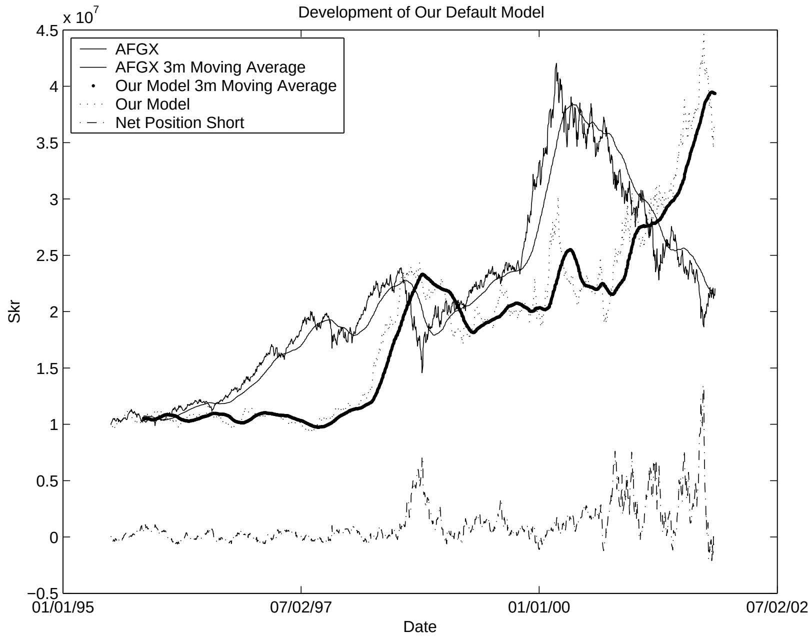
A Market Neutral Statistical Arbitrage Trading Model



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Abstract

The momentum effect is a systematic inefficiency in the market that can be exploited by a trading strategy. This conclusion is supported by theoretical and empirical evidence. But the academic research that tries to quantify the performance of this kind of strategy often relies on a methodology that is too simplistic. The question arises what performance a trader realistically could achieve in relation to the results presented in academic journals.

To answer this, we have written a computer program to run simulations with the added realism of transaction costs and more advanced trading rules based on a wider array of data than classic methodology allows. This has been done on Swedish stocks between 1995 and 2001. We then compare the simulation based on our own advanced model with a simulation that emulates a simplistic methodology.

It is found that the negative impact on return of including transaction costs is outweighed by the lower risk attributed to our more advanced trading rules, as indicated by e.g. Sharpe and standard measures of risk. We can thus conclude that the momentum effect might be even more attractive as a basis for a trading strategy than have been suggested in prior academic research.

As an academic paper, we think that the methodology (our simulation platform) used to obtain the conclusion in our thesis is more important than the conclusion itself. It is evident that a good evaluation of any trading strategy requires more realistic simulations than is commonplace in academia today.

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1 Introduction

1.1 Background

Technical analysts have always been the neglected outcasts of the world of academic finance. Business students learn in their first year that any attempts to study historical data in search of that elusive gold mine are futile. The market quickly abolishes such pretensions. And it is not hard to see why the lecturer has that sarcastic tone in his voice while preaching the laws of finance and their relentless effect on the pity chartist. Anyone who has read a book from the 80's on charting techniques knows why. Pen and paper are the tools, and with them one will find specific patterns of stock prices emerging and then it is just to fill in the blanks and the order book. No statistical or theoretical foundation, no portfolio view or risk control. But often with a closing chapter on the link between the stock market and astrology.

This tarnished image did not disappear even as the upholding arguments of the efficient market hypothesis (hereafter EMH) came under question in the 80's; the assumptions of the rational investor and the effect of arbitrage on bringing back prices to their fundamental value. A tidal wave of theory and empirical evidence has since then given the chartists right on their main point: historical data do provide some information valuable in predicting future prices. The reason being irrational investors and limited arbitrage.

The old school of technical analysis has not changed that much though except for better data and computing power, but the professional community of investment management did change. In conjunction with the surge of alternative investments in the 90's, many popular strategies were based on the new paradigm, trying to exploit systematic inefficiencies in the market. And the question of where the line between arbitrage profits and risk premium goes may be one of semantic rather than practical importance, especially in the more number-crunching inclined strategies.

In any case, the explosive growth of the hedge-fund industry, the availability of good data and more powerful computers, have moved the frontiers for the statistically interested investor and manager. The situation today is indeed horizons away from the pen and paper chartist of the 80's. Our own skills in programming and mathematics intersect with this new development and the gold-shimmering prospect of finding an untouched deposit of a steady stream of profits. This is of course the ancient romantic dream that have left many fortune hunters in dismay and destitution. So a more realistic goal for this master thesis becomes an attempt to use some of the new theory and empirical research that has come under the name of behavioral finance in recent years to construct a trading model which performance will be tested.

Specifically, we are looking at a strategy categorized as *market neutral statistical arbitrage*. It is an equity market neutral strategy of interest for investors who want to have an asset with low market correlation. This strategy has caught the attention of many academicians lately, as being a good example of a systematic inefficiency on the market. The methodology used when analyzing this phenomenon in most academic papers, called Cumulative Abnormal Return (CAR), is straightforward and easy to use. However, it is also very rigid and simplistic.

To assess the true potential of exploiting the momentum effect, we argue, one must simulate trading in a way that is much more realistic and that combines a variety of trading rules. We have done this by constructing a simulation platform, a computer program, amounting to a total of 220 pages of Java code.

1.2 Purpose

The purpose of this Master Thesis is to assess the merits in terms of risk and return of a self-made trading model based on the momentum effect. This is however not done in an absolute way, instead we want to see how performance changes in our sample when we introduce both transaction costs and more advanced trading rules *in relation* to the naive (or simplistic, see Appendix A.6 for a definition) strategy common in academic papers on the momentum effect. We can then determine whether it is feasible to exploit the momentum effect in a more realistic setting.

As a second, but in our view more important objective of this thesis, we want to demonstrate the simulation platform we have developed, and advocate its use as a superior methodology when evaluating trading strategies.

1.3 Delimitation

We limit the scale and scope of our thesis in the following areas:

- Our data is limited to 6 years of Swedish financial and fundamental data (see further Section 4). We have however stock quotes for more than ten years in Sweden, Germany, France and the United Kingdom. This data will be analyzed in the Appendix to estimate the robustness of our model and the underlying market inefficiency it tries to exploit.
- The technical details of our model and simulation platform are not the focus of this thesis and will not be examined in depth. It is not possible with the information in this thesis to replicate the simulation platform or the exact algorithms that constitute our own trading model. This would have required a lot of technical documentation that we have chosen to withhold.
- We have still not optimized our market neutral statistical arbitrage model in a way that would be recommendable in a real life setting. For example; we are fully invested at all times, we do not consider an optimal hedge, and we do always include 10 long and 10 short positions in our portfolio.

Further clarification and justification for the focus of the model within these limitations are given in more detail in Sections 3 and 5.

1.4 Outline and Reader's Guide

To our knowledge, no other master thesis in Sweden has been written in an attempt to produce a full-fledged trading system. This should be seen in light of the fact that the required computing power and data quality have not been available more than a few years for student use.

What we gain in realism is lost in simplicity, and thus to some extent also in replicability, transparency and focus. But realism *is* an objective of this thesis. As is our critique of simplistic methodologies, such as CAR, and their equally simplistic conclusions that do not extend beyond a mere theoretical domain, often without bearing on the real world.

Our thesis is structured as follows:

- **Previous Research**. First of all, we want to establish a theoretical and empirical foundation for the inefficiencies (in an EMH sense) we want to exploit. We provide a theoretical model that tries to explain the phenomenon of momentum in stock prices. Also, we highlight some empirical evidence on the momentum effect from different stock markets, using the classic CAR methodology. Furthermore, we look at other variables that could be used in the model, such as sentiment and fundamental variables.

- **An Overview of the Model and its Context**. Next, we look at our model in the context of different trading strategies used by hedge funds and make some notes on the technical structure of our simulation platform. This section does not lie on the otherwise straight line between purpose and conclusions, but is important for the general understanding of this thesis.
- **Data**. The data used as input in the model is described in this chapter.
- **Methodology – Signal Generation and Risk Control**. This chapter describes how we turn the input into output, i.e. a market neutral portfolio. Signal generation deals with how buy and sell signals are generated from the data. Risk control is necessary in order to optimize the risk-return profile on a portfolio level, by taking into consideration the risk implications of the generated buy and sell signals.

