testing efforts concentrated predominantly in the experimental environment, and the evidence from a more realistic empirical setting is almost completely missing. This gap is yet to be filled by new research of the emotional implications in decision-making. In the following several sections, I intend to summarise the research gaps that I identified and that require further hypotheses testing and investigation.

2.8.1. Comparison of the expected behaviour under Prospect Theory and Expected Utility Theory

Even though both theories are being juxtaposed since the introduction of Prospect Theory, the empirical research that would test and confirm the expectations of both frameworks remains extremely scarce relative to the importance of the topic. An essential exception is an empirical study of the disposition effect over the last 20 years, the discovery of which is attributable to the value function under Prospect Theory. The main challenge of comparing the theories is the intrinsic disparity in their nature. Expected Utility Theory is based on ex-ante choice and puts the equality sign between what economic agents think and what they do because they must be directed by the rational weighing of outcomes. Prospect Theory makes predictions on the ex-post basis and maintains that the decision-maker should be carried away by psychological forces that would distort the correct (in rationality terms) behaviour.

The analysis of the divergence between theories should be centred on the relation between risk and return, especially in the domain of negative outcomes (losses). In this case, unlike the traditional perspective, Prospect Theory predicts that because of the attention-narrowing and focusing on individual decisions rather than total wealth, an economic agent would turn risk-seeking, and the realised relation between risk and return is to become negative. An additional aspect to explore is the expected loss aversion bias, which should be manifested in the form of a stronger negative relation between return and risk for losses than a positive relation between these two variables for gains. It is something that should not be observed if individuals make a rational choice under the Expected Utility Theory's principles.

2.8.2. Research gaps in the impact of feelings on performance and behaviour

More empirical testing should be effectuated to explore if emotions can influence financial behaviour or having consequences for financial performance. So far, this topic was approached using only experimental and neuro-physiological methodologies. The traditional treatment of affect as a factor for the decision-making process is giving it a very modest role of the product of choice, not its driving force. More novel theories, such as Risk-as-Feelings hypothesis, grant feelings far more prominent place by arguing that a stronger degree of affect may push the realised choice far away from what is expected by the consequentialist decision-making framework. In fact, the stronger the emotions are, the more disparity should be expected between the predictions of the outcomes. The dual-process models forecast that in the more affect-rich environment, an economic agent, mediated by the attention-narrowing mechanism, should turn more concentrated on the decision and its short-term risk and consequences.

Another round of testing should be performed on the hypothesis of whether feelings improve or deteriorate performance. The extant research does not give a common answer to this problem because the results highly depend on the angle of view that a particular academic paper takes. Academics are equally successful in demonstrating that emotions harm investment results if they aim to expose the negative role of behavioural biases, or in proving that emotions are positive if they strive to highlight the fact that emotions facilitate quick and efficient decision processing.

2.8.3. Research gaps in the impact of feelings on risk-taking

The three manifestations of risk behaviour – the form of the value function, the form of the probability weighting function and loss aversion – so far are academically explored to a different extent. Nonetheless, all these factors of risk lack empirical testing of their possible alteration subject to changes in an emotional setting. As in the case of performance, the key hypothesis to be tested ensues from the dual-process theories backed by existing experimental studies. In the context of the value function, in the presence of stronger feelings, the form of the function should become more curved, i.e. a decision-maker should turn more risk-averse in the gains domain and more risk-seeking in the losses domain. Concerning the form of the probability weighting function, the existing behavioural theory implies several possible changes that may happen to the functional form of probabilities – it may become more curved, elevated or unequally shifted for gains and losses. Loss aversion bias is the least explored risk factor out of all. Loss aversion denotes the behavioural bias identified in the Prospect Theory model (Kahneman and Tversky (1979), whereby individual decision-makers dislike losses significantly stronger than they like equivalent gains. Loss aversion is fundamentally distinct from risk aversion because the latter encapsulates the general aversion to the dispersion of possible outcomes that is expressed via the concave form of the utility function, while the former is used to describe the specifically psychological aversion to losses when compared with gains. There is evidence derived from prior experiments that the bias can change in response to the changes in the affective environment (Harinck et al. (2007)).

An additional essential aspect that remains unclear is the interaction between the three forms of risk. The existing experimental and neurophysiological literature has intentionally approached them separately and independently in order to isolate the necessary effects. To the best of my knowledge, there were no attempts made to decompose behaviour, investment behaviour in particular, into various recognised realms of risk. Nevertheless, it is intuitive that the investment decision-making process is equally and continuously driven by the subjective perception of outcomes, probabilities and psychological dominance of losses over gains. Creating an empirically backed framework where the three facets of risk intersect, may be a valuable source of information about behaviour and the driver for future research.

2.8.4. Research gaps in the impact of feelings on the correlation between risk and return

Unlike the variables in the previously reviewed sections, such as performance and risk, the correlation between them has never been analysed in the emotional context. Therefore, this area represents one big research gap. Considering that academic evidence that both risk and return may be impacted by feelings, it makes sense to assume that their correlation is not immune to emotions either. However, the exact way of how feelings impact the correlation between risk and return remains unknown. The closest strand of literature that can shed light on this topic may be related to the attention and the attention-narrowing phenomenon. Risk is not one single factor that explains performance – there are many other variables that can contribute to the investment results, for example, experience, knowledge and skill, level of wealth, etc. However, it may be hypothesised that in a more affect-rich environment, the attention becomes concentrated on the essential factor out of all, which is risk – deviation of returns. If this is the case, the correlation between risk and return will be forced to increase. This effect should be even more substantial for losses than for gains, considering the long streak of evidence that losses are more psychologically pronounced.

2.9. Formal description of Prospect Theory

Grounded on the literature review and the short comparison between the traditional economic decision-making framework and the behavioural decision-making framework under risk and uncertainty outlined in Section 2.2, I devote this section to a more formal description of the behavioural theoretical perspective.

In my empirical chapters, I analyse two important phenomena of decision-making under risk and uncertainty. First, it is the nature of the relation between risk and return of individual investors when their performance is framed as losses and gains. Second, it is the impact of emotions on performance and risk behaviour. Unfortunately, a single behavioural theory that could incorporate both elements was not yet introduced by academia (Prietzel (2019)). Therefore, in this section, I will provide the formal treatment of Prospect Theory (Tversky and Kahneman), which is the most thorough and key driving force of all economic behavioural research. Further, in Section 2.10, I will propose a market model intended to highlight some of Prospect Theory's predictions of risk-return relation.

Prospect Theory has been formalised in the two key papers. The original Prospect Theory (OPT) was proposed in Kahneman and Tversky (1979). After more than a decade, another paper by the same authors outlined the concept of cumulative Prospect Theory (CPT, Tversky and Kahneman (1992)). The latest paper was largely the response to the critique of the original theory that under certain scenarios might violate the stochastic dominance principle. Consequently, the authors have incorporated the amended treatment of the non-linear probability function, which solved the problem. Nevertheless, Daniel Kahneman has remained the supporter of the original version of Prospect Theory. In the 1992 paper, the authors contend (Tversky and Kahneman (1992), p. 302): "Although the two models yield similar predictions in general, the cumulative version – unlike the original one – satisfies stochastic dominance. Thus, it is no longer necessary to assume that transparently dominated prospects are eliminated in the editing phase – an assumption that was criticised by some authors. On the other hand, the present version can no longer explain violations of stochastic dominance in non-transparent contexts (e.g., Tversky and Kahneman, 1986)". It should be added that since 1992, other evidence has been provided to demonstrate stochastic dominance violations (e.g. Birnbaum (2005)).

Still, cumulative Prospect Theory is the version mostly used in the modern economic analysis, hence it is the model of choice to be used in this section. The formal description of the Prospect Theory follows the approach adopted by Dhamy (2016).

2.9.1. Assumptions of Prospect Theory and the form of the value function

Comparing to Expected Utility Theory, Prospect Theory puts forth the following critical assumptions:

- The carriers of value are gains and losses, not the final level of wealth;
- The value of each outcome is multiplied by the decision weight, not by an additive probability.

Under the Expected Utility Theory, the valuation function U(·) is defined in the following way:

$$U(L) = \sum_{i=1}^{n} p_i \, u(W + y_i) \qquad \text{(Formula 2.4)}$$

where

$U(L)$ is the valuation function of the set of prospects,

p_i is the objective probability of the prospect I, W is the decision maker's current level of total wealth,

u(·) is the utility function of the decision maker's change in wealth.

Under the Prospect Theory, the valuation function V(·) to the decision-maker is described as follows:

$$V(L) = \sum_{i=-m}^{n} \pi_i v\,(y_i) \qquad \text{(Formula 2.5)}$$

where

$V(L)$ is the valuation function of the set of prospects,

$\pi_i$is the decision (probability) weight attributable to each prospect,

$v(y_i)$ is the utility function of prospect y_i.

2.9.2. Incremental form of prospects

Let a lottery L be presented as:

$$L = (y_{-m}, p_{-m};\ y_{-m+1}, p_{-m+1}; \dots;\ y_{-1}, p_{-1};\ y_0, p_0;\ y_1, p_1;\ y_2, p_2; \dots;\ y_n, p_n)$$

where $y_i = x_i - x_0, i = 1,2, \dots, n,$ is the increment (positive, negative, or zero) in wealth relative to reference wealth, x_0. The reference wealth is fixed at some status-quo level. Each increment is referred to as an outcome or prospect;

$m + 1 + n$ is the total number of prospects, m represents the outcomes in the domain of losses, n represents the outcomes in the domain of gains, and there is one outcome representing a reference point;

the sum of probabilities associated with each prospect is restricted to equal 1:

$$\sum_{i=-m}^{n} p_i = 1\,, p_i \geq 0, i = -m, -m+1, \ldots\ , n. \qquad \text{(Formula 2.6)}$$

and the restriction on the prospects is as follows:

$$y_{-m} < y_{-m+1} < \cdots < y_{-1} < y_0 < y_1 < y_2 < \cdots < y_n \qquad \text{(Formula 2.7)}$$

2.9.3. Utility function under Prospect Theory

Let $Y \subset R$ be the set of wealth levels relative to a reference point and y_i represent the increment in wealth relative to a reference point. A utility function, υ, is a mapping υ: $Y \rightarrow R$ that satisfies the following:

- υ is continuous;
- υ is strictly increasing;
- υ (0) = 0
- υ is concave for $y \geq 0$
- υ is convex for $y \leq 0$
- $-\upsilon(-y) > \upsilon(y)$ for $y > 0$

The utility function has the form:

$$\upsilon(y) = \begin{cases} y^{\gamma} & if\ y \geq 0 \\ -\lambda(-y)^{\gamma} & if\ y < 0 \end{cases} \qquad \text{(Formula 2.8)}$$

where λ and γ are constants, $\lambda > 0$ and $0 < \gamma < 1$.

λ is known as the coefficient of loss aversion, while γ denotes the degree of utility function's curvature.

The plot resulting from the utility function above is demonstrated in Figure 2.3.

2.9.4. Decision Weights under Prospect Theory

Prospect Theory does not use probability weights to evaluate gambles. Instead, it employs decision weights. Tversky and Kahneman (1992) define the decision weights, π_i as follows:

$$\pi_n = w^+(p_n) \quad \text{(Formula 2.9)}$$

$$\pi_{n-1} = w^+(p_{n-1} + p_n) - w^+(p_n) \quad \text{(Formula 2.10)}$$

$$\pi_i = w^+(\textstyle\sum_{j=i}^{n} p_j) - w^+(\textstyle\sum_{j=i+1}^{n} p_j) \quad \text{(Formula (2.11)}$$

$$\pi_1 = w^+(\textstyle\sum_{j=1}^{n} p_j) - w^+(\textstyle\sum_{j=2}^{n} p_j) \quad \text{(Formula 2.12)}$$

$$\pi_{-m} = w^-(p_{-m}) \quad \text{(Formula 2.13)}$$

$$\pi_{-m+1} = w^-(p_{-m} + p_{-m+1}) - w^-(p_{-m}) \quad \text{(Formula 2.14)}$$

$$\pi_{-j} = w^-(\textstyle\sum_{i=-m}^{-j} p_i) - w^-(\textstyle\sum_{j=-m}^{-j-1} p_i) \quad \text{(Formula 2.15)}$$

$$\pi_{-1} = w^-(\textstyle\sum_{i=-m}^{-1} p_i) - w^-(\textstyle\sum_{i=-m}^{-2} p_i) \quad \text{(Formula 2.16)}$$

As follows from the formulas above, if all outcomes in the lottery are in the domain of gains or the domain of losses, their decision weights, π_i, should add up to 1.

Another important note is that cumulative Prospect Theory can be extended to uncertainty and can accommodate any number of prospects.

For the estimation of the decision weights, Tversky and Kahneman (1992) employ the following probability weighting function, w(p):

$$w(p) = \frac{p^{\tau}}{[p^{\tau}+(1-p)^{\tau}]^{\frac{1}{\tau}}} \qquad \text{(Formula 2.17)}$$

where τ is the curvature coefficient.

Importantly, the curvature of the probability function can differ in the domain of losses and the domain of gains.

2.9.5. Estimated parameters in Prospect Theory

Tversky and Kahneman (1992) run empirical tests to estimate the parameters for the utility function and probability weighting function. They identify the following values for the parameters:

a) The value of probability weighting function's curvature coefficient, τ, equals to 0.61 in the domain of gains and 0.69 in the domain of losses
b) The value of the utility function's curvature coefficient, γ, equals to 0.88 in both domains.
c) The value of the utility function's loss aversion coefficient, λ, equals to 2.25.

2.10. Prospect Theory-based model with the analysis of risk-return relation

2.10.1. Introduction to Prospect Theory-based models

Prospect Theory has been formally used to accommodate a large number of economic and financial empirically observed phenomena, for example, mental accounting (Frazzini (2006)), equity premium puzzle (Barberis and Huang (2001), Benartzi and Thaler (1995)), momentum (Grinblatt and Han (2005)), narrow framing (Barberis, Huang and Thaler (2006)).

Unfortunately, to the best of my knowledge, there are no registered attempts to offer a Prospect Theory-based economic model that would explicitly incorporate the assumption about the relation between volatility and return. A cluster of studies in the organisation and accounting theory (see Section 2.7) dealing with the so-called 'Bowman Paradox' (Fiegenbaum and Thomas (1988), Fiegenbaum (1990), Chou et al. (2009)), offered Prospect Theory as the explanation of the negative risk-return relation observed in the financial results of underperforming firms across countries and industries. However, none of the researchers provided a formal model of firms' behaviour. With notable exceptions (e.g. Wang et al. (2017)), the phenomenon of the negative relation between risk and return, for example, observed in the stock markets, has not been attributed to Prospect Theory.

One of the well-documented empirical behavioural observations is the disposition effect. It denotes the tendency by investors to hold on to losing trades and close too fast their winning trades ((Dhar and Zhu (2006), Shefrin and Statman (1985)). I contend that by the nature of the phenomena, disposition effect is connected to the risk-return relation. If investors systemically overhold the losing positions in an attempt to wait until the price hits back to the break-even point, they inevitably accept high dispersion of realised trading results. Most of such overheld trades will be closed with losses, which will generate negative risk-return relation in the losses domain. For the gains area, the effect will be the opposite – smaller volatility will be associated with overall positive performance. This rationale has been referred to in other studies as well as a complementary observation (Grinblatt and Han (2005), Wang et al. (2017)). However, it has never been explored in the framework of a theoretical model.

Disposition effect attracted greater attention from the researchers than the risk-return relation or other market effects and biases when it comes to the economic modelling of its connection to Prospect Theory. The possibility that disposition effect can be explained by Prospect Theory has been voiced in a large number of studies starting from Shefrin and Statman (1985). Other examples of highly cited papers on disposition effect that followed the approach include Weber and Camerer (1998), Odean (1998), Grinblatt and Keloharju (2001), Dhar and Zhu (2006). As a consequence, the causal relation between Prospect Theory and disposition effect became something taken for granted by researchers until several theoretical models proposed during the last decade by Barberis and Xiong (2009), Kaustia (2010) and Vlcek and Hens (2011) concluded that such a relation is far from clear. These authors identified certain flaws in the Prospect Theory explanation. It was deduced that not all conditions outlined by Kahneman and Tversky (1992) and Shefrin and Statman (1985) could lead to the manifestation of the disposition effect. In many occasions, this phenomenon should not be observed, or even the reverse effect may take place. Such a sharp distinction between the empirical observation of disposition effect and the theoretical models has triggered an active and still ongoing debate in academia that is purposed to reconcile the paradox.

For example, Meng (2010) and Ingersoll and Jin (2012) proposed an intriguing resolution by suggesting that the reference point of the decision-makers must not remain still at the initial wealth as the unrealised gains or losses evolve but change together with them. Barberis and Xiong (2010) developed the idea of realisation utility. In this model, decision-makers derive utility only from realised gains or losses but not from unrealised. All these explanations found mixed empirical support so far (Jakusch et al. (2019)).

Another group of studies challenged the approach of using the parameters of the value function, loss aversion coefficient and probability function from the original theory (Kahneman and Tversky (1992)). The reasoning used in these studies is based on criticism of ecological validity of the research design employed by Kahneman and Tversky and their followers[20]. To elicit the parameters of the model, the authors of Prospect Theory informed their subjects of exact probabilities and outcomes of gambles used in experiments (or the probabilities could be easily inferred). Such a generous amount of information or completely emotionless environment of decision-making cannot be met in real-life financial markets. Among other research, Vlcek and Hens (2011) and Jakusch et al. (2019) concluded that for the disposition effect to be revealed, the fitted parameters must be significantly distinct from the original Prospect Theory. I use both papers as the starting point and the foundation for my model and subsequent analysis.

The study of Vlcek and Hens (2011) is stimulating because in their highly cited theoretical model, the authors make essential steps from homo economicus that makes judgements based on behavioural Prospect Theory (a strange mix), towards more behaviourally (and hence, realistically) acting decision-maker. It makes a difference between their work and another popular model by Barberis and Xiong (2009), in which an agent is capable of finding multi-period optimal investment solutions and exhibits other characteristically rational behaviour.

[20] Such argument is fully in line with the general critique of experimental research setup. A great summary of the challenges faced by experimental research can be found in Al-Ubaydli et al. (2017).

The paper of Jakusch et al. (2019) deserves attention because it is further approximating the theoretical model of Vlcek and Hens (2011) towards real-life investment decisions by applying it and exploring the model's predictions on the empirical dataset of individual brokerage clients' trades. These two studies of the possible interaction between Prospect Theory and disposition effect represent the closest pieces of academic work relating to my own data set and research framework.

I further extend and modify certain aspects and assumptions of the model for three primary purposes. First, I need to adapt the model to the data set and the real-life trading environment of the decision-makers in my study. Second, I want to explore the assumptions of the model concerning the relation between risk and return, not only disposition effect. Third, I focus on the distinction between the parameters and predictions of the model in affect-rich and affect-poor environments. To the best of my knowledge, the last two topics have not been explicitly discussed in academic research in the same context before.

2.10.2. Model setup – Ex-post versus Ex-ante model design

Hens and Vlcek (2011) review two alternative model designs – they refer to one of them as ex-post and another as ex-ante. In the ex-post conceptualisation, the initial decision to acquire a risky asset is considered to be already taken, and the analysis of this decision remains out of the model's scope (i.e. an investor already owns a risky stock). Only subsequent choices of a decision-maker, so-called liquidation decision, are taken into account and examined. In the case of ex-ante design, the rationale behind the primary decision to invest in a risky asset is also made part of the analytical framework. The consequence of the model design's selection is essential. Most of the researchers who use the ex-ante approach and try to explain the initial decision to invest with the Prospect Theory assumptions and parametrisation, fail to do so. The primary explanation of this effect is the loss aversion factor of Prospect Theory (Barberis and Xiong (2009)). It seems that an investor who exhibits disposition effect on the second step of the model, i.e. when contemplating liquidation of a risky asset, usually will not engage in buying a risky asset on the first step in fear of expected losses. However, Hens and Vlcek (2011) and Jakusch et al. (2019) argue that the ex-ante approach is inherently rationalistic, which dissonates with the Prospect Theory behavioural framework[21]. They doubt that investors can be expected to combine rationalistic multi-period optimisation of choice with the behavioural valuation of outcomes and probabilities.

The ex-post modelling seems more consistent with Prospect Theory analysis and behavioural perspective of decision-making in general. The original theory is also fundamentally ex-post neglecting the scrutiny of the initial decision to take a risk exposure. Besides, behavioural economic research has identified many empirically observed factors that can influence and explain the primary decision to buy risky assets, for example, sensation seeking (Zuckerman (2007)), overconfidence (Grinblatt and Keloharju (2001)) among others.

In my subsequent analysis, I will reply on the ex-post conceptualisation and focus exclusively on the liquidation decision – the second-period behaviour of an individual subject to the change in the value of the risky asset. For the ex-ante perspective's review, the one can consult Section 3.2 in Hens and Vlcek (2011).

[21] As Hens and Vlcek (p. 4-5, (2011)) reason their position: "…requiring dynamic optimisation [as in Barberis and Xiong (2009)], i.e. integrating into today's decision the correctly anticipated optimal future decisions, seems to be at odds with assuming reference point based behaviour on the other hand. The investor would then be very rational and very behavoural at the same time."

2.10.3. Assumptions of the model

I draft a one-stage multi-period model for investment portfolio allocation in the schematic financial market where only two assets are available – a risky instrument and a risk-free instrument. Reflecting on my dataset, a risky asset is a EUR/USD currency pair, and a riskless asset is a bank non-yielding deposit, i.e. $R_f = 0$. An investor who is faced with the portfolio choice decision has Prospect Theory-aligned preferences (Kahneman and Tversky (1979), Tversky and Kahneman (1992)).

Following Hens and Vlcek (2011), the price changes of the risky instrument are described by the binomial process; hence after the end of each period, there are two possible price outcomes. If the price goes up, it is referred to as an upside state U. The probability of this state is $p > 0$ at time t. The rise in value generates a return $R_U > 1$. The reverse price development leads to a downside state D with probability $1 - p$ with the associated loss $0 \leq R_D < 1$[22].

In the framework of the model, an investor makes valuations of the changes in wealth, not terminal wealth. In all the aspects, investor's preferences are described by Prospect Theory. An investor is considered to possess an initial endowment, W_0, and earn no other income. This initial level of wealth serves as the reference point for the evaluation of losses and gains across the return evolution. Due to the peculiarity of the currency pair risky instrument, an investor is assumed to take not only the long position in the risky asset but also the short one[23]. As in Hens and Vlcek (2011) and Jakusch et al. (2019), an investor in my model exhibits myopic behaviour, i.e. he is not prone to dynamic optimisation of choice but weighs

[22] In order for the price of the risky asset to remain positive, the non-arbitrage condition must be met: $0 \leq R_{D,t} < 1 \leq R_{f,t} < R_{U,t}$.

[23] In fact, a short position in a currency pair is equivalent to the long position in the reverse form of this currency pair. For instance, a short position in EUR/USD is the same as the long position in USD/EUR. Therefore, my allowance of shorting does not change the model of Hens and Vlcek (2011) significantly but adds a substantial approximation to real-life situation.

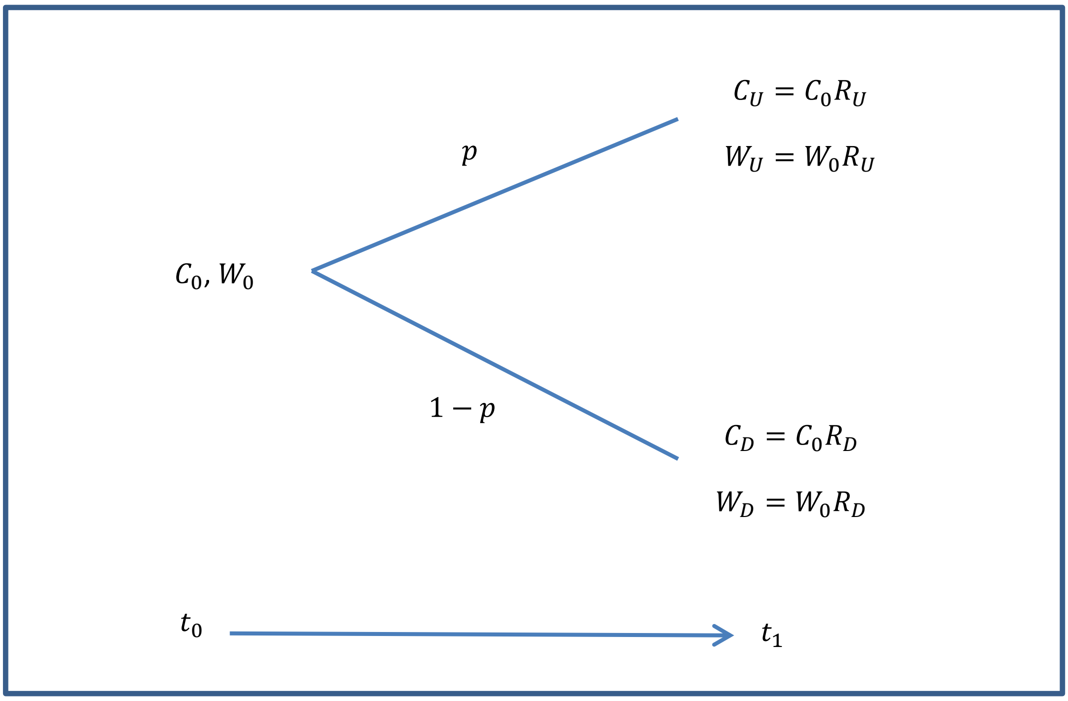
up each iteration of price change as an independent gamble. As Hens and Vlcek (2011) note, such assumption better corresponds to the real-life behaviour of small individual investors and finds better empirical support.

The valuation of prospects takes place according to the utility function and probability weighting function described in Tversky and Kahneman (1992) and Section 2.9 above. At each iteration, an investor can make only two types of decisions – either keep all of his wealth in the risky asset or close the position in the risky instrument in full. No partial sale can be made.

2.10.4. The first period of the model

Figure 2.6 exhibits the client's situation at the first iteration (first period).

Figure 2.6. Binomial process of wealth evolution from t_0 to t_1



In the period t_0 an investor makes an allocation into the risky asset (currency pair) that has an initial value of C_0. As the model's assumption specifies, no fractional investment is possible, hence investor's wealth, W_0 at t_0 equals to C_0.

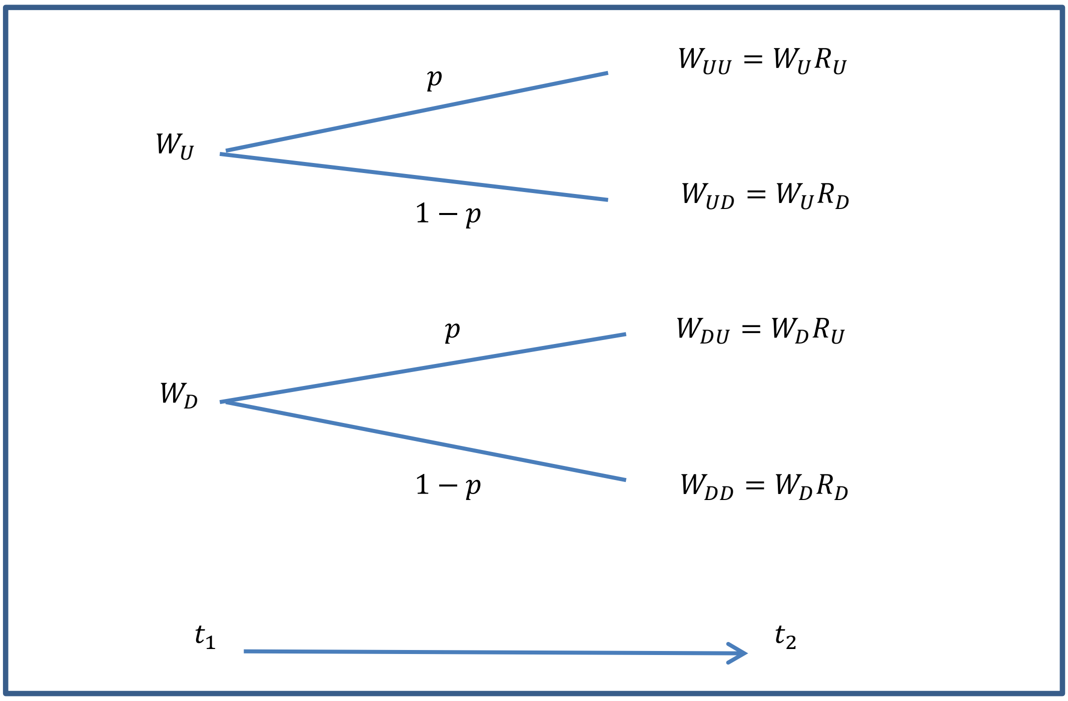
In the period t_1 the risky asset can be in two alternative states. With probability p the value of the risky instrument can go up to C_U, which will be the product of the initial value C_0 and the increment R_U. Or, with probability $1-p$ the value of the risky asset can decrease to C_D – the product of initial value C_0 and the downward value shift R_D. Investor's wealth will increase to W_U or decrease to W_D conditional upon the price change. In both states in t_1, the value of the risk-free asset, R_f , does not change because $R_f = 0$, according to the assumption of the model. As the model specifies, the decision to invest in the risky instrument is considered to be already taken. Therefore, the decision to sell[24] or keep the risky asset is transferred to the period t_1 and ongoing iterations (periods) of the model. Because all the parameters of the model remain constant over time, the structure of the second period and onwards will be the same as for the first period. Therefore, for demonstration purposes, I will only review in details the transition from the first to the second period.

2.10.5. The second period of the model

The evolution in the second period of the model is demonstrated in Figure 2.7.

[24] The decision to sell the risky asset is equivalent to the decision to invest the current wealth, W_t, into the risk-free asset, i.e. the bank deposit.

Figure 2.7. Binomial process of wealth evolution from t_1 to t_2



Immediately after the outcomes are revealed at the end of the first period, the investor is facing the risky asset liquidation decision. At the second iteration of risky asset's values, four options of price evolution are possible. These options are denoted with UU, UD, DU and DD subscripts on Figure X, reflecting the possible developments: UU stands for double upward movement of price, UD means an upward move followed by a decrease in price, DU is reverse in order and DD denotes the double downward shift in price. The investor's level of wealth in the second period equals to the product of his wealth in the first period and the return on the risky asset in the second period.

2.10.6. Subsequent periods of the model

Vlcek and Hens (2011) choose a two-step form for their model, whereby the price of an underlying risky instrument can only change twice. Such a restrictive assumption is at odds with real financial market complexity and needs to be relaxed. Technically, the model can have an unlimited number of steps if an investor does not take a liquidation decision. To keep my model manageable but ensure its flexibility, I allow the maximum of 100 steps of price evolution as this is enough to analyse the assumptions I want to explore. That is, if an investor keeps the risky instrument for 100 consecutive periods, the position gets automatically closed and the accumulated profit or loss get realised.

Considering the assumption of the constant amplitude, it is conventional for similar models with binomial evolution to combine intermediary nodes for simplification purposes, i.e. W_{UD} and W_{DU} as in Figure 2.7. Hence, at period t there can be $t+1$ possible outcomes. Variable j (j=1,2,3,…, t+1) denotes the order of the outcome, so that $j=1$ is the highest possible outcome at each step of the model and $j=t+1$ is the lowest possible outcome. Hence, the formula for the price of the risky instrument at the outcome j and time t is:

$$P_{j,t} = P_0 R_{U,t}^{t-j+1} R_{D,t}^{j-1} \qquad \text{(Formula 2.18)}$$

As in the second period, at every subsequent step of the model, $t \in \{3, \dots, 100\}$, an investor evaluates the prospects to make a liquidation decision, which can happen in any of the periods.

2.10.7. The liquidation decision

In the proposed model, an investor makes investment decisions based on Prospect Theory preferences. It means that the decision to liquidate the position in a risky instrument is taken by computing the difference in the utilities of two prospects, which are mutually exclusive. The first implies keeping the risky instrument one period forward and facing the gamble between the possible upward or downward change in price. The second prospect entails selling the risky instrument and realising profit or loss accumulated from prior period(s), which can be also interpreted as the investment into a risk-free asset. The analysis above can be written mathematically as

$$L = \Delta_t(U_t^{RP}, U_t^A \parallel \Theta) \qquad \text{(Formula 2.19)}$$

where L is the net utility of liquidation decision, U_t^{RP} is the utility of holding the risky instrument at time t, U_t^A is the utility of an accumulated sure gain/loss at time t and Θ denotes the set of Prospect Theory parameters, which are constant over time: $\Theta = [\![\gamma, \lambda, \tau]\!]$. γ stands for the utility function's curvature coefficient, λ is the utility function's loss aversion coefficient, τ is probability weighting function's curvature coefficient.

2.10.8. Prospect Theory analysis of intermediate steps of the model

As Vlcek and Hens (2011) only use a two-step model, there are no intermediate steps when an investor can decide to keep the risky asset onwards to the next period[25]. Hence, there is a maximum of four[26] nodes at the second (last) step of the model. When the number of possible steps is extended, the model becomes progressively more complex. Following Jakusch et al. (2019), to simplify the formulation of the model, I use a single variable that denotes the intermediate accumulated wealth (i.e. wealth accumulated at any of the intermediate nodes t), whether it is gain or loss. The variable I use is $R_{i,t}$, where $i \in \{\widehat{U}; \widehat{D}\}$, $\widehat{U}$ means intermediate accumulated gain, $R_{i,t} = \widehat{U}$ if $R_{i,t} > 1$, $\widehat{D}$ means intermediate accumulated loss, $R_{i,t} = \widehat{D}$ if $1 > R_{i,t} \geq 0$.

[25] This is true for the ex-post model design. For the ex-ante specification, there is one intermediary step.
[26] Given a constant amplitude of price changes over time, It is conventional to combine the outcomes that lead to the equivalent return, for example W_{DU} and W_{UD} as in Figure X. In this case, Vlcek and Hens (2011) model would have a maximum of three nodes.

The analysis of intermediate nodes is essential because it defines the usage of loss aversion coefficient. Jakusch et al. (2019) identify five scenarios for intermediate nodes that I describe below. For the first two scenarios, the utility of the risk-free asset (i.e. utility of the certain prospect of selling the risky instrument at the step t) is denoted as $U_t^A(W_0, R_{i,t}, R_{f,t} \parallel \Theta)$ and equals to $(W_0 R_{i,t} R_{f,t} - W_0)^\gamma$.

Case 1. Accumulated gains, $R_{i,t}$, are high enough to satisfy $R_{i,t}R_{U,t} > R_{i,t}R_{f,t} \geq R_{i,t}R_{D,t} \geq 1$. In this case, an investor evaluates the utility of the risky instrument at time t as

$$U_t^{RP} = w(p_t)\left(W_0 R_{i,t} R_{U,t} - W_0\right)^\gamma + w(1-p_t)\left(W_0 R_{i,t} R_{D,t} - W_0\right)^\gamma \quad \text{(Formula 2.20)}$$

where $w()$ is the decision weighting function calculated from the Prospect Theory probability weighting function in Formula 2.17. Because both prospects $R_{U,t}$ and $R_{D,t}$ are above the initial wealth, the coefficient of loss aversion, λ, is not applied.

Case 2. Accumulated gains, $R_{i,t}$, are moderately high satisfying $R_{i,t}R_{U,t} > R_{i,t}R_{f,t} \geq 1 > R_{i,t}R_{D,t} \geq 0$. For this scenario, the utility of the risky instrument at time t will include the coefficient of loss aversion because the possible downside change in price may cause the accumulated wealth to end up below the reference point of initial wealth:

$$U_t^{RP} = w(p_t)\left(W_0 R_{i,t} R_{U,t} - W_0\right)^\gamma - \lambda w(1-p_t)\left(W_0 - W_0 R_{i,t} R_{D,t}\right)^\gamma \quad \text{(Formula 2.21)}$$

The total utility of keeping the investment into the risky instrument equals to the utility of upwards change in wealth following the uptick of the price of the risky instrument multiplied by the corresponding decision weight and the utility of the decrease in wealth following the downtick of the value of the risky instrument multiplied by the loss aversion coefficient and the respective decision weight.

Case 3. This scenario considers a situation when the accumulated wealth gets to the losses domain, $0 \leq R_{i,t} < 1$. However, if the accumulated losses are relatively small so that

$R_{i,t}R_{U,t} > R_{i,t}R_{f,t} \geq 1 > R_{i,t}R_{D,t} \geq 0$, the investor still has a chance to win back the loss with the next iteration of holding the risky asset. The calculation of utilities of holding the risky instrument and liquidating the risky position will remain as in Case 2.

Case 4. Under this scenario, the losses become more vital so that $R_{i,t}R_{U,t} > 1 > R_{i,t}R_{f,t} > R_{i,t}R_{D,t} \geq 0$. Hence, the positive change of the value of the risky asset is enough to turn accumulated losses into gains, yet, the risk-free return is not high enough to do the same[27]. In this scenario, the utility of the liquidation decision will now include the loss aversion factor:

$$U_t^A = -\lambda(W_0 R_{i,t} R_{f,t} - W_0)^{\gamma} \qquad \text{(Formula 2.22)}$$

Case 5. The last scenario implies that the level of losses is so high that even the positive shift in the value of the risky instrument cannot cover up the accumulated loss: $1 > R_{i,t}R_{U,t} > R_{i,t}R_{f,t} > R_{i,t}R_{D,t} \geq 0$. For this scenario, the utilities of both parts of the gamble – upwards change in wealth and downwards shift in wealth will contain the loss aversion term:

$$-\lambda w(p_t)\big(W_0 - W_0 R_{i,t} R_{U,t}\big)^{\gamma} - \lambda w(1-p_t)\big(W_0 - W_0 R_{i,t} R_{D,t}\big)^{\gamma} \qquad \text{(Formula 2.23)}$$

The utility of the liquidation decision will also be multiplied by the loss aversion factor as in Case 4.

2.10.9. The parameters used in the model

In my model, I use three stylised investors, each of them featuring a specific form of Prospect Theory-based preferences. The first investor – Investor A carries the set of parameters that

[27] I demonstrate here the scenarios from Jakush et al. (2019) to describe all possible theoretical cases considered in their model. In my model, I assume that the risk-free rate equals to zero, hence the Case 3 in my particular formulation cannot exist. With zero risk-free return, Case 4 immediately follows Case 2.

fully match the original Prospect Theory model. I conjecture that Investor A is relatively emotionless, i.e. his portfolio selection choices are not impacted by any affective pressures surrounding the decision-making process. This is explained by the nature of the experimental design undertaken by the authors of Prospect Theory. The second investor – Investor B is an affect-poor decision-maker. His set of parameters reflects investment decisions that have a moderate degree of emotional influence. The parameters of Investor B equal to the average of the original Prospect Theory parameters and the ones used by Jakusch et al. (2019). Finally, Investor C is exactly matching the parameters from the model of Jakusch et al. (2019). I call this Investor affect-rich as he exhibits a strong form of influence of emotions on his decisions.

2.10.9.1. Attribution of parameters to investor types

In the original Prospect Theory Kahneman and Tversky used the following parameters for their model:

a) The value of probability weighting function's curvature coefficient, τ, equals to 0.61 in the domain of gains and 0.69 in the domain of losses
b) The value of the utility function's curvature coefficient, γ, equals to 0.88 in both domains.

The value of the utility function's loss aversion coefficient, λ, equals to 2.25. I attribute these parameters to the emotionless Investor A.

As discussed above, these parameters may not correspond well to the conditions of the real financial market. The Vlcek and Hens (2011) model's fitting tests undertaken by Jakusch et al. (2019) on the dataset from the discount broker in Germany on the retail investors revealed the following parameters: $\gamma = 0.37$, $\lambda = 1.1$, $\tau = 0.72$. I assign these parameters to my affect-rich Investor C.

Utility function's curvature coefficient of 0.37 from Jakusch et al. (2019) emphasises a substantially stronger curvature of the function compared to the original theory. The difference can be explained by the origin of the data for the parametrisation. Jakusch et al. (2019) use real investors trading on a real financial market. Kahneman and Tversky (1979, 1992) used students as subjects asking them to solve hypothetical cases of future prospects. As outlined in the research of Kahneman et al. (1999), Loewenstein et al. (2001), Hsee and Rottenstreich (2004), the difference in the elicited parameters between Kahneman and Tversky and Jakusch and his colleagues can be explained by the degree of emotional intensity and affective environment for the decision-makers at the time they choose the risky prospects. Students in the experimental research design of Kahneman and Tversky are placed in the naturally affect-poor environment (if not affect-free). They are not constrained by time or experience other pressures, for example, they do not face the risk of losing their money. Real individual investors in the dataset of Jakusch and his co-authors face typical pressures of the financial markets – the need to make quick decisions under the risk of losing their invested capital. Such psychological strains are known to engender physiological reactions associated with strong emotions in traders (Fenton-O'Creevy et al. (2012), Lo et al. (2005)).

The coefficient of loss aversion turned out to be significantly lower in the model of Jakusch et al. (2019) than in the original study. Jakusch et al. (2019) do not provide explicit reasoning on why such difference could have taken place. They rely on the version of explanation from Hwang and Satchell (2011), who believe that this result can be derived from the selection bias because the investors prone to the high level of loss aversion would avoid trading risky assets (stocks in the case of Jakusch et al. (2019) but also attributable to my dataset as well, which is represented by the even riskier type of marginal trading). As I discuss in the literature review's section on emotions and loss aversion, the research of this phenomenon is still rare, and the results are mixed. To test a possible impact of higher loss aversion coefficient on the relation between risk and return, I will introduce a special case of Investor D who will have all the parameters of Investor C (based on parameters from Jakusch et al. (2019)) with the exception of the arbitrarily chosen loss aversion coefficient of 4. For the affect-poor scenario (Investor B), I intend to use the coefficient of loss aversion that is the average between the one from the original model and the one from the model of Jakusch et al. (2019).

Jakusch's et al. (2019) fitted decision weighing function's coefficient equals to 0.72, which is slightly higher than in the original model. In general, it is much harder to test the decision weighting function using the binomial models as in Vlcek and Hens (2011). Prospect Theory contends that the most considerable swings in the decision weights relative to the objective probability weights take place in the ends of the probability curve, i.e. near very low probability and very high probability. Theoretical models described by binomial price evolution fail to catch the extreme probabilities. Therefore, it may be the case that the real coefficient of the function is further away from the one identified by Jakusch et al. (2019). In the experimental research parametrisations, this coefficient varied from 0.44 (Gonzalez and Wu (1999)) to 0.83 (Abdellaoui et al. (2005)). In my model, I use the original theory's coefficient for the emotionless scenario (Investor A), Jakusch et al. (2019) coefficient for the affect-rich scenario (Investor C) and the average between the two for the affect-poor scenario (Investor B).

2.10.9.2. The parameters of stochastic process of risky asset

I adopt the approach of Jakusch et al. (2019) concerning the stochastic process of the risky instrument, yet, in a substantially modified form. Grounded on the empirical research on the investment behaviour of individuals (Grinblatt and Keloharju (2000), Dhar and Kumar (2002), Kaustia (2010)), the authors establish the trend-following trading strategy for the decision-maker. Under this strategy, investors are inclined to overestimate the perspectives of risky assets (of an uptick at the next step of the model), whose price has been increasing in value in the recent past. Individuals also dislike risky instruments that showed an immediate history of negative price development. Consequently, in my model, I compute the parameters μ_t and σ_t that define the value of $R_{t,U}$ and $R_{t,D}$ at each step of the model as the average return and standard deviation of the risky instrument over the past 20 periods. For the evaluation of the risky asset price development at each step in the model, I apply the rolling window approach, whereby at each step 20 previous price change observations are used to define the value of $R_{t,U}$ and $R_{t,D}$.

Effectively, investors in my model will expect an increase in return and volatility from the risky asset that demonstrated the positive performance and higher dispersion track-record in the near past. Such an approach reflects the myopic focus of individual investors, whereby the decisions are taken independently for each step, there are no dynamic optimisation attempts, but traders still make inferences based on a simple backwards-looking strategy. In the domain of retail brokerage, such an approach can be associated with the extremely popular technical analysis rules.

Unlike other theoretical models that simulate the price evolution of a risky instrument, I take the real-time series for EUR/USD currency pair over the period between November 2011 and May 2015 ($m \in \{1, \dots, 45\}$)– the period that fully matches my empirical dataset. I use 1-hour price ticks over a selected time frame as the measurement interval of one period. All of my stylised investors A, B, C and D open a risky position on November 1, 2011 ($m = 1$) and review the holding/liquidation decision hourly following the change in the price of a risky instrument. If an investor decides to liquidate the position and realise profit or loss at the step t, my model implies that he will reopen a new risky position immediately at the next step, $t + 1$[28]. The opened position can be long or short depending on the average return, $\bar{R}_{20}$, over the last 20 steps as discussed above. For $\bar{R}_{20} \geq 0$, a long position is opened, for $\bar{R}_{20} < 0$, a short position is established. At the end of the month, I summarise all the realised (liquidated) trades in the domains of gains and losses and calculate the correlation between realised risk and return in both domains (ρ_m^+ and ρ_m^-, respectively). As follows from the described setup, investors A, B, C and D can take a distinct number of liquidation decisions (different number of trades) subject to the variation in the parameters of utility function and decision weighting function. The beginning of the next month marks the start of a new period of observations producing another set of values of risk-return correlations for gains and losses. May 2015 is the last month of observations ($m = 45$). Thus, I collect 45 correlation coefficients for each domain per each investor, which I can compare and make inferences.

As concerns the specification of the probability of the return evolution in the next node, p_t, I calculate the value of the probability of the uptick in the value of the risky asset (i.e. the probability of $R_{t,U}$) as

$$p_t = \frac{t-j+1}{t} = \frac{n_U}{n_D+n_U} \qquad \text{(Formula 2.24)}$$

where n_U is the number of upticks in the previous upticks of the risky instrument, and n_D is the number of downticks. Such a formulation reflects the approach of Jakusch et al. (2019), who in turn adopted it from Weber and Camerer (1998) and Barberis and Xiong (2009). In the offered specification of p_t, an investor is considered to be using a Bayesian approach to update his subjective probability by deriving information from the past upticks and downticks.

[28] For the sake of simplicity, I assume that the amount of invested capital at every step is the same and is not dependent on previously realised gains or losses.

2.10.10. Analysis of model's results and predictions

After running the model, I obtain the set of 45 observations for a number of variables that describe the trading performance and behaviour of each of the stylised investors: Investor A, Investor B, Investor C and Investor D. The discussion of the results is provided in the sections below. I compute the following parameters:

Return (%) – an average per-trade return from 45 observations for each type of an investor (calculated as absolute return/position volume).

Total standard deviation (%) – standard deviation of all trading positions returns for each type of an investor (an average for 45 observations).

Positive standard deviation (%) – an average of standard deviation of returns from realised (closed) gaining positions.

Negative standard deviation (%) – standard deviation of returns from realised (closed) losing positions.

Duration of holding gains (steps) – median number of steps until a gaining position gets realised (closed) by an investor.

Duration of holding losses (steps) – median number of steps until a losing position gets realised (closed) by an investor.

Risk/Return correlation – correlation coefficient between realised total risk and return for an investor.

Correlation Risk+/Return – correlation coefficient between realised positive standard deviation and return for an investor.

Correlation Risk-/Return – correlation coefficient between realised negative standard deviation and return for an investor.

Number of trades – observed number of realised round-trip trades (steps) during the specified period of 1 month by an investor.

The results of the model are presented in Table 2.3 below:

Table 2.3. Results of the theoretical model of portfolio choice for four types of an investor with varying parameters of Prospect Theory-like preferences.

