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HOUSE MONEY EFFECT AND OVERCONFIDENCE

Evidence on active individual day traders

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Abstract
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PURPOSE OF THE STUDY

The objective of this study is to gain knowledge what influence prior outcomes have on subsequent risk-taking and trading volume, if any. The traditional finance theory assumption of investor rationality is questioned, and the focus is on behavioral framework; especially on theories relying on the Prospect Theory, and overconfidence. The Expected Utility Theory is also viewed to compare behavioral theories and traditional finance theory.

This study also contributes by shedding light on the demographic data and trading data of individual day traders.

DATA

The unique data set of this study consists of almost 130,000 intraday trades made by 152 individual non-professional day traders between January 4, 1999, and March 16, 2001 in the Helsinki Exchanges. All these online trades are matched to trade data received from the Helsinki Exchanges. Values of the day traders' positions are marked to market every minute of all the trading days, which makes it possible to perform the study on intraday horizon. Intraday data is used in this study to avoid the ambiguity of the prospect theory reference point that is present in studies over longer time horizons but the tests cover also interday horizons.

RESULTS

The empirical test results of risk-taking behavior after prior outcomes are in line with earlier evidence on intraday horizon. Day traders show significant loss aversion, that is, they secure their winnings by taking less risk after morning gains, and try to get even by increasing their risk-taking after morning losses. Older traders are more loss averse than younger traders are. In interday horizon the results are different. Whereas professional traders show loss aversion also in interday horizons, the loss aversive behavior of individual day traders found in intraday horizon diminishes, and when the prior outcome period is extended to one month the house money effect seems to dominate loss aversion.

The results of trading volume and overconfidence show that individual and professional traders behave in a very similar way. The robust results over all studied prior outcome periods show that prior gains do not make day traders to trade more as overconfidence hypothesis suggests. On the contrary, prior losses have inducing effect on subsequent trading volume. Trader's age is negatively correlated to trader confidence level.

KEYWORDS

House money effect, overconfidence, behavioral finance, prospect theory, mental accounting, day trading

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1 INTRODUCTION

Increased risk-taking after prior gains, i.e. the house money effect, is a behavior observed among gamblers, and in experimental studies of financial decision-making situations. Despite active intraday trading is an extremely speculative form of stock market investing, neither Locke and Mann (2001) nor Coval and Shumway (2001) find evidence on the house money effect in their studies of professional intraday futures traders. Rather, they report evidence that supports loss aversive behavior, i.e. decreased risk-taking after prior gains. However, the unique data set of the current study consists of active and non-professional day traders who are more likely to be exposed to behavioral biases than the professionals [Odean (1998b)]. So, the trading behavior of the sample group of this study is maybe the closest to gambling that can be found from the real financial markets, which makes it ideal data set to study the house money effect.

Overconfidence is a more studied subject than the house money effect. In field of finance, trader overconfidence has been claimed for increasing trading volume to higher level than would be rational. Overconfident traders overestimate their contributions to past successes, and recall information related to their successes more easily than information related to their failures. Further, the increased trading volume results in larger commission costs, and therefore lowers the trader returns [Barber and Odean (2002)].

Mental accounting is a theory created by Thaler (1985) proposing that decision-makers do not treat all their wealth equally. For example, people can have one mental account for leisure, and another for food, and they can treat the money in separate mental accounts differently. Barberis and Huang (2001) document that there is a substantial experimental evidence on mental accounting, and suggest that people can even have separate mental accounts for individual stocks they own. They study loss aversion and propose that people can be loss averse over the fluctuations of their stock portfolio, or they can be loss averse over the fluctuations of individual stocks they own. The empirical tests of this study are performed with both the methods to see if mental accounting matters.

1.1 Research Problems and Objectives

The main research problems of this study are the following.

i) Do prior outcomes have impact on subsequent risk-taking?

ii) Do prior outcomes have impact on subsequent trading volume?

The first research problem is studied to shed further light on the existence of house money effect or loss aversion in the real stock market. To the writer's knowledge, there are no prior studies of risk-taking behavior after prior outcomes among individual non-professional traders in the real stock market. As earlier studies of professional traders present just the aggregate results without more detailed analysis of individual trader attributes, the present study contributes by augmenting the knowledge on individual trader properties: if there are some trader characteristics common to the traders behaving in accordance with the house money effect or loss aversion.

The second research problem is studied to gain knowledge on overconfidence, which has been claimed for increasing trading volume too much to be rational. If high trading volume really is a sign of overconfidence then the sample of this study consists of highly overconfident traders. Like in empirical tests of risk-taking behavior, also empirical tests of overconfidence contribute by adding to the existing knowledge on individual trader properties. Barber and Odean (2002), among others, document some characteristics common to overconfident investors. The present study concerns only on very active traders and aims to explain differences in confidence levels among them.

Intraday data is used in this study to avoid the ambiguity of the prospect theory reference point that is present in studies over longer time horizons. Existing literature [Kahneman and Tversky (1979)] stresses the importance of reference point noting that for investments that are held for a long time over a wide range of prices, the purchase price is at best a proxy of the true reference price. Purchase price can be used as a reference point in this study because of the unambiguousness of day traders' investment horizon.

The unique data set of this study consists of almost 130,000 intraday trades made by 152 individual non-professional day traders between January 4, 1999, and March 16, 2001 in the Helsinki Exchanges. The data is received from the leading Finnish online brokerage house. Values of the day traders' positions are marked to market every minute of all the trading days, which makes it possible to perform the study on intraday horizon. Two sets of prior outcome periods are used; in intraday horizon the decision-makers' behavior in the afternoon is studied after morning gains or losses, and in interday horizon the trader behavior in a day is studied after prior day(s) outcome. Interday horizons used in the tests are from one to twenty day long.

1.2 Summary of the Results

The empirical test results of risk-taking behavior after prior gains or losses are in line with earlier evidence on intraday horizon. That is, day traders show significant loss aversion in the afternoon after controlling for the morning outcome that has been documented also among professional traders by Locke and Mann (2001), and Coval and Shumway (2001). After morning gains the traders secure their winnings by taking less risk, and after morning losses they try to get even by increasing their risk-taking. Of the trader characteristics tested – success, experience, gender, and age – only age is detected to the changed risk-taking behavior. As expected, older traders are more loss averse than younger traders are.

However, the results of individual traders' risk-taking tests differ from the results obtained in empirical tests among professional traders in interday horizons. Whereas professional traders show loss aversion also in interday horizons, the loss aversive behavior of individual day traders found in intraday horizon diminishes, and when the prior outcome period is extended to one month the house money effect seems to dominate loss aversion.

The empirical test results of trading volume and overconfidence show that individual and professional traders behave in a very similar way. The robust results over all studied prior outcome periods show that prior gains do not make individual day traders to trade more as overconfidence hypothesis suggests. On the contrary, prior losses have inducing effect on subsequent trading volume. Coval and Shumway (2001) report similar behavior among professional traders. Like in empirical risk-taking tests, the only trader attribute that is found to have influence on overconfident behavior is trader's age, which is negatively correlated to a trader confidence level as expected.

Two mental accounting methods are used in the empirical tests. In the tests, day traders can have one "day trading" mental account, or they can have separate mental accounts for individual stocks they trade. The results in all empirical tests are practically equal no matter which mental accounting method is used. Unfortunately the data is not suitable for testing different mental account methods because the day traders typically trade with only one line of stock in same trading day.

1.3 Structure of the Study

The remainder of the paper is organized as follows. In chapter 2, theoretical background for decision-making under risk is reviewed. The focus is on prospect theory and other behavioral theories although also expected utility theory is discussed. Chapter 3 studies day trading and overconfidence, which is believed to be one of the main sources to cause the observed trading volume anomaly in the stock market. Chapter 4 reviews the existing literature on financial economic studies of mental accounting, decision-making under uncertainty, and overconfidence. Research hypothesis are presented in chapter 5, and chapter 6 describes sample selection process and the unique data set used in this study. Chapter 7 describes the accounting methodology for processing the data for the purposes of this study. Also methodology for testing the research hypotheses is presented in Chapter 7. The results for the empirical tests are presented in Chapter 8. Chapter 9 concludes the study.

2 DECISION-MAKING UNDER RISK

Expected utility theory has been the standard framework for decision-making under risk for many years now. Contradicting the assumption of rational agent in expected utility theory, behavioral finance has relaxed the ideal rationality assumption by using findings of psychology to explain human behavior. This has resulted in new theories of choice under uncertainty. Before discussing challenging frameworks for decision-making under uncertainty, let us have a short view on behavioral finance in general.

2.1 Behavioral Finance

For years a dominant framework used by academics to study stock movements has been the efficient market hypothesis. It calls for rationality, and traditionally the theory of financial economics assumes that representative agents in the economy are rational in two ways: they (1) make decisions according to the axioms of expected utility theory, and they (2) make unbiased forecasts about the future [Thaler (1999a)]. At the extreme, the theory assumes that every one of these representative agents behaves in accordance with the assumptions, but most economists recognize this to be unrealistic admitting that some agents on the market may not be completely rational. Still many researchers say that markets on aggregate are behaving rationally.

Behavioral finance questions the assumption of investor rationality, and tries to explain investor behavior with findings of psychology. Psychologists have found many behavioral biases in various human decision-making situations, and behavioral finance researchers have concluded that those biases exist also in financial decision-making situations. They have noted that although concept of investor rationality would be ideal, it really does not reflect the reality. DeBondt and Thaler (1995) argue that a good psychological finance theory is grounded on psychological evidence on how people actually behave. Opponents of behavioral finance have criticized behavioral finance for example by claiming that it results in essentially unrestricted universe of behavioral patterns. Yes, that is true, but that is also reality. The most recent acknowledgement for behavioral finance research was given last year when Daniel Kahneman received Economics Nobel prize "for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty"[1].

Perhaps the best-known behavioral theory is the prospect theory introduced by Kahneman and Tversky (1979). The prospect theory challenges the expected utility theory as a model of decision-making under uncertainty. The prospect theory is a basis of the house money effect and loss aversion, which are studied in this paper, and will be gone through in detail in later sections. Before that, let us have a short review on the expected utility theory.

2.2 *Expected Utility Theory*

According to the expected utility theory, representative agents in the economy maximize their expected utility. They make unbiased estimates on the future and behave rationally in accordance with the axioms of the expected utility theory. Expected utility is based on the following tenets.

1) Expectation: $U(x_1, p_1, \ldots, x_n, p_n) = p_1u(x_1)+\ldots+p_nu(x_n)$

   Expectation tenet states that utility of a gamble is weighted average of the expected utilities of its outcomes weighted with the probabilities of the outcomes.

2) Asset integration: agent having asset position w accepts gamble $(x_1, p_1, \ldots, x_n, p_n)$ iff $U(w+x_1, p_1, \ldots, w+x_n, p_n) > u(w)$

   Asset integration tenet states that a gamble is acceptable with current level of wealth, if its utility integrated with current wealth is greater than the utility of current wealth alone. This means that agent's utility is interpreted as the final states of his wealth, and thus a specific gamble could be accepted of rejected with different levels of initial wealth.

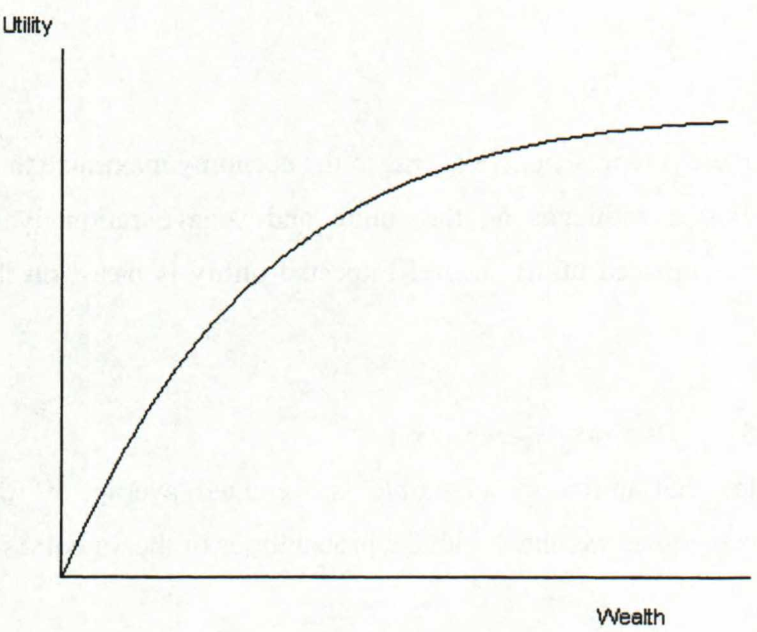
3) Risk-aversion: utility function u of a risk-averse agent is concave ($u''<0$)

   Concavity of the utility function implies diminishing marginal utility of wealth. That is, greater wealth implies higher utility but as the wealth increases, each

[1] Citation from http://www.nobel.se/economics/laureates/2002/.

additional unit of wealth adds smaller amount to the total utility. In theory, an agent can also be risk-neutral (u''=0), or risk preferring (u''>0), but in reality risk-aversion has been seen as a dominating attitude towards risk in the expected utility theory. Figure 1 presents the utility function of a risk-averse agent.

Figure 1. The utility function of risk-averse agent. The figure depicts an utility function of a risk-averse agent in the expected utility theory. The concave utility function reflects diminishing marginal utility of wealth.



Under the expected utility theory, any prior gain or loss can affect risky choice due to its impact on decision-maker's wealth. Agent's degree of risk-aversion is determined by the shape of his utility function, which - as stated in asset integration tenet above - is the function of his wealth. The utility function can exhibit increasing (u''>0) or decreasing (u''<0) absolute risk-aversion, or the degree of risk-aversion can be constant (u''=0). Increased risk-taking following a loss is consistent with the expected utility theory if agent's risk-aversion is an increasing function of wealth. Correspondingly, gains would result in reduced risk-taking with that kind of risk-aversion.

If decision-maker's risk-aversion is constant (i.e. the agent is risk-neutral), prior performance does not have any impact on subsequent risk-taking. If agent's utility function shows decreasing risk-aversion, prior losses would result in reduced risk-taking. In this case, gains from prior transactions would boost future risk-taking. The first two shapes of utility functions are rather theoretical, and as stated in tenet three above, a typical utility function is concave reflecting decision-maker's risk-aversion to be a decreasing function of his wealth.

2.3 Prospect theory

Kahneman and Tversky (1979) presented the prospect theory to challenge the expected utility theory as a model of decision-making under risk. While the expected utility theory compares outcomes of choices in terms of change in final assets, the prospect theory deals with gains and losses compared to certain reference point. Additionally, the prospect theory presents decision weights that differ from probabilities used in the expected utility theory. In the prospect theory, outcomes of gambles are named prospects. In this study, the following notation of prospects is used: prospect (200, .50; 100, .50) is a gamble that yields 200 with probability .50, and 100 with probability .50.

According to the prospect theory, there are two phases in the choice process: editing phase and evaluation phase. In editing phase the prospects are simplified and encoded. In evaluation phase the edited prospects are evaluated and the prospect of highest value is chosen. The major operations of the editing phase are coding, combination, segregation, and cancellation. Coding, combination, and segregation are applied to each prospect separately whereas two or more prospects are included in cancellation [Kahneman and Tversky (1979)].

Coding. People normally perceive outcomes as gains and losses rather than as final states of wealth.

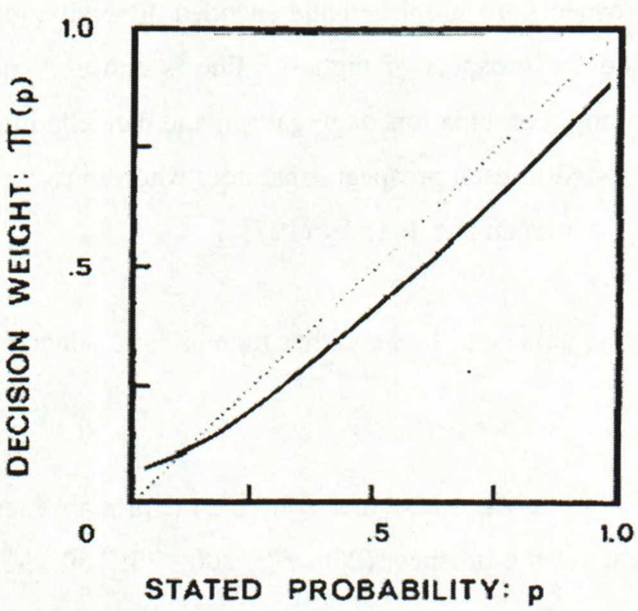
Combination. To simplify prospects the decision-makers sometimes combine the probabilities associated with identical outcomes. For example, the prospect (200, .30; 200, .20; 100, .50) can be reduced to (200, .50; 100, .50).

Segregation. In strictly positive or strictly negative options people code prospects by segregating those into two components: (i) the riskless component (the minimum gain or loss to be obtained or paid certainly), and (ii) risky component (the additional gain or loss by which the prospects differ). For example, the prospect (200, .60; 100, .40) is segregated into sure gain of 100 and risky prospect of (100, .60).

Cancellation. Common components in different prospects are ignored. For example, there is a choice between the prospects (200, .40; 100, .30; -100, .30) and (300, .40; 100, .30; -150, .30). The shared component (100, .30) is cancelled out and thus the choice is reduced to a choice between (200, .40; -100, .30) and (300, .40; -150, .30).

