STOCKHOLM SCHOOL OF ECONOMICS

Department of Finance

Efficiency of Stop-Loss Rules

- An Empirical Study of the Swedish Stock Market -

Robin Erdestam*

Major in Finance

Stockholm School of Economics

Olof Stangenberg**

Major in Finance

Stockholm School of Economics

ABSTRACT

Stop-loss rules, or predetermined policies for realizing losses based on past performance, are commonly used in the financial industry. Given the prevalence of these orders, we examine the efficiency of such stop-loss rules by measuring their marginal impact on expected return and risk, proxied by volatility, in comparison with the classic "buy-and-hold" portfolio strategy. Although stop-loss rules have been examined previously in the finance literature, this study provides a thorough analysis based on a novel data set of the complete trading records for all stocks in the OMX Stockholm 30 Index for the period January 2nd, 2006 to July 21st, 2008. Using this data set, we find strong evidence that stop-loss rules have a negative marginal impact on the expected return of a "buy-and-hold" portfolio strategy. This evidence is, furthermore, supported by our findings of short term reversals in stock returns. Moreover, although stop-loss rules seem to reduce the volatility when introduced on a "buy-and-hold" portfolio strategy, this reduction does not seem to compensate for the negative marginal impact on expected returns. As a result, we can conclude that stop-loss rules are inefficient even when we consider these policies' marginal impact on portfolio risk.

Keywords: Stop-loss, Performance Evaluation, Trading Rules, High Frequency.

Tutor: Kathryn Kaminski, Visiting Assistant Professor
Date & Time: October 14, 2008 at 10:15 A.M.
Location: Room R
Discussants: Johan Ring (21418)

* 20426@student.hhs.se
** 20659@student.hhs.se

Acknowledgements

We would first of all like to thank our tutor, Kathryn Kaminski, for her valuable input and guidance during the processes of conducting this study and writing the thesis.

– Thank you for all the effort you have put into this project.

Secondly, we would like to thank OMX and particularly OMX Market Research and Fredrik Jomar for all the help with the transaction data. Without your generous contribution this study would have been impossible to conduct.

Finally, we would like to thank our friends and families for your helpful support in times of need.

Contents

1. Introduction

There is currently a crisis that is gripping global finance. Stock prices have plummeted during the last year. How can investors protect themselves against these types of risks? A common alternative is to use stop-loss orders to limit the losses. Strategies based on stop-loss orders, which are also known as stop-loss rules, are predetermined policies with the purpose to reduce a portfolios risk exposure. The opinions regarding the usefulness of stop-loss orders or rules, of course, differ between different traders and investors. Based on high usage of stop-loss orders, some obviously finds them value adding. Others are more skeptical. When consulting the various information sites available for investors, there seems to be some very tempting and quite persuasive anecdotal evidence in support of stop-loss orders. For example, the following two quotes can be found at About Stocks and Market watch.

"A stop-loss order can minimize your downside and also secure the upside. They act as a safety net and it ensures your long-term success by preventing big hits to your account" or *"Stop loss orders are great insurance policies that cost you nothing and can save a fortune."*

Statements like these could easily seduce many investors into the belief that stop-loss orders and rules are the obvious solution for sleepless nights. However, if we attempt to dig a little deeper, it is clear that these conclusions about stop-loss orders are way too simplistic. This simplification fails to take into account the complex nature of dynamic trading strategies. Even if stop-loss orders may provide some of the benefits for downside protection, there are still numerous drawbacks and risks that should be considered before entering into a policy on based stop-loss orders.

It has, however, been more or less impossible for a trader or an investor to do a structured estimation of the benefits, drawbacks and risks of stop-loss rules. Most probably due to the fact that the historically widely accepted *Random Walk Hypothesis*, which is considered to be synonymous with market efficiency and investor rationality, sees little use of stop-loss rules or active trading. This view may explain the rather limited academic literature on trading rules such as stop-loss. Nevertheless, theoretical rationales for using stop-loss rules can be identified if the assumptions regarding random walk of stock returns and rational human behavior are relaxed.

To date, there is only one systematic examination of stop-loss rules' marginal impact on an existing portfolio strategy.[1] The empirical part of this study examines the profitability of stop-loss rules in the long run. Using US monthly returns from January 1950 to December 2004, they find considerable gains in expected returns from using stop-loss rules. The empirical results of Kaminski and Lo (2007), although interesting, give little guidance for the trader who plan to use stop-loss rules to stop losses that occur over a week, a day or a shorter time period – a situation that is more current in today's financial markets. Strategies based on monthly data provide no possible understanding of whether stop-loss orders could provide protection against these types of short term losses.

Given the limited academic literature, the gained interest from practitioners in the financial industry and the many different academic philosophies on market predictability, it is clear that there is a definite value in understanding the efficiency of stop-loss applied in the short term. As a result, we examine the efficiency of stop-loss rules in the short run using a method which is more consistent with-how investors actually use stop-loss rules. We are able to do this by using a novel data set, which contains the complete trading records for all the stocks included in the OMX Stockholm 30 Index for the period January 2nd, 2006 to July 21st, 2008.

We examine the marginal impact that stop-loss rules have on a "buy-and-hold" portfolio strategy. More precisely, we address the question of what marginal impact in expected return stop-loss rules have on a "buy-and-hold" portfolio strategy. In addition, we address the questions of what marginal impact in risk, proxied by volatility, and risk-adjusted return, proxied by the Sharpe ratio, stop-loss rules have on a "buy-and-hold" portfolio strategy. Consequently, the return, risk and Sharpe Ratio of a "buy-and-hold" portfolio strategy are simply compared to the return, risk and Sharpe ratio of a "buy-and-hold" strategy with an overlying stop-loss rule. We are aware that the use of expected return, volatility and the Sharpe ratio are limited in its ability to fully explain the impact of a dynamic strategy. However, we argue that it will provide a good first step into understanding efficiency of stop-loss rules.

The systematic examination of the efficiency of stop-loss rules based on high frequency transaction data makes this thesis the first of its kind. The thesis will, therefore, further enhance the limited literature on stop-loss rules and these policies' marginal impact on a portfolio's return and risk-adjusted return. Furthermore, this thesis will, from a practitioner's point view, provide an interesting empirical study; partially due to the transaction data analysis and partially due to the structured examination of the efficiency of stop-loss rules.

[1] See Kaminski and Lo (2007)

In a pre-study to the main examination, we firstly find a strong mean-reverting behavior of stock returns on short time increments. Applying the theoretical framework, presented by Kaminski and Lo (2007), this suggests that stop-loss rules are inefficient and have a negative marginal impact in expected return on a "buy-and-hold" portfolio strategy. Indeed, we then find that the marginal impact of stop-loss rules in the expected return on a "buy-and-hold" portfolio strategy is significantly negative. We also find strong evidence that the stop-loss rules lower the risk of the portfolios. However, the reduction in volatility does not fully compensate for the loss in expected returns, and the marginal impact in risk-adjusted return are, consequently, also significantly negative.

We can conclude that stop-loss rules do not seem to provide the type of downside protection that is advertised to investors – meaning that these kinds of policies may be more harmful than helpful. We can thus also conclude that reducing a portfolios risk exposure and limiting the downside may not be accomplished by just adding a simple trading policy, such as a stop-loss rule, to an investor's portfolio. Instead, investors should rely on risk analysis using, for example, value at risk estimation, hedging or just common sense.

The outline of this thesis is structured as follows: In chapter two, we outline some basics regarding trading and stop-loss orders, a summary of the findings in previous research on stop-loss rules, a framework for evaluating the efficiency of stop-loss rules and a discussion of stop-loss efficiency in a behavioral perspective. In section three, we lay out the foundation for our empirical analysis including hypothesis development, a detailed description of the data, and a summary of the relevant models and testing procedures. In chapter four, we present a pre-analysis of the data which complements our discussion in the literature review. In chapter five, we discuss our empirical analysis of stop-loss including both statistical analysis and a review of our empirical findings. In chapter six we finally summarize the empirical findings, present our conclusions and suggest areas for further research.

2. Literature Review

In the following chapter we aim to provide a brief review of the results from previous academic studies on stop-loss rules. We extend and apply the theoretical framework applied by Kaminski and Lo (2007), which the efficiency of stop-loss rules can be evaluated under. In addition, we discuss empirical aspects and risk in the context of the theoretical framework. Finally, we aim to broaden the perspective of efficiency, especially efficiency of stop-loss rules, in a discussion around irrational human behavior. However, to ensure a minimum level of knowledge regarding trading and stop-loss rules, we firstly provide a brief introduction to the fundamentals of trading orders.

The chapter is structured as follows: In section 2.1, we outline some fundamental knowledge of trading orders. In section 2.2, we summarize previous findings on stop-loss rules. In section 2.3, we provide the theoretical framework for measuring efficiency of stop-loss rules, first outlined by Kaminski and Lo (2007), which links the efficiency of stop-loss rules to the stochastic processes driving the underlying portfolio[2]. Furthermore, we present some empirical results and consider stop-loss rules' marginal impact on risk. In section 2.4, we discuss the relation between market efficiency and efficiency of stop-loss rules. In section 2.5 we lastly briefly present an alternative approach to look at the efficiency of stop-loss rules by putting stop-loss rules in the context of behavioral finance and give possible motivations for using stop-loss rules outside the perspective of measurable efficiency.

2.1 Fundamentals of Trading Orders

To give a better understanding of the topic a brief overview is provided, which include relevant aspects of trading orders. The discussion below mainly follows the discussion presented in Harris (2003). If the reader already possesses the basic knowledge of trading orders it is suggested to continue to section 2.2.

Trading orders are the fundamental building blocks of trading strategies. To trade effectively, a trader must specify exactly what he wants. The proper order used at the right time can make the difference between a good trade, a costly trade and no trade at all. Traders indicate that they are willing to buy or sell by making a bid or an ask. Bids and asks usually include information about the prices and quantities that traders will accept. The highest bid price in a market is the best bid and the lowest ask price is the best ask. The difference between the best bid and the best ask is called the spread. If the best ask – the lowest price someone is ready to sell for – and the best bid

[2] The stochastic processes driving the underlying portfolio are later-on referred to as underlying process.

– the highest price someone is ready to buy for – meets, the spread become zero and a trade takes place.

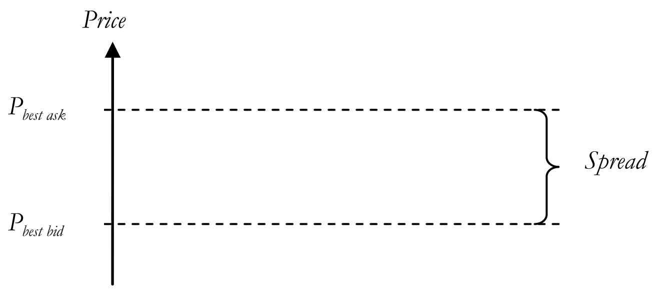

Figure 1.1 – Illustration of best ask, best bid and spread.

The bids and asks are put into the market by trading orders. However, different types of trading orders exist, why a distinction between these must be made. A *market order* is an instruction to trade at the best bid or ask price, depending on if it is a buy or a sell order. This means that a buying trader accept what the best selling trader offers. Consequently, the market order will always go through, but may also pay a penalty – a so called liquidity price - for the opportunity to always be able to trade.

> *<u>Example – liquidity price:</u> An asset has a best bid of 100 and a best ask of 102. If a trader uses a market order to buy the asset he/she has to pay 102. If the trader then chooses to immediately sell the asset by a market order he/she gets 100, assuming that the bid or ask do not change. The trader looses 2 by engaging himself/herself in these trades. This is the price or penalty a trader has to pay for being able to trade immediately.*

Another risk with market orders is the automatic acceptance of the current market conditions. Since the market conditions can change quickly, traders who use market orders to trade risk trading at worse prices than they expect. This is called risk execution price uncertainty.

> *<u>Example – execution price uncertainty:</u> A trader wants to sell his asset for a price of 100, which is the best bid of the asset is right now. The investor places a market order to sell his asset directly. However, the market conditions are at this point unstable, why many other traders also want to sell now, and before the trader's order goes through, the best bid declines to the price of 97. The trader consequently sells to a cheaper price than he/she expected when he/she initially observed the market conditions.*

A final main risk with market orders is the market impact due to the volume traded. If a trader wants to trade a significant amount of stocks with a market order, the market price probably is going to shift; upwards if the investor is buying and downwards when he is selling. The trader then must accept a higher price than the current market price if he is buying, and vice versa if he is selling. The risk of market impact increases with the volume a trader wants to trade, and decreases with the liquidity of stock the trader wants to trade in.

> *Example – market impact:* *If a trader decides to sell 10000 shares and the best bid is 100, but only for 5000 shares. That next best bid is 90 for 5000 shares. The market order will then fill at an average price of 95 and the trader must accept a lower price than the current market price.*

The next type of trading order is a *limit order*, an instruction to trade at the best price available, but only if it is no worse than the limit price specified by the trader. Standing limit orders are placed in a so called a limit order book, or just "order book". The order book contains all the existing asks and bids at a specific point in time. When a *market order* is placed the limit order book is reduced, since a trade automatically is made. When a *limit order* is placed, a trade only occurs, and the order book reduced, if it is placed outside the spread and matches another trading order.

The risks associated with limit orders are execution uncertainty – the uncertainty that the order fails to trade – and ex post regret. Ex post regret occurs when the market moves against the limit order and the asset is sold/bought to an under/over price.

> *Example – ex post regret:* *A trader has placed a limit order to sell an asset to a price of 100. The best bid is currently at 98. The trader feels comfortable to sell at this price, which he/she and probably the market think is a fair market price. Some information about the asset is released and the price which the market thinks is fair suddenly rises heavily to 110. The trader, however, fails to withdraw his limit order and sells at 100. The trader, consequently, sold to an underprice and now regret his trade.*

The final type of trading order presented here is *stop orders*, which stops an order from executing until the price reaches a stop price specified by the trader. Traders attach stop instructions to their orders; buy after a recent rise or sell after a recent fall. It is most common that the stop order is attached to a market order, i.e. the stop order becomes a market order when the price reaches the stop price. A stop order can also be attached to a limit order, but this combination is more unusual.

Traders most commonly use stop orders to stop their losses (stop-loss order) when prices move against their positions. The other type of stop order is used to protect a gain. These types of stop orders are called take-profit orders. Even if they are used in trading strategies, stop-loss orders are more commonly used.

Of course, drawbacks of using stop-loss orders and take-profit orders attached to market orders also exist. Stop-loss orders and take-profit orders attached to market orders share all disadvantages with market orders, i.e. liquidity price, execution price uncertainty and market impact. For stop-loss orders the most important drawback is the execution price uncertainty. In fact, this problem is more severe for stop-loss orders than for take-profit orders and regular market orders due to two main reasons. Firstly, stop-loss orders are only executed when prices are falling, while take-profit orders are executed when priced are rising. Secondly, a stop-loss order add positive feedback or momentum to the falling prices since a selling market order will take away the best bid on the market and thereby lower the prices, whereas take-profit adds a negative feedback i.e. the prices are stabilized. On top of that stop-loss orders seem to be clustered at certain even price levels, which causes price cascades (Osler, 2002)[3]. This results in that there might be a considerable difference between the stop price and the price that the order trades at. Consequently, even if stop-loss rules guarantee limitation to large losses, the losses may still be significantly larger than expected in extreme situations.

A final risk for traders who use stop-loss orders, which is not to the same extent is applicable for traders who use take-profit orders, is manipulation of the market. This is called gunning the market, which is mainly applicable in illiquid markets. In this case market manipulators gun the market by selling or short-selling a certain security to push down prices and activate the stop-loss orders. When the stop-loss orders, as mentioned above, are clustered around even price levels this further accelerate those price changes. The manipulators then buy the cheap assets on a broad front and profit when the prices soon rise again. The investors using stop-loss orders become the losers and the manipulators the winners, since the assets are sold below the "true" market price.

2.2 Findings Regarding Stop-Loss Rules in Previous Studies

As mentioned in the introduction stop-loss rules are widely used today, yet they have been given little attention in the historical academic finance literature; literature which primarily contains studies about limit orders and optimal order selection algorithms. As also discussed in the introduction, the historically widely accepted *Random Walk Hypothesis*, which is considered to be synonymous with market efficiency and investor rationality, can probably explain the lack of interest for stop-loss rules in the academic literature due to the fact that the *Random Walk Hypothesis* sees little use of stop-loss rules or active trading.[4] This does not mean, however, that

[3] Price cascades are fast and large movements of prices, here created by stop-loss rules triggered waves around certain price-levels.

[4] For a more comprehensive presentation of the Random Walk Hypothesis, we refer to section 2.4.

the academic field regarding stop-loss rules is totally unexplored. The main academic findings regarding stop-loss rules are below briefly presented. The findings are presented in a chronological order.

Shefrin and Statman (1985) develop a framework and label investors' general disposition to sell winners too early and hold losers too long. Stop-loss orders mitigate this disposition effect by allowing the investor to automatically make a loss realization at a predetermined point. Stop-loss rules' mitigating influence on the disposition effect might explain the popular use of such stop-loss orders.

Tschoegl (1988) take a closer look at the popularity of stop-loss orders and conjectures that the popularity can be derived from a behavioral pattern. The usage of stop-loss orders provide a way for the investors to react to shifts in the market, even if they do not know why the shift has occurred. Hence, stop-loss orders provide control limits procedures that shift the monitoring function to the brokers, which lower the monitoring costs.