Estimated variables	**Investor A**	**Investor B**	**Investor C**	**Investor D**
Return	-0.0056%***	-0.0046%***	-0.0044%***	-0.0045%***
	(0.000)	(0.000)	(0.000)	(0.000)
Total standard deviation	0.0879%***	0.0961%***	0.0937%***	0.0906%***
	(0.000)	(0.000)	(0.000)	(0.000)
Positive standard deviation	0.1035%***	0.0874%***	0.0735%***	0.0726%***
	(0.000)	(0.000)	(0.000)	(0.000)
Negative standard deviation	0.0739%***	0.1139%***	0.1389%***	0.1298%***
	(0.000)	(0.000)	(0.000)	(0.000)
Duration of holding gains	1.263	2.000	2.105	2.105
Duration of holding losses	1.000	3.658	5.658	4.921
Risk/Return correlation	0.16***	0.05	-0.16***	-0.16***
	(0.000)	(0.307)	(0.000)	(0.000)
Correlation Risk+/Return	0.59***	0.57***	0.46***	0.45***
	(0.000)	(0.000)	(0.000)	(0.000)
Correlation Risk-/Return	-0.46***	-0.51***	-0.56***	-0.56***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of trades (steps)	609	505	501	529

Note: The table displays the results of the model with the set of parameters outlined in Section 2.10.9. Four types of investors are considered: Investor A reflects an individual with the preferences from the original model by Kahneman and Tversky (1992); Investor B holds the preferences representing the mixture between Investor's A preferences and the model parameters described in Jakusch et al. (2019); Investor C replicates the parameters from Jakusch et al. (2019) model. Finally, Investor D has the parameters of Investor C with the coefficient of loss aversion equal to 4. The variables are estimated using 45 runs of the model. Each run of the model represents a one-month period between November 2011 and May 2015 using 1-hour price ticks of EUR/USD currency pair (hence, 45 one-month periods in total). For each of the variables in the table, an average of 45 observations is provided.

2.10.10.1. Disposition effect analysis and predictions

The theoretical models that I used as the source and the reference for my model (Barberis and Xiong (2009), Vlcek and Hens (2011), Jakusch et al. (2019) and others) were drafted with the primary goal of explaining the empirically observed disposition effect. Therefore, it is logical to start the analysis by comparing my results on the disposition effect with the above-mentioned models. What I find is the complete reflection of the outcome of Vlcek and Hens (2011) and Jakusch et al. (2019), which underlines the robustness of my theoretical framework. Specifically, the parameters of the original Prospect Theory model (Kahneman and Tversky (1992)), describing the behaviour of Investor A, cannot explain the disposition effect. In fact, when applying these parameters, the observed effect is reversed as the difference between the time duration of holding gains is longer than the duration of holding losses by 0.2 steps, which is significant at 5% confidence level.

Investor C, whose preferences are grounded on affect-rich parameters of the utility function (adopted from Jakusch et al. (2019)), exhibits the disposition effect that is statistically and economically significant. The duration of holding losses is 2.69 times longer than that of holding gains. It should also be noted that Investor C would hold gaining positions a bit less than one step longer than Investor A, which is significant at 1% level. Investor B, who is taking decisions in the affect-poor environment according to the model, demonstrates the disposition effect of 1.66 steps that is substantially smaller than Investor C. The difference exclusively comes from the holding of losing positions because the duration of holding gains is statistically indistinguishable for Investors B and C.

Investor D, who has the same parameters as Investor C with the stronger loss aversion coefficient (4 against 1.09), unveils weaker disposition effect compared to Investor C but stronger value relative to Investor B. Again, all the difference comes from overholding losing trades.

I make empirical testing of the disposition effect in the third empirical chapter – Chapter 6 of the Thesis, Research Question 2.1, Section 6.5. According to the prediction of the theoretical model, I should expect to observe the disposition effect in both affect-rich and affect-poor environments. In the affect-rich environment, the observed effect is expected to be more pronounced.

2.10.10.2. Analysis and predictions of performance and risk behaviour

After the examination of the disposition effect, I turn to the analysis of risk behaviour that is represented in the results as the standard deviation of returns. I explore three risk variables – total dispersion of returns, the volatility of returns in the positive domain, and the volatility of returns in the negative domain. It is logical to assume that the disposition effect and the manifestation of dispersion of returns should be connected. The longer one holds the trading positions, the wider should be the distribution of returns. Nevertheless, in the gains domain, this rationale does not seem to work, as I observe a drop in standard deviation (significant at 1% confidence level) when switching from Investor A to Investor B parameters, and the subsequent drop from Investor B to Investor C (significant at 5% confidence level). It may be explained by the small difference in the disposition effect observed for gains. Positive deviation of returns for Investor D is indistinguishable from Investor C, which is not surprising – loss aversion coefficient has no much impact on the gains territory.

The dispersion of returns is more aligned with the disposition effect in the zone of losses. Here, the longer is the holding period of losing positions, the more pronounced is the returns deviation. The changes in behaviour from Investor A to Investor B to Investor C are all significant at 1% level, marking the fact that my theoretical investors get progressively more risk-seeking. Interestingly, Investor D demonstrates more risk-averse decision-making in the losses domain as compared to Investor C (significant at 5% level). This finding helps to unveil the role of loss aversion coefficient on the risk behaviour. However, given the sharp change in the loss aversion coefficient, the impact seems relatively limited (at least, in the scope of a theoretical model).

Total standard deviation demonstrates a flatter pattern across investors. The only meaningful difference is between Investor A and the others. It is the result of the counterbalancing changes in the variation of returns in the domains of gains and losses.

I explore the risk behaviour measured by the standard deviation of returns and the changes in it pertinent to affect-poor and affect-rich environments in Chapter 6, Section 6.6. According to the predictions of my theoretical model, in the empirical setup, I should observe substantial changes in risk-taking behaviour in the domain of losses for affect-rich investment environment as compared to the affect-poor setting. In contrast, the deviation of returns in the domain of gains should stay relatively weak.

As regards the analysis of performance that I evidence in the results of the model, I find that for all types of investors, it is negative and significant at 1% level. However, the differences in performance between investors are now statistically meaningful. To learn more about the disparity of performance in different affective settings, I examine it in the framework of empirical study in Chapter 6, Section 6.2.

2.10.10.3. Analysis and predictions of the correlation between risk and return

Before setting up the theoretical model, I assumed that the correlation between risk and return has to be connected to the disposition effect grounded on the form of the utility function. According to the Prospect Theory, in the domain of gains, a decision-maker faces a concave form of the function. Therefore, higher return should accompany higher expected volatility, hence a positive correlation between both variables. In the losses domain, the convex form of the function brings about the opposite effect and the negative expected correlation between risk and return. The disposition effect is stemming from the same line of rationale. After I examine the results, I can state that it is valid only for the losses domain. The situation in gains domain proves to be more complicated. As I hypothesised above, it can be explained by the relatively small variation in the holding period of gaining trades across the tested stylised investors. In the losses zone, the ties between the disposition effect and risk/return correlation are plainly detectible.

I begin the discussion of findings with the correlation between return and total risk. Investor A exhibits a positive correlation coefficient between risk and return equal to 0.16. The coefficient is statistically significant at 1% confidence level. Such a correlation reflects the overall rational behaviour of Investor A, i.e. higher return is demanded per the unit of risk. It is quite different from Investor B, and Investor C. Investor B demonstrates the average risk-return correlation of 0.05 over the 45 observations, which is not statistically discernible from zero. In contrast, Investor C features the negative correlation coefficient of -0.16 (significant at 1% level). The resulting correlation coefficients for all the three investors are also statistically significantly different at 1% confidence level. Relating the coefficient to the form of the utility function, I can establish that Investor A is risk-averse, Investor B is risk-neutral, and Investor C is risk-seeking. Investor D's results are not meaningfully different from Investor C in any of the three correlation measures.

Once I break down the correlation between total risk and return into two semi-deviations – positive and negative risk – and return, my theoretical model evinces negative correlation coefficient in the area of losses and positive coefficient in the area of gains. This finding and prediction reflects my assumption about the nature of risk and return relation under the Prospect Theory preferences and parameters. Notably, the relation holds for all types of stylised investors that I explore, which indicates the fundamental character of the observed phenomena. I devote empirical Chapter 4 to the tests of my model's predictions concerning the risk-return relation in the domains of gains and losses.

Furthermore, I investigate the dynamics of correlation between the positive/negative risk (dispersion of gains/losses) and total return across differently affect-infused environments. I notice that the correlation between positive risk and return is well aligned with the distribution of returns in the gains domain. Thus, the correlation coefficient is the largest for Investor A and the smallest for Investor C. The difference between Investor A and Investor B is statistically significant at 1% level, while the distinction between Investor B and Investor C is smaller (significant at 5% level).

The correlation between negative risk and return demonstrates a different pattern. Here, a more substantial negative linear relation is witnessed for the most affect-rich setting (Investor C). It is lower than for Investor B (the difference is significant at 10% level), who is set to make decisions in the affect-poor environment. Finally, the least emotionally-infused Investor A shows a higher correlation than Investor B (significant at 1% level). What is the psychological rationale behind the negative correlation between return and negative risk? I believe that once an investor finds himself in the area of losses, he is ready to pay the return premium to avoid the disutility caused by the failing decisions (which is economically irrational). It means that an investor is prepared to experience even higher losses (up to a certain threshold) as the economic cost for getting back to the break-even. Sometimes, it becomes possible to wait until the open position hits back to the reference point. However, in more adverse scenarios, the losses from the position will keep accumulating until a desperate investor would close them down fearing disastrous consequences of irreversible loss of capital[29]. Consequently, the attempts to attenuate the disutility creates high dispersion of returns in the domain of losses resulting in the negative correlation between negative risk and performance.

I make empirical testing of the risk-return relations in different environments in the context of emotions in Chapter 5.

3. Data Description

The brokerage house that has provided the data set is a large specialised retail broker that offers investors Direct Market Access (DMA) to foreign currency trading (FX market) through an in-house developed electronic trading platform that is available on desktop computers, smartphones and even smartwatch. Thanks to the specifics of the FX market, customers can place orders and make trades 24/5. Another critical discrepancy from stock markets is a large amount of financial leverage available to investors[30]. Usually, the maximum leverage for opening a position is 100:1, which means that a trader with $1,000 on her account can increase exposure up to $100,000 and, consequently, gain or lose a 100 times greater amount than without having such an opportunity. In cases when opened

[29] Such high severity/low probability events in the framework of Kahneman and Tversky (1992) model produce risk aversion in the losses domain.
[30] In personal communication, the broker has provided the average leverage across traders equal to 33, meaning that on average the size of a trading position exceeds investors' capital 33 times.

positions generate losses, the leverage grows, and if it exceeds some maximum level predefined by the broker, e. g. 200:1, the exposure is automatically reduced so that the use of leverage is brought to approximately 100:1. Such exposure reduction is called a margin cut and is achieved by closing existing positions and/or opening new positions in the opposite direction. Margin cuts allow brokers to control their clients' losses and limit them by the margin amount - the trader's own assets. The factor of leverage creates an unprecedented environment of risk, incomparable to most of the other financial markets, which may consume trader's all invested capital or double it within a very short time frame. It has an inevitable magnifying impact on the emotional state of investors during trading activity.

The number of instruments in the FX market is limited (e.g. as compared to the stock market). Altogether, traders in the data set had access to only 48 financial instruments that included major currency pairs like EUR/USD, and USD/JPY, but also more exotic pairs like GBP/NZD or ZAR/JPY. The EUR/USD pair is by far the most popular trading instrument in the world, which was also reflected in the data set where this currency pair was on the top of the trading list for 60% of traders. For comparison, the next most popular pair, GBP/USD, was a hit for only 9% of traders. The limited number of similar instruments with the dominance of only a few of them creates a substantial benefit and advantage for an academic study of investors' behaviour because it helps to control for the multitude of extraneous characteristics pertaining to instruments themselves leaving any changes in performance or other variables exclusively to individual decisions.

A very valuable feature of the retail FX market is the popularity of so-called demo (demonstration) accounts, which provide a riskless training ground for beginner investors as well as the opportunity to test various strategies for more advanced traders. Typically, such a demo environment completely replicates live trading settings. The only difference is that live account implies real money deposits, while demo accounts are credited with virtual (paper) money. On top of that, many large brokers organise multiple trading contests run on their electronic platform. The brokerage house that provided the data for the current research organises not only a trading contest of that sort but also records and stores the resulting data[31]. I describe the trading contest in detail in Section 3.1.2.

I have acquired the complete Live trading orders history of 8,527 individual investors, who held accounts at a single Europe-based brokerage house during the period between November 2011 and May 2015. 618 investors had Contest accounts in addition to Live. Both accounts were matched by the broker using investors' unique parameters, such as phone number or email address. I managed to collect the same amount of data for the Contest accounts as I did for Live. In each of the three Empirical Chapters of the Thesis, I apply a specific data selection procedure depending on the perspective required by research questions.

In the first empirical chapter, I examine the relation between risk and performance of investors in the Live-only context. After applying a strict filter of a minimum of 200 transactions per investor, my working number of subjects shrinks to 3,670 individuals in the Live trading domain.

In the second empirical chapter, I carry on keeping my focus on the correlation between risk and return. However, I now evaluate two environments – Live and Contest and compare the interaction of risk and return in both with the purpose to elicit the role of emotions that I expect to observe in the correlation discrepancies. To maintain the connection and comparability to the first empirical chapter, I preserve the minimum number of trades criteria. Therefore, I isolate 166 individual investors who fit the selection requirements.

[31] In general, this is quite unusual for a broker to keep the contest data because it consumes precious space on company's servers. In this case, the data was stored as multiple trading contests of the broker were interconnected not only to other contests but also live trading environment.

In the third empirical chapter, I abandon the correlation analysis framework and shift to an independent examination of performance and risk. Thanks to that, I ease my minimum number of trades criteria to only 10 trades, which leaves me with 523 subjects, featured with both live and contest trading accounts.

The structure of raw data in my dataset is identical for Live and Contest settings. The dataset contains complete records of trade open and close orders. In addition, it includes a variety of orders' descriptive characteristics, such as traded currency pair, price on which the order was filled, order volume, order side (buy or sell), order direction (open or close), conditional price and conditions if any were applied (conditional open, stop-loss or take-profit close), date and time of the order, automated order identifier which points to strategy if the order was executed under one's conditions, order commission amount, and other information. Each record also includes several identifiers, which, firstly, allow distinguishing between the records of different traders, and, secondly, recognising separate trade orders. Also, the data about the traders' balances in USD is available for every settlement date. The raw data were processed and reorganised into the form that describes the trades through several characteristics, including its profitability (return on trade), duration in minutes, and volume in USD. Additionally, each trade was categorised by whether it was intraday, based on automated strategy, fully or partially executed under any predefined conditions.

Finally, aggregating all the data, a number of trading characteristics of a trader for both types of trading accounts were obtained: average daily balance, portion of intraday trades, portion of conditional orders, portion of automated trades, aggregated turnover, median duration of a trade, number of trades, number of instruments traded, standard deviation as well as semi-deviations of the returns on trades. I do not use the same number of variables in every chapter, varying the content depending on the specific needs of research questions.

I summarise some of the variables for all my subjects in Table 3.3.

Table 3.3. Descriptive statistics of the complete selection of 8,527 Live investors without filters applied.

Variable name	**AVG**	**MEDIAN**	**MIN**	**MAX**
RETURN	-0.045%	-0.013%	-1.494%	0.614%
STDEV	0.909%	0.370%	0.024%	15.495%
STDEV_PLUS	0.498%	0.261%	0.016%	5.695%
STDEV_MINUS	1.112%	0.401%	0.023%	17.029%
TRADES	464	178	2	4,933
INSTRUMENTS	10	8	1	39
TURNOVER	17.00	3.18	0.01	289.45
INTRADAY	78.82%	85.71%	10.71%	100%
DURATION	382	47	0.55	8,848
CONDITIONAL	26.41%	21.90%	0%	92.42%
AGE	38	36	21	67

Note: The table exhibits the descriptive statistics for the selected number of variables pertaining to the individual investors in the current research. All the values are displayed after exclusion of outliers using 1% winsorisation for each of the variables. All the variables are calculated per an investor (or an account). The decoding and meaning of variables: RETURN (%) – average return on an account (calculated as return/position_volume); STDEV (%) – standard deviation of the trading positions return (return calculated as return/position_volume); STDEV_PLUS (%) – standard deviation of positive positions return; STDEV_MINUS (%) – standard deviation of negative positions return; TRADES (N) – total number of transactions made on the account; INSTRUMENTS (N) – number of trading instruments used by investors; TURNOVER (mln USD) – aggregated turnover on the account; INTRADAY(%) – share of trades completed within a trading day; DURATION (min) – median duration of an average trade on the account; CONDITIONAL (%) – share of conditional orders as part of all orders placed; AGE – investor's age.

According to the summary statistics, an average investor can be described as a 38 years old male (92% of all investors), trading 10 instruments and completing more than 400 transactions, a quarter of them using conditional orders. Hefty 78% of trades are completed within the same day, each trade lasting 6 hours until closure.

On average, an investor would see his wealth decreasing after each trade by 0.045% of the invested capital. The fact that individual trading is a wealth-destructive activity is fully in line with other research in this area. For example, Barber and Odean (2000), one of the first studies of lay investors' performance, show that non-professional traders lose money on average, which is mainly attributable to trading costs. This observation and conclusions are very relevant to my findings. The more individual investors trade, the higher commissions they incur, while their gross trading remains comparable to market indexes. Barber et al. (2009) continue the same line of research and find that Taiwanese lay traders lose more than 2% of the annual GDP of Taiwan. Finally, Barber et al. (2014) reveal that out of all individual investors (mainly day-traders) trading on Taiwanese stock exchange between 1992-2006, only 20% ended up with positive net performance. It is surprisingly close to the figures published by retail brokers in Europe who now have to reveal these data thanks to the new regulation by ESMA (EU regulator of financial markets).

More specific data sets with subjects' selections relevant to the research questions posed in each of the Thesis chapters are described and discussed therein.

3.1. Affect-rich and affect-poor settings

The literature on emotional research frequently refers to affect-rich and affect-poor stimuli (for example, Hsee and Rottenstreich (2004), Suter et al. (2016)). In my study, I align these designations with Live and Contest trading environments from my dataset.

3.1.1. Live account as affect-rich setting

Live trading account is a standard type of real money brokerage account representing the continuous set of risky gambles with traders' own funds that they initially must deposit on their account with a broker. The nature of marginal trading implies that each trade may only partially be covered with an investor's capital. This part may vary from 0.5% to 100% of the gamble's value, and this is always an investor's choice reflecting his risk preference.

Depending on the size of the selected financial leverage, investor's capital may change faster or slower in reaction to the price change of the underlying instrument. This degree of risk sensitivity has an imminent effect on affect-richness of the gamble. However, even negligible risk sensitivity (small financial leverage) is still an essential emotional stimulus because it leads to possible loss of real personal money. Moreover, my review of the literature on neurophysiological and psychological inspection of individual traders revealed that real financial markets conditions enable acute emotional reactions, so fierce that professional traders describe their investments in the vivid terms of love and hatred. Therefore, I attribute all the bets, no matter which financial leverage is used by an investor, to the affect-rich domain.

3.1.2. Contest account as affect-poor setting

Contest account deserves a more detailed description, as it is rarely used by stockbrokers but is more popular with FX brokerage houses. For the broker that provided the dataset, the Trader Contest is part of the traders' Community, which is accessible from the broker's web site, with a separate section devoted to it. Anyone can become a member of the Community by filling in a registration form. A real email address and mobile phone number should be provided, as they are verified during the registration procedure. If members are caught on giving false information[32] or on manipulating or breaching Community rules, they are immediately expelled and lose entitlement for any prizes. The number of Community members has risen over approximately 10 years of its existence to 130,000[33] people from all

[32] Such cases usually occur when a member becomes eligible for a monetary prize in one of the community contests. Real prizes are only credited to Live accounts, thus requiring a person to have one. Live account opening procedure necessitates a prize receiver to send certified copies of identification documents and proof of address. At this stage any lies become evident. The most common cases include false age (should be over 18 years to open a Live account) or nationality (financial regulation that the broker complies with prohibits to open accounts for citizens of USA and a number of other countries).
[33] Certainly, only small portion of the registered members actively takes part in the Community on some regular basis. The broker does not collect such statistics, but refers to the figure of 5,000 active participants.

over the world, and there are 15+ different contests available, whereas Trader Contest is the largest and most famous of them. The contest is run monthly (from the first till the last day of a calendar month) and is open for any Community member without any prerequisites. There are also no rules regarding the continuity of participation. In this regard, every monthly Contest is run independently. On the first day of the month, each participant's Contest account is credited with $100,000. This amount and any trading proceeds are zeroed on the last day of the Contest when the final results are computed. In the Contest rules the broker declares four goals that a participant must follow in order to be successful in the competition:

1) Generate the maximum trading profit within 1 month with the maximum drawdown of the initial amount[34];
2) Showing good trading performance, to prompt other traders to copy participant's trades[35];
3) Demonstrate long-term steady results[36];
4) Actively explain trading decisions by maintaining a trading blog.

The broker outlines certain rules for the participants, e.g. minimum and maximum order size (100,000 and 5,000,000 currency units, respectively), or maximum 5 simultaneous transactions, but these limitations are primarily aimed at ensuring that participants take the competition seriously, do not do random trading, back their decisions with their beliefs and research, and strive to maximise their returns.

[34] In case of loss of the initial amount, a participant cannot continue to trade and should wait for the next month.
[35] Transactions made by participants in Trading Contest are a source for another contest conducted by the broker, which in short can be described as portfolio management competition. In this game participants have to sign up for trades (signals) from selected participants in Trading Contest, normally based on their performance. After that any transaction made by traders from the underwritten pool translates into portfolio profits or losses. Portfolio management game is thus won by a participant who can most aptly create a pool of the best traders from Trading Contest. In turn, Trading Contest's participants are rewarded for having subscribers, the more the better.
[36] Long-term performance is rewarded in yet another competition, which is called Trader of the Year. This is a rolling monthly contest, in which the participants have to have at least 6 months prior track record within the rolling year window. The winner should show the best average monthly performance and become eligible for $2,000 prize.

The rank of each participant is made up of 4 components, even though 2/3 of the score consists of performance (computed as an increase of equity). The other criteria, as was explained above, are used to motivate the best effort and punish those participants who try to win by random transactions – number of signal subscribers, orders quality, and trader's blog. Virtually, the only chance to win in the trading game is to conduct thoughtful transactions as is confirmed by the random inspection of the top three winners' strategies[37]. A vital motivational aspect is the monetary prize structure. The total prize fund is $28,000 every month. It is distributed across the best 30 traders. The exact structure is presented in the table below:

Table 3.4. The distribution of real money prizes for Contest participants.

Place	**Prize**
1st	6,000$
2nd	3,500$
3rd	2,500$
4th	2,000$
5th – 6th	1,500$
7th – 10th	1,000$
11th – 20th	500$
20th – 30th	200$

These gains are undoubtedly significant and desirable for contest's participants. For comparison, the average value of participants' Live account balances is $2,834. Therefore, a contest participant can win from 7% to 218% of their own live funds.

[37] Without the physical opportunity to review all Contest participants and their strategies, I cannot guarantee that some of them do not employ the option-like trading strategy, whereby they would open a single position in the beginning of the month with the biggest possible risk in order to reap a maximum random profit. Nevertheless, I filter out such possible gamblers by imposing a minimum limit of 10 transactions.

In addition to monetary incentives, there are substantial non-monetary reasons for optimal decision making among Contest participants. First, a trader can benchmark personal performance and gauge his skill against a large and representative group of peers. It may be a valuable tool both for experienced traders and beginners, who may test their preparedness to switch to Live trading. The number of Contest participants holds stably around the figure of 800 people in a single month. The second benefit from trading responsibly and engaging the best effort in the Contest does not have immediate monetary benefit but offers large potential later on. Noticeable results that anyone can trace usually attract interest from other investors, who start seeking advice or external manager's service. Hence good and consistent performance can translate into the beginning of a successful business story. Thirdly, a high ranking means a certain personal status in the community. Top three performers are asked to deliver a presentation telling about their strategies leading to success. Also, they are praised and acclaimed in traders' forums and generally become famous building up better self-image and emotional state.

The aggregation of all the financial and non-financial incentives discussed above creates a powerful mechanism, which stimulates contestants on the conscious level to exhibit their best skill in trading. It is also apparent that Contest trading is not affect-free because superior performance pays back in real money prizes and higher community status. Nevertheless, deficient performance does not have any straightforward monetary consequences. For the most part, the worst outcome of Contest trading is suffered self-esteem. Therefore, considering and comparing the bulk of trading activity in Live and Contest, I conclude that the latter is relatively affect-poor.

3.1.3. Interface of the investment platform

The investing process is inextricably linked to the trading interface of the user. Before the digital revolution in trading, the standard process of placing orders involved very moderate technical equipment, like telefax or phone. The development of electronic platforms in the 2000s has lead to the structural shift in the whole trading industry in multiple ways. First, electronic market access has dramatically decreased the costs of trading because huge bits of manual processing of orders and transactions have become redundant. Therefore, investing turned more democratic and affordable for the masses of laypeople. Second, electronic interfaces provide for enormous and smooth flow of trading-related information. Furthermore, built-in Artificial Intelligence systems are now available to set up and pick out the necessary useful bits from this information waterfall. Third, access to markets has become truly universal. Having a mobile phone in the pocket allows immediate order placement, analysis of pre-trade and post-trade information, tracking of investment performance, etc. All this knowledge is available 24/7.

The electronic platform provided by the brokerage house is a thoroughly developed system that can be equally used by the newbies or trading professionals. Its main interface can be seen in Figure 3.1.

Figure 3.1. Electronic trading interface provided to clients by the brokerage house.

The interface is made up of three clearly visible parts. The biggest part is the central space with the price chart of the currently selected trading instrument. This area is used for ‘drawing’, i.e. application of various methods from technical analysis. A user can set up the price chart according to the personal needs, for example, choosing different time frames, types of the graph, technical indicators, etc. Also, in this particular platform, a user can place orders (market or conditional) by clicking on the chart space at the specific price level.

The second component of the interface is the vertical area on the left. It is the main block used for placing orders as it is featured by large and colourful market orders-related Buy and Sell buttons, which is hard to miss. Below market orders area, there is a section for conditional orders. Further below, a user can track essential information, like changes in prices of the main instruments, current market liquidity levels.

The third critical element of the interface is the area in the bottom of the screen. It is used to reflect the up-to-date trading situation of the user. The user can inspect all the placed orders and their impact on total performance. It is the most ‘emotionally charged’ section. The profit/loss information is updated with every tick of the price, hence the change from the red colour indicating losses to the green colour indicating gains takes place uninterruptedly provoking the elicitation of positive and negative feelings familiar for any trader. Any conditional order or open position can be cancelled or closed from this area as well.

It is worth paying attention to the line of text in the very bottom of the interface. It shows the total capital owned by an investor, which is stored on the investor's account at the brokerage house. Besides, a trader can see her total leverage used by all currently open trading positions. The part of the capital that is still remaining or unused is called 'free margin'. Possibly, the most important figure on the whole interface is the 'total result' or Total Profit/Loss that sums up from all open positions by an investor.

When the one looks at the live screen of the platform, not just at the picture of it, the interface and the information on the screen appear to be extremely dynamic, with running numbers, evolving price charts, changing colours. All these vibrant commotions are capable of inducing the affective states in investors by themselves and require a great deal of attention and focusing in order to understand the continually changing environment.

3.2. Methodology

Throughout my thesis, I use similar research methods. The first two empirical chapters are primarily devoted to correlation analysis, while the last chapter adheres to the comparison of risk behaviour among individuals. In two of my empirical chapters, I use multiple regression techniques to explore the relations and dependencies between variables.

3.2.1. General principles

Across my research, I employ the return or profitability variable. I calculate the per-trader return, in line with the industry standard, in a three-step method. First, I convert every trade's return and position volume in USD (the exchange rate applicable to each trade is provided in the data set). Next, I measure the return per each trade as an absolute return for the trade divided by trade volume. Finally, I average the return across all trades of an investor[38]. The resulting figure can be interpreted as the return per 1 US dollar traded. Unfortunately, this method does not account for the leverage employed by a trader. However, the exact degree of leverage is tough to evaluate during the abrupt and volatile trading process. Nevertheless, such an approach, by standardising against position size, still produces a reasonable control for the implied investment risk of each transaction.

Furthermore, I frequently use and compute the positive and negative semi-deviations of returns. However, these are not precisely 'semi' deviations because they are mathematically computed against mean return that can be negative or positive, while in the case of my study I am more interested in the measurement against a status quo value. In trading, a typical status quo is the zero return[39]. Hence, I modify the formula in the following way:

$$var_{-} = \sqrt{\frac{1}{n_{-}} \sum I_{r<0} \cdot r^2} \qquad \text{(Formula 3.1)}$$

$$var_{+} = \sqrt{\frac{1}{n_{+}} \sum I_{r>0} \cdot r^2} \qquad \text{(Formula 3.2)}$$

[38] The approach is equivalent to summing up all trading profit of an investor and dividing it by the total traded volume.

[39] It should be noted that in trading, zero return does not coincide with the purchase price (offer for long position), but rather with the selling price (bid for long position). When a trader opens a position she momentarily gets into the loss domain valued by the size of the spread (difference between offer and bid prices).

where var_{-} and var_{+} are negative and positive modified semi-deviations with n_{-}, n_{+} and r being number of negative returns, number of positive returns and realised return on a trade, respectively.

For the goal of several research questions, I evaluate the Disposition effect (DE). For the computation of DE, I adopt a simple methodology of round-trip duration of transactions used by Shapira and Venezia (2001). In line with this approach, DE for each trader equals to:

$$DE_i = Dur^{-}_{Median,i} - Dur^{+}_{Median,i} \qquad \text{(Formula 3.3)}$$

where $Dur^{-}_{Median,i}$ is the median duration of transactions realised as losses, and $Dur^{+}_{Median,i}$ is the median duration of transactions realised as gains. Disposition effect for the whole sample of traders is computed as an average of individual values:

$$\overline{DE} = \frac{1}{N}\sum_{i=1}^{N} DE_i \qquad \text{(Formula 3.4)}$$

3.2.2. Methods used in Chapters 4 and 5

In the first empirical chapter (Chapter 4), I use three measures of the linear relation between risk and return variables. One measure is parametric Pearson correlation, while the other two are non-parametric Spearman rank-order correlation and Kendall’s correlation. The first and the most common statistic for measuring linear relation is Pearson ρ correlation, which is defined as the ratio of two variables’ covariance to the product of their standard deviations. So, the sample correlation coefficient r is:

$$r = \frac{\sum_{i=1}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad \text{(Formula 3.5)}$$

where:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$$

As Pearson's correlation is a parametric test, it has strong assumptions like bivariate normal distribution of the data. The coefficient is very sensitive to outliers and assumes a strictly linear relationship, so, in the case of non-normal data, it could be misleading.

To reduce the effect of outliers, the observations could be replaced by their ranks, which is implied by Spearman's rank-order correlation:

$$r_S = \frac{\sum_{i=1}^{n}\left(\left(rank(x_i) - \overline{rank(x)}\right)\left(rank(y_i) - \overline{rank(y)}\right)\right)}{\sqrt{\sum_{i=1}^{n}\left(rank(x_i) - \overline{rank(x)}\right)^2 \sum_{i=1}^{n}\left(rank(y_i) - \overline{rank(y)}\right)^2}} \qquad \text{(Formula 3.6)}$$

where $rank(x_i)$ and $rank(y_i)$ are the ranks of the sample's observations. Such an approach allows for relaxing the assumption about linearly related variables and shows high absolute correlation values for non-linear but a monotone relationship.

In a similar fashion, Kendall's correlation is a non-parametric test designed to assess the strength of the monotonic relationship between the two variables. Its estimate is:

$$\tau = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} sgn(x_i - x_j) sgn(y_i - y_j)}{n(n-1)} \qquad \text{(Formula 3.7)}$$

where

$$sgn(x_i - x_j) = \begin{cases} 1, if\ (x_i - x_j) > 0 \\ 0, if\ (x_i - x_j) = 0 \\ -1, if\ (x_i - x_j) < 0 \end{cases} ;\ sgn(y_i - y_j) = \begin{cases} 1, if\ (y_i - y_j) > 0 \\ 0, if\ (y_i - y_j) = 0 \\ -1, if\ (y_i - y_j) < 0 \end{cases}$$

Furthermore, in my study, I interpret the correlation between the return and risk as a measure of investors' rationality and use correlation coefficients as a dependent variable in regression analysis. In line with the recommendations in academic literature (e.g. Cox (2008)), I transform the correlation coefficient in the way to obtain approximately normally distributed non-limited variable which retains the dynamics of the original one. For this purpose, I use Fisher's z-transformation technique that transforms the correlation coefficient in the following way:

$$z = \frac{1}{2} \ln\left(\frac{1+r}{1-r}\right) \qquad \text{(Formula 3.8)}$$

To check the reliability of the results obtained using classic multiple linear regression, I use one of the robust regression methods called MM-estimators (see Verardi and Croux (2009) for more information). It combines two essential properties of a good robust estimator – high-breakdown point and high efficiency. The estimator compiles two types of robust estimators, S-estimator and M-estimator. It is defined as[40]:

$$\hat{\beta}_{MM} = arg \min_{\beta} \sum_{i=1}^{n} \rho\left(\frac{r_i(\beta)}{\hat{\sigma}_S}\right) \qquad \text{(Formula 3.9)}$$

Here $\hat{\sigma}_S$ is the robust estimator of residuals' dispersion which satisfies

[40] $r_i(\beta)$in Formulas 3.9, 3.10 and 3.11 is u.d.

$$\frac{1}{n}\sum_{i=1}^{n}\rho\left(\frac{r_i(\beta)}{\hat{\sigma}_S}\right) = const \qquad \text{(Formula 3.10)}$$

And $\hat{\beta}_S$ is the S-estimator, which is used as the initial value of $\hat{\beta}$ in the iterative calculation of $\hat{\beta}_{MM}$. It is defined as:

$$\hat{\beta}_S = arg \min_{\beta} \hat{\sigma}_S\big(r_1(\beta), \ldots, r_n(\beta)\big) \qquad \text{(Formula 3.11)}$$

In both Formula 3.9 and Formula 3.10, $\rho(u)$ is even, non-decreasing for $u > 0$ and less increasing than the square function. A good choice is Tukey's Biweight function:

$$\rho(u) = \begin{cases} 1 - \left[1 - \left(\frac{u}{k}\right)^2\right]^3 if\ |u| \le k \\ 1\ if\ \ |u| \le k \end{cases} \qquad \text{(Formula 3.12)}$$

where k is some constant chosen depending on the desired efficiency and breakdown point of the estimator.

Finally, to compare the regression models' coefficients across groups, I use the dummy variables and interaction terms. Thus, to examine two groups A and B differences, I add the dummy variable for, say, B and p variables which are predictors of initial model multiplied by B dummy:

$$y_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi} + \beta_{p+1} d_B + \beta_{p+2} d_B \cdot x_{1i} + \cdots$$
$$+\beta_{2p+1} d_B \cdot x_{pi} + \varepsilon_i, i = 1, \ldots, n \qquad \text{(Formula 3.13))}$$

Here, $\beta_j, j = 0, \ldots, p$ are coefficients of the model for group A, $\beta_j + \beta_{p+1+j}, j = 0, \ldots, p$ are coefficients of the model for group B, and $\beta_{p+1+j}, j = 0, \ldots, p$ are differences between the two groups' regression coefficients. As far as $\beta_{p+1+j}, j = 0, \ldots, p$ are separate coefficients in the model, its significance (difference from zero) can be statistically tested. So, if β_{p+1} statistically differs from zero, the intercept significantly varies across groups, if $\beta_{p+1+j}, j = 1, \dots, p$ statistically differs from zero – the effect of $X_j, j = 1, \dots, p$ significantly varies across groups.

3.2.3. Methods used in Chapter 6

In Chapter 6, I aim to explain the difference in the profitability of Contest and Live accounts with the help of the cross-section of multiple personal, trading and behavioural variables. This goal is best fulfilled with the use of multiple linear regression analysis. The regression equation takes the form:

$$y = \propto + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad \text{(Formula 3.14)}$$

I develop two regression specifications for the study. The first model includes 22 variables, while the second model is based on 26 variables. The magnitude of the variables is calculated per the trading position size of USD 1 million. The dependent variable is calculated as:

$$r_{\Delta}^{i} = r_{Live}^{i} - r_{Contest}^{i} \qquad \text{(Formula 3.15)}$$

where r_{Δ}^{i} is the difference in return for investor i, r_{Live}^{i} is the return on Live account for investor i, and $r_{Contest}^{i}$ is the return on Contest account for investor i.

4. Empirical Chapter: Do individual investors make rational decisions? Prospect Theory view on the negative relation between risk and return.

4.1. Research Question 1. Hypothesis development

Risk aversion is one of the fundamental principles in modern economic theory. The idea that economic agents exhibit rational behaviour by requiring a risk premium for the extra units of risk from investments and, as a consequence, face concave decision valuation function lies behind many prominent financial models, such as Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), Modern Portfolio Theory. Yet, the empirical testing of risk aversion in many domains of finance fails to provide unequivocal evidence of the dominating rationality. For example, the testimony from international stock markets or organisation theory that I discuss in the literature review, suggests that economic agents may instead agree to pay risk premium for extra units of risk that is against traditional economic perspective. However, all such evidence up to date is indirect – it does not test the decision-makers and their decisions directly. Rather, the scholars explore the consequences of these decisions, for instance, in the framework of corporate risk and profitability analysis or risk and return patterns of financial securities.

One of the possible explanations behind such indirectly observed irrationality patterns offered by researchers (Fiegenbaum (1990), Wang et al. (2017)) is the agents' behaviour aligned with Prospect Theory preferences. These preferences result in S-shaped form of the utility function and reverse S-shaped form of decision-weighting function, which altogether creates a fourfold pattern of risk attitudes (Kahneman and Tversky (1992)). In Section 2.10, I design an economic model of portfolio choice to test how the decisions of an individual investor with Prospect Theory-based risk preferences might impact the relation between realised investment performance and risk. My model is built on the papers of Barberis and Xiong (2009), Vlcek and Hens (2011) and Jakusch et al. (2019), who apply a similar framework to explore the association between Prospect Theory preferences and disposition effect. The model makes several curious predictions concerning disposition effect and risk behaviour. One of the key predictions is a positive correlation between risk and return in the domain of gains and negative correlation in the domain of losses.

My data allow a direct investigation of individual risk attitudes and the predictions of my theoretical model concerning risk and return relation. I intend to utilise the detailed data set that contains trading statistics of a large group of individual investors.

Consequently, my first research question is articulated in the following way:

Do individual investors change their risk behaviour subject to positive or negative trading results?

According to my adopted methodology, I measure risk behaviour based on the realised relation between risk and return. Is the correlation between risk and return a good measure of rationality? I contend that this is not only an adequate measure but it also directly follows from the decision-making theory. The concave form of the value function implies that an individual requires a risk premium for an additional unit of risk suggesting that there should be a positive correlation between risk and return. In turn, the convex form of the value function shows the opposite: an individual is ready to pay a risk premium to accept additional risk. This situation should lead to a negative correlation between risk and return. These analytical inferences are substantiated by the predictions of the theoretical model in Section 2.10.

In the discussion of the correlation between risk and return as the approximation of rationality, another essential perspective is the interaction between rationality and performance. From the traditional theory point of view, it should be expected that the two variables are positively related. In other words, rational behaviour should predict better investment results. Nevertheless, investment performance is made up not solely of the degree of rationality but other elements as well. For example, prior literature has broadly investigated the presence of skill and luck in profitability. I can admit and expect that an individual with a high level of rationality may still experience losses after a long streak of investment decisions.

In contrast, an investor who systematically agrees to pay risk premium for consuming extra risk (i.e. has a negative risk/return correlation) may still end up with overall positive performance. Or, there can be two individuals with an equivalent degree of rationality, yet disparate investment income. All of that may happen, for example, due to perfect market timing skills. If I manage to discover the empirical presence of the phenomenon discussed above but still establish a positive link between rationality and performance, it would indicate that rationality is a viable but non-perfect predictor of investment success.

My subsequent analysis is based on a simple idea that the strength of risk-return relation can indicate the degree of the subject's risk attitude. In principle, economic theory agrees that individual risk preferences are heterogeneous[41], that is the curvature of the decision valuation function is unique for each person. Consequently, on the scale of individual risk attitudes continuum, greater absolute measure of the relation between risk and return should signal a more curved valuation function. At the same time, a weaker gauge of the risk-return link

[41] For example, Arrow (1965) and Pratt (1964) proposed measurement techniques for individual risk preferences – absolute and relative risk aversion.

would indicate less curved function. In other words, a smaller price (cost) of risk per the unit of return.

Systematic risk aversion is what should be expected if individuals comply with strict rules of rationality principles put forth by neoclassic economic models. These models do not recognise reference-dependence. Thus all investment decisions should be made in accordance with the concave valuation function perspective. If this is the case, the relation between risk and return should remain steadily positive for traders independent of positive or negative overall performance. I will use this expectation as my null hypothesis:

H_0: Investors should exhibit risk-averse preferences in their decisions irrespective of the sign of their investment results. For gains and losses, investors should require a risk premium for extra units of risk consumed. The relation between risk and return should remain strictly positive.

Prospect Theory provides another conceptualisation of risk behaviour. According to this model, individuals tend to be risk-averse only above a specific reference point. Below such point, they are expected to manifest risk-seeking behaviour. From the risk-return relation perspective, it means that above some certain threshold risk and return should be positively correlated, while below the threshold, the correlation should turn negative as my model in Section 2.10 demonstrates. Besides, Prospect Theory (Kahneman and Tversky (1979), Tversky and Kahneman (1992)) also introduces the concept of loss aversion, which describes the tendency of decision-makers to assign a higher psychological weight to losses than to gains. Practically, this translates into the expectation that negative correlation between risk and return in the valuation area below the reference point should be significantly higher in modulus than the positive correlation in the area above the reference point. The outcome of the theoretical model also predicts this fact for the investor who takes decisions in the real financial market environment. Following this discussion, I formulate three alternative sub-hypotheses that together describe the individual risk behaviour under Prospect Theory:

H_a1: Investors should demonstrate risk-averse behaviour above the reference point. In the positive domain, the relation between risk and return should remain positive.

H_a2: Investors should demonstrate risk-seeking behaviour below the reference point. In the losses domain, the relation between risk and return should remain negative.

H_a3: Losses should loom larger than gains. Investors should demonstrate higher sensitivity to losses than to gains of equal value. The relation between risk and return in the negative domain should be greater in absolute value than in the positive domain.

4.2. Research Question 1. Empirical Analysis

4.2.1. Macro vs Micro-level perspective

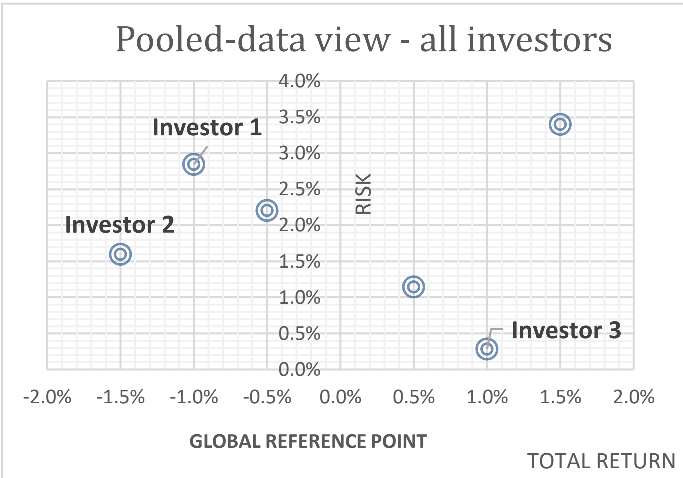
To add robustness and enhance the accuracy of my analysis of the research question and hypotheses, I plan to conduct my investigation at the two levels.

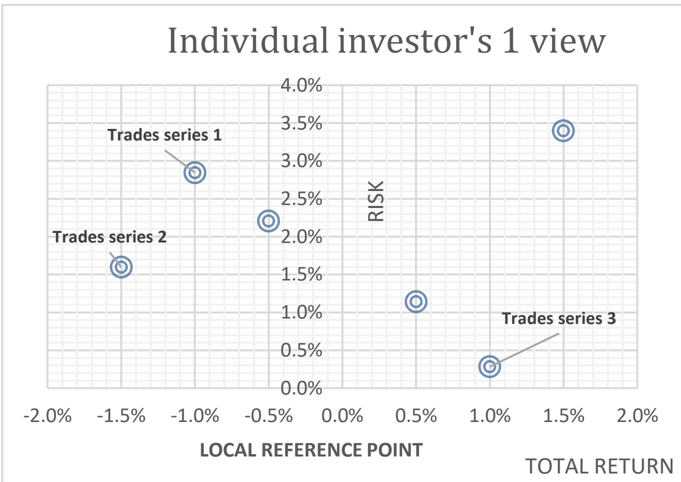
Firstly, I will explore if pooling the trading results across all investors in my sample can reveal any difference in risk behaviour. I call this perspective macro or pooled-data analysis because, for each subject, I only collect a single value of return and a single value of risk (measured as the variation of return). At this stage, I will evaluate the relation between gross risk and return across the board of my sample. The resulting relation should provide evidence of aggregated (gross) risk attitude. Specifically, it will show if all investors in my sample, in general, are risk-averse, risk-seeking or risk-neutral, and what is the role of trading success in the evinced risk preferences.

However, the macro approach fails to recognise heterogeneity in individual risk preferences. To evaluate the particularised shape of the judgment valuation function, I will need to scale down to individual trades of each investor. Obviously, even the most profitable traders have tough times of losing trades, while traders with the worst overall performance may have very good trades, meaning that each individual investor has a dispersion of trading activity around his personal reference point. At the micro level of analysis, I will step down to examine the risk behaviour patterns during good trades versus the bad trades for each individual trader. I plan that both levels of analysis will provide complementary information for hypotheses testing.

Figure 4.1. reflects the difference in macro and micro analysis perspectives.

Figure 4.1 Comparison between macro-level and micro-level perspectives.





Note: The panel on the left displays the macro view on the relation between risk and return. Each observation on this panel represents the risk-return coordinates of an individual investor. All observations taken together allow making an inference about the risk preferences of the aggregated sample of investors. Each investor finds its place on the graph relative to the single global reference point. The panel on the right is a single investor's perspective of the risk-return relation. Here each observation embodies the coordinates of the average risk and return of the sequence of 20 transactions of a single trader. The positioning of observations on the right panel against the local (investor-specific) reference point, which is zero return, allows making a conclusion about individual subject's risk behaviour.

4.2.2. Macro-level analysis of correlations between risk and return – a comprehensive view

As was specified above, at the macro level of analysis, each investor is represented with a single measure of profitability (average return) and risk (standard deviation of return) across his complete trading history. In this perspective, I aim to evaluate the gross risk behaviour patterns of the whole sample of investors. I start my investigation of the relation between risk and return by computing one parametric (Pearson correlation) and two nonparametric (Spearman rank correlation and Kendall's rank correlation) measures of correlation for all 3,670 investors in my selection irrespective of their performance.

Table 4.1. Correlation between risk and return for all individual traders based on Pearson, Spearman and Kendall correlation measures.

Correlation measure	Total return and total risk	Total return and positive semi-deviation	Total return and negative semi-deviation
Pearson correlation	-0.576*** (0.000)	0.337*** (0.000)	-0.626*** (0.000)
Spearman rank correlation	-0.234*** (0.000)	0.072*** (0.000)	-0.300*** (0.000)
Kendall rank correlation	-0.174*** (0.000)	0.043*** (0.000)	-0.215*** (0.000)

Note: The table shows the computed correlation coefficients between risk and return for all 3,670 subjects. Three measures of correlation are employed: Pearson, Spearman rank and Kendall rank correlations. For each of the coefficients, p-values are provided in the brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

All the three measures of correlation uncover an overall negative relation between profitability and total risk (first column in Table 4.1). Based on the most conservative technique – Kendall rank correlation, the correlation between pooled-data risk and return equals to -0.17. Furthermore, when I split the total risk measure into positive and negative semi-deviations (according to Formulas 3.4 and 3.5), I discover statistically significant positive relation between the total return and risk behaviour for gaining trades (positive semi-deviation – the second column in Table 4.1), which equals to 0.04 according to Kendall correlation measure, and significant negative relation between total return and risk behaviour for losing trades (negative semi-deviation – the third column in Table 4.1) - -0.22 as per Kendall rank correlation. What is more, for all the measures of correlation that I use, losing trades behaviour is more sizably related to the total return.

My results imply that for the aggregate of investors, a lower return is associated with higher volatility. This finding does not support the traditional model of risk-aversion dominance, which commands a positive relation between profitability and risk. At the first approximation, this picture complies with the Prospect Theory's predictions because all three risk behaviour patterns put forth by this theory can be found in the findings: the last column's result is explained by the convex value function for losses, the second column's positive correlation is the demonstration of concavity of the value function for gains. Inherent loss aversion effect clarifies the dominance of negative correlation over positive. In the losses domain, profitability becomes much more aligned with the factor of risk (negative variance) than other factors attributable to explaining trading performance, such as experience, cultural background, financial literacy, etc. In the domain of gains, the array of non-risk related variables is seemingly more powerful, making the connection between profitability and return less robust.