  The word methodology here is referring to how we derive the algorithms used when deciding what, when and how many stocks should be bought or sold at a specific moment. The methodology in a wider sense is referring to the Java program, or simulation platform, that we use to implement the algorithms.
- **Results – Portfolio Simulations**. The model's output is statistically analyzed and then compared with a simplistic strategy with static rebalancing and only price as an input variable.

Finally, we conclude on our findings. In the Appendix, we have an extensive discussion on the robustness of our model, based on out-of-sample tests of our model using price data from Germany, France, UK and Sweden. Basic financial and statistical concepts used in this thesis are explained in Appendix A.6.

2 Previous Research

This section begins with a theoretical background to our experiments, and continues with an illustrative model of irrational behavior. The section ends with a digression on our use of the stop-loss rule and a brief review of previous empirical studies.

2.1 Theoretical Justification for Momentum Strategies

The ambition of this section is to give a theoretical motivation for the momentum effect.[1] This motivation will be supported by Section 2.4, where we also deal with aspects of the momentum effect that are of more practical use to our trading model. This theoretical section is included since the momentum effect is of utmost importance to our trading model. We will thus first present the main lines of critique of momentum, and then the answers to these issues in turn.

Those who oppose the existence of the momentum effect argue mainly along one or both of the following two lines:

The markets are efficient According to the EMH, a continuation of stock prices not based on changes in fundamental values is not possible, or at the most a temporary anomaly.

Data mining Another explanation is that the effects discovered empirically simply are the results of data mining, i.e. the data is spurious.

2.1.1 Efficient Markets

The EMH has a long history in finance, and its proponents are some of the most prominent figures in financial economics such as Eugene Fama at University of Chicago.[2] To start off this section, we first discuss the concept of efficient markets and the implications they have for momentum strategies, since our trading system would not work if the markets were efficient, even if only in the weak form (see below).

In words, the EMH states that the current market price reflects the assimilation of all the information available. This means that given the information, no prediction of future changes in the price can be made. As new information enters the system, the unbalanced state is *immediately* discovered and quickly eliminated by a "correct" change in the market price, i.e. the momentum effect should not be possible.

In Fama (1970), the concept of efficient markets was for the first time formalized, even though the mathematical foundation had been put forth earlier in Mandelbrot (1966). Fama expresses the non-predictable characteristic of market prices formally as

$$E(\tilde{p}_{j,t+1}|\Phi_t) = [1 + E(\tilde{r}_{j,t+1}|\Phi_t)]p_{j,t}, \tag{1}$$

where $p_{j,t}$ is the price of security j at time t, $r_{j,t+1}$ is the one-period percentage return $(p_{j,t+1} - p_{t,j})/p_{t,j}$, Φ_t is the information reflected at time t, and the tildes indicate random variables. The expression $E(A|B)$ indicates the expected value of A given that event B has occured. Fama then goes on to state explicitly that this rules out any possibility of trading systems based solely on information in Φ_t that have expected profits or returns in excess of equilibrium expected profits or returns.

[1] The momentum effect is here defined as "the persistence in the returns of stocks over horizons between three months and one year" (Grinblatt and Han, 2002, p. 1). The typical set-up of a momentum strategy is to go long in past winners and take a short position in past losers.

[2] We will sometimes refer to the champions of the EMH as "traditionalists".

According to Fama, the EMH has three different shapes, based on how "large" the information set Φ_t is; the strong form (where groups of investors have more information than others, e.g. insiders), the semi-strong form (where the information set includes all the obviously publicly available data such as volume data, profit prognoses and sales forecasts), and the weak form (where the information subset is just historical price or return sequences). He concludes that the weak and semi-strong forms are heavily supported by empirical tests, while the status of the strong form is more ambigious, since it is very hard to test statistically due to shortage of data. He also discusses the existence of autocorrelation in price sequences, which is of utmost importance for momentum strategies, but concludes that they are either insignificant or too small to make any economic sense. Furthermore, he mentions trading strategies that beat buy-and-hold on a consistent basis when not regarding transaction costs. It is worth noting that we have tested our model *with* transaction costs.

The essence of Fama's paper is that one cannot systematically beat the market, using e.g. a momentum strategy. So why would a momentum strategy work? The theory presented above is *theoretically* sound, the problem is that the assumptions upon which the theory rests are not plausible nor applicable in reality. The most fundamental of these assumptions is that investors behave rationally, or, if they do not, that the deviations of irrational investors cancel each other out, which is the view expressed in e.g. Fama (1998). Another "efficient markets"-explanation is that the irrationality is exploited by arbitrageurs, something which has been put forth by de Long et al. (1990).

But research done the last 30 years has shown that investors in fact are *not* strictly rational nor possess unlimited computational capacity (Shiller, 1998). Instead of trying to compute expected values and arrive at sensible strategies through the use of Bayes' rule, investors commonly rely on various heuristics.[3] Particularly interesting for our thesis is the representativeness heuristic, by which is meant the "tendency for people to try to categorize events as typical or representative of a well-known class, and then, in making probability estimates, to overstress the importance of such a categorization, disregarding evidence about the underlying probabilities" (Shiller, 1998, p. 22). A manifestation of this somewhat abstract idea is the tendency of people to see patterns in strictly random sequences of numbers. People are also victims of various biases, of which conservatism bias is one of the most important. People with a bias towards conservatism tend to underweight new information in updating their weighting of new information (Jegadeesh and Titman, 2001). For a thorough exploration of these issues, we refer the interested reader to e.g. Shiller (1998).

The above biases and rules of thumb all point to deficiencies of the EMH, but what about the proposition that the effects of irrational investors trading according to various heuristics or biases cancel each other out? Experiments done by Kahneman and Tversky have shown that individuals tend to deviate systematically, and deviations will thus have a real impact (Shleifer, 2000).

What specifically do the heuristics and biases lead to? First and foremost, they generate over- and underreaction to e.g. news. These reaction effects are essential to the momentum effect, which will be shown below. We describe these two effects formally as follows:
Overreaction:

$$E[r_{t+1}|z_t = G, z_{t-1} = G, \dots, z_{t-j} = G] < E[r_{t+1}|z_t = B, z_{t-1} = B, \dots, z_{t-j} = B] \qquad (2)$$

[3]Bayes' rule states that, if $A_i, i = 1, \dots, n$ and B are events, then

$$P(A_i|B) = \frac{P(A_i)P(B|A_i)}{\sum_{j=1}^{n} P(A_j)P(B|A_j)},$$

see e.g. Råde (1999). In words, investors following Bayes' rule will weight information after how precise it is.

Underreaction:

$$E[r_{t+1}|z_t = G] > E[r_{t+1}|z_t = B], \tag{3}$$

where z_t is the news that the investor hears in period t, G is good news, B bad news and r_t is the period t return. Below, we will give examples of good and bad news. In words: overreaction occurs when the average return (an approximation of expected return) following a series of announcements of good news is *lower* than the average return following a series of bad news announcements. Underreaction in its turn occurs when the average return on the company's stock in the period following an announcement of good news is *higher* than the average return in the period following bad news (the notation as well as the definitions are from Shleifer (2000)).

The momentum effect and the phenomena described above that cause it, were first documented in Bondt and Thaler (1985), where empirical support for the overreaction effect is found.[4] Evidence of the underreaction effect can be found in Jegadeesh and Titman (1993).

The traditionalists have also tried to find other explanations than the irrational behavior of investors to the momentum effect. Fama and French (1993, 1996) have e.g. tried to relate the phenomenon to risk premia on investing in value stocks and small stocks, which would imply that the EMH is not violated. They take the comovements of stock prices in these categories as evidence that the securities share some common fundamental risk. But this has not been shown directly (Shleifer, 2000), and instead there could be a behavioral explanation, as shown by e.g. R. La Porta and Vishny (1997). A case can be made that similar stocks are influenced by the same investor sentiment, so that the stock prices are correlated. The upshot of this is that the comovement of stocks does not have to be explained by risk premia. Another setback for the EMH is that an implication of the rational explanation of the value/glamour evidence is that investors should expect lower returns when investing in glamour stocks because of those stocks' risk characteristics. But evidence points the other way, i.e. that investors are too optimistic about the future returns of growth stocks (J. Lakonishok and Vishny, 1994).