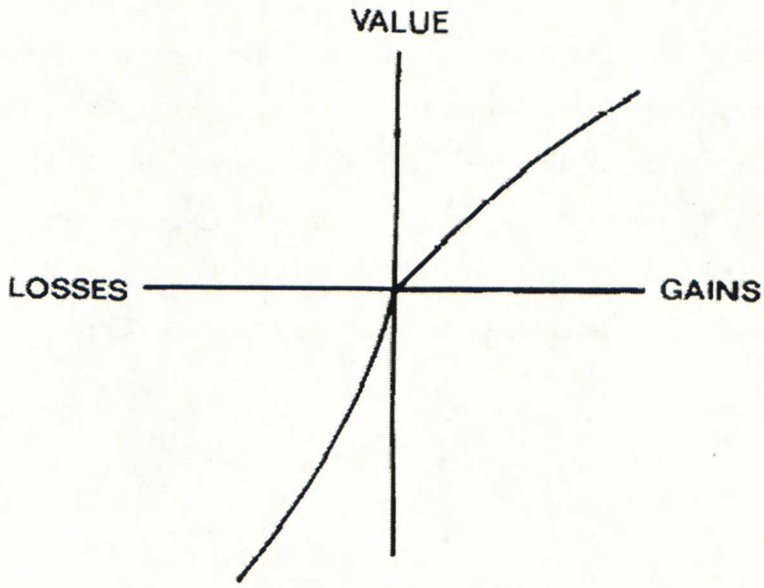
The value of each outcome is multiplied by a decision weight in the prospect theory. The weighting function, $\pi(p)$, does transform probabilities into decision weights. The key properties of the weighting function are that small probabilities are overweighted ($\pi(p)>p$), and that weights do not necessarily add to unity ($\pi(p)+\pi(1-p)\neq 1$). Prospect theory weighting function is depicted in figure 2.

Figure 2. Prospect theory weighting function. Source: Kahneman and Tversky (1979). The weighting function transforms probabilities into prospect theory decision weights. The weights do not necessarily add to unity, and typically small probabilities are overweighted.



Prospect theory value function, v(x), has the following three properties [Kahneman and Tversky (1979)]: (i) it is defined on deviations from the reference point, (ii) it is generally concave for gains and commonly convex for losses, and (iii) it is steeper for losses than for gains. Thus, the prospect theory suggests that decision-maker's attitude towards risk depends on prior performance. Remind that regardless of prior gains or losses the second derivative of utility function in expected utility theory is negative for a risk-averse decision-maker. Prospect theory value function is presented in figure 3.

Figure 3. Prospect theory value function. Source: Kahneman and Tversky (1979). The value function is (i) defined on deviations from the reference point; (ii) generally concave for gains and convex for losses; and (iii) steeper for losses than for gains.



The value of a prospect is defined as follows. Let's assume we have a prospect (x,p;y,1-p), i.e. a gamble that yields x with probability p and y with probability 1-p. If x and y are of opposite signs, the value of the prospect, V, according to prospect theory is:

$$V = \pi(p)v(x) + \pi(1-p)v(y) \tag{1}$$

According to Kahneman and Tversky (1979), the valuation of prospects is typically preceded by the editing phase in which the decision makers code the prospects. As noted earlier, they propose that in strictly positive or strictly negative options people code prospects by segregating those into two components: (i) the riskless component (the minimum gain or loss to be obtained or paid certainly), and (ii) risky component (the additional gain or loss by which the prospects differ). So, if x and y are of same signs (either $x<y<0$ or $x>y>0$), the V is defined as

$$V = v(y) + \pi(p)[v(x)-v(y)] \tag{2}$$

An essential feature of the prospect theory is that value is derived from the changes in wealth rather than expressed in the final states of wealth as in expected utility theory. Thus, one of the most critical parts of the prospect theory is the reference point, which is the individual's point of comparison against which alternative scenarios are contrasted. Typically the applicable reference point is the status quo, but Kahneman and Tversky (1979) suggest that in some situations gains and losses are measured against some other aspiration level that differs from the status quo and corresponds to an asset position that one expects to attain. In the prospect theory the risk attitude of decision-makers depends on whether they are in a win or a loss position relative to their reference point. It is easy to see that the careful setting of reference point plays important role in the prospect theory. In stock market transactions, reference point is typically seen as purchase price or some other price the stock is recently traded at.

2.4 Mental Accounting

Mental accounting is a theory created by Thaler (1985) proposing how decision-makers mentally "code" or "frame" gains and losses in ways that make them most pleasurable or least unpleasurable. Mental accounting is built on the prospect theory and especially on the value function of Kahneman and Tversky (1979). Thaler and Johnson (1990) developed mental accounting rules, which suggest that people edit prospects in "quasi-hedonic" way. According to their quasi-hedonic editing rules, decision-maker (i) integrates losses, (ii) segregates gains, (iii) segregates smaller gains from larger losses, and (iv) integrates (cancels) smaller losses from larger gains. The rules are derived from the properties of the prospect theory.

Barberis and Huang (2001) document that there is a substantial experimental evidence on people engaging in narrow framing, i.e. focusing on narrowly defined gains and losses. People can have many mental accounts for example clothing, traveling, furniture, investing etc. Investing mental account can further be divided in couple of ways. First, decision-maker can have one mental account for speculative trading, and another mental account for long-term investments. Second, people can have separate mental accounts for common stocks, bonds, derivatives etc. Barberis and Huang (2001) suggest that people can even have separate mental accounts for individual stocks they own. To see why mental accounting matters, consider the following example [Barberis and Huang (2001)].

> An investor is thinking about buying a portfolio of two stocks – one share of each. The shares of both stocks are currently trading at $100, and after careful thought, the investor decides that for both stocks, the share value a year from now will be distributed as (150, 0.5; 70, 0.5) independently across the two stocks. Let us suppose that the investor's loss aversion form is captured by equation 3, which is a simple form of utility function capturing loss aversion. In equation 3, X is the gain or loss, and $v(X)$ is the utility of that gain or loss.
>
> $$v(X) = \begin{cases} X & for\ X \geq 0 \\ 2X & for\ X < 0 \end{cases} \tag{3}$$
>
> If he is loss averse over portfolio fluctuations, the expected utility of the investment is
>
> $$0.25 * v(100) + 0.50 * v(20) + 0.25 * v(-60) = 5 \tag{4}$$
>
> while if he is loss averse over individual stock fluctuations, it is
>
> $$2 * [0.50 * v(50) + 0.50 * v(-30)] = -10 \tag{5}$$
>
> which is not as attractive.

In expected utility theory, a decision-maker has only one "mental account", which is individual's total wealth. Thaler (1999b) emphasizes that if people have only one mental account (i.e. total wealth), the way a decision is framed will not alter choices. He states that "framing does alter choices in the real world because people make decisions piecemeal, influenced by the context of the choice".

2.5 House Money Effect

The prospect theory suggests higher degree of risk-aversion after gains. However, the prospect theory by Kahneman and Tversky (1979) is based on one-shot gambles. It suggests that in the domain of losses people are willing to take risks to avoid a loss, and in the domain of gains people are risk-averse to secure their gains. Thaler and Johnson (1990) extended the prospect theory to sequence of gambles. They propose that after incurring losses on a specific mental account, the investor will subsequently act in a more risk-aversive manner in gambles on the same mental account. Similarly, after gains on a specific mental account, the investor will increase subsequent risk-taking on that mental account. So, if (i) the decision-maker treats sequential decision-making situations as separate gambles, and (ii) the decision-maker has prior gains (losses) on the same mental account then the subsequent risk-taking after prior gains (losses) is less (more) risk-averse than in the first gamble on that mental account.

Wealth effect and correlation in profit opportunities are rational explanations to increased risk-taking after prior gains. Wealth effect refers to prior gain's impact on decision-maker's wealth in expected utility theory. Thus, if traders with declining absolute risk-aversion have become significantly wealthier from prior trading they will subsequently trade in a less risk-averse manner. Coval and Shumway (2001) note that if profit opportunities are positively correlated across the trading day, traders will assume high risk when they expect to earn high average profits.

Thaler and Johnson (1990) use the prospect theory as a framework when studying how prior gains and losses affect subsequent risk-taking behavior of investors. Their results give support to risk-seeking behavior after prior gains. They find that "after a gain, subsequent losses that are smaller than the original gain can be integrated with the prior gain, mitigating the influence of loss aversion and facilitating risk-seeking". This is also called the house money effect; gambler jargon of coding the losses as reductions in a gain while being ahead (as if losing some of "their money" doesn't hurt as much as losing one's own cash).

Other studies have provided mixed evidence on the house money effect. In survey study, Battalio et al (1990) find some supporting evidence on the house money effect but they also find evidence suggesting that the house money effect may diminish as the size of the potential loss approaches the initial stake. In their experimental study, Weber and Zuchel (2001) are able to induce people to behave in accordance with the house money effect by manipulating the presentation format of the decision problem.

To the writer's knowledge, the house money effect is found among gamblers and in surveys, but not in the real financial markets. Locke and Mann (2001) do not find the house money effect among professional futures traders in intraday or interday trading horizon. Also Coval and Shumway (2001) study the risk-taking behavior of futures traders but find no evidence on the house money effect. On the contrary, they report behavior opposite to the house money effect, namely loss aversion.

2.6 Loss Aversion

As mentioned earlier, the evidence on the existence of the house money effect is mixed. Coval and Shumway (2001) report the behavior opposite to the house money effect, i.e. increased risk taking after prior losses. Thaler and Johnson (1990) named the behavior as "the break-even effect", and Weber and Zuchel (2001) called it "the escalation of commitment". In gambler jargon, the behavior is called "chasing your money". In the present study, term "loss aversion" is used to describe the increased (decreased) risk taking after prior losses (gains).

There are few explanations to increased risk-taking after prior losses. Remind that according to the expected utility theory, loss aversion can be present if agent's risk-aversion is an increasing function of his wealth. In that case the agent would like to take more risk after incurring losses than he would have taken with his initial level of wealth. However, decision-makers are typically expected to be risk-averse so the behavior is not expected to find if expected utility theory holds.

Behavioral explanation for loss aversion is based on the one-stage prospect theory. If initial wealth is used as reference point of the prospect theory value function in all sequential decisions, risk-taking after a loss is at least as great as initial risk-taking. This is due to the convex shape of value function in the domain of losses, in which any new loss hurts relatively less and gain feels relatively good.

There is also another behavioral explanation for loss aversion. Well-known psychological theory of cognitive dissonance (introduced by Leon Festinger in 1957), and its extension called the self-justification hypothesis state that agents do not like to admit that their past decisions were incorrect. If agents behave in accordance with the self-justification hypothesis, they do stick to their initial decision and loss aversive behavior will exist [Weber and Zuchel (2001)].

2.7 Disposition Effect

The disposition effect is the tendency to sell stocks that have gained value and hold onto stocks that have lost value [Shefrin and Statman (1985)]. The disposition effect is one implication of extending Kahneman and Tversky's (1979) prospect theory to investments, and offers explanation to decision-maker's choices under uncertainty that do not satisfy the conditions of expected utility theory. In addition to the prospect theory, there are three other behavioral issues behind the disposition effect: mental accounting, regret aversion, and self-control [Shefrin and Statman (1985)].

Grinblatt and Keloharju (2001), and Odean (1998a), among others, have found evidence of the disposition effect. Most recent evidence has been found by Kempas (2002), who studied the disposition effect on Finnish stock market among individual day traders using the same data set as in the present study. Since loss aversion is an essential feature of the prospect theory, which in turn is a cornerstone of the disposition effect, it is likely that some evidence on loss aversion will be found in the empirical part of this study.

3 DAY TRADING AND OVERCONFIDENCE

Economists have come to believe that overconfidence is one of the main sources to cause the widely observed trading volume anomaly in the equity market: trading volume is too high to be justified by rational trading needs. Overconfidence is considered the "most robust finding in the psychology of judgment" [DeBondt and Thaler (1995)], and together with theories related to the prospect theory it has been the most popular topic to study among behavioral finance researchers.

In addition to overconfidence, Grinblatt and Keloharju (2001), among others, list the disposition effect, a misguided belief in contrarianism or momentum, and love of gambling to be possible behavioral motivations to trade. Of the more rational motivations to trade, Grinblatt and Keloharju mention portfolio rebalancing, tax-loss trading, and life cycle considerations.

3.1 Overconfidence Bias

Many different definitions of "overconfidence" can be found in the literature of cognitive psychology and behavioral finance. In all definitions an overconfident individual has incorrect beliefs about distribution of either mean or variance of a payoff process. So overconfidence is used to imply the systematic overestimation of the accuracy of decision-maker's probability judgments, or the overestimation of the precision of one's knowledge, or both. Psychologists have found that people can be overconfident in various ways:

(i) they tend to overestimate the precision of their knowledge or their ability to do well on tasks;

(ii) they have unrealistically positive self-evaluations, and thus believe that they are better than an average person; and/or

(iii) they overestimate their contributions to past successes, and recall information related to their successes more easily than information related to their failures. This is also known as the self-attribution bias.

Overconfidence can be defined with respect to judgments involving subjective confidence intervals (i.e. paragraph (i) above). In many of these calibration studies, when decision-makers are asked to make price forecasts P_{low} and P_{high}, so that there is only an X% chance that the future price will be lower than their price prediction P_{low}, and an X% chance that the future price will be higher than their price prediction P_{high}, the observed intervals are often too narrow. While the expected price predictions should create a confidence interval with a range of (100 – 2X)%, the observed intervals actually only cover some of the predicted range. Svenson (1981) made a survey study that has become the classic example of unrealistically positive self-evaluations in behavioral finance studies. He asked from a sample of students to evaluate their driving skills. As much as 82 per cent of the students judged themselves to be in the top 30 per cent of the group.

Overconfidence is strongest for questions of moderate to extreme difficulty, and increases with the personal importance of the task [Griffin and Tversky (1992)]. People were also found to be more confident of their predictions in fields where they have self-declared expertise [Heath and Tversky (1991), Griffin and Tversky (1992)].

Exceptions to overconfidence are reported (i) for tasks where predictability is high, (ii) for tasks where fast and precise feedback about the accuracy of the judgments is provided, and (iii) for highly repetitive tasks [Kahneman and Riepe (1998)]. Correspondingly, expert bridge players, race-track bettors, and meteorologists were found to be well-calibrated in their predictions. When easy judging tasks are involved, empirical results indicate that individuals may even be underconfident. Subbotin (1996) investigated the effect of outcome feedback on over- and underconfident judgments in a general knowledge task. His results indicate that outcome feedback reduces the bias and improves calibration of underconfident judgments, but has no effect in the case of overconfident judgments.

According to Barber and Odean (2002), overconfidence is augmented by self-attribution bias, illusion of knowledge, and illusion of control. The self-attribution bias means that people tend to attribute their successes to their personal abilities and their failures to bad luck or the actions of others. According to the attribution theory in psychology, when events occur that confirm the validity of an individual's actions, the individual attributes this to his own high ability, while events that disconfirm the action are attributed to external noise or sabotage. So, the self-attribution bias results in higher level of confidence after successes but does not fix the confidence level downwards after failures.

Another source of overconfidence is the illusion of knowledge. When people are given more and more information on which they can base their forecasts, the accuracy of their forecasts tends to improve more slowly than their confidence in the forecasts [Barber and Odean (2002)]. Thus, the more people get information, the more they think they know. But people are poor at making intuitive probabilistic assessments and statistical conclusions. People also have a strong tendency to overestimate how much they understand or know about a phenomenon. Albert Einstein put it: "Information is not knowledge."

The third source of overconfidence, the illusion of control, means that people behave as if their personal active involvement can influence the outcome of chance events [Barber and Odean (2002)]. The psychologists have found that in chance determined events (such as coin flipping), observing a sequence of successes often leads observers to believe there is an element of control or skill being exerted over the outcomes. It has been observed in experimental settings that when factors such as involvement, choice and familiarity are introduced into chance situations, people become more confident and they start to believe that they can control the outcome of chance events.

The behavioral problem in the illusion of control is that people are poor at assigning the appropriate relative contributions of skill and luck. If people tend to exhibit this illusion in situations which they know are governed by chance, it is little wonder that the problem is severe when decisions are evaluated in an environment as complex as stock market. Investors may develop an illusory sense of control because they are directly involved in the investment process and they make their own choices [Goetzmann and Kumar (2002)].

Familiarity with a certain set of stocks may further complicate the illusion of control where investors may fail to realize that more knowledge or more information does not necessarily imply control over the outcome (i.e. returns earned by the portfolio). Huberman (2001) finds that investors do indeed have a strong tendency to invest in stocks that they are familiar with.

Goetzmann and Kumar (2002) argue that the lack of diversification may result from the illusion of control. They claim that the illusion of control creates an inappropriate level of overconfidence and overconfident investors may mistakenly believe that they can earn superior performance by active trading and consequently they may choose not to diversify. Thus, the lower level of diversification among active investors can be seen as another manifestation of investor overconfidence.

Increased trading volume after prior success has been seen as the major implication of trader overconfidence [Odean (1998b)]. Barber and Odean (2002) report that investors who switch from phone based to online trading trade more actively than before switching. They document that especially men and young people are subject to overconfidence. Similar results are also documented by Barber and Odean (2001a).