4.2.3. Macro-level analysis of correlation: comparison between winning and losing investors

In the previous section, I evaluated the risk-return relation for all my subjects and found the traces of overall risk-seeking behaviour. Yet, the primary purpose of my analysis is to investigate if risk behaviour characteristics are getting modified by investors subject to changes in profitability. For the null hypothesis to hold, I must confirm that investors performing above or below the global reference point demonstrate a consistently positive correlation between their risk and return variables. However, if investors behave according to Prospect Theory, three-pattern behaviour should be reflected: positive correlation coefficient for the performance above the reference point, the negative correlation coefficient for the results below the reference point, and larger correlation coefficient for losing investors than for gaining ones. Typically, in the studies on trading and investment performance, the traditional reference point is zero return. I believe that for the purpose of this study it is the right choice so I will hold on to it as well. In the next step, I divide the investors into two groups: the ones with a total return above 0% are designated as 'Gainers', while the other part of traders performing below 0% is attributed to 'Losers'. Out of 3,670 traders in my selection[42], 1,193 individuals (32.5%) got to the 'Gainers' group. The rest of 2,477 individuals (67.5%) showed the result below 0%. I evaluate the correlation between risk and return for each of the groups. The proceeds are provided in Table 4.2:

[42] Considering that the criteria for the selection was the minimum of 200 transactions (only position-opening trades were considered), the overall trading result represents a relatively sustainable measure of trading success.

Table 4.2. Correlation between total risk and return for individual traders with performance above and below the reference point based on Pearson, Spearman and Kendall correlation measures.

Correlation measure	Correlation between risk and return for 'Gainers' group	Correlation between risk and return for 'Losers' group
Pearson correlation	0.811*** (0.000)	-0.900*** (0.000)
Spearman rank correlation	0.579*** (0.000)	-0.702*** (0.000)
Kendall rank correlation	0.414*** (0.000)	-0.526*** (0.000)

Note: The table shows the computed correlation coefficients between risk and return for 1,193 'gainers' and 2,477 'losers'. Three measures of correlation are employed: Pearson, Spearman rank and Kendall rank correlations. For each of the coefficients, p-values are provided in the brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

Grounded on the most conservative correlation technique, the gross correlation between total risk and return equals to 0.41 for the outperforming group of investors, and -0.53 for underperformers. All coefficients are statistically significant at the 1% level.

Examination of the relation between total risk and total return provides the support for the alternative hypotheses: all the three behavioural patterns put forth by the Prospect Theory are observable. 'Gainers' group demonstrates a substantial positive link between the two variables pointing to overall risk aversion. 'Losers' group, on the contrary, reveals a high negative correlation between total risk and total return and, according to my methodology, convex value function. Also, for each of the correlation measures the negative correlation of 'Losers' is higher than the positive correlation of 'Gainers' (in absolute value) highlighting the loss aversion.

Based on the aggregate-level correlation study above, it can be stated that individual investors tend to behave in accordance with the Prospect Theory's prescriptions and the predictions outlined in the theoretical model in Section 2.10. Successful individuals with the return above the reference point demonstrate positive relation between risk and return factors, while less successful investors performing below the reference threshold display the risk-seeking behavioural pattern. Besides, as predicted by the Prospect Theory, losses accentuate the interaction between risk and return, making the connection stronger than in case of gains.

In the next section, I conduct several robustness checks to substantiate the obtained findings.

4.2.4. Robustness analysis of the macro-level correlation between risk and return

I use two different methods to test the robustness of correlation analysis: trimming 1st and 99th percentiles and trimming 5th and 95th percentiles of total return and total risk.

The results of robustness tests for the large data set are presented in Table 4.3:

Table 4.3. Robustness tests of correlation between total risk and total return for all subjects based on Pearson, Spearman and Kendall correlation measures.

Correlation measure	**1% Trimmed total return**	**1% Trimmed total risk**	**5% Trimmed total return**	**5% Trimmed total risk**
Pearson correlation	-0.512*** (0.000)	-0.428*** (0.000)	-0.352*** (0.000)	-0.174*** (0.000)
Spearman rank correlation	-0.247*** (0.000)	-0.238*** (0.000)	-0.264*** (0.000)	-0.193*** (0.000)
Kendall rank correlation	-0.180*** (0.000)	-0.174*** (0.000)	-0.187*** (0.000)	-0.139*** (0.000)

Note: The table displays the computed correlation coefficients between risk and return for the whole data set of 3,670 investors after two robustness checks are applied to the data. Three measures of correlation are employed: Pearson, Spearman rank and Kendall rank correlations. For each of the coefficients, p-values are provided in the brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

Compared to non-robust results, the findings for all subjects' correlation between total risk and return changed substantially for Pearson correlation method, which is predictably the most sensitive to the information hidden in the top and bottom percentiles of the data set. For example, when trimming 5% from the top and bottom of the risk variable, Pearson correlation rose from the initial -0.58 to -0.17. The difference between trimming 1% and 5% of data was also substantial for Pearson correlation. For non-parametric methods, the change has been much less dramatic. In particular, Spearman correlation has risen from -0.23 to -0.19 for 5% trimmed total risk and remained unchanged for other robustness approaches. In turn, Kendall rank correlation has risen from -0.17 to 0.14 for 5% trimmed total risk.

I can conclude that, generally, the result is unchanged – investors in aggregate demonstrate risk-seeking behaviour. As expected, the largest impact of trimming is on Pearson correlation measure that is more sensitive to outliers

Next, I apply the same tests to 'Gainers' group and 'Losers' group. The proceeds are provided in the table below. 'Gainers' group is displayed in Section A and 'Losers' group in Section B.

Table 4.4. Robustness tests of correlation between total risk and total return for individual traders with performance above and below the reference point based on Pearson, Spearman and Kendall correlation measures.

Section A. 'Gainers' group correlation between total risk and total return after trimming the outliers.

Correlation measure	**1% Trimmed total return**	**1% Trimmed total risk**	**5% Trimmed total return**	**5% Trimmed total risk**
Pearson correlation	0.791*** (0.000)	0.821*** (0.000)	0.567*** (0.000)	0.476*** (0.000)
Spearman rank correlation	0.568*** (0.000)	0.567*** (0.000)	0.526*** (0.000)	0.495*** (0.000)
Kendall rank correlation	0.403*** (0.000)	0.402*** (0.000)	0.367*** (0.000)	0.342*** (0.000)

Section B. 'Losers' group correlation between total risk and total return after trimming the outliers.

Correlation measure	**1% Trimmed total return**	**1% Trimmed total risk**	**5% Trimmed total return**	**5% Trimmed total risk**
Pearson correlation	-0.830*** (0.000)	-0.835*** (0.000)	-0.722*** (0.000)	-0.710*** (0.000)
Spearman rank correlation	-0.701*** (0.000)	-0.689*** (0.000)	-0.672*** (0.000)	-0.632*** (0.000)
Kendall rank correlation	-0.523*** (0.000)	-0.513*** (0.000)	-0.494*** (0.000)	-0.459*** (0.000)

Note: The table displays the computed correlation coefficients between risk and return for 'Gainers' and 'Losers' groups after two robustness checks are applied to the data. Three measures of correlation are employed: Pearson, Spearman rank and Kendall rank correlations. For each of the coefficients, p-values are provided in the brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

As for the complete data set, the largest shifts as a result of robustness checks could be observed for Pearson correlation, which varied from 0.79 (1% trimmed total return) to 0.48 (5% trimmed total risk) for 'Gainers' group, and from -0.83 (1% trimmed total return) to -0.71 (5% trimmed total risk) for 'Losers' group. Two non-parametric methods proved to be less sensitive to the selected robustness tests.

After the robustness tests, all three behavioural patterns observed before have preserved. It can still be asserted that the correlation analysis supports the explanation of investors' behaviour grounded on the premises of Prospect Theory.

4.2.4.1. Robustness test of the macro-level correlation using EUR/USD currency pair

The Foreign Exchange market, which defines the context and the boundaries of the current research, is known to be heavily dominated by one single currency pair – EUR/USD. This is equally true for institutional market and retail trading. In my dataset, as I demonstrate in the Data Description section, EUR/USD pair is the most popular for 60% of all the subjects. That is why it is essential to test my results against the dominating pair-specific influence.

To conduct such analysis, I use the same approach as for obtaining the results for Table 4.1. However, I only keep the subjects' EUR/USD round-trip transactions. At the same time, I preserve the requirement of minimum 200 trades. I find that out of the total sample of 3,670 traders, approximately half of them, or 1,734 individuals, fit the criteria for the robustness test. The results are shown in Table 4.5.

Table 4.5. Correlation between risk and return for all individual traders' EUR/USD trades based on Pearson, Spearman and Kendall correlation measures.

Correlation measure	**Total return and total risk**	**Total return and positive semi-deviation**	**Total return and negative semi-deviation**
Pearson correlation	-0.730*** (0.000)	0.194*** (0.000)	-0.692*** (0.000)
Spearman rank correlation	-0.143*** (0.000)	0.169*** (0.000)	-0.229*** (0.000)
Kendall rank correlation	-0.100*** (0.000)	0.112*** (0.000)	-0.158*** (0.000)

Note: The table shows the computed correlation coefficients between risk and return for 1,734 subjects based on their EUR/USD trades. Three measures of correlation are employed: Pearson, Spearman rank and Kendall rank correlations. For each of the coefficients, p-values are provided in the brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

The comparison of Table 4.5 and Table 4.1 indicates that there is no significant influence of EUR/USD currency pair on total results. For the correlation between total risk and total return, the most substantial discrepancy can be spotted for Pearson correlation measure, which can be explained by the higher impact of outliers. The other two methodologies – Spearman and Kendall – give a more consistent output.

A very similar picture is observed for the correlation between return and positive and negative risk. All the results are significant at 1% level and have the same signs.

4.2.5. Regression analysis of the macro-level relation between risk and return

A useful alternative methodology that can be employed to investigate the relation between risk and return is regression analysis, which has the advantage of providing more detailed information about the relation between variables. In the current section, I intend to regress risk and return variables to examine further evidence of the valuation function's form.

For the analysis of the dependencies between risk and return, either risk can be measured as the price of the unit of return or return can be evaluated as the premium per the unit of risk. I start with the former approach and specify the model:

$$Risk_{i,j} = \propto_i + \beta_i Return_{i,j} + \varepsilon_{i,j}$$

where i represents either 'gainers' or 'losers' group, j = 1,…,Ni represents investor in each group, $\propto_i$ is the intercept for the respective group, β_i is the slope coefficient for the respective group, and $\varepsilon_{i,j}$ is the error term.

The results of the regression analysis are displayed in Table 4.6.

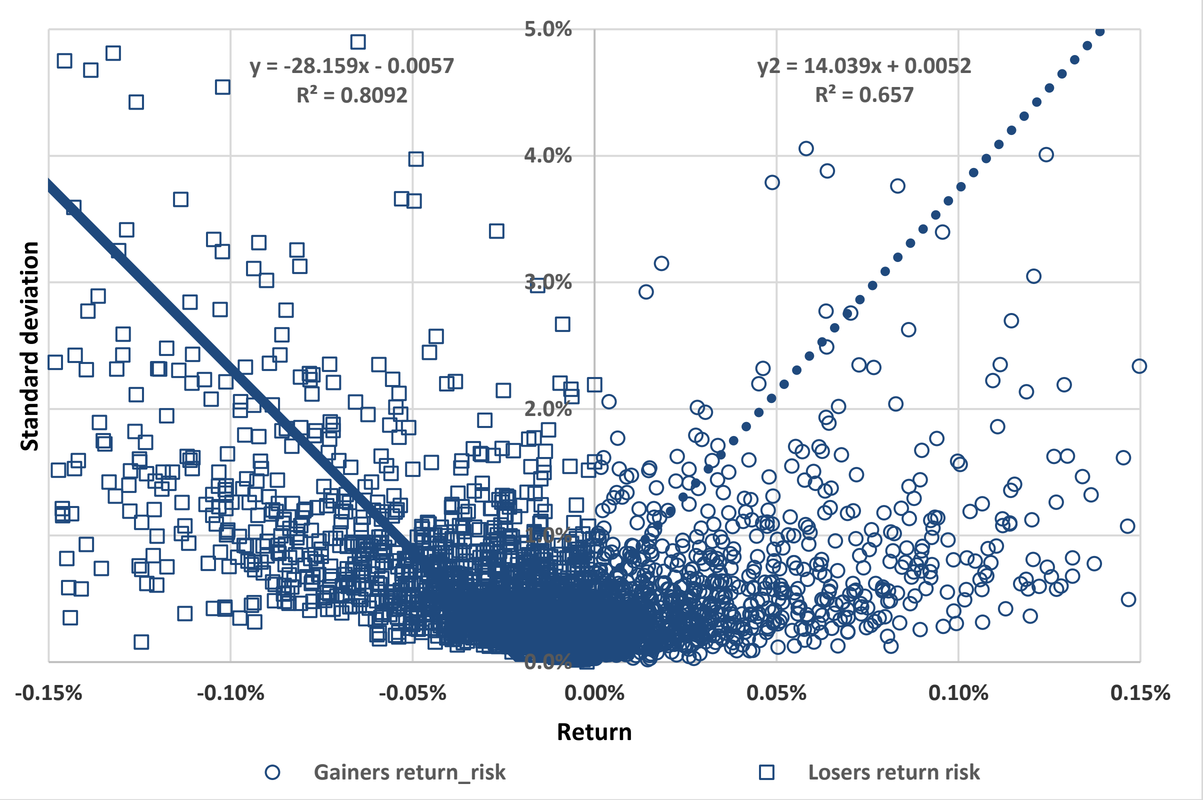
Table 4.6. Regression results for 'Gainers' and 'Losers' groups

Regression Parameter	Gainers Group	Losers Group	Difference
$\boldsymbol{\alpha_i}(\boldsymbol{intercept})$	0.052* (0.085)	-0.057 (0.105)	0.109** (0.019)
$\boldsymbol{\beta_i}(\boldsymbol{slope})$	14.039*** (0.000)	-28.159*** (0.000)	42.198*** (0.000)
R-squared	0.66	0.81	
Number of observations	1,193	2,477	3,670

Note: This table displays the main summary statistics for two regressions, in which Risk is a dependent variable and Return is the independent variable. The first column with results describes the risk-return relation for 'Gainers' group that includes investors with positive overall trading performance (above the reference point). The second column reports the regression results for 'Losers' group that covers investors with overall negative performance (below the reference point). p-values for the regression coefficients are provided in parenthesis. The third column presents the analysis of the hypothesis of the equality of constant and slope coefficients: $\alpha_{Gainers} = \alpha_{Losers}$ and $\beta_{Gainers} = \beta_{Losers}$ using an interaction variable method. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

The same approach and analysis are also presented in the graphical form in Figure 4.1.

Figure 4.1. Risk-return analysis for 'Gainers' group and 'Losers' group.



Note: The scatter plot displays the relation between risk (vertical axis) and return (horizontal axis) for every investor in the data set. The area to the right from the reference point comprises the investors from 'Gainers' group, whereas the area to the left includes the members of 'Losers' group. Firm lines are regression lines for each respective group of investors. The chart shows the regression models for each group. 'Gainers' group regression model is Risk = 0.052 + 14.039*Return. 'Losers' group regression model is Risk = -0.057 – 28.159*Return. Not all observations are displayed. Any positive (negative) outliers above (below) 0.15% (-0.15%) of return are excluded from the chart, so are the observations with standard deviation above 5%.

The intercept coefficients for 'Gainers' and 'Losers' groups equal to 0.05 and -0.06, respectively. I use the interaction variable approach to examine the significance of the difference between the coefficients of the two groups. Intercepts of the two regressions are significant at the 95% level. The slope coefficient is negative and significant for the 'Losers' group (equals to -28.16) and positive and significant for 'Gainers' group (equals to 14.04). The difference between slope coefficients of the two groups is also highly statistically significant.

Regression analysis reinforces to an extent the findings of the correlation study. Again, all three behavioural patterns are clearly demonstrated in the results. Beta coefficient for outperformers highlights the positive relation between risk and return, while for underperformers, it is strongly negative. In addition, the negative slope is two times steeper than the positive slope, which is an indication of loss aversion bias. Every 1% of return costs 28% in terms of standard deviation for underperforming investors and 14% for outperformers. These facts propagate the explanation of investors behaviour by Prospect Theory rather than neoclassical theory.

4.2.6. Robustness checks of macro-level regression analysis

Further, I conduct robustness check of my regression to see how investors with extreme values of risk or return distort the results. One of the issues with the OLS regression method is a high weight given to large residuals (or outliers) in the process of estimating coefficients that would minimise the sum of squared residuals. However, not all outliers are equally 'harmful'. Some may not affect the estimated coefficients. Others can distort the intercept coefficient. The most problematic are those that are capable of impacting the slope coefficient. A good robustness method should attribute less weight to outliers. For this purpose, I use the MM-estimator robust regression technique (Salibian-Barrera and Yohai (2006), Verardi and Croux (2009)) that I describe in the methodology section in more details. I also include the interaction variable to measure the statistical significance of the difference between slope coefficients of 'Gainers' and 'Losers'. The results are reported in the table below:

Table 4.7. Regression results for 'Gainers' and 'Losers' groups using a robust regression technique.

Regression Parameter	Gainers Group	Losers Group	Difference
$\boldsymbol{\alpha_i}(\boldsymbol{intercept})$	0.003*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
$\boldsymbol{\beta_i}(\boldsymbol{slope})$	4.233*** (0.000)	-9.411*** (0.000)	13.644*** (0.000)
R-squared	0.49	0.81	
Number of observations	1,193	2,477	3,670

Note: The table displays the main summary statistics for two regressions, in which Risk is a dependent variable and Return is an independent variable. MM-estimator robust regression technique with 85% efficiency level is applied. The first column with results describes the risk-return relation for 'Gainers' group that includes investors with positive overall trading performance (above the reference point). The second column reports the regression results for 'Losers' group that covers investors with overall negative performance (below the reference point). The third column presents the results of the interaction variable analysis showing the significance of the difference between the coefficients of 'Gainers' and 'Losers'. p-values for the regression coefficients are provided in brackets. *** shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level.

The slope coefficients obtained using the MM-estimator method are approximately three times smaller than for the non-robust model - 4.233 for 'Gainers' group and -9.411 for 'Losers' group, yet still highly significant. 1% of return hike is worth approximately 4% of total volatility for outperforming investors but -9% of total risk for losing investors. The difference between the coefficient for 'Gainers' and 'Losers' groups is also preserved. Using the interaction variable method, I show that the difference in the slope coefficient for the two groups is statistically significant.

The results demonstrate that all three behavioural risk patterns remain after application of the robustness test. All outperforming investors taken together exhibit positive relation between risk and return, whereas underperforming investors with the average return below the reference point show the evidence of combining worsening performance with increased risk, which is the sign of risk-seeking behaviour. On top of that, the negative slope is twice as steep as the positive beta for 'Gainers'.

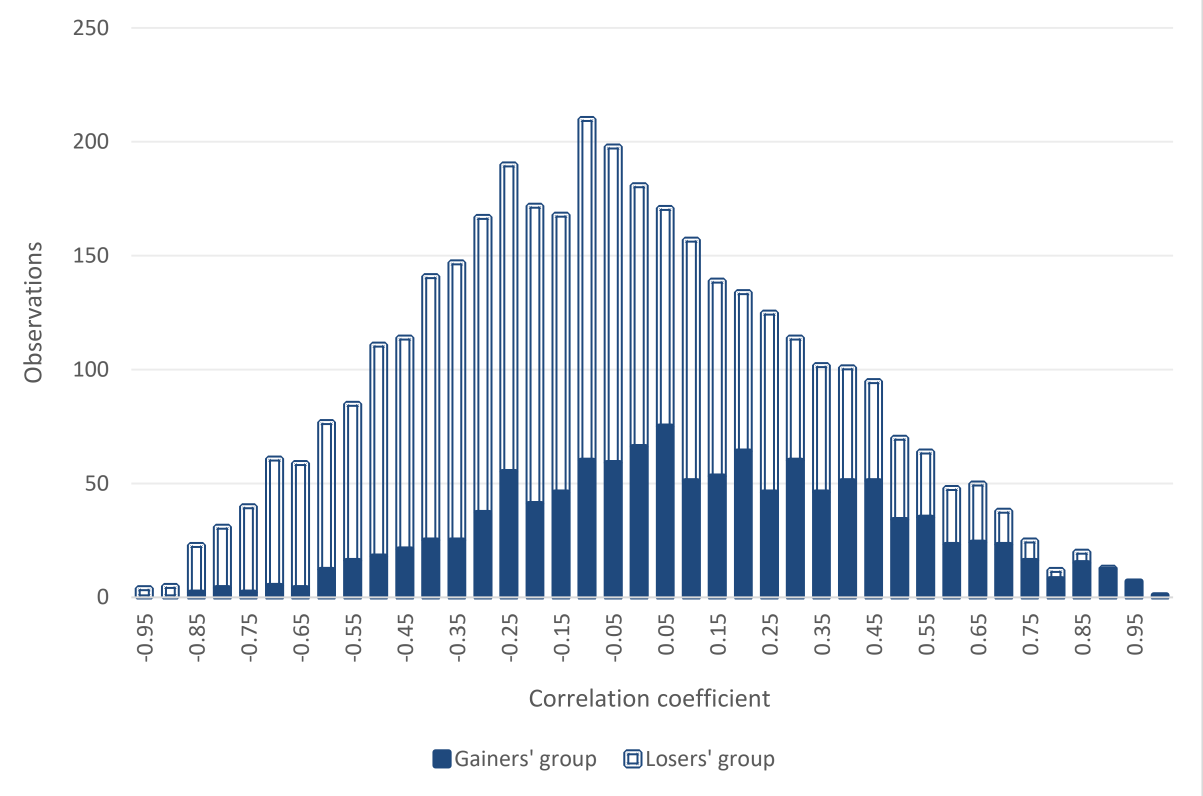
4.2.7. Micro-level analysis of correlations

The macro perspective that I explore in the prior sections provides information about group behaviour of the investors in my sample. It shows how the risk of the group is changing with respect to aggregate return. However, it says nothing about the behaviour of an individual investor because for every individual I operate with only two values of average return and total risk and cannot estimate the individual degree of rationality. Yet, it is evident that even if the gross average return of an investor is positive, individual transactions are susceptible to volatility around the reference point, which is zero profit. Some of the trades are certainly closed with profit, while the other end up in losses. Measuring how the profitability of individual transactions relates to their contribution to risk can produce evidence of individual risk behaviour of an investor. I call this angle of view the micro perspective of realised risk preference. Of course, looking at each transaction is not feasible, therefore I only approach it by combining the sequence of returns of 20 transactions, for which I compute the average profitability measure and the risk measure (standard deviation of these 20 returns). Considering that my initial criteria of sample selection are minimum 200 transactions per investor, I obtain the string of minimum of 10 observations of risk and return variables depending on the number of executed transactions, for which I calculate a correlation coefficient. This approach allows computing the so-called internal correlation coefficient between risk and return attributable to each investor. In addition, this methodology overlaps with the one I applied in the theoretical model construction in Section 2.10. Hence, the results of the micro-analytical perspective can be paralleled with the predictions of the model.

I now can assess my initial hypotheses about the shifts in risk behaviour of outperforming investors versus the underperforming investors from a different standpoint. At the macro level, I find that there is a substantial disparity in risk preference of gainers and losers: gainers tend to have a positive relation between risk and return, while losers demonstrate the opposite tendency. Now, at the micro-level, I can assign an individual (internal) coefficient of risk-return relation to each gross outperformer and underperformer. It should help me to further expand my understanding of realised individual behaviour.

I start the examination with the overview of individual correlation coefficients distribution across the two groups of investors specified according to their trading success – 'Gainers' and 'Losers'. To concur with the macro analysis results and Prospect Theory framework, I expect that the members of 'Gainers' group will tend to have a positive correlation between risk and return, while investors in the 'Losers' group should reveal a negative correlation bias. Another essential point of interest is the distribution of correlations itself. As I briefly discussed in the Literature Review section, the analysis of investors heterogeneity is scarce. Nevertheless, the existing papers demonstrate the broad diversity of individual behaviour. I expect that subjects in my study should reveal the same degree of heterogeneity and the correlation between risk and return among them would be similarly dispersed as in the case of disposition effect in the study of Dhar and Zhu (2006).

Figure 4.2. Distribution of individual correlations between risk and return for two groups of investors – ‘Gainers’ and ‘Losers’



Note: The figure displays the distribution of correlations between risk and return variables. Each column represents the number of individual investors with the individual correlation coefficient falling into the specified correlation range. The columns are split into two sections corresponding to investors’ profitability category. ‘Gainers’ group includes investors with an overall positive return. In turn, ‘Losers’ group comprises investors with the overall negative profitability.

Figure 4.2. exposes several findings. As expected, following other observed behavioural patterns, for example, individual distribution of disposition effect (Dhar and Zhu (2006)), the individual risk-return relation measure is considerably dispersed with the centre of the total distribution (for all the subjects) being positioned in the negative zone: the average correlation coefficient is -0.074, median equals to -0.093 and 59% of all observations have negative sign. The average coefficient for all investors confirms the predictions of the theoretical model that I construct in Section 2.10. The correlation coefficient that I obtain in the model for the Investor C (a stylised individual with Prospect Theory-like preferences and the parameters of the utility function matching the ones in the paper of Jakusch et al. (2019) for the real traders) equals to -0.16.

The other results are shown in Table 4.8.

Table 4.8. Main parameters of correlation coefficient distribution for all investors, 'Gainers' group and 'Losers' group.

Parameter	All subjects	Gainers Group	Losers Group
Average	-0.074*** (0.000)	0.089*** (0.000)	-0.152*** (0.000)
Median	-0.093	0.073	-0.166
Standard deviation	0.377	0.363	0.358
Percentage below zero	59%	41%	68%
Number of observations	3,670	1,193	2,477

Note: The table shows main parameters of correlation distribution for all subjects and the two performance groups. P-values are provided in brackets. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

The average correlation coefficient among the members of 'Losers' group is significantly below zero and is equal to -0.15 (median - -0.17). The opposite may be told about the average coefficient for the 'Gainers' group. It is equal to 0.09 (median – 0.07). It is noteworthy that 2/3 of 'Losers' group is featured with a negative relation between risk and profitability. 'Gainers' group is substantially more successful in this respect – almost 60% of its members demonstrate a positive correlation. Also, the negative correlation in absolute value is larger than the positive correlation.

Generally, this result is in line with my expectations. It signals the presence of all three behavioural patterns implied by Prospect Theory: a positive correlation between risk and return in the gains domain – for investors who are predominantly gainers; a negative correlation between risk and return for overall losing investors; and, finally, negative correlation exceeding positive one. Nevertheless, I also observe a picture where some of my subjects demonstrate risk behaviour that sharply contrasts the patterns of an 'average' investor. For example, 14% of 'Gainers' have individual correlation coefficient between risk and return below -0.3, while for 12% of 'Losers' it is above 0.3. This fact signifies that the relation between profitability and rationality (measured using risk-return interconnection), though present, is far from perfect.

4.2.7.1. Robustness test of micro-level correlations using EUR/USD currency pair data

As conferred in section 4.2.4.1., EUR/USD currency pair is the most popular trading instrument among the investors. Therefore, it is necessary to evaluate the impact of this pair on the relation between risk and return not only on the macro-level of analysis but also a micro level. For this purpose, I make a selection among my subjects of the individual investors having a minimum of 200 transactions with EUR/USD instrument and compute the correlation between risk and return for this particular subgroup. Altogether, 1,734 traders out of 3,670 fall under the necessary criteria. For this group, I calculate individual correlation coefficients following the approach from the previous section. The results are exhibited in Table 4.9.

Table 4.9. Main parameters of correlation coefficient distribution for all investors (from Table 4.6) compared with the correlation parameters for the subjects' EUR/USD trades only.

Parameter	**All subjects**	**All subjects with EUR/USD trades**
Average	-0.074*** (0.000)	**-0.083*** (0.000)**
Median	-0.093	**-0.100**
Standard deviation	0.377	
Percentage below zero	59%	
Number of observations	3,670	**1,734**

Note: The table compares the main parameters of correlation distribution for all subjects with the selection of subjects actively using EUR/USD currency pair as an investment instrument. P-values are provided in brackets. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

The comparison of the correlation for the total sample of investors with the subset of the active users of EUR/USD instrument shows a close resemblance of correlation coefficients. Following these findings, EUR/USD currency pair alone has no major impact on the relation between individual-level risk and return.

4.2.8. Disentangling Total Risk into Positive Risk and Negative Risk

My examination of individual behaviour so far concerned total risk as an input variable for the correlation analysis. However, total risk represents the combination of two critical components: positive risk and negative risk. Effectively, positive risk comprises the distribution of returns to the right-hand-side from the reference point that includes all winning trades. Negative risk describes the dispersion of losing transactions placed to the left from the reference point. Using only the total risk measure to judge the risk-return relation hardly can provide the exhaustive picture of individual behaviour. For instance, there can be two investors with an equally positive correlation between risk and return, yet for one of them, the change in total risk may be caused by the alteration in the gains domain (larger positive volatility), while for the other it can ensue from negative risk variation (smaller negative volatility). Therefore, the study of positive and negative risk relation to profitability serves as the robustness test of my findings in the prior section describing individual investors’ manifested rationality.

To evaluate the individual behaviour from this new perspective, I compute the correlation between the series of returns[43] and positive (negative) semi-deviations. I expect that the

[43] The methodology that I use here is the same as in the case of total risk and total return calculation. For each investor in my data set, I take sequential non-overlapping strings of individual transactions’ returns, so that each string contains 20 transactions. Next, I calculate the average return and semi-deviation for each string. The final step is to compute correlation between the obtained sequence of return and risk variables.

subjects will tend to exhibit risk-seeking behaviour to the left side of the reference point (negative semi-deviation) and risk-averse behaviour to the right side of the same point (positive semi-deviation). In other words, an average individual investor, when experiencing losses over some unlucky decision-making streak, would lean to staying relatively more risk-seeking. The same average investor would tend to close the positions earlier when on a gaining streak, thus exposing himself to a relatively stronger risk aversion. The total risk measurement would merely reflect the balance between the two flanks of behaviour.

Also, I expect that individuals with positive average total return, i.e. more successful investors, should manifest more pronounced risk aversion – higher correlation between positive and negative risk and total return, which will uncover the evidence of loss aversion.

The proceeds of my analysis are provided in Table 4.10.

Table 4.10. Analysis of the correlation between return and negative/positive risk of individual investors split into 'Gainers' and 'Losers' groups.

Section A. Correlation between return and positive semi-deviation

Parameter	Gainers Group	Losers Group
Average	0.471*** (0.000)	0.265*** (0.000)
Median	0.480	0.271
Standard deviation	0.233	0.259
Percentage below zero	2.68%	14.82%
Number of observations	1,193	2,477

Section B. Correlation between return and negative semi-deviation

Parameter	Gainers Group	Losers Group
Average	-0.330*** (0.000)	-0.451*** (0.000)

Median	-0.358	-0.463
Standard deviation	0.274	0.236
Percentage below zero	87.85%	96.41%
Number of observations	1,193	2,477

Note: The table displays the main parameters of the distribution of individual correlations between return and positive (Section A) / negative (Section B) risk for 'Gainers' and 'Losers' groups. P-values are provided in brackets. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

'Gainers' group's members with the coefficients of 0.47 for positive risk and -0.33 for negative risk show the evidence of stronger inclination towards rational decision-making because for underperforming investors the respective coefficients are 0.27 and -0.45. Moreover, 143 investors (12%) in 'Gainers' group exhibit a positive correlation between total return and both positive and negative risk, thus proving plain risk aversion as implied by the assumption of traditional financial theory. Remarkably, there are 84 such individuals in 'Losers' groups as well. Yet, percentage-wise they make only around 3% of the group's members. In turn, 'Losers' group comprises 364 investors (15%) featured with negative correlation for the two sides of risk[44]. This behavioural pattern is beyond the scope of either the traditional model or Prospect Theory.

The results of my investigation fully comply with initial expectations and the predictions of the theoretical model in Section 2.10. Even though investors from both groups demonstrate a positive (negative) correlation between return and positive (negative) semi-deviation, it is more pronounced for one of the groups. Further, I use a parametric test (t-test) and a non-parametric test (Mann-Whitney test) to verify if the difference between both groups is significant for both positive and negative risk. Both tests confirm the statistical significance of the difference at the 1% confidence interval. Outperforming investors and

[44] There are also 31 (3%) such observations in 'Gainers' group.

underperforming investors represent statistically different groups in terms of the correlation between their risk and return variables.

My final approach to corroborate the findings of the relation between risk and return in general and micro-level correlation analysis is the application of regression methodology to the individual investor-level data.

4.2.9. Micro-level regression analysis of risk and return

As discussed before, the macro-level perspective provides the opportunity to examine the aggregated interaction between risk and return. However, individual patterns of risk behaviour, which can support or counter the macro view, remain unclear. In this section, I intend to fit and inspect a regression model for risk and return for each investor in the data set. Consequently, I will generate 3,670 regression models, where the return is the independent variable and risk serves as the dependent variable. As a result, I will collect an equal amount of slope coefficients. The investor-level data allow me making an in-depth analysis of individual risk behaviour patterns by splitting the investors subject to the demonstrated degree of rationality based on each investor's slope coefficient that carries inside the relation between risk and return.

The approach that I use to elicit utility function shapes for individual investors in the micro-analysis can be paralleled with a questionnaire-based method by Fairchild et al. (2016). The authors used university students as subjects asking them to fill in a questionnaire to obtain information about the participants' risk preferences. The questionnaire covered all the spectrum of prospects – fully in the losses and gains domain as well as mixed ones. Such a method allowed the authors to compute individual estimates of utility function parameters - coefficients of risk aversion and risk-seeking and loss aversion. This analysis was complemented with the physiological examination during a trading game (measuring GSR, eye-tracking and heart rate) and the self-reporting of conscious emotions during the game.

Considering the variety of functional forms that the decision valuation function can take, I identify seven possible scenarios that an investor can reveal and to which I plan to attribute the series of beta coefficients: strong risk aversion, weak risk aversion, strong risk-seeking, weak risk-seeking, strong S-type behaviour, weak S-type behaviour, risk neutrality. The description of each scenario is presented in the table below:

Table 4.11. Description of possible scenarios of the investor-level risk-return regression analysis

Scenario	**Description**
Strong risk aversion	The relation between positive risk/total return and negative risk/total return have a positive slope coefficient. Slope coefficients for positive and negative risk are significant at the 95% level.
Weak risk aversion	The relation between positive risk/total return and negative risk/total return have a positive slope coefficient. There is no restriction with respect to the significance of the coefficients.
Strong risk-seeking	The relation between positive risk/total return and negative risk/total return have negative slope coefficient. Slope coefficients for positive and negative risk are significant at the 95% level.
Weak risk-seeking	The relation between positive risk/total return and negative risk/total return have negative slope coefficient. There is no restriction with respect to the significance of the coefficients.
Strong S-type behaviour	Individuals demonstrate risk aversion in gains domain and risk-seeking behaviour in losses domain. Slope coefficients for positive and negative risk are significant at the 95% level.
Weak S-type behaviour	Individuals demonstrate risk aversion in gains domain and risk-seeking behaviour in losses domain. There is no restriction with respect to the significance of the coefficients.
Risk neutrality	Significance of slope coefficients for positive or negative risk is below the 95% level.

The scenarios above in full describe the possible behavioural patterns of all 3,670 investors. Some of them are associated with existing financial paradigms. For example, strong and weak risk aversion can be attributed to the explanation of behaviour by traditional theory's assumptions on rationality. In turn, strong and weak forms of S-type behaviour characterise Prospect Theory assumptions. Strong and weak risk-seeking does not have a readily available explanation by any of the dominating modern financial models, yet technically the valuation function can take such form, therefore, I include it into the analysis. Finally, risk neutrality describes the investing realm, in which only return is an essential factor while risk is ignored.

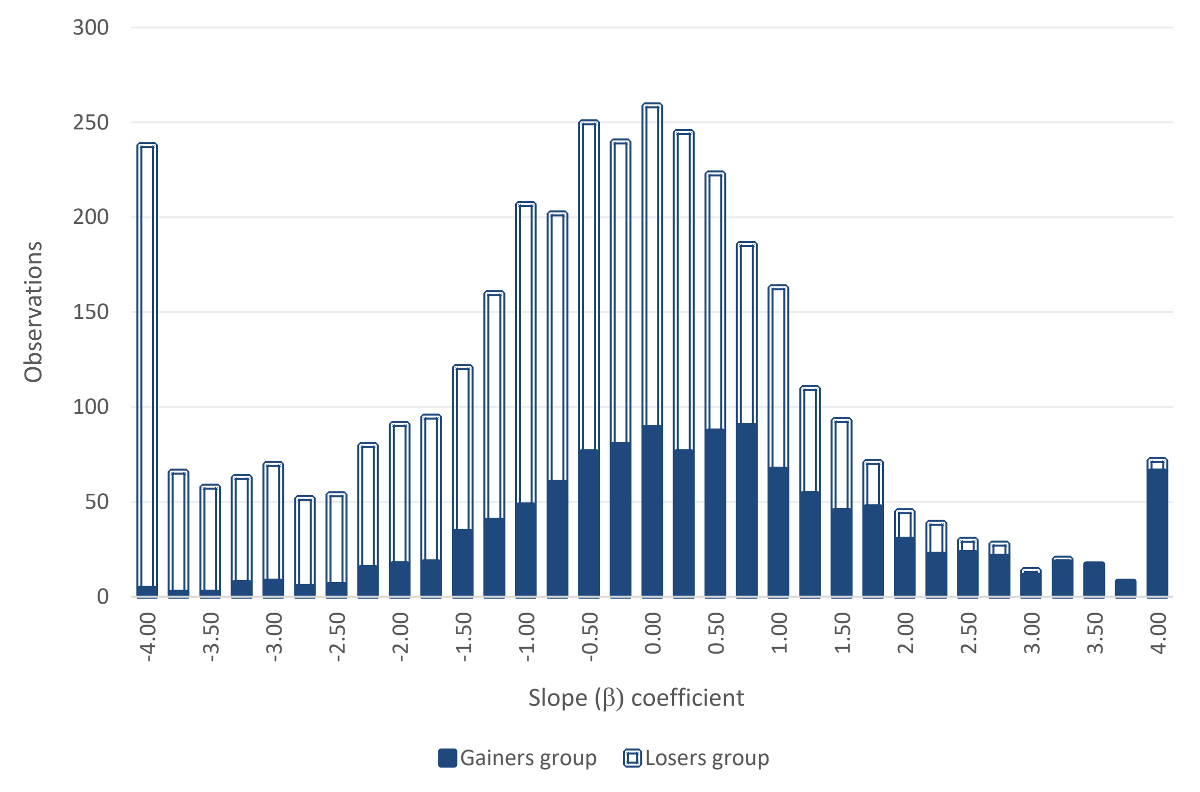
I will use the same regression model as in section 4.2.5:

$$Risk_{i,j} = \alpha_j + \beta_j Return_i + \varepsilon_{i,j}$$

where α and β coefficients denote the intercept and the slope, respectively for the risk type j and $\varepsilon_{i,j}$ is the error term.

For consistency, I present the results of the regression coefficients for two of my groups, 'Gainers' and 'Losers', independently. Figure 4.3. demonstrates the distribution of slope (β) coefficients for each individual investor. I expect to confirm the findings of my correlation analysis implying that investors' behaviour can be described with Prospect Theory and they would exhibit positive slope (beta) coefficients for positive risk, and negative slope coefficients for negative risk. Additionally, I assume 'Gainers' group' members will show a higher propensity towards rationality, and their slope coefficients will be higher on average.

Figure 4.3. Distribution of individual slope (β) coefficients of the regressions with risk as the dependent variable and return as the independent variable for two groups of investors – ‘Gainers’ and ‘Losers’.



Note: The figure displays the distribution of slope coefficients of the fitted linear regressions where risk is a dependent variable and return is an independent variable. Each column represents the number of individual investors with the individual slope coefficient falling into the specified range. The columns are split into two sections corresponding to investors’ profitability category. Gainers’ group includes investors with an overall positive return. In turn, ‘Losers’ group comprises investors with the overall negative profitability.

In the table below, I provide the summary statistics of slope coefficient distribution. In addition to total risk, I also compute the statistics for the string of regressions with positive risk (positive semi-deviation) and negative risk (negative semi-deviation) representing the dependent variable.

Table 4.12. Descriptive statistics of intercept and slope coefficients across 3,670 regressions of risk-return regression for the distribution of investors.

Section A. 'Gainers' group

	Total Risk		**Positive Risk**		**Negative Risk**	
Parameter	Intercept coefficient (α_1)	Slope coefficient (β_1)	Intercept coefficient (α_2)	Slope coefficient (β_2)	Intercept coefficient (α_3)	Slope coefficient (β_3)
Average	0.004	0.419	0.003	1.548	0.005	-1.300
Median	0.002	0.288	0.002	1.075	0.003	-0.778
Standard deviation	0.013	1.737	0.009	1.717	0.016	4.814
Percentage below zero	1.09%	42.83%	1.68%	7.38%	0.42%	83.99%
Number of observations	3	1,193	1,193	1,193	1,193	1,193

Section B. 'Losers' group

	Total Risk		**Positive Risk**		**Negative Risk**	
Parameter	Intercept coefficient (α_1)	Slope coefficient (β_1)	Intercept coefficient (α_2)	Slope coefficient (β_2)	Intercept coefficient (α_3)	Slope coefficient (β_3)
Average	0.003	-1.155	0.003	0.533	0.005	-2.481
Median	0.002	-0.830	0.002	0.264	0.002	-1.617
Standard deviation	0.011	1.753	0.007	1.086	0.011	2.519
Percentage below zero	0.36%	72.47%	0.00%	26.08%	1.29%	95.36%

Number of observations	2,477	2,477	2,477	2,477	2,477	2,477

Note: The table displays major distribution parameters for intercept and slope coefficients of 3,670 regressions fitted for each individual investor's risk (dependent variable) and return (regressor) variables. Investors are split into two groups, 'Gainers' and 'Losers' according to their total accumulated profitability over the trading period. Three different measures of risk are employed: total risk (Columns 1 and 2), Positive semi-deviation (Columns 3 and 4), Negative semi-deviation (Columns 5 and 6).

Figure 4.3. and summary statistics from Table 4.12. jointly ascertain the substantial difference in risk-return relations between 'Gainers' and 'Losers' groups of investors measured by the slope coefficient. Again, as in the case with correlation analysis, 'Gainers' group's members demonstrate a higher degree of rationality determined by the positive relation between risk and return. On average, for well-performing investors, a unit of return brings about 0.42 units of total risk. This figure can be further broken down into positive and negative risk interaction with return. Here we can find evidence of a positive slope in the case of the positive risk (1.55) and a negative slope for the negative risk (-1.30). For 'Losers' group, the average result is steeper for the negative risk, whereby the beta coefficient is highly negative (-2.48). Less successful investors also prove to show weaker risk aversion for positive risk (beta equal to 0.53).

Having computed two beta coefficients for each investor – one for gaining and another for losing string of transactions, I am now capable of making a projection of the form of the utility function for the investors in my sample. In such projection, the beta coefficient for gaining transactions reflects the curvature in the gains domain of the function, while the beta coefficient for losing trades describes the form of the function in the losses domain. The complete form that includes both domains shall fall into one of the respective behavioural categories or scenarios outlined in Table 4.11. Importance or popularity of each scenario may provide a more definite answer to my research question and help understand, which of the existing theories can better explain the financial decisions made by individuals.

Table 4.13. The breakdown of individual investors according to their manifested form of the value function expressed in risk-return relation.

Scenario type	All investors	Gainers group	Losers group
Strong risk aversion	49 (1.3%)	38 (3.2%)	11 (0.4%)
Weak risk aversion	299 (8.2%)	191 (16%)	108 (4.4%)
Strong risk-seeking	175 (4.8%)	14 (1.2%)	161 (6.5%)
Weak risk-seeking	727 (19.8%)	88 (7.4%)	639 (25.8%)
Strong S-type behaviour	856 (23.3%)	350 (29.3%)	506 (20.4%)
Weak S-type behaviour	2,637 (71.9%)	914 (76.6%)	1,723 (69.6%)
Risk neutrality	436 (11.9%)	134 (11.2%)	302 (12.2%)

Note: The table presents the breakdown of the investors in the data set grouped according to their overall accumulated performance: positive (2nd column with results) and negative (3rd column with results). Investors are matched against their dominating behaviour reflecting the form of the value function: risk-averse (concave form), risk-seeking (convex form), S-type (concave in gains domain, convex in losses domain), risk neutral (linear form). The behaviour expression is deemed firm if the slope coefficient in the model $Risk_{i,j} = \alpha_j + \beta_j Return_i + \varepsilon_{i,j}$ is significant at the 95% level. The behaviour scenarios represent the assumptions of key modern financial theories: S-type behaviour reflects the assumption of Prospect Theory; risk aversion is derived from the neoclassical economic theory (Expected Utility Theory). Global risk seeking scenarios and risk neutrality are used as complementary behavioural patterns.

It should be noted that the scenarios in the table above do not sum up to 100% because subjects included in the weak form of each behavioural pattern include investors exhibiting the solid form of the same pattern.

The results reveal an explicit confirmation of S-type behaviour dominance. Prospect Theory assumption of concavity in the gains domain and convexity in the losses domain help explain the decisions of 23% of investors in my data set within the boundaries of my methodological framework and strict limits of statistical significance (at 95% level). Relaxing the statistical significance constraint, I find that more than 70% of the subjects are disposed to fall into the S-type behavioural pattern. In turn, the weight of firm risk aversion followers remains at a very small level of 1%. Even loosening the statistical significance burden, the figure oscillates at 8%. The third set of behavioural scenarios – risk-seeking – seem to be more popular than risk aversion for financial decision making. Almost 5% of investors act along the lines of this pattern at the 95% significance level. Even more essential 20% of investors exhibit the weak form of the same behaviour model.

An interesting and important comparison can be made between ‘Gainers’ and ‘Losers’ investor groups. Unsurprisingly, the large share of risk-seeking behaviour demonstration, the least rational pattern, can be observed within the ‘Losers’ group – 7% and 26% for the firm and weak forms, respectively. In turn, ‘Gainers’ group’s members tend to get into more ‘rational’ segments: risk aversion and S-type behaviour. The difference between the two groups here is substantial, e.g. 12% for weak risk aversion, 10% for firm S-type behaviour and 7% for weak S-type behaviour in favour of more successful investors. Risk neutrality category does not reveal any distinction between the groups staying at around 11% - 12% level.

4.3. Summary and discussion of Research Question 1 results

Alternative financial models, most importantly Expected Utility Theory and Prospect Theory, make disagreeing assumptions about individual behaviour during the decision-making process, specifically the valuation of prospects. The resulting value functions also look different. According to the neoclassical theory, humans are genuinely risk-averse, while Prospect Theory puts forth a more complex framework of S-shaped value function with risk aversion prevailing only above the individual reference point. Below the point, subjects tend to become risk-seeking.

The primary purpose of my study above was to conduct empirical testing of a group of investors’ trading history trying to identify, which of the financial models can better explain the observed behaviour. Pursuing this goal, I examined the relation between risk and return using two popular methodologies – correlation analysis and regression analysis. To verify the predictions of the impact of Prospect Theory preferences on the relation between risk and return, I set up a theoretical model in Section 2.10. These predictions led me to the suggestions that the sign of correlation coefficient and the slope of the regression should indicate the form of the value function. Positive correlation and positive regression beta should point to the concave form of the function, implying a rational behavioural pattern of the positive risk premium for extra units of risk consumed. Alternatively, negative correlation and negative beta may indicate a less rational risk-seeking line of behaviour. For a more in-depth and thorough study, I split the investors in my data set into two groups – 'Gainers' and 'Losers' according to their total average performance during the observation period. I also established a constraint of a minimum of 200 trades per investor to achieve a more robust elicitation of behaviour.

Further, I conducted my testing at the two levels of data aggregation. Primarily, I analysed the results at the macro level, at which the reference point is zero total average performance attained by investors. For each investor, I collected only two aggregated observations of return and risk (standard deviation). Secondly, I explored the data at the micro level, at which the reference point is closer to the zero return of a single trade. This approach allowed me collecting a string of risk and return variables for each subject and computing within-subject (individual) correlation and regression coefficients.