Carr and Jarrow (1990) investigate a particular trading strategy, the so called *Stop-loss Start Gain strategy*, which includes stop-loss orders. The authors find that under a *geometric Brownian motion*, which according to Hull (2005) can be included in a random walk process, this decomposition of stop-loss strategy is equivalent to the famous Black-Scholes options pricing model. The terminal payoff of the investigated stop-loss rule is, thus, identical to that of a call-option.

Osler (2002) examines stop-loss orders and take-profit orders on the currency market. Based on the complete order book of the Royal Bank of Scotland, Osler concludes that exchange rate trends are unusually rapid at certain exchange rate levels, where stop-loss orders are shown to cluster. Furthermore, Osler finds that the response to stop-loss orders is larger and last longer than the response to take-profit orders. These results indicate that stop-loss orders are triggered in waves and contribute to price cascades.

Macrae (2005) and later on Ma et al. (2008), emphasize that previous common literature have failed to address the true effect stop-loss rules have on expected future returns. They illustrate with a few, mainly simulated, examples that stop-loss strategies have hidden costs and, given some assumptions, alter the return distribution in a way not typically expected[5]. These hidden

[5] The stop-loss rules do not just create a cut-off on the negative side in the distribution of returns, which the authors assume to be expected; the shape as a whole is affected and the probability of a small loss could increase dramatically.

costs may hurt the overall performance. To what extent the performance is affected depends on how the distribution is altered, which depends on how the rule is set.

Kaminski and Lo (2007) develop an analytical framework for measuring stop-loss rules impact on expected return and volatility. The analytical framework shows that the efficiency of stop-loss rules can be linked directly to the stochastic process driving the underlying portfolio. They also empirically investigate if a simple stop-loss rule adds an expected return premium and by applying the standard household asset-allocation problem involving just two asset classes: stocks and long-term bonds. Furthermore, they investigate how their stop-loss rule affects risk by measuring the impact on portfolio volatility and risk-adjusted returns. Based on monthly returns, the authors find a significant stopping return premium and a decrease of portfolio volatility over the time period 1950-2004, which implies that they also find an increase in risk-adjusted returns for the same period. Finally, Kaminski and Lo (2007) compare the empirical results to several return-generating processes[6]. However, the positive stopping premium found in the empirical tests cannot be explained by any of these simulated return-generating processes. Both the empirical and simulated results can be seen in Appendix III.

Existing previous findings regarding stop-loss rules consider; explanations of the popularity of stop-loss rules, pricing theories of stop-loss rules, market characteristics created by stop-loss rules and one study considers the efficiency of stop-loss rules. However, no previous study has ever studied the efficiency of stop-loss rules in the more natural trading context of transaction data.

2.3 Efficiency of Stop-Loss Rules

Whether or not stop-loss rules are efficient can be directly determined by the underlying process.[7] If past returns carry some information about what future prices stop-loss rules might be value-adding, and hence efficient. In section 2.3.1 it will be shown that stop-loss rules only can be efficient if a decrease in a security price indicates that prices on that security will continue to fall.

---

[6] The Random Walk Hypothesis, an AR(1) with positive ρ (momentum), a regime-switching model and a behavioral regime-switching model.

[7] This holds under the assumption of this study's definition of efficiency. Of course, efficiency could be measured in various ways, but for simplicity we restrain our definition of efficiency to a positive marginal impact in expected return. However, to give broader perspective of efficiency of stop-loss rules we present and discuss efficiency from a behavioral perspective in section 2.5.

2.3.1 A Theoretical framework

Stock returns can be described by various stochastic processes, some better than others. However, this section will be limited to present two different types of stochastic processes that stock returns could be approximated by; a *random walk* and an *autoregressive stochastic process* (AR(1)). The efficiency of stop-loss rules is then analytically evaluated under the different processes presented.

A random walk is basically a sum of random numbers. A simple example can be described as a flip of a coin, where heads increases a past sum with one and tails decreases it with one. In this study's setting a random walk can more formally be described as:

The natural log return $\{r_t\}$ satisfies the Random Walk hypothesis if:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim \textit{White noise}(0, \sigma_\varepsilon^2) \qquad (1)$$

In (1) μ represents some constant number and ε_t represents a random number with a mean equal to zero and a variance equal to σ_ε^2, which defines *white noise*. The return r_t from (1) can in a price context be seen as $r_t = log\left(\frac{Price_t}{Price_{t-1}}\right)$. Under the random walk hypothesis, the probability distribution f of the return in next period, r_{t+1}, follows:

$$E[f(r_{t+1})|r_t, r_{t-1}, r_{t-2}, \dots] = E[f(r_{t+1})] \qquad (2)$$

For simplicity (2) is restricted to that expected return and expected conditional return are equal:

$$E[r_{t+1}|r_t, r_{t-1}, r_{t-2}, \dots] = E[r_{t+1}] \qquad (3)$$

This implies that the expected return in the next period with all available information $E[r_{t+1}|r_t, r_{t-1}, r_{t-2}, \dots]$, is equal to the expected return for next period without any information

$E[r_{t+1}]$, which suggests that the return for the next period r_{t+1}, is completely unpredictable and random with respect to past returns.

For the AR(1)-process there is a dependence structure in the returns, i.e. future returns depend on past returns to some extent, which implies that they are predictable with respect to past returns. More formally the AR(1)-process can be written as:

$$r_t = \mu + \rho(r_{t-1} - \mu) + \varepsilon_t,\ \varepsilon_t \sim \textit{White Noise}(0, \sigma_\epsilon^2),\ \rho \in (-1,1) \qquad (4)$$

If there is positive dependence in the price changes, returns follows a momentum process, i.e. positive returns tend to be followed by more positive returns. This corresponds to $\rho \in (0,1)$. If, on the other hand, there is negative dependence, returns follows a mean-reverting process. This corresponds to $\rho \in (-1,0)$.

It will now be shown, by following the analytical framework presented by Kaminski and Lo (2007), that stop-rules cannot be efficient under the random walk hypothesis.

Past cumulative return $R_t(J)$ of a portfolio strategy over a window of J periods can in a simplified way be written as the following sum of log returns:

$$R_t(J) = \sum_{j=1}^{J} r_{t-j+1} \qquad (5)$$

When the past cumulative return crosses some lower boundary all securities are sold and switched into cash or invested in some less volatile asset e.g. a long term bond. The return for every period of the strategy with the stop-loss rule can then be described as:

$$r_{st} = s_t r_t + (1 - s_t) r_f - \kappa |s_t - s_{t-1}| \qquad (6)$$

In equation (6) s_t indicates whether the cumulative return has crossed the lower boundary and will be either zero or one. r_t indicates the return of the strategy without a stop-loss rule. With probability p_0, s_t will be zero and then all capital is invested in a less volatile asset with return r_f. The transaction cost of switching the investment from one asset to another is represented by κ, and is assumed to be greater than zero. The expected returns of the strategy can then be compared with and without stop-loss rules. The marginal difference on expected returns compared to a strategy without a stop-loss rule can then by the stop-loss rule, Δ_μ, be written as:

$$\Delta_\mu = E[r_{st}] - E[r_t] = E\big[s_t r_t + (1 - s_t) r_f - \kappa |s_t - s_{t-1}|\big] - E[r_t]$$

$$= E[r_t] - p_0 E[r_t | s_t = 0] + p_0 r_f - \kappa P(s_t \neq s_{t-1}) - E[r_t]$$

$$= p_0\big(r_f - E[r_t | s_t = 0]\big) - \kappa P(s_t \neq s_{t-1}) \qquad (7)$$

In the case when the stock return follows a random walk $[r_t | s_t = 0] = E[r_t] = \mu_{r_t}$, because past returns carry now information to predict future returns (there is a one-to-one relationship s_t and past returns. Thus, the stopping difference, Δ_μ, can be written as:

$$\Delta_\mu = E[r_{st}] - E[r_t] = p_0\big(r_f - \mu_{r_t}\big) - \kappa P(s_t \neq s_{t-1}) \qquad (8)$$

Since a positive volatility-return relationship has been showed to exist[8], μ_{r_t} will almost always be greater than r_f, thus the stop-loss rule is inefficient, not even considering the transaction cost κ.

Main take-away: As long as μ_{r_t} is greater than r_f stop-rules cannot be profitable under the random walk hypothesis; even if transaction costs are considered to be negligible.

For the case when the stock price follows an AR(1)-process, a lower bound of the profit of a stop-loss rule can then be approximated by:

[8] Illustrated by e.g. Markowitz (1952).

$$E[r_{st}] - E[r_t] \geq p_0(r_f - \mu + \rho\sigma) - \kappa P(s_t \neq s_{t-1})^9 \qquad (9)$$

For a mean-reverting process it can be seen that stop-loss rules cannot be efficient.[10] For a momentum process stop-loss rules can be efficient if ρ and σ are large enough. This is consistent with the intuition that in the presence of momentum, losses are likely to persist; therefore, exiting out or switching to a risk-free asset after certain cumulative losses can be more profitable than staying fully invested.

Main take-away: A stop-loss rule can be profitable under an AR(1)-process. If $\rho \in (0,1)$, and the returns follows a momentum process, stop-loss rules can be profitable if ρ and σ are large enough and if κ small enough. If $\rho \in (-1,0)$, and the returns follows a mean-reverting process, stop-loss rules cannot be profitable.

The question of whether or not stop-loss rules are efficient can, as seen above, under a few assumptions in theory be clearly answered. However, in practice the question quickly becomes less straightforward for various reasons. Mainly due to the fact that it is more or less impossible to get a perfect match between real returns and one specific stochastic process, which implies that actual tests of specific strategies are required for. Consequently, specifications of the stop-loss rules must be taken into account when evaluating the efficiency of stop-loss rules in an empirical study.

2.3.2 Empirical Evidence on Stock Returns

Early studies on stock price patterns showed strong support for the random walk hypothesis. Fama (1965) finds that stocks indeed approximately follow random walks. He finds no systematic evidence of profitability of technical trading strategies, such as buying stocks when their prices just went up or selling them when their prices just went down. On a given day, the price of a stock is as likely to rise after a previous day's increase as after a previous day's decline.

However, more recent studies have indicated that the random walk hypothesis may not hold. For example Lo and Mackinlay (1988) report significant positive serial correlation in weekly returns,

---

[9] For the full proof we refer to Kaminski and Lo (2007).

[10] Since ρ is negative and we assume that $r_f < \mu$.

suggesting that stock prices follow momentum processes for short periods. Fama and French (1988) report negative serial correlation in market returns over observation intervals of three to five years, suggesting that stock prices follow mean-reverting processes in the long term.

Nevertheless, the empirical results are over time mixed and are thus hard to interpret into a reliable pattern. Based on these empirical results it is, therefore, very difficult to predict whether or not stop-loss rules are efficient. Even if the latest evidence tends to lean towards a dependence structure, it is hard to draw any distinct conclusion. It could be that stock prices for some periods follow random walks and for other periods or return windows tend to be mean-reverting or follow a momentum. It could also be the case that some stocks follow a random walk, while others behave autoregressive in some way. These arguments can be referred to the discussion around different levels of market efficiency. It is probably a huge difference between big stocks in liquid markets compared to smalls stocks in relatively illiquid markets. Consequently, previous studies cannot offer any clear answers regarding whether stop-loss rules are efficient. It is possible that stop-loss rules are efficient for some instruments, for some periods and for some return windows, while inefficient in other situations.

2.3.3 Marginal Impact on Risk

If the efficiency of stop-loss rules solely is based on expected returns, risks are totally ignored. Ignoring risk and only considering expected return may not be accurate when measuring the efficiency of a stop-loss rule; a stop-loss rule could generate so much additional risk to the underlying portfolio that the risk adjusted performance decreases, even if the expected return increases.

The scenario above may, at a first glance, seem unlikely. A stop-loss rule only includes shifting the investment back and forth between the initial portfolio and a less volatile asset, which means that the portfolio based on a stop-loss rule spends more time in a less volatile asset, compared to a portfolio with a "buy-a-hold" strategy. This implies that a stop-loss rule probably lowers the portfolio volatility and thus reduces the overall risk. An exception to this scenario could occur if the strategy results in switching between assets very frequently.

It is crucial to recognize that risks can be measured in several ways. Even if volatility as a measurement is widely established, such static measures may not, according Kaminski and Lo (2007), be totally sufficient performance statistics for dynamic portfolio strategies such as stop-loss rules. However, Kaminski and Lo (2007) still emphasize the value of measuring a stop-loss rule's impact on portfolio volatility, since it highlights one, of possibly many, risk characteristics of a dynamic portfolio strategy.

A risk-adjusted version of Δ_{μ}, presented in (7), can for example be written as a difference in Sharpe ratios. The marginal difference between Sharpe ratios, Δ_{SR}, can be written as:

$$\Delta_{SR} = \frac{E[r_{st}] - r_f}{\sigma_{st}} - \frac{E[r_t] - r_f}{\sigma_t} \qquad (10)$$

σ_{st} and σ_t in (10) represent the standard deviations of the strategy including the stop-loss rule and the strategy without the stop-loss rule respectively.

2.4 Markets Efficiency Implies Stop-loss Rules Inefficiency

The random walk hypothesis is widely used within the field of finance. The hypothesis implies that the future path of security returns is no more predictable than the path of cumulated random numbers. It involves two separate hypotheses: (1) successive price changes are independent and (2) the price changes conform to some probability distribution. For the purpose of this study the first hypothesis is the important one, since the existence of independence makes stop-loss orders inefficient, as shown in previous section.

If the first hypothesis holds, it is consistent with the weak form of market efficiency, which implies that the present price of a stock impounds all the information contained in a record of past prices. Consequently, no technical analysis could make above-average returns by interpreting charts of history returns (Hull, 2005).

With the theoretical framework, presented in section 2.3, and the random walk hypothesis' connection to market efficiency, it can be concluded that stop-loss rules will always be inefficient as long as the market is efficient. This conclusion may not be intuitive, especially not the connection between the random walk hypothesis and market efficiency. Therefore, to clarify this reasoning an intuitive discussion regarding the random walk hypothesis is presented below.

2.4.1 The Random Walk Hypothesis – An Intuitive Discussion

The existence of independent stock returns (see equation (1)) might seem unintuitive; few people believe that stock prices are entirely random. Some theoretical foundations and challenges for the random walk hypothesis are therefore here presented and discussed. The intuitive discussion will mainly follow the discussion presented in Harris (2003).

In statistical terms independence means that the probability distributions of stock return during a time period *t* are independent of the sequence of return during previous time periods. That is, knowledge of the sequence of return leading up to the time period t are of no help in assessing the probability distribution of the return during time period *t* (Fama, 1965). However, it is probably not reasonable that stock prices are characterized by perfect independence. For the purpose of this study it is enough if the actual degree of dependence in the series of price changes is not sufficient to allow past returns to be used to predict the future in a way which makes expected profits greater than they would under a naïve buy-and-hold strategy. From a statistical point of view, knowledge of the dependence tells us quite a bit about the shape of the distribution of price changes. For trading purposes however, the knowledge of the dependence is unimportant as long as a sequential change ε is small. Any profit the trader may hope for would be washed away in transaction costs.

To be able to discuss if stock prices are predictable or not, a clear distinction between market values and fundamental values must firstly be made. The market value of an instrument is the current trading price. The fundamental value on the other hand, is the "true value" of an instrument, which in financial terms can be described as the present value of all present and future expected net benefits of the instrument. Everyone would agree upon this fundamental value if everyone knew everything known about the instrument, if they all used proper analysis to predict and discount all uncertain future cash flows and if they all perceived the benefits and costs of holding the instrument equally. However, since all these conditions never occur in practice, traders often differ in their opinions about fundamental values.

Fundamental values are not perfect foresight values. Fundamental values depend only on information that is currently available to traders. Perfect foresight values depend on all current and future information about values. Fundamental values are the best estimates of perfect foresight values.

Prices are completely informative when they equal fundamental values. Efficient markets produce prices that are very informative. Yet, all traders are not informed. The traders that do not base their trades on information about fundamental values are called noise traders.[11] The difference between fundamental value and market value is noise. Informed traders try to identify

[11] They might for example be subject to the behavioral biases described in section 2.5.

the noise in prices by estimating fundamental values. Since traders generally do not observe fundamental values, they cannot easily determine whether prices are informative or noisy.

Changes in fundamental values are completely unpredictable. Since fundamental values reflect all available information, they change only when traders learn unexpected new fundamental information. If fundamental value changes were predictable, current fundamental values would not fully reflect the information upon which the predictions are based. Fundamental value changes must therefore be unpredictable. Since prices are very close to fundamental in efficient markets, price changes in efficient markets are quite unpredictable, which suggests that the random walk hypothesis might hold.

The validity of the random walk hypothesis depend on if stock markets are efficient or not. Several arguments exist, both for and against the market being efficient[12] and the market will be efficient only as long as informed traders trade so that market values quickly converge to fundamental values. However, informed traders face several considerable risks that might prevent them in performing those trades. An informed trader may suffer temporary losses for an undetermined period due to noise market movements. The cash outflow from temporary losses may prevent him/her from trading on the fundamental value, simply because the investor's pockets not are deep enough.

> *<u>Example – Temporary losses' implications of trading on fundamental values:</u> This simple example is taken from the market situation before the stock market crash in 2000. Leading economists, such as Alan Greenspan, said that the stock market was overvalued in the beginning of 1997. However, due to a rising market the following years an investor who made a bet on the stock market being overvalued at that time would have lost 33.4 percent the following year and 28.6 percent the year after that. The investor would, however, have gained in the longer run after the crash. But even if investors had gained in the long run, few dared to challenge the current market tendencies and invest for a market crash. Consequently, temporary losses prevented most investors to trade on the fundamental values.*

To summarize this discussion it can be concluded that the random walk hypothesis do not require that stock prices move entirely randomly; the requirement is rather efficient markets.