3.2 Day Trading

The most active players on stock market are day traders. The definition of a day trader is not unambiguous, but generally a day trader is one who buys and sells securities for short-term gains, usually exiting positions by the end of the trading day. Bentley (2000) has identified several trading styles that day traders use to profit from the markets. First, and probably the most classic type of day trader is referred as the scalper. A scalper enters and exits a position very frequently, holding a position only long enough to make a very small profit and exiting the position at the first sign of reversal. The scalper may make 20, 50 or even 100 trades a day, sometimes on just one stock. Day traders in sample of this study can be classified as scalpers. Another trading style, referred as swing trading, involves trading with a longer time frame than scalpers. Instead of looking for a very small profit over the next several minutes, swing traders look for larger gains over one to five days. Swing traders usually utilize technical analysis, and try to identify short-term uptrends and downtrends, and support and resistance levels. Swing traders may also trade on news events such as earnings releases, stock splits, and upgrades and downgrades, with hope to earn excessive profits over short term. In addition to the scalpers and the swing traders, there are several other types of traders, who try to earn short-term profits, but who might hold positions up to 10 days, and are therefore not considered as day traders.

Day trading and day traders have credited with creating the volatility that exists in today's markets especially in the United States. They have been blamed for the inflation of Internet stocks, for the unprecedented gains of dot-com initial public offerings, and for anything that hints of irrationality in a stock move [Bentley (2000)]. Naturally, such a speculative type of trading is also one reason for the observed trading volume anomaly. According to Senate Permanent Subcommittee on Investigations, there were 4,000 to 5,000 full-time day traders in USA in the end of 1999. On average, they made 29 trades per day.

One clear reason for the popularity of day trading is the Internet. During the last decade the Internet has become an excellent tool for investors, providing them with many benefits. The keen competition among the online brokerage firms has resulted in a great drop in trading commissions. Via online trading orders can be executed faster and easier in few seconds by just a couple of mouse clicks. The Internet has also provided individual investors with real-time quotes and other information inexpensively that was earlier available only to professional investors.

The Internet has also elicited some disadvantages. Online bulletin boards, which have become an increasingly popular forum for investors to share information, are pretty excellent channel for distributing disinformation. Many bulletin boards allow users to hide their identity behind multiple aliases, so readers can never be certain whom they are dealing with. While some messages are true, some are posted by people who try to pump up a company or pretend to reveal inside information about upcoming announcements. Barber and Odean (2001b) and Barber and Odean (2002) document that after going online, investors trade more actively, more speculatively, and less profitably than before.

A famous behavioral finance academic, Richard H. Thaler, urges for studies on day trading [Thaler (1999a)] and hopes that such studies help academics understand well known anomalies in the financial markets such as what will become known as the Great Internet Bubble. Day trading enables studies on certain behavioral biases as the possible motives to trade are significantly lesser. By the definition of day trading, traders seek for small gains by buying and selling securities frequently. Study on day trading does not have to consider heterogeneous investment horizons, where a decision to sell might be due to sudden need for money to buy a car, or to start unloading a security portfolio because of change in life cycle, say retirement.

As overconfidence is typically not associated with repetitive tasks having fast and clear feedback, day traders may be even less overconfident than other investors who trade more infrequently, although Odean (1998b), Barber and Odean (2000) and Gervais and Odean (2001), among others, argue that overconfidence bias makes investors to trade actively. Day traders have fast but not necessarily clear feedback of their trading success. The feedback is not clear if day traders behave in accordance with the disposition effect and for that reason do not close their losing positions by the end of the day.

4 PREVIOUS STUDIES

4.1 Mental Accounting

Barberis and Huang (2001) create and study two market models differing from each other by the broadness of mental accounts used by loss aversive market participants. In one model people are loss averse over the fluctuations of their stock portfolio, and in another model investors are loss averse over the fluctuations of individual stocks they own. In particular, they allow the possibility for the investor to have different risk aversions while he invests in different stocks at the same time. The latter behavior is named the "separate mental accounting" by Thaler (1985).

Barberis and Huang (2001) propose that of the two models, individual stock accounting may be the more successful one. However, it has its shortfalls too. For example, the model predicts that the correlation between returns on different stocks is the same as the correlation between their cash flows. So, Barberis and Huang (2001) summarized that while individual stock accounting may offer a simple way of understanding a wide range of facts, a model that combines individual stock accounting with broader forms of mental accounting – portfolio accounting or even loss aversion over total wealth fluctuations – is likely to be better.

4.2 Decision-making under Uncertainty, and Overconfidence

Thaler and Johnson (1990) perform a survey to gain knowledge on decision-making under uncertainty on prospect theoretical framework. They formulate and test several "editing rule" hypotheses to find out how gains and losses are encoded by decision-makers. In other words, "editing rule" tries to model when the prior outcomes are combined with the potential payoffs of current prospects and when the prior outcomes are ignored or neglected. They test the following editing rules:

(i) *Prospect theory with memory*. Prior outcomes are incorporated into the perceived "balance" of the relevant mental account.

(ii) *Prospect theory, no memory*. Prior outcomes are irrelevant in decision-making.

(iii) *Concreteness*. Decision-maker uses only the information explicitly displayed, and does no active editing.

(iv) *Hedonic editing*. The rule is based on the hypothesis that people edit the gambles in the way that would make the prospects appear most pleasant or least unpleasant. The rules for hedonic editing follow from the following principles:
 a) segregate gains
 b) integrate losses
 c) segregate small gains from larger losses
 d) integrate (cancel) smaller losses from larger gains

(v) *Quasi-Hedonic editing*. Otherwise same as hedonic editing, but in case of a two-stage gamble involving a prior loss, subsequent losses will not be integrated with the initial loss.

The test is performed as a survey using a sample group of undergraduate and MBA students. The results give support to "quasi-hedonic editing hypothesis", and thus also to the house money effect. They also report the existence of break-even effect, i.e. loss aversion in situations when the gamble provided opportunity to receive a gain that would exactly offset the prior loss. Although the test provided some evidence on decision-making under risky situation, Thaler and Johnson conclude that people could still behave otherwise in the real financial market when actually playing with real money.

Weber and Zuchel (2001) make experimental setting to gain knowledge on the impact of prior outcomes on choice under risk in two-stage decision-making problem, and find a strong framing effect. They are able to induce the house money effect and escalation of commitment by manipulating the presentation format of the decision problem. They explain the results by framing effects based on the prospect theory value function, thus implying the importance of the value function reference point.

In the experiment participants are investing real money given by Weber and Zuchel on the games. Although the setting might reflect reality better than the survey made by Thaler and Johnson (1990), there still exists one major drawback in their setting. The participants may not treat the initial capital given to them as their own money, thus treating it as a gain, which can result in incorrect reference points. In other words, if the participants do not treat the money given to them as their own money, they operate in the domain of gains in the prospect theory value function during the entire test. So, there is always a problem related to the location of reference point if people do not use their own money.

Coval and Shumway (2001) study overconfidence, house money effect, and loss aversion of market makers in the Treasure Bond futures contract at the Chicago Board of Trade. They perform the tests in both intraday and interday horizons. They report strong evidence that the traders are highly loss-averse and thus take far more often additional afternoon risk following morning losses than morning gains. The professional futures traders place an above-average number of afternoon trades, trade at above-average trade sizes, and have above-average return volatility during afternoons after morning losses. Coval and Shumway (2001) document that no relationship exists between profit and risk across trading days. They conclude that the "horizon effects can be quite important in identifying loss-averse behavior".

Locke and Mann (2001) study overconfidence and house money effect among professional futures traders. They use intraday data of 334 professional futures traders for 1995. Their results state that professional futures traders fail to exhibit the house money effect. Actually they find that the traders do take subsequently less risky positions after high recent income compared to prior losses thus supporting loss aversion.

However, their evidence on risk-taking behavior after prior gains is consistent with Gervais and Odean (2001) model of overconfidence and learning. Their findings provide support for the notion that the most successful traders are more likely to be overconfident. Additionally, Locke and Mann find that traders with more experience are less likely to take more risk after a period of abnormally good profits than their less experienced colleagues. Besides of that they present just the aggregate results without more detailed analysis of individual trader properties. The present study aims to confirm the findings of Coval and Shumway (2001), and Locke and Mann (2001), and to augment the knowledge on individual traders: are there some trader characteristics common to the traders behaving in accordance with the house money effect or loss aversion.

Increased trading volume after prior success has been seen as an implication of trader overconfidence [Odean (1998b)]. Barber and Odean (2002) report that investors who switch from phone based to online trading trade more actively than before switching. They document that especially men and young people are subject to overconfidence. Similar results are also documented by Barber and Odean (2001a).

5 HYPOTHESES

Increased risk-taking after prior gains, i.e. the house money effect, is a behavior observed among gamblers, and in experimental studies of financial decision-making situations. Despite active day trading is an extremely speculative form of stock market investing, neither Locke and Mann (2001) nor Coval and Shumway (2001) find evidence on the house money effect in their studies of professional intraday futures traders. Rather, they report evidence that supports loss aversive behavior, i.e. decreased risk-taking after prior gains. However, the unique data set of the current study consists of active and non-professional day traders who are more likely to be exposed to behavioral biases than the professionals [Odean (1998b)]. So, the trading behavior of the sample group of this study is maybe the closest to gambling that can be found from the real financial markets, which makes it ideal data set to study the house money effect.

Overconfidence is more studied subject than the house money effect. In field of finance, trader overconfidence has been claimed for increasing trading volume to higher level than would be rational. Overconfident traders overestimate their contributions to past successes, and recall information related to their successes more easily than information related to their failures. Further, the increased trading volume results in larger commission costs, and therefore lowers the trader returns [Barber and Odean (2002)].

The research hypotheses are divided into two groups based on the studied biases. The first group of hypotheses concentrates on risk-taking behavior of day traders, and the second group on testing and studying overconfidence and trading volume. However, as trading volume can also be used as a proxy for risk-taking, for instance like Coval and Shumway (2001) do, no clear distinction between those groups of hypothesis can be made. So, the possible evidence supporting overconfidence, that is, increased trading volume following prior gains, could also be interpreted as evidence supporting the house money effect. Both groups of hypotheses are studied in intraday horizon as well as in interday horizons.

In addition to the categorizations mentioned above, to see if different mental accounting has impact on results, all the intraday tests are made using both single stock mental accounting and portfolio mental accounting. Single stock mental accounting refers to traders having separate mental account for each line of stock traded, and portfolio mental accounting means that a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day. Unfortunately the data is not suitable for studying mental accounting in interday horizon due to trading is heavily concentrated on one line of stock per trader, and the results would be highly similar between different mental accounting types. So in interday trading horizon only portfolio mental accounting is used.

Earlier studies of the house money effect present aggregate results without more detailed analysis of individual trader properties. The present study aims to augment the knowledge on individual traders: are there some trader characteristics common to the traders behaving in accordance with the house money effect or loss aversion. Similar analysis of overconfidence hypotheses is also made because earlier characterizations of overconfident investors are not made with day traders.

5.1 Hypothesis on Risk-Taking Behavior

One of the main contributions of the study is to gain knowledge on how traders' risk-taking behavior changes after prior gains or losses. According to value function of the (one-stage) prospect theory, people should be more risk-averse in the domain of gains, thus supporting loss aversion. But the house money effect and loss aversion hypotheses made here are based on two-stage prospect theory model in which the opposite risk behavior is expected.

Hypothesis 1 is used to find out whether prior gains or losses have inducing impact on the subsequent risk-taking, i.e. whether the sample traders are subject to the house money effect or loss aversion in intraday horizon. Mental accounting plays a major role in the first hypothesis; if traders treat morning and afternoon as sequential gambles instead of just one gamble, the house money effect is expected to arise. In interday horizon increased risk-taking following prior gains, i.e. the house money effect, is expected to be present because it is more probable that sequential trading days are treated as separate gambles than one gamble. On the other hand if morning and afternoon are seen to be more like one gamble than two sequential gambles, loss aversion should dominate according to the one-stage prospect theory.

Hypothesis 1 – House money effect and loss aversion:

H0: *Prior gains or losses do not have impact on subsequent risk taking.*

H1: *Traders take more risk after gains (house money effect).*

H2: *Traders take more risk after losses (loss aversion).*

The other hypotheses of the first group are used to identify the properties triggering the shift in risk-taking behavior. The rest of the hypotheses on risk-taking behavior are formulated with an assumption of traders treating the morning and afternoon trading periods as different gambles, thus reflecting the existence of house money effect.

First trader characteristic, success, is studied with hypothesis 1.1. Overall success has been claimed to increase overconfidence, and it is also hypothesized to induce risk-taking behavior proposed by the house money effect.

Hypothesis 1.1 – Success:

H0: *Risk taking after prior gains or losses does not depend on trader's success during his trading career.*

H1: *More successful traders take more (less) risk after prior gains (losses) than less successful traders.*

Barber and Odean (2001a) find that men are more prone to overconfidence than women. Hirshleifer (2001) report that men are typically more subject to behavioral biases than women. And because women are seen generally seen to be more risk-averse than men the hypothesis 1.2 suggests that prior success has greater effect on men than on women.

Hypothesis 1.2 – Gender:

H0: *Risk taking after prior gains or losses does not depend on trader's gender.*

H1: *Men take more (less) risk after prior gains (losses) than women.*

According to Hirshleifer (2001), people with less experience are typically more likely to expose to behavioral biases. As time goes by they should learn to behave more rationally. Hypothesis 1.3 predicts that traders with less experience are more likely to take additional risk after prior gains, which is also in line with overconfidence model developed by Gervais and Odean (2001). In addition, gambler term "chasing your money" is used to describe increased risk-taking after losses, and is especially interpreted as a beginner characteristic. So, results confirming hypothesis 1.3 can be seen as evidence on the house money effect as well as on overconfidence.

Hypothesis 1.3 – Experience:

H0: *Risk taking after prior gains or losses does not depend on trader's experience.*

H1: *Less experienced traders take more (less) risk after prior gains (losses) than more experienced traders.*

Last hypothesis in the set of risk-taking hypotheses group is also based on the results of overconfidence studies. According to Barber and Odean (2001a) and Barber and Odean (2002), among others, young people are more likely to take risk than older people. Actually, age can also be seen as another proxy of experience. Whereas in hypothesis 1.3 trader experience is based on the length of trading career, in age hypothesis experience is based on a common knowledge of life.

Hypothesis 1.4 – Age:

H0: *Risk taking after prior gains or losses does not depend on trader's age.*

H1: *Younger traders take more (less) risk after prior gains (losses).*

Hypotheses 1 and 1.1 – 1.4 are estimated nine times: in intraday horizon using single stock mental accounting, in intraday horizon using portfolio accounting, and in seven different interday horizons using portfolio mental accounting. In intraday horizon, the single stock mental accounting is expected to show more significant results since it is not likely that traders follow their total portfolio all the time during a trading day. It is more likely they follow quotations of the stocks they have invested in separately than continuously calculate the total position of portfolio consisting of multiple stocks.

The results of interday tests are expected to show more significant behavior in line with the house money effect due to ambiguousness of intraday mental accounting. In intraday horizon it is not clear that traders evaluate their success at or about at the snapshot time which is required to be done to intentionally behave according to the hypotheses. But traders are very probably reviewing their trades and success after each trading day, and that should have an effect on their behavior if they are subject to the biases.

5.2 Hypotheses on Trading Volume

As mentioned in the previous section, risk-taking behavior is studied mainly to have more knowledge on the existence of house money effect and loss aversion, but can also give a hint of trader overconfidence. Increased trading volume is often used as a proxy of risk-taking, and it has also been seen as strong evidence on overconfidence, and is thus hypothesized to appear also in the present study if the traders are overconfident.

The volume hypotheses are suggesting increasing trading volume after successful trading. Of course possible foundations of behavior consistent with loss aversion – increased risk-taking after prior losses in order to break even – can also result in an increase in trading volume as the volume could also be used as a proxy of risk-taking. Naturally, abnormally high trading volume would help the losing traders to get even with a smaller change in stock price. The double role of trading volume, that is, a measure of both overconfidence and risk-taking, makes it hard to make any conclusions since it is difficult to make a distinction between the two biases. Despite of the difficulty to make conclusions, it is worth studying the influence of prior success on subsequent trading volume due to gaining a better knowledge of its impact, and receiving evidence motivating for further research on the subject.

The three different mental accounting methods used in the risk-taking hypotheses are used also in volume hypotheses 2 and 2.1-2.4. Hypothesis 2 suggests that overconfidence of traders makes them to subsequently trade more after successful trading.

Hypothesis 2 – Overconfidence:

H0: *Prior performance does not have impact on subsequent trading volume.*

H1: *Traders trade more (less) after prior gains (losses).*

Hypothesis 2.1 is tested to find out whether overall success has impact on trading volume after prior gains or losses. A ground for the hypothesis stems from traders' willingness to attribute too much of their success to their own abilities and not enough to their good luck. Successful traders are thus prone to become overconfident.

Hypothesis 2.1 – Success:

H0: *Trading volume after prior gains or losses does not depend on trader's success during his trading career.*

H1: *More successful traders trade more (less) after prior gains (losses) than less successful traders.*

Barber and Odean (2001a), among others, report that women are less likely to expose to overconfidence than men. Prince (1993) suggests that men are inclined to feel more competent than women do in financial matters. Indeed, the descriptive statistics presented in chapter 8 clearly shows that only about 20 percent of the person customers of the Finnish online brokerage house are women. Furthermore the proportion of women in the sample group of active day traders is even smaller, only about 10 percent. Hypothesis 2.2 is used to test whether men are more overconfident than women.