The results of the macro analysis revealed the dominance of Prospect Theory-driven explanation of investors' behaviour, featuring all three essential patterns: positive relation between risk and return in the domain of gains, negative relation in the losses domain, and evidence of loss aversion, whereby negative relation turned out to be larger than positive relation. To be more specific, Spearman rank correlation between total risk and return for 'Gainers' group equalled to 0.58, whereas for 'Losers' group it was -0.70. These findings were substantiated by regression analysis. In the model with risk as the dependent variable and return as a regressor, slope coefficient for 'Gainers' group was 14.04 and the beta for

'Losers' group was equal to -28.16. At the aggregate investor-level, risk is twice more sensitive to profitability for less successful investors.

The micro-level analysis allowed constructing a distribution of correlation and slope coefficients for the subjects. This method brought to light sizeable heterogeneity of individual risk-return relations. Continuing the examination of two groups of investors according to their total average profitability, I discovered that correlation distributions for both groups are statistically significantly different. The mean correlation coefficient of 'Gainers' equalled to 0.09 and for 'Losers' this figure was -0.15. Finally, I applied regression analysis to the micro-level data to match investors' trading behaviour to seven behavioural patterns or scenarios that included risk-averse, risk-seeking, risk-neutral and S-type (or S-shape) behaviour. I found that the assumptions of Prospect Theory provide the best explanation for around a quarter of investors under the constraint of 95% statistical significance level. Relaxing the constraint, Prospect Theory managed to explain the financial decisions of almost ¾ of all investors. The other patterns were much less successful, yet they helped outline the difference between 'Gainers' group and 'Losers' group.

My research showed that there is a considerable connection between the trading success of individuals and the degree of their rationality. More profitable investors demonstrate an apparent proclivity towards more rational financial judgements as inferred from their revealed relation between realised risk and return. Moreover, this relation can serve as a useful and reliable tool to differentiate between successful and unsuccessful investors. As my analysis demonstrated, winning individuals can make better decisions in both instances of occurring scenarios – in case of gains or losses. However, even the most profitable investors could not avoid negative correlation or negative beta in the risk-return framework. Comprehensive rationality turned out to be a very rare trait, around 3 times more uncommon than its antipode – comprehensive risk-seeking behaviour.

Considering the identified association between investors' performance and risk-return correlation, it becomes practical and appealing to evaluate the factors that impact the degree of the linear relation between risk and return variables. Basically, if such factors exist, they can be interpreted as influencing the extent of individual rationality. In the second research question, I intend to use multiple linear regression methodology to examine the link between an array of personal, risk and trading variables pertinent to the subjects in my data set, and individual correlation coefficients.

4.4. Research Question 2. Hypotheses development

My second research question ensues from the results of the study that I conducted in Research Question 1. The question is formulated in the following way: what is the role of diverse personal and trading factors in the degree of individual rationality? As in the first research question, I proxy rationality with the individual-level correlation between risk and return. In the next sections, I plan to investigate the effect of a group of variables that I collected from the data set on individual correlation coefficients of my subjects. This analysis implies the use of multiple regression techniques, wherein correlation coefficients serve as a dependent variable, and a collection of trading and personal factors are used as regressors. To make a more detailed analysis, I follow the approach in the first research question and break up the investors into two groups – 'Gainers' and 'Losers' – depending on their total average return. Investors with the total average return above zero are included into 'Gainers' group. The rest investors will fall into 'Losers' group.

Further, I list the groups of variables along with my expectations of their impact on the dependent variable.

Risk variables:

- **Total risk (variable name: stdev_total - standard deviation) –** I compute total risk as a statistical measure of standard deviation of individual transactions' returns. According to my methodology, one observation of risk is calculated for a string of 20 consecutive transactions. Considering that the minimum trades requirement is 200, I possess at least 10 standard deviation observations for every investor.
- **Positive risk (variable name: stdev_positive - positive standard semi-deviation) –** calculated according to Formula 3.2. Just as total risk variable, I collect at least 10 observations of positive risk per each investor.
- **Negative risk (variable name: stdev_negative - negative standard semi-deviation) -** calculated according to Formula 3.1. Just as total risk variable, I collect at least 10 observations of negative risk per each investor.

Expected sign: The findings in the first research question point to the negative correlation between total risk and return, and negative risk and return. At the same time, the correlation between positive risk and return appeared to be positive. Yet, the main question with risk variables here is the dependence of the correlation coefficient on the level of risk. The value function in Prospect Theory or Expected Utility Theory reflects the diminishing sensitivity of psychological perception to change in wealth, hence I hypothesise that the link between risk and return at a higher level of volatility should wane. It is equally valid for positive and negative risk variables. Therefore, my prediction is the negative relation between risk variables and risk-return correlation.

Personal variables:

- **First deposit (variable name: First_deposit)** – the monetary size of the first deposit made by an investor to the account (in USD currency).
- **Availability of second deposit (variable name: If_second_deposit)** – binary variable reflecting the fact that an investor has made a second deposit to the account.

- **Second deposit (variable name: Second_deposit)** – the monetary size of the second deposit made by an investor to the account (in USD currency).
- **Time between first and second deposit (variable name: Days_between_deposits)** – number of days that pass between the first deposit and the second deposit.
- **Deposit-to-income ratio (variable name: Deposit_to_income)** – is calculated as the monetary size of the first deposit divided by the self-reported annual income of an investor. Annual income is an investor's self-reported value
- **Deposit-to-fortune ratio (variable name: Deposit_to_fortune)** – is calculated as the monetary size of the first deposit divided by the self-reported fortune of an investor. Fortune is an investor's self-reported value
- **Male (variable name: Male)** – sets the investor's gender to 1 if it is male, and 0 if female.
- **Age (variable name: Age)** – an investor's age.
- **Developed country nationality (variable name: Developed_country)** – the country of an investor belonging to the OECD (Organisation for Economic Cooperation and Development) country club. 0 = non-OECD country, 1 = OECD country.
- **Contest (variable name: Contest)** – funds on the Live account are received from participation in one of the trading contests. 0 = non-contest participant, 1 = contest participant.

Expected sign: In the study, I use correlation as a proxy for rational behaviour, therefore in my expectations, I try to assess the interaction between the highlighted independent variables and the degree of rationality of decisions. As some models of the role of emotions in decision making imply (e.g. Loewenstein and O'Donoghue (2004) or Mukherjee (2010)), the individual risky choice varies between two qualitatively different systems of judgement: rational and emotional, or cognitive and affective. The proximity to one of the extremes depends on the peculiarities and strength of relating stimuli. More important stimuli drive the choice towards higher affectivity. Logically, the invested money and its significance for an investor should be one of such weighty factors. Four of the variables – the size of the first deposit, deposit-to-fortune ratio, deposit-to-income ratio and Contest money[45] may represent and outline the level of importance for an investor. Accordingly, I hypothesise negative beta for these factors. Furthermore, the variables related to the second deposit are associated with less successful investors because usually, the second deposit is only necessary if the first deposit is depleted due to losses. Based on the findings in the first research question, trading success is negatively connected to rationality. Therefore, I expect the presence of the second deposit and its size to be negatively related to correlation, while days between deposits should have positive beta because a fewer number of days indicates quicker loss of the initially invested funds.

Finally, Age and Developed_Country variables are frequently used as proxies for the experience and financial knowledge (see e.g. Chen et al. (2007)). I expect to observe the positive impact of both on the degree of rationality (correlation).

Trading variables:

- **Intraday trades (variable name: %_of_intraday)**– the share of intraday trades among all investor's transactions. Intraday means a transaction is opened and closed within a single trading day.
- **Number of trades (variable name: N_trades)** – number of transactions completed on an investor's account during the observation period.
- **Number of instruments (variable name: N_instruments)** – number of trading instruments used by a trader during the observation period.

[45] In my view, Contest as a source of investable funds brings about the bias of 'house money effect' (Thaler and Johnson (1990)), which causes higher risk taking for 'cheap' money, hence less rational decisions.

- **Conditional orders** – a portion of conditional orders. I used ten sub-variables that described five various types of conditional orders: 1) Market open (variable name: Market_open) – portion of trades opened with a market order; 2) Market close (variable name: Market_close) – portion of trades closed with a market order; 3) Conditional open (variable name: Conditional_open) – portion of traders opened with a conditional order; 4) Stop-loss close (variable name: Stop_loss_close) – portion of trades closed with a stop-loss order; 5) Take-profit close (variable name: Take_profit_close) – portion of trades closed with a take-profit order.
- **Turnover (variable name: Turnover)** – aggregated trading turnover on investor's account.
- **Duration (variable name: Duration)** – median duration of trades on investor's accounts.

Expected sign: Continuing the line of thoughts about the positioning of risky choice between rationality and emotions, I suggest that excessive trading should prompt the choice away from the rational pole. Hence, I expect these factors to have a negative beta. Prior research (e.g. Barber et al. (2017)) claimed that day trading is negatively related to rationality and profitability. In this regard, I predict that the share of intraday trades, number of trades, turnover and number of instruments also should have a negative beta. Based on the same logic, duration should have a positive beta, because shorter time frames between the opening and closing of investments indicate excessive trading. Concerning the use of conditional orders, though this area of research is scarce, there is evidence from Linnainmaa (2010) who compared market orders to conditional orders in terms of profitability and inferred psychological awareness of financial decisions. He discovered that in terms of intraday returns an average investor is better off using conditional orders. Also, intuitively, market orders are placed 'in the heat of the moment' with virtually immediate effect, leaving very limited time for cognitive processing of huge amount of information that generally accompanies a trade. Conditional orders provide for a better opportunity of pre-placement and post-placement information processing and correction. In this context, conditional orders are expected to comprise a higher degree of rationality than market orders. Therefore, I predict that conditional orders should have a positive beta in the regression, while market orders should be featured with negative beta.

4.5. Research Question 2. Empirical Analysis

I commence the empirical section with the set of descriptive statistics of my variables presented in Table 4.14.

Table 4.14. Descriptive statistics of investors' data set.

Variable name	All subjects				'Gainers' group				'Losers' group			
	Average	Median	Min	Max	Average	Median	Min	Max	Average	Median	Min	Max
Section A. Risk variables												
Stdev_total (%)	0.87%	0.39%	0.00%	24.92%	0.80%	0.41%	0.02%	22.29%	0.91%	0.38%	0.00%	24.92%
Stdev_positive (%)	0.53%	0.27%	0.00%	28.96%	0.85%	0.36%	0.02%	28.96%	0.37%	0.25%	0.00%	14.94%
Stdev_negative (%)	1.14%	0.44%	0.00%	40.19%	0.72%	0.44%	0.02%	19.51%	1.34%	0.43%	0.00%	40.19%
Section B. Personal variables												
First_deposit (USD)	1100	392	0	12747	1303	401	0	19565	1022	392	0	10259
If_second_deposit (binary)	75.29%				73.18%				76.30%			
Second_deposit (USD)	619	130	0	9957	654	133	0	9091	598	130	0	9958
Days_between_ Deposits (days)	91	21	0	985	87	17	0	1037	93	23	0	940
Deposit_to_income (%)	3.26%	1.19%	0.00%	35.65%	3.70%	1.18%	0.00%	48.36%	3.10%	1.21%	0.00%	33.20%
Deposit_to_fortune (%)	1.30%	0.47%	0.00%	15.65%	1.48%	0.48%	0.00%	19.00%	1.22%	0.46%	0.00%	13.44%
Male (binary)	91.80%				91.28%				92.05%			
Age (years)	39	38	22	68	39	38	22	66	39	38	22	69
Developed_country	55.67%				53.31%				56.80%			

(binary)												
Contest (binary)	6.62%				6.87%				6.50%			
Section C. Trading variables												
%_of_intraday (%)	82.40%	87.08%	26.77%	100.00%	79.30%	83.52%	27.91%	100.00%	83.87%	88.79%	24.00%	100.00%
N_trades (number)	935	529	203	7066	1038	551	204	8481	888	521	202	6355
N_instruments (number)	14	12	1	44	13	11	1	43	15	13	1	45
Market_open (%)	83.99%	96.07%	1.20%	100.00%	82.93%	95.20%	2.02%	100.00%	84.50%	96.52%	1.00%	100.00%
Market_close (%)	64.28%	67.11%	6.29%	100.00%	67.07%	71.43%	7.81%	100.00%	62.94%	64.93%	5.54%	100.00%
Conditional_open (%)	16.00%	3.93%	0.00%	98.80%	17.07%	4.80%	0.00%	97.98%	15.50%	3.48%	0.00%	99.07%
Take_profit_close (%)	15.38%	11.22%	0.00%	73.00%	17.34%	12.48%	0.00%	81.45%	14.45%	10.72%	0.00%	66.66%
Stop-loss_close (%)	20.19%	16.21%	0.00%	65.82%	15.46%	10.12%	0.00%	60.16%	22.46%	19.29%	0.00%	66.75%
Turnover (mln USD)	34.20	11.11	0.54	440.14	38.34	12.45	0.54	518.47	32.47	10.54	0.57	427.63
Duration (minutes)	162	38	2	2841	196	46	2	2798	145	35	2	2848

Note: In all sections, I winsorised 1% of extreme observations. The dataset includes descriptive statistics for 3,670 individual investors. First deposit variable can equal to zero because some of the subjects are winners of trading contests organised by the brokerage house. According to the rule of the contest, the prize must be transferred onto the Live account. Such prizes do not count as deposits. Variables meanings are provided in section 4.4.

Table 4.15. Correlation matrix for independent variables included in the dataset.

Section 1. Risk variables

	Stdev_positive	Stdev_negative
Stdev_positive	1	0.13*** (0.000)
Stdev_negative	0.13*** (0.000)	1
N_trades	0.00 (0.952)	0.01
N_instruments	0.07*** (0.000)	-0.03* (0.069)
Turnover	0.01 (0.505)	0.10*** (0.000)
Duration	0.20*** (0.000)	0.13*** (0.000)
Conditional_open	0.03* (0.051)	-0.05*** (0.001)
Take_profit_close	-0.01 (0.431)	0.03** (0.039)
Stop_loss_close	0.00 (0.762)	-0.16*** (0.000)
First_deposit	0.00 (0.586)	0.02 (0.163)
Second.deposit	0.04*** (0.007)	0.08*** (0.000)
Days_between_deposits	0.04** (0.012)	0.03* (0.060)
Deposit_to_income	0.00 (0.856)	0.01 (0.431)
Gender	0.01 (0.397)	0.00 (0.808)
Age	-0.03** (0.021)	-0.02* (0.089)

Developed_country	-0.03**	-0.02
	(0.029)	(0.115)
Contest	0.01	0.02
	(0.363)	(0.129)

Section 2. Personal variables

	First_ deposit	Second_ deposit	Days_between_ deposits	Deposit_ to_income	Gender	Age	Developed_ country	Contest
Stdev_positive	0.00	0.04**	0.04***	0.00	0.01	-0.03**	-0.03*	0.01
	(0.904)	(0.013)	(0.009)	(0.762)	(0.431)	(0.046)	(0.069)	(0.431)
Stdev_negative	0.02	0.08***	0.03**	0.01	0.00	-0.02	-0.02	0.02*
	(0.164)	(0.000)	(0.034)	(0.364)	(0.672)	(0.102)	(0.130)	(0.090)
N_trades	0.04***	0.18***	0.12***	0.06***	-0.02	0.18***	0.05***	-0.01
	(0.004)	(0.000)	(0.000)	(0.000)	(0.115)	(0.000)	(0.003)	(0.505)
N_instruments	-0.03**	0.06***	0.08***	-0.01	0.03**	-0.09***	0.06***	0.03*
	(0.021)	(0.000)	(0.000)	(0.276)	(0.039)	(0.000)	(0.000)	(0.060)
Turnover	0.22***	0.25***	0.05***	0.21***	-0.02	0.10***	0.06***	0.04***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.203)	(0.000)	(0.000)	(0.004)
Duration	0.06***	0.08***	0.08***	0.02	0.01	-0.01	-0.03*	-0.04***
	(0.000)	(0.000)	(0.000)	(0.102)	(0.250)	(0.348)	(0.062)	(0.005)
Conditional _open	0.07***	0.00	0.03**	0.04***	-0.01	0.01	0.04**	-0.05***
	(0.000)	(0.780)	(0.021)	(0.008)	(0.276)	(0.312)	(0.011)	(0.000)
Take_profit _close	0.10***	0.03*	0.03*	0.02	-0.02	-0.01	0.02*	-0.08***
	(0.000)	(0.061)	(0.069)	(0.151)	(0.102)	(0.250)	(0.081)	(0.000)
Stop_loss_close	0.07***	-0.01	0.10***	-0.03*	0.04***	-0.12***	0.12***	-0.11***
	(0.000)	(0.345)	(0.000)	(0.060)	(0.004)	(0.000)	(0.000)	(0.000)
First_deposit	1	0.25***	0.20***	0.31***	0.06***	0.13***	0.24***	-0.70***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Second.deposit	0.25***	1	0.69***	-0.02	0.05***	0.02	0.06***	-0.32***
	(0.000)		(0.000)	(0.102)	(0.001)	(0.179)	(0.000)	(0.000)
Days_between _deposits	0.20***	0.69***	1	-0.02	0.05***	-0.01	0.09***	-0.28***
	(0.000)	(0.000)		(0.143)	(0.002)	(0.349)	(0.000)	(0.000)
Deposit_to _income	0.31***	-0.02	-0.02	1	-0.04***	0.06***	0.07***	-0.07***
	(0.000)	(0.113)	(0.203)		(0.005)	(0.000)	(0.000)	(0.000)

Gender	0.06*** (0.000)	0.05*** (0.001)	0.05*** (0.000)	-0.04*** (0.003)	1	-0.02 (0.134)	0.03** (0.039)	-0.11*** (0.000)
Age	0.13*** (0.000)	0.02 (0.102)	-0.01 (0.276)	0.06*** (0.000)	-0.02 (0.203)	1	0.13*** (0.000)	-0.07*** (0.000)
Developed _country	0.24*** (0.000)	0.06*** (0.000)	0.09*** (0.000)	0.07*** (0.000)	0.03** (0.021)	0.13*** (0.000)	1	-0.15*** (0.000)
Contest	-0.70*** (0.000)	-0.32*** (0.000)	-0.28*** (0.000)	-0.07*** (0.000)	-0.11*** (0.000)	-0.07*** (0.000)	-0.15*** (0.000)	1

Section 3. Trading variables

	N_trades	**N_instruments**	**Turnover**	**Duration**	**Conditional_open**	**Take_profit_close**	**Stop_loss_close**
Stdev_positive	0.00 (0.867)	0.07*** (0.000)	0.01 (0.373)	0.20*** (0.000)	0.03* (0.060)	-0.01 (0.276)	0.00 (0.912)
Stdev_negative	0.01 (0.250)	-0.03** (0.039)	0.10*** (0.000)	0.13*** (0.000)	-0.05*** (0.000)	0.03** (0.016)	-0.16*** (0.000)
N_trades	1	0.14*** (0.000)	0.52*** (0.000)	-0.12*** (0.000)	-0.03** (0.035)	-0.05*** (0.002)	-0.06*** (0.000)
N_instruments	0.14*** (0.000)	1	0.01 (0.367)	0.31*** (0.000)	0.02 (0.203)	-0.06*** (0.000)	0.13*** (0.000)
Turnover	0.52*** (0.000)	0.01 (0.471)	1	-0.21*** (0.000)	-0.09*** (0.000)	-0.08*** (0.000)	-0.14*** (0.000)
Duration	-0.12*** (0.000)	0.31*** (0.000)	-0.21*** (0.000)	1	0.17*** (0.000)	0.13*** (0.000)	0.06*** (0.000)
Conditional _open	-0.03* (0.053)	0.02 (0.102)	-0.09*** (0.000)	0.17*** (0.000)	1	0.28*** (0.000)	0.33*** (0.000)
Take_profit _close	-0.05*** (0.002)	-0.06*** (0.000)	-0.08*** (0.000)	0.13*** (0.000)	0.28*** (0.000)	1	0.13*** (0.000)
Stop_loss_close	-0.06*** (0.000)	0.13*** (0.000)	-0.14*** (0.000)	0.06*** (0.000)	0.33*** (0.000)	0.13*** (0.000)	1
First_deposit	0.04*** (0.004)	-0.03** (0.021)	0.22*** (0.000)	0.06*** (0.000)	0.07*** (0.000)	0.10*** (0.000)	0.07*** (0.000)
If_second _deposit	0.17*** (0.000)	0.07*** (0.000)	0.14*** (0.000)	0.06*** (0.000)	-0.02 (0.203)	0.00 (0.908)	0.01 (0.250)

Second.deposit	0.18***	0.06***	0.25***	0.08***	0.00	0.03**	-0.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.713)	(0.044)	(0.541)
Days_between_deposits	0.12***	0.08***	0.05***	0.08***	0.03**	0.03**	0.10***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.016)	(0.039)	(0.000)
Deposit_to_income	0.06***	-0.01	0.21***	0.02*	0.04***	0.02	-0.03*
	(0.000)	(0.276)	(0.000)	(0.070)	(0.002)	(0.201)	(0.060)
Gender	-0.02*	0.03**	-0.02	0.01	-0.01	-0.02	0.04**
	(0.093)	(0.022)	(0.102)	(0.330)	(0.348)	(0.179)	(0.011)
Age	0.18***	-0.09***	0.10***	-0.01	0.01	-0.01	-0.12***
	(0.000)	(0.000)	(0.000)	(0.273)	(0.501)	(0.250)	(0.000)
Developed_country	0.05***	0.06***	0.06***	-0.03**	0.04**	0.02*	0.12***
	(0.002)	(0.000)	(0.000)	(0.021)	(0.012)	(0.092)	(0.000)
Contest	-0.01	0.03*	0.04***	-0.04***	-0.05***	-0.08***	-0.11***
	(0.360)	(0.060)	(0.004)	(0.004)	(0.002)	(0.000)	(0.000)

Note: The table displays the correlation matrix between all independent variables, for which the data was collected. The variables are split into three groups: Section 1 includes correlations between Risk variables and all other variables, Section 2 accentuates Personal variables, Section 3 comprises Trading variables. Variables meanings are provided in the section 4.4. P-values are reported in the parantheses. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

I use the correlation between risk and return as my dependent variable. To correct for the skewed distribution of the correlation coefficient, I apply Fisher's z transformation of correlation, which approximates the distribution to normal[46] as described in the methodology section.

Overall, the relations between variables seem reasonable. For example, Turnover is positively connected to the amount of deposits placed for trading, the number of trades, as well as to portion of intraday trading, which is logical – more active trading generates higher volume. All other revealed linear relations also seem consistent.

To test my hypotheses from various perspectives, I specify a regression model that I apply to three selections of investors: for all my subjects together, for 'Gainers' group and for 'Losers' group independently:

$$\begin{aligned}\rho_{i,j}^{Return,Risk} = {} & \alpha_j + \beta_{1,j} * Stdev_{positive_{i,j}} + \beta_{2,j} * Stdev_{negative_{i,j}} + \beta_{3,j} * N_{trades_{i,j}} + \beta_{4,j} \\ & * N_{instruments_{i,j}} + \beta_{5,j} * Turnover_{i,j} + \beta_{6,j} * Duration_{i,j} + \beta_{7,j} \\ & * Condotional_{open_{i,j}} + \beta_{8,j} * Take\ profit_{close_{i,j}} + \beta_{9,j} * Stop\ loss_{close_{i,j}} \\ & + \beta_{10,j} * First_{deposit_{i,j}} + \beta_{11,j} * Second_{deposit_{i,j}} + \beta_{12,j} \\ & * Days\ between\ deposits_{i,j} + \beta_{13,j} * Deposit\ to\ income_{i,j} + \beta_{14,j} \\ & * Gender_{i,j} + \beta_{15,j} * Age_{i,j} + \beta_{16,j} * Developed_{country_{i,j}} + \beta_{17,j} * Contest_{i,j} \\ & + \varepsilon_{i,j}\end{aligned}$$

where α is the intercept, ε is the error term, i = 1,…,N (number of investors), j = 1,2,3 denotes the type of dependent variable: for 'Gainers' group (Model 1), 'Losers' group (Model 2) and all investors (Model 3).

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[46] I run all regressions based on non-transformed correlation coefficients as well to find that there is only minor difference in regression coefficients.

The proceeds of the regression analysis are presented below.

Table 4.16. Regression analysis of the relation between risk and return for investors from 'Gainers' group (Model 1), investors from 'Losers' group (Model 2) and all investors in the data set (Model 3).

Variable name	'Gainers' group (1)	'Losers' group (2)	All investors (3)	Interaction (1) & (2)
Stdev_positive (%)	2.4038*** (0.000)	8.7300*** (0.000)	5.4046*** (0.000)	-6.3260*** (0.000)
Stdev_negative (%)	1.8475 (0.145)	-1.2590*** (0.000)	-2.2495*** (0.000)	3.1060** (0.010)
LN_N_trades (number of observations)	0.0007 (0.962)	0.0949*** (0.000)	0.0769*** (0.000)	-0.0942*** (0.000)
LN_N_instruments (number of observations)	0.0094 (0.448)	-0.0045 (0.638)	-0.0241*** (0.003)	0.0140 (0.364)
LN_Turnover (USD)	-0.0088 (0.352)	-0.0252*** (0.001)	-0.0161** (0.010)	0.0164 (0.164)
LN_Duration (minutes)	0.0172** (0.022)	0.0195*** (0.001)	0.0315*** (0.000)	-0.0023 (0.807)
Conditional_open (%)	0.0356 (0.435)	0.0364 (0.294)	0.0684** (0.021)	-0.0008 (0.988)
Take_profit_close (%)	-0.3065*** (0.000)	-0.4575*** (0.000)	-0.2795*** (0.000)	0.1509* (0.083)
Stop_loss_close (%)	1.0869*** (0.000)	1.0900*** (0.000)	0.9180*** (0.000)	-0.0029 (0.972)
LN_First_deposit (USD)	0.0240** (0.013)	0.0120* (0.086)	0.0168*** (0.006)	0.0121 (0.297)
LN_Second_deposit (USD)	0.0002 (0.965)	-0.0040 (0.267)	-0.0030 (0.315)	0.0042 (0.464)
LN_Days_between_ Deposits (days)	-0.0025 (0.711)	0.0017 (0.738)	-0.0024 (0.581)	-0.0043 (0.611)
Deposit_to_income (%)	-0.0009 (0.257)	0.0001 (0.983)	-0.0002 (0.626)	-0.0009 (0.338)
Male (binary)	0.0398 (0.295)	0.0122 (0.667)	0.0263 (0.284)	0.0276 (0.552)
LN_Age (years)	-0.1231*** (0.005)	-0.1004** (0.001)	-0.1342*** (0.000)	-0.0227 (0.662)
Developed_country (binary)	-0.0099 (0.653)	0.0221 (0.170)	0.0144 (0.305)	-0.0320 (0.230)
Contest (binary)	0.1551** (0.021)	0.0366 (0.448)	0.0766* (0.071)	0.1186 (0.142)
Constant	0.1119 (0.546)	-0.7241*** (0.000)	-0.3886*** (0.000)	0.8361*** (0.000)
R-squared	**0.20**	**0.29**	**0.22**	
Number of observations	**1,193**	**2,477**	**3,670**	

Note: The table displays regression coefficients for three regressions: with all investors correlation between risk and return as dependent variable (Model 3), with 'Gainers' group investors correlation between risk and return as dependent variable (Model 1) and with 'Losers' group investors correlation between risk and return as dependent variable (Model 2). The last column demonstrates the difference between the variables in Model 1 ('Gainers') and Model 2 ('Losers') using the interaction variable technique. Because of multicollinearity effect, I omitted several variables from the regression that had correlation above 0.80 or below -0.8 with at least one other variable: Market_open (correlated with Conditional_open), Market_close (correlated with Take_profit_close-Stop_loss_close), Deposit_to_fortune (correlated with Deposit_to_income), %_of_intraday (correlation with Duration), If_second_deposit (correlated with Second_deposit). Huber-White consistent p-values are provided in the parentheses. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

In the next sections, I review the results of regression analysis and the impact of the three groups of variables on the correlation between risk and return. After that, I advance my investigation by comparing outperforming investors ('Gainers') against underperforming ('Losers') to understand, which variables can explain the difference in profitability and/or traces of rational behaviour. For this purpose, I intend to use the interaction variable technique, a parametric test (t-test) and non-parametric test (Mann-Whitney U test).

4.5.1. The influence of Risk variables

My initial expectation was that the risk variables should be negatively related to the dependent variable. It turned out to be valid only for the negative semi-deviation variable, yet beta coefficients were statistically significant only for Models 2 ('Losers' group) and 3 (All investors). For positive risk, I observe positive betas, whereas positive risk is a statistically significant factor for all three models.

According to my results, for the average of outperforming investors, an increase in positive risk by 1% translates into 0.024 rise in risk-return correlation. Even the hike in negative risk proves to have a positive effect on the degree of rationality for investors from 'Gainers' group, which is an indication that successful traders may act in line with the prerequisites of the traditional economic model. Yet, as mentioned before, the negative risk variable's coefficient fails the acceptable significance threshold.

For underperforming investors, a change in positive risk is far more significant for the dependent variable than an equal shift in negative risk, possibly reflecting the fact that for such investors choices in the gains domain present more challenging environment. One percentage point increase in positive risk for the average trader in this group would raise the correlation coefficient by 0.087. The equivalent growth in negative risk would result in the reduction of correlation by 0.013.

In the last model that combines all investors, underperformers dominate, therefore variables' coefficients are more consistent with Model 2. 1% increase in positive risk would augment the correlation of an average investor by 0.054. At the same time, a corresponding rise in negative risk would lessen the correlation by 0.025.

Interestingly, judging from the median values, an average investor from both groups copes pretty evenly with the negative risk (median values respectively equal to 0.44% and 0.43%), however, when it comes to positive risk, the results become noticeably disparate (0.36% for outperformers and 0.25% for underperformers). The inability to properly align positive risk behaviour with the negative one and psychological factors behind this phenomenon may be one of the reasons for bad performance coupled with weaker rationality of decisions as my findings demonstrate. I develop this discussion further in Section 4.5.3.

4.5.2. The influence of Trading variables

Next, based on the principle of excessive trading, I predicted that higher values of trading variables should have a negative impact on the degree of rationality. 'Number of trades' variable appears not to conform to overtrading assumption, or at least has stronger alternative explanations behind it, for example, gain in experience as the most probable replacement. The factor is highly statistically significant in Model 2 ('Losers' group) and 3 (All subjects). As far as all investors are concerned, a 10% increase in the number of trades results in correlation rise by approximately 0.01[47]. Additional evidence in favour of experience hypothesis is the fact that for more successful investors from 'Gainers' group the average number of trades is higher than for 'Losers' group (1,069 against 916), and this difference is statistically significant at 1% level[48]. It may be an indirect confirmation of the link between elevated experience and superior trading. Therefore, investors from 'Losers' group might achieve a better level of risk aversion with more trades.

Another variable, 'Number of instruments' only partially fits my initial expectation. It is negative and significant only in the model with all investors and remains insignificant in the other two models. Increasing the number of instruments used by an investor by 10% translates into the loss in correlation by approximately 0.002.

The other variable with the primary hypothesis related to excessive trading and the expectation of negative beta is 'Turnover'. I discovered that the expectation was correct and statistically significant for two models out of three – all investors and 'Losers'. For instance, a 10% surge in this factor for 'Losers' model leads to the loss of correlation coefficient by the factor of 0.003.

'Duration' variable can be described as the opposite side of a coin in the context of trading activity. Longer duration of a round-trip trade is the indicator of less active trading, which is substantiated by slightly negative correlation with 'Number of trades', 'Turnover' and moderately negative correlation with the share of intraday trades. I expected that 'Duration' should be positively associated with rationality. This assumption was supported in all three

[47] In the model with non-transformed independent variables, every 1,000 trades increase the correlation coefficient between risk and return by 0.03.
[48] Using t-test stats and at 5% level using Mann-Whitney U test. See Table 4.14.

models. 10% upsurge in the duration of trade means approximately 0.002 improvement in correlation for 'Gainers' and 'Losers', and 0.003 increase in correlation coefficient if all investors are included in the model.

The three variables belonging to conditional orders cluster: 'Conditional open', 'Take profit close' and 'Stop-loss close', produce some interesting findings. My primary assumption was that market orders should be inferior to conditional orders in terms of impact on rationality. As market orders variables ('Market open' and 'Market close') are highly correlated with conditional orders variables[49], I excluded them from the regression specification. However, to evaluate the betas, I run another set of regressions replacing conditional orders variables with the market orders ones. The resulting beta coefficients are demonstrated in Table 4.17.

Table 4.17. Beta coefficients of market orders' variables in the alternative regression specification.

Variable name	**'Gainers' group (1)**	**'Losers' group (2)**	**All investors (3)**
Market_open (%)	-0.4002 (0.689)	-0.0786** (0.039)	-0.1114*** (0.001)
Market_close (%)	-0.3244*** (0.000)	-0.5206*** (0.000)	-0.4002*** (0.000)

Note: The regression specification is the same as in section 4.5. with conditional orders variables replaced by market orders variables. P-values on Huber-White consistent t-statistics are provided in the parentheses. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

As is observable in tables 4.16 and 4.17 the initial assumption is true and statistically significant for all variables except 'Take profit close'. The use of this type of order reduces the degree of rationality exposed by the correlation between risk and return. Notably, a 10% increase in the use of this order type causes 0.03 loss of correlation for 'Gainers' group and 0.05 – for 'Losers'

[49] It is so, because the use of market orders equals to 100% minus the use of conditional orders.

group. In contrast, active use of stop-loss orders provides an essential backing for the degree of rationality, also when comparing it to its antipode order type – ‘Market close’. Unexpectedly, investors in ‘Losing’ group employ stop-loss orders substantially more frequently: the median use of this order type for ‘Gainers’ group is 10% while for ‘Losers’ group it is 20%. It seems that this factor might be important for rationality but less essential for profitability. As I stated before, they are far from being perfectly correlated.

4.5.3. The influence of Personal variables

In this cluster of variables, only a few have a statistically significant impact on the degree of rationality. One of such variables is ‘Age’, which is negatively influencing the level of risk aversion. For all three models, 10% growth in the age variable decreases the correlation between risk and return by approximately 0.01. This finding is against my initial expectation, which was guided by the growth in experience logic. Obviously, it does not work for this data set. Younger subjects demonstrate a stronger tendency to risk aversion.

One possible explanation can be derived from the paper of Mata et al. (2011), who conduct a meta-analysis of the research in the area of age and risk-taking association. The authors find an interesting pattern in the experimental literature. According to them, the age-related variation in risk-taking practices depends on the amount of learning involved in the administration of the task. Learning capabilities generally fade with age. Consequently, older adults display stronger risk-seeking behaviour compared to younger counterparts when the required experience from learning results in risk-averse behaviour, and vice versa, older adults are more risk averse when the experience gained from learning results in risk-seeking behaviour. Considering the learning effect and direction of the risky investment activity, it can be the case that older adults are not quick enough to learn how to become more risk-averse.

Another probable explanation for the observed phenomenon can be the selection bias. Marginal trading, just as predominantly intraday stock trading represents a deliberate risky activity. It can be the case that a sub-group of older investors in my dataset are more consciously engaged in this type of risk-taking practice, hence, they represent only a narrowly specified category of more risk-loving individuals. As a consequence, any generalisations for large groups of the population should be made with great care (which I also mention in the limitations of my research). Younger investors in my dataset can represent a less experienced (in terms of risk-taking) category of investors, but the one that is willing to try their success in the new form of capital investment.

It should also be kept in mind that most of the research identifying a positive link between age with risk aversion is predominantly experimental (see Albert and Duffy (2012) for review). There are also noteworthy studies finding the opposite effect (e.g. Denburg et al. (2001)). The nature of experiments that test the relation between age and risk aversion can depend on the nature of the experimental design, as is shown by Mata et al. (2011). In the natural environment of real-life investments, the situation can be significantly distinct. I suggest that more empirical research can shed more light on this phenomenon.

The other two noteworthy variables are the size of the first deposit and Contest participation. I hypothesised that these variables should have a negative sign because of higher implied affect-richness. Yet, I discovered that First deposit factor is positive and significant for all three groups. Contest participation turned out to be positive and significant for 'Gainers' and all investors' models. It can be explained with the strong alternative factors, for example, correlation analysis of independent variables demonstrates that the size of the first deposit is positively correlated with the origination of an investor from a developed country. It can be a sign of better financial literacy as confirmed by the studies on the subject.

The other variables: gender-related, country of domicile-related, size of the second deposit, days between deposits and 'deposit-to-income' ratio were statistically insignificant.

4.5.4. The difference between 'Gainers' and 'Losers' groups

In the sections above, I analysed the impact of the set of trading, personal and risk variables on the degree of investors' rationality. Yet, there is another essential aspect that may provide useful complementary information about the interplay between the difference in regression coefficients for successful and unsuccessful investors, profitability and inclination towards rational behaviour. I am set to examine the variation of all my independent variables relating to 'Gainers' and 'Losers'. In case a particular variable appears to diverge for the two groups, and simultaneously be an influential factor for rational behaviour, then such variable deserves close attention and further research as a potential indicator of deep-seated, systematic trading success, possibly attributable to better inborn skills or capacity, grounded on the fundamental trait of superior rationality. In other words, some individuals may be inherently better than others, for instance, when making investment decisions, because they tend to exhibit closer alignment between risk and return. To elicit and evaluate the discussed relations, I use an interaction variable technique covered in the Methodology section.

From the last column of Table 4.16., I find that one of the key elements that make the difference between good and bad investors is the way how they treat gaining positions, more specifically, the dispersion of gains that investors from both groups afford. The volatility of gains is a significantly more sensitive issue for underperforming investors with respect to the level of rationality they demonstrate. Yet, the sign for the two groups of investors remains the same – positive risk volatility is also a positive factor for risk/return correlation.

In a similar vein, negative risk dispersion also appears to diverge for ‘Losers’ and ‘Gainers’. In contrast to positive risk, the sign of the variable coefficient varies from positive for underperformers to negative for outperformers. However, it is only statistically significant for the latter. Another variable that displays significant disparity for both groups similarly relates to behaviour when experiencing gains. It regards the processing of Take-Profit conditional orders. The sign of coefficients is negative for both groups meaning that the variable has a negative impact on rationality, however, the effect is more pronounced for ‘Losers’.

Finally, Number of Trades variable exhibits meaningful discrepancy for underperforming and outperforming investors. If the investment experience hypothesis discussed earlier is correct, ‘Losers’ reveal higher sensitivity to the experience gained through more active trading, while successful investors seem not to unveil any link between the number of completed trades and the degree of rationality proxied by correlation.

Further to the analysis above, I take a bit different stance on the independent variables. It can be the case that a variable can be structurally disparate for performance groups yet remain insignificant for rationality. To identify such cases, I test for the difference in distributions of each independent variable from the perspective of ‘Gainers’ and ‘Losers’ performance groups.

Table 4.18. Analysis of the statistical significance of differences between ‘Gainers’ and ‘Losers’ groups of investors applied to trading, personal and risk variables.

Variable name	**t-test** **H_0: Gainers-Losers =0** **H_a: Gainers-Losers ≠0**	**Mann-Whitney U test** **H_0: Gainers = Losers** **H_a: Gainers ≠Losers**
Stdev_positive (%)	0.0132*** (0.000)	12.97***
Stdev_negative (%)	-0.0086*** (0.000)	-1.00
N_trades **(number of observations)**	149.48*** (0.000)	2.079**
N_instruments **(number of observations)**	-1.4258*** (0.000)	-4.248***
Turnover (USD)	5.8695** (0.016)	2.216**
Duration (minutes)	51.8381*** (0.000)	5.316***
Conditional_open (%)	0.0157* (0.058)	2.680***
Take_profit_close (%)	0.0285*** (0.000)	3.903***
Stop_loss_close (%)	-0.0697*** (0.000)	-12.035***
First_deposit (USD)	280.3821*** (0.000)	0.819
Second_deposit (USD)	56.3784 (0.243)	0.441
Days_between_ **Deposits (days)**	-6.2527 (0.295)	-2.958***
Deposit_to_income (%)	0.0060* (0.085)	0.564
Age (years)	-0.3457 (0.385)	-0.116

Note: The table presents the results of two statistical tests: t-test and Mann-Whitney U test that are used to explore the null hypothesis that investors from ‘Gainers’ and ‘Losers’ samples represent the same population: H_0: Gainers = Losers. The alternative hypothesis states that the two samples of investors do not belong to the same population: H_a: Gainers ≠ Losers. The analysis is applied to all selected variables of the data set. t-scores (for t-test in the parentheses) and z-scores (for Mann-Whitney U test) are provided for each variable. For t-test mean comparison calculation, the extreme data values are winsorised at 1%. In addition, for t-test I also report differences in means between two groups of investors. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

Table 4.18. demonstrates that a more successful investor (a member of ‘Gainers’ group) is featured with a higher variation of positive returns, number of trades, turnover, share of conditional open and take profit close orders and lower number of instruments used and the use of conditional stop-loss orders. The results for other variables are insignificant or mixed – either means or distributions are equal according to t-test and Mann-Whitney U test.

I also use Pearson χ^2 test to compare distributions of binary variables: availability of second deposit, gender, developed country of domicile and origination of funds from Contest. The proceeds are reported in Table 4.19.

Table 4.19. Analysis of the statistical significance of differences between 'Gainers' and 'Losers' groups of investors applied to the selection of binary variables.

Variable name	**Pearson's χ^2 test** **H_0: Gainers=Losers** **H_a: Gainers≠Losers**
Male	0.5651
Developed_country	0.5891
Contest	0.0721

Note: The table presents the statistic of Pearson's χ^2 test for categorical variables to explore the null hypothesis that investors from 'Gainers' and 'Losers' samples represent the same population: H_0: Gainers = Losers. The alternative hypothesis states that the two samples of investors do not belong to the same population: H_a: Gainers ≠ Losers. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

None of the binary variables in my data set evidenced statistically significant difference for 'Gainers' and 'Losers' groups.

Combining the results from Table 4.16 that describes regression coefficients pertaining to the set of my independent variables that help explain the degree of rationality, and Table 4.18 (and 4.19) that illustrates the group difference of the same variables yet in profitability context, I can identify several ways in which a particular variable co-influences performance and rationality. Altogether, I single out four possible scenarios that I summarise below.

The first scenario includes the group of variables that can help differentiate between 'Gainers' and 'Losers' from the perspective of rationality as well as profitability. For example, 'Number of trades' variable allows statistical separation of good and bad investors: unsuccessful investors make fewer transactions. At the same time, from the rationality perspective, more trades for 'Losers' group is a positive factor, while it is insignificant for 'Gainers' group. The other two essential variables that also fit the same criteria are associated with the behaviour in the gains domain. Semi-deviation of winning transactions turns out to be an important factor delineating good and bad investors from both performance and rationality positions. The same applies to the use of take-profit conditional orders. Outperforming investors use this type of orders by 2.9% more, however, from rationality stance, this behaviour hurts risk/return correlation, statistically more significantly for underperforming investors.

The second scenario comprises variables that help explain the between-group variation in profitability but not in the degree of rationality (i.e. interaction variable between the groups is statistically insignificant). For instance, my findings demonstrate that underperforming investors use a larger number of investment instruments. The difference for an average investor in both groups is approximately 1.5 instruments in favour of 'Losers'[50]. However, this variable proves to have an insignificant discrepancy between the groups from rationality perspective. Further, 'Gainers' turnover is on average USD 5.87 million higher, yet regression analysis indicates that growing turnover has a negative impact on risk/return correlation, especially for underperforming investors. The next variable in this category is Duration of a trade. Even though the variable does not explain the difference in regression coefficients of 'Gainers' and 'Losers', both coefficients are statistically significant and have a positive sign, meaning that longer duration is positive for the rationality of decisions. At the same time, outperforming investors demonstrate 52 minutes longer holding period of an average trade. Other two factors from the category have to do with the conditional orders. Successful investors on average use conditional orders by 1.5% more frequently but stop-loss orders by 7% rarer. Both variables fail to distinguish between investors from rationality perspective but for different reasons. The use of Conditional orders factor turns out to be unimportant for correlation between risk and return,

[50] Number of used instruments is conceptually different from diversification. The peculiarity of marginal trading predisposes traders to hold only 2-3 open positions simultaneously, which can be in different instruments. The respective number of instruments reflected in Table 4.15 Section C is the result of accumulation over the whole period of investment activity. Thus, the variable shows whether a trader remains focused on few instruments or on many instruments, rather than the degree of diversification pertinent to a subject.

while the use of stop-loss orders appear to be equally important with an even positive effect for 'Gainers' and 'Losers'.

The third category includes variables that have an influence of rationality but cannot explain the between-group variation from the profitability perspective. Three variables can be attributed to this class: The size of first deposit, investor's age and participation in Contest[51]. 'Age' variable demonstrates essential negative influence on the correlation between risk and return for 'Gainers' and 'Losers'. Contest participation has an impact, which is positive, only on outperforming investors, while the size of the first deposit is similarly positive for both performance groups.

Finally, the fourth category of variables proved not to have statistically significant implications neither for rationality nor for the disparity in profitability. It includes all the remaining variables: the value of the second deposit, days between the first and the second deposit, deposit-to-income ratio, gender, and geographic origin of an investor.

After the variables that I review in this section, it is fair to ask the question about why some investors perform better than others. My examination of various groups of factors indicates that the reason is not hidden in demographic or other variables of this type. Neither age nor the origin from a developed country (or gender) of an investor does not explain the difference between gainers and losers. At least, this is the case with the use of my dataset.

At the same time, the factors associated with trading behaviour and investments decisions demonstrate a much better coherence with the difference between good and bad investors. However, investment decisions that translate into investment behaviour (for example, where

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[51] I include here the variables that failed the statistical significance test of performance group difference (Table 4.15 and 4.16) using any of the testing methods – parametric t-test, non-parametric Mann-Whitney U test and Pearson's χ^2 test for binary variables.

and how often to place stop-loss orders, etc.) are only the markers of other powerful forces that govern the decision-making process in humans. In the next two empirical chapters, I analyse the role of emotions in rationality, decision making and performance. I also believe that emotions and, more specifically, emotion regulation, can be responsible for the difference in the results of individual investors.

Emotion regulation capacity is a puissant source of behaviour and performance. In economic science, the study of the influence of emotion regulation on performance is still in the inchoate state (with some noteworthy exceptions, e.g. (Fenton-O'Creevy et al. (2011), Fenton-O'Creevy et al. (2012)). However, in sports science, the intersection of emotion regulation and performance is an essential part of the scientific framework (see Lane et al. (2016) for review). It is firmly established that sportsmen extensively use emotion regulation in their goal achievement and it has a significant impact on performance (Hanin (2010), Lane et al. (2011), Stanley et al. (2012)). It is especially true for endurance sports, for example, long-distance running or cycling. I believe there is a direct parallel between behaviour in sports and investments as the emotions palette in both cases is extremely comparable (for example, elation, anxiety, anger, despair) but also extremely intense. As a subject of future research of the topic, the study of emotion regulation strategies when taking financial decisions and new approaches to measuring emotions among investors, e.g. neurophysiological or emotional intelligence study, should provide a better understanding of the empirically observed difference in performance between the groups of investors.

4.6. Summary and discussion of Research Question 2 results

In this research question, I strived to examine the factors that can explain the relation between risk and return. In the first research question, I found that there was a significant difference between successful and unsuccessful investors in terms of their manifested degree of rationality. Essentially, I defined the degree of rationality as the level of correlation between risk and return. From a theoretical point of view, more rational individuals should demonstrate a higher level of such correlation: the concept of risk premium required for an additional unit of risk lies at the heart of modern finance. In turn, it is reasonable to suggest that rational behavioural pattern should be featured with more prominent success in investing. Effectively, I provided such evidence in the first research question. 'Gainers' group that included successful traders with positive overall profitability proved to have a higher correlation between risk and return variables than 'Losers' group. Further, I considered that it is essential to understand which factors influence the studied correlation coefficient and, in my interpretation, the level of rationality. It might provide additional information about the connection between rationality and profitability.

I collected 24 variables from my data set that were attributed to the investors. These variables were arbitrarily placed into three broad categories: risk variables, personal variables and trading variables. Based on these variables and Fisher's z transformation technique, I created three regression specifications with different dependent variables: all subjects' correlation between risk and return, 'Gainers' group (successful investors) correlation between risk and return, and 'Losers' group (unsuccessful investors) correlation between risk and return. This approach allowed me evaluating the difference in the impact of each variable on the level of return represented by the specific group.