2.1.2 Data mining and Spurious Data

Jegadeesh and Titman (1993) first made the momentum effect more widely accepted by getting their findings published in the Journal of Finance. One common answer from the traditionalists was that the data was spurious, i.e. that Jegadeesh and Titman had looked at too short periods, special periods and so on. This critique was answered by Jegadeesh and Titman (2001), where they repeat their tests with more recent data and with longer periods of earlier data. Of course, to really "prove" the momentum effect, one would have to test all available data from all countries, but the Jegadeesh and Titman tests at least seem to confirm that there exists or has existed a momentum effect for American stocks.

One case that has been made against the momentum research is that the returns only reflect recent U.S. history. An attempt at dealing with this claim was made in Rouwenhorst (1998), where momentum strategies in 12 European countries, including Sweden, between 1985 and 1990 are tested. Rouwenhorst found that the strategies worked in all 12 countries, and hence that the momentum effect is not restricted to the United States. See Section 2.4 for further discussion.

[4]The authors do not investigate the momentum effect explicitly, but that stocks have momentum is an implication of the fact that they tend to revert.

2.2 A Model of Over- and Underreaction

With this model we will attempt to *illustrate*, nota bene not prove, the concepts of over- and underreaction and how those can affect the prices of stocks leading to the momentum-effect.[5] The model is thus a theoretical motivation to why our trading model could work in reality.

The model is a so called "representative agent"-model, i.e. there is only one agent in the model. We further assume that the investor is risk neutral and that 100% of earnings are paid out as dividends.[6] Hence, the agent's valuation of the earnings-stream will equal the price of the stock. This investor is not aware of the true underlying process governing the earnings process, which is a random walk (i.e. completely random):

$$N_t = N_{t-1} + y_t, \tag{4}$$

where N_t is the earnings in period t and

$$y_t = \begin{cases} y & \text{with probability } 0.5 \\ -y & \text{with probability } 0.5, \end{cases}$$

is the period t shock to earnings. The earningsprocess is a martingale, since $E[N_{t+1}|N_t] = N_t + E[y_{t+1}] = N_t + (0.5)y - (0.5)y = N_t$ and $E(|N_t|) < \infty$.[7] If the investor were fully rational, and would have the computational capacity to realize that the earnings-stream is a random walk, her valuation of the stock would just be

$$P_t = E_t\left[\frac{N_{t+1}}{1+\delta} + \frac{N_{t+2}}{(1+\delta)^2} + \dots\right] = \frac{N_t}{\delta}, \tag{5}$$

where δ is the investor's discount factor.[8] With this valuation, there would be no over- or underreaction and hence no momentum effect.

The investor in the model at hand is however not fully rational, and instead believes that the shocks to earnings are governed by either one of two models, either a mean-reverting model or a model of positive autocorrelation (earnings trend). She will then use whichever model she thinks governs earnings to forecast dividends and prices. Depending on the shocks to earnings the investor observes at time t, she will shift between the two models. Both the two models and the process by which the investor switches between the two are Markov

[5] The model is Barberis', Shleifer's and Vishny's model as presented in Shleifer (2000).

[6] The assumption of risk neutrality is done for the sake of simplicity.

[7] We have used the definition of a martingale found in Djehiche (2000).

[8] Equation (5) holds, since N_t is a martingale and hence the expression reduces to

$$N_t \sum_{n=1}^{\infty} \frac{1}{(1+\delta)^n},$$

which is a geometric series, and can be rewritten as

$$N_t \left(\sum_{n=0}^{\infty} x^n - 1\right), \tag{6}$$

where $x = \frac{1}{1+\delta}$. The sum equals $\frac{1}{1-x} = \frac{1}{1-\frac{1}{1+\delta}} = \frac{1+\delta}{\delta}$ (see e.g. Adams (1995, p. 530)). Equation (6) thus reduces to $N_t(\frac{1+\delta}{\delta} - 1) = N_t\frac{1}{\delta}$, so $E_t\left[\frac{N_{t+1}}{1+\delta} + \frac{N_{t+2}}{(1+\delta)^2} + \dots\right]$ equals $\frac{N_t}{\delta}$.

processes (see Appendix A.6 for an explanation of Markov processes).
Model one[9]:

	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_L	$1 - \pi_L$
$y_t = -y$	$1 - \pi_L$	π_L

This will be a mean-reverting model if $\pi_L \in (0, 0.5)$.
Model two:

	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_H	$1 - \pi_H$
$y_t = -y$	$1 - \pi_H$	π_H

The shocks according to model two will be positively autocorrelated if $\pi_H \in (0.5, 1)$.

We can write the transition matrix for the Markov process governing the switches between the two models as

	$s_{t+1} = 1$	$s_{t+1} = 2$
$s_t = 1$	$1 - \lambda_1$	λ_1
$s_t = 2$	λ_2	$1 - \lambda_2$,

where $s_t = i, i = 1, 2$ means that at time t, the investor believes that model i governs the earnings shocks.

As mentioned above, the valuation of the stock would be really simple if the investor knew the process was a random walk, but now we have to take into account that the investor's beliefs regarding the governing process change over time between the mean-reverting model and the model of positive autocorrelation. According to the strings of news she receives, where news is defined as the shock to earnings in a specific period, she updates her beliefs according to Bayes' rule. A shock is considered as good news if it is positive and as bad news if it is negative. To make this formal, assume that the investor at time t calculates q_t, the probability that the shock observed in period t was generated by model 1, using the new data to update her beliefs from the preceding period, q_{t-1}. This means that $q_t = P(s_t = 1|y_t, y_{t-1}, q_{t-1})$. The process of updating can be expressed as $q_{t+1} =$

$$\frac{((1-\lambda_1)q_t + \lambda_2(1-q_t))P(y_{t+1}|s_{t+1} = 1, y_t)}{((1-\lambda_1)q_t + \lambda_2(1-q_t))P(y_{t+1}|s_{t+1} = 1, y_t) + (\lambda_1 q_t + (1-\lambda_2)(1-q_t))P(y_{t+1}|s_{t+1} = 2, y_t)} \tag{7}$$

This expression follows from the definition of transition probabilities above and the use of Bayes' rule. To get a feeling for how this updating works, we have plotted a string of shocks and the corresponding q_ts in Table 1. When the investor sees a string of positive or negative shocks, she gets more and more certain that the earnings are generated by the positive autocorrelation model, i.e. q_t sinks. When she observes shocks of alternating good and bad news, she gets more and more convinced that the earnings are generated by model 1, i.e. q_t goes up.

We are now ready to explore how the investor values the stock. As we mentioned above, a fully rational investor would, according to the EMH, value the stock as $P_t = \frac{N_t}{\delta}$, but this investor believes that the earnings are generated by the model-switching scheme described above. Thus, she will value the stock according to the following formula

$$P_t = \frac{N_t}{\delta} + y_t(p_1 - p_2 q_t), \tag{8}$$

[9]This is a transition matrix, which means that if the initial state is $y_t = -y$, the next state will be $y_{t+1} = -y$ with probability π_L etc.

Table 1. Illustration of how the investor changes her beliefs about which model governs the earnings according to the shocks to earnings she observes, when the shock to earnings is 10. q_t is the probability that she assigns to the earnings being generated by model 1, i.e. the mean-reverting model. The q_ts are rounded to four decimal places.