Hypothesis 2.2 – Gender:

H0: *Trading volume after prior gains or losses does not depend on trader's gender.*

H1: *Men trade more (less) after prior gains (losses) than women.*

Gervais and Odean (2001) model a development of overconfidence as time goes by and suggest that the less experienced investors are more likely to be exposed to overconfidence than their more experienced counterparts. More precisely, the greatest expected overconfidence in a trader's life cycle comes early in his career, and as time goes by, he tends to develop a more realistic assessment of his abilities as he ages. In this study, experience is measured with age and the length of trading career in the brokerage providing the data. The corresponding hypotheses are the following:

Hypothesis 2.3 – Experience:

H0: *Trading volume after prior gains or losses does not depend on trader's experience.*

H1: *Less experienced traders take more (less) risk after prior gains (losses) than more experienced traders.*

Hypothesis 2.4 – Age:

H0: *Trading volume after prior gains or losses does not depend on trader's age.*

H1: *Younger traders take more (less) risk after prior gains (losses) than older traders.*

6 DATA

The unique transaction data set is one of the most important attributes of this study. The data for the study is obtained from a leading Finnish online brokerage house and from the Helsinki Exchanges. The data obtained from the online brokerage house includes two separate files; a trade data file and a customer information file. The data received from the Helsinki Exchanges includes stock price file and statistics of online trading.

The sample period of this study starts on January 4, 1999, and ends on March 16, 2001. The sample period is selected based on the availability of the trade data obtained from the Finnish online brokerage house.

6.1 Stock Market Data

Stock price data is received from the Helsinki Exchanges. The data includes all stock market transactions made in the Helsinki Exchanges between January 1987 and December 2001. Date, time, trading session, security, selling broker, buying broker, price, and quantity can be identified from each trade. HEX also provided online trading statistics from 1999 to 2001. The online trading statistics file consists of trading volume and number of trades categorized by brokers on a monthly level. The statistic is based on the trades made with using online broker ID's admitted to brokers.

For intraday tests of this study, trading days are divided into two periods, morning and afternoon trading periods, to determine prior success and subsequent risk taking. For snapshot time, i.e. the minute ending the morning trading period, is chosen to be 2.00 p.m. which is the mid-time of the trading hours in the Helsinki Exchanges. The afternoon trading period of the study starts immediately after that at 2.01 p.m.

Trading hours in the Helsinki Exchanges changed during the sample period on September 1, 2000. Nevertheless the mid-time of the Continuous trading session remains at 2 p.m. as trading time was extended thirty minutes before and after the earlier trading hours. Trading times for sample period are presented in Table 1.

Table 1. Trading hours in the Helsinki Exchanges during the sample period. In pre-trading session, brokers enter orders into the system. The order book becomes public and orders are matched in Matching session. Orders not matched are transferred to Continuous trading session in which orders are matched real-time based on price and time priority. After-market trading sessions I and II are only for negotiated deals.

	Jan 4, 1999 to Aug 31, 2000	Sep 1, 2000 to Mar 16, 2001
Pre-trading	9.30 a.m. - 10.10 a.m.	9.00 a.m. - 9.40 a.m.
Matching	10.10 a.m. - 10.30 a.m.	9.40 a.m. - 10.00 a.m.
Continuous trading	10.30 a.m. - 5.30 p.m.	10.00 a.m. - 6.00 p.m.
After-market trading I	5.30 p.m. - 6.00 p.m.	6.00 p.m. - 6.15 p.m.
After-market trading II (T+1)	9.00 a.m. - 9.30 a.m.	8.30 a.m. - 9.00 a.m.

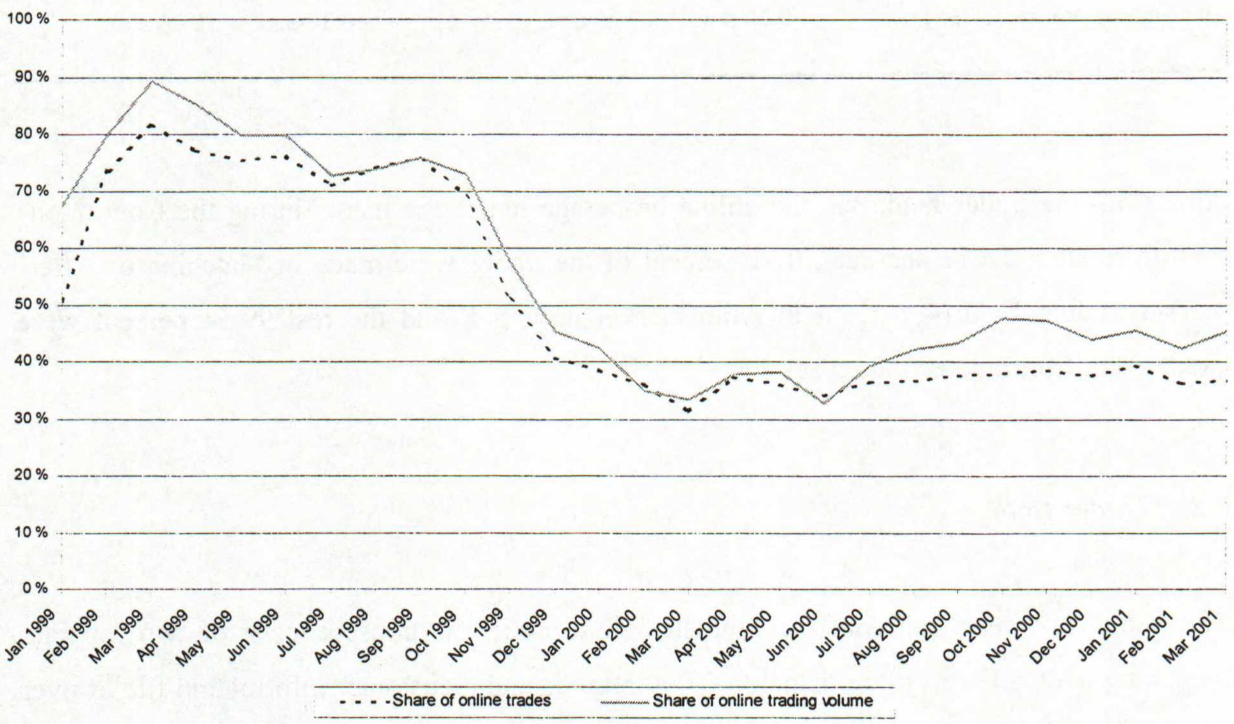
Almost all the trades made via the online brokerage house are made during the Continuous trading session. To be accurate, 0.32 percent of the trades were made in Matching or After-market trading II, 0.14 percent in After-market trading I, and the rest 99.54 percent were executed in Continuous trading session.

6.2 Trader Data

The trader data received from the Finnish online brokerage house consist of two separate files; a trade data file of more than 1,900,000 records and a customer information file of over 24,000 records. The trade data file includes information such as customer identification number, date, time, security, buy-sell indicator, price, quantity, total trade price, and brokerage commission. The customer information file consists of information such as customer identification number, name, social security number (Y-code for companies), language, address, gender, email, etc. The two files are linked with customer identification number.

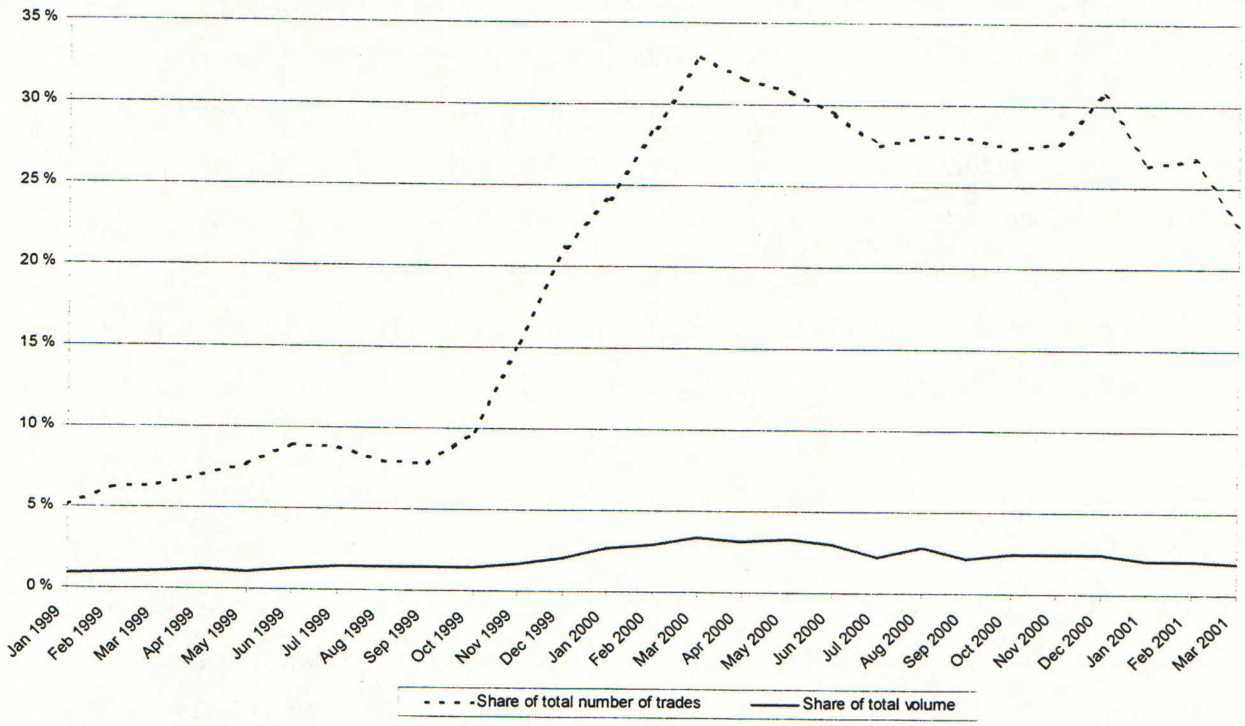
The trader data provides an extensive view on online trading in Finland. The brokerage providing the data was a leading online brokerage in Finland during the sample period; the trade data of this study counts for 39.7 percent of all online trades (48.5 percent of online trading volume) made in the Helsinki Exchanges during the sample period. Figure 4 presents the market share of the online brokerage house of the total online trading volume and the number of online trades in the Helsinki Exchanges during the sample period.

Figure 4. The market share of the online brokerage house that provides the data. The online brokerage house providing data for this study was a leading online brokerage in the Helsinki Exchanges during the sample period. The figure depicts the online brokerage's market share of all online trades (dash line) and online trading volume (solid line) made in the Helsinki Exchanges during the sample period.



As Figure 5 clearly shows, online trading made its break-through in Finnish stock market during the sample period. The online trading's share of total trading volume nearly six-folded from about 5 percent to approximately 30 percent. At the same time the competition between brokers became keener and the online brokerage house providing the data was not as dominant player in the industry at the end as it was at the beginning of the sample period. Nevertheless it has been the largest online brokerage in terms of both trading volume and number of trades during every month in the sample period. A single exception is June 2000 when the online brokerage was the second largest in terms of trading volume by less than two-percentage margin.

Figure 5. Online trading volume and number of online trades in the Helsinki Exchanges. The figure depicts online trading's share of total trades (dash line), and online trading's share of total Euro volume (solid line) in the Helsinki Exchanges during the sample period.



The average trade size of online trades in the Helsinki Exchanges declined from EUR 10,918 in January 1999 to EUR 5,769 in March 2001. The average trade size of the online brokerage providing the data has almost every month been larger – by 10.39 percent on average – than the average size of all online trades made in the Helsinki Exchanges. Despite the larger average trade size the descriptive data obtained from the online brokerage house can be seen to provide a quite good estimation of the Finnish online trading industry. The descriptive statistics of the trader data is presented in chapter 8.

6.3 Sample Selection

The trade data file obtained from the Finnish online brokerage house consists of over 1,900,000 trades made by over 24,000 traders between January 4, 1999 and March 16, 2001.

The selection process to identify day traders starts with dropping professional traders out. The professionalism is based on the traders' customership contract in which traders have to state whether they are professional traders or not[2].

After eliminating professional traders, all intraday trades are selected from the trade data file. A trade is defined as an intraday trade if at least one buy and one sell transaction with same line of security was made during the same trading day. The aim of this paper is to study the behavior of active individual day traders, so to eliminate the possibility of mistakes and effect of occasional day traders only traders who have made at least 100 trades in at least 20 separate trading days are included in the sample. After that, 23 companies that fulfill the day trading criteria are dropped out of the data set. The last step of selection process was to eliminate the trades not defined as intraday trades. So, after removing 67,707 trades made by the selected day traders, the final sample data of this study consists of 152 traders and 129,504 day trades. The sample data is described in detail in chapter 8.

The definition of a day trade presented in previous paragraph drops out of the sample those trades that might initially have been intended as intraday trades but were not completed until next trading day. However, as presented in chapter 8, the number and impact of those omitted trades is likely to be insignificant since over two thirds of the sample traders' trades are day trades by definition. Additionally, the average size of day trades (EUR 10,613) is significantly larger than the average size of other trades (EUR 5,866) made by the sample traders. It is worth noting that one reason for the larger average trade size of intraday trades is the opportunity use leverage without any extra cost in intraday horizon. The costs of buy transactions are subtracted from the revenues from sell transactions at the end of trading day, and the positive (negative) difference is the receivable (payable) to a day trader. However, the online brokerage house delimits the use of leverage by requiring a security deposit, which amounts to one third of the value of the open position.

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[2] A professional investor has been defined in Chapter 1, Section 4, Paragraph 4 of the Finnish Securities Markets Act. In this Act, a professional investor is a company, or an institution, or a customer to whom an investment firm has notified in writing that he is deemed a professional investor. The condition for the latter is that the customer's investment activity is clearly professional in terms of its scope and organization.

7 METHODOLOGY

This chapter is divided into two distinct parts, the data processing methodology, and the methodology to test the hypotheses. The data processing methodology is highly similar to data processing used in Locke and Mann (2001), and Coval and Shumway (2001). Some extensions, for example the development of data history to portfolio mental accounting purposes was not found in any studies so far, so those extensions are carefully developed to reflect the reality. Research hypotheses are tested using OLS regression methodology.

7.1 Data Processing

Data processing starts by the sample selection process described in the previous chapter. After that, trade data file is modified to ease data computations. The trading day used in this study is defined to be Continuous trading session in the Helsinki Exchanges. Trading hours of the Helsinki Exchanges are presented in table 1. For calculations of this study, the trading time of trades executed in Matching or After-market trading II sessions is changed to the first minute of Continuous trading session. Similarly, the trading times of After-market trading I trades are adjusted to the last minute of Continuous trading session. The modifications are made to ease the computing of the data, and do not affect the results of the study.

7.1.1 Position Calculation

Day traders are assumed to have zero position at the beginning of each trading day. Actually this assumption seems to be a quite good approximation since 66.88 percent of all the studied days end to flat position. The value of actual open positions at the end of trading days counts on average for less than five percent of the average daily trading volume. So a zero opening position seems to be a good approximation.

From assumed zero starting position the trading history is built on each trader with each line of security on minute-by-minute level. The trading history construction begins with calculating running position on each minute of trading day. The position increases with buys and decreases with sales, and is held constant during the minutes no trades are executed. Typically the intraday trades are not clear round trips having one equal size buy and sell thus resulting zero position but rather building and reducing position during the day.

7.1.2 Average Cost Calculation

After positions at each minute are calculated, the positions are valued with the average cost calculation method. The term cost is used in a generic sense so that long position cost is the average purchase price and short position cost is the average sale price. Brokerage commissions are included in the prices, and the per share cost for each trader's position at each minute is determined to be the quantity-weighted average cost for the prevailing position. When trader makes the first trade of the day, the average cost is calculated with equation 6.

$$AVGCOST = P - \frac{FEE}{Q} \tag{6}$$

where P = stock price,

FEE = brokerage fee, negative (positive) for purchases (sells), and

Q = number of shares purchased (sold).

The average cost of position does not change if subsequent trades are position reductions; otherwise the average cost is recalculated. If the position changes from long to short, or from short to long, the average cost is calculated as in the case of first trade of the day using stock price, quantity, and commission of the latest trade. On the other hand, if subsequent trade adds to existing position – i.e. position changes either from long to more long, or short to more short position – the average cost is calculated with equation 7.

$$AVGCOST_t = \frac{AVGCOST_{t-1} * POSITION_{t-1} + P_t * Q_t - FEE_t}{POSITION_t} \tag{7}$$

where $AVGCOST_{t-1}$ = average cost of position before the trade,

$POSITION_{t-1}$ = number of shares before the trade,

P_t = purchase (sell) price of stock,

Q_t = number of shares purchased (sold),

FEE_t = brokerage fee, negative (positive) for purchases (sells), and

$POSITION_t$ = number of shares after the trade.

An example of average cost calculation is presented in table 2. Trader 1 opens a position at 10:30 by buying 1,000 shares at EUR 20.00, totaling EUR 20,050 when brokerage commissions are included; after the trade the average cost of the position is EUR 20.05. In the next trade Trader 1 adds to the position, buying 2,000 shares at EUR 22.00. The average per share cost increases with building the position: after the second trade, the position average cost is calculated as (EUR 20.05*1,000 + EUR 44,110)/3,000 resulting in the average cost EUR 21.39. Continuing with the example, as Trader 1 liquidates the position by selling, the average cost of the remaining position is unchanged in position reductions until 10:44, when the trader "switches" positions, moving from long to short. At that point, the average cost is adjusted to the average sale price of the new short position, EUR 22.94 (equals to EUR 68,828/3,000).