I found that particular variables had a statistically significant impact on the dependent variables characterising the degree of rationality, while for certain variables beta coefficients diverged for 'Gainers' and 'Losers' groups. For example, the number of completed trades, the number of financial instruments used during trading and the number of days between the first and the second deposit had significant positive betas only for 'Losers' group, meaning that the correlation between risk and return for this group of investors tended to be higher for a higher level of the mentioned variables. Next, the share of intraday trades and the presence of the second deposit were featured with the significant negative influence on the degree of rationality of 'Losers' group but no influence on 'Gainers'. In contrast, the average duration of a transaction had a positive impact only on 'Gainers group'.

The other significant variables had a concurrent effect on both groups of investors. The share of transactions closed with Stop-loss conditional order had positive betas, while disposition effect, the proportion of take profit conditional orders in all closing orders and investors' age had a simultaneous negative impact on the dependent variables.

Subsequently, I analysed the factors that could help differentiate between 'Gainers' and 'Losers' from the perspective of rationality as well as profitability. Altogether, I managed to detect three such variables: number of trades used, the use of take-profit conditional orders and positive semi-deviation of returns (positive risk). I concluded that these variables require further research as they potentially play a more fundamental role in the quality of financial decisions, on the one hand, rooted in the intrinsic degree of rationality of individuals, and on the other hand, being pertinent to some investors more than to the others. These factors may help understand why certain investors can be successful while others underperform.

5. Empirical Chapter 2. The role of affect in the degree of rational behaviour

5.1. Research Question and hypotheses development

In the previous chapter, I explored the risk behaviour and risk attitude of individual investors in the context of a real market environment. My research question and hypotheses were focused on the analysis of rationality that I proxied via the correlation between risk and return. Two notorious financial theories – Expected Utility Theory and Prospect Theory – provide competing expectations of risk/return relation as part of the decision-making process. The results that I obtained in the first empirical chapter turned out to be better explained by Prospect Theory.

Rationality principle is one of the cornerstones of the Expected Utility Theory. Axiomatically, individuals must require a higher return for extra units of consumed risk. By design, the Expected Utility Theory implies that humans always keep in mind the long-term wealth perspective. Short-term losses are regarded simply as changes to the total wealth, which do not undermine the stability of risk-averse behaviour. These facts lead to the expectation of a robust positive correlation between return and risk under the traditional theory. In turn, Prospect Theory manifests the short-term ‘myopic’ perspective of the judgemental process. In this framework, individuals’ rationality can be challenged by immediate negative performance, which will encourage risk-seeking behaviour. That is, readiness to take a higher risk without any compensating level of return.

Using an extensive data set containing live investment transactions of individual traders, I evaluated the correlation between risk and return across the board of all my subjects. My special interest was to assess if the correlation remains positive at any level of return as predicted by the Expected Utility Theory, or it turns negative if an investor experiences loss as expected by the Prospect Theory. I discovered that the gross correlation coefficient between total risk and return was negative and equalled to -0.17[52]. This figure was made up of the positive correlation of 0.04 between the return and positive risk (positive semi-deviation of return), and negative correlation of -0.22 between the return and negative risk (negative semi-deviation of return). Furthermore, I scaled down my examination to the level of an individual investor. For that, I dissected the historical trading performance of each of my subjects into the series of 20 trades and computed risk and return measures for each section[53]. Next, I calculated the correlation coefficient between risk and return for each of the investors in my sample, obtaining 3,670 individual correlations. Evaluating the sign and magnitude of the coefficients, I found that among all investors, the average correlation equalled to -0.07. However, when splitting the subjects into 'Gainers' and 'Losers', according to their overall positive or negative performance[54], I observed that correlation for good performers was on average as high as 0.09, while for bad performers it on average hit -0.15. These results support the predictions of the Prospect Theory having all three major components of Prospect Theory's value function get

[52] These figures are calculated using nonparametric Kendall rank correlation methodology. The other two methods used were parametric (Pearson) and another nonparametric (Spearman rank). The results for these two methods proved to be even more substantial: Pearson (Spearman rank) correlation between return and gross risk equaled to -0.58 (-0.23), Pearson (Spearman rank) correlation between return and positive semi-deviation equaled to 0.34 (0.07), Pearson (Spearman rank) correlation between return and negative semi-deviation equaled to -0.63 (-0.30).
[53] Considering the minimum criteria to the data set of 200 trades, I ended up with minimum 10 observations of risk and return per each investor.
[54] Characteristically, 'Gainers' group included only 33% of investors, while the other 67% fell into 'Losers' group.

reflected in my findings: positive risk-return relation in the gains domain, negative risk-return relation in the losses domain, and the presence of loss aversion featured by the prevalence of losses impact over gains.

Such a meaningful difference in correlations for outperforming and underperforming investors reveals the link between rationality and investment performance. Therefore, it becomes essential to investigate the forces behind the discovered correlation behaviour more profoundly. Also, particular attention should be paid to the negativity of correlation in the losses domain that contradicts some of the traditional theory's main prerequisites and causes underperformance among investors. In the previous chapter, I used the regression technique to explore the impact on risk/return correlation of multiple trading, personal and risk factors. Indeed, some of the independent variables proved to be statistically significant. For the most part, those were trading variables like the intensity of trading (share of intraday trading, number of trades), order management (use of market, take-profit and stop-loss orders) and few others. However, trading variables are themselves an outcome of some systemic decision-making practices or approaches by individual investors. I intend to explore if emotions felt at the moment of investment decision can be advocated as such a robust force that can intervene and deteriorate investors' rationality.

The analysis of the extant literature that I conducted in the literature review section indicated that affect or emotions experienced at the moment of choice (for example, investment choice) can be a powerful mediator for the cognitive evaluation of outcomes and probabilities and can, at extreme cases, radically impact the rationality of behaviour. A growing body of evidence from academia, predominantly using experimental setting, demonstrates how affect influences return and risk parameters of investment choices. To the best of my knowledge, the correlation between these two variables has not yet been examined in this context, the more so empirically.

However, it is sensible to suggest that if return and risk individually can be mediated by feelings, so might be the correlation between the two. It brings me to the following research question:

What is the effect of emotions on risk and return relation?

Traditional financial theory gives a simple answer to this question. There should be no impact. The optimal, rational behaviour is to maximise return on each unit of risk consumed, whether it is expressed, e.g. by Sharpe ratio or in another way. The only element that traditional theory recognises is that at higher levels of wealth, its growth does not bring as much utility, i.e. individuals become less sensitive to risk. Yet, it does not lead them even to risk neutrality, not to say about risk-seeking behaviour. In any case, the change in sensitivity should not be explained by feelings. In the discussed framework, feelings are the product of decisions, not its predecessor.

Behavioural financial perspective undergoes a gradual change in its attitude towards the role of emotions. If Prospect Theory, a cornerstone of behavioural agenda, is ignorant of the affect factor, more recent research that I cover in the literature review, for instance, the seminal work on Risk-as-Feelings hypothesis (Loewenstein et al. (2001)), is increasingly focusing on emotions as the driving force behind decision-making machinery. Nevertheless, at the current stage, it is very far from reaching the unity of opinions regarding the scope, magnitude or positivity/negativity of the emotions impact. As one of the commonly shared principles, researchers point out vividness as a factor that influences the emotional intensity and consequently, the degree of judgemental suboptimality. Vividness can be defined as an effect elicited by various dimensions of proximity – temporal, physical, and sensory – that can have a powerful impact on behaviour. It is operated by 'showing' mental images or representations of future outcomes under concern. The more vivid, either positive or negative, are such images, the stronger is an immediate emotional reaction to the future outcome, and the larger can be a possible deviation from the optimal choice (Loewenstein (1996), p. 280). Another version of the same effect was dubbed ‘affect gap’ (Pachur et al. (2014)). The authors contended that even evaluation of a very similar set of prospects, yet with different emotional implications, can yield surprisingly diverse choices made by the same individuals. In their and similar analysis (e.g. Rottenstreich and Hsee (2001)), two types of outcomes were identified: affect-rich and affect-poor. Affect-poor outcomes leave the decision-maker much higher chances to stay within the boundaries of rationality when making a choice. In turn, affect-rich outcomes transform the whole evaluation process (hidden both in the value function and probability-weighting function) and may cause substantial damage to the rationality of judgements.

I now turn to the theoretical model of portfolio choice by an individual investor that I have constructed and described in Section 2.10 to test certain assumptions with respect to the relation between risk and performance and the possible role that emotions play therein.

In the analysis, I portray three investors, or stylised investor types, having Prospect Theory-based preferences with a distinct set of parameters of the utility function. The parameters reflect higher or lower curvature of the function and different apprehension of losses versus gains directed by loss aversion coefficient. Further, I relate each set of parameters with the various degree of affect pertinent to decision-making environment. Thus, Investor A represents the emotionless environment and has the parameters from the original Prospect Theory model. Investor B acts in the affect-poor environment, while Investor C mirrors the parameters of the function approximated for the real financial market, and hence can be presumed to act in the affect-rich environment.

Following my theoretical study, I conclude and predict that investors A, B and C will behave differently in terms of realised volatility of returns and correlation between risk and performance. In particular, in the domain of gains, Investor A will exhibit higher volatility of returns than Investor B, who, in turn, will demonstrate higher volatility as compared to Investor C. In the domain of losses, the picture will be reversed. As for the correlation coefficient, it is decreasing from Investor A to Investor C in the zone of gains and in the zone of losses.

Considering the above said, I intend to test empirically whether individual investors will demonstrate a distinct line of behaviour, measured by the correlation between risk and return, when taking the set of standard investment decisions under the two environments with varying emotional charge: affect-rich and affect-poor. In order to approximate affect-rich and affect-poor settings, I will use the data set of a large international brokerage house that I describe in the data and methodology section. One part of the data set represents the live trading activity of a group of individual investors taking risk on their own invested capital. The other part of the data set contains detailed trading statistics of a trading contest organised by the same brokerage company and maintained over a long period. Contest participants, though trading in a real online platform with real trading conditions, are required by rules to maximise dedicated virtual capital provided by the broker. Both sets of data only partially overlap. It means that only a fraction of live investors participated in the contest, and vice versa, only part of the contest participants had live accounts. The combination of the two types of accounts, in my view, provides an ideal empirical setting to test behaviour in affect-rich versus affect-poor realm. Live setting is clearly rich in terms of emitted emotions because investors risk their own funds in a complex environment of sequential investment decisions with virtually immediate effect[55] and the need

[55] The trading platform is designed in such a way that investors observe their P/L immediately after the investment decision. Any investment automatically starts at a loss, visible to an investor, because of the bid-ask spread.

for fast real-time processing. Also, academic studies (e.g. Tuckett and Taffler (2012), Coates and Herbert (2008)) and multiple professional investment online forums confirm that live investing is a highly emotionally charged activity, which is self-reported by investors themselves, or measured objectively using neurophysiological methods (e.g. Lo and Repin (2002), Lo et al. (2005)).

Comparing to live investments routine, participation in the Contest is undoubtedly an affect-poor activity. Maximum real harm that it can produce is the unpleasant feeling of being worse than others. Nevertheless, it should be noted that affect-poor does not mean that Contest trading is affect-free. First, virtual money investment games are a common practice in the field of experimental economics and finance testing emotional behaviour (see, for example, Patterson and Daigler (2014), Kuhnen and Knutson (2011)). Second, doing one's best in the Contest is the utmost benefit to the participant. Excellent Contest performance is remunerated with high real money prizes and reputational gains in the online community, not to say about the rise in personal self-esteem (the details about the Contest are provided in the section 2.7.1.2). Therefore, it is hard for participants to stay emotionally uninvolved when it comes to investment choices.

To summarise the discussion above – I will use the data from two trading environments, where individuals make investment decisions in a natural way[56]. One of the environments – real money Live trading – is aimed to represent affect-rich realm, while the other – virtual money Contest trading – shall represent affect-poor setting. With this at hand, I plan to test the following hypotheses:

[56] By the term 'natural way', I mean the setting, in which individuals are fully motivated to maximise the return of each investment. In addition, they take investment decisions in regular, day-to-day surroundings, not being pressured by some external observers, such as experimenters.

I. Correlation between risk and return in the domain of gains should differ in affect-poor and affect-rich settings. In the affect-rich environment, the correlation between risk and return should be lower as follows from the proceeds of the theoretical model developed in Section 2.10.

II. Correlation between risk and return in the domain of losses should differ in the affect-poor and affect-rich settings. In the affect-rich setting, correlation coefficients should be more pronounced, i.e. be more negative in the losses domain, as follows from the results of the theoretical model in Section 2.10.

III. Correlation between total risk and return should differ in the affect-poor and affect-rich settings. In the affect-rich setting, correlation coefficients should be more pronounced, i.e. be more negative in the losses domain, as follows from the results of the theoretical model in Section 2.10.

5.2. Empirical analysis

The current study is built on the findings and the proceeds of the correlation analysis in the previous chapter. Therefore, to preserve the continuity and comparability, I intend to follow the last chapter's methodology, structure and sequencing.

5.2.1. Macro vs Micro analysis perspective

As in the previous study, I plan to conduct my research on the two levels to get a more comprehensive picture of investors' behaviour. Primarily, I will select all subjects in my data set having an account and trading history in both instances: Live and Contest. For each individual in this selection, I will compute average return and standard deviation, which I will further split into positive semi-deviation and negative semi-deviation. Hence, I will have the building blocks for correlations. The next step is the computation of the correlation between risk and return independently in Live and in Contest. I call this approach macro perspective or pooled-data analysis because in the end, I will obtain a single figure of risk/return correlation per each setting that will illustrate the aggregated relation between the two variables – risk and return – for all the investors combined. For example, strong positive correlation coefficient, e.g. 0.5, will mean that the profitability of investors, in general, is positively related to the deviation of returns, which is in line with the traditional view on how the risk and return should be aligned. This approach will say nothing about the behaviour of an individual investor, though. One person's performance can have zero correlation with the risk-taking behaviour, while another trader can have it close to 1, which will average to the coefficient of 0.5. To have a better understanding of the distribution of correlations across investors and get the insight into individual behaviour, another method should be applied. I call this method a micro perspective or individual-level analysis. To implement it, I break down individual trading history into an equal series of 20 trades in each of the bits. For each section of sequential trades, I compute return and standard deviation and find the correlation between the two. As a result, I get a correlation coefficient for each investor in my selection. Having such individual correlations allows executing further comparative examination of behaviour.

5.2.2. Macro level analysis of correlations

As mentioned in Section 3 on Data Description, after filtering my data set for investors simultaneously having Live and Contest accounts, I obtained 618 records. Further, I applied the criteria of a minimum of 10 trades to have a more consistent calculation of return and risk variables. The robustness tests demonstrate that this criterion is optimal to elicit the integral information about the behaviour. This procedure left me with 523 investors. For each of these investors, I calculated a single measure of average return and standard deviation in each of the instances: Live and Contest.

5.2.2.1. Discussion before the analysis of macro level correlations

Having risk and return variables for each subject, I intend to calculate correlation coefficients independently for Live and Contest settings. If the behaviour of investors is in line with traditional theory, the coefficients should be positive and significant. The coefficients close to zero shall mean that investors in the sample are on average risk-neutral. Negative coefficients would indicate investors' exhibited inclination towards risk-seeking behaviour. If this is the case, such a pattern might point to the explanations best fitted into the behavioural theory of decision-making. I also plan to compare correlation coefficients across the instances, i.e. Live versus Contest. My goal is to verify if there is any statistically significant difference between the two. Presence of such difference might flag that otherwise identical environments provide the ground for qualitatively distinct investment decisions, which can be attributed to the factor of inherent variation in emotional charge.

To test the assumptions outlined above, I proceed by computing two measures of correlation – parametric (Pearson) and non-parametric (Spearman). I expect that Spearman correlation analysis will provide a more conservative measurement because it can better deal with outliers. In addition to finding the linear relation between risk and return, I also calculate a couple of other correlation coefficients: between risk values in Live and Contest, between return values in Live and Contest, and mixed relations between risk and return from different settings. I expect that this examination will yield additional useful input. For example, a positive correlation between risk variables in the two instances would suggest common behavioural patterns – a sign of consistency in risk-taking practices. The same may be told about the other three parameters.

5.2.2.2. Results of the analysis of macro level correlations

The proceeds of the analysis are shown in the Table 5.1 and Table 5.2.

Table 5.1. Pearson Correlation analysis between risk and return on Contest and Live accounts.

	STDEV_ LIVE	**STDEV_ CONTEST**	**RETURNS_ LIVE**	**RETURNS_ CONTEST**
STDEV_LIVE	1			
STDEV_CONTEST	**0.18***** (0.000)	1		
RETURNS_LIVE	**-0.42***** (0.000)	-0.05 (0.228)	1	
RETURNS_CONTEST	-0.05 (0.183)	**-0.17***** (0.000)	0.01 (0.884)	1

Note: The table displays the results of correlation analysis of risk and return in the two settings: Live and Contest. Correlations are computed using parametric Pearson technique. In each setting, the data is collected and studied for 523 individual investors. STDEV_LIVE means standard deviation variable in the Live environment. STDEV_CONTEST means standard deviation variable in the Contest environment. RETURNS_LIVE and RETURNS_CONTEST variables represent profitability variables in Live and Contest settings, respectively. P-values are provided in brackets. *** Shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level

Table 5.2. Spearman Correlation analysis between risk and return on Contest and Live accounts.

	STDEV_LIVE	**STDEV_CONTEST**	**RETURNS_L**	**RETURNS_C**
STDEV_LIVE	1			
STDEV_CONTEST	**0.25***** (0.000)	1		
RETURNS_L	**-0.23***** (0.000)	-0.04 (0.373)	1	

RETURNS_C	-0.03 (0.526)	-0.03 (0.484)	0.07 (0.132)	1

Note: The table displays the results of correlation analysis of risk and return in the two settings: Live and Contest. Correlations are computed using non-parametric Spearman technique. In each setting, the data is collected and studied for 523 individual investors. STDEV_LIVE means standard deviation variable in the Live environment. STDEV_CONTEST means standard deviation variable in the Contest environment. RETURNS_LIVE and RETURNS_CONTEST variables represent profitability variables in Live and Contest settings, respectively. P-values are provided in brackets. *** Shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level

The main finding of the analysis using the parametric method reveals that correlation between return and risk in both settings is negative and significant at the 1% confidence interval. The coefficient of -0.42 for the relation between Live risk and Live return suggests a considerably strong tendency for linear counter-movement of both variables. The corresponding figure of -0.17 for the Contest environment also is indicating the negative relation and is significant at 1% interval. The robustness check using Spearman approach confirms the negative coefficient for the Live domain, though the figure increases to -0.23. For the Contest setting the situation changes, and the coefficient here becomes statistically indistinguishable from zero. These results fully correspond to the proceeds of my theoretical model, whereby the correlation between total risk and return turns out to be negative and significant in the affect-rich setting (Investor A) and insignificant for the affect-poor setting. The other noteworthy result includes the correlation between risk in Live and Contest equal to 0.18 using Pearson method and even a stronger value of 0.25 applying the non-parametric technique. The other coefficients turn out to be insignificant at 10% confidence interval.

5.2.2.3. Discussion of the results of macro level correlations analysis

It is hard to explain the obtained outcome of the negative correlation between risk and return using the expectations of traditional financial theory. Underperforming individuals should not accept higher risk profiles of their investments compared to outperforming investors. At the same time, negative correlation can be explained by Prospect Theory, which predicts that when someone loses the money he will tend to take (unpaid) extra risk. Considering that approximately ¾ of my subjects were losing their capital on average after all the transactions they made with a broker[57], it is unsurprising that risk-seeking behaviour stimulating negative risk/return relation has outplayed the risk-averse behaviour in the gains domain that is associated with a positive correlation between the same variables. Besides, Prospect Theory highlights another essential factor – loss aversion – which also might have impacted my findings. According to the model, the effect of loss aversion is strongest around the zero return mark, where most of all trades in my data set reside. Loss aversion by its nature should produce asymmetry in correlations between gains and losses domains 'favouring' losses approximately twice as solidly as gains[58]. In my view, these two factors may be responsible for the negative correlations that I discover.

[57] This figure is almost the same for both of examined settings, Live and Contest. Interestingly, thanks to the latest changes in regulation, since recently brokers working in the US, EU and many other regions are obliged to publish the average ratios of losers to winners in their investment accounts. Normally, losers dominate with most brokerage companies showing ratios between 60% and 80%. In this regard, my data set can be considered as perfectly aligned with the industry.

[58] The coefficient of around 2x has first appeared in the work of Kahneman and Tversky (1979) featuring the birth of Prospect Theory. Later it was confirmed by many other studies.

5.2.2.4. Comparison of macro level correlations in Live and Contest

At the cross-setting comparison level, as expected, I establish the presence of the difference between Live and Contest risk/return correlation coefficients, which is sustained under both computation methods. To verify that the identified discrepancy is significant, I run statistical tests for the equality of two correlation coefficients from separate samples. The results of the test are reported below:

Table 5.3. The results of testing for the equality of two correlation coefficients.

Method	**Setting**	**Correlation Coefficient**	**Difference in Coefficients**
Pearson	Live	-0.42	0.25***
	Contest	-0.17	(0.000)
Spearman	Live	-0.23	0.20***
	Contest	-0.03	(0.001)

Note: The table presents the comparison of risk/return correlation coefficients between Live and Contest instances. To conduct the analysis, correlations are first transformed using Fisher r-to-z transformation technique, then I compute the proper z-score to evaluate the statistical significance of the difference between two correlation coefficients from the independent samples. The analysis is performed for the coefficients found using parametric (Pearson) and non-parametric (Spearman) techniques. P-values are provided in brackets. *** Shows significance at 1% level, ** shows significance at 5% level, * shows significance at 10% level

The tests confirm that the observable difference in coefficients between Live and Contest environments are statistically significant at 1% level (Hypothesis III). The obtained results show that on average investors are more risk-seeking in Live environment than in Contest environment. This finding corresponds to the behavioural framework and its predictions outlined in the theoretical model in Section 2.10. Such outcome poses challenges not only for the standard economic model of decision-making but also for the original Prospect Theory. The latter does not have readily available arguments or instruments to explain this sizable divergence in behaviour when dealing with the set of kindred investment decisions. Yet, this behavioural variation can well fit the theories featuring the role of emotions in the risky choice, for example, Risk-as-Feelings hypothesis that I cover in the literature review. These models imply that more affect-rich environment should impact and alter the standard building blocks of the judgemental processing, such as valuation function and probability function, by amplifying their intrinsic characteristics. As applied to my findings, if I admit that the negative correlation coefficients are explained by the valuation elements put forth by Prospect Theory, then it should follow that in the more affect-rich setting, which is Live, these elements will reveal themselves more intensively, and the correlations should be more negative than in Contest instance. In particular, I refer to the convex form of the valuation function in the loss domain and to the loss aversion bias. It is exactly what I observe. At this point, I can state that the proceeds of my study so far support my hypothesis about the role of emotions on investors' behaviour, and, more specifically, on the correlation between risk and return. However, in the further sections, I plan to undertake a more detailed investigation of risky choices by my subjects and its influence on the risk/return co-movement.

Before I proceed, I would like to emphasise two other findings that I cover in the computed figures above.

5.2.2.5. Analysis of additional findings at the macro level

The first finding addresses the returns in the two settings and demonstrates that the returns are linearly unrelated, having a correlation coefficient indistinguishable from 0. The same regards correlation between standard deviation in one environment and realised return in another. They are very close to zero, showing just how isolated is risk-return relation between the two domains. The second finding is that risk-taking behaviour in the two settings is linked tighter: the correlation coefficient is positive and statistically significant at 1% level. Effectively, a trader who is more susceptible to a higher dispersion of returns would convey this preference from one trading environment to another[59]. Yet, the fragility of this connection forces to believe that there are powerful external factors that make traders behave so disconnectedly in two very similar settings.

As a final remark for this section, I find it noteworthy to compare the correlation coefficients for risk and return with the results in the Empirical Chapter 1 (Section 4), which included larger data set, yet exclusively for Live accounts, and more stringent selection criteria. Imposing a requirement of minimum 200 transactions (compared to minimum 10 transactions in the current study), the prior research covered 3,670 subjects. There, I found that the correlation between risk and return using Pearson approach equalled to -0.58 and applying Spearman method it was -0.23. Obviously, the results of the two studies appear to be almost identical, which may serve as an additional robustness test.

[59] On top of risk behaviour, it is noteworthy to examine correlations between other trading patterns in Live and Contest setting. The picture that we see is akin to the risk-taking patterns, i.e. all variable pairs have weak positive correlation, significantly different from zero at 1% level: a) Portion of intraday trades $\gg \rho = 0.39$ (t-stat = 9.79; p-value = 0.000); b) Number of trades $\gg \rho = 0.2$ (t-stat = 4.60; p-value = 0.000); c) Portion of conditional orders $\gg \rho = 0.3$ (t-stat = 7.20; p-value = 0.000); d) Duration of trades $\gg \rho = 0.2$ (t-stat = 4.64; p-value = 0.000). Correlations were computed using Pearson method.

5.2.3. Macro level analysis with risk bifurcation

5.2.3.1. Definition of the problem with macro level correlations analysis

The investigation that I conduct in the previous sections has a serious shortcoming. From the Prospect Theory framework, we know that individuals are subject to diverse risk behaviour depending on their positioning relative to the reference point. Combining the two risk-taking domains into a single risk variable degrades the overall understanding of the risk choices made by investors. For example, I calculate the correlation coefficient between risk and return for the Contest setting using Spearman method to be equal to -0.03, which is not statistically significant. Yet, does it mean that the subjects are relatively risk-neutral across the change-in-wealth scale, or they simply level off their risk-averse decisions in the gains domain with risk-seeking decisions in the losses domain? To have a clearer answer to this question, I need to evaluate the factor of risk as two separate values: the one representing positive risk part and the one for negative risk part, in other words, positive semi-deviation, and negative semi-deviation variables. Importantly, this step should also help me better test my hypothesis, because I will get a chance to examine the affect-rich and affect-poor instances independently for the two sides of valuation function – gains and losses, which are implied to diverge in terms of behaviour.

I must note here that my split of total risk will not fall into exactly 'semi' deviations because true semi-deviations would be mathematically computed against the mean return of each investor that can, of course, be negative or positive, while in my case I am more interested in the measurement against a status quo value. In trading, a common status quo is the zero return[60].

[60] Normally, in trading zero return does not coincide with the purchase price (offer for long position), but rather with the selling price (bid for long position). When a trader opens a position she momentarily gets into the loss domain valued by the size of the spread (difference between offer and bid prices).

Hence, I modify the formula of semi-deviations to come to a more natural psychological sense of this notion:

$$var_{-} = \sqrt{\frac{1}{n_{-}} \sum I_{r<0} \cdot r^2} \qquad \text{(Formula 5.1)}$$

$$var_{+} = \sqrt{\frac{1}{n_{+}} \sum I_{r>0} \cdot r^2} \qquad \text{(Formula 5.2)}$$

where var_{-} and var_{+} are negative and positive modified semi-deviations with n_{-}, n_{+} and r being number of negative returns, number of positive returns and realised return on a trade, respectively. The reference point is the zero return.

Consequently, for each of my subjects, I calculate two additional variables – positive and negative semi-deviations. As a next step, I intend to expand my prior correlation analysis by computing the correlation coefficients for all my old and new variables.

5.2.3.2. Discussion before the analysis of correlations with risk bifurcation

I divide my expectations from the forthcoming analysis into two sub-sets. The first sub-set concerns the prospects of splitting the total risk into positive and negative parts and assessing their linear associations with return independently in Live and Contest environments. Here, I will rely on the core premises of Prospect Theory and the theoretical model implications in Section 2.10. Accordingly, I anticipate that the relation between positive risk and return should be positive reflecting the concave part of the valuation function, the relation between negative risk and return should be negative echoing the convex section of the value function, and finally, correlation between negative risk and return should be stronger than the correlation between positive risk and return signalling the impact of loss aversion bias.

The second sub-set of expectations is related to comparing correlations between Live and Contest settings. In this case, as in the previous section, I expect that the results for the Contest setting will be subtler than for Live in the domain of losses but reversed for the domain of gains. That is, the correlation between positive risk and return for Live should be weaker, while the correlation between negative risk and return for Contest should be stronger (i.e. less negative). Moreover, the discrepancy in coefficients for the negative risk should be more salient. These hypotheses are based on the literature that explores the role of emotions in decision-making, which I revise in detail in the literature review section. For example, the evidence on the salience of more emotional outcomes was provided by Rottenstreich and Hsee (2001) and Hsee and Rottenstreich (2004), who demonstrated in the series of experiments that affect impacts decisions by altering the form (curvature) of valuation function and probability weighting function. The authors labelled the affect-rich outcomes processing as 'valuation by feelings' and affect-poor outcomes administration as 'valuation by calculation'. At extremely affect-rich outcomes, the change in the curvature of the value function may even lead to the binary form of derived value, i.e. all-or-nothing. Just as a card player who experienced a harsh loss is ready to make an all-in bet for his remaining capital. The mechanism of such decisions was described by Loewenstein (1996)[61].

Further, the hypothesis on the salience of the negative risk in a more emotional environment is associated with the influence of affect on loss aversion. Loss aversion bias and its interaction with feelings is currently the least studied component of the three-element structure of risk under

[61] According to Loewenstein (1996, p.274-276), the value function is influenced by the three forms of attention-narrowing mechanism under strong affective states: extreme focus on the emotion at the expense of other forms of consumption, which get incrementally ignored; collapsing of one's time-perspective towards the current necessity to mitigate the visceral factor (short-sighted trade-offs of immediate over longer-term benefit prevail); and decaying inclination for altruism and boosted selfishness.

Prospect Theory. Nevertheless, some of the experimental papers (e.g. Dhar and Wertenbroch (2000) or Hsee and Kunreuther (2000)) find proof of higher loss aversion under more emotion-rich environment. This is how Camerer ((2005), p.9) reasons on the matter: “My intuition is that loss-aversion is often an exaggerated emotional fear reaction, an adapted response to the prospect of genuine damaging survival-threatening loss, which overreacts to small losses in our long lives that are not truly life-threatening”.

5.2.3.3. Results of the correlation analysis with risk bifurcation

Again, I compute correlations using Pearson and Spearman techniques. The results are reported in Tables 5.4 and 5.5.

Table 5.4. Pearson correlation analysis between risk and return on Contest and Live accounts incorporating positive and negative semi-deviations.

	STDEV_PLUS_L	**STDEV_MINUS_L**	**STDEV_PLUS_C**	**STDEV_MINUS_C**	**RETURNS_L**	**RETURNS_C**
STDEV_PLUS_L	1					
STDEV_MINUS_L	0.25*** (0.000)	1				
STDEV_PLUS_C	0.29*** (0.000)	0.06 (0.200)	1			
STDEV_MINUS_C	0.07* (0.094)	0.14*** (0.001)	0.47*** (0.000)	1		
RETURNS_L	0.21*** (0.000)	-0.60*** (0.000)	-0.07* (0.091)	-0.03 (0.559)	1	
RETURNS_C	-0.04 (0.410)	-0.06 (0.181)	0.15*** (0.001)	-0.34*** (0.000)	0.01 (0.884)	1

Note: The table reports the results of correlation analysis of risk and return in the two settings: Live and Contest. Correlations are computed using parametric Pearson method. In each setting, the data is collected and studied for 523 individual investors. STDEV_PLUS_L means positive risk (or positive semi-deviation) variable in the Live environment, STDEV_MINUS_L means negative risk (or negative semi-deviation) variable in the Live environment. STDEV_PLUS_C means positive risk (or positive semi-deviation) variable in the Contest environment, STDEV_MINUS_C means negative risk (or negative semi-deviation) variable in the Contest environment. RETURNS_LIVE and RETURNS_CONTEST variables represent profitability variables in Live and

Contest settings, respectively. P-values are provided in brackets.*** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

Table 5.5. Spearman correlation analysis between risk and return on Contest and Live accounts incorporating positive and negative semi-deviations.

	STDEV_ PLUS_L	STDEV_ MINUS_L	STDEV_ PLUS_C	STDEV_ MINUS_C	RETURNS _L	RETURNS_ C
STDEV_ PLUS_L	1					
STDEV_ MINUS_ L	0.54*** (0.000)	1				
STDEV_ PLUS_C	0.32*** (0.000)	0.11*** (0.009)	1			
STDEV_ MINUS_ C	0.08* (0.064)	0.28*** ((0.000))	0.53*** ((0.000))	1		
RETUR NS_L	-0.10** (0.020)	-0.20*** (0.000)	-0.12*** (0.008)	0.03 (0.564)	1	
RETUR NS_C	-0.01 (0.829)	-0.07 (0.101)	0.12*** (0.005)	-0.17*** (0.000)	0.07 (0.132)	1

Note: The table reports the results of correlation analysis of risk and return in the two settings: Live and Contest. Correlations are computed using non-parametric Spearman technique. In each setting, the data is collected and studied for 523 individual investors. STDEV_PLUS_L means positive risk (or positive semi-deviation) variable in the Live environment, STDEV_MINUS_L means negative risk (or negative semi-deviation) variable in the Live environment. STDEV_PLUS_C means positive risk (or positive semi-deviation) variable in the Contest environment, STDEV_MINUS_C means negative risk (or negative semi-deviation) variable in the Contest environment. RETURNS_LIVE and RETURNS_CONTEST variables represent profitability variables in Live and Contest settings, respectively. P-values are provided in brackets. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

Based on Pearson method, the correlation between positive risk and return in Live environment equals to 0.21, while for negative risk and return it is -0.60. Both figures are statistically significant at 1% level. The non-parametric method produces considerably different result for the same coefficients: -0.10 for positive risk and return, significant at 5% level and -0.20 for negative risk and return, significant at 1% level. The correlations values for Contest setting make 0.15 for positive risk and return and -0.34 for negative risk and return under Pearson approach. Again, both figures are significant at 1% level. The values obtained using Spearman method equate to 0.12 for positive risk and return and -0.17 for negative risk and return. Another essential variables are correlations between various risk measures. For example, the linear relation between positive and negative risk in Live turns out to be 0.25 based on Pearson and 0.54 using Spearman method. For the Contest setting, the corresponding figures equal to 0.47 and 0.53 under Pearson and Spearman, respectively. The final coefficients to be noted describes the link between same side risk in different instances, that is, for example, positive risk in Live with positive risk in Contest. They also are positive at 0.29 (0.32) for positive risk and 0.14 (0.28) for negative risk using Pearson (Spearman) approaches. All the relations are statistically significant at 1%.

5.2.3.4. Discussion of the results of correlation analysis with risk bifurcation

My first set of predictions of the results considered that bifurcated risk variables would behave according to Prospect Theory. Pearson correlation coefficients, indeed, reflect such behaviour. In Live environment, positive risk was positively associated with return, negative risk and return had negative relation, and the presence of loss aversion was also clearly observable, which is implied by the difference in losses domain (-0.60) and gains domain (0.21) correlation between risk and return. Spearman method provides a more intricate picture. Specifically, the result for positive risk seems falling out of the Prospect Theory's framework.

Nevertheless, it is essential to compare these results with my investigation in the previous chapter (Chapter 4). Chapter 4 is based on a much larger and, therefore, more reliable data set. In that chapter, I explored the data set of 3,670 Live-only investors derived from the same population as used for the current study. A much stricter selection rule was applied requiring

200 minimum trades to be executed by subjects opposite to only 10 trades in the present paper. Even though in Chapter 4 I did not analyse Contest statistics, for the case of Live environment, the results acquired from a more trustworthy dataset can help to better gauge individual behaviour.

Contrasting the correlations in both studies, I must conclude that Pearson approach generated higher homogeneity of results. At the same time, Spearman technique provided much less consistent figures. I compare both papers in the table below:

Table 5.6. Comparison of correlations for the two samples of investors under Pearson and Spearman techniques.

Risk domain/ correlation technique	**Correlation coefficients in Chapter 5**	**Correlation coefficients in Chapter 4**
Pearson/Positive risk	0.21	0.34
Pearson/Negative risk	-0.60	-0.63
Spearman/Positive risk	-0.10	0.07
Spearman/Negative risk	-0.20	-0.30

Note: The table exhibits correlation coefficients from two studies (outlined in Chapter 4 and Chapter 5 of the Thesis) that use the same population of investors. In the previous research the selection was made under the criteria of minimum 200 trades per investor and comprised 3,670 individuals. Current paper (Chapter 5) imposed the selection rule of minimum 10 trades (and the existence of active Contest account) and comprised 523 persons. All correlation coefficients were significant at 1% level for both papers at the exception of correlation between positive risk and return under Spearman method that was significant at 5%.

The results for negative risk are surprisingly close for Pearson approach, and somewhat close under Spearman. Yet, correlations for positive risk are considerably more dispersed. The overall picture of Live risk/return relations derived from both studies provides for several essential conclusions that are consistent with Prospect Theory perspective: correlation between negative risk and return is deeply negative, and this effect is strong both statistically and economically; for positive risk, the link with return is weak being very close to zero, yet with a substantial evidence of remaining positive and statistically significant; loss aversion bias is observed under both techniques and in both studies, which proves the pervasiveness of this phenomenon and serves as additional robustness test.

As per the Contest setting, unfortunately, I do not possess the correlation figures from larger samples as was the case for Live. It restrains the capacity for complementary robustness checks. However, the results that I obtained for the Contest setting are not contradictory for different calculation techniques. Both Spearman and Pearson measures demonstrated compliance with Prospect Theory framework – positive coefficient for positive risk and return and negative value for negative risk and return. The traces of loss aversion also reveal themselves in the findings – more markedly for Pearson method and less for Spearman approach. Overall, I can state that my first set of expectations was confirmed by the proceeds of correlations analysis.

5.2.3.5. Comparison of correlations in Live and Contest in the context of risk bifurcation

The second sub-set of predictions was based on the comparative examination of correlations in Live and Contest realms. I conjectured that because of the influence of emotions, the results for the Live setting should be more prominent than for Contest in the domain of losses but weaker in the domain of gains. I examine the differences between Live/Contest correlation coefficients in the table below:

Table 5.7. Analysis of differences in correlation coefficients between Live and Contest environments.

Method	Setting	Correlation Coefficient	Difference in Coefficients
Pearson	STDEV_PLUS_L/RETURN_L	0.21	0.06
	STDEV_PLUS_C/RETURN_C	0.15	(0.159)
	STDEV_MINUS_L/RETURN_L	-0.60	0.26***
	STDEV_MINUS_C/RETURN_C	-0.34	(0.000)
Spearman	STDEV_PLUS_L/RETURN_L	-0.10	0.22***
	STDEV_PLUS_C/RETURN_C	0.12	(0.000)
	STDEV_MINUS_L/RETURN_L	-0.20	0.03
	STDEV_MINUS_C/RETURN_C	-0.17	(0.390)

Note: The table displays the paired comparison of correlation coefficients between Live and Contest instances. The differences in coefficients are reported in the last column. STDEV_PLUS_L means positive risk (or positive semi-deviation) variable in the Live environment, STDEV_MINUS_L means negative risk (or negative semi-deviation) variable in the Live environment. STDEV_PLUS_C means positive risk (or positive semi-deviation) variable in the Contest environment, STDEV_MINUS_C means negative risk (or negative semi-deviation) variable in the Contest environment. RETURNS_LIVE and RETURNS_CONTEST variables represent profitability variables in Live and Contest settings, respectively. P-values are provided in brackets.*** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

Based on the findings above, the only statistically significant differences were identified for negative risk in Live and Contest applying Pearson technique, and for positive risk under Spearman method. As I already mentioned, Spearman method in the current study has demonstrated a meaningful discrepancy in results with my prior research where I analysed a much larger sample of investors. If I substitute Live correlations in the Table 5.7 with the coefficients from the last column of Table 5.6 that displays the results from the previous study of 3,670 traders, the picture will change considerably. For example, the difference for positive risk under Pearson approach will be equal to 0.19, which is significant at 1% level. As for Spearman method, the updated difference for positive risk will turn insignificant, yet for negative risk it will become statistically significant at 1%. I can conclude that when using the Live parameters from the larger sample, my predictions from the second sub-set will be mostly confirmed for the convex part of the value function. The results in the domain of gains fail to confirm my initial hypothesis. In what concerns loss aversion, under Pearson technique, the in modulo discrepancy of correlations for negative and positive risk in Live (0.39) was indeed more pronounced than in Contest (0.19) as anticipated. Spearman correlation coefficients grounded on 523 investors demonstrated quite the opposite result – loss aversion in Contest was more substantial. However, when I applied Spearman correlations from the last column of Table 5.6, the situation was back to expected: modulo difference for Live was 0.23 and for Contest only 0.05.

5.2.3.6. Additional findings revealed by risk bifurcation

In addition to the main hypotheses, there were several other noteworthy outcomes concerning risk-taking featured by correlation study. First, I spotted consistency in traders' risk behaviour in Live and Contest modes with respect to losses and gains domains. Negative and positive semi-deviations were positively correlated at 1% level, demonstrating that individual investors exhibit coherent risk preferences no matter if they lose or succeed. This finding substantiated the long-revealed role of personality peculiarities in risk-taking routines (e.g. see Zuckerman (1994), Zuckerman (2007) studies on sensation seeking). More risk-loving individuals would prefer more risk to less risk under any market circumstances.

Second, the same conclusion can be made when looking at the relation between equidirectional risk-taking in Contest and Live. The correlation between positive semi-deviations in both trading modes was around 0.3, which is significant at 1% level. For negative semi-deviation, the figure was a bit smaller but statistically significant as well. Third, I observed that risk behaviour was more correlated within the single setting than equidirectionally within different settings. This may be a sign of the fact that there was a larger ‘emotional gap’ between Live and Contest trading than between gain and loss domains. However, all these conclusions require further study on larger and more elaborated data sets.

5.2.4. Micro level analysis of correlations

So far, I was exploring the correlations between risk and return for the aggregate of my sample. As discussed before, this approach gives a general understanding of risk/return relation in the group of subjects. However, it is instrumental to understand how risk and return interact on the individual trader level. I already applied this line of analysis in Chapter 4 for Live-only subjects.

5.2.4.1. Discussion before the analysis of correlations at micro level

In the current research, I intend not only to retake a similar approach to investors in the Live setting, but also do the same for these subjects in the Contest setting and compare between the two. The main goal of this examination is to evaluate if individual behaviour in Live and Contest differs in terms of the risk/return relations as it did at the aggregated sample level. I start with the sample selection by applying two rules that must be met by the subjects: a co-ownership of accounts in Live and Contest, and minimum criteria of 200 trades made in each of the two instances. Because of strictness of these requirements, my selection includes only 166 individuals. Nevertheless, I deem this number satisfactory for the purpose of supplementary robustness test. I believe that with minimum 200 trades, I can obtain stable markers of behaviour for my limited selection of investors. Besides, most experimental studies ground their analysis and conclusions on equal or even smaller data sets.

Further, I plan to split the traders in Live and Contest into two groups – 'Gainers' and 'Losers' according to the respective performance above or below my reference point, which I choose to be zero return in line with my prior research and the general practice. Table 5.8 reports the number of traders in each of the obtained groups.

Table 5.8. Composition of 'Gainers' and 'Losers' sub-groups in Live and Contest environments.

	Live	**Contest**
Gainers	45 (27%)	39 (24%)
Losers	121 (73%)	127 (76%)
Total	166 (100%)	166 (100%)

Note: The table displays the sub-groups of investors from the selected sample of 166 individuals having Live and Contest accounts. The division into sub-groups is grounded on the accumulated performance of each subject. If the return is above zero, which is the reference point, an investor will get to the 'Gainers' sub-group. Alternatively, she will be included in 'Losers' sub-group. The figures in the parentheses shows the share of a sub-group in the selection.

The figures in the table above demonstrate that about ¼ of my sample got to the 'Gainers' sub-group. The result for Live and Contest turned out to be alike. Yet, this is a bit less than what I discovered in my prior analysis of a large Live-only data set of 3,670 investors, where the share of 'Gainers' was around 33%. Still, the difference is not sizeable, which is an extra argument in favour of the appropriateness of the present sample.

After splitting the sample, I intend to compute average correlation coefficients for 'Gainers' and 'Losers' members. My expectation is to observe the evidence of risk behaviour in line with Prospect Theory: positive correlation between risk and return for outperforming traders, negative correlation for underperforming traders, and the sign of loss aversion revealed by smaller positive correlation. Furthermore, I assume that in line with the theoretical model outcomes in Section 2.10, positive correlation should be higher for Contest in the domain of gains and in the domain of losses.

5.2.4.2. Results of the correlation analysis at micro level

Table 5.9. summarises the findings of correlation coefficients in both environments and for the two groups of investors.

Table 5.9. Average correlation coefficients for investors in Live and Contest split into 'Gainers' and 'Losers' groups.

Investors' group/ Risk perspective	**Live Positive**	**Live Negative**	**Contest Positive**	**Contest Negative**
'Gainers' Group	0.478***	-0.342***	0.412***	-0.222***
	(0.000)	(0.000)	(0.000)	(0.000)
'Losers' Group	0.284***	-0.412***	0.232***	-0.368***
	(0.000)	(0.000)	(0.000)	(0.000)
Total	0.337***	-0.393***	0.274***	-0.333***
	(0.000)	(0.000)	(0.000)	(0.000)

Note: The table displays average correlation coefficients for the respective groups of investors: outperforming investors in Live (Live 'Gainers' group), outperforming investors in Contest (Contest 'Gainers' group), underperforming investors in Live (Live 'Losers' group), underperforming investors in Contest (Contest 'Losers' group). Live Positive and Contest Positive mean correlation coefficients between return and positive risk (positive semi-deviation of return). Live Negative and Contest Negative mean correlation coefficients between return and negative risk (negative semi-deviation of return). P-values are provided in brackets.*** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

In line with my prior findings, I observed that at the level of individual investors Prospect Theory fitted well to explain the correlation coefficients and the difference between ‘Gainers’ and ‘Losers’ groups. In Live the average correlation between return and positive risk reached 0.34, whereas when separated for groups got to 0.48 and 0.28 for ‘Gainers’ and ‘Losers’, respectively. The outcomes for Live negative risk correlations also corresponded to my expectations, making -0.39 for all investors, -0.34 for ‘Gainers’ and -0.41 for ‘Losers’. The consistency of these numbers is corroborated by the comparison with the results in Chapter 4 for 3,670 Live investors. Table 5.10 presents the correlation values from both papers.

Table 5.10. Comparison of Live correlations between risk and return for two studies with the sample of 166 investors and 3,670 investors.

Investors’ group/ Risk perspective	**Study of 166 investors**	**Study of 3,670 investors**
‘Gainers’ Group/ Positive Risk	0.478	0.471
‘Losers’ Group/ Positive Risk	0.284	0.265
‘Gainers’ Group/ Negative Risk	-0.342	-0.330
‘Losers’ Group/ Negative Risk	-0.412	-0.451

Note: The table shows correlation coefficients from two studies. In the current study, the selection includes 166 Live investors that also had Contest accounts, while my prior paper was focusing exclusively on a large array of Live traders. Correlations in the table represent average values from the distribution of coefficients for the selection of individuals that fall into specific groups: ‘Gainers’ and ‘Losers’, according to their performance, and two categories of computed correlations – between return and positive risk (positive semi-deviation) and return and negative risk (negative semi-deviations). Both papers used the same methodology to compute correlation.

As follows from the comparison above, despite a limited selection of investors in the current study, the figures of coefficients are very similar.

Unfortunately, I do not possess the proceeds of correlations for any larger group of trading Contest participants. Therefore, the existing findings should be taken with additional care. Nevertheless, I should note that the figures for Contest remain consistent with Live and with my expectations: ‘Gainers’ group in Contest outperformed the respective ‘Losers’ group, correlations were positive and significant above the reference point, and negative below the reference point. There was also an evidence of loss aversion, as negative correlations loomed larger than positive ones.

5.2.4.3. Comparison of Live and Contest correlations at micro level

Now I can contrast the results for Live and Contest. My expectation was that Contest correlations between risk and return should be higher on both sides from zero – positive and negative – when compared against Live. Table 5.11 below demonstrates the differences between two instances.

Table 5.11. Comparison between Live and Contest correlation coefficients of individual investors.