Time	Shock	q_t
0	10	0.5000
1	10	0.4000
2	10	0.3429
3	-10	0.7318
4	-10	0.5573
5	10	0.8223
6	-10	0.9110
7	10	0.9364
8	-10	0.9433
9	10	0.9451
10	10	0.7436

where $p_1 = \frac{1}{\delta}(\gamma_0^T(1+\delta)(I(1+\delta)-Q)^{-1}Q\gamma_1)$ and $p_2 = -\frac{1}{\delta}(\gamma_0^T(1+\delta)(I(1+\delta)-Q)^{-1}Q\gamma_2)$. The transpose of a matrix or vector x is written x^T. $\gamma_0^T = (1,-1,1,-1)$, $\gamma_1^T = (0,0,1,0)$, $\gamma_2^T = (1,0,-1,0)$.

$$Q = \begin{pmatrix} (1-\lambda_1)\pi_L & (1-\lambda_1)(1-\pi_L) & \lambda_2\pi_L & \lambda_2(1-\pi_L) \\ (1-\lambda_1)(1-\pi_L) & (1-\lambda_1)\pi_L & \lambda_2(1-\pi_L) & \lambda_2\pi_L \\ \lambda_1\pi_H & \lambda_1(1-\pi_H) & (1-\lambda_2)\pi_H & (1-\lambda_2)(1-\pi_H) \\ \lambda_1(1-\pi_H) & \lambda_1\pi_H & (1-\lambda_2)(1-\pi_H) & (1-\lambda_2)\pi_H \end{pmatrix}$$

The transpose of the matrix Q describes the transitions between the models and the earnings shocks,

A plot of the earnings and corresponding prices is given in Figure 1 to make the reader aware of how the model looks. To give an indication of how the "true" price differs from the value perceived by the representative investor, we have plotted some values for both the price process discussed above and the prices if the investor knew the underlying process was a random walk in Figure 2. This shows the essence of the momentum effect, the over- and undershooting of price in relation to the "rational" price.

The difference between the "true" price and the actual price is represented by the last term in Equation (8), which can be thought of as the deviation from the fundamental value. This bias gives rise to the over- and underreaction effect. If the overreaction effect holds, then, according to our claims above, we would observe a lower return on the stock following a period of good news, than following a string of bad ones. If, on the other hand, the underreaction effect holds, we would observe a result in line with Equation (3), i.e. the return on a company's stock is higher following an announcement of good news than the return following bad news. To test these effects within the framework of the presented model, we simulate the earnings of 50 "companies" for 6 periods, where one period could be e.g. a year. A company is defined as a six-period earnings string.

If overreaction existed in the given model, we should observe that r_+^4 is lower than r_-^4, in line with Equation (2).[10] This is the observation of Shleifer (2000), but we want to take the analysis further, by getting an indication of the significance of the results, which is not done in Shleifer (2000). To test this, we run the described simulation of 50 firms 100 times in Matlab. This leaves us with a sample of 100 observations.

To check the existence of the overreaction effect we look at the average difference between r_+^4 and r_-^4. This is done by constructing a 99% confidence interval for the average difference. The distribution of the differences is plotted in Figure 3. Knowing that each run is

[10]We denote the return on stocks of companies with four consecutive years of positive earnings shocks r_+^4.

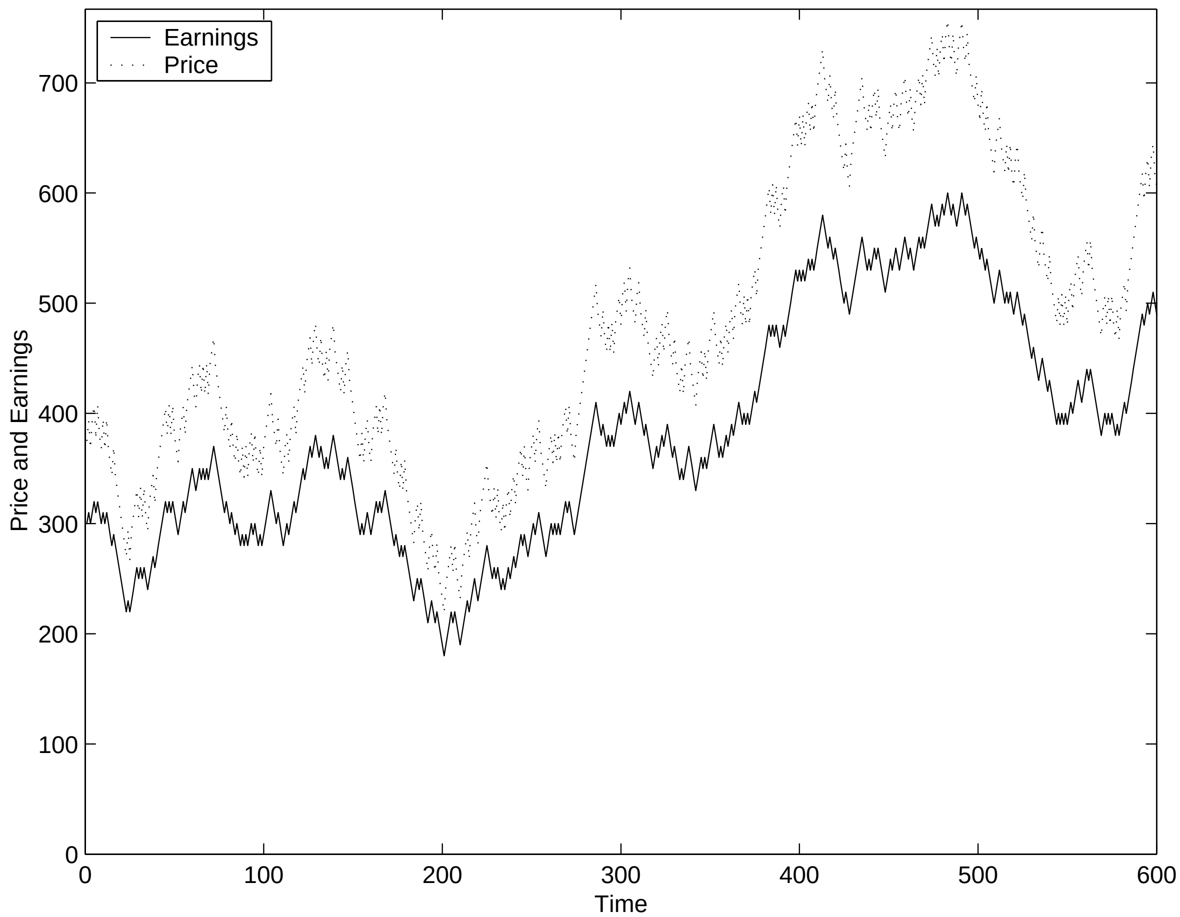

Figure 1. Realizations of earnings over 600 periods and the corresponding prices. To see the difference between irrational and rational pricing, see Figure 2.