2.5 A Behavioral Perspective on the Efficiency of Stop-Loss Rules

Efficiency or inefficiency can be seen as the capacity or incapacity to produce a desired effect. This study has defined efficiency as a positive marginal increase in expected returns and inefficiency as the corresponding negative marginal impact. However, the desired effect of a stop-loss strategy may not always be a positive marginal increase in expected returns, other

---

[12] See for example Fama (1965) or Lo and Mackinlay (1988).

effects outside economic profits may be wished for. Consequently, this study's definitions of efficiency may be questioned if the desired effect is not a positive marginal increase in expected returns.

To give a broader picture of what efficiency of stop-loss rules might consist of, the following section provides some brief motivations for using stop-loss rules from an alternative perspective and efficiency can thus be seen as a positive marginal increase in rational behavior. This perspective is described in the field of behavioral finance, which briefly is introduced below.

Behavioral finance is, according to Sewell (2007), *"the study of the influence of psychology on the behavior of financial practitioners and the subsequent effect on markets*". It helps to explain why and how markets and investors might be inefficient or act irrational. Consequently, behavioral finance can provide additional insights into the efficient market theory, according to Shiller (2002) it can offer a more nuanced view to the value of efficient market assumptions. Furthermore, behavioral finance may to some extent explain the irrational human behavior observed in the financial markets. For a more extensive introduction to the field of behavioral finance see, for example, Sewell (2007).

This section will show that when taking behavioral finance and irrational human behavior into account clear rationales for using predetermined and consequent strategies such as stop-loss rules appears.

Kahneman and Tversky (1979) present a model of decision making under risk (e.g. financial decisions) that they call prospect theory. Expected utility theory is unable to explain why people are often simultaneously attracted to both insurance and gambling. They find that attitudes towards risk concerning gains might be very different from attitudes towards risk concerning losses. Under uncertainty an aversion to realization of losses is identified. Furthermore, Kahneman and Tversky (1991) present a reference-dependent model of riskless choice, the central assumption of the theory being loss aversion, i.e. losses and disadvantages have greater impact on preferences than gains and advantages. These behavioral findings have implications on the rational assumptions underlying the financial market, since investors have a bias to realize profits relative losses. Several authors have later on formalized and tested Kahneman's and Tversky's findings. The observed effect was named the *disposition effect*. Another effect that later was observed and confirmed is *loss aversion*, which can be seen as being included in the disposition effect.[13]

[13] See for example Grinblatt and Keloharju (2000).

Shefrin and Statman (1985), as mentioned in section 2.1, develop a framework and label investors' general disposition as selling winners too early and holding losers too long. Odean (1998) tests the disposition effect, the tendency of investors to sell winning investments too soon and hold losing investments for too long. A strong preference for realizing winner rather than losers is empirically demonstrated. Odean (1999) also finds evidence of the disposition effect which leads to profitable stocks being sold too soon and losing stocks being held for too long.

Linnainmaa (2006) finds that the usage of limit orders can explain a significant part of many behavioral patterns, where the disposition effect is one. He finds that 46% of the disposition effect in Helsinki Exchanges should be referred to the usage of limit orders, rather than to irrational human behavior. This might somehow moderate the expectations of the existence of the disposition effect, even if it should not be ignored.

Consequently, it is reasonable to assume that behavioral biases, e.g. the disposition effect, are present, which suggests that traders behave irrationally. Aligned with what Shefrin and Statman (1985) presented, stop-loss rules play an important role in this situation. A predetermined and rational decision rule – such as a stop-loss rule – will work as a mechanism to evade the disposition effect or loss aversion and help investors to make rational decisions. Other behavioral biases, besides the disposition effect, can of course also be mitigated with the usage of stop-loss rules.[14]

In summary, it can be concluded that several behavioral biases can be lessened with stop-loss rules. This suggests that stop-loss rules have a positive marginal impact on rational behavior, independently of what marginal impact a stop-loss rule has on the underlying portfolio's expected return. Stop-loss rules are, thus, effective from a behavioral perspective.

[14] For example: c*ontrarian behavior* discussed by Grinblatt and Keloharju (2000) and *ambiguity aversion* discussed by Ellsberg (1961) and Rakesh and Weber (1993).

3. Foundations of the Study

The aim with this chapter is to establish an understanding of how this study is conducted by providing the foundations that this study is based on. More specifically, we formalize the questions we want to answer into expectations of the outcome by phrasing hypotheses based on previous research on stop-loss rules, the theoretical framework and the pre-study in chapter four. We briefly describe and discuss the quantitative data sets, which are the base for the analysis. We finally present the procedures, models and variables used on the data sets to test the stated hypotheses.

The chapter is structured as follows: In section 3.1, we develop and phrase our expectations regarding efficiency of stop-loss rules. In section 3.2, we provide a description of the data, which is followed by presentation of the assumptions and adjustments made regarding the data. We also discuss potential implications for the study that can be referred to the assumptions and adjustments we make. In section 3.3, we describe the procedures, models and variables used in this study. We first define the stop-loss rule and then provide the testing procedures for it. Finally, we specify and motivate the parameters of the stop-loss rule.

3.1 Hypothesis Development

As discussed earlier, this study aims to examine the efficiency of stop-loss rules. In addition, this study considers risks and examines expected risk-adjusted return. After defining efficiency as a positive marginal impact in expected return on a "buy-and-hold" portfolio strategy is the aim is operationalized in two questions: (1) What marginal impact in expected return do stop-loss rules have on a "buy-and-hold" portfolio strategy?, (2) What marginal impact in risk do stop-loss rules have on a "buy-and-hold" portfolio strategy, and what marginal impact in risk-adjusted returns do stop-loss rules have on the same strategy? To answer these questions we examine and analyze them with a quantitative approach, with a main focus on high frequency transaction data. Before examining and analyzing the quantitative data, however, a formalization of the procedures is needed.

3.1.1 Hypothesis 1 – Efficiency and Impact on Expected Returns

In hypothesis one, which is the core hypothesis, we proceed in an effort to understand the efficiency of stop-loss rules. In particular, the hypothesis is developed to investigate what marginal impact in expected return stop-loss rules have on a "buy-and-hold" portfolio strategy.

Kaminski and Lo (2007) offer an analytical framework for evaluating the efficiency of stop-loss rules. They show that the marginal impact of stop-loss rules can be directly referred to which stochastic process that is driving the underlying portfolio. Our expectations regarding the efficiency of stop-loss rules are directly dependent on our expectations of which stochastic process that best describe stock returns. The processes that are included in the analytical framework are a random walk, a mean-reverting AR(1)-process and a momentum AR(1)-process.

In alignment with classic finance theory[15], a first assumption when trying to understand efficiency of stop-loss rules would be to expect markets to be efficient, which implies that the random walk hypothesis holds. Stop-loss rules are then, in light of the theoretical framework, expected to be inefficient. However, based on other empirical results regarding the behavior of stock returns, and the empirical results regarding efficiency of stop-loss rules is this assumption insufficient.[16] When forming the expectations of the efficiency of stop-loss rules a more comprehensive investigation is required.

The empirical results regarding the behavior of stock returns are mixed. Even if the latest results are tending towards a dependence structure, it is hard to draw any distinct conclusion regarding the characteristics of the dependence structure. Previous studies have used other types of data and time increments compared to this study, which makes it even harder to construct valuable anticipations. A clear expectation of whether or not stop-loss rules are efficient can, thus, not be formed by examining empirical results regarding the behavior of stock returns.

In the absence of being able to determine which of the described stochastic process that best describe stock returns individually, focus is put on earlier results regarding the efficiency of stop-loss rules. The only existing empirical study examining the efficiency of stop-loss rules is presented by Kaminski and Lo (2007). Based on monthly returns, this study finds that their simple stop-loss rule have positive marginal impact on the underlying portfolio. These results may not, however, be accurate for this study's expectations; mainly due to the different time increments and type of data used in the separate studies. Consequently, even if the empirical results presented by Kaminski and Lo (2007) provide an indication of what to expect regarding the efficiency of stop-loss rules, they do not provide a satisfactory base for any conclusions in the light of other results. A pre-study of the data set is, hence, required.

The pre-study, which will be presented in chapter four, indicates that the underlying portfolio is mean-reverting. When evaluating the four sources of information; the assumption of efficient markets, the empirical evidence regarding stock returns in combination with the theoretical

[15] See for example Fama (1965).
[16] On behavior of stock returns: see for example Fama and French (1988). On efficiency of stop-loss rules see Kaminski and Lo (2007).

framework, the empirical findings of stop-loss efficiency and the findings of the pre-study, we let the findings from the pre-study finally determine our expectations.

Hence, in the light of the theoretical framework we hypothesize that stop-loss rules are inefficient and have a negative marginal impact in expected return on a "buy-and-hold" portfolio strategy.

Hypothesis 1: *The expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*[17]

3.1.2 Hypothesis 2 and 3 – Efficiency and Risk

Hypothesis two and three are extensions of the study and are included due to the fact that the definition of efficiency totally ignores changes in risk. If stop-loss rules have a significant impact on the risk of the underlying portfolio it may be accurate to consider, or at least control for, the changes in risk. By considering stop-loss rules' marginal impact in risk, unreasonable conclusions regarding the efficiency based upon expected returns are to some extent controlled for. By investigating what marginal impact stop-loss rules have on the risk of a portfolio strategy and what impact stop-loss rules have on risk-adjusted returns hypothesis two and three will complement hypothesis one to better understand the efficiency of stop-loss rules.

Firstly, hypothesis two aims to examine if stop-loss rules have an impact on the risk of the underlying portfolio at all. When measuring risk we use a straightforward approach and let volatility represent risk, even if volatility may be challenged as a dynamic risk measurement.

A first reasonable expectation of stop-loss rules impact on the underlying portfolio would be a reduction in volatility. This is due to the fact that a portfolio with a stop-loss rule should spend more time in a less volatile asset, compared to a portfolio with a "buy-a-hold" strategy. Furthermore, Kaminski and Lo (2007) also find that stop-loss rules reduce volatility, which strengthen the initial expectation.[18] Consequently, the theoretical reasoning and the empirical results are consistent with each other. Since no other inconsistencies have been observed, we align our expectations with the theoretical discussion and the results found by Kaminski and Lo (2007) and expect stop-loss rules to reduce the volatility on a "buy-and-hold" portfolio strategy.

[17] See the specification of the stop-loss rule in section 3.3.
[18] Note that the different type of data and the different time increments do not impact our expectations to the same extent as for hypothesis one. This since the characteristic of a reduced volatility should remain even if the type of data is different.

Hypothesis 2: *The volatility is reduced using a stop-loss rule on a "buy-and-hold" portfolio strategy.*[19]

The third and final hypothesis is to some extent dependent upon the expectations of hypotheses one and two, given a positive risk-return relationship[20]. The expected risk-adjusted return will always increase if the expected return is anticipated to increase, while the volatility is anticipated to decrease. This relationship is found by, for example, Kaminski and Lo (2007). However, given our expectations of hypotheses one and two it could be hard to anticipate an outcome of a risk-adjusted return. The expectations on hypothesis one contributes to reduce the risk-adjusted return, while the expectations on hypothesis two contributes to increase the risk-adjusted return. What to expect simply becomes a trade-off between how much the expected return is anticipated to decrease compared to how much the volatility is anticipated to decrease.

In the absence of empirical findings, besides the results presented by Kaminski and Lo (2007), we make some (strong) assumptions and deliberate towards an expectation. To phrase a hypothesis based on strong assumptions may not be entirely accurate, and can of course be challenged. However, considering that hypothesis three depend upon hypothesis one and two, and that it is an extension of the study we content with this type of reasoning.

Let the expected risk-adjusted return be represented by the Sharpe ratio (equation (10)). Now assume that reduction in expected returns due to stop-loss rules (from hypothesis one) are at least of the same relative magnitude as the reduction in volatility due to stop-loss rules (from hypothesis two). Furthermore, assume that r_f in equation (10) is positive. It can then be shown that the "stop-loss" Sharpe ratio always will be smaller than the "buy-and-hold" Sharpe ratio.

To check for some kind of plausibility, a comparison between the assumptions and Δ_μ and Δ_σ, from the simulated return-generating processes presented by Kaminski and Lo (2007), is made. It is observed that the assumptions hold in two out of three cases, which we consider to be plausible enough.

Accordingly, we anticipate that the risk-adjusted return[21] of a portfolio will decrease when using the stop-loss rule on a "buy-and-hold" portfolio strategy.

---

[19] See the specification of the stop-loss rule in section 3.3.
[20] More specifically is it a positive volatility-return relationship.
[21] Measured as the Sharpe ratio (equation (10))

Hypothesis 3: *The risk-adjusted expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*[22]

[22] See the specification of the stop-loss rule in section 3.3.

3.1.3 Summary of the Hypotheses

We end this section by summarizing the hypotheses developed in the two previous sections. Main previous findings, theories and assumptions – which we base our expectations upon – are also presented.

Table 3.1 – Summary of the Hypotheses

Hypotheses	**Previous findings, Theories and Assumptions**
Hypothesis 1: *The expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*	• Assuming market efficiency is the in the light of other findings insufficient. • The theoretical framework, presented in section 2.2, and the empirical results of stock returns do not offer a clear answer regarding the impact on expected returns. • The empirical results of the impact on expected returns, presented by Kaminski and Lo (2007), find a positive marginal impact. However, due to the difference in data set compared to this study, these findings may not be totally applicable. • The conducted pre-study indicates that the data set in this study is mean-reverting, which together with the theoretical framework suggests that the marginal impact of stop-loss rules is negative.
Hypothesis 2: *The volatility is reduced using a stop-loss rule on a "buy-and-hold" portfolio strategy.*	• A theoretical reasoning suggests that the volatility would be reduced by stop-loss rules, since stop-loss rules implies more time in low volatility instruments compared to a "buy-and-hold" strategy. • Kaminski and Lo (2007) empirically finds that the volatility is reduced by stop-loss rules.
Hypothesis 3: *The risk-adjusted expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*	• A trade-off between expectations of hypotheses one and two. • Risk is represented by the Sharpe ratio. • $(E[r_{st}] - E[r_t])/E[r_t] \geq (\sigma_{st} - \sigma_t)/\sigma_{st}$, $r_f \geq 0$ • The assumptions between the relationship "change in expected returns" and "change in volatility" hold for two out of three observed simulated return-generating processes presented by Kaminski and Lo (2007).

3.2 Data

The quantitative data is the base for the analysis in this study and below follows a description of this data together with a presentation and discussion of the assumptions and adjustments made regarding the data.

3.2.1 Description of the Data

As mentioned earlier this study is mainly based on transaction data. More specifically, the main data set used in this study contains the complete trading records of all the stocks included in the OMX Stockholm 30 Index[23], which are the 30 largest and most liquid stocks on the Stockholm Stock Exchange. The stocks which are included in the data set are: ABB, Alfa Laval, Assa Abloy B, AstraZeneca, Atlas Copco A, Atlas Copca B, Boliden, Electrolux B, Eniro, Ericsson B, Hennes & Mauritz B, Investor B, Lundin Petroleum, Nokia, Nordea, Sandvik, SCA B, Scania B, SEB A, Securitas B, Skanska B, SKF B, SSAB A, Svenska Handelsbanken A, Swedbank A, Swedish Match, Tele 2 B, TeliaSonera, Volvo B, and Vostok GAS. Each trade made in one of these stocks corresponds to one observation in the data set.

After cleaning this data set from, for the study, unnecessary information, each observation includes a date-stamp, a time-stamp, a stock identifier[24], and the price. OMX Market Research provided this data for the period from January 2st 2006 to July 21st 2008, which was the whole period for which this type of data was available for, at the time the data was collected. To clarify, an example of a few observations is provided from the data set in table 3.2 below.

Table 3.2 – An example of three observations in the data set

Date	Time	ISIN	Price
…	…	…	…
2007-06-14	16:20:58	SE0000108656	26.260000
2007-06-14	16:20:59	SE0000108656	26.260000
2007-06-14	16:21:02	SE0000108656	26.240000
…	…	…	…

When testing the stop-loss rules, returns from a low volatile asset are included in the simulations. This study let the Stockholm Interbank Offered Rate (STIBOR), which is the rate banks pay when they borrow from each other, represent this return. More specifically, this data set consists

[23] The stocks in the data set are the ones which were included in the OMXS30 in July 2008, except Nokia.
[24] ISIN (International Securities Identification Number) is used as stock identifier.

of the STIBOR T/N, which stands for *tomorrows next* and is the rate of overnight loans. STIBOR is calculated as an average from a number of bank rates in Sweden. This data set was collected at Riksbanken for the period from January 1st 2006 to July 21st 2008, which is the same period as for the trading records. This data set is later referred to as STIBOR data.[25]

Descriptive statistics for the data can be seen in Appendix II.

3.2.2 Assumptions and Adjustments

A number of assumptions and adjustments are made on the two data sets used in this study. In this section we present these assumptions and adjustments, and in section 3.2.3 we discuss which potential implications these assumptions and adjustments have for the study.

A first consideration regarding the data set is extreme data points, which is exemplified by plotting the data for ABB in figure 3.1 below. Even if every stock, of course, has its own characteristics, ABB represents the whole data set in this example.