Investors' group/ Risk perspective	Difference in correlation (Live – Contest)	Expectation
'Gainers' Group/ Positive risk	0.066 (0.119)	Positive difference
'Losers' Group/ Positive risk	0.052** (0.048)	Positive difference
'Gainers' Group/ Negative risk	-0.126** (0.032)	Negative difference
'Losers' Group/ Negative risk	-0.044* (0.097)	Negative difference

Note: The table shows the differences in correlation coefficients reflecting various perspectives of Live and Contest settings. 'Gainers' group includes investors performing above zero return during the reviewable trading history. 'Losers' group comprises the underperforming investors. Live Positive and Contest Positive mean correlation coefficients between return and positive risk (positive semi-deviation of return). Live Negative and Contest Negative mean correlation coefficients between return and negative risk (negative semi-deviation of return). The statistical significance of differences in correlations is evaluated using t-test. P-values are provided in brackets.*** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

The results demonstrated in the table generally confirm my expectation of more pronounced correlation values for Live than for Contest in the losses domain. However, for gains domain, the results are mixed. For 'Gainers' group the difference is not statistically significant and weakly significant for 'Losers' group, yet the sign goes against my expectations. Hence, I can confirm the Hypothesis II but cannot confirm the Hypothesis I with my empirical findings. One of the possible reasons for that is a low number of subjects in the study.

5.2.4.4. Discussion of correlation analysis at micro level

At the individual investor's (micro) level of analysis, I found supplementary evidence in favour of my hypothesis II and III, which implied that emotions may play their role in investors' behaviour by impacting risk decisions that practically translates into differences in correlation between risk and return. When making risk choices in Live environment, which is dominated by more explicit affective reactions, most notably, stronger feeling of fear and anxiety, investors tend to demonstrate behaviour that is more aligned with the main features of Prospect Theory. Unsurprisingly, these strong feelings are mostly manifested in the losses spectrum of returns. In the domain of losses investors become more risk-seeking in Live environment and more exposed to loss aversion bias. My analysis also established that investors' behaviour and decisions in Contest setting are not affect-free. Rather, my subjects exhibited reactions that appeared to remind closely the behaviour in Live. However, I discovered statistically significant difference in the correlations in two instances, which clearly pointed to the possibility that emotions do impact profitability or/and risk variables. This is exactly the perspective taken by the researchers who proposed so called dual-process models of decision making (e.g. Loewenstein et al (2001), Slovic et al. (2002), Kahneman (2003) among others). I should also add that this viewpoint contradicts the traditional decision-making framework. To elaborate our understanding of the role of feelings any further, it is important to decompose return and risk variables and compare them in more details in the settings with different degree of affect involved.

5.3. Summary and discussion of Research Question results

In Chapter 4, I have undertaken an empirical study of correlation between risk and return across a large set of retail investors. My results provided evidence in favour of Prospect Theory assumptions about behaviour of an individual decision maker: it appeared that on average outperforming investors demonstrated risk-aversion, while individuals with performance below zero evinced risk-seeking behaviour. Moreover, losses proved to have higher value than gains as is predicted by the theory.

The purpose of the current chapter was exploring possible reasons behind the observed behaviour. I conjectured that emotions or affective (visceral) states can be an influential factor that guides the decision-makers to obviously irrational, myopic choices. My assumption was primarily based on the growing body of literature exposing the role of feelings in economic decisions and the consequences that emotional implications can have on rationality. Hence, I focused my research question on understanding the role of feelings in choices of individuals extractable from the relation between risk and return. The main hypothesis that I bore in mind was based on the expectation that it should be possible to elicit the so-called affective gap, i.e. the impact of affect on behaviour, if I contrast two types of decision environments – affect-rich that is featured with high level of feelings, such as fear, savouring, anxiety, with affect-poor setting, which is also filled with the same feelings, however, to a substantially smaller extent.

To practically replicate such environments, I used the empirical dataset from a large brokerage house containing trading data for a group of investors having two types of accounts: a real money account that stood for affect-rich setting, and trading contest account that represented affect-poor setting. Altogether, I managed to identify 523 individuals with the required specification. As mentioned above, I focused my study on examining risk/return correlation for the aggregate of the investors and at the individual investor level expecting that in the affect-rich environment all three elements of risk behaviour under Prospect Theory will be statistically more dominant compared with affect-poor background. The expectations were grounded on the predictions of the theoretical model of portfolio choice developed in Section 2.10.

At the aggregate investor level, or macro level, I discovered that using Pearson correlation technique in the affect-rich environment the correlation between risk and return equalled to -0.42, while in the affect-poor environment it was only -0.17. Repeating the analysis using a more conservative Spearman method, I found the coefficients to be -0.23 for Live accounts, and -0.03 for Contest accounts. The difference in correlation coefficients was statistically significant at 1% level for both calculation methods. Further, I broke down total risk into positive and negative semi-deviations and recalculated correlations between return and both types of risk. When applying the figures from the previous chapter that contained a larger data set, my hypothesis of stronger correlation coefficients for the affect-rich setting was largely confirmed for all three elements of risk behaviour.

Next, I have undertaken to explore risk and return relations at the level of an individual investor. For each of my subjects, I computed the personal correlation coefficient grounded on the individual series of returns and positive/negative semi-deviation of returns. Each of the series comprised 20 sequential trades. This approach allowed me separating investors and their attributable correlation coefficients into 'Gainers' and 'Losers' categories while grouping total risk into positive and negative semi-deviations. I hypothesised that correlations in Live environment should be more prominent than in Contest environment. Effectively, on average in Live investors should demonstrate more risk-averse behaviour in gains domain and be more risk-seeking in losses domain. I found statistically significant confirmation of my expectations for three out of four analysed manifestations of behaviour. The members of 'Gainers' group in Live had 0.07 higher correlation coefficient for positive risk than in Contest (more risk-averse as expected), yet it was not enough to pass the significance threshold. In case of negative risk for the same group, the difference in average correlation coefficient between Live and Contest was found to be -0.13 (more risk-seeking in Live as expected), significant at 5% level. The members of 'Losers' group also evinced higher correlation coefficient for positive risk in Live (on average 0.05 higher than in Contest, significant at 5% level), and lower coefficient in Live for negative risk (on average -0.04 compared to Contest, significant at 10% level). Thus, I managed to confirm two out of three initial hypotheses.

My research provides the contribution to the literature on human economic behaviour reinforcing the evidence that most individuals do not take decisions according to traditional Expected Utility Theory's prescriptions. Rather their choices are better described with Prospect Theory premises, which imply short-term approach to choosing between prospects that leads to flawed risk-seeking behaviour and myopic loss aversion. I also discover that the degree of rationality is related to profitability, i.e. irrationality has its clear economic cost. Yet, the reasons behind the biases in judgments put forth by Prospect Theory are far from clear. In the current study, I endeavour to test one of the theories that seek to explain the psychological roots behind the irrationality phenomenon. A group of academics (for example, see Loewenstein et al (2001), Loewenstein and Lerner (2003)) believe that the key driver of biased behaviour is hidden in the domain of uncontrollable (anticipatory) human emotional reactions, which are very hard to test because they are not readily available to be observed in the laboratory or in the field. It is utmostly complicated to set an individual to make decisions in the affect-poor environment, and after that, modulate a person into stronger emotions to survey and compare how similar decisions are taken. People do not like that much to be monitored when they are feeling angry, desperate or fearful. Fortunately, the unique combination of differently modulated environments has been created by online retail brokers who created a marketing instrument of contest trading, which represents an investment game with paper money but real monetary prizes. Some of the contestants also trade with their own funds, and the two environments – Live and Contest – possess all the needed features to test for the difference in affective reactions as affect-rich and affect-poor domains. I describe them in more details in Section 3.1. After evaluating investors' behaviour in both settings, I find that there is a statistically significant disparity in the way how the subjects manifest their degree of rationality that I measure as the strength of the correlation between individual risk and return variables. It seems that in a more emotionally-rich environment, the judgement value function becomes more S-shaped, meaning that risk-aversion becomes stronger in the gain's domain, and risk-seeking gets more powerful in the loss's domain. Also, loss aversion bias shows the evidence of higher intensity. This finding makes the feelings factor an essential contributor to rationality and profitability puzzle. At the same time, there is a need for further research on the role of emotions in risk behaviour.

6. Empirical Chapter 3. The role of risk and emotional engagement in trading behaviour and manifestation of behavioural biases by investors

6.1. Research Question 1. Hypothesis development

As was demonstrated in the literature review, there are two competing viewpoints on the influence of emotions on performance in general, and on financial performance, in particular. The first approach put forth by traditional financial theory manifests the ‘no impact relation’. It is believed that feelings are the post-product of a cognitive evaluation during decision-making. Hence, emotional intensity variation cannot have any practical consequences for realised behaviour and outcomes. Alternatively, the dual process models that emerged in the last few decades argue that emotions are integral to judgement. More specifically, emotions can mediate the cognitive processing of judgments, and have a direct impact on behaviour and outcomes. If this is so, modifying feelings intensity for comparable decisions should lead to the deviation in outcomes and, consequently, in performance.

Following the competing stances on this important matter, I formulate Research Question 1: Does variation in emotional intensity pertaining to the investment decision have an influence on financial performance?

In order to elicit the change in emotional intensity, I employ the two types of trading accounts from my data set – Live and Contest. Importantly, trading on the two accounts is identical in all the parameters except for affective infusion. The genuine and natural contrast between these two instances in terms of the emotional accompaniment of financial trading can be easily verified by checking out countless Internet trading forums. A great deal of attention on such virtual forums is devoted to discussing how to preserve composure, protect oneself against emotional traps, and hold on to initial trading strategy when switching from virtual (Demo) account to real (Live) account

The null hypothesis directly ensues from the traditional financial perspective. Accordingly, there should be no difference between the performance on Live and Contest accounts because investors have the same amount of cognitive abilities and trading skills when operating in Live or Contest environment. As explained in Section 3.1.2., they are also motivated to maximise their abilities and skills in Contest setting.

H_0: $P_L = P_C$,

where P_L is Live account performance, and P_C is Contest account performance.

The alternative hypothesis represents the position of dual process theories. If the change in emotional intensity can impact outcomes by modifying behaviour, it can be envisaged that investment performance on Live and Contest will deviate.

H_a: $P_L \neq P_C$,

where P_L is Live account performance, and P_C is Contest account performance.

It is hard to make reliable projections about outperformance or underperformance of Live or Contest, because prior empirical research did not provide unambiguous guidance. As was discussed in the literature review, under diverse research designs, emotions proved themselves as having both positive and negative consequences for performance. However, I believe that the studies of Coates and colleagues ((Coates et al. (2009), Coates and Herbert (2008)), which showed that emotions are beneficial for performance, could be more applicable to my research, as they were conducted in a more natural environment and under the conditions of more trustworthy return analysis. Therefore, my expectation is to find evidence of Live outperformance.

6.2. Research Question 1. Empirical Analysis

I break my analysis into several sections. First, I evaluate the difference in key trading variables in the two modes. Then I examine the difference in profitability in Live and Contest and assess the performance distribution parameters. After that, I discuss the possible reasons behind the results that I discovered. Next, I switch from the aggregate (macro) analysis level to trader (micro) level to find the support for my conclusions. Finally, I conduct and discuss several robustness checks.

6.2.1. Difference in behaviour in Live and Contest

I commence the empirical analysis with the overview of a set of key trading variables summarised in the table below:

Table 6.1. Between-traders statistics of average values for the group of trading variables in Live and Contest.

Variable (average per trader)	**Value on Live**	**Value on Contest**	**Difference (t-stat; p-value)**
Portion of non-intraday trades	21.5%	34.6%	-13.1%*** (p-value = 0.000)
Number of trades	877	448	429*** (p-value = 0.000)

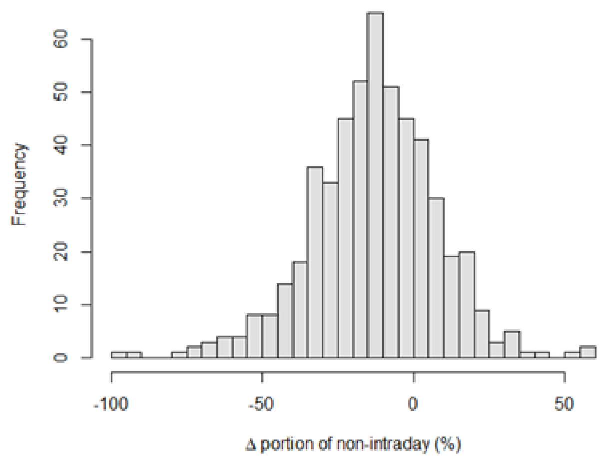
Portion of conditional orders	22.5%	43.1%	-20.6%*** (p-value = 0.000)
Duration of trade (in hours)	4.11	7.82	-3.69*** (p-value = 0.000)

Note: The table above displays a group of major trading variables. For each of the variables an average per trader result is provided. There are two values for each variable – one for Live account and one for Contest account. The last column shows the difference between Live and Contest settings for each variable with pertaining significance level and p-value. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

Table 6.1. displays between-trader's statistics of average values for the given variables. For example, the figure for the portion of non-intraday trades on Live accounts means that on average Live traders open and close 21.6% of transactions within one day. The statistics presents a picture in which an average Live trader tends to complete transactions within one day more often, makes two times more trades, and places conditional orders two times more regularly. Also, the holding period, though utmost short for both account types, is substantially shorter for an average Live transaction. In order to further substantiate the findings, I also look at within-subject variations for the same parameters. I compute each observation as $L_{i,j} - C_{i,j}$, where $L_{i,j}$is a value of jth variable for ith trader in Live account and $C_{i,j}$ is a value of jth variable for ith trader in Contest account. The results are presented in graphical form to illustrate considerable individual variability.

Figure 6.1. Difference in main trading variables in Live and Contest environments

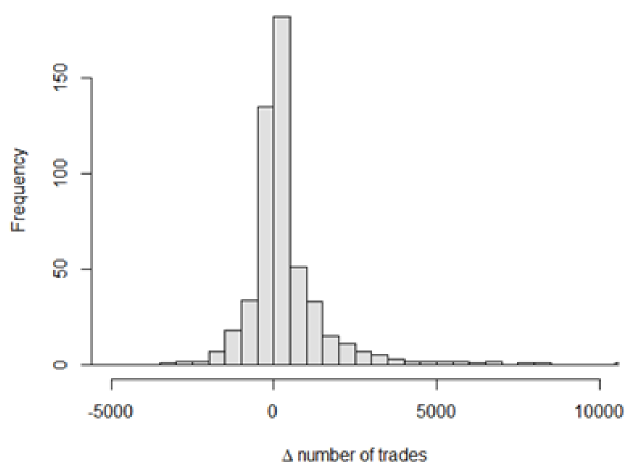
Section A. Delta in the portion of non-intraday trades



Mean	-13.1
Median	-12.3
SD	20.8

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	23870	0.000
Welch's t-test (H1: live ≠ contest)	-14.4	0.000

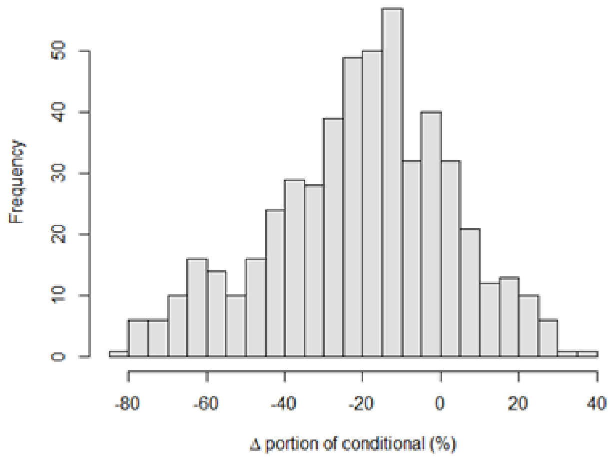
Section B. Delta in the number of trades in Live and Contest environments



Mean	429
Median	106
SD	1634

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	90982	0.000
Welch's t-test (H1: live ≠ contest)	6	0.000

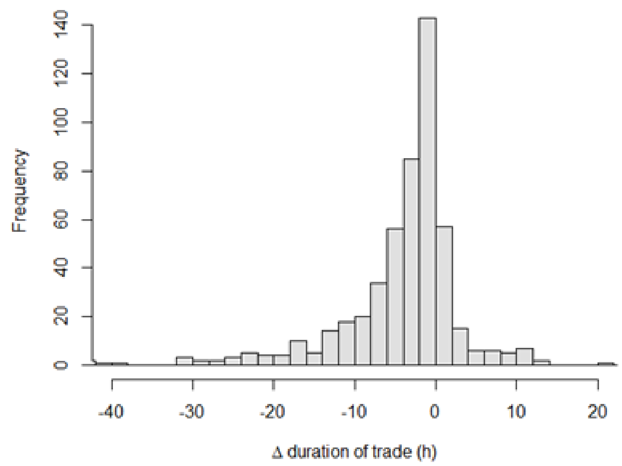
Section C. Delta in the portion of conditional orders in Live and Contest environments



Mean	-20.6
Median	-18.8
SD	23.3

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	13738	0.000
Welch's t-test (H1: live ≠ contest)	-20.2	0.000

Section D. Delta in the duration of trades in Live and Contest environments



Mean	-3.69
Median	-2.32
SD	15.9

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	23470	0.000
Welch's t-test (H1: live ≠ contest)	-5.3	0.000

Note: The portion of non-intraday trades (Section A) and the portion of conditional orders (Section C) are measured in percentage, the number of trades (Section B) is measured as absolute quantity, the duration of a trade (Section D) is measure in hours. For each investor I compute the respective parameter's difference between Live and Contest account activity. The analysis presents the distributions for all investors in the data set. I measure the key statistical parameters of the distribution, and test for significance of the difference using parametric and non-parametric tests. The mean difference in the share of non-intraday trades across traders is 13.1% in favour of Contest account, the mean difference in the number of trades across traders is 429, whereby Live account is featured with more trades, the average difference in the share of conditional orders is 20.6%, again in favour of Contest account. Finally, an average trade on Contest account lasts 3.69 hours longer than on Live account. Also, Live and Contest account distributions for all four parameters are significantly different under Wilcoxon and Welch's t-tests.

As it can be observed, the disparity of within-subject behaviour for the given variables bolsters the results in Table 6.1. Even though the degree of individual variation is large (that is in line with other studies emphasising sharp dissimilarity in individual investors behaviour (e.g. Dhar and Zhu (2006), see Barber and Odean (2013) for review), within-trader's variations are skewed towards more and shorter trades, less non-intraday trading and conditional orders. These findings suggest that an average trader spends substantially more time, energy, and attention on Live trading, which fits the assumption of more intense emotional impact in Live mode. Naturally, such reaction should be expected to a more emotion-evoking stimulus because as the literature maintains, strong visceral factors like fear (of financial loss) have overarching attention and motivation-grabbing capacity (Frijda (2007)). Attention-grabbing makes investors sit in front of the monitor to follow price movements reflected in the profit/loss account, while the motivational precedence of feelings produces extra trading with the short duration within short session frames. Such active participation obviously requires fewer conditional orders. Additionally, there is recent evidence in the literature (see Kocher et al. (2017)) that higher vividness provokes more frequent trading activity[62].

6.2.2. Difference in performance in Live and Contest

From the 'difference-in-behaviour' section above, which emphasises significant deviation in key trading variables implied by the conceivable role of emotional intensity, I move on to the more direct analysis of profitability. I start by computing median returns for Live and Contest settings and for every trader in the data set. The return is calculated on per trade basis and per unit of traded volume.

[62] In Kocher et al (2017) experimental study, the authors achieved higher vividness effect by substantially increasing the size of the stake.

Table 6.2. Descriptive statistics of traders' profitability based on median per-trader returns

	Live account	Contest account	Live$_i$ - Contest$_i$
Mean	0.005%[63]	-0.017%	0.022%*** (p-value = 0.000) Wilcoxon stat = 84512 (p-value = 0.000)
Median	0.012%	-0.019%	
Kurtosis	23.2	3.16	
Skewness	-2.96	-0.89	
Standard Deviation	0.059%	0.095%	

Note: The table introduces the results for the examination of returns on Live and Contest accounts. The first column includes the four distribution moments for Live account, and the second column for Contest account. The last column presents the difference between the average returns on Live and Contest accounts across all traders in the data set. I use both parametric and non-parametric tests to check for significance. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

The table above reveals at minimum two noteworthy and interesting findings[64].The mean disparity in Live and Contest performance across traders is statistically significant. In line with my expectation and findings of Coates and his colleagues (Coates et al (2009), Coates and Herbert (2008), but against part of the literature, and the mainstream beliefs in the industry and among lay traders, emotionally intense Live performance is actually better than the results on apparently less emotionally charged Contest accounts. The exact difference of median returns for an average trader in my data set equals to 0.022% in favour of Live account per every conducted round-trip trade. Although at first glance such deviation may seem economically negligible, one should remember that investors transact on marginal accounts, and the ratio of own funds to the position size at the transaction opening may be as high as 1:100. According to

[63] I need to remind that these figures are gross-of-fees. Traders pay commission of approximately 0.003% for each leg of a trade (depending on the generated volume). Hence round-trip commission is 0.006%. The same commission is applied against Live and Contest trades.

[64] I repeated the same calculations using average returns instead of median returns on an individual trader level. The resulting descriptive statistics of paired differences (Live – Contest) is similar to my median analysis. On average, Live accounts performance per every transaction is 0.011% higher than on Contest accounts. The difference is statistically significant at 95% confidence interval (H_a: Live ret > Contest ret) under t-test (t-stat = 1.77; p-value = 0.039), Wilcoxon test (stat = 82395; p-value = 0.000).

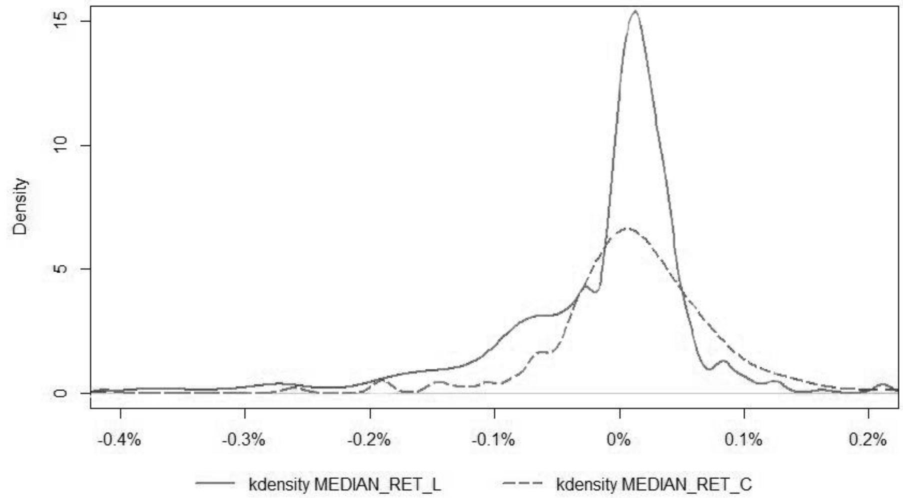
the broker's data, the mean leverage is approximately 33x[65]. In other words, to appraise the impact of 0.022% per transaction on a person's equity (amount of own funds), this figure must be multiplied by 33 to obtain 0.73%. It should also be recalled that an average trader during the life of the account makes 877 trades in Live and 448 in Contest.

6.2.3. Possible explanations of the difference in behaviour and performance in Live and Contest

I observe substantial deviation in the second, third and fourth moments of Live and Contest performance distributions. It can be inferred that traders in the data set modify their appetite for risk when switching from paper money to real money. They become more cautious with personal risk policy as there exists an almost twofold drop in standard deviation around average trader return. Additionally, the concentration of results around the mean rises dramatically as evidenced by an eightfold upsurge in kurtosis. In effect, it can be conjectured that traders align their behaviour when the emotional charge of financial decisions escalates, which results in increased homogeneity of performance. For a better understanding of the structure of this phenomenon, I employ kernel density function to graphically display the dynamics of Live and Contest results distributions.

[65] Practically, this signifies that an average trading position is maintained with only small fraction of own funds (3%).

Figure 6.2. Distributions of Live and Contest trading performance of all traders in the data set using Kernel Density Function.



Note: The graphs are created using R kdensity function. MEDIAN_RET_L denotes median return for Live. MEDIAN_RET_C means median return for Contest.

Figure 6.2. provides a clear visual description of distributional statistics. A significantly smaller number of traders allow either too high or too low returns when trading on Live, as the cross-group median profitability shrinks to a more consistent figure around zero for Live. One can also visually detect negative skewness on both account types, while it is more pronounced with Live trading.

6.2.4. Individual trader (Micro) level analysis

As outlined in the prior research on behavioural patterns, findings on the macro level can only roughly reflect the state of affairs on the micro level – the level of individual investors. For example, although the general tendency towards overstaying losing positions and closing winning position too early is a very well documented bias, Dhar and Zhu (2006) discovered that around 20% of traders are not exposed to disposition effect or even exhibit opposite bias.

Considering that, I undertake to explore the difference in Live/Contest trading performance on the per-person level with a purpose to extract more information from the data set. To accomplish this goal, I compute within-subject paired difference in mean per-trade returns for each trader. Next, I run two one-sided statistical tests with different alternative hypotheses formulated in Table 6.3:

Table 6.3. Statistical tests formulation on the within-subject difference between Live and Contest average returns.

	H_0	**H_a**
Test 1	$\mu_i^{Live} = \mu_i^{Contest}$	$\mu_i^{Live} < \mu_i^{Contest}$
Test 2	$\mu_i^{Live} = \mu_i^{Contest}$	$\mu_i^{Live} > \mu_i^{Contest}$

I place each trader in one of the three groups depending on tests results. Group 1 includes traders for whom Test 1 H_0 can be rejected with p-value = 0.05%. Likewise, individuals are added to Group 3 when we can reject Test 2 H_0 with p-value = 0.05%. All other traders are comprised in Group 2. I use both parametric (Welch's t-test) and non-parametric (Randomisation and Wilcoxon) tests to obtain more robust results. The findings are presented below:

Table 6.4. Proportion of traders with statistically significant within-trader difference between Live and Contest per-trade performance.

Test name	**Group 1 (Live < Contest) Test 1 H_a**	**Group 2 (Live = Contest) Test 1&2 H_0**	**Group 3 (Live > Contest) Test 2 H_a**
T-test	10%	56%	34%
Randomisation	12%	49%	39%
Wilcoxon	18%	49%	33%

Note: The table groups all the traders from the data set in one of three columns subject to the difference between their Live and Contest accounts performance. Column 1 combines all the traders who manage to significantly outperform on Contest account. Column 3 includes all the traders who outperformed on Live account. Column 2 comprises all other traders who did not get into either Column 1 or Column 3.

It can be noticed that there is no homogeneity in the figures above. Just as other behavioural traits and biases reviewed, emotional impact does not affect traders in the same way or by a similar magnitude. Approximately half of all subjects have not exhibited statistically meaningful distinction in performance. Nevertheless, one can also detect the roots of positive bias for Live accounts observed in aggregate data analysis. The bias hides behind the fact that 1/3 of traders do better in the more emotional Live setting. Simultaneously, around 10% of investors find it more comfortable and productive to deal with paper risk on the Contest account.

Grounded on the analysis above, I conclude that Live and Contest modes reflect disparate behavioural trading patterns and results. This disparity is statistically and economically significant, which allows rejecting the null hypothesis and confirming that traders do not take similar financial decisions in the two investigated settings.

6.2.5. Robustness analysis

To validate the findings, I perform several robustness tests.

The data set is subject to certain industry-specific factors and limitations that possibly may influence and obscure current findings. Primarily, the data set is severely exposed to only one currency pair – EUR/USD. This is a completely normal situation for an online brokerage, but it may be the case that the results are too sensitive to only single currency pair. Secondly, the subjects vary a lot in terms of their trading activity. For the general analysis, I used a cut-off point of minimum 10 trades on each account type. Thirdly, it may be argued that the difference between Live and Contest environments may stem from the learning effect. That is, traders first open Contest accounts and train in the riskless venue, and only then switch to Live accounts where they can obtain better outcome thanks to the improved skill. To test how all these factors influence the findings, I run a series of non-parametric robustness tests using specifications and methodology as in Table 6.3 and Table 6.4, and 95% confidence interval. Findings are displayed in Tables 6.5, 6.6, and 6.7.

Table 6.5. Proportion of traders with statistically significant within-trader difference between Live and Contest per-trade performance for all financial instruments except EUR/USD, and for intraday trades only.

Robustness check type	Group 1 (Live < Contest) Test 1 H_a	Group 2 (Live = Contest) Test 1&2 H_0	Group 3 (Live > Contest) Test 2 H_a
Non EUR/USD currencies	10%	56%	34%
Only intraday trades	16%	48%	36%

Note: The table groups all the traders from the data set in one of three columns subject to the difference between their Live and Contest accounts performance. Column 1 combines all the traders who manage to significantly outperform on Contest account. Column 3 includes all the traders who outperformed on Live account. Column 2 comprises all other traders who did not get into either Column 1 or Column 3.

The results do not change significantly: there are still 3 times more people in Group 3 than in Group 1. I may conclude that EUR/USD currency pair does not have a complementary influence on performance differential, so is the selection of intraday trades only.

Table 6.6. Proportion of traders with statistically significant within-trader difference between Live and Contest per-trade performance for varying minimum number of trades criteria.

Robustness check type	Group 1 (Live < Contest) Test 1 H_a	Group 2 (Live = Contest) Test 1&2 H_0	Group 3 (Live > Contest) Test 2 H_a
Number of trades >= 10	12%	49%	39%
Number of trades >= 25	12%	48%	40%
Number of trades >= 50	12%	46%	42%

Number of trades >= 75	13%	45%	42%
Number of trades >= 100	14%	44%	42%

Note: The table groups all the traders from the data set in one of three columns subject to the difference between their Live and Contest accounts performance. Column 1 combines all the traders who manage to significantly outperform on Contest account. Column 3 includes all the traders who outperformed on Live account. Column 2 comprises all other traders who did not get into either Column 1 or Column 3.

I determine that the minimum number of trades selection criteria is not meaningful for the findings. Moreover, Table 6.6 demonstrates that my general discoveries are consistent across traders because as the minimum trades requirement is augmented, the number of investors who fit into it gradually declines: For 10 trades – 525 traders, 25 trades – 440 traders, 50 trades – 365 traders, 75 trades – 310 traders, 100 trades – 273 traders.

Table 6.7. Proportion of traders with statistically significant within-trader difference between Live and Contest per-trade performance considering the learning effect (time distribution of Live and Contest trades).

Robustness check type	**Group 1 (Live < Contest) Test 1 H_a**	**Group 2 (Live = Contest) Test 1&2 H_0**	**Group 3 (Live > Contest) Test 2 H_a**
All trades	12%	49%	39%
70% of contest trading is before the first trade on live acc.	8%	57%	35%
70% of contest trading is between the first and the last live trades	13%	45%	42%
70% of contest trading is after the last trade on live acc.	9%	50%	41%

Note: The table groups all the traders from the data set in one of three columns subject to the difference between their Live and Contest accounts performance. Column 1 combines all the traders who manage to significantly outperform on Contest account. Column 3 includes all the traders who outperformed on Live account. Column 2 comprises all other traders who did not get into either Column 1 or Column 3.

The figure of 70% has been selected arbitrarily to represent a time frame during which traders can learn how to improve their Live performance based on obtained Contest account training[66]. If learning effect did take place, I would expect that traders with 70% of trades on Contest occurring before Live activity should have displayed better Live performance than people from other two buckets (simultaneous Live/Contest activity, and 70% of Contest transactions occurring after the first Live transaction). However, we can observe a similar outcome for all the 3 buckets of traders.

6.3. Summary and discussion of Research Question 1 results

Traditional financial theory and non-consequentialist models make distinct predictions regarding the expected profitability of an individual investor under various conditions. The key factor in charge of the discrepancy in theoretical frameworks is the degree of emotional intensity relating to the decision making. In the traditional financial perspective, feelings cannot interfere with the behaviour and outcomes of judgements, no matter how forceful the emotions are at the time of a decision. In the dual-process model perspective, stronger feelings pertaining to a decision will cause a larger deviation from outcomes expected under a consequentialist view. In other words, if we take a similar set of decisions that vary only in terms of emotional intensity and compare respective performance, we should be able to check, which of the models has better descriptive capacity.

[66] I have also rerun the tests with 60% and 80% time proportions, and got the same result.

In the analysis above, I compare the performance of traders in two different investment environments available in my data set: Contest (paper trading) and Live (real money trading). Both settings are identical in terms of investment characteristics, such as trading platform and infrastructure, commissions' structure, the scope of financial instruments, etc. The examination is conducted on two levels: macro – aggregated performance of all investors in the data set, and micro – individual trader level.

I start with identifying that individual traders exhibit dissimilar behavioural patterns in Live and Contest for an array of significant trading variables. For example, Live trading is featured by more active involvement in the process with shorter trade duration, more market orders, a higher number of trades and generally more trades completed intraday. Next, I find statistically significant divergence in trading results for two account types, whereby more 'emotional' Live accounts outpace less 'emotional' Contest performance by 0.022% per the average trade, and that on the micro level third part of traders do better when trading with real money and risk against only 10% of subjects who do the opposite. This difference is very substantial if we consider that most of the trades are conducted using high margins. My findings are in line with the non-consequentialist theoretical perspective, which reflects the strand of literature supporting the vital role of feelings and their attributes (such as intensity) in financial decision making, behaviour and performance.

An essential contribution of my work is the discovery of 'Live-over-Contest' outperformance. This is direct evidence of the positive role of emotions in financial decision making – an issue that is still very much debated in the literature. The meaning of this finding must be carefully interpreted in light of the big debate around this topic in the academic literature. The academic work that explores the direction of the impact of emotions on decision-making so far has produced the results that were highly dependent on the angle of view on the subject. Therefore, to comment on the nature of my result, I first have to define the category of emotions that my research can be attributed to.

Primarily, I must make a distinction between expected and immediate emotions. Expected emotions, which are part of the rational decision-making framework, by construct, have a positive influence on decisions. Individuals try to forecast their feelings (e.g. regret) derived from the outcomes of decisions. Subsequently, they optimise their behaviour by maximising positive emotions and minimising negative emotions.

Immediate emotions are different because the expected consequences of the decisions do not determine immediate emotions. Instead, the factors surrounding the decision itself are of critical importance. These factors (vividness of the decision's outcome is the most powerful of them – I discuss it in details in Section 2.5.1) are quite different from the parameters of the consequentialist analysis (used in the expected emotions framework), which are formed by beliefs and possible outcomes. As I demonstrated in the empirical analysis, my results (for example, the discrepancy between Live and Contest trading) are hardly explainable by the rational perspective, which is instrumental for the expected emotions. Yet, they fit well the non-consequentialist view. Thus, my focus in further discussion is fully concentrated on the category of immediate emotions.

Loewenstein and Lerner (2003) summarise two main types of immediate emotions – anticipatory (integral) influences and incidental influences.

Integral influences are directly connected to decision outcomes. Thinking about possible outcomes brings about the palette of immediate (on-line) visceral responses. Depending on the valence of the expected outcomes, these responses can be positively or negatively charged. For example, choosing the parameters of an investment order before placing it – timing or stop-loss level – can generate thrill from the possible gain. At the same time, potential adverse outcomes can beget fear. On top of that, the intensity of anticipatory emotions is correlated with the 'hedonic significance' of the decision results. The decision to open the door to let your cat in will generate zero feelings, while the beloved one not seen for half a year will make the keys tremble in hand.

Incidental influences are unrelated to decision outcomes. Such effects can have dispositional nature, for example, an individual fearful of interpersonal contacts deciding to take a particular route to work without realising the reason. It can also have situational nature when a good sleep at night, followed by a good mood, leads to the decision to buy a lottery ticket on the way to work.

Incidental emotions have been in the focus of scientists for a long time and generally were considered as a type of biases that do not allow humans taking rational decisions. The idea that emotions are deteriorating performance goes back deep in history. For centuries, it was believed that to succeed in various aspects of life, emotions must be contained. This attitude has received support in the modern academic research focusing primarily on incidental emotions and emotions playing the role of biases that distract attention and distort beliefs and valuations. Many academic studies that took this angle of view found the negative role of emotions on performance (These studies are almost exclusively designed as experiments where the authors directed their subjects into a specific mood and measured the consequences of their decisions. This approach may work well with the assessment of judgement quality over short periods but is less practical when the goal is to evaluate the role of emotions on some long-lasting sequence of decisions, for example, investment decisions made on daily, monthly or less regular basis.

Loewenstein et al. (2001) Risk-as-feelings theory that had a big influence on my work, accommodates both incidental and integral emotions in their model (see Figure 3 on page 270 of the original paper, and Figure 2.2. on page 38 of the current thesis) by recognising that background moods can play their role on the decisions in multiple ways just as vividness and other inherently integral factors. This consideration is later elaborated in Loewenstein and Lerner (2003).

In the current empirical study, the subjects make hundreds of decisions that are reflected in their realised trading orders. Of course, it can be suggested that there is a certain degree of incidental emotions behind every decision. For example, some of the subjects might have a bad day at work, and when they come back home and sit in front of the trading platform that can leave a trace on their trading behaviour and performance. Or, on the contrary, they might have learnt some excellent news right before placing orders, which also might affect trading performance. Besides, individual traders may have various dispositional incidental influences. At the same time, it would also be fair to admit that considering so many decisions per subject and variable timing of these decisions, positively painted and negatively painted incidental emotions should net out. Following this rationale, I can come to the conclusion that the positive difference in the return between Live and Contest accounts is mostly credited to anticipatory emotions. It means that subjects get emotionally charged when they think about the outcomes of their investment decisions during the decision-making process. Live accounts produce more substantial emotional charge than Contest accounts. Thus, the outperformance of Live accounts can be interpreted as evidence of anticipatory emotions' positive effect on performance.

So far, empirical findings, which for the most part were obtained through indirect methodologies, did not provide any unambiguous conclusion regarding this matter. At the industry level, my result can also be considered as surprising. There is a long-established belief around negative connotation of emotions in trading, where they are labelled as bad, destructing or disastrous. It is hardly possible to find a popular trading book that would not claim that all problems traders have, ensue because they cannot suppress immediate emotions. Nevertheless, my analysis of a group of day traders provides an input that may be a step to reconsider the impact of emotions on traders, at least in the limited ‘more emotional/less emotional environment’ framework.

6.4. Research Question 2

Both consequentialist and non-consequentialist frameworks of decision-making agree that outcomes, in this case, changes in performance, are preceded and mediated by risk behaviour. Intuitively, if I managed to find so substantial difference in the profitability of Live and Contest trading, the roots of this effect may originate in variations of the approach to risk.

This assumption is corroborated by the outcomes of the theoretical model that I construct in Section 2.10. Grounded on the theoretical studies of Barberis and Xiong (2009), Vlcek and Hens (2011) and Jakusch et al. (2019), I introduce several types of investors. Each of the stylised investors manifests diverse parameters of Prospect Theory-based preferences. For example, Investor A in my model exhibits the parameters from the original Prospect Theory model, which I presume to be the benchmark for the emotionless decision-making framework design. Further, I bring in Investor C, whose parameters of decision processing are matching the real-life financial markets environment from the paper of Jakusch et al. (2019). The discrepancy in the parameters between the two types of investors is striking pointing to a much stronger curvature of the value function of Investor C. The authors do not provide a direct explanation concerning the reasons behind such a difference in the parameters. However, the difference can be well explained by the dual-process theories of decision-making, for instance, 'Risk-as-feelings' hypothesis by Loewenstein et al. (2001). This prominent theory postulates that an equivalent decision contemplated under risk or uncertainty in the settings with varying degree of emotional intensity will be processed differently. The dissimilarity in the treatment will be primarily derived from the modified parameters of the value function and decision-weighting function. The theoretical model that I create demonstrates that the modification of parameters from Investor A to Investor B (this investor has the parameters that reflect the average between Investors A and C) to Investor C lead to substantial changes in behaviour.

As discussed in the literature review, Kahneman and Tversky (1979) established the multifaceted nature of risk. In their perspective, there are three risk factors that shape behaviour: the form of the value function, the form of the probability (decision) weighting function, and loss aversion. Prospect Theory, just as other consequentialist models, maintains that risk behaviour is a product of cognitive, algebraic-type processing and integration of beliefs and expected outcomes. A growing body of literature assumes that cognition is only part of the story, while emotional processing provides at least equally important contribution. My goal is to investigate the impact of feelings on the three risk factors using my unique data set and determine which of the models can better describe the empirical risk behaviour of investors. I formulate my second research question in the following way:

What is the effect of emotions on different facets of financial risk exhibited in trading behaviour?

Further, in order to thoroughly examine this main question, I will subdivide it into two more specific questions:

RQ2-1: What is the effect of emotions on the curvature of the value function delineating risk averse/risk seeking behaviour?

RQ2-2: What is the effect of emotions on loss aversion and the probability weighting function?

6.5. Research Question 2-1. Hypothesis development

Earlier reported Figure 2.3. in the literature review section reflects two theoretical views on the form of the value function. In Prospect Theory, a convex form of the function in the losses domain and concave form in the gains domain are explained by the three key factors: a short-term perspective of a decision-maker, reference point, and psychophysical account of prospects valuation. According to the theory, an individual elicits the psychological value from the continuous function of scope (e.g. size of monetary gain or loss) of a stimulus. Consequently, increasing scope (i.e. increasing gain or loss) should produce larger psychological value (and utility) both in gains and losses domains, though at decreasing pace. In addition, Prospect Theory suggests that psychological value derived from a stimulus is independent of the qualities and attributes of the stimulus itself. In other words, the value of a ticket to the concert of our favourite musician is just the market price of the ticket. This approach was dubbed 'valuation by calculation' (Hsee and Rottenstreich (2004)).

Essentially, the proceeds of my theoretical model in Section 2.10, Table 2.3, indicate that the parameters used in the original Prospect Theory (Kahneman and Tversky (1992)) cannot explain the behavioural phenomena that were observed empirically in the academic literature. For instance, applying these parameters does not expose the disposition effect. In contrast, the result is reversed. Nevertheless, when I apply the parameters from the real market study, which are naturally more affect-rich, the disposition effect is observable and statistically significant.

Furthermore, I discover that the parameters representing affect-rich environment produce a visible effect on the form of the value function, i.e. the degree of risk-aversion in gains zone and risk-seeking behaviour in the domain of losses. I use these findings as the prediction of my empirical study.

Applying the value function analysis under the original Prospect Theory to my Live and Contest modes, I will test several outcomes. First, the concave part of the value function implies that when traders experience a gain, they should turn risk-averse and afford less risk. Practically, it means that they will close their open positions quicker than if they were risk-neutral or risk-seeking[67], and afford less realised volatility throughout the pool of their trades. In contrast, in the losses domain, traders should demonstrate risk-seeking behaviour, affording higher risk, stimulating longer holding periods of positions and higher realised volatility. Second, as a logical consequence of keeping winning trades shorter than losing positions, I will try to detect the disposition effect in my dataset. Third, because the original Prospect Theory does not admit the interference of emotions into behaviour, I should not be able to find any significant discrepancy in risk-taking practices between Live and Contest. To evaluate these hypotheses, I plan to introduce and examine several variables. I will proxy risk with negative semi-deviation (for losses domain) and positive semi-deviation (for gains domain). Also, I will compute the disposition effect as described in my methodology section. Consequently, null hypotheses take the following form:

$$H_0^{Var-}: Var_-^{Live} = Var_-^{Contest}$$

$$H_0^{Var+}: Var_+^{Live} = Var_+^{Contest}$$

[67] Technically speaking, if a trader is risk averse she should close a gaining position when the utility of the achieved certain gain is larger than the utility of expected future outcomes.

$H_0^{DE}: DE^{Live} = DE^{Contest}$,

where Var_{-}^{Live} is negative semi-deviation in Live environment, Var_{+}^{Live} is positive semi-deviation in Live environment, $Var_{-}^{Contest}$ is negative semi-deviation in Contest environment, $Var_{+}^{Contest}$ is positive-semi-deviation in Contest environment, DE^{Live} is Live environment Disposition effect, $DE^{Contest}$ is Contest environment Disposition effect.

An alternative, or rather complementary, set of thinking to the original Prospect Theory is called 'valuation by feelings' ((Hsee and Rottenstreich (2004)) – Investor C in my theoretical model in Section 2.10. This model delineates environments by the strength of affective infusion, whereby in affect-poor states people behave closer to the parameters described in the original Prospect Theory – Investor B in the theoretical model, while under stronger emotions, positive or negative, individuals have a propensity towards a more binary-like structure of judgement, i.e. everything/nothing, or gains/losses. In other words, the degree of risk aversion and risk-seeking may get more extreme than suggested by the original Prospect Theory, and most of the psychological value is to be derived from the mere appearance of stimuli themselves, tending to ignore the pertaining degree of scope. Practically, it means that traders will try to close gaining positions very quickly because they will derive most of the utility from very small profits and fear the risk of losing what is still unrealised. This behaviour will lead to the declining volatility of realised profitable trades. In the same vein, in the losses area, I should expect to detect longer time horizon for holding losing positions. Traders placed into the affect-rich setting will elicit most of the negative value from unrealised losses very quickly. Hence, they will be much less sensitive to the continuing or growing loss as all their mental concentration and 'prays' will be devoted to getting back to the break-even point. Accordingly, I should witness an extension of losing positions holding period, and escalation of variation in realised losses. The resulting alternative hypotheses will take the following form:

$H_a^{Var-}: Var_-^{Live} \neq Var_-^{Contest}$ (expecting that Var_-^{Live} is larger than $Var_-^{Contest}$)

$H_a^{Var+}: Var_+^{Live} \neq Var_+^{Contest}$ (expecting that Var_+^{Live} is smaller than $Var_+^{Contest}$)

$H_a^{DE}: DE^{Live} \neq DE^{Contest}$

6.6. Research Question 2-1. Empirical Analysis

6.6.1. Analysis of Disposition effect

I start my investigation from the analysis of Disposition effect (DE). The results of DE computation are reported in Table 6.8.:

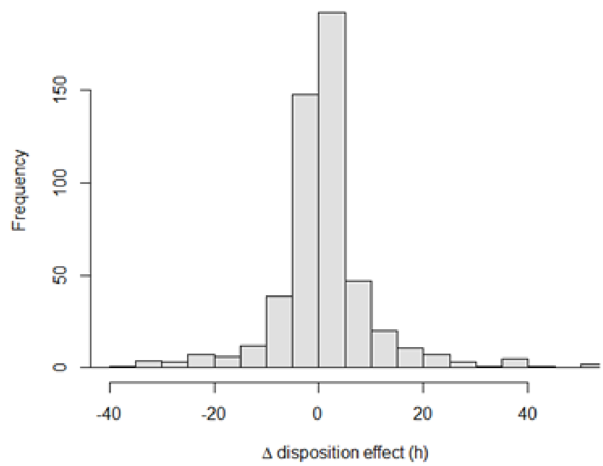
Table 6.8. Disposition effect in Live and Contest settings.

	Duration for losses	**Duration for gains**	**Disposition effect**	**t-stat (p-value)**
Live	472.77 minutes	311.95 minutes	160.82 minutes	
Contest	545.05 minutes	509.46 minutes	35.59 minutes	
Difference (Δ)	-72.28 minutes	-197.51 minutes	125.23 minutes	1.4* (0.084)

Note: The first column presents the median duration in minutes of closed trading positions that resulted in a loss for Live and Contest accounts. The second column displays the median duration for gaining closed trades. The third column reflects the difference between Column 1 and Column 2, which is the disposition effect according to my methodology. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

There are several conclusions that can be made based on the table above. First, I manage to show that when switching from Contest to Live setting, Disposition effect increases by more than 2 hours (125 minutes). This is a substantial change, considering that 2 hours is 65% of the median duration of a trade for an average investor in Live environment. This difference is statistically significant at the 10% level[68]. Second, median durations in Live setting are shorter for negative and positive outcomes of trades. However, the effect is much stronger for gains. Third, I spot the presence of DE in both environments, even though in Contest it makes only 7% of the median duration of a trade for an average investor. Finally, to double-check my results, I also apply Wilcoxon paired test to compare distributions of DE^{Live} and $DE^{Contest}$, and find that they are different with 1% p-value. The graphical analysis is provided in Figure 6.3.

Figure 6.3. The difference between DE^{Live} and $DE^{Contest}$ distributions using Wilcoxon test and Welch's t-test.



Mean	2.09
Median	0.36
SD	39.13

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	78849	0.002
Welch's t-test (H1: live ≠ contest)	1.4	0.084

Note: The figure displays the distribution of differences in Disposition effect between Live and Contest settings for each investor, and uses Wilcoxon paired test and Welch's t-test for the analysis of significance. The difference in DE is measured in hours. Hence, for an average investor, the difference equals 2.09 hours.