Table 2. Average cost calculation example. The table presents hypothetical trade history for trader 1. The following information about each trade is presented: time, buy/sell indicator, volume (i.e. number of shares bought or sold), prevailing market price, position after the trade, and average cost of the position after the trade. In addition, "total amount" column stands for Share Price multiplied by Volume plus (minus) brokerage fee when buying (selling).

Time	Buy/Sell	Volume	Total Amount	Share price	Position	Position average cost
10:30	Buy	1,000	20,050	20.00	1,000	20.05
10:31	Buy	2,000	44,110	22.00	3,000	21.39
10:35	Sell	500	10,973	22.00	2,500	21.39
10:40	Sell	1,000	20,948	21.00	1,500	21.39
10:44	Sell	3,000	68,828	23.00	-1,500	22.94
10:49	Sell	1,000	21,945	22.00	-2,500	22.54
10:53	Buy	4,000	88,220	22.00	1,500	22.06
10:58	Sell	1,000	23,940	24.00	500	22.06

Special cases are when more than one trade occurs within a minute. In such cases the total amount of buys and sells are first aggregated to one single trade using the same calculation method as in equations 6 and 7, and the end of the minute position is calculated. The aggregated trade is then treated similarly to any other trade in the average cost calculation.

7.1.3 Return Calculation

Returns on trades can be either realized or unrealized. In the trading history, both return types and their sum are calculated for each trader at every minute of each trading day. Realized returns are generated when a trade results in a reduction in absolute position value. This includes times when trader's position is eliminated, changes from long to short, short to long, long to less long, or short to less short. The realized return is the revenue from a trade less the average position cost times the realized amount. Revenue from a trade is positive (negative) if the trade is purchase (sell), and the realization amount is positive (negative) if the trade is purchase (sell). So, equation 8 is used to calculate realized returns.

$$RETURN = REVENUE - REALIZATION\ AMOUNT * AVGCOST \qquad (8)$$

where $REVENUE$ = revenue from a trade reducing position,
$REALIZATION\ AMOUNT$ = number of shares purchased (sold), and
$AVGCOST$ = average cost of position

Positions are marked to market (i.e. unrealized returns are calculated) on each minute of the trading day by comparing the average cost per share to the prevailing market price of the stock. The prevailing market price of a stock at a particular minute is defined to be the quantity-weighted average price of all the trades executed in the Helsinki Exchanges with the line of stock during the minute, and the price is held constant during minutes when there is zero aggregate trading. Marked-to-market value states the return that a trader would most likely receive if he eliminated his position at the minute. In practice a trader would have to pay brokerage commissions of the realization, and depending on bid and offer quotations and position size, marked-to-market value can differ from the actual return if the position would have been realized. However, marked-to-market value provides a good approximation of unrealized return, and it is calculated with equation 9.

$$MTM = POSITION * (P - AVGCOST) \tag{9}$$

where $POSITION$ = position at the minute,

P = stock price at the minute, and

$AVGCOST$ = average position price.

Total Euro return on a trader at any minute of the trading day is the sum of cumulative realized return and marked-to-market (MTM) measure. It can be treated as approximately the final return on the particular day if the trader would close his position at the moment and quit trading for that day.

Table 3. Return calculation example: hypothetical trading history for trader 1 with stock NOK1V. Revenue is the number of realized stocks multiplied by selling price plus (minus) brokerage fee when purchasing (selling). The share price used in marking-to-market calculations is the quantity-weighted average price of all trades executed in the Helsinki Exchanges at the minute. To keep it simple, it is also used as a purchase or selling price in revenue calculation in the example, but in real data calculations the real purchase or sell stock prices are used. Total return is the sum of mark-to-market return and cumulative realized return.

Time	Position	Position average cost	Share Price	Revenue	Mark-to-market	Realized return	Total return
10:02	2,000	22.20	22.20	0	0	0	0
10:03	1,000	22.20	22.70	22,643	500	443	943

The example in table 3 illustrates the return calculation technique. At 10:02, trader 1 opens a long position of 2,000 NOK1V shares with an average cost of EUR 22.20. At 10:03 trader 1 realizes 1,000 stocks of NOK1V. Unrealized (mark-to-market) return is EUR 500 (equals to

1,000*(EUR 22.70 – EUR 22.20)) and realized return is EUR 443 (equals to EUR 22,643 – 1,000* EUR 22.20), summing up to total return of EUR 943.

While it is easy to measure Euro returns, the percentage return calculation is a bit more complicated in two aspects. First, how to calculate return from short selling, and second, which capital is the intraday return calculated on. First problem in percentage return calculation is defining what to consider as the invested amount in case of short selling. It's easy to calculate return on long position; buying at X_0 and selling at X_1 would result in return r as in equation 10.

$$r = \frac{X_1 - X_0}{X_0} \tag{10}$$

where X_1 = revenue from sale

X_0 = total cost of purchase

Strictly mathematically, there is no capital tied up before realization when selling short. Thinking that way leads one to define the return from short selling as -∞, 0, or ∞. In practice traders need to have a security deposit given to the broker in order to be able to sell short. A practical definition for short selling returns would be to consider selling as investment of $-X_0$ and buying as receiving $-X_1$ [Luenberger (1998)]. The return on a short position could then be calculated similar to the return on a long position, that is, on the amount of chronologically first transaction. So, return on short selling is calculated with equation 10 where X_0 is a negative of the amount received at selling and X_1 is a negative of the amount paid when buying.

Second consideration in defining percentage intraday return deals with the capital the return is calculated on. Due to ambiguity of invested capital, there are several methods to calculate the percentage return yielding to different results. Let's consider the problem with a simple example in Table 4.

Table 4. Percentage return calculation example: hypothetical trading history of Trader 1. Example used to illustrate the calculation of percentage return. Column "total" is calculated as Amount multiplied by Price, column "Capital requirement 1" is investment in the trade at the minute, column "Capital requirement 2" is the total amount invested at each minute of the trading day, and column "Capital requirement 3" is calculated as the largest "Capital requirement 2" at or prior the trade.

Time	Buy/Sell	Amount	Price	Total	Capital requirement 1	Capital requirement 2	Capital requirement 3
11:00	Buy	2 000	10,00	20 000	20 000	20 000	20 000
12:00	Sell	2 000	11,00	22 000	-	-	20 000
13:00	Buy	1 000	10,00	10 000	10 000	10 000	20 000
14:00	Buy	2 000	10,50	21 000	21 000	31 000	31 000
15:00	Sell	3 000	11,00	33 000	-	-	31 000
16:00	Sell	2 000	11,00	22 000	22 000	22 000	31 000
17:00	Buy	2 000	11,50	23 000	-	-	31 000

Simple method to calculate day's return on Trader 1 is to set the sum of Capital requirement 1, i.e. the sum of all investments during the day, to investment X_0, and the sum of all realizations to receiving X_1. Applying $X_0 = 73{,}000$ and $X_1 = 78{,}000$ to equation 10 would result in a return of 6.85%.

However, it doesn't seem correct that trader 1 has invested EUR 73,000 while the largest investment at time during the day is only EUR 31,000. By its nature, active day trading is more like reinvesting the capital many times in a day than investing the sum of all investments only once. For that reason, capital investment of a day is considered as the largest investment at time during the day. Using this calculation method, equation 10 with $X_0 = 31{,}000$ and $X_1\text{-}X_0 = 5{,}000$ (=78,000-73,000) results in a return of 16.13%, which is much larger than the return calculated with the first method. Overall, the calculation method used in this study always results in an absolute return larger than or equal to the return defined in simple return calculation method.

The intraday horizon research hypotheses of this study predict that morning returns have impact on risk-taking in the afternoon. Morning returns are calculated as returns on the largest investment at any time before the snapshot time, and afternoon returns are calculated on the largest investment at time during the whole trading day. Daily returns used in interday tests are calculated as returns on the largest investment at time during the day.

7.1.4 Combining Separate Lines of Securities

Day traders may have separate "day trading" mental accounts for each security traded, or they may have only one "day trading" mental account as mentioned earlier. The trading history developed so far is applied in intraday tests using single stock mental accounting. Single stock mental accounting refers to traders having separate mental account for each line of stock traded, and portfolio mental accounting means that a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day. All trading histories of separate lines of stocks a trader has traded during one trading day are aggregated to study the portfolio mental accounting. Portfolio mental accounting is used to test both intraday and interday hypotheses.

The returns used in portfolio mental accounting tests are simply sums of the above-calculated returns on each stock for same trader on the same day. That is, the total Euro return for a trader is the sum of total returns on separate lines of stocks for the trader on the same day. Also capital investments in each security are summed to calculate percentage return on the portfolio. Percentage returns are then calculated on the largest aggregate investment same way as in single stock mental accounting described earlier.

7.2 Methodology to Test the Hypotheses

The research problems of this paper are the risk-taking behavior and overconfidence of active day traders. To test the risk-taking behavior after prior gains or losses in intraday horizon, a trading day must be divided into two subsequent trading periods, morning trading period and afternoon trading period. For snapshot time, i.e. the minute ending the morning trading period, is chosen to be 2.00 p.m. which is the mid-time of trading hours in the Helsinki Exchanges. Afternoon trading period starts immediately after that at 2.01 p.m. The snapshot time plays a big role in the study because it is assumed that a trader evaluates his success at or about at the snapshot time and treats afternoon trading period as a different gamble.

7.2.1 Testing Risk-taking Hypotheses

Hypothesis 1 is used to study the risk-taking behavior of day traders after prior gains or losses. To test hypothesis 1 in intraday trading horizon using single stock mental accounting, let's first define average standard deviation of trader i trading period (TP) returns in equation 11, which is run for each trader for two trading periods; morning trading period, and afternoon trading period.

$$\overline{\sigma_{i,TP}} = \sqrt{\frac{\sum_{j=1}^{S}\sum_{k=1}^{T}\left(r_{i,k,j,TP} - \overline{r_{i,k,j,TP}}\right)^2}{S*T-1}} \tag{11}$$

where $\overline{\sigma_{i,TP}}$ = average standard deviation of trader i returns in trading period TP,

$\overline{r_{i,k,j,TP}}$ = average return on trader i in trading period TP, and

$r_{i,k,j,TP}$ = return on trader i from stock j in trading period TP on day k.

The regression in equation 12 is run for each trader to test hypothesis 1 in intraday trading horizon using single stock mental accounting. The average standard deviations used in equation 12 are calculated using the equation 11.

$$\sigma_{i,j,t,PM} - \overline{\sigma_{i,PM}} = \alpha_i + \beta_i * \left(r_{i,j,t,AM}\right) + \gamma_i * \left(\sigma_{i,j,t,AM} - \overline{\sigma_{i,AM}}\right) + \varepsilon_i \tag{12}$$

where $\sigma_{i,j,t,PM}$ = standard deviation of trader i returns on day t afternoon with stock j,

$\overline{\sigma_{i,PM}}$ = average standard deviation of trader i afternoon returns,

$r_{i,j,t,AM}$ = morning return on trader i from stock j on day t,

$\sigma_{i,j,t,AM}$ = standard deviation of trader i returns on day t morning with stock j,

$\overline{\sigma_{i,AM}}$ = average standard deviation of trader i morning returns,

α_i, β_i, γ_i = regression coefficients, and

ε_i = error term for trader i.

The regression coefficient β_i is of special interest because it captures the trader behavior after prior gains or losses. β_i is positive for traders behaving according to the house money effect, and negative for traders behaving in accordance with loss aversion.

To test hypothesis 1 using portfolio mental accounting in intraday trading horizon, let's first define average standard deviation of trader *i* trading period (*TP*) returns in equation 13, which is run for each trader for two trading periods; morning trading period, and afternoon trading period.

$$\overline{\sigma_{i,TP}} = \sqrt{\frac{\sum_{k=1}^{T}\left(r_{i,k,TP} - \overline{r_{i,k,TP}}\right)^2}{T-1}} \tag{13}$$

where $\overline{\sigma_{i,TP}}$ = average standard deviation of trader *i* returns in trading period *TP*,

$\overline{r_{i,k,TP}}$ = average return on trader *i* in trading period *TP*, and

$r_{i,k,TP}$ = return on trader *i* in trading period *TP* on day *k*.

The regression in equation 14 is run for each trader to test hypothesis 1 in intraday trading horizon using portfolio mental accounting. The average standard deviations used in equation 14 are calculated using the equation 13.

$$\sigma_{i,t,PM} - \overline{\sigma_{i,PM}} = \alpha_i + \beta_i * \left(r_{i,t,AM}\right) + \gamma_i * \left(\sigma_{i,t,AM} - \overline{\sigma_{i,AM}}\right) + \varepsilon_i \tag{14}$$

where $\sigma_{i,t,PM}$ = standard deviation of trader *i* returns on day *t* afternoon,

$\overline{\sigma_{i,PM}}$ = average standard deviation of trader *i* afternoon returns,

$r_{i,t,AM}$ = morning return on trader *i* on day *t*,

$\sigma_{i,t,AM}$ = standard deviation of trader *i* returns on day *t* morning,

$\overline{\sigma_{i,AM}}$ = average standard deviation of trader *i* morning returns,

α_i, β_i, γ_i = regression coefficients, and

ε_i = error term for trader *i*.

The regression in equation 15 is run for each trader to test hypothesis 1 in interday trading horizon. The portfolio mental accounting is used in all interday tests of this study due to the data is not applicable to single stock mental accounting in interday trading horizon. The regression is run for each trader with prior return period K = 1, 2, 3, 4, 5, 10, and 20. Since different K's are overlapping the results will probably be highly similar to most of K's.

$$\sigma_{i,t} - \overline{\sigma_i} = \alpha_i + \beta_i * \left(r_{i,t-1,K}\right) + \varepsilon_i \qquad (15)$$

where $\sigma_{i,t}$ = standard deviation of trader *i* returns on day *t*,

$\overline{\sigma_i}$ = average standard deviation of trader *i* daily returns

$r_{i,t-1,K}$ = return on trader *i* on *K* day period starting from day *t-K-1*,

α_i, β_i = regression coefficients, and

ε_i = error term for trader *i*.

Hypotheses 1.1-1.4 are tested to find out if there are any common attributes with day traders behaving in accordance with the house money effect that differ from the attributes of day traders subject to loss aversion. All hypotheses studied are estimated in one regression presented in equation 16. But let's remind the hypotheses and define independent variables next.

Hypothesis 1.1 proposes that more successful traders take more risk after prior gains than their less successful counterparts. $Success_i$ is calculated for each trader to make the successful traders out of the less successful traders. The problem with a success measure is that in the regression it is constant for trader *i* for the whole sample period, whereas actually the measure should be dynamic. To this study, the most appropriate applicable measure of success is the total return from all intraday trades.

To test the impact of gender on risk-taking and volatility of returns, dummy variable $Gender_i$ is used. It is set to one if trader *i* is a male, and it is zero if trader *i* is a female. In the sample group, most of traders (88.82 per cent to be precise) are males so the dummy variable is violating the rule of thumb stating that at least twenty per cent of observations should be included in each regression dummy variable group. The results of hypothesis 1.2 are analyzed keeping this shortfall in mind.

Hypothesis 1.3 suggests that more experienced traders take less risk after prior gains. Again a problem of having constant measure is faced. Just like a success measure, an experience measure should also be dynamic for similar reasons. Even if a dynamic measure could be used, however, it is impossible to find out the real trader experience since the data is received only from the relatively new online brokerage house. Nevertheless, the number of intraday trades is used as a proxy for investing experience, which is as good measure as any dynamic experience measure that could be employed with the data available. The distribution of experience is normalized by using natural logarithm of number of intraday trades in equation 16.

Hypothesis 1.4 states that younger traders take more risk after prior gains than older traders. Independent variable Age_i is the age of trader i in years in the beginning of the sample period, i.e. on January 1st, 1999. So, Age_i is calculated as the year of birth minus 1999.

$$\beta_i = \alpha_{all} + \chi_{all} * (Success_i) + \eta_{all} * (Gender_i) + \delta_{all} * (Experience_i) + \phi_{all} * (Age_i) + \varepsilon_{all} \tag{16}$$

where β_i = regression coefficient, which captures risk-taking behavior of trader i after prior success, received from equation 12, 14, or 15,

$Success_i$ = total return for trader i from all intraday trades,

$Gender_i$ = dummy variable (1 for males, 0 for females),

$Experience_i$ = natural logarithm of number of intraday trades,

Age_i = age of trader i in years in the beginning of the sample period,

α_{all}, χ_{all}, η_{all}, δ_{all}, ϕ_{all} = regression coefficients, and

ε_{all} = error term.

The predicted signs of regression coefficients are presented in table 5.

Table 5. Expected signs of regression coefficients. Success, gender, experience, and age are characteristics that are expected to have influence on the risk-taking behavior after prior gains or losses. Success is total return for a trader from all intraday trades, gender is dummy variable (1 for males, 0 for females), experience is natural logarithm of number of intraday trades a trader has made, and age is the age of a trader in years in the beginning of the sample period.