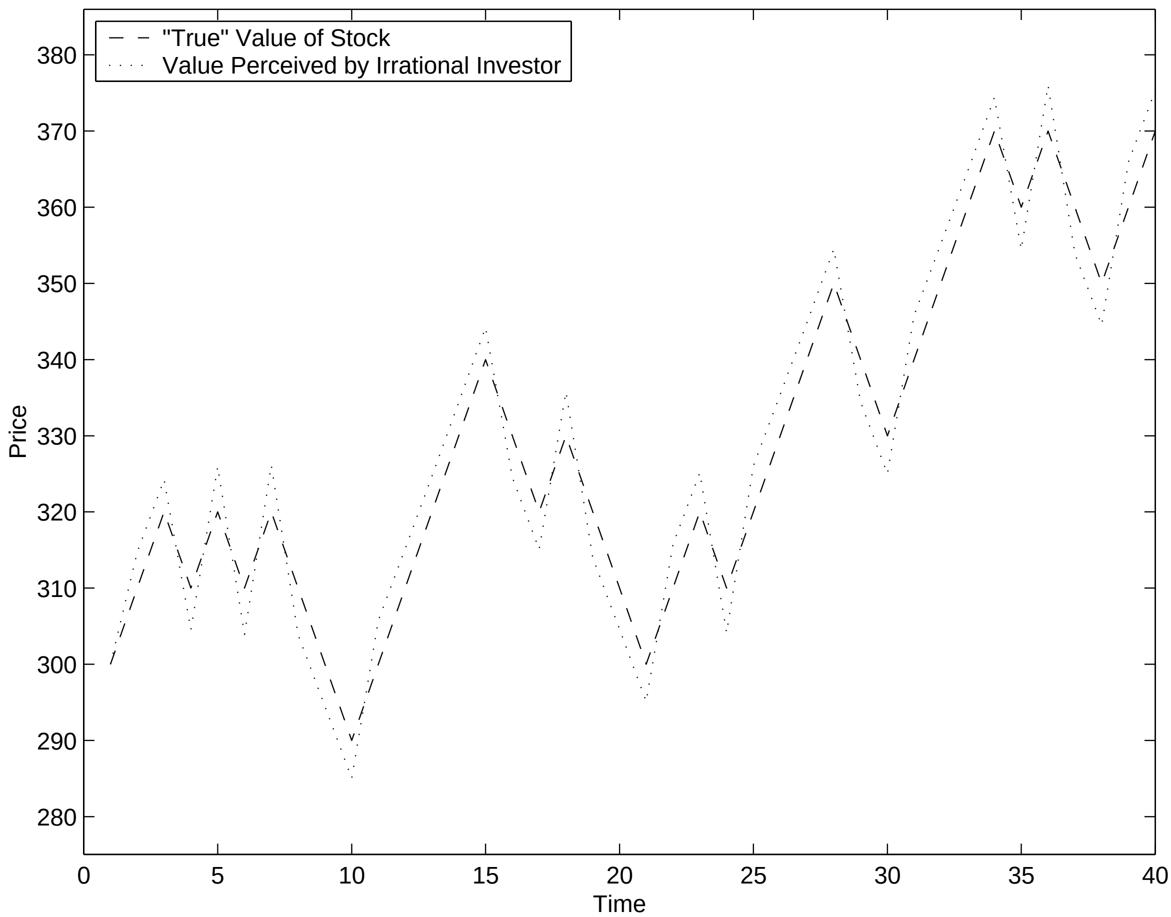

Figure 2. The essence of the momentum effect. 40 realizations of the earnings and the corresponding prices if the investor knows the underlying process is a random walk vs. the prices perceived by the investor when she does not know the price process. This price pattern can be exploited by a trading strategy.

independent of the others and assuming that each run is identically distributed, with finite expectation and variance, we can, by the central limit theorem (see e.g. Gut (1995, pp. 173-174)), construct a confidence interval of the following form:

$$\bar{x} - \frac{t_{n-1,\alpha/2}s_x}{\sqrt{n}} < \mu < \bar{x} + \frac{t_{n-1,\alpha/2}s_x}{\sqrt{n}}, \tag{9}$$

where $\bar{x}$ and s_x are the sample mean and standard deviation respectively, n is the sample size and μ is the mean of the population (see e.g. Newbold (1995)). We find that

$$P(-4.15 \cdot 10^{-3} < \mu < -4.09 \cdot 10^{-3}) = 0.99,$$

which is consistent with the overreaction effect, since the average return difference is so clearly below zero.

To check for the existence of the underreaction effect, we examine the average difference between r^1_+ and r^1_-. This is done by constructing a 99% confidence interval for the average difference. The distribution of the differences is plotted in Figure 4. The 99% confidence interval for $r^1_+ - r^1_-$, calculated analogously to above, is

$$\mu \in (2.62 \cdot 10^{-4}, 3.06 \cdot 10^{-4})$$

This is consistent with the formal definition of underreaction, Equation (3) above, in the sense that it is clearly above zero.

When considering our results, please note that we have used a specific parameter setting (for π and λ). The model will not produce significant over- and underreaction results for all possible parameter specifications. For a further discussion of the stability issue, the interested reader is referred to the original working paper (Barberis and Shleifer, 1997), and the discussion below.

2.2.1 Conclusions and Discussion

To conclude, we first state three criteria that are generally considered as relevant when evaluating models of this kind (Hong and Stein, 1999):

- The assumptions underlying the model should be a priori plausible or consistent with casual observation
- The model should explain existing evidence in a parsimonious and unified way
- The model should make a number of further predictions that can be subject to out-of-sample testing and that are ultimately validated

The assumptions are very robust, since they are based on the results of research both in financial economics and in experimental psychology, see e.g. Bondt and Thaler (1985) and Kahneman and Tversky (1979). One draw-back though, is that there is only one agent, which means that the model fails to capture the effect of traders with heterogenous beliefs. This issue has been addressed in the famous study by Hong and Stein (1999). They also provide a unified account of over- and underreaction, but with two groups of traders.

An interesting question is how the model would change if the investor were risk averse, which is assumed in e.g. CAPM. We would then have needed to specify a utility function for the investor, which would affect her valuation of the stock. This would increase the arbitrariness of the model, since utility functions are not observable in reality.

The most obvious strength of the model employed is that it is parsimonious and that it is unified, i.e. it covers both the under- and overreaction effects. A weak side is that it really

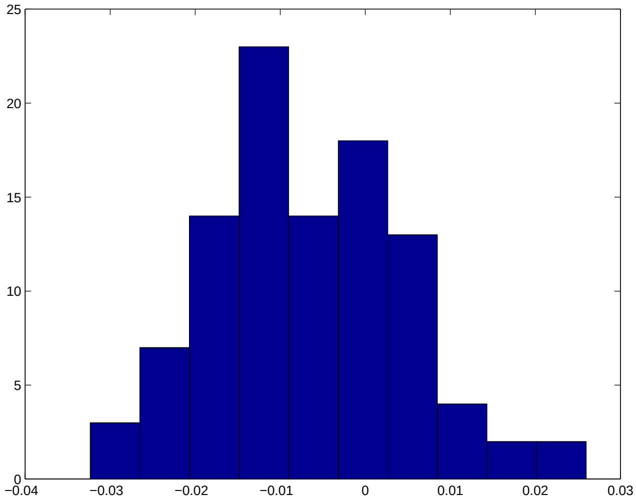

Figure 3. A histogram describing the distribution of results of the simulation of the overreaction effect. The mean of the differences is $-4.12 \cdot 10^{-3}$ and the standard deviation is $9.96 \cdot 10^{-5}$. The existence of the overreaction effect is significant.

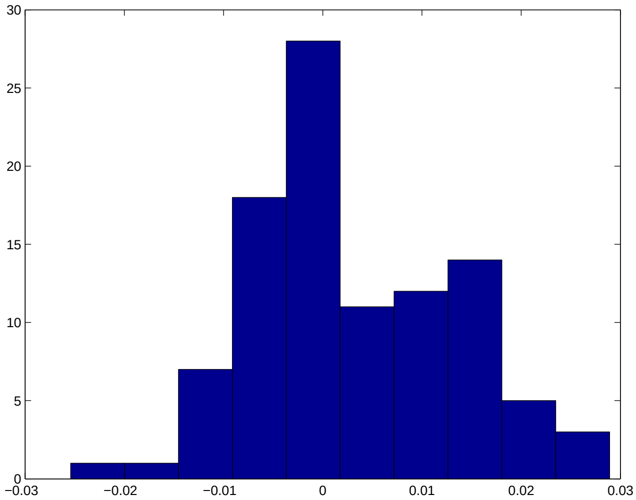

Figure 4. Results of the simulation of the underreaction effect. The mean is $2.84 \cdot 10^{-4}$ and the standard deviation $8.55 \cdot 10^{-5}$. Our findings are consistent with the underreaction effect.

does not make any further predictions, but this issue is not relevant for our thesis. There are some points which the model above does not address, e.g. how arbitrageurs would affect the results. One may argue that the addition of arbitrageurs would eliminate the effects. This is not necessarily the case, since arbitrage is quite risky in this setting. No one can perfectly predict when and how prices will reach the fundamental value. Trend following arbitrage trading can result in a self-feeding bubble, that makes prices deviate even further from the fundamental value (de Long et al., 1990). This accentuates stock momentum even further. Increased volatility is not only beneficial however, since exact timing will most probably be harder.

Regarding the results of the theoretical model above, we have seen that the representativeness heuristic and the conservatism bias could be explanations for the over- and underreaction effects, which together drive the momentum effect. As can be seen below, this claim is also supported by empirical evidence, see e.g. Table 2. Underreaction and overreaction cause over- and undershooting of prices, in the sense that prices of a stock keep irrationally trending up after the release of good news, and vice versa when the news is bad. The model depicted above implies that a typical investor can be seen as using the representativeness heuristic, i.e. she sees systematic patterns in sequences that are in fact completely randomly generated. This explains the momentum effect according to this model.