My results for the Disposition effect support the alternative hypothesis. I find the evidence of DE change under the impact of underlying emotional factors when a trader switches from less

[68] Prior research of Disposition effect has revealed that the bias tends to disappear at short trading frequencies (Kumar and Lim (2008)). Sometimes, it is explained in the vein of positive learning curve as more frequent realization of trades helps correcting DE. Moreover, higher frequency lessens the attachment to the traded asset or opened position. For example, Daniel Kahneman advises to behave like short-term traders in the sense that they can duly handle DE. From this point of view, this is all the more surprising evidencing the presence of Disposition effect in my high frequency data set.

emotional trading mode to more emotional trading mode. The change takes place even within the frameworks of high-frequency intraday trading.

The findings in this Section also fully support the results of my theoretical model in Section 2.10. The traders in my empirical dataset exhibited the same behavioural phenomena as the stylised Investors B and C in the proceeds of the model. This is an indication that the parameters of the original Prospect Theory cannot explain the empirically observed behaviour of investors acting in the real financial marketplace.

6.6.2. Analysis of value function and risk-taking behaviour

I continue my study with the examination of risk patterns. I disentangle the total risk of traders into two semi-deviations as in Formula 3.1 and Formula 3.2. As suggested by my hypotheses, I intend to compare semi-deviations in gains and losses domain for Live and Contest. Under risk-as-feelings model and the predictions of the theoretical model in Section 2.10, I should expect to find that traders get more risk-averse in the zone of gains, and more risk-seeking in the zone of losses. In other words, positive semi-deviation in Live should be smaller than in Contest while the opposite should hold for negative semi-deviation. Table 6.9 reports average and median values for risk parameters for Live and Contest settings:

Table 6.9. Average and Median values for Total risk, Positive semi-deviation and Negative semi-deviation in Live and Contest environments.

	Live environment		**Contest environment**	
Risk type	**Average value**	**Median value**	**Average value**	**Median value**
Total risk	0.419%	0.286%	0.438%	0.409%
Positive semi-deviation	0.318%	0.216%	0.414%	0.384%

Negative semi-deviation	0.592%	0.340%	0.472%	0.445%

Note: The first and second columns display the average and median values of risk factors for Live setting. The third and fourth columns show respective values for Contest setting. Positive and negative semi-deviations are computed using Formulas 2.4 and 2.5.

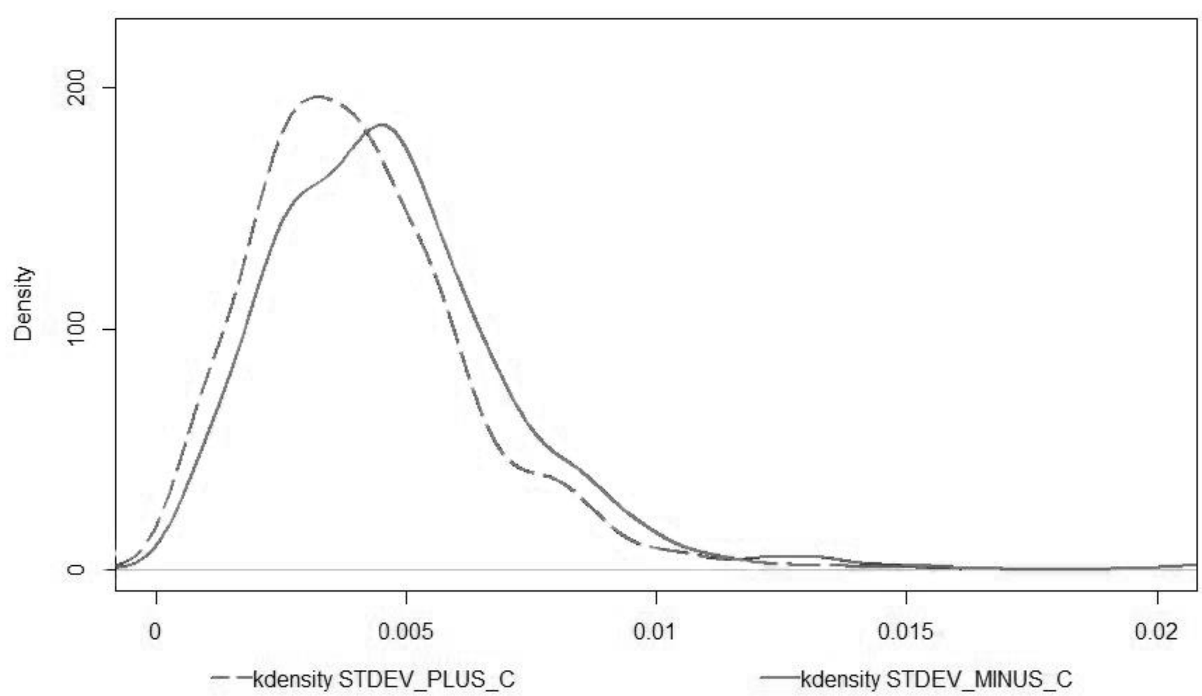
It is noticeable at first glance that for both settings, all risk parameters are skewed to the right, however, if for Contest this bias is very small, in Live environment, there are more traders with considerable exposure to risk on both sides of risk spectrum (i.e. positive and negative). In addition, the average difference between total realised risk in the two settings is negligible, while median values vary significantly. Based on medians, when traders are in Live context, they turn sizeably more risk-averse as risk-as-feelings perspective suggests. Yet, the result for losses domain cannot be readily defined because average and median values are contradictory. Another conclusion that follows from the table above is the fact that positive semi-deviation is smaller than negative semi-deviation across the environments and calculation methods. This is what should be expected from an S-shaped value function, which is in line with Prospect Theory and non-consequentialist models. However, it is observable that in Live setting, the difference between semi-deviations is sharper. This is an additional indication of possible emotional impact under more affect-rich environment, which is predicted by my alternative hypotheses.

Comparing the results in Table 6.9 with the proceeds of the theoretical model in Table 2.3, I can conclude about their accordance in almost all aspects. For example, in both instances, I find that the average total risk measure is statistically indistinguishable, which is the consequence of counterbalancing changes in the dispersion of returns in gains and losses. At the same time, as I noted above, in the real investors' data, the Live results are skewed. It is the indication of heterogeneous risk-taking practice by the subjects. I do not model heterogeneity in my theoretical framework; yet, this is a perspective topic for future research. Risk measures in positive and negative domains also match in the theoretical model and the empirical setting.

Positive semi-deviation is significantly higher for Contest (Investor B in my model) than for Live (Investor C in the model). In the case of negative semi-deviation, the effect is reversed. This fact reflects the upwards shift in risk aversion from affect-poor to affect-rich environment in the zone of gains and the opposite upshot in the area of losses.

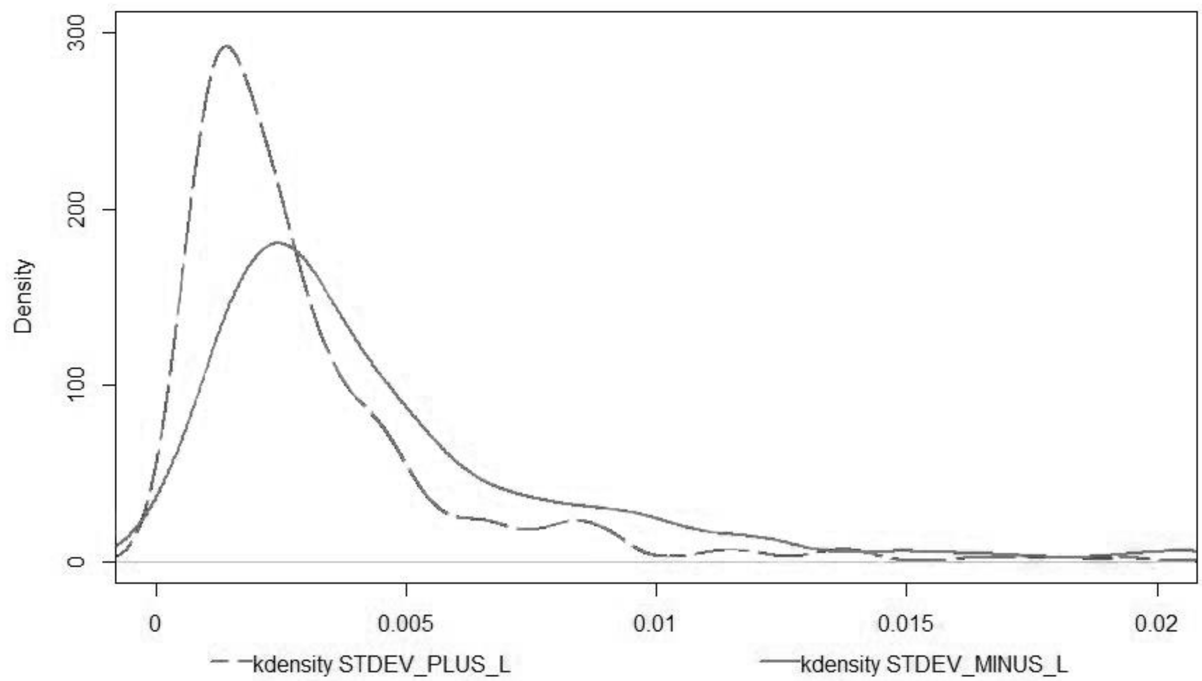
To investigate the changes in risk aversion/risk-seeking in more details, I conduct the graphical study of semi-deviation distributions of individual investors. Figures 6.4 and 6.5 below use kernel density function to depict the distributions of positive and negative semi-deviations in Live and Contest settings, where each observation is the designated volatility of a single trader. To confirm my alternative hypotheses, I should identify the visible disparity in the distributions as negative semi-deviation should be shifted to the right side from positive semi-deviation. What is more, this effect should be more intense in Live mode.

Figure 6.4. Distribution of realised semi-deviations in Contest settings using Kernel Density Function.



Note: STDEV_PLUS_C denotes positive semi-deviation in Contest setting. STDEV_MINUS_C denotes negative semi-deviation in Contest setting.

Figure 6.5. Distribution of realised risk measured by standard semi-deviation in Live settings using Kernel Density Function.



Note: STDEV_PLUS_L denotes positive semi-deviation in Live setting. STDEV_MINUS_L denotes negative semi-deviation in Live setting.

From the graphs above, I find that in both settings semi-deviations seem to evolve as described in the theoretical framework outlined in Section 2.10, whereby positive semi-deviation is smaller than negative, which again highlights the presence of S-shaped value function in Live and Contest. Also, visually it appears that the difference in the deviations in the two domains is more pronounced in Live compared to the Contest environment. To corroborate the results of Table 6.9. and graphical observations, I run two series of statistical tests. In the beginning, I compare semi-deviations inside the same setting (within-environment test). If positive semi-deviation is smaller than negative semi-deviation traders' value function is S-shaped along with Prospect Theory. I use Wilcoxon signed-rank statistics to test the null hypothesis of positive and negative semi-deviations equality. The results of the tests are presented in Section A of Table 6.10. Finally, I compare negative-to-negative and positive-to-positive semi-deviations across Live and Contest (cross-environment testing) to check the expectation of more extreme risk aversion and risk-seeking behaviour based on the greater curvature of the value function in Live trading as compared to Contest activity. As predicted by the alternative hypotheses, positive semi-deviation in Live should be smaller than in Contest, while the opposite picture should be observed in case of the negative semi-deviation. The results are provided in Section B of Table 6.10.

Table 6.10. Results of comparison of positive and negative semi-deviations using Wilcoxon signed-rank test.

Section A. Within-environment analysis of semi-deviations

Setting	Value of statistic	P-value
Live	27381	0.0000
Contest	49334	0.0000

Section B. Cross-environment analysis of semi-deviations

Domain	Value of statistic	P-value
Positive	32511	0.0000
Negative	64390	0.2300

Note: The tables show the results of Wilcoxon test. Section A provides the statistics for the within-setting analysis of semi-deviations, where positive and negative semi-deviations are compared for Live and Contest environments independently. Section B displays the statistics for comparison of positive (negative) semi-deviation in Live and positive (negative) semi-deviation in Contest.

Based on Table 6.10. Section A results, I can state that negative and positive distributions of semi-deviations are different both in Live and Contest environments with the 1% p-value.

However, in Live, the discrepancy of distributions is larger according to statistic values. This outcome reinforces my graphical analysis and the output for Disposition effect in Live and Contest, implying that the value function in the Live setting is more S-shaped than in Contest. Yet, the cross-environment analysis of risk that I present in section B of Table 6.10. provides a clear indication that sharper divergence between positive and negative semi-deviations in Live, is due to the changes in gains valuations (positive semi-deviations) rather than losses valuations (negative semi-deviations).

Overall, my results suggest that participants turned substantially more risk-averse for gains trades when changing from Contest to Live trading, in line with the predictions of the alternate hypothesis. At the same time, their risk behaviour did not change (statistically significantly) in the losses domain when they switched from Contest to Live. Even though, according to my alternative hypothesis, the subjects should have become more risk-seeking. As a result, I can reject only two null hypotheses out of three.

As a concluding remark, the findings and the statistical tests that I obtain in this section match well with the conclusions and predictions of the theoretical model outlined in Section 2.10. All of the relations between the volatility in gains and losses domains for Live and Contest correspond to the observed predictions for Investor B and Investor C in the model.

6.6.3. Robustness analysis using the individual trader-level data

To get a better understanding of risk behaviour and verify my conclusions, I shift down from the aggregate level of risk analysis to the scale of an individual trader as I did with returns in the Research Question 1. First, I break up individual traders' total risk into positive and negative semi-deviations, and compute Live-to-Contest ratios:

$R_i^+ = Var_{i,+}^{Live} / Var_{i,+}^{Contest}$ (Formula 6.1)

and

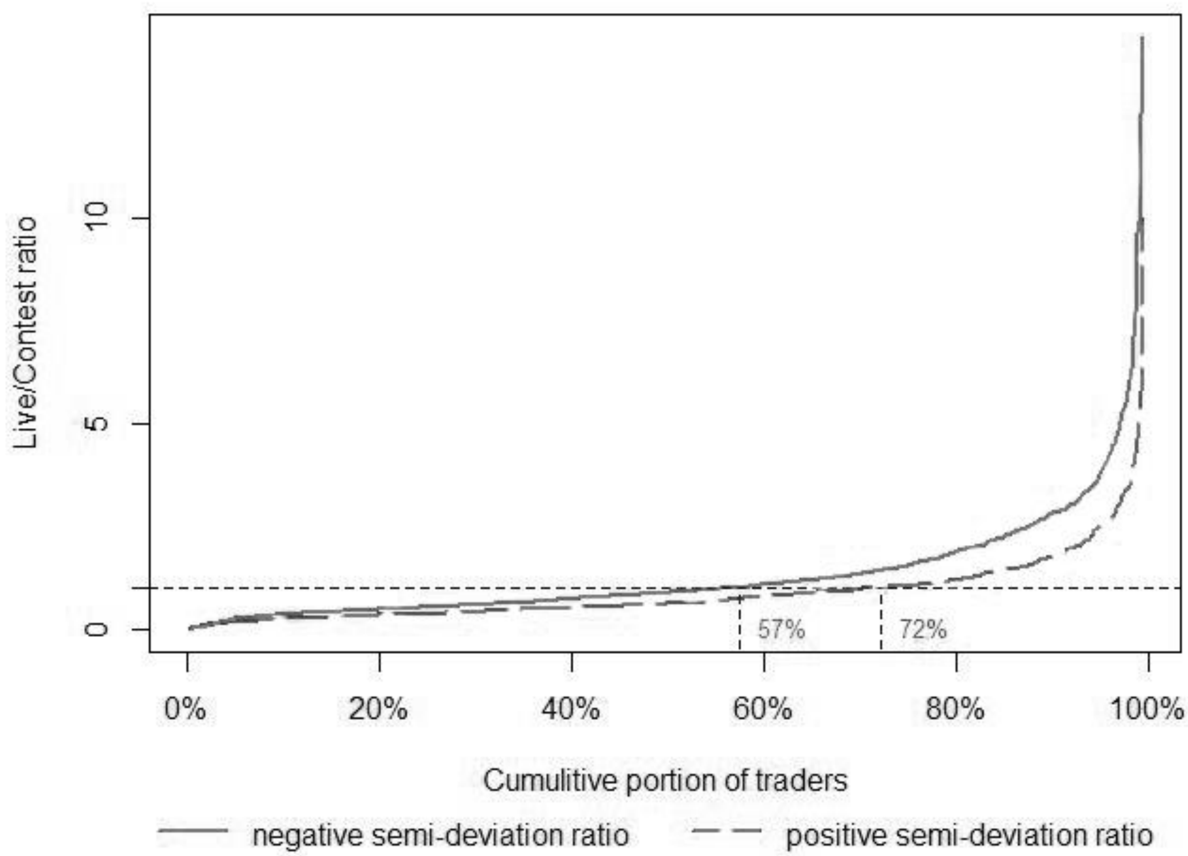
$R_i^- = Var_{i,-}^{Live} / Var_{i,-}^{Contest}$, (Formula 6.2)

where

R_i^+ and R_i^- denote each trader's positive and negative semi-deviation ratios, respectively; $\frac{Var_{i,+}^{Live}}{Var_{i,+}^{Contest}}$ is the proportion of positive semi-deviation in Live to positive semi-deviation in Contest; and $\frac{Var_{i,-}^{Live}}{Var_{i,-}^{Contest}}$ is the proportion of negative semi-deviation in Live to negative semi-deviation in Contest.

Figure 6.6 demonstrates the outcome:

Figure 6.6. The ratio of positive and negative semi-deviations in Live and Contest settings.



Note: Negative semi-deviation ratio demonstrates the individual trader's multiple of negative semi-deviation In Live account to negative semi-deviation in Contest account. Positive semi-deviation ratio is the respective multiple for positive semi-deviations.

For 72% of investors, positive semi-deviation in Live is smaller than in Contest, and this is in line with my findings: traders tend to cut their gains faster in a more emotional environment. However, a similar figure for negative semi-deviation conflicts with the concept of risk-seeking behaviour in a more emotional Live environment. 57% of traders actually prefer to take more realised risk in the Contest setting. This result shows that individuals are more risk-averse on both sides of the risk spectrum in Live setting, nevertheless, they turn comparatively more aversive to positive deviations in return than to negative.

Further, I conduct the statistical tests of within-subject risk behaviour by applying the methodology that I used in performance analysis. I formulate and implement two statistical tests to explore within-subject paired differences in variance of per-trade returns just as I did with performance (see Tables 6.3 and 6.4).

Table 6.11. Statistical tests formulation on the within-subject difference between Live and Contest realised variance.

	H0	**Ha**
Test 1	$var_i^{Live} = var_i^{Contest}$	$var_i^{Live} < var_i^{Contest}$
Test 2	$var_i^{Live} = var_i^{Contest}$	$var_i^{Live} > var_i^{Contest}$

Once again, I use a 95% confidence interval and apply the same methodology to place all subjects into 3 groups as with profitability difference. I employ F-test to carry out the analysis.

Table 6.12. Proportion of traders with statistically significant within-trader difference between Live and Contest per-trade variance.

Test name	**Group 1 (Live < Contest) Test 1 Ha**	**Group 2 (Live = Contest) Test 1&2 H0**	**Group 3 (Live > Contest) Test 2 Ha**
F-Test	80%	9%	11%

The data illustrates that 80% of all traders react to the hike in emotional intensity by significantly curbing bearable volatility of their returns, i.e. turning more risk-averse. Only one in 10 investors exhibit altered behaviour.

The evidence collected from the analysis above guides to believe that in addition to the changes in behaviour dictated by the shifts in the curvature of the value function, there are other psychological forces or factors that impact traders' revealed actions when placed into the environments of varying emotional intensity. These factors are especially influential in the domain of losses. I assume that these factors could be loss aversion and the changes in probability (decision) weighting function.

6.7. Research Question 2-2. Hypotheses development

6.7.1. Hypotheses development for loss aversion

The theoretical model constructed in Section 2.10 does not provide much information about such elements of risk behaviour as loss aversion and the form of the decision-weighting function. The evidence that I obtain from the model as regards loss aversion is that this bias has no much impact on the variables that I try to assess. Investor D modelled as Investor C with a much stronger loss aversion coefficient, does not exhibit a significantly distinct patterns of behaviour except stronger risk aversion in the losses domain. My empirical dataset provides for the indirect analysis of loss aversion in Contest and Live. The possible findings may give a clearer direction regarding the enhancement of the theoretical model and future empirical research.

I construct my hypotheses based on earlier figures 2.4 and 2.5, which reflect the theoretical view of the non-consequentialist model on the expression of loss aversion and decision weighting function. In both figures, I designate affect-poor stimulus processing to represent the shape of functions for the Contest account of my data set, while affect-rich stimulus processing denotes the trading on Live account. As in the case with the value function, if emotions have no impact on behaviour, as argued by consequentialist theories, there should be no statistically significant difference between Live and Contest. I will use this baseline scenario as the null hypotheses. Such a baseline scenario also corresponds to my theoretical model results. In contrast, alternative hypotheses will imply the statistically significant difference following 'Risk-as-Feelings' perspective or another related model.

To explore the role of feelings in the preference for loss aversion and the shape of the weighting function, I will employ the data on conditional close orders – stop-loss and take-profit – that have been successfully executed and changed the position's status from open to closed. Conditional orders may serve as a valuable tool to measure loss aversion because by placing them traders deliberately and unequivocally demonstrate their future expectations of traded instrument's price development and their attitude towards potential risk.

I approach the study of loss aversion in Live and Contest settings firstly determining the presence of the bias in my data. I develop the analysis framework and hypotheses based on two categories of data: the returns of conditional orders and the share of each type of conditional orders. For the null hypothesis, I assume that the main driving force behind the profitability and number of conditional orders is the form of the value function. In the domain of gains people face concave function, which propels risk-averse behaviour, i.e. individuals strive to secure the positive result sooner rather than later. This is the same theoretical implication that produces disposition effect, which I explored in the first part of Research Question 2. Yet, with respect to conditional orders, it means that people should be inclined to place take-profit orders closer to the market price and have them executed swiftly. With losses, it is different, as people tend to put them off to some distant time. Stop-loss orders should be realised less frequently based on this logic because they will be placed further from the market price. Therefore, I should expect to find two things: first, that the absolute return of stop-loss orders is higher than the absolute return of take-profit orders; and second, that the number of realised conditional stop-loss orders is smaller than the number of realised take-profit orders. This is equally applied to Contest and Live settings:

$$H_0^{Live,Contest}: abs\_r(SL) \geq rTP$$

$$H_0^{Live,Contest}: n\_trSL \leq n\_trTP$$

where abs_r(SL) means absolute return of stop-loss orders, rTP means the return of take-profit orders, n_trSL means number of realised stop-loss transactions, and n_trTP means number of realised take-profit transactions.

The alternative situation will take place if loss aversion is a relatively more influential factor impacting traders' preferences regarding the number of conditional orders. In this case, traders are supposed to demonstrate the lower absolute return of stop-loss orders than take-profit orders' return, and opt for proportionally more stop-loss orders than take-profit orders because losses generate more anxiety than changes in unrealised gains. The prevention or limitation of negative price developments becomes a more important psychological necessity. Again, I extend the same approach to Live and Contest environments:

$$H_{\mathrm{a}}^{Live,Contest}: abs\_r(SL) < rTP$$

$$H_{0}^{Live,Contest}: n\_trSL > n\_trTP$$

where abs_r(SL) means absolute return of stop-loss orders, rTP means the return of take-profit orders, n_trSL means number of realised stop-loss transactions, and n_trTP means number of realised take-profit transactions.

After that, I compare loss aversion in both environments. As put forth by the consequentialist perspective, the null hypothesis reflects the view that feelings have no impact on this risk factor, hence loss aversion in Live should not exceed the one in Contest environment. In contrast, my alternative hypothesis supports the standpoint of the part of literature exposing the higher degree of loss aversion in more emotional settings (see Figure 6.4).

$$H_0: Loss\ Aversion^{Live} \leq Loss\ Aversion^{Contest}$$

$$H_a: Loss\ Aversion^{Live} > Loss\ Aversion^{Contest}$$

6.7.2. Hypotheses development for probability weighting function

The family of theoretical models that I discuss in Section 2.10.1 attempt to test and confirm the predictions of Prospect Theory (Kahneman and Tversky (1992)). Specifically, they focus on the elicitation and analysis of the disposition effect, which is recognised as one of the natural products of Prospect Theory (Barberis and Xiong (2009)). However, the disposition effect has mainly to do with the value function's parameters – the extent of risk-aversion, risk-seeking, and loss aversion. Probability weighting function, even though exploited as in the original

Prospect Theory model, largely remains out of the analytical framework. It is not surprising because the non-linear characteristics of the decision weighting function are most vividly manifested for extreme probabilities, i.e. around certainty (100%) and impossibility (0%). The two-step theoretical models (e.g. Barberis and Xiong (2009), Vlcek and Hens (2011)) that examine the consequences of small variations in a risky asset around the reference price cannot detect the effect of the decision weighting function properly. Thus, the main tools for the study of the decision weighting function are the parameters elicitation techniques offered by Abdellaoui and his co-authors (e.g. Abdellaoui (2000), Abdellaoui et al. (2005)), Gonzalez and Wu (1999) and others. Consequently, in my investigation of the impact of emotions under risk and uncertainty on the decision weighting function, I will rely not on my theoretical model in Section 2.10 but on the literature that I explore in Section 2.6.3.

To examine how emotions under risk and uncertainty impact the probability weighting function, I focus on the between-setting segment of the conditional orders-related behaviour. I implement this by evaluating and comparing distributions of stop-loss and take-profit conditional orders' returns for Live and Contest settings.

The literature generally refers to four possible reactions of the probability weighting function to affective stimuli: no reaction (cognitive consequential theories like the Prospect Theory); more emphasised inverse S-shaped functional form (curvature-related changes, e.g. Rottenstreich and Hsee (2001)); more optimism or savouring (elevation-related changes, e.g. Abdellaoui et al. (2005)); more pessimism or dread (elevation-related changes, e.g. Abdellaoui et al. (2005)). In my analysis, I concentrate on 'more savouring' and 'more dread' reactions and hypothesise how it should translate into stop-loss and take profit orders' returns in Live and Contest.

My assumption is that if the reaction to the more affect-rich stimulus is more optimism with respect to probabilities evaluation, a trader will tend to place take profit orders further away from the current price, and further away from the level preferred in the affect-poor environment. Having the price hit this higher level in a more emotional (Live) environment, a higher return on take-profit orders in Live setting should be expected. Analogically, in the losses domain, more optimistic reaction to a more intensive emotion will motivate a trader to place stop-losses order further away from the current price and from the level in the less affective setting. This will cause underperformance of stop-loss orders' return in the Live environment. In line with the assumptions of more optimistic reaction, my null hypotheses are:

$$H_0^{SL}: SL^{Live} < SL^{Contest}$$

$$H_0^{TP}: TP^{Live} \geq TP^{Contest}$$

where SL stands for stop-loss conditional orders return, and TP stands for take-profit conditional orders return.

If the elevation of the probability function is affected by the dread sensations (that is, function in Live is above the function in Contest for losses domain, and reversed for gains domain), I assume that both, take-profit orders and stop-loss orders will be placed closer to the current price in the Live environment resulting in a higher return of stop-loss orders and lower return of take-profit orders. My alternative hypotheses follow the more pessimistic reaction perspective:

$$H_\mathrm{a}^{SL}: SL^{Live} \geq SL^{Contest}$$

$$H_\mathrm{a}^{TP}: TP^{Live} < TP^{Contest}$$

where SL stands for stop-loss conditional orders return, and TP stands for take-profit conditional orders return.

6.8. Research Question 2-2. Empirical analysis

6.8.1. Analysis of loss aversion based on profitability of conditional orders

Starting from the examination of returns of conditional orders, I expect that if investors attach more value to losses than to gains, i.e. they are loss averse, it should be exhibited in the distance from the prevailing market price to the conditional order's execution price. Specifically, traders are assumed to place stop-loss orders closer to the actual market price of traded instruments than take-profit orders. In this case, it must translate into smaller (absolute, ignoring the sign) returns for stop-loss orders compared to take-profit orders. This rationale should equally hold for Live and Contest settings.

Table 6.13. summarises conditional returns in Live and Contest:

Table 6.13. Average per-transaction return by the type of conditional order generated by traders in Live and Contest settings.

Setting/Order type	Stop-loss	Take-profit	Difference (p-value)
Live	|-0.18%|	0.25%	-0.07%*** (- 0.002)
Contest	| -0.30%|	0.49%	-0.19%*** (0.000)

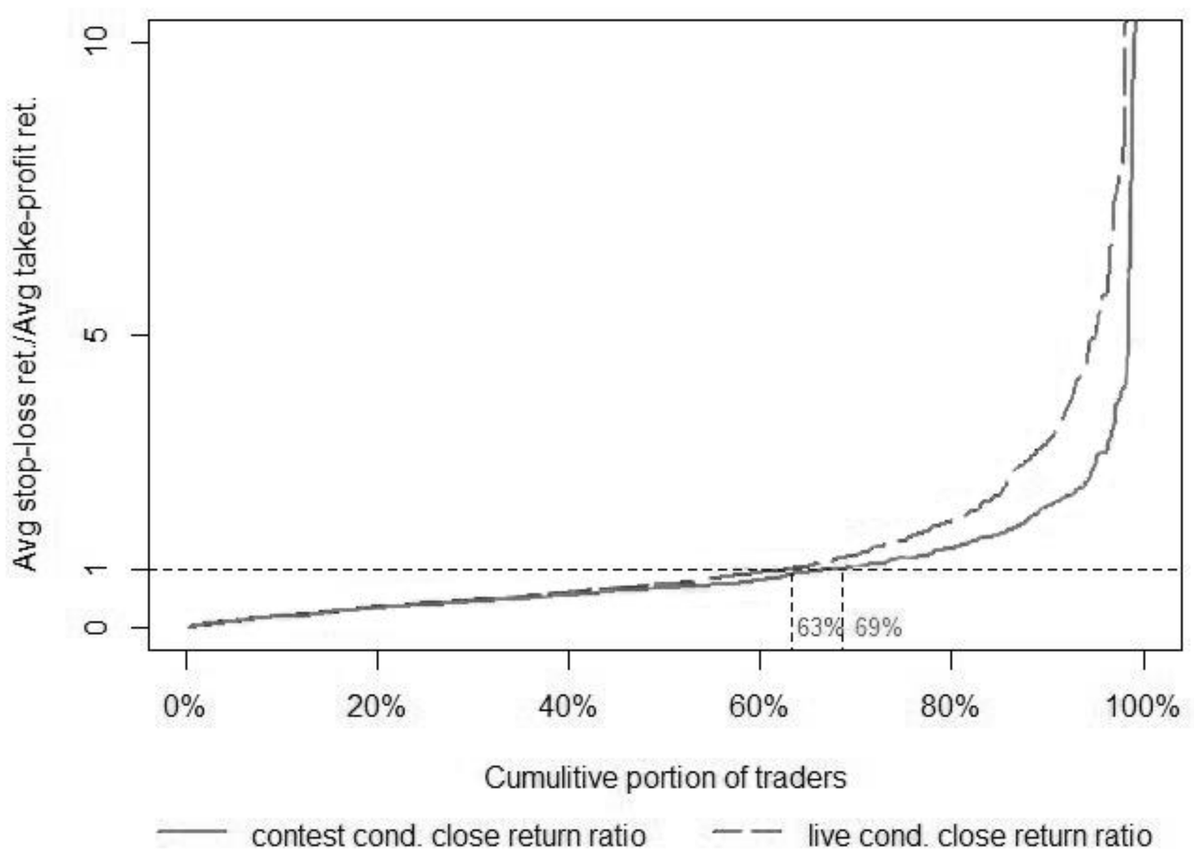
Note: Column two displays the returns of stop-loss conditional orders. Stop-loss orders' goal is to limit the amount of losses, hence the negative sign. In my analysis, I am interested in the absolute return, ignoring the sign that is why I take the stop-loss return by the modulus. To analyse the difference in returns I use Welch's t-test. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

The average per-transaction loss generated by stop-loss orders in Live and Contest is respectively 0.18% and 0.30%. It means that an average stop-loss order that is finally hit by the price and gets realised results in such substantial loss for an investor. On the take-profit order side the returns are 0.25% per average realised take-profit trade in Live, and 0.49% in Contest. My results show that the absolute performance figure for stop-loss orders is smaller than its take-profit vis-à-vis for both instances – Live and Contest. Both differences are statistically significant with 1% p-value. This corresponds to my alternative hypotheses, implying the presence of loss aversion in the traders' behaviour. Traders tend to place stop-loss orders closer to current market values of open positions than take-profit orders, which would be a natural behaviour if traders were subject to loss aversion. That is, they would value the disutility of a unit of loss higher than the utility of the unit of gain. Also, if computed as average returns, the loss aversion for Contest accounts is more pronounced that for Live. For Live setting, the difference between the conditional order types is only 0.07% or 39% when calculated as Take-profit-to-Stop-loss ratio. For Contest, the respective figures are 0.19% and 63%. This outcome complies with my null hypothesis about the role of emotions in loss aversion.

6.8.2. Robustness analysis of loss aversion using the individual-trader data

To investigate these aspects in more details, I turn to the level of an individual trader and compute the ratio of stop-loss return to take-profit return for each investor. Figure 6.7. displays the result:

Figure 6.7. Ratio of average stop-loss return to average take-profit return in Live and Contest modes.



Note: Contest conditional close return ratio represents the multiple of individual trader's Contest account average stop-loss return to take profit return. Live conditional close return ratio is the same representation for Live account.

The outcome demonstrates high heterogeneity among traders. Nevertheless, 63% of traders in Live and 69% in Contest manifest inclination towards loss aversion. Once again, loss aversion pattern measured as the ratio at the individual level is at minimum equally large in Contest setting as it is in Live. This fact may be a testimony of how innate loss aversion behavioural pattern is. Again, this result yields the support for the null hypothesis regarding the impact of feelings on loss aversive behaviour. The analysis of the profitability of conditional orders cannot provide the evidence of more pronounced reaction of loss aversion to the rise in emotional intensity.

6.8.3. Analysis of loss aversion based on the quantity of conditional orders

Next, I turn to the quantity of conditional orders realised by traders. In the data set, I have more than 103,000 realised Live conditional orders (22.5% of 458,000 total Live orders) and more than 100,000 realised Contest conditional orders (43.1% of 234,000 total Contest orders) spread across all the subjects. My analysis is summarised in Table 6.14. The findings confirm the alternative hypothesis for both settings, as the number of stop-loss orders exceeds the quantity of take-profit orders by approximately two times. The effect is surprisingly homogeneous in Live and Contest, repeating a similar phenomenon of similarity from the return analysis measured as the ratio (Figure 6.7).

Table 6.14. Proportion of stop-loss and take-profit orders in Live and Contest settings averaged across the pool of traders.

	Stop-loss orders (%of all positions)	**Take-Profit orders (%of all positions)**	**p-value for difference**
Live	66.1%	33.9%	0.000
Contest	69.5%	30.5%	0.000

Note: The second column presents the share of stop-loss orders in all conditional orders. The third column presents the share of take-profit orders in all conditional orders. To compute the statistical significance of the difference between two types of conditional orders, I employ Welch’s t-test analysis.

Just as in my prior examination, I complement the aggregate results with the individual level study. Table 6.15 below provides the breakdown of two ratio intervals, where each ratio represents the composition of Stop-loss/Take-profit number of executed orders per each trader:

Table 6.15. Stop-loss/Take-profit executed orders ratio per each trader aggregated by setting and ratio magnitude.

Setting/Ratio Interval	**<1**	**>1**
Live	27.32%	72.67%
Contest	15.82%	84.18%

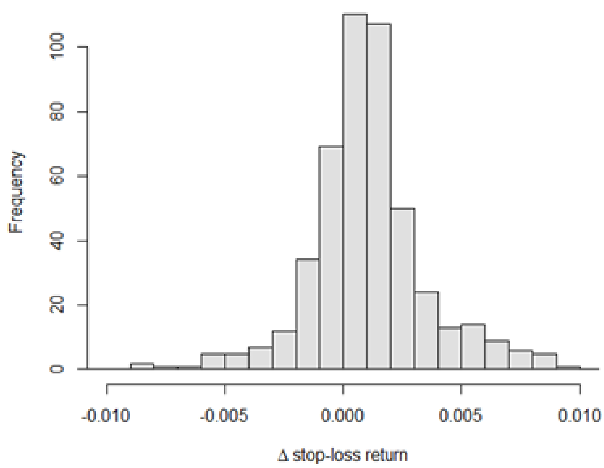
Note: For each individual trader I compute the ratio of stop-loss-to-take-profit orders. The ratio shows the preference of one conditional order type over another. The first column indicates the share of investors preferring take-profit orders to stop-loss orders. The second column shows the share of investors preferring stop-loss orders over take-profit orders.

Most traders clearly prefer stop-loss orders to take-profit orders. These findings support my alternative hypotheses, meaning that loss aversion is present in my high frequency trading data. Yet, when comparing two trading modes, Live and Contest, for the manifestation of loss aversion, it is not possible to reject the null hypothesis on the role of emotions in this behavioural bias. My subjects are equally loss averse in both environments. This conclusion follows from both approaches that I applied: returns of conditional orders, and preferences for the specific type of conditional orders.

6.8.4. Analysis of probability weighting function

To conduct the testing of the hypotheses concerning the probability weighting function outlined in section 6.7.2., I compute the difference between stop-loss order per-trade returns in Live and Contest for each trader in the data set. As can be seen in Figure 6.8, the mean divergence is substantial: for an average transaction closed by the stop-loss order, Live outperforms Contest setting by 0.1%. We need to recall here that an average transaction return differential, which I calculate in Table 6.2., and which includes all types of orders, is only 0.022%, that is 4.5 times smaller. The stop-loss returns mean differential is also highly statistically significant as corroborated by the t-test (t-stat = 7.16; p-value = 0.000). I also conduct Wilcoxon test to compare the whole distributions, and find that distributions are also statistically dissimilar (W = 86918; p-value = 0.000).

Figure 6.8. The distribution of per-trader disparity between stop-loss returns in Live and Contest per average transaction.

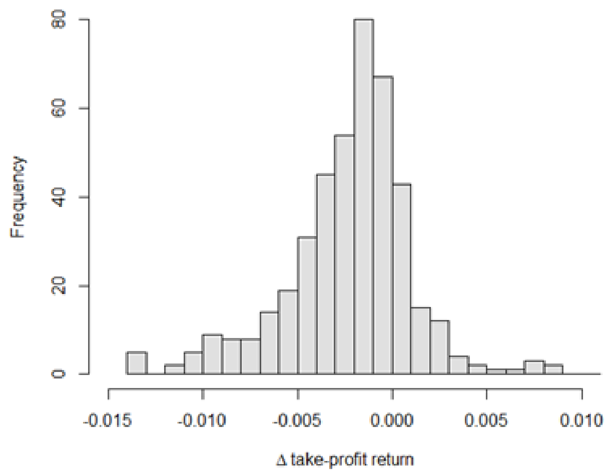


Mean	0.0010
Median	0.0009
SD	0.0031

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	86918	0.000
Welch's t-test (H1: live ≠ contest)	7.16	0.000

Next, I repeat the same approach with take-profit orders return as exhibited in Figure 6.9. Here the discrepancy between Live and Contest is even more striking. On average, every Live transaction of an average trader involving take-profit conditional order underperformed Contest by 0.21% (t-stat = -10.5; p-value = 0.000). Distributions of the per-trader difference between Live and Contest returns were significantly disparate (Wilcoxon W-stat = 12788; p-value = 0.000).

Figure 6.9 The distribution of per-trader disparity between take-profit returns in Live and Contest per average transaction.



Mean	-0.0021
Median	-0.0018
SD	0.0042

	statistic	p-value
Wilcoxon test (H1: live ≠ contest)	12788	0.000
Welch's t-test (H1: live ≠ contest)	-10.52	0.000

The findings in Figures 6.8 and 6.9 support my alternative hypotheses, which bolster the pessimistic account in the impact of emotions on probability weighting. In a more affect-rich environment, traders tend to place conditional orders of both types much closer to the current price. This type of behaviour is exactly what should be expected if the decision weighting function is shifted downwards for gains and upwards for losses. In this case, a decision-maker would underestimate (beyond curvature) objective probabilities for gains, and overestimate objective probabilities for losses by making more conservative bets on future price change on both sides of the return spectrum.

Further, I notice that the difference in mean returns between Live and Contest settings for both order types is approximately twofold (if we ignore the sign). That is, 0.1% per average trade for stop-loss orders, and 0.2% per average trade for take-profit orders. I assume that this is the evidence of the fact that in the losses domain traders are confronted with a harsh psychological dilemma as their trading turns more emotional (i.e., when they switch from Contest to Live modes). On the one hand, they experience an ardent desire to keep the losing position until reaching the break-even point, which propels an intense risk-seeking behaviour. On the other hand, a more pessimistic perception of probabilities creates the dread perspective of the consequences of keeping the losing position, which in turn produces risk aversive behaviour. I can imagine that this inner conflict of two counteracting forces is dealt with by investors very heterogeneously depending on personal psychological profiles. Indirect evidence of this assumption can be found in Figure 6.5. As it can be observed, risk-taking in gains domain is far more consistent than in losses domain, and the right tail of the returns distribution in losses domain is much fatter indicating less homogeneity. However, this interesting finding should be investigated more thoroughly in a separate study.

6.9. Summary and discussion of Research Question 2 results

The main goal of the analysis conducted in the Research Question 2 was to investigate if the difference in trading performance in Live and Contest environments could be explained by risk-taking praxis of investors under concern. Following this purpose, I examined the variance of returns of individual traders to verify if the form of the utility function corresponds to the consequentialist models and the predictions of my theoretical model outlined in Section 2.10. If that was the case, the deviation of return in the gains (concave) domain would be higher than the deviation of returns in the losses (convex) section of the function. That was exactly the case. Moreover, as the main outcome, I also evidenced that the degree of distinction between positive and negative semi-deviations of returns is more pronounced in Live than in Contest mode. I believe that this serves as a substantiation of the role that feelings play in risky behaviour, and how they shape the value function of a decision-maker. Mediated by the vividness of real losses, traders become increasingly sensitive to any minor deviations from the status quo (zero return), which, eventually leads to a higher level of risk aversion in Live environment. I complemented my investigation with the analysis of disposition effect, a well-studied behavioural bias. It is known that high trading frequency is an offsetting factor for the bias. Yet, I managed to reveal it in both settings, though insignificant at 95% confidence interval. Importantly, the difference between Live and Contest metrics of disposition effect was still significant at 10% level. One of my findings challenged the predictions of 'risk-as-feelings' hypothesis. I discovered that in Live and Contest investors were aligned, at least statistically, in terms of the degree of risk-seeking behaviour in the losses domain. However, the non-consequentialist perspective suggests higher risk-seeking in a more affect-rich environment. I hypothesised that this might be the impact of two other facets of risk, loss aversion and probability weighting function.

Loss aversion is another well-studied phenomenon, which implies greater psychological weight and more value derived from losses than from gains of equal magnitude in mixed gambles. To evaluate this bias, I employed returns and quantity of conditional orders used by traders. The presence of loss aversion would be manifested if investors put stop-loss orders closer to the market price than take-profit orders. It would mean that for the same amount of money (same magnitude) they are afraid of losses more than they passion for gains. Essentially, it means that the absolute returns of stop-loss orders should be smaller than the returns of take-profit orders. Computing the returns statistics, I figured out that in Live and Contest settings investors do place stop-loss conditional orders closer to the spot price than take-profit orders, as stop-loss orders are featured by smaller absolute returns, just as expected. Next, I compared the preference towards both types of conditional orders by calculating the number of executed orders given to the broker. I hypothesised that more explicit fear of losses should make investors focus too much on stop-loss orders, and as a result, stop-loss orders should outnumber take-profit orders. My analysis demonstrated that stop-loss orders turned out to be two times more frequently selected, again pointing to the presence of loss aversion among my subjects. Finally, I compared my loss aversion indicators for Live and Contest to verify the hypothesis that loss aversion is impacted by the growth in emotional intensity, and that loss aversion in Live should be more prominent than in Contest. This perspective found support in prior literature. Surprisingly, I found that the results for loss aversion were coherent and indistinguishable for both trading environments. With my data set I failed to confirm the hypothesis that emotional intensity has an impact on loss aversion. It meant that loss aversion bias could not explain the difference in risk behaviour that I discovered in the value function analysis.

I also used the statistics on conditional orders to gauge how affect influences the decision weighting function. For that, I compared the returns of same type conditional orders in the two trading modes. The literature on the probability weighting function discusses two fashions in which the function can evolve in response to affective stimuli: change in curvature (e.g. Rottenstreich and Hsee (2001)) and a shift (e.g. Abdellaoui et al. (2005)). My special focus was on the latter. The theory implies that the shift of the weighting function can occur as a result of pessimism (dread) factor influence or optimism (savouring) factor influence. I managed to explicitly validate an upward shift in the losses section and the downward shift in the gains section of the probability function, which denote more pessimism or dread in the evaluation of probabilities for both sides of the spectrum. Consequently, I believe that the similar degree of risk-seeking behaviour in the losses domain in Live and Contest that I discovered may be caused by the two counteracting psychological forces. The interplay of these two forces fits well into the theoretical framework of the role of affect in risky behaviour, set forth by recent literature (e.g. Loewenstein et al. (2001), Slovic et al. (2002), Kahneman (2003), Pfister and Bohm (2008), Mukherjee (2010) among others): on one side, an average trader experiencing a loss on his open position has a strong disposition towards not closing it until the loss is recovered (i.e. sharp convexity of the value function expressed in explicit risk-seeking); on the other side, the 'more dread' psychological account from escalating loss brings in a more pessimistic stance in the valuation of probabilities, which leads to the desire to cut the loss quickly. In a more affect-rich environment, the two counteracting forces pick up, and their resolution might depend on investor's personality qualities and traits, for example, degree of neuroticism or other personality attributes.

6.10. Research Question 3

In the previous two research questions, I have identified a meaningful difference in returns and risk behaviour between the two trading environments. In the last step, I will try to investigate how my profitability and risk variables interact. As I mentioned before, the theoretical framework reflected in Figures 2.1 and 2.2 imply that performance follows from the risk behaviour. Therefore, knowing about the implied dependence, it is logical to use multiple regression analysis techniques to examine the relation between risk and return, and use profitability as the dependent variable. In addition to risk variables, prior research considered other categories of variables to explain investment returns. I managed to extract from the data set an array of some of these variables that could help explain the difference in performance between Live and Contest. I arbitrarily split these variables into three groups: personal, behavioural and trading. I formulate my third research questions in the following way:

How do risk, personal, behavioural, and trading variables explain the difference between Live and Contest settings returns?

All the variables that I use in this research question can be inspected in Table 6.16. Section A includes the variables that describe the investment characteristics of the subjects. For example, it covers investors’ trading activity, use of different types of orders, profitability and volatility of performance. To compare how live and contest trading were distributed in time, the following additional characteristics were computed: portions of the contest trades that were made before the first, after the last or between the first and the last trades on live account. These variables are observable in Section B. In addition, I obtained person-specific data set on each trader containing the age, gender, marital status, domicile, occupation, and the origin of investment. These variables are available in Section C. Most traders in the sample were unmarried (77%) men (93%) living in developed countries (83%) and aged between 26 and 48 (80%). Additionally, 83% of analysed traders worked in non-financial field and 57% use their earnings as an investment for trading. Largely, these attributes match the ones in the big dataset that describes 8,527 investors (see Table 2.3 in Section 2.7 on Data Description).

Table 6.16. Descriptive statistics of traders' data set.