Coefficient	Independent Variable	Expected Sign
χ_{all}	Success	+
η_{all}	Gender	+
δ_{all}	Experience	-
ϕ_{all}	Age	-

7.2.2 Testing Overconfidence Hypotheses

While the risk-taking after prior performance is the main research problem of the study, also overconfidence of the traders is interesting. According to hypothesis 2, prior gains make people to trade more. To test hypothesis 2 in intraday trading horizon using single stock mental accounting, let's first determine average trading volume of trader *i* in trading period *TP* in equation 17, which is run for each trader for two trading periods; morning trading period, and afternoon trading period.

$$\overline{Volume_{i,TP}} = \frac{\sum_{j=1}^{S}\sum_{k=1}^{T} Volume_{i,k,j,TP}}{S*T} \qquad (17)$$

where $\overline{Volume_{i,TP}}$ = average Euro volume of trader *i* trades in trading period *TP*, and

$Volume_{i,k,j,TP}$ = Euro volume of trader *i* trades on day *k* with stock *j* in trading period *TP*.

The regression in equation 18 is run for each trader to test hypothesis 2 in intraday trading horizon using single stock mental accounting. The average volumes used in equation 18 are calculated using equation 17.

$$\frac{Volume_{i,j,t,PM} - \overline{Volume_{i,PM}}}{\overline{Volume_{i,PM}}} = \alpha_i + \beta_i * \left(r_{i,j,t,AM}\right) + \gamma_i * \left(\frac{Volume_{i,j,t,AM} - \overline{Volume_{i,AM}}}{\overline{Volume_{i,AM}}}\right) + \varepsilon_i \quad (18)$$

where $Volume_{i,j,t,PM}$ = afternoon trading volume of trader *i* on day *t* with stock *j*,

$\overline{Volume_{i,PM}}$ = average afternoon trading volume of trader *i*,

$r_{i,j,t,AM}$ = morning return on trader *i* from stock *j* on day *t*,

$Volume_{i,j,t,AM}$ = morning trading volume of trader *i* on day *t* with stock *j*,

$\overline{Volume_{i,AM}}$ = average morning trading volume of trader *i*,

$\alpha_i, \beta_i, \gamma_i$ = regression coefficients, and

ε_i = error term for trader *i*.

The regression coefficient β_i is of special interest because it captures the trader behavior after prior gains or losses. β_i is positive for traders who increase their trading volume after prior gains, i.e. for overconfident traders.

To test hypothesis 2 using portfolio mental accounting in intraday trading horizon, let's define average euro volume of trader *i* in trading period *TP* in equation 19, which is run for each trader for two trading periods; morning trading period, and afternoon trading period. Average volume defined in equation 19 is the same as the average volume resulting from equation 17 if trader makes intraday trades with only one line of stock per day. So, trading volumes of different stocks are summed in equation 19 to reflect trading volume of trader's portfolio.

$$\overline{Volume_{i,TP}} = \frac{\sum_{k=1}^{T} Volume_{i,k,TP}}{T} \quad (19)$$

where $\overline{Volume_{i,TP}}$ = arithmetic average of trading volumes in trading period *TP*,

$Volume_{i,k,TP}$ = trading volume of trader i in trading period TP on day k, and

T = number of days when trader i has made intraday trades.

The regression in equation 20 is run for each trader to test hypothesis 2 in intraday trading horizon using portfolio mental accounting. The average volumes used in equation 20 are calculated using equation 19.

$$\frac{Volume_{i,t,PM} - \overline{Volume_{i,PM}}}{\overline{Volume_{i,PM}}} = \alpha_i + \beta_i * (r_{i,t,AM}) + \gamma_i * \left(\frac{Volume_{i,t,AM} - \overline{Volume_{i,AM}}}{\overline{Volume_{i,AM}}} \right) + \varepsilon_i \qquad (20)$$

where $Volume_{i,t,PM}$ = afternoon trading volume of trader i on day t,

$\overline{Volume_{i,PM}}$ = average afternoon trading volume of trader i,

$r_{i,t,AM}$ = morning return on trader i on day t,

$Volume_{i,t,AM}$ = morning trading volume of trader i on day t,

$\overline{Volume_{i,AM}}$ = average morning trading volume of trader i,

α_i, β_i, γ_i = regression coefficients, and

ε_i = error term for trader i.

The regression in equation 21 is run for each trader to test hypothesis 2 in interday trading horizon. Only portfolio mental accounting is used in intraday trading horizon due to the data is not applicable to single stock mental accounting in interday trading horizon as mentioned earlier in chapter 6. Equation 21 is run for each trader with prior return period K = 1, ..., 5, 10, and 20. Market change on day *t-1* is used as a controlling variable.

$$\frac{Volume_{i,t} - \overline{Volume_i}}{\overline{Volume_i}} = \alpha_i + \beta_i * (r_{i,t-1,K}) + \gamma_i * |MarketChange_{t-1}| + \varepsilon_i \qquad (21)$$

where $Volume_{i,t}$ = trading volume of trader i on day t,

$\overline{Volume_i}$ = average trading volume of trader i,

$r_{i,t-1,K}$ = return on trader i on K day period starting from day *t-K-1*,

$\left| MarketChange_{t-1} \right|$ = absolute value of HEX All-share index change on day *t-1*,

α_i, β_i, γ_i = regression coefficients, and

ε_i = error term for trader *i*.

Hypotheses 2.1. – 2.4. are tested to find out if there are any common attributes with the traders that are observed to increase their trading volume after prior gains, i.e. attributes common to overconfident traders. All hypotheses mentioned are estimated with the regression presented in equation 16. Independent variables used in equation 16 are defined above when hypotheses 1.1. – 1.4. are discussed. The predicted signs for characteristic measures are same as used in volatility study, and are presented in table 5.

8 RESULTS

Descriptive trader statistics and the results of the empirical tests are presented in this chapter. Whereas main interest is on the results of the empirical tests, contribution of the trader statistics should not be undervalued. Very few studies are conducted on individual day traders and thus all data available gives us better knowledge on them and their behavior.

8.1 Descriptive Statistics

One of the main contributions of this study are the descriptive statistics of trader data since data sets liked the one used in this study are rarely available to researchers. Table 6 presents statistics of the Finnish online brokerage house customers. As mentioned earlier in chapter 6, the online brokerage house providing the data for this study was the leading online brokerage house in Finland during the sample period, so the statistics in table 6 can therefore seen to approximately describe Finnish online trading industry as whole during the sample period, that is, from January 1999 to March 2001.

At the end of the study period, the online brokerage house had a total of 24,261 customers of which 22,194 (91.48%) were persons and 2,067 (8.52%) were companies. Of the persons, 4,900 (22.08%) were women and 17,294 (77.92%) were men. Women made on average 63 percent less trades than men, and had about five percent larger average trade size. The proportion of women is in line with the findings of Barber and Odean (2001a) who had a data set of over 35,000 investors. They also reported men trading more than women on almost equally large average trade size. Table 6 also shows that middle-aged people are on average most active individual players in the stock market. The average trade size seems to increase with trader's age, which sounds quite natural.

Table 6. Descriptive statistics of all customers of the Finnish online brokerage house. The table reports descriptive statistics of all customers of the online brokerage house providing data for this study. Average number of trades is the number of trades divided by the number of traders. Average trade size is the total sum of trades divided by the number of trades.

		Number of Traders	Percentage of All Traders	Average Number of Trades	Average Trade Size (EUR)
	Total	24261	100.00 %	41.31	7 335.37
Person/Company	Person	22194	91.48 %	40.57	7 068.01
	Company	2067	8.52 %	49.29	9 698.21
Gender	Female	4900	20.20 %	17.27	7 422.15
	Male	17294	71.28 %	47.17	7 031.28
Language	Finnish	23343	96.22 %	41.29	7 191.52
	Swedish	730	3.01 %	42.87	8 430.05
	Other	188	0.77 %	38.03	21 934.79
Age	- 25	5811	23.95 %	15.56	4 232.82
	26 - 35	7309	30.13 %	37.70	6 047.02
	36 - 45	4287	17.67 %	58.59	7 359.84
	46 - 55	3239	13.35 %	62.94	7 969.78
	56 -	1548	6.38 %	51.28	10 602.15
Day traders		152	0.63 %	1 284.28	9 014.89
Others		24109	99.37 %	33.48	6 820.06

The last two rows of table 6 show the difference between a typical Finnish online investor and a day trader in the sample of this study. Day traders in the sample of this study cover only 0.63 percent of the total number of investors but they have clearly different investing strategy than the others. Namely, the day traders have made almost forty times more trades than the other investors, and their average trade size is about 32 percent larger. So, the active day traders, who count for 0.63 percent of traders, make almost 20 percent of all trades that count for over 24 percent of the total volume.

Traders are chosen to the sample based on the amount of their intraday trades. The sample selection process is described in detail in chapter 6. In addition to intraday trades, sample traders make also longer lasting trades, referred as overnight trades from now on, as shown in table 7.

Table 7. All trades made by sample traders. Number of trades states the number of sample traders' trades that are counted as intraday trades or other ("non-intraday") trades. Total trading volume is the Euro value of trades, and average trade size is the total trading volume divided by the number of trades.

	Number of Trades	Percentage of Trades	Total Trading Volume (Mill. EUR)	Percentage of Total Trading Volume	Average Trade Size (EUR)
Intraday trades	129 504	66.34 %	1 374.37	78.10 %	10 612.55
Other trades	65 707	33.66 %	385.44	21.90 %	5 866.00

Table 7 shows that approximately two thirds of the sample traders' trades are classified as intraday trades giving support to the assumption that day traders have separate mental accounts based on the length of investments for intraday trades and overnight trades. Average size of intraday trades is almost double the size of overnight trades; the difference can be seen as a strong evidence on the mental accounting assumption and thus stating that intraday trades are (at least typically) meant to be performed in intraday horizon. The larger average intraday trade size also indicates higher risk taking, which is not surprising considering the speculative nature of day trading.

Last table introducing descriptive trader statistic results of this study is table 8, which presents the descriptive statistics of intraday trades used in the empirical tests of this study. Two additional columns are inserted in table 8 compared to table 6; trading activity to show how active the traders have been when trading, and trading intensity to describe how often trading takes place in relation to the length of trader's customership to the brokerage.

Table 8. Descriptive statistics of the sample traders. Average number of trades is the number of trades divided by the number of traders. Average trade size is the total sum of trades divided by the number of trades. Trading activity is the average number of trades divided by the average number of intraday trading days. Trading intensity is calculated by dividing the average number of intraday trading days by the average length of customership in days.

		Number of Traders	Percentage of All Traders	Average Number of Trades	Average Trade Size (EUR)	Trading Activity	Trading Intensity
	Total	152	100.00 %	1 284.28	9 014.89	10.11	34.43 %
Gender	Female	17	11.18 %	1 073.82	8 863.60	9.11	31.07 %
	Male	135	88.82 %	1 310.79	9 030.50	10.22	34.86 %
Language	Finnish	145	95.39 %	1 268.06	8 272.38	10.00	34.79 %
	Swedish	6	3.95 %	1 488.17	12 863.59	10.37	25.92 %
	Other	1	0.66 %	2 414.00	51 111.16	34.49	48.95 %
Age	- 25	9	5.92 %	795.11	9 481.91	7.67	30.20 %
	26 - 35	47	30.92 %	1 107.87	9 336.00	9.15	35.21 %
	36 - 45	47	30.92 %	1 363.60	8 895.06	10.50	33.62 %
	46 - 55	40	26.32 %	1 399.38	8 824.05	10.51	34.15 %
	56 -	9	5.92 %	1 769.00	8 908.17	12.61	40.64 %

Statistics in table 8 show that day traders make on average 10.11 trades per day. The largest number of trades per day for one trader is 122 (of which 88 were made with one line of security), and the smallest was just 2 trades. The proportion of women is only about a half of what is reported in table 6. Among day trader sample, women on average trade less and with smaller average trade size than men.

It is also quite interesting to notice that the average number of trades and trading activity increase with age. Typically young people are seen be more involved with risky activities than older people but among this day trader sample the relation is vice versa. It is also surprising that the youngest people have the largest average trade size. However, sample size is quite small so no robust conclusions can be made.

Day trading is a high-risk activity because the position is meant to be closed before the end of the day. Stocks suitable for day trading must therefore be volatile in order to have large enough price movement in a day. Also, especially in a small stock market like the Helsinki Exchanges where many lines of stock are illiquid with large spreads, a day trader must be careful in his stock selection. Table 9 presents the 15 most actively traded lines of stock among day traders.

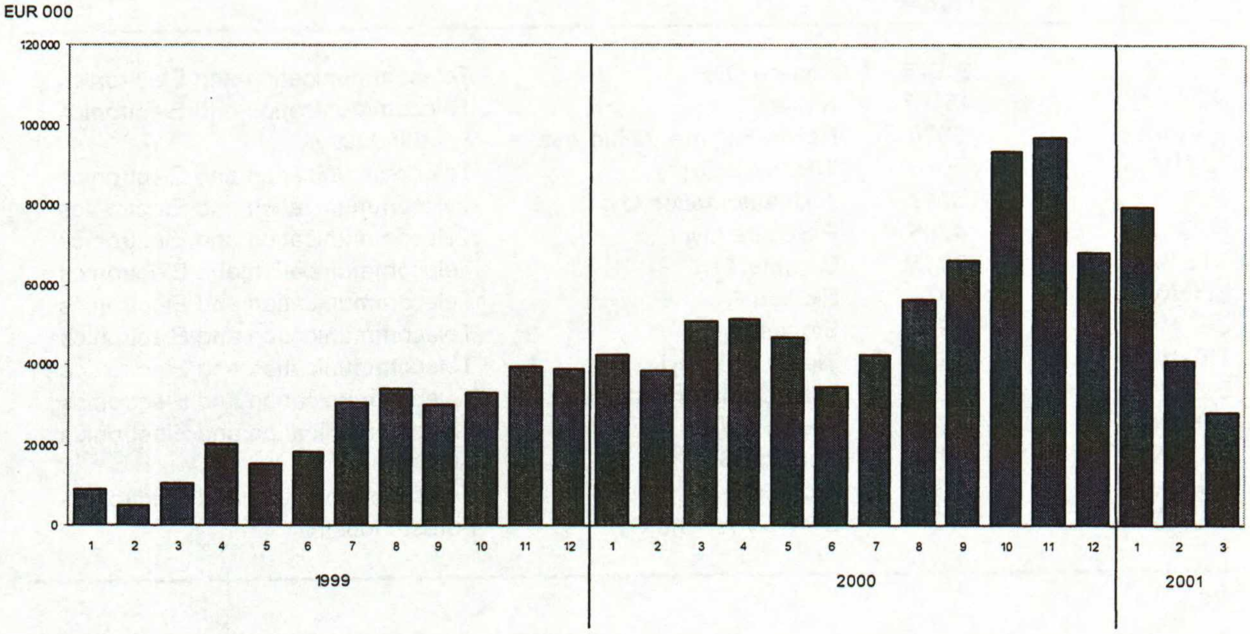
Table 9. Fifteen most actively traded share series among day traders. Industry is presented as it was received from the Helsinki Exchanges. BENSV share listed on I-list (investors list) would be categorized into Telecommunication and Electronics industry if it were listed in the Helsinki Exchanges Main List.

Trading Code	Number of Trades	Security Name	Industry
SRA1V	21975	Sonera Oyj	Telecommunication and Electronics
NOK1V	15167	Nokia Oyj	Telecommunication and Electronics
RAIVV	6820	Raisio Yhtymä Vaihto-osake	Food Industry
TJT1V	5656	TJ Group Oyj	Telecommunication and Electronics
JOT1V	5117	JOT Automation Oyj	Telecommunication and Electronics
FSC1V	4206	F-Secure Oyj	Telecommunication and Electronics
CTL1V	2946	Comptel Oyj	Telecommunication and Electronics
ELQAV	1977	Elcoteq A	Telecommunication and Electronics
SFT1V	1970	Stonesoft Oyj	Telecommunication and Electronics
TIE1V	1527	Tietoenator Oyj	Telecommunication and Electronics
ELIAV	1273	Elisa Communications	Telecommunication and Electronics
POS1V	1243	Perlos Oyj	Telecommunication and Electronics
BENSV	1017	Benefon S	I-List
PHA1V	930	Proha Oyj	Telecommunication and Electronics
UPM1V	901	UPM-Kymmene Oyj	Forest Industry

The data in table 9 is not surprising since stocks in the telecommunication industry are highly volatile and thus suitable for day trading. Also the first two stocks in table 9 were the most liquid share series in the Helsinki Exchanges during the sample period. Although food industry typically cannot be seen among the most volatile industries, the existence of Raisio Yhtymä share on the list was expected since Raisio Yhtymä was often on news especially in 1999. At the time, the RAIVV stock was liquid and volatile, and Raisio Yhtymä's stock price was highly based on "dot-com sized" expectations of its "Benecol" product.