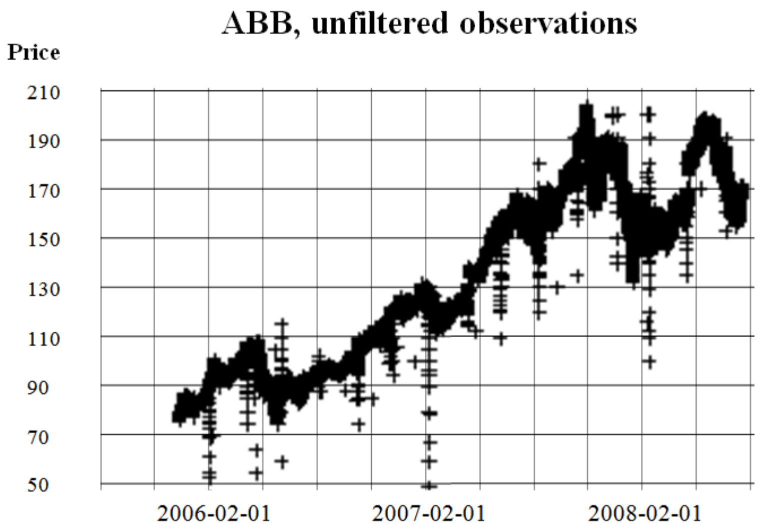

Figure 3.1 – Unfiltered ABB transaction data for the period 2006-01-01 – 2008-08-21

As can be seen in figure 3.1, there are some very extreme observations with very high absolute returns. It is of course very hard to determine why these observations occur. Some could be trading mistakes and others could be misinterpretation of information. These observations are all by definition included in a very strong mean-reverting trend, which will lower the overall

[25] This implies that "the data set" refers to the OMX trading records.

efficiency of stop-loss rules. However, influence from extreme observations could make the results hard to interpret into an overall pattern. The observations are therefore filtered with a simple condition, which is specified as follows:

$$if\ \left(\left|\frac{price_t}{price_{t-5}}-1\right|>0{,}05\ or\ \left|\frac{price_t}{price_{t-10}}-1\right|>0{,}05\right), then(delete\ price_t) \quad (11)$$

In equation (11) t refers to the transaction number.

The exact specification of the filter could always be discussed. This simple filter in (11) adjusts for the most extreme cases and 0.066 percent of the observations are deleted (compare figure 3.1 with figure 3.2).

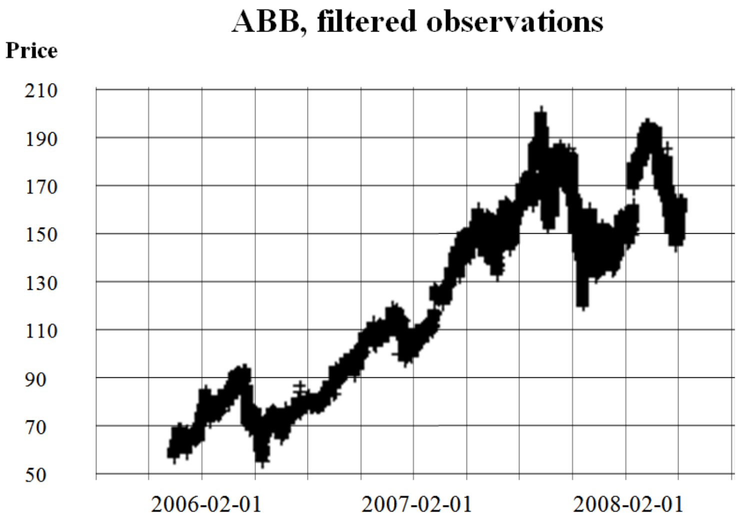

Figure 3.2 – Filtered ABB transaction data for the period 2006-01-01 – 2008-08-21

The other main consideration with the data set is the different time periods between each observation. This characteristic makes it hard to measure the returns in a straight forward way. The data set is, therefore, adjusted to a time-series with constant time difference between the observations. To create a time-series with constant time between each observation, two main approaches can be used. The first approach is to aggregate the transaction data over some fixed time period. This approach provides an exact length of the time periods between the observations, but an approximation of the price since it consist of an average. This approach implies that some kind of aggregated return is calculated. The second approach is to use a sub-sample and only use data at certain points in time with a constant time difference in between. This approach, in contrast to the former, provides an exact price, but an approximation of the time periods between the observations. This approach implies that the market only is observed at certain points in time. When considering the closeness to reality of the simulations, transaction data is preferred in front of aggregated data. Consequently, the second approach with time approximations is chosen and the market is only observed at certain points in time.

To be as exact as possible it is preferable to observe the data set as often as possible. However, the approximations in time will become inaccurate if the data set is not adjusted in an appropriate way. One appropriate way to adjust the data into periods could be to fit the data around some point in time, t_0, to a symmetric distribution, since the approximations will then cancel out each other on average.

The unadjusted data and a symmetric distribution represented by a normal distribution, with mean equal to the median of the data and a standard deviation of 20 percent of the mean, can be seen in figure 3.3 below.

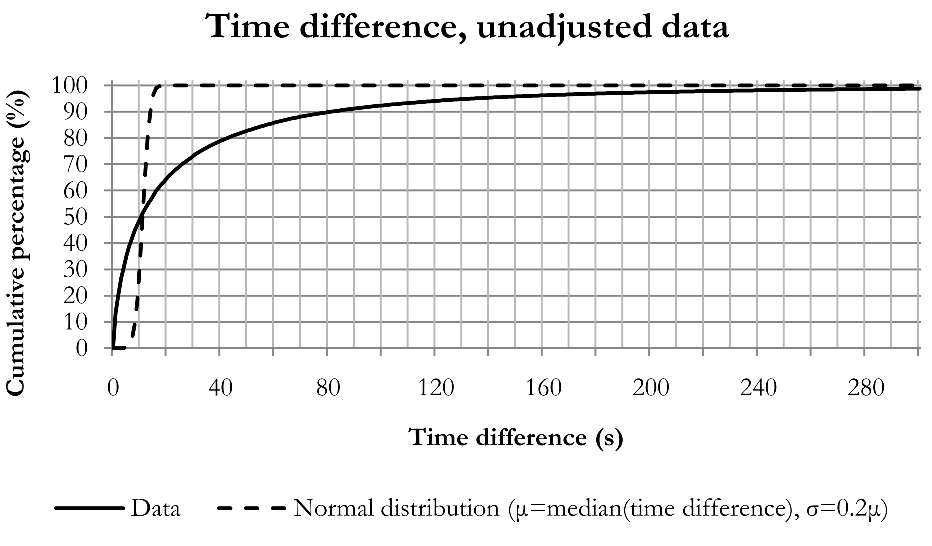

Figure 3.3 – Cumulative share of time difference between each observation for the data and a normal distribution for the unadjusted data set

Note that the observations with time differences of 300 seconds or less represent 99 percent of the data set. The same cumulative share for 120 seconds and 60 seconds are 94 percent and 86 percent respectively.

The data set is adjusted to a symmetric distribution by ignoring the observations closest to each other, i.e. every observation with a time difference less than t_{min} is ignored. Also note that the time differences will shift for the remaining observations, since some observations will be "deleted". The adjusted data, which has been adjusted to match the time 60 seconds per period, can be seen in figure 3.4 below.

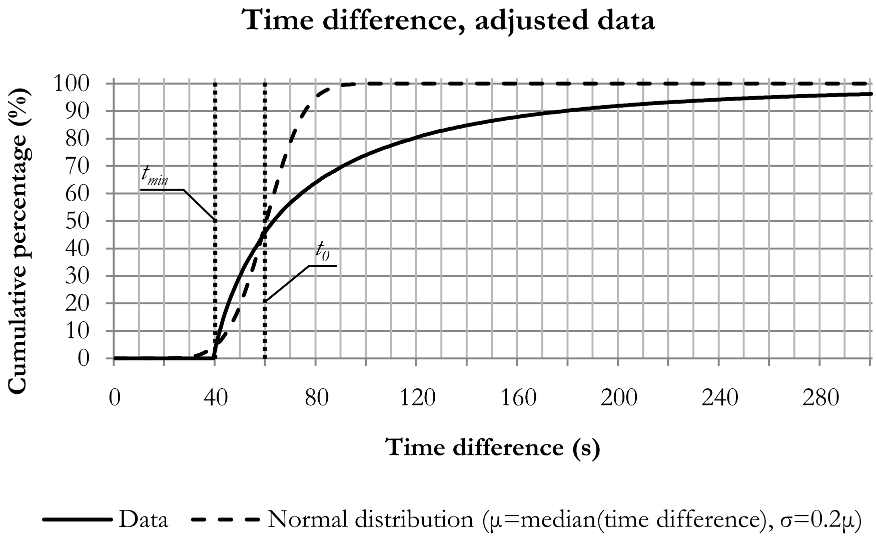

Figure 3.4 – Cumulative share of time difference between each observation for the data and a normal distribution for the adjusted data set

Note the data set's fat tail compared to a symmetric distribution, which could have implications for the characteristics of the returns. However, the approximation, with t_0 = 60 seconds and t_{min} = 40 seconds, are hopefully still accurate enough for the purpose of this study.

As a final note it can be concluded that when using the STIBOR data as low volatile return when testing stop-loss rules it is assumed that this rate is constant on a daily basis.

3.2.3 Implications for the Study

A numerous of choices regarding the data set may have implications on the findings for this study. This section presents these choices followed by a brief discussion regarding the implications and potential biases for the results.

The first choice regarding the data set, which will bias the results of the efficiency of stop-loss rules, is the choice to ignoring the order book when testing the efficiency of stop-loss rules. This data is mainly ignored for practical reasons. The size of order book data for the same period as the trading records is simply too large to include in the analysis.

Ignoring the order book and only basing the analysis on trading records implies that the main risks with markets orders are ignored. The main risks, presented in section 2.1, are liquidity price, execution price uncertainty and market impact. By overlooking these risks it is assumed that a trader always can trade to the observed market price, which probably will bias the level of efficiency upwards to some extent. In this study the most liquid stocks from Stockholm Stock Exchange are included, which mitigates the problem to some extent. However, the problem and bias still exists, which must probably be considered when making conclusions regarding the findings.

The next choice regarding the data set, which may have implications for the results, is the exclusion of extreme data points. By observing figure 3.1 and 3.2 it can be seen that the most extreme returns are excluded. The behavior of a set of data around extreme observations is, as mentioned earlier, by definition mean-reverting (otherwise it would not have been extreme observations), which may introduce a bias to the results considering the theoretical framework. Assuming that a reduction of a mean-reverting behavior will increase momentum behavior, this implies that the level of efficiency could be biased upwards by including a filter. However, this potential bias can in all probability be ignored, as the filter excludes so few observations.

A final choice regarding the data set, which have implications for the study and may bias the results, is the adjustment to time periods as discussed in previous section. By only using a sub-set as a base for the analysis will of course imply some kind of approximation of the results. Firstly, due to the fact that the time period only are approximated around $t_0 = 60$ seconds. Secondly, due to the fact that a fat tail appears around the approximation of t_0 (see figure 3.4). Finally, due to the fact the dynamics between each observation is lost. This may result in a bias of the results, even if the direction is very hard to foresee. It is, however, reasonable to believe that the large amount of observations will moderate the problem, even if the problem will be recognized when conclusions are made.

3.3 Model Specification and Testing Procedures

This section empirically applies the theoretical framework for evaluating efficiency of stop-loss rules, presented by Kaminski and Lo (2007). The stop-loss rule (or strategy) is firstly defined and then put into a testing procedure. The parameter settings for testing the strategy are, finally, provided and motivated.

3.3.1 The Strategy

The stop-loss rule presented in this section mainly follows the framework presented by Kaminski and Lo (2007).[26] There are four main reasons for applying the chosen stop-loss rule in this study. Firstly, this stop-loss rule is simple, which implies that the study tests the characteristics of stop-loss orders, rather than the characteristics of an advanced algorithm trading strategy. Secondly, this stop-loss rule is generic, since it tests every period and is not restricted by e.g. the investment horizon or the time for the investment. Thirdly, the stop-loss rule is similar to an experienced and already tested stop-loss rule, which allows us to compare the empirical results and discuss potential differences. Finally, this stop-loss rule is practical and effective from a programming and simulating perspective, which is absolutely crucial when analyzing very large amounts of data.

Consider an investor with a portfolio P with the return r_t. Now suppose that the investor wants to impose an overlying stop-loss rule S to the portfolio P. Imposing this kind of stop-loss involves an exit decision based on some kind of negative cumulative return in the past. Assume that the investor wants to track the cumulative return $R_t(J)$ of the portfolio P over a window of J periods in time, to make the exit decision. Every decision is made at the end each period and implemented in the beginning of the next period. More formally, the decision to exit can be defined as the following product:

$$R_t(J) \equiv \prod_{j=1}^{J}(1 + r_{t-j+1}) \qquad (12)$$

The exit of portfolio P is made at time t when the cumulative return $R_t(J)$, crosses some lower boundary γ.

[26] See Kaminski and Lo (2007) to observe the exact differences.

Now suppose that the investor, after exited portfolio P , keeps his money in cash account F with the return r_f , until the past cumulative return $R_t(I)$, of the portfolio P crosses an upper boundary δ. More formally, the decision to re-enter can be defined as the following product:

$$R_t(I) \equiv \prod_{i=1}^{I}(1 + r_{t-i+1}) \qquad (13)$$

The re-enter of portfolio P is made at time t when the cumulative return $R_t(I)$, crosses some upper boundary δ.

The investor now has re-entered his initial position a portfolio P with the return r_t , and the stop-loss procedure can be repeated into a dynamic rule once again. This strategy or stop-loss rule can be summarized in the following definition:

Definition – stop-loss rule: *The stop-loss rule $S(\gamma, \delta, J, I)$ for a portfolio P with the return r_t is a dynamic binary asset-allocation rule, s_t, between P and a cash account F with the return r_f . Let s_t be defined of:*

$$s_t \equiv \begin{cases} 0 \text{ if } R_{t-1}(J) & < \ -\gamma \text{ and } s_{t-1} = 1 & \text{(exit)} \\ 1 \text{ if } R_{t-1}(I) & > \ \delta \text{ and } s_{t-1} = 0 & \text{(re-enter)} \\ 1 \text{ if } R_{t-1}(J) & \geq \ -\gamma \text{ and } s_{t-1} = 1 & \text{(stay in)} \\ 0 \text{ if } R_{t-1}(I) & \leq \ \delta \text{ and } s_{t-1} = 0 & \text{(stay out)} \end{cases} \qquad (14)$$

The return of the stop-loss rule $S(\gamma, \delta, J, I)$, which can be denoted by r_{st} is then defined by:

$$r_{st} \equiv s_t r_t + (1 - s_t) r_f - \kappa |s_t - s_{t-1}| \qquad (15)$$

r_f represents the STIBOR[27] rate κ represent the transaction cost for switching the investment between P and F.

[27] STIBOR is a daily reference rate based on the interest rates at which banks offer to lend unsecured funds to other banks in the Stockholm money market. It is similar to the more well known LIBOR rate.

3.3.2 Testing the Strategy

The testing procedure of the stop-loss rule is rather straight forward. When testing hypothesis one, which examines whether or not stop-loss rules have a positive marginal impact on a portfolio's expected return compared to a "buy-and-hold" strategy, Δ_μ (see equation (16)) is firstly calculated.[28] Simple t-tests, with null hypothesis $\Delta_\mu = 0$, are then conducted for a number of settings of J, I, γ, δ and κ.

$$\Delta_\mu = r_{st} - r_t \qquad (16)$$

When testing hypotheses two and three, which examines stop-loss rules impact on risk and comparing the risk-adjusted returns on the underlying portfolio with and without stop-loss rules, similar approaches are applied. Firstly, the standard deviations between the two strategies are compared in an F-test with null hypothesis $\Delta_\sigma = 0$. More specifically, Δ_σ in (17) is calculated and then tested for a number of settings of J, I, γ, δ and κ.

.

$$\Delta_\sigma = \sigma_{r_{st}} - \sigma_{r_t} \qquad (17)$$

When comparing the risk-adjusted returns in hypothesis three, the difference between the two strategies' Sharpe ratios is firstly calculated.[29] As for hypothesis one, simple t-tests with null hypothesis $\Delta_{\mathrm{SR}} = 0$ are then conducted for a number of settings of J, I, γ, δ and κ.

$$\Delta_{\mathrm{SR}} = \frac{r_{st} - r_f}{\sigma_{\mathrm{st}}} - \frac{r_t - r_f}{\sigma_{\mathrm{t}}} \qquad (18)$$

[28] See equation (7) for a theoretical comparison.
[29] See equation (10) for a theoretical comparison.

3.3.3 Parameter Specification

Before setting the parameters of J, I, γ, δ and κ to finally obtain Δ_μ, some main considerations must be taken into account. For example: What type of trading is the main target for a study based on transaction data? What are reasonable settings, given a specific type of trading?

Comparing this study with Kaminski and Lo (2007), which uses aggregated monthly data, this study is dealing with a very different situation since it is based on transaction data. Furthermore, Kaminski and Lo (2007) are applying the standard household asset-allocation problem and use $J = \{3,6,12,18\}$, which is a long-term perspective. This study, on the other hand, has its main focus on the short perspective, since it wants to exploit the power of transaction data compared to aggregated daily or monthly data. Consequently, the settings of J will be focused on periods below the periods that could be created on aggregated daily data, which more easily can be collected and processed.

The settings of γ must be reasonably compared to the settings of J, which means that $P(R_{t-1}(J) > \gamma)$ must not take unreasonable levels close to one or zero. The settings of δ and , are, on the other hand, not obvious. Mainly due to the fact that to buy stock is an independent strategy in itself and not a part of the stop-loss order. When setting δ this study follows Kaminski and Lo (2007) and set $\delta = 0$. When setting I, on the other hand, the approach is extended and test for the same values as for J, instead of just testing for $I = 1$.