Section A. Descriptive statistics for the set of major trading variables for Live and Contest accounts across the pool of investors

	LIVE ACCOUNTS				CONTEST ACCOUNTS			
Variable name	AVG	MEDIAN	MIN	MAX	AVG	MEDIAN	MIN	MAX
BALANCE	2834	920	40	234323	107154	101613	0	321310
INTRADAY	78%	83%	6%	100%	65%	67%	0%	100%
TRADES	877	350	10	16426	448	202	10	8689
INSTRUMENT	14.6	12.0	1.0	52.0	18.3	17.0	1.0	49.0
ORDERS	23%	19%	0%	84%	43%	40%	0%	100%
STRATEGY	4.81%	0%	0%	100%	0.06%	0%	0%	14%
TURNOVER	52	14	0.06	1504	2801	1318	3	40820
DURATION	248	62	0.01	10008	469	270	2	13558
MO	87%	96%	1%	100%	69%	81%	0%	100%
CO	13%	4%	0%	99%	31%	19%	0%	100%
MC	68%	71%	0%	100%	46%	45%	0%	100%
SLC	23%	18%	0%	99%	38%	38%	0%	100%
TPC	10%	5%	0%	84%	16%	13%	0%	71%
STDEV	0.4195%	0.2856%	0.0020%	8.5054%	0.4376%	0.4086%	0.0615%	1.7695%
STDEV_PLUS	0.3185%	0.2164%	0.0016%	4.2694%	0.4139%	0.3840%	0.0000%	1.4505%
STDEV_MINUS	0.5923%	0.3405%	0.0000%	20.7084%	0.4719%	0.4451%	0.0683%	2.3586%
RETURNS	-0.02%	-0.01%	-1.68%	1.05%	-0.03%	-0.02%	-0.99%	0.29%
DEffect	-10784	103	-2104132	660794	-1283	523	-1328432	262176

Section B. The set of behavioural and personal variables descriptive statistics

Variable name	AVG	MEDIAN	MIN	MAX

BEFORE	30%	12%	0%	100%
COINCIDE	54%	60%	0%	100%
AFTER	16%	0%	0%	100%
CONT_LIVEp	5519	6911	-781921	280624
CONT_LIVEm	-3981	6016	-2073711	1390491
AGE	36.5	35	21	71

Section C. The set of personal variables descriptive statistics

Variable name	N	SHARE
DOM_ DEVELOPED	434	83%
INVEST_ EARNINGS	299	57%
MARRIED	122	23%
OCCUPATION_ FINANCE	90	17%
FEMALE	38	7%

Note: All the variables are calculated per an investor (or an account). The decoding and meaning of variables: Section A: BALANCE (USD) – average daily balance of the account (computed as 0.5*(ending daily balance - initial daily balance)); INTRADAY(%) – share of trades completed within a trading day; TRADES (N) – total number of transactions made on the account; INSTRUMENT (N) – number of trading instruments used by investors; ORDERS (%) – share of conditional orders as part of all orders placed; STRATEGY (%) – share of automated trades as part of all trades completed; TURNOVER (mln USD) – aggregated turnover on the account; DURATION (min) – median duration of an average trade on the account; MO (%) – share of trades initiated with a market order; CO (%) – share of trades initiated with a conditional order; MC (%) – share of trades closed with a market order; SLC (%) – share of trades closed with a stop-loss order; TPC (%) – share of trades closed with a take-profit order; STDEV (%) – standard deviation of the trading positions return (return calculated as return/position_volume); STDEV_PLUS (%) – standard deviation of positive positions return; STDEV_MINUS (%) – standard deviation of negative positions return; RETURNS (%) – average return on an account (calculated as return/position_volume); DEffect (sec) – disposition effect computed as difference between median durations of winning and losing positions. Section B: BEFORE (%) - the portion of the subject's trades on contest account, which were made before the subject's first trade on live account; COINCIDE (%) - the portion of the contest's trades, which were made between the first and the last trade on live account; AFTER (%) - the portion of the contest's trades, which were made after the last subject's trade on live account; CONT_LIVEp (sec) - difference between median durations of winning positions on contest and live accounts; CONT_LIVEm (sec) - difference between median durations of losing positions on contest and live accounts; AGE – investor's age. Section C: DOM_DEVELOPED – investors with the domicile in developed countries; INVEST_EARNINGS – investors specifying earnings (regular income) as the source of their investment capital; MARRIED – investors who chose their family status as married; OCCUPATION_FINANCE – investors specifying that they work in financial industry; FEMALE – investors specifying their gender as female.

6.11. Research Question 3. Hypotheses development

The full list of variables that I plan to use in my analysis is presented below with explanations. As far as I know, the existing literature does not provide straightforward evidence of the impact of these variables on the possible difference between two diverse emotional contexts, especially in the financial domain. Therefore, it is hard to make qualified literature-based predictions of the possible impact on the dependent variable, which is the difference in return between Live environment and Contest environment ($r_{\Delta}^{i} = r_{Live}^{i} - r_{Contest}^{i}$).

1. ***Risk variables:***
    a. **Positive standard semi-deviation in Contest –** calculated according to Formula 3.2. Shows the second parameter of the distribution of positive returns in the Contest setting.
    b. **Negative standard semi-deviation in Contest -** calculated according to Formula 3.1. Shows the second parameter of the distribution of negative returns in the Contest setting.
    c. **Positive standard semi-deviation in Live -** calculated according to Formula 3.2. Shows the second parameter of the distribution of positive returns in the Live setting.
    d. **Negative standard semi-deviation in Live** – calculated according to Formula 3.1. Shows the second parameter of the distribution of negative returns in the Live setting.

Expected sign: One of the cornerstones of financial theory is the relation between risk and performance. At the same time, according to 'Risk-as-Feelings' theory, risk behaviour is directly connected to emotional states. Consequently, when comparing affect-poor environment (Contest) with affect-rich environment (Live) the shift in risk behaviour, gauged by the change in risk variables, should not only demonstrate high impact on performance variables but also explain a great deal of the difference in performance. Another important consideration is the fact that traditional finance believes in direct relation between risk and return. Therefore, for Live risk variables I expect a positive impact on the differential between Live and Contest performance, while for Contest risk variables it should be negative.

2. ***Personal variables***[69]:

   Age – minimum age to participate in the financial market is 18. The maximum age is not limited.

   Gender – there is an overwhelming dominance of males in our data set. Only 3.5% of all traders (18 people) who had two types of accounts were females[70].

   Country of domicile – I split the traders into two categories: living in developed and developing countries[71].

   Marital status – I split the traders into two categories: married and non-married[72].

   Professional occupation – I split the traders into two categories: working in finance and taking non-financial positions.

[69] From all the personal variables we use in the study, only Age, Gender and Country of Domicile are obligatory verified by the brokerage house (through passport data and proof of address). Marital status and Professional occupation are self-reported and not validated. Source of income is verified on selective basis.
[70] According to the brokerage house that provided the data set, the very tiny representation of women is traditional for this industry. It is well-known from the research in various domains, financial and non-financial, that women are much less aggressive and risk-loving than men. Considering the very high degree of risk in marginal day-trading, the small portion of women in this market should come as a little surprise. Effectively, this tiny share of female day-traders is by itself a reliable proof of the difference in the level of risk appetite between the genders.
[71] The selection of developed countries was based on the OECD member state list.
[72] The non-married traders are detailed in the data set as divorced, single and widowed.

Source of Income – I divide traders into two categories: earnings and other sources[73].

Expected sign: Personal variables that I analyse are related to experience with financial decisions. From this viewpoint, more experience should be associated with less difference between Live and Contest return, as more experienced individuals are believed to better control their emotions. Hence, higher age and professional occupation in finance should be negatively related to the dependent variable. Other variables are less tightly connected to the experience. I hypothesise that investors from developed countries should be more trained in financial decisions all else being equal because they more frequently come across such decisions and financial education information in their daily routine. Also, financial market participation ratio is much higher in the developed countries. The same should regard males from 'gender' variable, married from 'marital status' variable, and investors with earnings as the main source of income.

3. ***Behavioural variables***:

Learning effect – the variable compares the trading time frames in Live and Contest and reflects the proportion of overlapping and non-overlapping trading. There are three sub-variables included: 1) Time proportion when Live trading occurred before Contest trading; 2) Time proportion when Live trading overlapped with Contest trading; 3) Time proportion when Live trading occurred after Contest trading.

Disposition effect – there are two sub-variables included in the analysis: 1) disposition effect in Live, and 2) disposition effect in Contest. Disposition effect

[73] The other defined sources of income category include Heritage and Savings.

was computed as the difference between median durations of winning and losing positions (in minutes).

Expected sign: Learning effect is associated with experience obtained in one of the settings before the other, or simultaneously in both. My expectation is that if an investor had a preliminary training in one of the settings, the results on the other should improve. Therefore, trading in Contest before or simultaneously with Live should be negatively related to the difference in Live and Contest performance. The literature on disposition effect clearly highlights its negative role for performance.

4. ***Trading variables[74]:***

Account balance – the average daily balance of Live and Contest accounts.

Intraday trades – the difference between the portion of intraday trades on Live and Contest accounts.

Number of trades – the difference between the number of transactions made by a trader in Live and Contest.

Number of instruments – the difference between the number of trading instruments used by a trader during investment period in Live and Contest.

Conditional orders – the difference between the portion of conditional orders in Live and Contest trading. I used ten sub-variables that described five various types of conditional orders: 1) Market open – portion of trades opened with a market order; 2) Market close – portion of trades closed with a market order; 3) Conditional open – portion of traders opened with a conditional order; 4) Stop-

[74] All trading variables are duplicated for Live and Contest accounts.

loss close – portion of trades closed with a stop-loss order; 5) Take-profit close – portion of trades closed with a take-profit order.

Strategy – the difference between the portion of automated trades initiated by the trading algorithm employed by a trader in Live and Contest.

Turnover – the difference between the aggregated turnover on Live and Contest accounts

Duration – the difference between the median duration of trades on Live and Contest accounts.

Expected sign: Except for the size of the account balance, all other variables are constructed as the difference between the value in Live and Contest settings. Account balance in Live environment is associated with the trading success and wealth of investors. As is known from the literature, wealthier investors are generally more skilful in terms of financial decisions. Therefore, it is expected to have positive relation with the dependent variable. In Contest, investors are provided with the paper capital, hence this variable is only about the trading skill but not wealth. Still, I expect this variable to be negatively correlated with the dependent variable. Hence, disposition effect in Live should have negative correlation with the dependent variable, and disposition effect in Contest should have positive correlation with the dependent variable. Intraday trades, Number of trades, Conditional orders, Number of instruments, Strategy, Duration, and Turnover represent the group of variables attributed to trading activity. My suggestion is that higher difference between Live and Contest in trading activity is an indication of larger susceptibility of individual traders to emotional reaction. As I discovered in Research Question 1, profitability in more emotional Live environment exceeds Contest, that is why my expectation for these variables is a positive impact on the dependent variable.

6.12. Research Question 3. Empirical analysis

I run two regression models. The first model does not include variation parameters, while they are included in the second model. I take this step in order to explore my hypothesis about the impact of risk variables on the difference between Live and Contest returns.

Table 6.16. The impact of personal, behavioural and trading variables on the difference between Live and Contest returns

Variable name	**Model 1**	**Model 2**
(Intercept)	1414 (0.000)***	853 (0.001)***
AGE (Years)	-6.39 (0.814)	-2.75 (0.472)
ACCOUNT_BALANCE_LIVE ($)	0.039 (0.000)***	0.0343 (0.000)***
ACCOUNT_BALANCE_CONTEST ($)	-0.0096 (0.000)***	-0.0082 (0.000)***
INTRADAY_TRADES (%)	885.2 (0.034)**	317.8 (0.272)
NUMBER_OF_TRADES (N)	0.0049 (0.873)	-0.0192 (0.407)
NUMBER_OF_INSTRUMENTS (N)	11.70 (0.017)**	8.44 (0.028)**
CONDITIONAL_ORDERS (%)	205.1 (0.810)	145.9 (0.850)
STRATEGY (%)	-207.1 (0.263)	-470.2 (0.052)*
TURNOVER ($)	-0.0055 (0.646)	0.00238 (0.772)
DURATION (min)	0.0661 (0.712)	-0.138 (0.332)
MARKET_OPEN (%)	-43 (0.905)	-41 (0.359)
MARKET_CLOSE (%)	67.7 (0.889)	-465.9 (0.749)
STOP_LOSS_CLOSE (%)	-723.9 (0.038)**	-1643.1 (0.000)***
LEARNING_BEFORE (%)	-121.7 (0.379)	-44.8 (0.726)
LEARNING_COINCIDE (%)	-313.3 (0.041)**	-185 (0.074)*
DISPOSITION_CONTEST (min)	-25.67 (0.000)***	-11.48 (0.019)**
DISPOSITION_LIVE (min)	4.36 (0.268)	0.18 (0.912)
DEVELOPED (binary)	595.2 (0.184)	-19.9 (0.960)
SOURCE_EARNINGS (binary)	-249.2 (0.018)**	-103.6 (0.145)

STATUS_MARRIED (binary)	-137.60 (0.263)	-120.5 (0.223)
OCCUPATION_FINANCE (binary)	129.9 (0.492)	100.7 (0.799)
GENDER_FEMALE (binary)	246.2 (0.102)	194.7 (0.194)
STDEV_PLUS_CONTEST (return/position volume)		-0.1815 (0.000)***
STDEV_MINUS_CONTEST (return/position volume)		0.1829 (0.000)***
STDEV_PLUS_LIVE (return/position volume)		0.1261 (0.000)***
STDEV_MINUS_LIVE (return/position volume)		-0.0729 (0.000)***
Adjusted R^2	0.3212	0.6694
F-statistic	11.74	40.150
p-value	0.000	0.000
df	522	522

Note: The dependent variable is the difference between the performance in Live and Contest accounts. Variables are calculated per $1 mln position size. *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level. Disposition effect (in Live and Contest) variables are measured in hours. Huber-White consistent p-values are provided in the parenthesis. Age is measured in years; Account balance in Live and Contest, and Turnover are measured in monetary (USD) value; Intraday trades, Conditional orders, Strategy, Market open, Market close, Stop-loss close, Learning variables are measured as percentage differential between Live and Contest; Number of trades and Number of instruments are measured as absolute difference between Live and Contest; Duration and Disposition effect are measured in minutes; Personal variables except age are denoted as binary variables. Risk variables (standard deviations) are measured as absolute return weighted by position size.

The magnitude of the variables is calculated per the trading position size of USD 1 million. The minimum trader's capital that is required to open and keep the position of that size is 100 times smaller, i.e. USD 10,000[75]. As was mentioned earlier, according to the information from the brokerage house, the average leverage used by the traders is around 33. Consequently, taking an intercept for the Model 1, which is USD 1,414 it may be inferred that the turnover of USD 30,300 of trader's own funds on average generates the difference of 4.7% (USD 1,414/USD 30,300) between trader's Live and Contest accounts that are unexplained by the Model 1 independent factors.

[75] The leverage of 1:100 is a standard condition for the retail Forex brokerage industry.

The variables in Model 1 explain 32% of the variation in the performance differential between Live and Contest settings. According to Model 1, the following variables have an impact on the difference between Live and Contest performance:

Table 6.17. The influence of statistically significant variables on the difference between Live and Contest accounts' performance according to Model 1 specification.

Variable	Impact on differential between Live and Contest	Significance
Account Balance Live	Rise	***
Account Balance Contest	Drop	***
Δ Intraday trades	Rise	**
Number of instruments	Rise	**
Δ Stop-loss orders close	Drop	**
Learning effect (Coincide)	Drop	**
Disposition effect (Contest)	Drop	***
Source of Income (Earnings)	Drop	**

Note: *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

The variables of Account balances in Live and Contest behave in line with my prediction. Higher balances reflect more successful investors. Every $1,000 in Live account yields an extra $39 of the difference between Live and Contest return (per $1,000,000 turnover). For trading activity variables, only the difference in Intraday trades and Number of instruments have a significant impact on the dependent variable. Yet, the impact is as predicted. For example, each per cent of the difference in the Intraday trading between Live and Contest results in $885 outperformance of Live account (per $1,000,000 turnover). The regression shows that a higher percentage of stop-loss orders in Live has a negative role in Live/Contest performance differential. Interestingly, the disposition effect variable is only significant in Contest environment, even though it is in line with my expectation. Personal variables are all statistically insignificant, except for the Source of Income, which states that Earnings (as a source of income) play a negative role in the dependent variable. It seems that for my subjects regular income, in contrast to irregular one, provides for better quality decisions in Contest that in Live.

Adding risk factors to the array of variables from Model 1 significantly improves the explanatory power, which grows twofold. Additionally, there are minor changes in the list of statistically significant independent variables:

Table 6.18. The influence of statistically significant variables on the difference between Live and Contest accounts' performance according to Model 2 specification.

Variable	**Impact on differential between Live and Contest**	**Significance**
Account Balance Live	Rise	***
Account Balance Contest	Drop	***
Δ Strategy	Drop	*
Number of instruments	Rise	**
Δ Stop-loss orders close	Drop	***
Learning effect (Coincide)	Drop	*
Disposition effect (Contest)	Drop	**
Standard deviation PLUS Contest	Drop	***
Standard deviation Minus Contest	Rise	***
Standard deviation PLUS Live	Rise	***
Standard deviation Minus Live	Drop	***

Note: *** Means significant at 1% level, ** means significant at 5% level, * means significant at 10% level

I should also note that even though adding risk variables reduces the intercept almost twofold, it is still significant in Model 2. I can estimate that for the average trader, even accounting for risk (as I measured it) still leaves the room for approximately 2.8% (of the own capital turnover) differential between Live and Contest trading[76].

6.13. Summary and discussion of Research Question 3 results

The main outcome of the regression analysis is that I found direct empirical evidence supporting the concepts laid out in the non-consequentialist theories by Loewenstein et al. (2001), Slovic et al. (2002), Kahneman (2003) and others on the emotional nature of risky behaviour. As implied by these theories, individuals should react to affective stimuli by significantly modifying their behavioural risk-taking patterns, which should impact the performance of their activity. My results show that risk variables indeed provide for a substantial (both economically and statistically) explanation of the variation in performance observed for two differently emotionally-charged trading environments.

I discovered that even after controlling for personal, trading, and other variables, there is a still room for significant outperformance of Live over Contest for an average investor. Effectively, when calculated based on investor’s own funds turnover, the difference was 2.6% to 4.3% in favour of the Live setting. In my view, there is a high chance that the unexplained part of the variation could be progressively explicated using more advanced risk measures that I could not apply in the current research because I only possessed data on the realised transactions. It may be the case that a very large part of variance impacting behaviour remains hidden in the non-

[76] The value of 2.8% from the own capital of an investor is based on the average leverage multiple taken by investors, which is known to equal 33. Considering that I compute the intercept of the Model 2 based on the trading turnover of USD 1,000,000, the amount of own capital required by investor to generate such trading turnover equals to USD 30,300 ($1,000,000/33). The intercept in Model 2 ($853) divided by the own capital ($30,300) gives approximately 2.8%

realised component of a trade. Nevertheless, even realised transactions shed light on the necessity to develop and involve emotional factors into financial models to better understand and forecast the decisions made by individual investors.

I also found that larger size of Live Account Balance (an indirect indication of wealth), the higher share of intraday trades in Live trading, and more instruments used in Live trading, all result in better individual Live performance as compared to Contest trading.

Simultaneously, traders with the larger size of Contest Account Balance, the larger share of executed Stop-loss orders, Earnings as a source of investment capital, higher disposition effect on Contest account, and concurrent trading period in both settings, are capable of decreasing the performance differential in Live and Contest.

I could not confirm that variables found influential for performance in other studies, such as Age, Gender, trading frequency (number of trades) or Turnover influenced the Live-Contest performance variation.

Fenton-O'Creevy et al. (2012) stipulate that emotion regulation may play an essential role in tempering emotions' impact on performance. The authors find proof in favour of their hypothesis by identifying the positive correlation between traders' experience and heart rate variability (HRV). In my research setting, I could not test the assumption directly. Nevertheless, my findings that some investors reveal an outperformance of Live accounts over Contest, while another group of investors demonstrate the opposite phenomenon, may indicate that there are factors that help some investors in emotions regulation. In Research Question 3, I test several possible factors for such a role, for example, experience, age, gender. I do not find direct evidence that performance differential between Live and Contest is somehow impacted by any of these factors. However, emotions regulation can find its way to performance via other factors, such as personality traits, which can influence performance by mediating trading behaviour. It is definitely one of the interesting topics for future research.

7. Conclusions and Discussion

7.2. General summary and discussion of the thesis

There is increasing evidence in academic research that traditional approach to decision-making under risk and uncertainty fails to explain and predict individual behaviour correctly. In lots of real-life scenarios, the observed economic choices deviate from the prescriptions of Expected Utility Theory, sometimes even turning upside down. During decades of studies, virtually all main principles of neoclassic economic perspective got challenged, which has put under question the consistency of the belief in rational economic agents as well as their rational expectations. A seminal work by Tversky and Kahneman has offered a psychologically more coherent framework of human behaviour that was called Prospect Theory (Tversky and Kahneman (1979)). In this model, individuals are not fully rational in the sense of traditional theory, rather they are striving their best to reach some level of wealth maximisation and self-interest under the severe limitation of their imperfect information and cognitive capacity. There are important implications that follow from the disagreement between traditional and behavioural explanations of economic choice because all key fundamental theories in finance are established on the base of the neoclassic assumption of rationality. Hence, the analysis of rational behaviour becomes one of the keys to understanding the future development of modern finance. Unfortunately, one of the biggest challenges on the way to testing rationality of individuals is the lack of naturally observed empirical data that record human behaviour in an unconstructed environment of real-life economic decisions with readily available objective results of these decisions. Luckily, after the massive spread of the Internet and IT, the number of electronic registers that record human behaviour have largely increased. In the investments industry, IT innovation has created a new industry of online retail electronic investment platforms, which provide STP brokerage services[77]. Such companies log in very small details every investor's move as well as a huge amount of metadata that, for example, document when and how each of the investment decisions has been taken and how frequently a person has accessed the account.

In Section 2.10, I develop a theoretical framework following the models of Barberis and Xiong (2009), Vlcek and Hens (2011), Jakusch et al. (2019). My model pursues several goals. First, I analyse the theoretical implications and predictions of Prospect Theory for the relation between risk and return, which up to date was not thoroughly covered by the academic research. Second, I examine how distinct parameters of the utility function can be associated with different degree of affect surrounding the decision-making environment. I introduce three stylised types of investors, each featured with diverse coefficients of utility function's curvature and loss aversion. Based on the modelling results, I make a series of predictions that I further integrate into the hypotheses of the empirical chapters.

[77] STP brokerage stands for straight-through processing brokerage and denotes the case when upon receipt of client's order, a broker will immediately and automatically pass it over for execution at the marketplace or with external liquidity provider in case of OTC transaction.

7.2.1. Summary and discussion of the first empirical chapter

In the first empirical chapter, I am using one of such databases from a large online brokerage house that contains the trading statistics of 8,000 investors to investigate the following research question: Do individual investors change their risk behaviour subject to positive or negative trading results? If they do, this would be a direct confirmation of Prospect Theory assumptions. If they do not and remain risk-averse independent of performance, this would highlight their inherently rational behaviour in line with Expected Utility Theory. To evaluate the form of the value function and the degree of rationality, I employ correlation analysis between risk and return. The positive correlation between these two variables should point to the concave form of the function, meaning that investors bear additional risk in exchange for a positive risk premium. In turn, negative linear relation would expose convex value function and the fact that investors are ready to consume additional risk and experience negative risk premium. In the case of zero correlation coefficient, risk neutrality is to be confirmed. Besides, I assume that the strength of linear relation is a good indicator of the persistence of rationality. A relatively more positive correlation between risk and return should be reliable evidence of stronger risk aversion, hence rationality level. The same can be told about a relatively more negative correlation, which would outline a sharper degree of irrationality.

My results show an unambiguous confirmation of the hypothesis supporting behavioural theory's explanations of choice. Using parametric and non-parametric methods to compute the correlation, I find that aggregating investors' risk and return measures, there exists a statistically significant positive correlation between these two variables in the gains domain and significant negative correlation in the losses domain, respectively 0.07 and -0.30 using Spearman method. The fact that the negative coefficient is noticeably larger than a positive one, may reflect the greater psychological weight of losses for a decision-maker that is predicted by Prospect Theory and dubbed ‘loss aversion’ bias. As a result of the bias, the relation between total risk and return is negative and equals to -0.23 under Spearman approach.

Next, I divide my dataset into two groups, according to the overall profitability of the subjects. ‘Gainers’ group involves traders, whose results are above zero after realisation of all transaction under review. ‘Losers’ group comprises all underperformers with the same threshold of zero return. With this bifurcation, I explore if good performance is related to a higher degree of rationality. In other words, if outperformers would have a higher level of correlation between risk and return. This is just another angle of view on the research question. I expect that ‘Gainers’ who more frequently would experience profitable trades, should demonstrate more risk-averse behaviour resulting in a positive correlation between risk and return variables. The reverse scenario is anticipated for ‘Losers’. The results verify my hypotheses: Spearman rank correlation between total risk and return for ‘Gainers’ equals to 0.58 and for ‘Losers’ it is -0.70. The same situation is found using coefficients in regression analysis: 1% of return is ‘priced’ at 28% of standard deviation for ‘Losers’ and 14% for ‘Gainers’. Again, I reveal that the psychological factor of loss aversion with its stronger impact of risk in losses domain is playing its role in behaviour.

The approach above exhibits only gross evidence of investors’ choices uncovered by risk/return correlation. It does not allow to explore the heterogeneity of individual risk preferences and value functions. To make the respective investigation, I obtain a specific correlation measure for each individual investor by breaking their trading history into even series of 20 transactions in each of minimum 10 sequences. For each of such sequences, I calculate average return and positive and negative realised volatility (positive and negative semi-deviation of returns), which provide for the estimation of a personal correlation coefficient. My findings demonstrate a vast dispersion of individual coefficients. The average correlation for all subjects equals to -0.07 and is statistically significant at 1% level. Standard deviation is 0.38, while 59% of investors have their coefficient below zero. For hypothesis testing purposes, I again break all traders into 'Gainers' and 'Losers' groups. For outperforming investors, the average of individual correlation coefficients equals 0.09 (41% of observations fall below zero), significant at 1% level. For underperformers, the mean coefficient is -0.15 (68% investors hitting below zero correlation), also significant at 1%. This outcome substantiates the initial assumption of more aligned risk aversion among 'Gainers' and risk-seeking pattern among 'Losers'. Further, inside each performance group, I independently evaluate the relation between return and positive risk (positive semi-deviation) and return and negative risk (negative semi-deviation). As expected, in both groups, investors exhibit risk aversion for gains and risk-seeking for losses. Nevertheless, 'Gainers' prove a far stronger positive correlation in gains domain than 'Losers' – 0.47 against 0.27, and less strong correlation in losses domain - -0.33 versus -0.45.

As a next step, I use a univariate regression technique with return as independent variable and risk (positive and negative) as the dependent variable to construct a risk-return relation model autonomously in losses and gains sections of the value function for each individual investor. Based on this analysis, I attribute the subjects to a specific pattern of behaviour. For instance, a trader having positive risk/return correlation in gains domain and negative correlation in losses domain may be ascribed to S-type behaviour that is predicted by Prospect Theory. The other patterns include universal risk aversion prescribed by Expected Utility Theory and universal risk-seeking that does not have a clear theoretical attribution. In addition, I introduce the concept of weak and strong forms of each behavioural model. To take the strong form, a correlation coefficient has to be statistically significant at least at 5% level. Otherwise, I designate it to be weak. Using this method, several noteworthy conclusions can be made. Most investors are inclined to Prospect Theory's backed S-type behaviour – 72% of my subjects exhibited this pattern in a weak form and almost a quarter had it in a strong form. This is by far the most popular model. The second place is occupied by weak (20%) and strong (5%) forms of universal risk-seeking pattern, which is surprising considering that there is no theory to support it. Finally, plain risk aversion is exhibited by only 8% of investors in a weak form and 1% in a strong form. I also reveal that 12% of traders have insignificant correlation coefficient in gains and losses domains. This case can be labelled as risk-neutral behaviour. On top of that, I discover that outperforming investors are substantially more predisposed to plain rational behaviour and less to being fully risk-seeking than underperformers. For example, 16% of 'Gainers' prove to have a weak form of risk aversion against only 4% of 'Losers'. In contrast, 26% of 'Losers' unveil the weak form of plain risk-seeking pattern versus only 7% of 'Gainers'.

In general, in the first empirical chapter, I establish that the vast majority of individual investors change their risk behaviour conditional on their profitability in line with my research question and hypothesis. At the between-subject analysis scale, outperforming traders exhibit a higher degree of rationality comprised in a positive correlation between risk and return that points to the concave form of the decision valuation function. At the within-subject level, investors tend to be risk-averse in the gains domain and risk-seeking in losses domain. Besides, there is an undoubted proof of loss aversion bias that impacts investor's choice. Throughout my analysis, investors tend to outweigh loss over gain that is observable in sharper correlation coefficients for the former. This evidence supports the predictions of Prospect Theory. I also identify the link between profitability and rationality. Rational behaviour that is represented by positive relation between risk and return, remains a largely unattainable goal for individual investors, however, striving towards it makes a lot of practical sense as this aspect quite well delineates good and bad trading results. Another essential question is what impacts the degree of rationality. I try to examine it by regressing the set of trading and personal variables collected from the data set on risk/return correlation. Surprisingly, age has a negative effect on rationality level. This is against intuition and the academic research that puts forth the experience principle that should propel human performance in different aspects of life. The other variables that happen to be significant for rationality are explicitly and implicitly connected to risk-taking patterns. For example, negative and positive semi-deviations of return, various activity-related factors like turnover and number of trades, as well as the use of different conditional orders. This fact guides me to believe that there may be hidden variable or variables that stand behind the risk-related factors in explaining the degree of rationality and human choice. In addition, my discovery of a large group of investors that fit neither Expected Utility nor behavioural theoretical frameworks and demonstrate plain risk-seeking leads to the search of alternative explanations of investors' behaviour. In the second and third empirical chapters, I test the factor of emotions as a potential hidden variable that can fill the gap in understanding the mechanics of economic decisions.

Both Expected Utility Theory and Prospect Theory fall under the category of consequentialist perspective, which implies that a decision-maker configures her choice by multiplying the value of each outcome by its subjective probability. The greatest difficulties for consequentialist theories occur when decisions are taken 'in the heat of the moment'. It is hardly possible to ignore this fact, because, as discussed in Kahneman (2003), and Kahneman (2011), the majority of decisions in many spheres of human life are taken under harsh pressure of time or other circumstances. Financial trading as one of the social sides of human activity is not an exception. Thousands of books and specialised online forums discussing the trading experience are filled with the highly emotionally-charged language of thrill, fear or disappointment. Without understanding the role of feelings in the decision-making process, it will be hard to produce models that could carefully deal with a vast category of individual behaviour. Several models and theories strive to incorporate affect. The featured ones include Loewenstein (1996), Sloman (1996), Loewenstein et al. (2001), Slovic et al. (2002), Mukherjee (2010). However, evidence, especially the empirical verification of the impact of feelings, is still extremely scarce. For the most part, it comes from non-financial areas, for example, sports (Pope and Shweitzer (2011)).

7.2.2. Summary and discussion of the second empirical chapter

In the second empirical chapter, I explore how emotions may impact the correlation between risk and return. I collect unique data on the selection of 618 investors who have a trading track record on two types of accounts: Live and Contest. The live account involves investing own funds, while Contest represents a trading game that is operated with virtual money. Both environments are similar in all the aspects, for instance, commissions, market access, market microstructure, etc. The only critical difference is the natural feelings elicited when risking own capital and paper capital. Confirming my hypothesis, I identify the disparity in the relation between risk and return in both settings that highlight the dissimilarity of the form of investors' value functions. I replicate the methodological approach of the first chapter and study correlations on macro and micro levels. At the macro (pooled-data) level, I find a statistically significant negative correlation between risk and return variables on both account types. For Live mode, Pearson correlation coefficient is -0.42 (Spearman = -0.23), significant at 1%. For Contest mode, Pearson correlation coefficient equals to -0.17 (Spearman = -0.03), though only Pearson correlation is significant. The difference between the environments is also statistically significant at 1% level substantiating my expectations. Moreover, the disparity between Live and Contest correlation coefficients remains after I substitute total risk with positive and negative semi-deviations and repeat the analysis of risk/return correlations.

At the micro-level of correlation analysis, in order to compute individual correlations as I did in the first empirical chapter, I select the investors having a minimum of 200 transactions in both account types. This leaves me with only 166 subjects, yet with reliably compelling trading history. Next, I split these investors into ‘Gainers’ and ‘Losers’ groups relative to their performance above or below the threshold of zero accumulated return. I hypothesise that correlation between risk and return for the two groups should be stronger in modulo in Live than in Contest, which would corroborate the ‘emotional gap’ concept. I again find evidence of my expectations – all pairs of correlation are indeed statistically stronger in Live mode, except for the relation between positive risk and return for ‘Gainers’ group, which would fit the significance criteria in case of a larger number of analysed subjects.

7.2.3. Summary and discussion of the third empirical chapter

Considering that I discover the supporting evidence of the input of feelings into risk and return relation, in the third empirical chapter I extend the research question aiming to fill the gap in the empirical research of emotions’ impact on the explicit manifestations of financial behaviour, performance and risk-taking practices of individual investors. I continue employing the data set of 618 traders and the two account types: affect-poor Contest (virtual trading competition) account and affect-rich Live (real money) account. From this data set, I extract and evaluate return and risk variables in multiple perspectives, for example, by order types and trading frequency. The empirical chapter is split into three parts. In the first part, I explore the change in trading behaviour and performance in response to switching between Live and Contest settings. The second part is devoted to the study of the three facets of financial risk – changes in the shape of the value function, loss aversion, and decision weighting function, and how they react to the degree of affect. Finally, the third part examines if risk variables and the set of other trader-specific variables can explain the individual difference in variation of Live and Contest returns.

The main finding of the first part is that investors demonstrate unequal profitability in the two emotionally disparate trading modes that I attribute to the emotional influence. On average, a single trade in Live outperforms a Contest trade by 0.022% of the transaction volume. Translated into the trader's own equity terms, the difference is close to 0.7% per the invested dollar. Furthermore, traders display a clear distinction in their investment behaviour in Live and Contest. I reveal an essential, almost twofold, shift in the four key variables: a) Share of non-intraday trades, b) Number of trades (trading frequency); c) Share of conditional orders; d) Duration of trades. When in Live setting, investors prefer spending more time in front of the electronic trading platform generating new transactions and following existing ones. This inclination is strongly significant statistically and economically. Moreover, it also proves to be consistent among investors, despite high individual heterogeneity.

In the second part, addressing the facets of financial risk, I confirm my hypothesis based on the ideas laid out in Rottenstreich and Hsee (2004) stating that for more affect-rich decisions, the value function for prospects should be more curved, i.e. proportionally more value should be obtained by the activation of a stimulus itself. Indeed, I uncover that the disparity between the distributions of positive and negative semi-deviations is substantially sharper in Live environment compared to Contest (significant at 1% level). This should be the case if investors are progressively more risk-averse in the gains domain and risk-seeking in the losses domain. Yet, I discover that the difference in semi-deviations mainly ensues from the positive section of the value function. Surprisingly, negative semi-deviations are statistically indistinct. Thus, in the losses domain, the value/utility function does not react to the shift in affect level. I reinforce the analysis of variance with the examination of the disposition effect in the two account types suggesting that a trader with steeper value function for gains and losses should expressly demonstrate the tendency towards higher disposition bias in the Live setting. Prior research has identified that disposition effect tends to abate with the hike in trading frequency. I manage to substantiate this assumption by failing to find statistically significant disposition bias in Live or Contest, even though, in absolute terms, I witness sizeable traders' inclination towards overholding losing positions (statistical insignificance was mainly due to large individual heterogeneity). Nevertheless, the difference between disposition effect in both trading modes proves to be significant at 10% level and equals to 2 hours and 5 minutes on average. It means that in Live an average trader's holding balance is 2 hours longer in favour of losing trades than in Contest (this is significant keeping in mind that average realised trade's duration is 4.11 hours in Live mode and 7.82 hours in Contest mode). I believe that this result serves as additional validation of the disparate Live/Contest value function curvature hypothesis.

Further, I focus on the other two facets of risk – loss aversion bias and the form of the probability weighting function. For that, I use conditional orders' profitability statistics. I assume that conditional orders should better reflect the implicit beliefs of investors than market orders when it comes to the expression of loss aversion and judgement of probabilities. I measure loss aversion by the distance of conditional orders to the prevailing market price. On average, the closer a trader places the conditional order, the smaller should be the gain (loss) of respective realised take-profit (stop-loss) order. It is hypothesised that with loss aversion present, traders should be prone to keeping their stop-loss orders significantly closer to the spot price than take-profit orders. Indeed, I identify clear evidence of loss aversion expressed this way in both settings: on Live accounts, the return of an average transaction closed with a take-profit order equals to 0.25% compared to respective loss of 0.18% for a trade closed with a stop-loss order. For Contest accounts, the result is similar on a relative basis – take-profit order's gain of 0.49%, and stop-loss order's loss of 0.30%. The difference is statistically significant in both settings at 1% level. The most intriguing and unexpected finding is the fact that loss aversion bias turns out to be stable across the trading modes. When evaluated on an individual trader level, I find that 63% of investors exhibit loss aversion in Live, which compares to 69% in Contest. Moreover, I also measure the absolute preference of traders to each of the order types and discovered a similar twofold dominance of stop-loss orders in both environments: 66% (69%) of realised conditional orders in Live (Contest) are stop-loss orders. This is an obvious indication that the subjects are more concerned with limiting their losses than with ensuring their gains.

The final attribute of risk behaviour that I analyse is the decision weighting function. Again, as in the study of loss aversion, I exploit the conditional orders' returns data set. With the special emphasis on the losses domain, I test the assumption regarding the shift of the probability weighting function discussed in the literature (e.g. Gonzalez and Wu (1999), Abdellaoui et al. (2005)) that is associated either with the pessimistic account (downward shift) or optimistic account (upward shift). I hypothesise that the surge of pessimism (or dread sensations) in Live trading compared to Contest should generate more conservative placement of conditional orders keeping the objective change of the value of stimuli constant for both settings[78]. I manage to find support for the assumption concerning the losses domain of returns that are associated with stop-loss conditional orders. The disparity between the profitability of trades realised by stop-

[78] Knowing that investors use the same financial instruments set in Live and Contest, and having thousands of transactions in the data set, allows me assuming that in an average trade decision an investor faces similar objective distribution of outcomes and probabilities. On top of that, I also do consider the expected difference in the subjective valuation of the outcomes, whereby the small loss (gain) brings about more psychological damage (benefit) in more affect-rich (Live) environment reflecting on a more S-shaped form of the value function.

loss orders in Live and Contest was highly economically and statistically significant (on average Live account outperformed Contest by 0.1% of position's value per single transaction). I believe that such difference in stop-loss orders positioning is primarily explained by the systematic pessimism of traders – overvaluation of probabilities in the losses domain. For gains domain, I also identify the signs of dread account, however, my data did not make it possible to separate the elevation of the probability function from other alterations in the functional shape (change in curvature or no change at all). In my view, the results help understand why I failed to find the difference in negative semi-deviations in Live and Contest in the first part of the empirical chapter. The dread of expected catastrophic losses that distorts objective probability weighting comes into conflict with the inclination towards risk-seeking behaviour when the loss is experienced. The value function account urges an investor to keep a losing position as long as it returns to break even, while the probability weighting function account propels the feeling of fear of an unbearable loss that forces an investor to close a losing trade at a certain psychological threshold. The larger is the size of the mounting losing position relative to a person's capital, the stronger is the role of dread experience. This is the empirical evidence of the effect of the fourfold pattern of risk attitude that has been predicted by Prospect Theory (Kahneman and Tversky (1979, 1992)). I only observe it in losses domain and not in gains because, seemingly, for losses, this phenomenon is far stronger and it is identifiable even in high frequency/low-value intraday data set that I examine in the study.

Pursuant to the silo-based investigation of the role of emotions in risk and return, I explore how risk variables help explain the variation in performance in Contest and Live settings. The regression analysis demonstrates that adding risk factors to the array of behavioural, personal and trading parameters raises the explanatory power of the model (measured as adjusted R2) twofold from 32% to 67%. Essentially, at least one-third of the difference in Live and Contest profitability is associated with the change in risk behaviour – the degree of risk aversion, measured as the standard deviation of returns. I believe that this result corroborates the main idea of Loewenstein et al. (2001) and other researchers advocating the 'risk-as-feelings' framework. Risk behaviour is not merely the product of thought through cognitively-processed investment decisions. The great deal of it ensues from immediate affective implications. I examine two trading environments that, being similar otherwise, are critically distinct by the level of emotional charge. I find that individual traders do change their risk attitude, most probably, unconsciously, and this change materially impacts performance. In the same vein, I confirm the empirical premise, summarised in Kahneman (2011) that negative realisations, in general, are more important for humans, and they play a greater role in shaping our decisions, and the consequences of these decisions. For investors, it means that the overall success of trading activity primarily lies in their ability to make good decisions for bad trades.

I also would like to make few notes about the observations that have not been in the focus of the current study but that are noteworthy. First, following multiple research of investors performance and behaviour, I witness significant heterogeneity in the data and the proceeds of analysis. For example, the statistics of traders' profitability, disposition effect, loss aversion, usage of conditional orders or portion of intraday trades varies widely across the subjects. Consequently, the notion of an average individual should be considered with great care in financial research. Second, my study continues the line of research highlighting the fact that gross of fees average trader's returns hover around zero, and any pick-ups in trading activity translate into losses net of fees.

7.2.4. Limitations of the research

My research has certain limitations. Primarily, these are data set related limitations. I explore a very limited section of the financial markets, which concerns individual, non-professional investors that for the most part, do not do finance or investments for a living. Also, my data set covers a specific type of financial instruments that includes high frequency, intraday currency pairs trading at high leverage. Therefore, the results that I obtain need further verification using other groups of investors and different types of instruments. Additionally, my dataset represents a cross-section of returns, not time-series data. Consequently, I cannot apply more advanced econometric methods, such as GMM (Generalised Method of Moments) or SDF (Stochastic Discount Factor) to elicit the parameters of the utility function and decision-weighting function or develop a more advanced measure of risk.

Further, in the current research, I study realised behaviour, not the expected one. It is more aligned with Prospect Theory or ‘Risk-as-Feelings’ framework than Expected Utility Theory. Yet, this is part of a larger debate of whether it is correct to compare prescriptive type theory with descriptive one, or in other words, how people should behave with how they really behave. In essence, ‘Risk-as-Feelings’ hypothesis states that human actions are frequently hidden even from our own understanding and sometimes can harm our well-being. From this perspective, analysing what people say that would do in a certain scenario is a weak indicator of how realised behaviour would look like. Another important issue is the use of proxies to test risk behaviour. All of the aspects of risk preferences and their manifestations are very hard to measure directly in the empirical setting. Almost always, various facets of risk would interact and mix together. That is why my methodology to evaluate the changes in the form of the value function, probability weighting function or the presence of loss aversion bias should be regarded as an attempt to proxy these phenomena and distinguish between them. Undoubtedly, there are other approaches and approximations to elicit risk behaviour from the empirical data.

On top of that, there is a limitation associated with the methodology that I use in Chapter 1. In this chapter, I study the relation between risk and performance of investors and also try to differentiate between investors based on the demonstrated risk/return relation. For this purpose, I employ correlation analysis and complement it with a linear one-factor regression model. However, it is widely accepted in finance to use more sophisticated models in such analytical frameworks, for example, Fama-French multi-factor model (Fama and French (2015)) as the most widespread example for the research of equity instruments. Extant literature also proposes some relevant global risk factors for the FX market and currency instruments that form the core of my dataset. I can mention the carry trade factor (Lustig et al. (2011)), global FX volatility factor (Menkhoff et al. (2012)) or commodity factor (e.g. Ready et al. (2013)) among others.

Nevertheless, considering the very high frequency of the dataset, it is doubtful that any of these risk factors could have a significant impact on my results. Normally, these factors' role should grow with the elongation of observation periods to weeks, months or even years. I assume that on the scale of days and even hours the variations in investors' performance are mostly influenced by pure luck or innate investors' qualities and skills rather than the fundamental forces standing behind the values of financial instruments. Therefore, the simple approach to the measurement of risk is suitable to elicit the differences in the behaviour of investors without additional controls.

7.2.5. Implications and contribution of the research

My research contributes to the academic literature in a number of ways. The primary input concerns the fields of behavioural finance, investments and the nascent discipline of emotional finance. In the first empirical chapter, I bridge the gap of empirical testing of rational behaviour by individual investors. For that, I develop a new methodology that proxies the degree of rationality with the level of the linear relation between risk and return. This approach provides for the first-of-a-kind comparison between two major theories of decision making – traditional Expected Utility Theory and behavioural Prospect Theory. In the framework of this study, I find a confirmation of the extant experimental literature that the majority of individuals are inclined to be risk-seekers in the domain of losses and averse to risk in the area of gains as predicted by Prospect Theory. Furthermore, I provide empirical evidence that rationality is positively associated with profitability.

In the second and third empirical chapters, I employ a unique dataset that comprises complete trading statistics from two types of investment accounts – Live and Contest – for the same group of 618 investors. The two accounts are identical in all aspects except for the degree of emotional charge associated with the investment process. Exploiting such natural control of emotional implications of decision-making, I develop a methodological approach to explore the impact of feelings on the correlation between risk and return, and further to study how feelings independently interact with the profitability of investors as well as the three facets of risk behaviour – a form of the value function, a form of the probability weighting function and loss aversion bias. My findings contribute to the empirical confirmation of ‘Risk-as-Feelings’ hypothesis and other dual-process theories.

The results of my research provide some useful implications for investors in financial markets. The confirmation of 'Risk-as-Feelings' hypothesis gives an idea of the limited role of financial knowledge and skill in trading success. I manage to demonstrate that feelings elicited during the investment process are by themselves a powerful factor that influences investors performance. It leads to the conclusion that contributing to the self-training in emotions management and analysing own behaviour from the angle of emotions may improve trading results. However, it still remains unknown to what extent such self-analysis and self-training can help investors to outperform.

7.2.6. Future research

My analysis in Chapters 5 and 6 is grounded on the comparison of the behaviour of the same economic agents in different environments. Such an approach is appealing because it allows offsetting some of the main criticism of experimental research design and, at the same time, control for the array of disturbing factors. The possibility to obtain scientifically significant findings from such cross-setting analysis makes it an attractive and reasonable goal for future research. The main challenge that arises for the prospective studies is the scarcity of empirical datasets. However, modern financial services get more and more electronic, which leaves hope that more multi-domain data may become available for academics. One example of the dataset to look after is the history of individual financial decisions when using credit cards and making investments. Such data is already available with the so-called challenger banks like Revolut or N26.

An intriguing domain for future research may be based on my findings that the degree of rationality is related to the level of profitability of individual investors. A critical aspect of this relationship is whether the degree of rationality can be trained or this is instead an inborn quality. In other words, is it true that good investors are born like that and certain psychological characteristics, like superior emotional intelligence, help them outperform while others are fated to losses? Answering this question assertively may trigger important consequences for the asset management industry and the financial industry in general. Nevertheless, the future study of the link between emotions and performance is aggravated by the complexity of data collection. It is difficult to incentivise real investors to answer tens of psychological questions.

Another prospective future research should further investigate the connection between emotions and various behavioural biases. It is widely accepted in academia and the industry that the emotional origin of biases is much harder to deal with and to correct. I discovered that the disposition effect might be rooted in emotional implications. However, a more thorough study of this and other behavioural caveats is required.

In Chapter 4, I examine the relation between rationality and the investment performance of individual investors. Chapters 5 and 6 extend this study to add another angle of the role of emotions in rationality, performance and behaviour. Following my research, I discovered that some traders in my dataset managed to demonstrate systematic outperformance, while the others (the largest part by far) had poor results. My empirical dataset could not help me to shed light on the source of such consistent outperformance or underperformance, even though I established connections between performance and emotions. The question to be answered here is whether successful individual investors can be trained, for example, by learning some emotions regulation strategies (e.g. Fenton-O'Creevy et al. (2012)) or born with some inherent qualities that allow making the right wealth-maximising investment decisions (most of the time).

Why is this problem significant? Nowadays, more and more small individual investors get engaged in investments in the financial markets. The majority of them lose money. Sometimes these losses are significant even at the national scale (Barber et al. (2017)). The ex-ante knowledge about one's skills and predispositions could potentially prevent individuals from the direct involvement in something they cannot properly handle, but motivate them to choose other gateways, for example, professional fund managers or advisers.

Even the richest empirical dataset cannot provide the answer to the question about the inborn or trained investment skills alone without the aid of neurophysiological, experimental and interview research methods. Excellent guidelines for future research in this area are provided by Scherer (2005) for the measurement of emotions using questionnaires. Fenton-O'Creevy et al. (2012), Lo et al. (2005) and Coates et al. (2008, 2009) provide a starting point for the neurophysiological study design. Taffler and Tuckett (2015) introduce the way for the interview-type research design of the role of emotions in decision-making, which can be extended to laypeople.

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