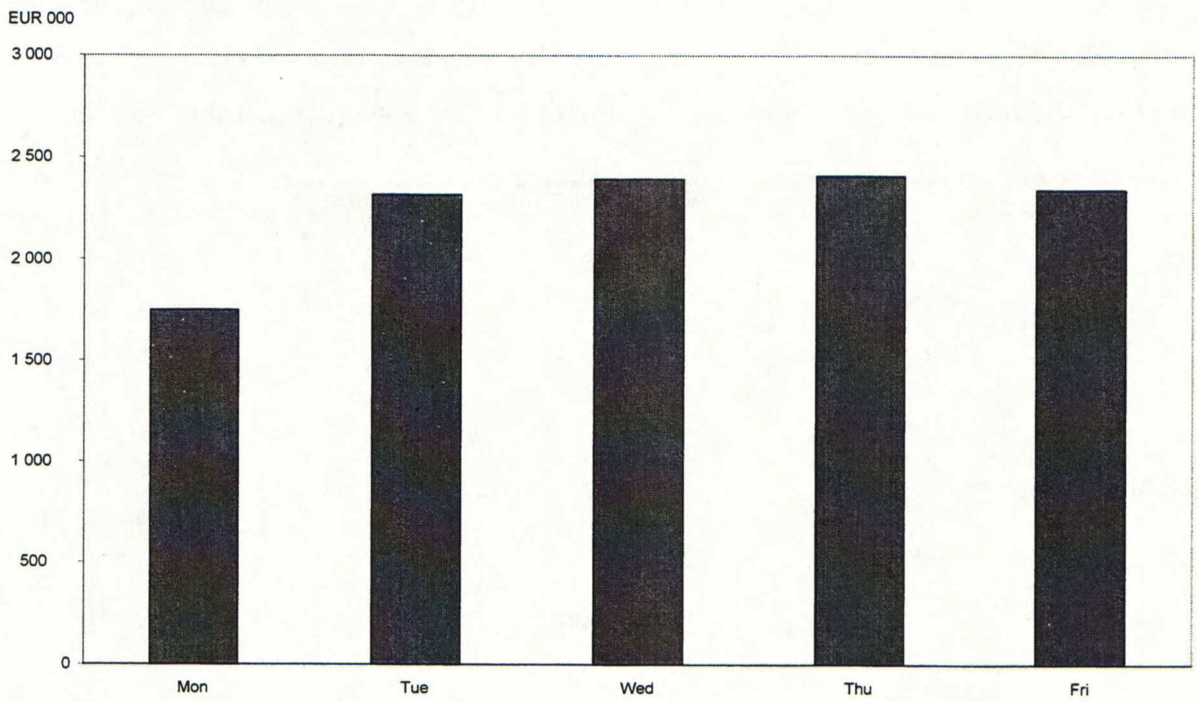
Figure 7 depicts data on the development of monthly trading volume of day traders. The trading volume increases almost every month except the sharp decline in last two months in the sample period. It should be reminded that the sample data covers only half of the last month in figure 7, so the fall appears to be too sharp in the figure. Also during summer months the trading volume seems to have a relatively small fall as expected. Again, it should be reminded that the sample size is too small and the sample period too short to make any robust deductions from the data.

Figure 7. Trading volume development of day traders month-by-month during the sample period. The figure presents the total trading volume on a monthly basis from the beginning of January 1999 to March 16, 2001. Note that the data covers only about half of the last month in the figure.



The last set of data presenting trading statistics is shown in figure 8. Figure 8 is made to gain knowledge on any possible weekday trading pattern. However, the trading volume is almost equal on all other weekdays than Monday. Trading volume of day traders was on average one third larger on other weekdays than on Mondays during the sample period.

Figure 8. Average trading volume on weekdays. The average trading volume on weekdays is calculated as the total trading volume on each weekday divided by the number of same weekday (that were trading days in the Helsinki Exchanges) during the sample period.



8.2 Volatility hypotheses

Hypothesis 1 suggests that traders take more (less) risk after prior gains (losses), i.e. they are subject to the house money effect. The problem in studying the mentioned phenomenon in intraday horizon is in finding a moment during a trading day when the traders evaluate their prior success. In this study the trading days are divided into two equally long trading periods, and it is assumed that traders evaluate their prior gains or losses at or about at the snapshot moment.

The regression that is used to test hypothesis 1 is estimated in a variety of ways. First, it is estimated with a simple pooled-OLS regression method. Table 10 presents the regression results in intraday horizon using both single stock mental accounting and portfolio mental accounting.

Table 10. Intraday risk-taking behavior study results, pooled data. Table shows results of intraday risk-taking regressions using both single stock mental accounting (i.e. a trader has separate mental account for each line of stock traded) and portfolio mental accounting (i.e. a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day). In the regression, dependent variable is abnormal afternoon volatility, and independent variables are morning return, and abnormal morning volatility.

		Single stock	Portfolio
Intercept	Estimate	-0.001	-0.001
	t-value	-0.733	-0.627
Morning return	Estimate	-0.481	-0.408
	t-value	-13.441 **	-11.187 **
Abnormal morning volatility	Estimate	0.437	0.459
	t-value	58.795 **	52.954 **
	N	16767	12841
	F-value	1817.687 **	1484.903 **
	Adjusted R^2	0.178	0.188

** significant at 1% level

The results in table 10 clearly show that day traders on average are not subject to the house money effect in intraday horizon. Contrary, loss aversive behavior is strongly supported. The results are of high statistic significance regardless of mental accounting methodology used. The similarity of results with different mental accounting methods was expected because in most of the days the day traders trade with only one line of stock. The results are slightly stronger with single stock mental accounting but the difference is likely due to the larger number of observations.

The controlling variable, abnormal morning volatility, is also of high statistic significance in both single stock mental accounting and portfolio mental accounting case. This indicates that traders who assume significant morning risk tend to continue to do so in the afternoon. The finding was expected since the snapshot moment is not a natural "break point" and thus the traders have perhaps not treated it as an end of one gamble.

The contrived snapshot moment results in also another problem concerning the prevailing inventory a trader is likely to have at the beginning of the afternoon trading period. While in interday trading horizon the day traders are assumed to have a flat position at the beginning, it cannot be assumed in intraday horizon because a position taken in the morning is most probably not realized before the snapshot moment resulting in a nonzero starting position in the afternoon, which means that there is unintended risk-taking in the afternoon trading period. Kempas (2002) report that traders are subject to disposition effect in intraday trading horizon, which supports the assumption of traders not having a flat position in any single moment of the day before closing time, especially when the value of their position is in the red. However, Coval and Shumway (2001) study the influence of afternoon starting positions on the risk-taking after prior gains or losses, and document that traders are loss aversive even without the starting inventory at the beginning of the afternoon trading period.

The results are in line with previous studies [Locke and Mann (2001), Coval and Shumway (2001)] that document a strong risk-taking behavior in accordance with loss aversion among professional futures traders. Individual traders and professional traders seem to have similar risk-taking behavior after prior gains or losses in intraday trading horizon. However, some differences arise when the analysis is extended to interday horizon. Table 11 presents the results estimated with a simple pooled-OLS regression method in several interday horizons.

Table 11. Interday risk-taking behavior study results, pooled data. Table shows results of interday risk-taking regressions. In the regressions, dependent variable is the daily abnormal volatility of minute-to-minute returns, and independent variable is prior K day return, K = 1, 2, 3, 4, 5, 10, and 20.

	K =	1	2	3	4	5	10	20
Intercept	Estimate	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	t-value	-0.275	-0.208	-0.143	-0.130	-0.080	0.213	0.487
Prior K day return	Estimate	-0.147	-0.030	0.009	0.011	0.022	0.053	0.048
	t-value	-1.635	-0.463	0.163	0.237	0.530	1.816	2.427 *
	N	12842	12690	12538	12386	12234	11474	9954
	F-value	2.673	0.214	0.027	0.056	0.281	3.299	5.892 *
	Adjusted R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

* significant at 5% level

The results in table 11 provide valuable information about risk-taking behavior after prior gains or losses. The loss aversive risk-taking behavior diminishes in the intraday horizon analysis. There is still some evidence on loss aversion in first two days but the behavior according to the house money effect seems to continuously increase with time, and in ten and twenty day horizons the house money effect is already dominating the loss aversive behavior. Unfortunately the results in table 11 are lacking statistical significance except in twenty-day horizon, which shows statistical significance at two percent confidence level.

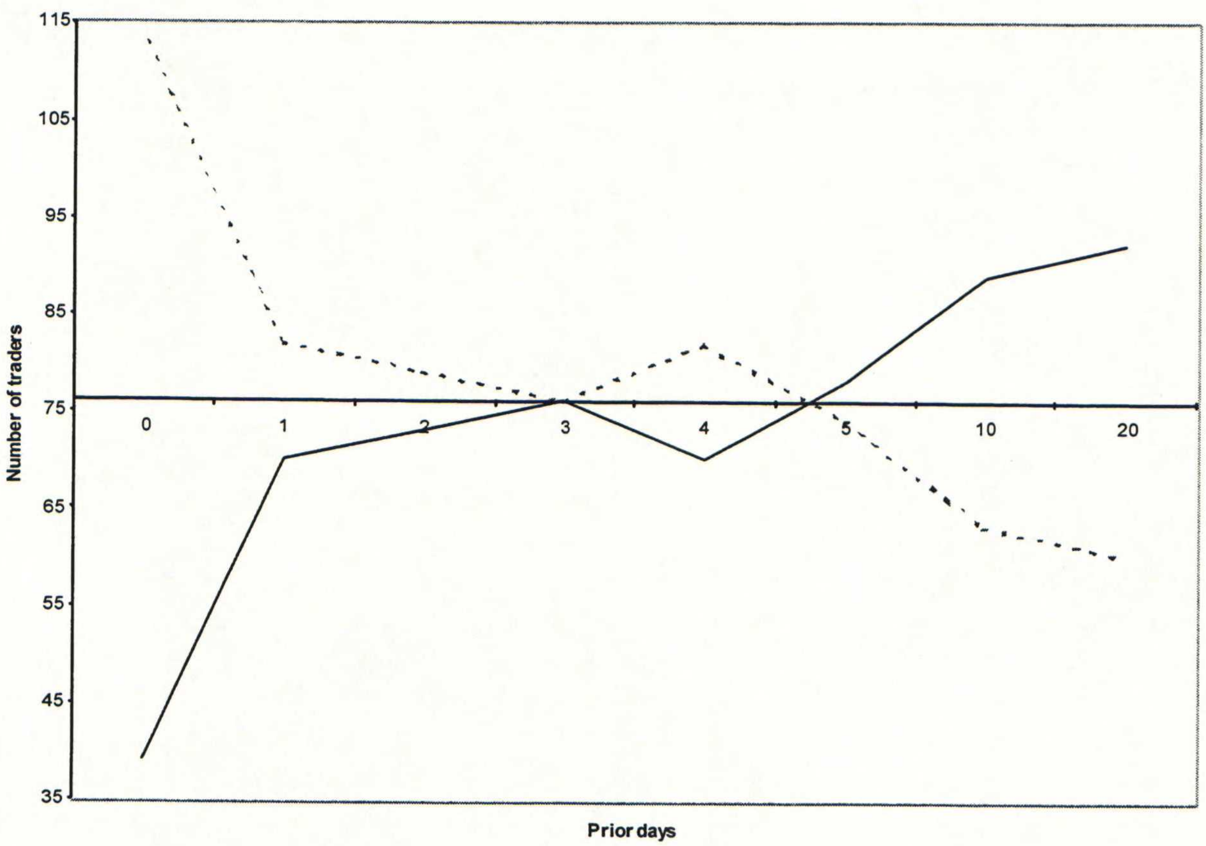
The earlier evidence of interday risk-taking behavior after prior gains or losses is mixed. Coval and Shumway (2001) report that no detectable relationship exists between profit and risk across trading days. Their interday analysis is limited to one day horizon only, and is thus in line of the results in table 11. More interesting results of professional futures traders' interday risk-taking behavior is reported by Locke and Mann (2001), who use one to five day long trading horizons in prior outcome determination in their interday analysis. They find that professional traders on average show statistically significant loss aversive behavior in all the interday trading horizons studied. From theoretical perspective that means that professional traders seem to treat sequential trading days as one long gamble instead of several gambles as implicitly expected. The results in table 11 suggest that individual traders do in fact behave more according to two-stage prospect theory than professional traders do although almost all the results are statistically insignificant.

One explanation to the different behavior between individual and professional traders can be derived from the findings of Camerer et al. (1997), who study New York City taxi drivers. Daily income to the drivers is the fares they collect minus a fixed car rental fee. Camerer et al. find that taxi drivers typically set a daily income target and quit working after they have achieved the target. Same kind of way to think can explain the observed risk-taking behavior of professional traders. It must be taken into account that while taxi drivers set their daily income target, traders probably set their income target in longer horizon since there is more uncertainty involved in trading than in the demand of taxi drives. So, as their living depends on their trading success, professional traders are likely to behave in a more disciplined manner than individual traders. They probably have specific, let' say, yearly budget that they continuously evaluate during a year. That is, they treat one year as one gamble, and their risk-taking behavior is in accordance with the prospect theory.

Also individual traders can make "budgets". But since trading is not necessarily their main source of income, they are not so committed to their budgets as professional traders. Individuals are more subject to behavioral biases ("greed and fear") and will easier change their investment strategy after prior gains or losses than professionals. So, individuals are likely to have weekly or monthly budgeting periods compared to yearly budgeting of professionals. This would explain the different risk-taking behavior observed between individual traders and professional traders in interday trading horizons.

The problem in pooled data is that it treats all traders like one representative agent thus bypassing heterogeneity of individual investors. To make a distinction between individual traders, simple trader-by-trader OLS regressions are estimated. Figure 9 presents the results.

Figure 9. Risk-taking behavior results, individual trader data. The figure plots the number of traders behaving according to the house money effect (solid line), and loss aversive traders (dashed line) with different horizons of prior success. Zero prior day shows the number of traders in intraday horizon with portfolio mental accounting (i.e. a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day).



The results of intraday risk-taking behavior after prior gains or losses are clearly observable also in trader-by-trader OLS regressions as depicted in figure 9. Portfolio mental accounting is used in figure 9, but also with single stock mental accounting the results are practically the same. However, figure 9 reveals that about one fourth of the traders increase (decrease) their risk-taking after losses (gains) while majority of traders behave in loss aversive manner in the intraday horizon.

Interday results of trader-by-trader OLS regression are more blurred. The results are in line with the pooled data results, which state that there is no detectable relationship between prior returns and subsequent risk-taking between trading days. Nevertheless, ten and twenty day trading horizons seem to be exceptions, and the house money effect seems to dominate in those horizons also in trader-by-trader analysis. The evidence in figure 9 supports the budgeting period hypothesis that was made earlier.

Like figure 9 depicts, some traders are loss aversive and some are behaving in accordance with the house money effect in all the prior success horizons studied. Hypotheses 1.1 – 1.4 are studied in order to find out whether there are some characteristics identifying traders with either of the risk-taking behaviors. Table 12 presents the results of hypotheses 1.1 – 1.4 in intraday trading horizon using both single stock and portfolio mental accounting.

Table 12. Intraday risk-taking behavior study results, trader characteristics. Table shows results of the intraday risk-taking regressions using both single stock mental accounting (i.e. a trader has separate mental account for each line of stock traded) and portfolio mental accounting (i.e. a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day). Age is the age of a trader in the beginning of the sample period; Success is a trader's total success in the sample period; dummy variable Gender is one if the trader is a male and zero if the trader is a female; and Experience is a natural logarithm of total number of trades made by a trader in the sample period.

	Single Stock		**Portfolio**	
	Estimate	t-value	Estimate	t-value
Intercept	0.110	0.144	0.168	0.217
Age	-0.013	-1.583	-0.016	-1.878
Success	0.002	0.614	0.002	0.661
Gender	-0.021	-0.081	-0.119	-0.442
Experience	-0.001	-0.010	0.028	0.222
N	152		152	
F-value	0.785		1.021	
Adjusted R^2	0.021		0.027	

None of the studied characteristics is significantly detected to the risk-taking behavior after prior gains of losses in intraday trading horizon according to the results in table 12. Age is the only variable that seems to have at least a weak relation to the risk-taking behavior. Using both single stock mental accounting and portfolio mental accounting, the younger a trader is the more he is subject to the house money effect as hypothesis 1.1 predicts. The other three variables – success, gender, and experience – are so insignificant that no analysis of those can be made.

Table 13. Interday risk-taking behavior study results, trader characteristics. Table shows results of interday risk-taking regressions with prior K day return, K = 1, 2, 3, 4, 5, 10, and 20. Age is the age of a trader in the beginning of the sample period; Success is a trader's total success in the sample period; dummy variable Gender is one if the trader is a male and zero if the trader is a female; and Experience is a natural logarithm of total number of trades made by a trader in the sample period.

	K =	1	2	3	4	5	10	20
Intercept	Estimate	-1.872	-0.882	-1.028	-1.020	-0.851	-0.447	-0.498
	t-value	-1.103	-0.763	-0.961	-1.214	-1.024	-0.613	-0.695
Age	Estimate	0.014	0.014	0.007	0.010	0.011	0.005	0.012
	t-value	0.748	1.095	0.587	1.088	1.184	0.670	1.545
Success	Estimate	-0.001	0.002	0.002	0.004	0.004	0.003	0.001
	t-value	-0.189	0.511	0.538	1.247	1.099	0.931	0.266
Gender	Estimate	-0.799	0.057	0.070	0.044	-0.054	-0.003	-0.081
	t-value	-1.356	0.142	0.189	0.150	-0.186	-0.013	-0.325
Experience	Estimate	0.297	0.055	0.131	0.124	0.106	0.076	0.047
	t-value	1.075	0.293	0.755	0.909	0.788	0.645	0.404
	N	152	152	152	152	152	152	152
	F-value	1.147	0.477	0.393	1.088	1.040	0.519	0.905
	Adjusted R^2	0.004	-0.014	-0.016	0.002	0.001	-0.013	-0.003

Table 13 shows the results of OLS regressions used to estimate the trader characteristics in several interday trading horizons. Like in the intraday trading horizon, none of the trader characteristics studied is of statistic significance in any of the interday prior return horizons. The results can be due to small sample size but, anyway, it is interesting to notice that there are no differences in observed risk-taking behavior after prior gains or losses between day traders grouped by age, success, gender, or experience since those attributes have been detected to behavioral biases in many earlier studies, for example in Barber and Odean (2000).