When setting κ, an inductive approach is used, since an introduction of a transaction cost always will lower the return and thus the efficiency. If stop-loss rules are shown to be efficient for $\kappa = 0$ reasonable transaction cost are introduced. Reasonable values can be retrieved at a broker e.g. Avanza. In the context of this thesis reasonable values of κ are placed around 0.0003.

4. Pre-Study – Conditional Performance

This chapter aims to provide additional insight to expectations regarding the efficiency of stop-loss rules discussed in the literature review. As discussed previous studies cannot, together with the theoretical framework, offer a clear answer to whether or not stop-loss rules are efficient. To get some insightful answers to the addressed question we will conduct a pre-study of the data set. More specifically, we will examine the conditional performance of the underlying portfolio, given a recent fall.

The chapter is structured as follows: In section 4.1, we give a short background and motivation why this pre-study is required. We also present the potential implications of the pre-study. In section 4.2, we present the model specification used in the pre-study. Finally in section 4.3, we present and discuss the empirical findings of the pre-study.

4.1 Conditional Performance as an Efficiency Indicator

Efficiency of stop-loss rules can, as demonstrated earlier, be directly linked to how the underlying process behaves. If the underlying process follows a random walk or is mean-reverting stop-loss rules can never be efficient. On the other hand, if the underlying process shows momentum behavior, stop-loss rules can be efficient.

What type of stochastic process that drives the underlying portfolio is, however, not obvious. As mentioned earlier, the validity of the random walk hypothesis depends on that informed traders trades so that market prices converge to fundamental values and the results, referred to in section 2.4, do not answer this question clearly. It could be the case that the underlying process shifts over time. Furthermore, the underlying process could show different tendencies over short and long periods. Based on the empirical results, no clear anticipation of which stochastic process that best represent the underlying process can therefore be made. Of course, the different stochastic processes can be tested for applying several testing procedures. However, it would be rather extensive to test for one stochastic process for the whole period and thereby apply the procedures presented by e.g. Lo and Mackinlay (1988). This pre-study is therefore limited to examine tendencies and trends by examine the conditional performance. The pre-study will, consequently, conduct an examination of how the underlying portfolio performs given certain conditions, such as a recent fall or a heavy rise. By examining the conditional performance we could get a hint of whether a specific stochastic process seems to dominate the underlying portfolio for some specific conditions and get a hint of whether or not stop-loss rules are efficient.

Since recent falls are of the most interest for this study, the pre-study will be limited to testing the conditional performance after a recent fall. Three different return behaviors will be observed in the pre-study. The different behaviors are; random walk behavior, mean-reverting behavior and momentum behavior. Random walk behavior implies that the conditional performance is not significantly different compared to the unconditional performance after a recent fall. Mean-reverting behavior implies that the conditional performance is significantly larger than the unconditional performance after a recent fall. Finally, momentum behavior implies that the conditional performance is significantly smaller than the unconditional performance after a recent fall.

If the pre-study results offer indications of random walk or mean-reverting behavior of the underlying process after a recent fall, it indicates that stop-loss rules are inefficient. Conversely, if the pre-study identify momentum effects of the underlying portfolio after a recent fall it indicates that stop-loss rules could be efficient.

4.2 Testing the Conditional Performance

By testing the conditional performance of the underlying process, we get an indication of how the cumulative returns of the included stocks behave under some given conditions. We could, for example, test if the returns for the included stocks are negative for the nearest hour, given a fall of a certain magnitude in the last five minutes.

The data set on which the pre-study is based is the same data set that later on will be used for testing the efficiency of stop-loss rules. This data set is comprehensively described in section 3.2. In short the data set used in the pre-study contains the complete trading records of all the stocks included in the OMX Stockholm 30 Index for the period from January 2st 2006 to July 21st 2008.

More formally this type of test can specified as follows; given a certain performance, specified as past cumulative return, over the last J periods of time.

$$R_t(J) = \prod_{j=1}^{J}\left(1 + r_{t-j+1}\right) - 1 \qquad (19)$$

We observe the future performance, also given by cumulative return, over the nearest I periods of time.

$$R_{t+I}(I) = \prod_{i=1}^{I}(1 + r_{t+i}) - 1 \qquad (20)$$

One sample t-tests of the future performance, $R_{t+I}(I)$, relative to the average I-period return for entire the data set, are then carried out for a number of settings and combinations of $R_t(J)$, J and I. In setting values for the different parameters a rather broad approach has been used. However, before setting the parameters of $R_t(J)$, J and I to obtain $R_{t+I}(I)$, one main consideration must be taken into account. The testing of the conditional performance must to be aligned with the parameter settings on the later tested stop-loss rule to give any valuable results. The settings of the parameters of the stop-loss rule are therefore mainly considered when the specification of $R_t(J)$, J and I of the conditional performance is made. A motivation for the settings of the stop-loss rule can be seen in section 3.3.3.

For the past cumulative return window 2 days, 1 day, 5 hours, 1 hour, 30 min, 10 min and 5 min are used. For future cumulative return window the periods are doubled. For the loss parameters, numbers that seem reasonable for the different time-periods are used.

Two different methods for testing the conditional performance are also used. The first method checks all data points for which $R_t(J)$ is smaller than the loss parameter. This might produce clustering effects around very large decreases in the stock price, why a second method is required. Conditional on that $R_t(J)$ is smaller than the loss parameter the second method skips to look large negative returns for the following J minutes. By using the second method overlapping intervals are to some extent considered. However, this method does not handle this problem in fully accurate manner. It can be argued that a more formal procedure regarding overlapping intervals is required to receive adequate answers. On the other hand, since this particular pre-study finds really strong statistical results (see table 4.1 and 4.2 in section 4.3), the applied method may be sufficient to handle overlapping intervals. Consequently, in the light of the strong results, presented in table 4.1 and 4.2 in next section, we ignore the more formal procedures regarding overlapping intervals.

4.3 Empirical Findings of the Conditional Performance

The result for the combinations of $R_t(J)$, J and I and the conditional performance is presented in table 4.1 and 4.2 below.

Table 4.1 – Empirical findings from testing conditional performance, without clustering filter

Pre-period (J)	Post-period, (I)	Cumulative past return, ($R_t(J)$), percent	N, conditional	Mean conditional return, ($R_t(I)$), percent	Mean I-period unconditional return, percent	Sig. (percent)
60	120	0.5	1 372 730	0.04360	0.0011495	<0.01***
300	600	1.0	1 647 041	0.07063	0.0006914	<0.01***
480	960	2.0	1 093 161	0.09728	-0.0049847	<0.01***
960	1920	3.0	1 020 948	0.09253	-0.0411312	<0.01***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

As seen in table 4.1, the conditional return, $R_t(I)$, given a recent fall, $R_t(J)$, are significantly larger than the average I-period return on a 0.1 percent level for all tested combinations of J and I. These results indicate a mean-reverting behavior given a recent fall. However, and as mentioned above, may clustering effects in overlapping intervals bias the results. Consequently, we apply a clustering filter for shorter periods, which is presented in table 4.2 below.

Table 4.2 – Empirical findings from testing conditional performance, with clustering filter

Pre-period (J)	Post-period, (I)	Cumulative past return, ($R_t(J)$), percent	N, conditional	Mean conditional return, ($R_t(I)$), percent	Mean I-period unconditional return, percent	Sig. (percent)
5	10	0.1	113 816	0.16578	0.0005660	<0.01***
10	20	0.1	117 581	0.13936	0.0006546	<0.01***
30	60	0.1	83 337	0.13177	0.0009015	<0.01***
60	120	0.5	55 257	0.12598	0.0011495	<0.01***
300	600	1.0	12 147	0.17183	0.0006914	<0.01***
480	960	2.0	5 879	0.33774	-0.0049847	<0.01***
960	1920	3.0	2 763	0.40159	-0.0411312	<0.1***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

The results that can be seen in table 4.1 and 4.2 are consistent with each other and both show that the returns conditional on a loss are significantly larger than the unconditional returns, which implies a mean-reverting behavior given a recent fall. This holds for all tested time periods and loss parameters, which indicates that the cumulative conditional return of the underlying portfolio has a mean reverting behavior. Hence, based on these results it is questionable whether stop-loss rules really are efficient.

One puzzling result is that the mean unconditional returns for J =5, 10, 30, 60 and 300 min are positive, while the mean unconditional returns for 480 and 960 min are negative. The returns are calculated based on essentially the same data. Some data points in the beginning of the time periods cannot be included for the cumulative returns. I.e. if J = 960, then 959 data points can not be included for each stock (959*30 = 28870 for the whole sample). The difference in unconditional cumulative returns could possibly be explained by the fact that returns are large and positive for the first day. However, one day should not have such a large impact in samples consisting of 2.5 years of data. A more reasonable explanation could potentially be that the arithmetic mean is not a good estimator for this data and it is thus strange results are generated. Even if we not can in a sufficient manner explain these puzzling results, we do not investigate this further due to the purpose of this pre-study.

5. Empirical Findings

In the following chapter we present the empirical findings of stop-loss rules marginal impact on a "buy-and-hold" strategy based on the model specification presented in previous chapter. We aim to present and discuss the level of efficiency together with a discussion where we try to explain the characteristics of the results.

The chapter is structured as follows: We present and analyze the findings and its main implications for the stop-loss rules' marginal impact on expected returns in section 5.1. In section 5.2, we consider risk and present and analyze the findings on stop-loss rules' marginal impact on risk and risk-adjusted expected return.

5.1 Hypothesis 1 – Marginal Impact on Expected Return

Hypothesis 1: *The expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*

As discussed in section 3.1, it is expected that stop-loss rules are inefficient. More specifically, in the light of the model specification and equation (15), it is expected that that the difference in expected return, Δ_μ, is negative for the tested stop-loss rules.

The empirical results of the tests on Δ_μ are plotted in figure 5.1. In addition, complete presentations of the results are viewed in table 8.1-8.5 in Appendix I. The first apparent feature is that Δ_μ is significantly negative for all the tested combinations of γ, I and J when κ is equal to zero, which implies that testing for κ greater than zero is redundant. Best performance values of Δ_μ are obtained when both γ and I are high. Worst performance values of Δ_μ are obtained when both γ and I have low values. These results seem to hold for all the tested combinations of J. The observed characteristics of Δ_μ may depend upon several factors, which together with other characteristics will be discussed later on in this section. Independently of any of the observed characteristic all observed values of Δ_μ are significantly lower than zero, which unambiguously suggests that stop-loss rules are inefficient and have a negative marginal impact in expected return on a "buy-and-hold" portfolio strategy. The empirical findings therefore support hypothesis one by the analysis of the data set.

Furthermore, the inconsistency with the findings presented by Kaminski and Lo (2007) (see Appendix III), can probably be explained by the differences in characteristics between aggregated monthly data and transaction data.[30]

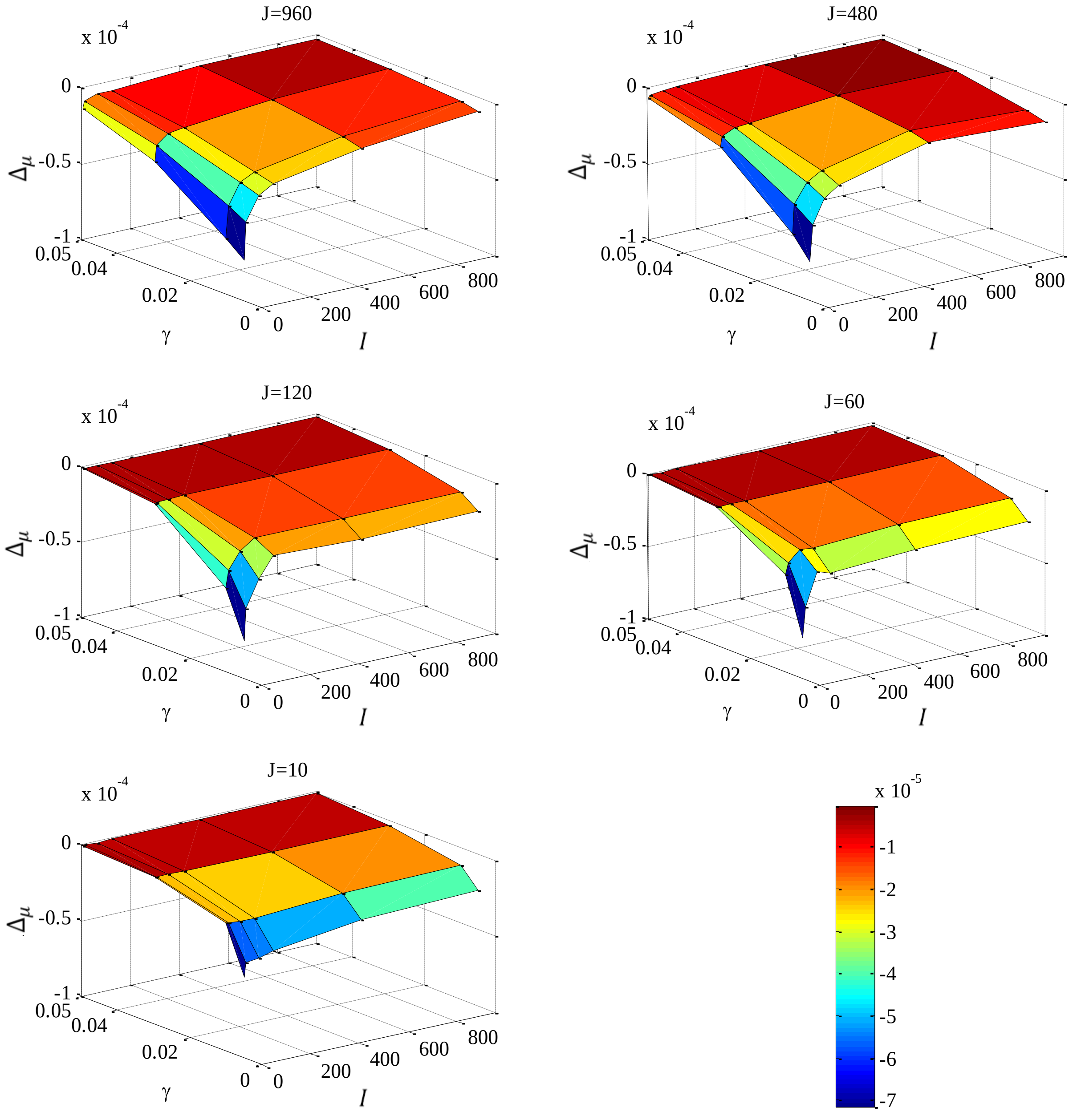

Figure 5.1 – Stopping premium for the stop-loss rule, Δ_μ, for the parameters: γ = 0.5-5%, I=1-960 periods, J=10, 60, 120, 480, and 960 periods.

[30] This inconsistency will be further discussed in chapter six.

Figure 5.1 also demonstrates other additional features, which now will be discussed. Firstly, figure 5.1 shows that Δ_μ approaches zero for when γ increases[31]. Secondly, figure 5.1 shows that Δ_μ decreases with I, especially for small values of I and large values of J.

The first feature is consistent with both the empirical findings and the simulated findings presented by Kaminski and Lo (2007), even if their empirical results show a positive marginal impact from stop-loss rules (see Appendix III). This suggests that the impact from stop-loss rules is reduced for when γ increases, which makes sense if considering that the probability that the stop-loss strategy will be active, p_0, monotonically decreases with γ (see figure 5.2), which is also expected. Furthermore, given that every stop-loss order seems to contribute to the total inefficiency[32], the first feature suggests that Δ_μ decreases when γ increases.

However, this suggestion may provide a skewed picture of the efficiency of individual stop-loss orders, since the probability of using stop-loss orders in the rule p_0, also shifts with γ. Hence, to further investigate the efficiency of stop-loss orders Δ_μ is adjusted to Δ_μ/p_0, which can be seen in figure 5.3. This adjustment allows for interpreting the characteristics of stop-loss orders in a more accurate manner.

[31] Note that the lower boundary γ, is defined as negative (-γ) in equation (14).

[32] In contrast to the empirical findings, but aligned with the simulated findings, presented by Kaminski and Lo (2007).