But, having said this, one can still question the exact parameter specifications of this model, and the circumstances under which it produces economically significant results. We e-mailed Professor Shleifer and asked him if he could motivate these parameter settings (e.g. the transition probabilities) from an empirical standpoint. He replied and commented that he could not, but that we indeed had an important point in questioning this and that he also very much would like to know the answer to this question and possibly weak link in his model. Once again, theoretical reasoning needs to be complemented with empirical facts in order to say something meaningful about reality.

2.3 Theoretical Motivation for the Stop-Loss Rule

This section offers a theoretical motivation for the use of the stop-loss rule, which is often incorporated in trading models. In its most simple form, the stop-loss rule means that one liquidates a losing position when its price exceeds or drops below a certain limit, depending on if it is long or short. Its use is motivated by the fact that one gains by taking small rather than large bets when one is subject to "bankruptcy costs". Assume a situation where one *does not* limit one's bets. A well-known such situation is the *martingale betting strategy*, a version of which we will go through briefly here.[11] The strategy is called the *martingale* betting strategy since the sequence S_n defined below is a martingale with respect to itself. Assume that a game is played where the player bets on the result of a toin coss. The player wins her bet if the coin comes up a head and loses if it is a tail. The strategy is simple: double the bet until the preferred side of the coin comes up, which it is bound to do, say at time T. The profit of this strategy every time one wins is

$$2^T - (1 + 2 + 4 + \cdots + 2^{T-1}) = 1 \tag{10}$$

The first term on the left-hand-side of Equation (10) is the player's gain at time T and the second term is the money she has lost up to and including time $T-1$. Let S_n denote the

[11] This example is adapted from Djehiche (2000).

accumulated gain up to the nth toss, $S_0 = 0$. Then S_n evolves according to

$$S_{n+1} = \begin{cases} S_n - 2^n & \text{with probability } 0.5 \\ \\ S_n + 2^n & \text{with probability } 0.5 \end{cases}$$

The probability that the game stops after the nth toss, i.e. that the player wins, is given by

$$P(T = n) = \frac{1}{2}\frac{1}{2}\dots = \frac{1}{2^n},$$

for $n \geq 1$, since there is a probability of a half that the coin comes up head. This means that the mean loss of the gambler tends to the following limit as n grows large:

$$\sum_{n=1}^{\infty} \frac{1}{2^n}(1 + 2 + \cdots + 2^{n-1}) = \infty,$$

where the sum in parentheses is the same as the second term of the left-hand-side of Equation (10). This implies that the initial capital of the gambler, or investor, needs to be infinite, if she intends to pursue her martingale betting strategy. Otherwise, after a string of unfavourable events, the gambler will go bankrupt (this is the strategy pursued by casinos when limiting the maximum size of bets). The essence of the stop-loss rule is precisely to minimize the risk of losing large "bets", so therefore the managers of funds using the stop-loss rule will not be needing unlimited funds, or at least not *as much* access to capital.

2.4 Empirical Evidence Using CAR

Now, we turn our attention to the empirical evidence of primarily the momentum effect. These general facts will later be used as guidance when we test different trading rules in our model. Also, we will later emulate the simplistic methodology (as in only using the price variable, no transaction costs, static rebalancing etc) used here, to compare it with our own model as stated in the purpose of this thesis.

The research cited in the following text often takes the form of a statistical test for abnormal returns in a market neutral portfolio that is rebalanced periodically a few times a year in accordance with a ranking scheme based solely on price changes. It is thus a static version of the more dynamic model that we try to build.

2.4.1 The Momentum Effect

As we have seen in Section 2.1 above, the momentum effect is basically return continuation in the medium term in both negative and positive direction, followed by mean reversion over the longer term. The reason: economically irrational investors.

The basic methodology of the momentum studies cited in Table 2 is, as stated above, to rank stocks after a "ranking period". Normally, the 10-20% best and worst performers form a long and short portfolio, respectively. This combined portfolio is a close to zero β investment that in theory should yield 0% in return (save transaction costs and interest on short positions). Then, one looks at a "test period" directly after the ranking period and test statistically if the strategy yields any abnormal return above 0%, in which case the momentum effect would be present. The results are presented as a Cumulative Abnormal Return (CAR) in the test period. Different lengths of the ranking and test periods are then studied. Transaction costs are excluded in the cited research, leading to an overstatement of achievable returns. Furthermore, these strategies are very simplistic, which also affects performance, as we will see later. And CAR, accompanied with a t-statistic, does definitely not give the whole picture necessary to correctly assess the true potential (in a negative or positive sense) of the momentum effect.

Table 2. A brief summary of empirical research on the momentum effect.

Paper	**Data Sample (Period)**	**Results**	**Other Conclusions**
L.K.C. Chan and Lakonishok (1999)	NYSE, Amex, Nasdaq (1973-1993 and 1994-1998)	Significant momentum effect, both for ranking based on 6-month return and changes in earnings expectations.	Continuing positive and negative trends in the months following portfolio formation are attributed to "conservatism bias" among investors, being slow to adjust to new information.
D. Schiereck and Weber (1999)	Frankfurt Stock Exchange (1961-1991)	Significant momentum effect. See Table 3.	Beta, risk or firm size does not account for momentum, but behavioral theory does provide a plausible explanation. The momentum effect is similar to what is found in US data despite differences in markets. Predictable reversals of earnings and price for the winning and losing portfolios.
M. Finn and Kling (1999)	S&P 500 (1983-1998)	Significant momentum effect. A long/short portfolio would yield 7.8% with a tracking error of 4.8% and beta close to zero, with respect to the S&P 500.	Most of the profit from a long/short strategy using large capitalized stocks comes from the short side, due to high analyst coverage and limited short selling by large investors in this universe. The momentum effect decreases with company size. If one controls for B/M and size, economic sector is of a less importance, probably sample specific however.
Jegadeesh and Titman (2001)	NYSE, Amex (1965-1997)	Reaffirms support for previous studies that a long/short portfolio can earn approximately 1% excess return per month.	Significant mean reversion of momentum in the 13-60 month period following portfolio formation. The momentum effect can not be explained by cross-sectional dispersion of expected return, only by behavioral theories.
Swaminathan and Lee (1999)	NYSE, Amex (1965-1995)	Significant momentum effect.	Trading volume works as a good predictor. The best shorting candidates are high volume low momentum with a ranking period of six months. The best buy candidates overperformed less than the sell candidates underperformed.
Daniel and Titman (1999)	NYSE, Amex, Nasdaq (1963-1997)	Significant momentum effect. 13% yearly return if one takes a long position (20% most extreme) in high B/M high momentum and shorted the low B/M low momentum stocks, t-statistic 5.66.	Stronger momentum effect for low B/M stocks, since they are more susceptible to investor sentiment. Rejection of adaptive market efficiency in favor of behavioral explanations.
O'Neal (2000)	S&P (1989-1999)		Much of the observed momentum in individual stocks are attributed to industry momentum.

In the study by D. Schiereck and Weber (1999), who studied the German market, the results of their investigation of the momentum effect are compared with the classic study by Jegadeesh and Titman (1993) using US data. Table 3 shows that the two studies have similar return patterns and that there are significant momentum effects when the ranking period is more than or equal to 3 months. The CAR increases generally at a decreasing rate as the test period reaches 6 to 12 months where mean reversion sets in. Note that the CAR is measured as a total up until the end of the test period, and not as a monthly return.