8.3 Volume hypotheses

The second set of hypotheses deals with trading volume. The volume is typically used as a proxy of overconfidence but it can also be seen as a proxy of risk-taking. Thus the results of the volume study can be seen as additional evidence on the risk-taking after prior gains or losses as well as on overconfidence.

Hypothesis 2 suggests that traders increase (decrease) their trading volume after prior gains (losses), i.e. they are overconfident. Like in volatility hypotheses tests, the regressions used to test hypothesis 2 are estimated in a variety of ways. Table 14 presents the simple pooled-OLS regression results in intraday trading horizon using both single stock mental accounting and portfolio mental accounting.

Table 14. Intraday volume study results, pooled data. Table shows the results of intraday volume regressions using both single stock mental accounting (i.e. a trader has separate mental account for each line of stock traded) and portfolio mental accounting (i.e. a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day). In the regression, the dependent variable is the abnormal afternoon volume, and independent variables are the morning return and the abnormal morning volume.

		Single stock	Portfolio
Intercept	Estimate	-0.003	-0.001
	t-value	-0.365	-0.169
Morning return	Estimate	-1.655	-1.355
	t-value	-6.687 **	-5.810 **
Abnormal volume in morning	Estimate	0.548	0.582
	t-value	84.237 **	80.346 **
	N	16767	12841
	F-value	3594.288 **	3260.925 **
	Adjusted R^2	0.300	0.337

** significant at 1% level

The regression results in table 14 show that day traders are not subject to overconfidence if overconfidence is measured with the subsequent trading volume after prior gains. Contrary, day traders tend to trade less (more) after prior gains (losses), and the results are of high statistic significance despite the mental accounting method used. The results are slightly stronger when using single stock mental accounting method.

Also the controlling variable, abnormal morning volume, is of high significance in both mental accounting cases. This indicates that traders who trade much in the morning will trade much also in the afternoon. Significant positive correlation of morning and afternoon volumes was expected because if there is significant opening position in the beginning of the afternoon trading period then heavy trading is expected to result in a flat position at the end of the trading day.

The result in table 14 stating that prior gains (losses) tend to reduce (induce) subsequent trading volume is evidence that gives support to a loss aversive behavior of day traders in intraday horizon. Although the opening position in the afternoon trading period seems to be detected to the risk-taking in the afternoon (i.e. the abnormal morning volume has significant positive correlation with the abnormal afternoon volume), risk-taking in the afternoon is still higher after prior losses than after prior gains.

The results are in line with previous studies [Locke and Mann (2001), and Coval and Shumway (2001)] that report decrease in the afternoon trading volume after morning gains among professional futures traders. So, in addition to similar risk-taking behavior after prior gains or losses between individual and professional traders, indication of overconfidence is also similar between the investor groups. It is worth noting that Barber and Odean (2000), among others, report overconfidence of individual investors but their sample group is much broader than in this study, or in other intraday studies. Thus, all day traders can be highly overconfident compared to investors trading less frequently but among day traders there is no sign of additional overconfidence after prior gains in intraday trading horizon.

The results of both volatility and volume regressions in intraday horizon are strongly supporting the fact that loss aversion dominates the house money effect. The results are not surprising because the contrived snapshot moment is not a natural moment to evaluate the prior success, which implies that a one-stage prospect theory should prevail. In addition, Kempas (2002) document significant evidence of loss aversive behavior among day traders from a different viewpoint. Namely, he study disposition effect and report that the day traders are realizing winning position quicker than loosing positions. However, after day(s) of prior success period it is likely that the two-stage prospect theory, and thus the house money effect, should be present. The results of longer trading horizons are presented in table 15.

Table 15. Interday volume study results, pooled data. Table shows the results of interday volume regressions. In the regressions, dependent variable is the daily abnormal volume, and independent variable is the prior K day return, K = 1, 2, 3, 4, 5, 10, and 20. The other controlling variable – the market change – is the absolute change in HEX All-share index on day T-1.

	K =	1	2	3	4	5	10	20
Intercept	Estimate	-0.018	-0.019	-0.021	-0.022	-0.022	-0.024	-0.024
	t-value	-1.529	-1.640	-1.762	-1.846	-1.868	-1.991 *	-2.044 *
Prior K day return	Estimate	-1.974	-1.684	-1.641	-1.487	-1.278	-0.881	-0.494
	t-value	-3.046 **	-3.644 **	-4.293 **	-4.449 **	-4.291 **	-4.219 **	-3.505 **
Market change	Estimate	0.827	0.833	0.846	0.854	0.846	0.841	0.849
	t-value	2.411 *	2.429 *	2.466 *	2.491 *	2.467 *	2.453 *	2.475 *
	N	12842	12690	12538	12386	12234	11474	9954
	F-value	7.542 **	9.544 **	12.123 **	12.802 **	12.111 **	11.807 **	9.047 **
	Adjusted R^2	0.001	0.001	0.002	0.002	0.002	0.002	0.001

* significant at 5% level
** significant at 1% level

The loss aversive and non-overconfident trader behavior observed in intraday horizon keeps up also in interday trading horizons according to the results in table 15. The results are of high statistic significance in all the studied interday horizons. The figures indicate that after day(s) of prior gains the subsequent trading volume decreases, and vice versa. So contrary to hypothesis 2, a representative day trader is not overconfident when the subsequent trading volume is used as a proxy of trader overconfidence.

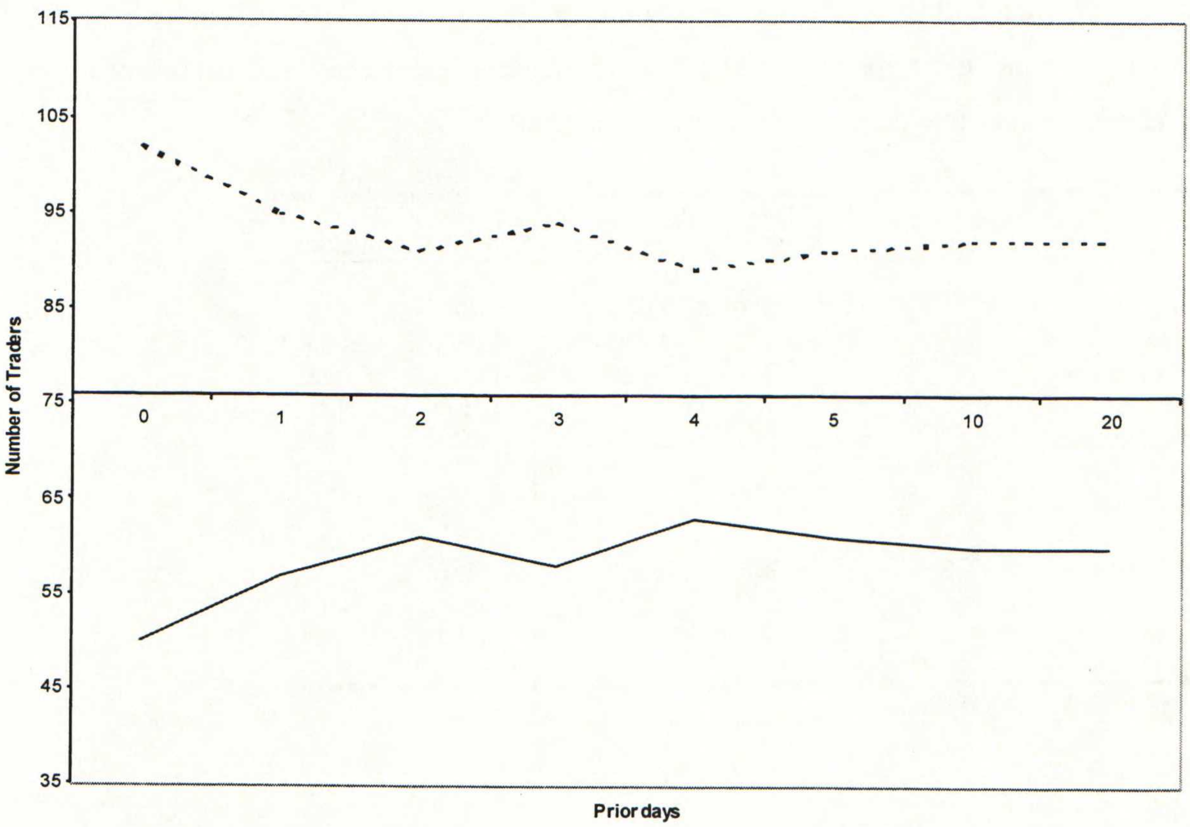
The controlling variable, the market change in T-1, seems to be one reason for the increased trading volume. Although the weight-limited HEX Portfolio index is used as a benchmark in most of the studies in Finnish stock market, the unrestricted HEX All-share index (price index) is used in this study because it reflects better the investments of day traders. The market change is measured with the absolute value so the results indicate that a large change – no matter whether increase or decrease – makes the investors to trade more. It would be interesting to know if the result is due to belief in mean reversion but that is beyond the scope of this study.

If trading volume is used as a proxy of risk-taking, traders are behaving in a loss aversive manner in all the studied interday horizons. Risk-taking behavior according to the results in table 15 conflicts with the volatility study results of ten and twenty day prior success horizons. That is, risk-taking results of the individual day traders seem to depend on the proxy used: volatility study results give support to the house money effect, and volume study results are supporting a loss aversive behavior.

Expected utility theory and two-stage prospect theory propose that both risk-taking and trading volume should increase after prior gains. One explanation for the observed behavior, i.e. increased risk-taking and decreased trading volume, can be in mental accounting. After large gains, a trader can make a big acquisition from other mental account, let's say a trader buys a car, and moves more than the winnings to the other mental account to fund the acquisition. So, the sum of money on the trader's day trading mental account actually decreases despite of the prior winnings. As a consequence trading volume decreases but the reduction in the sum on day trading mental account does not have similar impact on risk-taking behavior.

Another explanation can be in loss aversion. Kahneman and Tversky (1979) document that people's hate of losses is about fifty per cent larger than their love of gains. If loss aversion is a very dominant bias the traders can treat sequential trading days as one gamble because they have not made peace with their losses and try to get even. So, they increase their trading volume to gain more on small stock price movements. After days of losses, day trader can alter his risk-taking behavior by investing in less volatile and safer investments with high trading volume to get even and at the same time avoid loosing more.

Figure 10. Volume study results, individual trader data. The figure plots the number of traders decreasing (increasing) their trading volume after prior gains (losses) (solid line), and the number of traders increasing (decreasing) their trading volume after prior gains (losses) (dashed line) with different horizons of prior success. Zero prior day shows the number of traders in intraday trading horizon with portfolio mental accounting (i.e. a trader has only one “day trading” mental account which consists of all the lines of stocks traded on one trading day).



Solid line (dashed line) in Figure 10 depicts the number of traders increasing (decreasing) their trading volume after prior gains. The difference remains clear over all the studied prior gain or loss periods stating that most of traders trade less after prior gains. So, the results of pooled-OLS regression are applicable also in individual trader level.

However, about one third of the traders are behaving overconfidently in all the studied prior gain horizons. Hypotheses 2.1 – 2.4 are studied to find out what kind of traders are subject to overconfidence. Table 16 presents the results of hypotheses 2.1 – 2.4 in intraday trading horizon using both single stock mental accounting and portfolio mental accounting.

Table 16. Intraday volume study results, trader characteristics. Table shows the results of intraday volume regressions using both single stock mental accounting (i.e. a trader has separate mental account for each line of stock traded) and portfolio mental accounting (i.e. a trader has only one "day trading" mental account which consists of all the lines of stocks traded on one trading day). Age is the age of a trader in the beginning of the sample period; Success is trader's total success in the sample period; dummy variable Gender is one if the trader is a male and zero if the trader is a female; and Experience is a natural logarithm of total number of trades made by a trader in the sample period.

	Single Stock		**Portfolio**	
	Estimate	t-value	Estimate	t-value
Intercept	5.492	1.686	4.434	1.346
Age	-0.062	-1.736	-0.075	-2.064 *
Success	-0.011	-0.836	-0.004	-0.315
Gender	-0.123	-0.109	-0.157	-0.137
Experience	-0.781	-1.473	-0.483	-0.902
N	152		152	
F-value	2.023		1.750	
Adjusted R^2	0.026		0.019	

* significant at 5% level

Results in Table 16 are close to the intraday volatility regression results presented in Table 12. However, results in Table 16 show that the negative correlation between trader's age and subsequent trading volume using portfolio mental accounting is statistically significant at five percent level whereas the significance was slightly lower in the volatility regressions. The other variables – success, gender, and experience – are practically irrelevant measures of the subsequent trading volume after prior gains or losses.

The negative estimate value of the trader age coefficient supports hypothesis 2.4. In line with the result, Barber and Odean (2001a), and Barber and Odean (2002), among others, document that younger investors are more prone to overconfidently increase their trading volume after prior gains than older people. To see whether the result is robust over different prior gain periods, Table 17 presents the OLS regression results of individual day traders to find out the results in interday trading horizons.

Table 17. Interday volume study results, trader characteristics. Table shows the results of interday volume regressions with prior K day return, K = 1, 2, 3, 4, 5, 10, and 20. Age is the age of a trader in the beginning of the sample period; Success is a trader's total success in the sample period; dummy variable Gender is one if the trader is a male and zero if the trader is a female; and Experience is a natural logarithm of total number of trades made by a trader in the sample period.

	K =	1	2	3	4	5	10	20
Intercept	Estimate	6.419	7.611	-2.580	-6.006	-3.294	3.779	0.020
	t-value	0.442	0.666	-0.312	-0.696	-0.445	0.661	0.004
Age	Estimate	-0.282	-0.265	-0.138	-0.224	-0.216	-0.166	-0.149
	t-value	-1.758	-2.100 *	-1.510	-2.349 *	-2.648 **	-2.626 **	-2.489 *
Success	Estimate	0.059	0.046	0.052	0.039	0.035	0.040	0.029
	t-value	1.039	1.021	1.609	1.163	1.209	1.758	1.358
Gender	Estimate	-7.443	-5.994	0.144	-1.416	-1.399	-2.253	-1.900
	t-value	-1.477	-1.512	0.050	-0.473	-0.545	-1.136	-1.009
Experience	Estimate	1.551	1.053	0.950	2.202	1.754	0.625	1.061
	t-value	0.657	0.566	0.705	1.568	1.458	0.672	1.202
	N	152	152	152	152	152	152	152
	F-value	1.411	1.722	1.180	1.828	2.146	2.591 *	2.091
	Adjusted R^2	0.011	0.019	0.005	0.021	0.029	0.040	0.028

* significant at 5% level
** significant at 1% level

Finally, table 17 shows the results of OLS regressions used to estimate the trader characteristics in interday trading horizons. Trader age is statistically significant in longer trading horizons indicating that the younger traders trade more after prior gains. The result is in line with hypothesis 2.2, which suggests that young traders are more subject to overconfidence than their older colleagues.

9 CONCLUSIONS

The study concerns the risk-taking behavior and overconfidence after prior outcomes among active individual non-professional day traders. The empirical test results of risk-taking after prior gains or losses are in line with earlier evidence in intraday horizon. That is, the day traders show a significant loss aversion in the afternoon after controlling for morning outcome that has been documented also among professional traders by Locke and Mann (2001), and Coval and Shumway (2001). After morning gains the traders secure their winnings by taking less risk, and after morning losses they try to get even by increasing their risk-taking. Of the trader characteristics tested – success, experience, gender, and age – only age is detected to the changed risk-taking behavior. As expected, older traders are more loss averse than younger traders are.

One interesting finding of the study is that the results of individual traders' risk-taking tests differ from the results obtained in empirical tests among professional traders in interday horizons. Whereas professional traders show loss aversion also in interday horizons, the loss aversive behavior of individual day traders found in intraday horizon diminishes, and when the prior outcome period is extended to one month the house money effect seems to dominate loss aversion.

The empirical test results of trading volume and overconfidence show that individual and professional traders behave in similar way. The robust results over all studied prior outcome periods show that prior gains do not make individual day traders to trade more as overconfidence hypothesis suggests. On the contrary, prior losses have an inducing effect on subsequent trading volume. Coval and Shumway (2001) report similar behavior among professional traders. Like in the empirical risk-taking tests, the only trader attribute that is found to have influence on overconfident behavior is trader's age, which is negatively correlated to a trader confidence level as expected.

Two mental accounting methods are used in the empirical tests. In the tests, day traders can have one "day trading" mental account, or they can have separate mental accounts for individual stocks they trade. The results in all empirical tests are practically equal no matter which mental accounting method is used. Unfortunately the data is not suitable for testing different mental account methods because day traders typically trade with only one line of stock in same trading day.

This is one of the first studies with individual day trader data. Day trading has been claimed for creating noise and excessive trading volume in the stock market. Hopefully data sets like the one used in this study will become more available for finance research in the future. It would be interesting to see studies on the influence of day trading on the stock prices. Also different mental accounting methods can be studied to gain knowledge on the effect those have on a trading behavior of stock market participants.

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