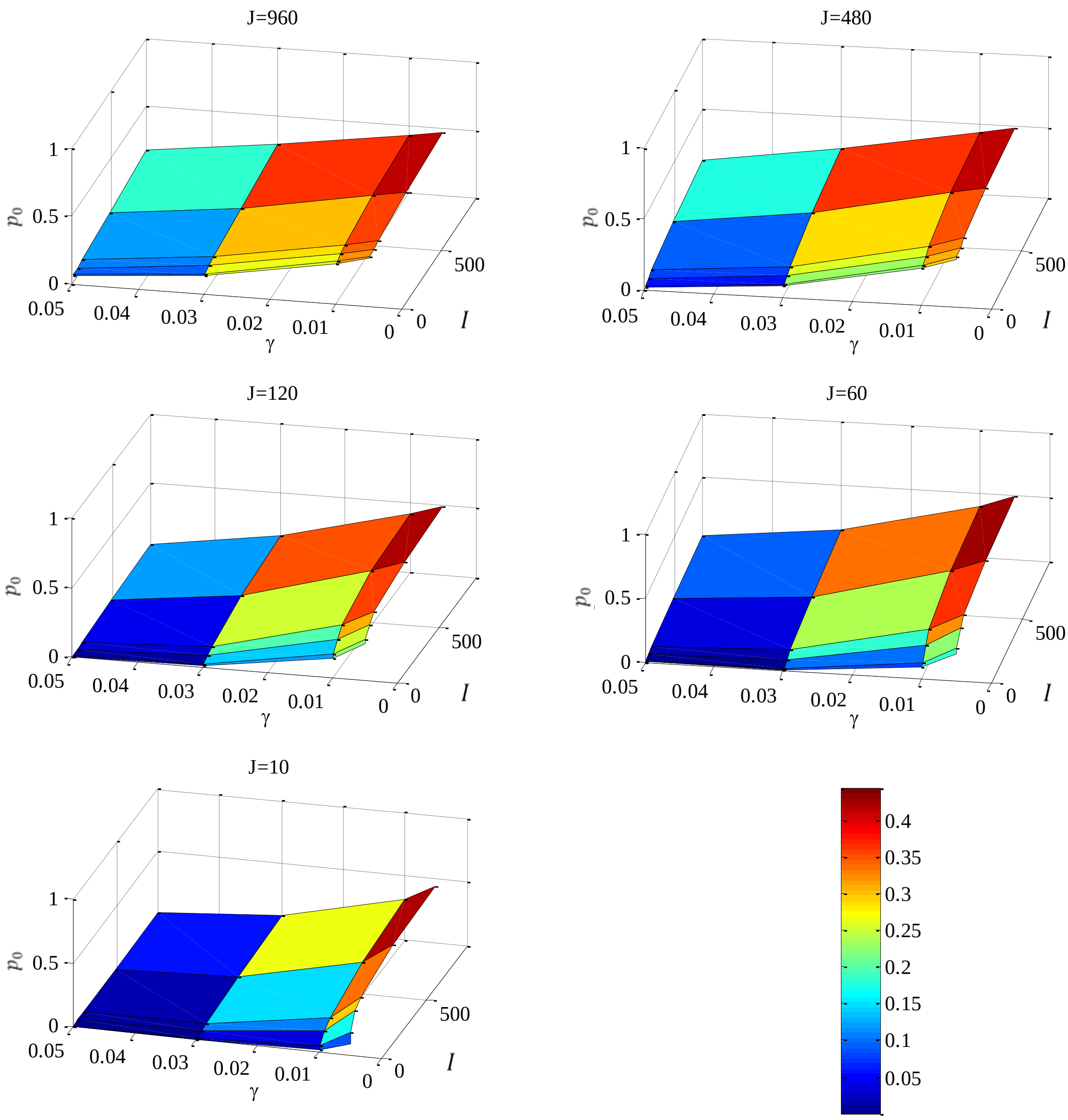

Figure 5.2 – Probability that the stop-loss strategy will be active for the stop-loss rule, p_0*, for the parameters:* γ *= 0.5-5%, I=1-960 periods, J=10, 60, 120, 480, and 960 periods.*

Figure 5.3 clearly shows that differences in Δ_μ with respect to γ almost totally can be explained by differences in p_0, which implies that the inefficiency of stop-loss orders is rather independent of changes in γ. Even if it does not seem to hold for small values of J and I, it may be explained by extreme values. Finally, the described characteristics seen in figure 5.2 and 5.3 are also rather consistent with the empirical and simulated findings presented by Kaminski and Lo (2007) (see Appendix III).

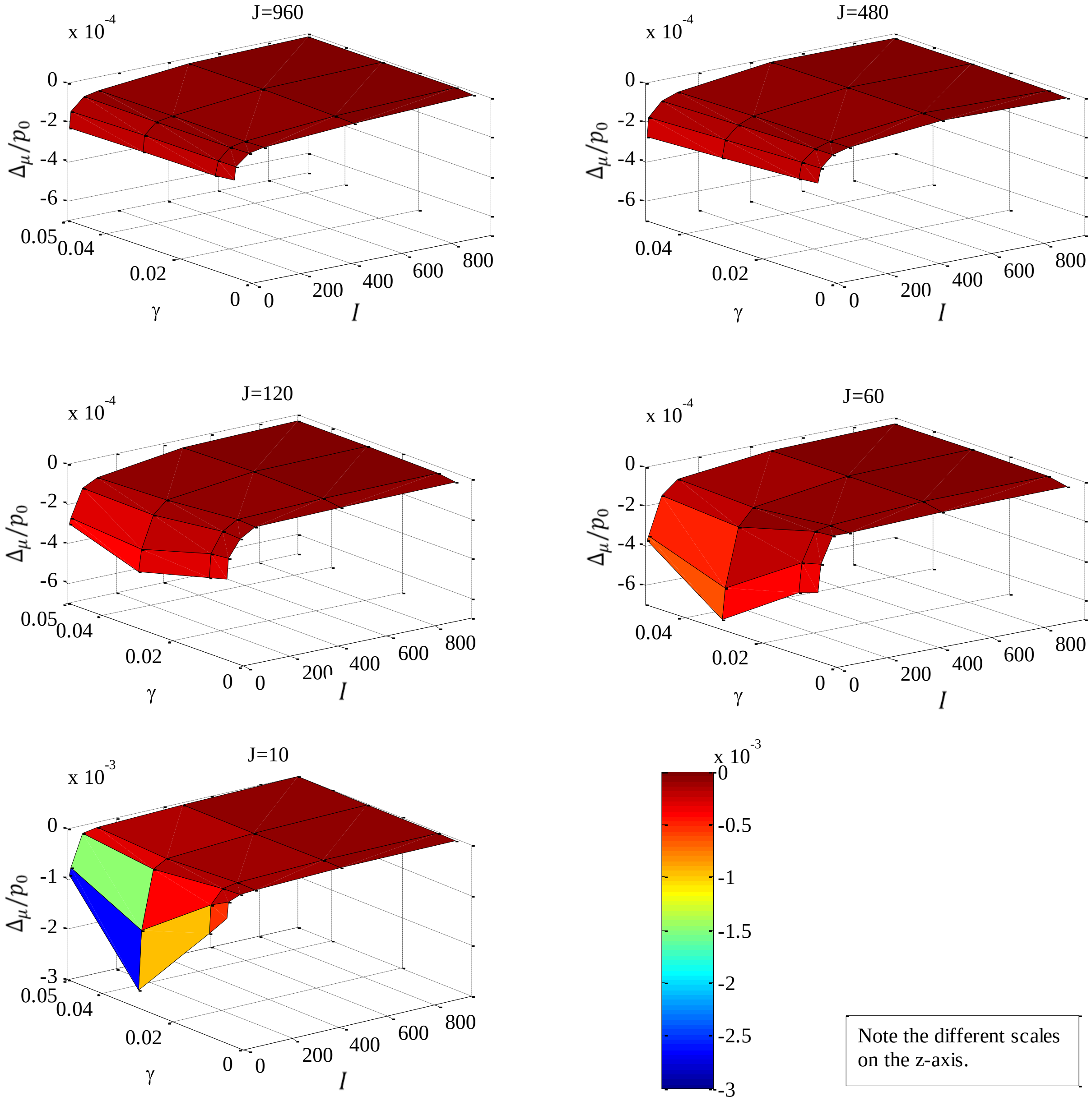

Figure 5.3 – Stopping premium adjusted for the probability that the stop-loss strategy will be active for the stop-loss rule, Δ_μ / p_0*, for the parameters:* γ *= 0.5-5%, I=1-960 periods, J=10, 60, 120, 480, and 960 periods.*

The other feature, where Δ_μ changes with I, do not seem to be explained by adjusting the stopping premium Δ_μ with p_0, which indicates that the inefficiency of stop-loss orders mitigate when the length of the re-entering window increases, especially when the re-entering window is small. Exactly what this relationship depends upon is, however, hard to determine and beyond the scope of this thesis, why this identification is left for further research.

5.2 Hypothesis 2 and 3 – Risk and Risk-Adjusted Expected Return

---

Hypothesis 2: *The volatility is reduced using a stop-loss rule on a "buy-and-hold" portfolio strategy.*

We expect stop-loss rules to reduce the volatility on a "buy-and-hold" portfolio strategy, which is aligned with the theoretical discussion presented in section 2.3.2 and with the findings presented by Kaminski and Lo (2007).

The empirical results of the tests on Δ_σ are plotted in figure 5.4. In addition, complete presentations of the results are viewed in table 8.1-8.5 in Appendix I. Consequently, the empirical findings support hypothesis two based upon the analysis of the data set.

Two features can be identified from figure 5.4. Firstly, the tested stop-loss rules' impact on volatility seems to be larger for low values of γ. Secondly, the difference in standard deviation is larger for large values of I. The first feature is consistent with the empirical and simulated findings presented by Kaminski and Lo (2007) (see Appendix III), and can be explained using a rather straight forward approach. For lower values of γ the portfolio is more often "stopped out", which can be seen in figure 5.2. During these periods the return is equal to the more stable STIBOR rate, which reduces the overall volatility. The second cannot be as easily explained as the first feature. A possible explanation will be discussed, even if other explanations are also possible.

For a given γ and J, a large I will after an exit increase the "stopped out" period compared to a small I.[33] This implies less shifting back and forth between the different instruments, which may result in a lower volatility.

Hypothesis 3: *The risk-adjusted expected return is reduced using the stop-loss rule on a "buy-and-hold" portfolio strategy.*

When testing hypothesis three, it can be seen in figure 5.5, that the Δ_{SR} is negative for all the tested combinations of γ , I and J, which implies that the risk-adjusted returns are smaller with the stop-loss strategies than without. The results can be confirmed in table 8.1-8.5 in Appendix I, which show that all the results are significant on a 0.1 percent level.

---

[33] This is supported by the higher values of p_0 for larger values of I, which can be seen in figure 5.2.

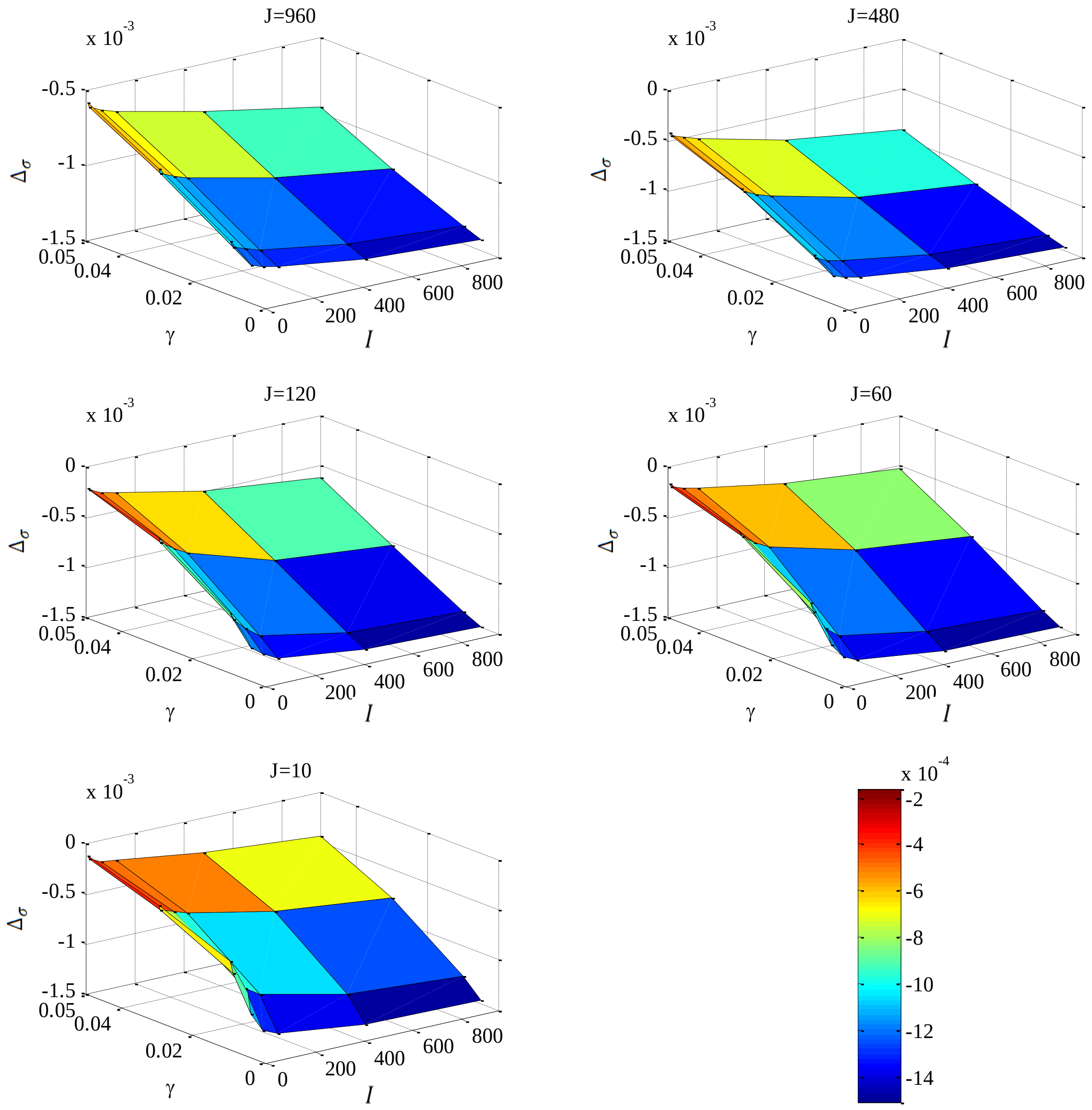

Figure 5.4 – Difference in standard deviation for the stop-loss rule, Δ_σ, for the parameters: γ = 0.5-5%, I=1-960 periods, J=10, 60, 120, 480, and 960 periods.

This suggests that the decrease of the standard deviation for the stop-loss strategy, which can be seen in figure 5.3, does not compensate for the decrease in expected return, which can be seen in figure 5.1. This result is, thus, consistent with hypothesis one, which also conclude that stop-loss rules are inefficient. Aligned with section 5.1, it can therefore be concluded that stop-loss rules are inefficient and have negative marginal impact in risk-adjusted expected return on a "buy-and-hold" portfolio strategy. The empirical findings support hypothesis three based upon the analysis of the data set.

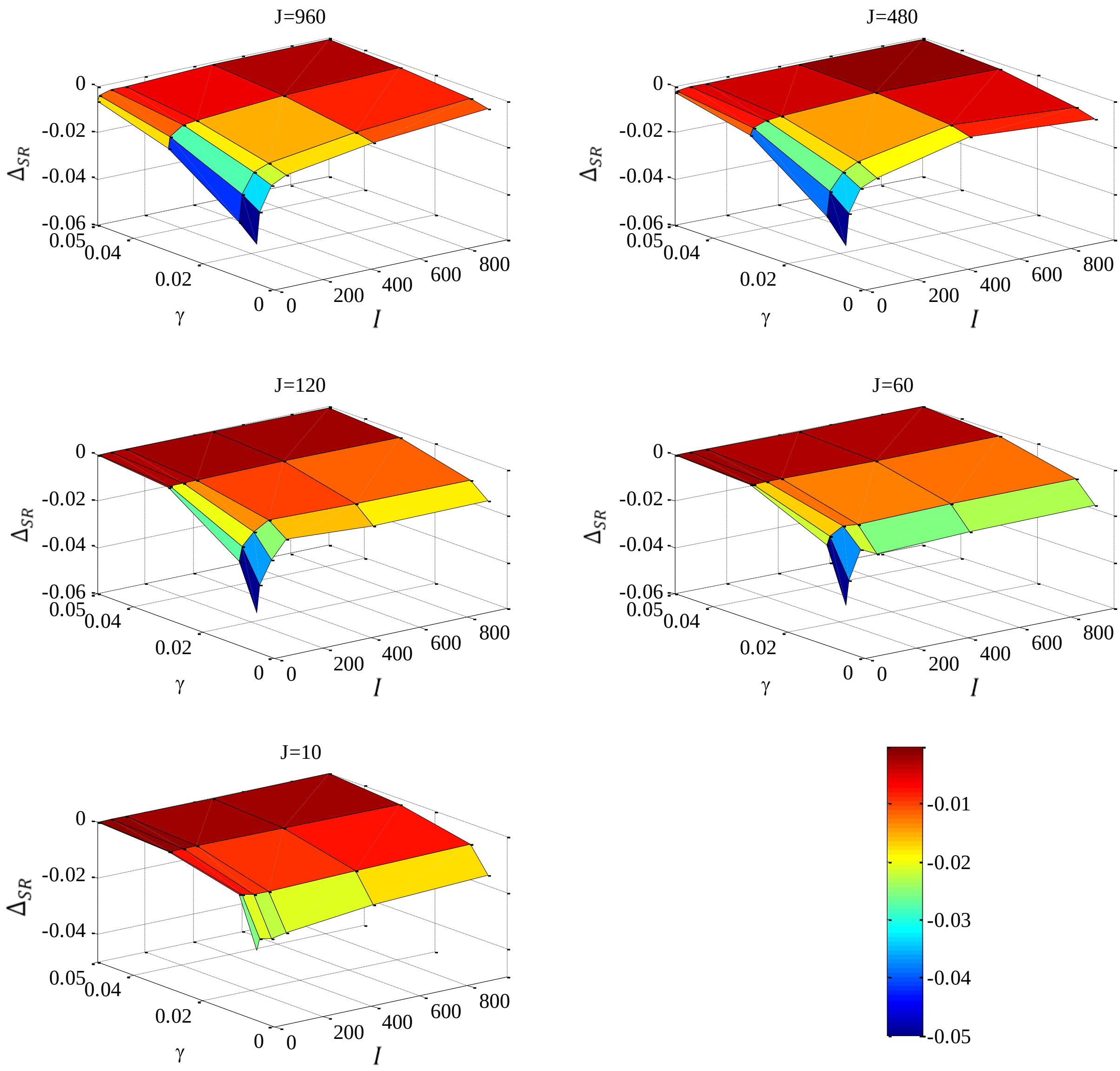

Figure 5.5 – Difference in Sharpe ratio for the stop-loss rule, Δ_{SR}, for the parameters: γ = 0.5-5%, I=1-960 periods, J=10, 60, 120, 480, and 960 periods

Furthermore, the inconsistency with the results presented by Kaminski and Lo (2007) may be explained with the same reasoning as was put forth regarding the inconsistency between differences in expected returns, discussed in section 5.1.