The latest study on the momentum effect for Swedish data was done as a Master Thesis at Stockholm School of Economics in 2000, presented in Table 4. The CAR numbers are here presented on a monthly basis, not total. They also found significant results comparable to previous studies. However, during 1992 when Sweden devaluated its currency, the losing

Table 3. The momentum effect in Germany, compared with Jegadeesh-Titman's results for USA, 1961-1990. 20 W-L means that the 20 winning and 20 losing stocks in the ranking period form the market neutral long/short portfolio. Sample size: 357 most traded stocks. Reproduced from D. Schiereck and Weber (1999)

Strategy	$CAR_{\text{rank period}}$	CAR_3	CAR_6	CAR_9	CAR_{12}
One-month rank period					
20 W 1961-90	13.18%	0.00%	0.35%	0.02%	0.78%
(t-statistics)		(0.02)	(2.38)	(0.17)	(5.64)
20 L 1961-90	-10.43	-0.20	-0.15	-0.25	-0.70
		(-1.24)	(-1.03)	(-1.70)	(-4.65)
20 W-L 1961-90	23.61	0.20	0.50	0.28	1.49
		(0.78)	(2.14)	(1.24)	(6.35)
20 W-L 1961-70	22.06	-0.62	0.73	0.22	0.96
20 W-L 1971-80	21.37	0.82	0.74	0.38	1.33
20 W-L 1981-90	27.41	0.41	0.04	0.24	2.17
Three-month rank period					
20 W 1961-90	20.76	0.31	1.46	2.10	3.47
		(0.99)	(3.10)	(3.32)	(4.78)
20 L 1961-90	-19.58	0.38	-0.07	-0.80	-2.06
		(1.06)	(-0.18)	(-1.40)	(-3.05)
20 W-L 1961-90	40.35	-0.07	1.53	2.90	5.52
		(-0.15)	(2.45)	(3.40)	(5.57)
20 W-L 1961-70	39.01	-1.35	0.02	1.46	3.59
20 W-L 1971-80	36.32	0.13	1.17	1.42	2.17
20 W-L 1981-90	46.73	1.00	3.40	5.81	10.81
20 W-L 1965-89	Na	-0.03	1.56	2.61	5.40
Jegadeesh-Titman	Na	0.96	1.74	5.40	8.28
Six-month rank period					
20 W 1961-90	30.07	0.28	1.95	3.12	4.15
		(0.46)	(2.24)	(2.95)	(3.66)
20 L 1961-90	-29.44	0.37	-1.51	-2.73	-3.92
		(0.67)	(-2.09)	(-2.78)	(-3.34)
20 W-L 1961-90	59.51	-0.09	3.46	5.84	8.07
		(-0.11)	(3.06)	(4.06)	(4.95)
20 W-L 1961-70	55.90	-0.39	0.05	0.74	2.26
20 W-L 1971-80	53.38	0.88	4.99	8.31	8.83
20 W-L 1981-90	69.31	-0.77	5.33	8.48	13.13
20 W-L 1965-89	Na	0.09	4.32	6.75	8.76
Jegadeesh-Titman	Na	2.52	5.70	9.18	10.32
Twelve-month rank period					
20 W 1961-90	47.05	1.77	3.06	3.06	4.14
		(1.88)	(3.27)	(2.33)	(2.59)
20 L 1961-90	-45.90	0.98	-1.84	-0.83	-1.07
		(0.83)	(-1.57)	(-0.52)	(-0.47)
20 W-L 1961-90	92.95	0.80	4.90	3.89	5.21
		(0.53)	(3.26)	(1.88)	(1.87)
20 W-L 1961-70	81.12	-2.01	0.96	0.27	1.06
20 W-L 1971-80	83.71	4.83	8.85	8.55	5.31
20 W-L 1981-90	114.04	-0.43	4.90	2.85	9.24
20 W-L 1965-89	Na	1.11	5.40	4.95	3.52
Jegadeesh-Titman	Na	3.93	6.84	8.37	8.16

portfolio with negative momentum suddenly outperformed the winning portfolio, resulting in a large loss for the long/short portfolio. The authors therefore eliminated one year of data to evaluate the impact of the devaluation, and one can clearly see the improvement in performance. Eliminating bad data is of course a dubious way of proving a strategy profitable, but it highlights an important aspect of our strategy: risk control. If one does not take into consideration the composition of the long and short positions, one will surely end up with a lot of exposure to various risk factors. A long stream of steady profits can disappear literally overnight.

2.4.2 The Role of Volume, Fundamental and Sentiment Variables

The most important variable when modeling the momentum effect is of course the price itself, as was evident in Shleifer's model. It incorporates investors' beliefs and will thus also indicate whether a specific stock is "neglected", with negative momentum, or a "glamour" stock with positive momentum. But there are other variables to consider.

Table 4. The momentum effect in Sweden 1980-1999. Stockholm Stock Exchange, between 118 and 233 stocks. The Table is reproduced from Söderström (2000).

Strategy	**CAR$_3$**	**CAR$_3$** 1 year after devaluation eliminated	**CAR$_6$**	**CAR$_6$** 1 year after devaluation eliminated	**CAR$_9$**	**CAR$_9$** 1 year after devaluation eliminated	**CAR$_{12}$**	**CAR$_{12}$** 1 year after devaluation eliminated
Three-month rank period								
10% W-L 1980-1999, monthly return	-0.37%	-0.05%	0.22%	0.63%	0.25%	0.53%	0.16%	0.56%
(t-statistics)	(-0.83)	(-0.12)	(0.61)	(2.40)	(0.92)	(2.12)	(0.53)	(2.54)
monthly standard deviation	3.90%	3.61%	2.80%	2.22%	2.51%	2.15%	2.77%	1.95%
Six-month rank period								
10% W-L 1980-1999, monthly return	0.37	0.85	0.66	0.99	0.47	0.87	0.19	0.68
(t-statistics)	(0.70)	(1.86)	(1.99)	(3.30)	(1.49)	(3.43)	(0.59)	(3.11)
monthly standard deviation	2.27	1.90	2.96	2.52	2.90	2.16	2.93	1.90
Nine-month rank period								
10% W-L 1980-1999, monthly return	0.64	0.96	0.79	1.36	0.52	1.13	0.12	0.74
(t-statistics)	(1.25)	(2.03)	(2.13)	(4.19)	(1.52)	(4.53)	(0.34)	(3.78)
monthly standard deviation	4.38	3.96	3.30	2.71	3.11	2.13	3.20	1.75
Twelve-month rank period								
10% W-L 1980-1999, monthly return	0.37	1.07	0.45	1.26	0.30	1.01	0.02	0.62
(t-statistics)	(0.68)	(2.36)	(1.03)	(4.26)	(0.76)	(4.19)	(0.05)	(3.12)
monthly standard deviation	4.67	3.76	3.76	2.48	3.52	2.08	3.15	1.77

The volume variable can be viewed in two ways. Either as a proxy for analyst coverage, where high volume means bad momentum characteristics (high analyst coverage is bad for long positions, but can be good for short positions since analysts tend to push valuations to their upper limits), since the price will be less exposed to sentiment changes and irrational pricing. Or as a proxy for strong positive feedback trading, if the volume exhibits an increasing trend during price increases or decreases. The volume variable is therefore an example of a variable that can be used in many ways to find the optimal composition of a momentum portfolio.

Fundamental variables can be effectively used for value stocks, where a lot of the value-creating process is reflected in the quarterly reports. Piotroski (2000) constructed a market neutral portfolio using US data on high B/M firms between 1976 and 1996. He ranked the stocks quarterly using 9 measurements of fundamental strength and achieved a 23% annual return. The problem with this approach in our case is that we have not got quarterly data and that we focus on the price variable where growth stocks are more prone to trend. We will however use the P/E, M/B and market cap variables as proxies for analyst coverage and growth characteristics. Furthermore, we have data on analysts' beliefs about cash flow one year ahead, which in essence is a combination of a fundamental and a sentiment variable.

2.4.3 Conclusions

Reviewing this section, we find empirical support for the existence of the momentum effect and some interesting results on more specific characteristics of the momentum effect. We will not in this thesis discuss exactly how we translate these specific facts into algorithms; a non-mathematical summary is however given in Table 12 in Section 5. Not all of the variables in our model are even directly referenced in this section, but rather used as proxies for underlying phenomena.

One specific issue needs commenting, though. In the simplistic strategy that we emulate later in this thesis, we use a 6-month ranking period and a 4-month holding period. These parameter values yield approximately the best results, judging both from the empirical results presented here and our own simulations. In the more advanced model that we have constructed ourselves, one of the rules also has these settings, although somewhat modified by giving more weight to price changes the last week.

3 An Overview of Our Model and Its Context

3.1 Different Hedge Fund Strategies

We will here give a brief overview of the hedge fund market in order to better understand the context of the kind of model we try to build and the strategy behind it.