The characteristics of the result for Δ_{SR} are similar to the characteristics of the results for Δ_{μ}, which suggests that the conclusions made for expected returns can also be made for risk-adjusted expected returns.

6. Conclusion

In this concluding chapter we will provide a short summary of the initial questions together with the main empirical findings. We will, furthermore, present some concluding remarks regarding this study and finally provide some suggestions on further research.

6.1 On the Findings

This thesis contributes to the literature regarding stop-loss rules by empirically examining the efficiency based on transaction data. We find considerable evidence that stop-loss strategies are inefficient when looking at short time increments. However, as mentioned earlier, the definition of efficiency and inefficiency may be questioned. If considering rationality when defining efficiency, as demonstrated in section 2.5, stop-loss rules are always efficient. Nevertheless, limiting efficiency to a positive marginal impact in expected return on a "buy-and-hold" portfolio strategy, the following evidence are observed: firstly, we find a strong mean-reverting behavior for the underlying process, which contain the complete trading records of all the stocks included in the OMX Stockholm 30 Index for the period from January 2st 2006 to July 21st 2008. This finding indicates that stop-loss rules are inefficient if applying them on the same underlying process. Secondly, we find that the marginal impact in expected returns for stop-loss rules is significantly negative on a "buy-and-hold" portfolio strategy. This finding holds for all the conducted tests. Finally, we find that even if stop-loss rules reduce the volatility on a "buy-and-hold" portfolio strategy, it does not compensate for the reduction in expected returns. Consequently, the marginal impact on risk-adjusted expected returns for stop-loss rules is significantly negative on a "buy-and-hold" portfolio strategy, when measuring risk-adjusted expected return as the Sharpe ratio. This finding also holds for all the conducted tests. As discussed in section 3.2.3, it should be noted that the results may be biased in an unpredictable way due to the periodicity. However, considering the results consistency with the pre-study, the simulated return-generating processes presented by Kaminski and Lo (2007) and the characteristics of both the simulated return-generating processes and the empirical findings presented by Kaminski and Lo (2007) it is probably reasonable to oversee these potential biases.

One aspect that further strengthens the empirical findings is the fact that all the tests ignored the transaction cost κ, which just would have reduced the efficiency of stop-loss rules further. Another aspect that also strengthens the empirical findings is simplification and overlooking of the order book. As discussed in section 3.2.3, this simplification biases the result upward, which suggests that the results in reality could be expected to be even lower than concluded in this study.

Despite the strength of our evidence, it is inconsistent with the empirical findings presented by Kaminski and Lo (2007), since they found a positive marginal impact in expected return and risk-adjusted expected returns. The discrepancy in empirical findings might have various explanations, two of them are provided below. The first explanation lay in the different types of data and time perspective used to carry out the analysis. Kaminski and Lo (2007) use 54 years of monthly U.S. equity data and event windows between 3-18 months. We use 30 months of transaction data and event windows between 10 minutes and 2 days. The monthly data set is probably much less noisy compared to the transaction data set, which can be explained by the characteristics of data aggregated at one month time intervals. Transactions most probably oscillate around larger trends; oscillations which are captured in transaction data, but vanishes in monthly aggregated data. Borrowing the expressions of Taleb (2004) two things are observed, actual returns and the variability of the portfolio. Over a short time increment, observations consists mainly of the variance, not returns, while monthly data consists to a larger extent of actual returns. Given a rather noisy environment with some sort of market equilibrium it is, consequently, not surprising that we find a mean-reverting behavior, even if the finding of Kaminski and Lo (2007) imply momentum-like effects for large negative equity returns. A second explanation could lay in the different time periods or the different markets that the study is based upon; 1950 to 2004 in the U.S. compared to January 2st 2006 to July 21st 2008 in Sweden. Which of these factors that creates the most discrepancy is of course hard to determine. However, it can be concluded that there are differences and that this might have an impact on the results.

The gravity of our results' inconsistency with the empirical findings presented by Kaminski and Lo (2007) might be mitigated due to the fact that our empirical findings are rather consistent with the simulated return-generating processes presented by Kaminski and Lo (2007). To what extent the inconsistency is mitigated is, however, hard to determine.

As a final note we reflect on the fact that stop-loss strategies seem to be unprofitable, which may suggest that it would be profitable to short-sell this strategy; to sell winners and buy losers, a contrarian strategy. This is consistent with Lehmann (1990) who finds that contrarian strategies based on weekly returns almost always are profitable (even when correcting for transaction costs and for volumes issues like bid-ask spreads). However, in this study the strategies are based on much shorter time horizons than a week, which might affect the results. The noisy data problem, which is discussed above, might be more severe for this study's data set. Furthermore, the return of the strategies in this study should be more sensitive to transaction costs, since more trades are probably conducted than for Lehmann's stocks. Another issue might lay in the size of the data set; with a very large data set the statistical significance can become a problem, since even the smallest variation might turn out to be significant.

6.2 Suggestions for Further Research

Stop-loss orders and stop-loss strategies have gained a lot of interest in the last couple of years. The academic field is, however, relatively unexplored. We have made an empirical study on the efficiency of stop-loss rules, which hopefully will shed further light on the subject. However, due to practical reasons we have made several simplifications of the reality when we simulated the stop-loss rules. A natural first suggestion for further research is to consider the issues ignored in this study, such as transaction costs or the order book, even if we argue that these simplifications do not change our conclusions.

As mentioned, we are aware that the use expected return, volatility and the Sharpe ratio are limited in its ability to fully explain the impact of a dynamic strategy. We, therefore, suggest further research with other approaches evaluating efficiency stop-loss rules.

The model and parameters used in this study may not cover all dynamics of stop-loss orders and stop-loss rules. Consequently, we would like to encourage further research based on other models and parameters. In particular, we suggest further research on the efficiency of stop-loss rules on an extended number of parameters (J, I, γ, δ and κ), on another type of stop-loss rule, or on something else than a "buy-and-hold" portfolio strategy.

As we discussed in previous sections the stock market conditions during the last two and a half years might have an impact on the results. We would, therefore, also like to encourage further research studies to cover other or longer time periods compared to the sample period used in this study. It would also be of great interest to conduct similar studies on other markets.

We would also like to encourage studies which more comprehensively consider the determinants of efficiency besides the underlying stochastic processes. It would, for example, be very interesting to determine relationships between the level of efficiency and parameters such as exiting or re-entering decisions; either empirically or analytically.

As a final suggestion for further research, we encourage studies on transaction data aligned with Shefrin and Statman (1985), which empirically show that stop-loss rules mitigate the disposition effect and are efficient from a behavioral perspective.

7. References

7.1 Literature

Alvesson, M., and Sköldberg, K., 1994, Tolkning och Reflektion*,* Studentlitteratur, Lund.

Andersson, S., 1982, Positivism kontra hermeneutik, Bokförlaget Korpen, Göteborg.

Carr, P., and Jarrow, R., 1990, The Stop-Loss Start-Gain Paradox and Option Valuation: A New Decomposition into Intrinsic and Time Value, *Review of Financial Studies 3*, 469–492.

Davidson, B., and Patel, R., 2003, Forskningsmetodikens grunder. Att planera, genomföra och rapportera en undersökning, Lund: Studentlitteratur.

Ellsberg, D., 1961, Risk, Ambiguity, and the Savage Axioms, *The Quarterly Journal of Economics*, 75(4), 643-669.

Eriksson, L., and Wiederheim-Paul, F., 2006, Att utreda forska och rapportera, Liber, Malmö.

Fama, E., 1965, The Behavior of Stock Market Prices, *Journal of Business 38*, 34-105.

Fama, E., and French, K., 1988, Permanent And Temporary Components of Stock Prices, *Journal of Political Economy 96*, 246-273.

Grinblatt, M., and Keloharju, M., 2000, What Make Investors Trade?, Yale University, Working Paper.

Harris, L., 2003, Trading & Exchanges: Market Microstructure for Practitioners, Oxford Press, Oxford.

Hull, J.C., 2005, Options, Futures and Other Derivatives, 6^{th} ed., Prentice Hall, New Jersey.

Kaminski, K., and Lo, A.M., 2007, When Do Stop-Loss Rules Stop losses?, EFA 2007 Ljubljana Meetings Paper.

Kahneman, D., and Tversky, A., 1979, Prospect Theory: An Analysis of Decision Under Risk, *Econometrica 47*, 263-291.

Kahneman, D., and Tversky, A., 1991, Loss aversion in riskless choice: A reference-dependent model, *The Quarterly Journal of Economics,* 106(4), 1039–1061.

Lehmann, B.N., 1990, Fads, Martingales, and Market Efficiency, National Bureau of Economic Research, NBER Working Papers 2533.

Linnainmaa, J., 2006, The Limit Order Effect, University of Chicago, Working Paper.

Lo, A.W., and MacKinlay, A.C., 1988, Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test, *The Review of Financial Studies*, 1(1), 41-66.

Ma, W., Morita, G., and Detko, K., 2008, Re-Examining the Hidden Costs of the Stop-Loss, University of Washington, Working Paper.

Macrae, R., 2005, The Hidden Cost of the Stoploss, *AIMA Journal April 2005*.

Markowitz, H., 1952, Portfolio Selection, *Journal of Finance 7*, 77-91.

Odean, T., 1998, Are investors reluctant to realize their losses?, *The Journal of Finance*, 53(5), 1775–1798.

Odean, T., 1999, Do investors trade too much?, *The American Economic Review*, 89(5), 1279–1298.

Osler, C.L., 2002, Stop-Loss Order and Price Cascades in Currency Markets, *FRB of New York Staff Report No. 150*.

Rakesh, S., and Weber, M., 1993, Effects of Ambiguity in Market Experiments, *Management Science 39*, 602–615.

Sewell, M., 2007, Behavioral Finance, University College London, Working Paper.

Shefrin, M., and Statman, M., 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, *Journal of Finance 40*, 777–790.

Shiller, R.J., 2002, From Efficient Market Theory to Behavioral Finance, Cowles Foundation Discussion Paper No. 1385.

Taleb, N.N., 2004, Fooled by Randomness: The Hidden Role of Chance in the Markets and in Life, New York.

Tschoegl, A., 1988, The Source and Consequences of Stop Orders: A Conjecture, *Managerial and Decision Economics 9*, 83–85.

7.2 Electronic References

Encyclopædia Britannica, Definition of scientific method, Retrieved June 15, 2008 from: http://www.britannica.com/dictionary?book=Dictionary&va=scientific%20method&query=scientific%20method,

About Stocks, Statement describing stop-loss orders, Retrieved June 28, 2008 from: http://stocks.about.com/od/tradingbasics/a/stoploss.htm,

Market watch, Statement describing stop-loss orders, Retrieved June 28, 2008 from: http://www.marketwatch.com/news/story/stop-loss-orders-offer-downside protection/story.aspx?guid=%7B824F59C3-A41C-4F6C-A51B-B4F6B79AEA70%7D,

7.3 Public Statistics

Riksbanken, STIBOR fixing rate, Retrieved July 23, 2008 from: http://www.riksbank.se/templates/stat.aspx?id=16738

Avanza, Transaction costs, Retrieved August 15, 2008 from: http://www.avanza.se/aza/kundservice/pro/start.jsp?list=4&localnav=229

8. Appendices

8.1 Appendix I – Results from Testing the Stop-loss Rule

Table 8.1 – Results on Δ_μ, Δ_σ and Δ_{SR} of the stop-loss rule (J=960, δ=0 and $\varkappa$=0).

J	I	γ	δ	$\varkappa$	Δ_μ	t-value	p_0	Δ_σ	N	f-value	Δ_{SR}	t-value
960	960	0.05	0	0	-1.96E-06	-5.16***	0.17	-9.55E-04	6 335 942	1.28***	-0.00098	-5.18***
960	960	0.03	0	0	-3.28E-06	-6.98***	0.29	-1.18E-03	6 335 942	1.50***	-0.0018	-7.48***
960	960	0.01	0	0	-6.81E-06	-12.34***	0.43	-1.39E-03	6 335 942	1.84***	-0.00424	-14.73***
960	960	0.005	0	0	-9.46E-06	-16.59***	0.46	-1.43E-03	6 335 942	1.95***	-0.00615	-20.53***
960	480	0.05	0	0	-2.76E-06	-8.56***	0.12	-8.11E-04	6 335 942	1.18***	-0.0014	-8.74***
960	480	0.03	0	0	-6.34E-06	-14.90***	0.23	-1.07E-03	6 335 942	1.37***	-0.00349	-16.25***
960	480	0.01	0	0	-1.3E-05	-25.07***	0.39	-1.33E-03	6 335 942	1.72***	-0.00821	-30.05***
960	480	0.005	0	0	-1.6E-05	-28.69***	0.43	-1.39E-03	6 335 942	1.84***	-0.01021	-35.41***
960	120	0.05	0	0	-5.58E-06	-20.66***	0.08	-6.79E-04	6 335 942	1.12***	-0.00283	-21.26***
960	120	0.03	0	0	-1.2E-05	-31.05***	0.17	-9.42E-04	6 335 942	1.27***	-0.00628	-33.48***
960	120	0.01	0	0	-2.3E-05	-46.56***	0.33	-1.23E-03	6 335 942	1.56***	-0.01372	-54.55***
960	120	0.005	0	0	-2.6E-05	-50.29***	0.38	-1.31E-03	6 335 942	1.68***	-0.01626	-60.58***
960	60	0.05	0	0	-5.96E-06	-23.15***	0.07	-6.48E-04	6 335 942	1.11***	-0.00302	-23.79***
960	60	0.03	0	0	-1.4E-05	-37.35***	0.16	-9.09E-04	6 335 942	1.24***	-0.00724	-40.11***
960	60	0.01	0	0	-2.8E-05	-57.49***	0.32	-1.21E-03	6 335 942	1.53***	-0.01641	-66.89***
960	60	0.005	0	0	-3.2E-05	-62.06***	0.37	-1.28E-03	6 335 942	1.64***	-0.0195	-74.24***
960	10	0.05	0	0	-8.72E-06	-36.18***	0.06	-6.06E-04	6 335 942	1.10***	-0.00441	-37.16***
960	10	0.03	0	0	-2E-05	-58.35***	0.14	-8.67E-04	6 335 942	1.22***	-0.01071	-62.41***
960	10	0.01	0	0	-4.2E-05	-88.95***	0.30	-1.17E-03	6 335 942	1.49***	-0.02448	-102.84***
960	10	0.005	0	0	-4.8E-05	-96.79***	0.36	-1.25E-03	6 335 942	1.60***	-0.02946	-115.04***
960	1	0.05	0	0	-1.3E-05	-56.65***	0.06	-5.79E-04	6 335 942	1.09***	-0.00658	-58.18***
960	1	0.03	0	0	-3E-05	-91.62***	0.14	-8.35E-04	6 335 942	1.20***	-0.01612	-97.70***
960	1	0.01	0	0	-6.2E-05	-137.81***	0.30	-1.14E-03	6 335 942	1.45***	-0.03636	-158.06***
960	1	0.005	0	0	-7.3E-05	-149.81***	0.35	-1.22E-03	6 335 942	1.55***	-0.04367	-176.32***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

Table 8.2 – Results on Δ_μ, Δ_σ and Δ_{SR} of the stop-loss rule (J=480, δ=0 and $\varkappa$=0).

J	I	γ	δ	$\varkappa$	Δ_μ	t-value	p_0	Δ_σ	N	f-value	Δ_{SR}	t-value
480	960	0.05	0	0	-2.24E-06	-6.22***	0.15	-9.09E-04	6 350 342	1.24***	-0.00113	-6.29***
480	960	0.03	0	0	-4.78E-06	-10.19***	0.28	-1.18E-03	6 350 342	1.49***	-0.00268	-11.21***
480	960	0.01	0	0	-1.3E-05	-22.57***	0.44	-1.41E-03	6 350 342	1.89***	-0.0082	-27.94***
480	960	0.005	0	0	-1.6E-05	-27.21***	0.48	-1.46E-03	6 350 342	2.03***	-0.01066	-34.78***
480	480	0.05	0	0	-1.84E-06	-6.20***	0.09	-7.47E-04	6 350 342	1.15***	-0.00091	-6.18***
480	480	0.03	0	0	-3.81E-06	-9.14***	0.21	-1.05E-03	6 350 342	1.35***	-0.00204	-9.70***
480	480	0.01	0	0	-8.51E-06	-15.90***	0.40	-1.35E-03	6 350 342	1.76***	-0.00526	-18.89***
480	480	0.005	0	0	-1.2E-05	-21.47***	0.45	-1.42E-03	6 350 342	1.90***	-0.00782	-26.58***
480	120	0.05	0	0	-3.39E-06	-15.94***	0.04	-5.35E-04	6 350 342	1.07***	-0.00168	-16.12***
480	120	0.03	0	0	-8.71E-06	-26.12***	0.12	-8.41E-04	6 350 342	1.20***	-0.00458	-27.57***
480	120	0.01	0	0	-2.3E-05	-46.58***	0.32	-1.22E-03	6 350 342	1.54***	-0.01343	-54.25***
480	120	0.005	0	0	-2.8E-05	-52.92***	0.39	-1.31E-03	6 350 342	1.69***	-0.01725	-63.95***
480	60	0.05	0	0	-3.58E-06	-18.21***	0.03	-4.96E-04	6 350 342	1.06***	-0.00178	-18.40***
480	60	0.03	0	0	-1E-05	-32.59***	0.10	-7.91E-04	6 350 342	1.17***	-0.00533	-34.24***
480	60	0.01	0	0	-2.7E-05	-58.68***	0.29	-1.18E-03	6 350 342	1.49***	-0.01611	-67.63***
480	60	0.005	0	0	-3.4E-05	-66.38***	0.37	-1.28E-03	6 350 342	1.63***	-0.02075	-79.32***
480	10	0.05	0	0	-4.44E-06	-25.22***	0.03	-4.44E-04	6 350 342	1.05***	-0.0022	-25.47***
480	10	0.03	0	0	-1.4E-05	-48.49***	0.09	-7.32E-04	6 350 342	1.15***	-0.00728	-50.68***
480	10	0.01	0	0	-4E-05	-90.67***	0.27	-1.12E-03	6 350 342	1.43***	-0.02338	-103.24***
480	10	0.005	0	0	-5E-05	-102.30***	0.34	-1.23E-03	6 350 342	1.57***	-0.0303	-120.70***
480	1	0.05	0	0	-6.14E-06	-37.37***	0.02	-4.14E-04	6 350 342	1.04***	-0.00304	-37.77***
480	1	0.03	0	0	-2E-05	-73.64***	0.08	-6.94E-04	6 350 342	1.13***	-0.01044	-76.75***
480	1	0.01	0	0	-6E-05	-138.63***	0.26	-1.08E-03	6 350 342	1.39***	-0.03396	-156.41***
480	1	0.005	0	0	-7.4E-05	-156.59***	0.33	-1.19E-03	6 350 342	1.51***	-0.04404	-182.63***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

Table 8.3 – Results on Δ_μ, Δ_σ and Δ_{SR} of the stop-loss rule (J=120, δ=0 and $\varkappa$=0).

J	I	γ	δ	$\varkappa$	Δ_μ	t-value	p_0	Δ_σ	N	f-value	Δ_{SR}	t-value
120	960	0.05	0	0	-1.43E-06	-5.80***	0.06	-2.01E-03	6 361 142	1.10***	-0.00069	-5.71***
120	960	0.03	0	0	-4.43E-06	-10.90***	0.19	-1.03E-03	6 361 142	1.33***	-0.00238	-11.59***
120	960	0.01	0	0	-1.5E-05	-27.09***	0.42	-1.41E-03	6 361 142	1.90***	-0.00988	-33.70***
120	960	0.005	0	0	-2.3E-05	-38.97***	0.50	-1.50E-03	6 361 142	2.14***	-0.01615	-51.23***
120	480	0.05	0	0	-1.26E-06	-6.33***	0.04	-5.01E-04	6 361 142	1.06***	-0.00061	-6.24***
120	480	0.03	0	0	-4.49E-06	-12.37***	0.14	-9.15E-04	6 361 142	1.25***	-0.00235	-12.98***
120	480	0.01	0	0	-1.5E-05	-28.54***	0.39	-1.36E-03	6 361 142	1.79***	-0.0098	-34.79***
120	480	0.005	0	0	-2.4E-05	-41.29***	0.47	-1.46E-03	6 361 142	2.03***	-0.01626	-53.20***
120	120	0.05	0	0	-1.06E-06	-8.46***	0.01	-3.17E-04	6 361 142	1.02***	-0.00052	-8.39***
120	120	0.03	0	0	-4.63E-06	-17.97***	0.06	-6.49E-04	6 361 142	1.11***	-0.00233	-18.38***
120	120	0.01	0	0	-1.5E-05	-31.84***	0.28	-1.20E-03	6 361 142	1.51***	-0.00888	-36.60***
120	120	0.005	0	0	-2.2E-05	-41.71***	0.40	-1.35E-03	6 361 142	1.76***	-0.01421	-50.99***
120	60	0.05	0	0	-9.13E-07	-8.36***	0.01	-2.75E-04	6 361 142	1.02***	-0.00044	-8.29***
120	60	0.03	0	0	-4.90E-06	-21.96***	0.03	-5.63E-04	6 361 142	1.08***	-0.00245	-22.34***
120	60	0.01	0	0	-2.2E-05	-50.08***	0.22	-1.09E-03	6 361 142	1.40***	-0.01236	-56.24***
120	60	0.005	0	0	-3.5E-05	-68.91***	0.35	-1.28E-03	6 361 142	1.64***	-0.0216	-82.46***
120	10	0.05	0	0	-8.76E-07	-9.60***	0.00	-2.30E-04	6 361 142	1.01***	-0.00042	-9.54***
120	10	0.03	0	0	-5.37E-06	-28.23***	0.02	-4.80E-04	6 361 142	1.06***	-0.00267	-28.60***
120	10	0.01	0	0	-3.2E-05	-83.26***	0.16	-9.77E-04	6 361 142	1.29***	-0.01775	-91.27***
120	10	0.005	0	0	-5.3E-05	-112.95***	0.29	-1.18E-03	6 361 142	1.50***	-0.03145	-131.19***
120	1	0.05	0	0	-7.65E-07	-9.75***	0.00	-1.98E-04	6 361 142	1.01***	-0.00037	-9.69***
120	1	0.03	0	0	-5.87E-06	-34.43***	0.01	-4.30E-04	6 361 142	1.05***	-0.00291	-34.82***
120	1	0.01	0	0	-4.4E-05	-122.62***	0.14	-9.06E-04	6 361 142	1.24***	-0.02381	-132.66***
120	1	0.005	0	0	-7.5E-05	-170.88***	0.26	-1.11E-03	6 361 142	1.41***	-0.0433	-194.45***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

Table 8.4 – Results on Δ_μ, Δ_σ and Δ_{SR} of the stop-loss rule (J=60, δ=0 and $\varkappa$=0).

J	I	γ	δ	$\varkappa$	Δ_μ	t-value	p_0	Δ_σ	N	f-value	Δ_{SR}	t-value
60	960	0.05	0	0	-1.16E-06	-5.40***	0.04	-5.41E-04	6 362 942	1.07***	-0.00056	-5.28***
60	960	0.03	0	0	-3.87E-06	-10.37***	0.15	-9.43E-04	6 362 942	1.27***	-0.00203	-10.84***
60	960	0.01	0	0	-1.5E-05	-26.30***	0.40	-1.40E-03	6 362 942	1.86***	-0.0094	-32.45***
60	960	0.005	0	0	-2.6E-05	-43.54***	0.49	-1.51E-03	6 362 942	2.16***	-0.01823	-57.54***
60	480	0.05	0	0	-9.23E-07	-5.47***	0.02	-4.26E-04	6 362 942	1.04***	-0.00044	-5.36***
60	480	0.03	0	0	-4.07E-06	-12.60***	0.10	-8.15E-04	6 362 942	1.19***	-0.00209	-13.03***
60	480	0.01	0	0	-1.6E-05	-29.14***	0.37	-1.35E-03	6 362 942	1.75***	-0.00979	-35.27***
60	480	0.005	0	0	-2.8E-05	-47.52***	0.47	-1.47E-03	6 362 942	2.06***	-0.01905	-61.76***
60	120	0.05	0	0	-7.13E-07	-6.59***	0.01	-2.73E-04	6 362 942	1.02***	-0.00034	-6.51***
60	120	0.03	0	0	-4.39E-06	-18.84***	0.04	-5.88E-04	6 362 942	1.09***	-0.0022	-19.17***
60	120	0.01	0	0	-1.8E-05	-38.16***	0.27	-1.19E-03	6 362 942	1.51***	-0.01061	-43.92***
60	120	0.005	0	0	-3.2E-05	-58.05***	0.40	-1.37E-03	6 362 942	1.81***	-0.02041	-71.97***
60	60	0.05	0	0	-6.44E-07	-6.87***	0.00	-2.37E-04	6 362 942	1.01***	-0.00031	-6.79***
60	60	0.03	0	0	-4.15E-06	-20.49***	0.02	-5.10E-04	6 362 942	1.07***	-0.00206	-20.75***
60	60	0.01	0	0	-1.7E-05	-40.15***	0.20	-1.08E-03	6 362 942	1.39***	-0.00976	-44.85***
60	60	0.005	0	0	-2.8E-05	-54.26***	0.35	-1.31E-03	6 362 942	1.68***	-0.0175	-65.36***
60	10	0.05	0	0	-5.15E-07	-6.67***	0.00	-1.95E-04	6 362 942	1.01***	-0.00025	-6.60***
60	10	0.03	0	0	-3.95E-06	-23.61***	0.01	-4.22E-04	6 362 942	1.04***	-1.95E-03	-23.80***
60	10	0.01	0	0	-2.51E-05	-70.65***	0.11	-8.97E-04	6 362 942	1.24***	-1.35E-02	-76.07***
60	10	0.005	0	0	-5.09E-05	-111.17***	0.25	-1.15E-03	6 362 942	1.46***	-2.98E-02	-127.88***
60	1	0.05	0	0	-3.77E-07	-5.90***	0.00	-1.61E-04	6 362 942	1.01***	-1.82E-04	-5.84***
60	1	0.03	0	0	-3.61E-06	-24.52***	0.01	-3.72E-04	6 362 942	1.03***	-1.78E-03	-24.66***
60	1	0.01	0	0	-3.26E-05	-101.90***	0.09	-8.08E-04	6 362 942	1.18***	-1.72E-02	-108.18***
60	1	0.005	0	0	-7.14E-05	-170.80***	0.21	-1.05E-03	6 362 942	1.36***	-4.04E-02	-191.56***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

Table 8.5 – Results on Δ_μ, Δ_σ and Δ_{SR} of the stop-loss rule (J=60, δ=0 and $\varkappa$=0).

J	I	γ	δ	$\varkappa$	Δ_μ	t-value	p_0	Δ_σ	N	f-value	Δ_{SR}	t-value
10	960	0.05	0	0	-8.66E-07	-4.87***	0.03	-4.48E-04	6 364 442	1.05***	-4.13E-04	-4.75***
10	960	0.03	0	0	-3.88E-06	-12.32***	0.10	-7.94E-04	6 364 442	1.18***	-1.98E-03	-12.70***
10	960	0.01	0	0	-1.16E-05	-22.52***	0.32	-1.30E-03	6 364 442	1.67***	-7.07E-03	-26.57***
10	960	0.005	0	0	-2.36E-05	-40.23***	0.44	-1.48E-03	6 364 442	2.07***	-1.62E-02	-52.26***
10	480	0.05	0	0	-6.79E-07	-4.93***	0.02	-3.48E-04	6 364 442	1.03***	-3.25E-04	-4.82***
10	480	0.03	0	0	-3.70E-06	-14.18***	0.06	-6.59E-04	6 364 442	1.11***	-1.86E-03	-14.45***
10	480	0.01	0	0	-1.32E-05	-27.31***	0.27	-1.22E-03	6 364 442	1.54***	-7.78E-03	-31.48***
10	480	0.005	0	0	-2.61E-05	-45.50***	0.42	-1.45E-03	6 364 442	1.98***	-1.76E-02	-58.23***
10	120	0.05	0	0	-4.48E-07	-5.03***	0.00	-2.25E-04	6 364 442	1.01***	-2.15E-04	-4.95***
10	120	0.03	0	0	-3.40E-06	-18.05***	0.02	-4.76E-04	6 364 442	1.06***	-1.68E-03	-18.21***
10	120	0.01	0	0	-1.58E-05	-39.31***	0.15	-1.01E-03	6 364 442	1.32***	-8.72E-03	-43.14***
10	120	0.005	0	0	-3.32E-05	-62.67***	0.34	-1.34E-03	6 364 442	1.74***	-2.11E-02	-76.63***
10	60	0.05	0	0	-4.03E-07	-5.07***	0.00	-2.01E-04	6 364 442	1.01***	-1.94E-04	-4.99***
10	60	0.03	0	0	-3.28E-06	-18.99***	0.01	-4.36E-04	6 364 442	1.05***	-1.62E-03	-19.12***
10	60	0.01	0	0	-1.62E-05	-44.34***	0.11	-9.25E-04	6 364 442	1.25***	-8.77E-03	-47.82***
10	60	0.005	0	0	-3.58E-05	-70.70***	0.30	-1.28E-03	6 364 442	1.63***	-2.21E-02	-84.53***
10	10	0.05	0	0	-3.52E-07	-5.75***	0.00	-1.55E-04	6 364 442	1.01***	-1.70E-04	-5.69***
10	10	0.03	0	0	-3.10E-06	-20.39***	0.00	-3.83E-04	6 364 442	1.04***	-1.52E-03	-20.48***
10	10	0.01	0	0	-1.50E-05	-50.92***	0.04	-7.45E-04	6 364 442	1.15***	-7.80E-03	-53.34***
10	10	0.005	0	0	-3.70E-05	-86.43***	0.17	-1.08E-03	6 364 442	1.38***	-2.10E-02	-97.16***
10	1	0.05	0	0	-1.89E-07	-4.17***	0.00	-1.14E-04	6 364 442	1.00***	-9.08E-05	-4.13***
10	1	0.03	0	0	-2.61E-06	-19.86***	0.00	-3.32E-04	6 364 442	1.03***	-1.28E-03	-19.90***
10	1	0.01	0	0	-1.47E-05	-59.87***	0.02	-6.19E-04	6 364 442	1.10***	-7.46E-03	-61.75***
10	1	0.005	0	0	-4.69E-05	-135.60***	0.09	-8.72E-04	6 364 442	1.22***	-2.51E-02	-145.81***

*, ** and *** denote significance at the 5%, 1% and 0.1% level respectively.

8.2 Appendix II – Descriptive Statistics for the Data Set and for the STIBOR Data

Table 8.6 – Overview descriptive statistics for the adjusted data set

Descriptive statistics of one period returns, overview	
N	6 365 336
Mean	3.042E-6
Std Deviation	0.00343
t-value *(mean=0)*	2.24

Table 8.7 – Overview descriptive statistics for STIBOR data

Descriptive statistics of one period returns for STIBOR data, overview	
N	933
Mean	1.87E-7
Std Deviation	4.91E-8
t-value *(mean=0)*	114.05

Table 8.8 – Quantile statistics for the adjusted data set

Descriptive statistics for the data set of one period returns, quantile	
99%	0.00467290
90%	0.00227273
75% Q3	0.00000000
50% Median	0.00000000
25% Q1	0.00000000
10%	-0.00227273
1%	-0.00465116

8.3 Appendix III – Some Results Presented by Kaminski and Lo (2007), *I*=1 Month

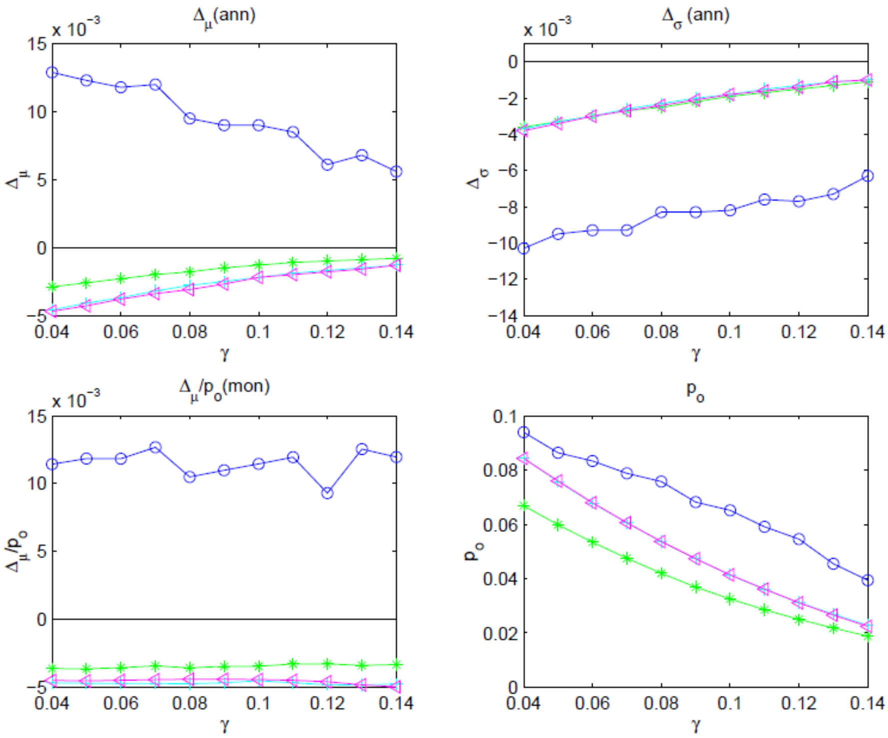

Figure 6: Empirical and simulated performance metrics Δ_μ,Δ_σ, $\frac{\Delta_\mu}{p_o}$, and p_o for the simple stop-loss policy with stopping thresholds $\gamma = 4$–14%, $\delta = 0\%$, $J = 12$ months. The empirical results ($\circ$) are based on monthly returns of the CRSP Value-Weighted Total Market Index and Ibbotson Associates Long-Term Bond Index from January 1950 to December 2004. The simulated performance metrics are averages across 10,000 replications of 660 monthly normally distributed returns for each of three return-generating processes: IID (+), an AR(1) ($\triangle$), and a regime-switching model ($*$).

Figure 8.1 – Figure 6 from Kaminski and Lo (2007), preseneting some empirical and simulated results.