The term "hedge fund" has evolved over time to include a multitude of skill-based investment strategies with a broad range of risk and return objectives. The common element among these strategies is the use of investment and risk management skills to seek positive returns regardless of market direction. A hedge fund can use investment techniques that include derivatives, leverage and arbitrage in any market in order to generate specific risk-return profiles. The largest incentive to invest in a hedge fund is the diversification benefit for the investor's portfolio due to the attractive risk-return profiles of hedge funds, often due to the low correlation with stocks, the largest asset class.

Below are some quick facts about the hedge fund industry:

Table 5. Hedge fund history at a glance. Reproduced from Säfvenblad (2001).

History:

1949 AW Jones formed the first hedge fund. He used long/short equity positions and leverage, and charged a performance-based incentive fee.

1966 Fortune ran an article on Jones' fund, and public interest led to many new hedge funds.

1970 Hedge funds entered their first crisis as equity markets fell. Industry studies estimated that hedge fund assets under management fell by 70%.

1986 Institutional Investor ran an article on the Tiger fund which renewed interest in hedge funds.

1992 George Soros speculates against several European currencies with his Quantum fund and makes a fortune.

1997 Hedge funds blamed for triggering the Asian currency crisis

2000 6000 hedge funds, $ 450 billion in assets

Asset allocation within hedge fund universe in 2000:

- Long/Short Equity 40%
- Event Driven 15%
- Managed Futures 14%
- Global Macro 14%
- Fixed Income Arbitrage 7%
- Convertible Arbitrage 4%
- Other 6%

The classification of different hedge funds is not entirely straightforward since some funds may use a combination of strategies, if they disclose anything at all. Strategies can be categorized in many ways. Using the definitions by Morgan Stanley as in Tables 6 and 7 below, we can see that our return generating technique is categorized as a statistical arbitrage investment process.

In Table 8, we see how three data-providers have divided the hedge fund universe into sub-categories. The performance data gives an indication of the similarities between groups of funds and what their characteristics are.

Table 6. The investment process main and sub-category designations for hedge funds. The categories are Morgan Stanley's.

Hedge Fund Strategies
• Directional Trading – Discretionary Trading – Strategic Allocation – Systematic Trading • Relative Value – Convergence Arbitrage – Merger Arbitrage – *Statistical Arbitrage* • Specialist Credit – Distressed Securities – Positive Carry – Private Placements • Stock Selection – Long Bias – No Bias – Short Bias – Variable Bias

Table 7. Definition of Statistical Arbitrage.

An approach is defined to be Statistical Arbitrage if . . .
• positions are entered into on the basis of systematic models designed to find opportunities where the relative value of two or more assets is currently different from a theoretically or quantitatively predicted value, and • manager intervention is limited to reducing or eliminating the trades entered into in less than 25% of cases, and • the portfolio is comprised solely of individual securities within one particular asset class, and • the portfolio net exposure is never more than 20% long or 20% short, and • the approach does not conform to Convergence Arbitrage or Merger Arbitrage

3.2 Our Model – an Optimization Problem

There are basically three important aspects of choice that define the characteristics of a strategy. Our choices are displayed in Table 9.

In essence, the problem of building a statistical arbitrage model that yields an optimal risk-return profile is an optimization problem. The input data makes up the independent variables, the model itself is the function, and some risk-return measure is the dependent target variable. Certainly, this is not the ordinary linear maximization problem that is analytic and algebraically solvable. The function is unknown, the full data-set is unknown and the data is stochastic. Mathematically, we have a multi-variable problem with many local maxima that are not stable over time.

The idea is thus, in a semi-deductive way, to try to localize approximate areas in the

Table 8. Performance Jan. 1990 - Dec. 1999 from three different hedge fund data providers. Reproduced from Könberg and Lindberg (2000).

Benchmark Indexes	**Average Annual Return**	**Annual Standard Deviation**	**Sharpe Ratio**
S&P 500 Composite	18.90%	13.15%	1.05
MSCI World US	12.99%	14.75%	0.53
Lehman Government	7.46%	4.10%	0.57
Lehman Corporate	8.47%	4.80%	0.70
Lehman Govt./Corp.	7.70%	4.25%	0.61
GSCI Commodity	6.55%	18.02%	0.08
Salomon Bros. Treasury	7.74%	4.57%	0.57
Salomon Bros. Govt. Corporate	7.87%	4.58%	0.60
Salomon Bros. Wgbi US All Maturities	7.96%	6.50%	0.44
US Treasury Constant Maturities 3 month	5.12%		
Hedge Fund Research Indexes			
Convertible Arbitrage	11.57%	3.50%	1.84
Distressed Securities	16.83%	6.57%	1.78
Emerging Mkt. Asia	14.45%	14.42%	0.65
Equity Hedge	24.80%	8.58%	2.29
Equity Market Neutral	11.38%	3.16%	1.98
Equity Non - Hedge	23.25%	13.48%	1.35
Event-Driven	17.59%	6.68%	1.87
Fixed Income Total	8.88%	4.00%	0.94
Fixed Income : Arbitrage	9.54%	4.95%	0.89
Fixed Income : Convertible Bonds	17.53%	9.89%	1.26
Fixed Income : High Yield	11.22%	7.28%	0.84
Fixed Income : Mortage-Backed	11.14%	4.63%	1.30
Macro	20.99%	9.24%	1.72
Market Timing	17.75%	8.17%	1.55
Merger Arbitrage	13.02%	4.67%	1.69
Relative Value Arbitrage	14.39%	4.12%	2.25
Short Selling	0.38%	19.77%	-0.24
Statistical Arbitrage	11.93%	3.73%	1.82
Fund of Funds	12.78%	6.06%	1.26
MAR Hedge Fund Indexes			
Event-Driven	13.85%	4.89%	1.79
Distressed Securities	18.23%	8.43%	1.56
Risk Arbitrage	20.23%	17.96%	0.84
Global Emerging	16.85%	17.51%	0.67
Global Established	18.95%	9.32%	1.48
Macro	15.59%	7.33%	1.43
Market Neutral	11.92%	2.60%	2.62
Market Neutral: Arbitrage	14.97%	6.33%	1.56
Market Neutral: Long/Short	10.69%	1.61%	3.46
Short Sellers	0.51%	17.47%	-0.26
Fund of Funds	11.26%	4.60%	1.33
Diversified	11.83%	4.96%	1.35
Niche	10.68%	5.60%	0.99
EACM Hedge Fund Indexes			
EACM100	15.62%	4.25%	2.47
Relative Value	10.47%	3.42%	1.56
Long/short Equity	9.72%	3.00%	1.53
ConvHedge	10.50%	4.43%	1.21
BondHedge	7.65%	4.53%	0.56
Rotational	14.09%	6.98%	1.29
Event	13.47%	5.37%	1.55
Arbitrage	10.21%	6.35%	0.80
Bank	15.56%	6.95%	1.50
Multi	14.71%	5.35%	1.79
EQ HEDG	22.31%	9.80%	1.75
DomLong	23.48%	13.15%	1.40
DomOpp	21.77%	9.77%	1.70
Gl/Int	21.69%	11.54%	1.44
GLOB AA	19.84%	10.63%	1.39
Discretionary	18.29%	9.92%	1.33
Systematic	21.41%	17.28%	0.94
Short	-0.93%	22.32%	-0.27

domain of the function and variables where one is likely to find good results, and then do a rough optimization with the computer's help. By avoiding to search for maxima in areas where there are no theoretical or empirical evidence pointing in that direction, one also averts data-mining. Only stable maxima are of interest here since they are likely to persist in the future and yield profitable trading opportunities.

This is the overarching principle that lies behind what is described in Section 5 (Meth-

Table 9. Our strategy.

Aspect of Choice	Our Choice	Justification
Return Generating Technique	Statistical Arbitrage	Strategies based on fundamental analysis, advanced macro-models or experience within an industry are not interesting since we have not got the necessary competence. What remain are basically the more technically inclined strategies, where programming, statistics and knowledge of the anomalies of the markets are the critical knowledge factors.
Investment Style	Market Neutral Trading with a horizon of between a few weeks and a few months	Given our statistical arbitrage technique, a market neutral approach is suitable because it isolates the effect of the arbitrage, and the link with academic papers on behavioral phenomena is clear. Furthermore, the important momentum effect that we want to exploit appears within the chosen trading horizon. If this horizon is too short, transaction costs will be prohibitively large, and if it is too long, prices mean revert and the effect disappears. One could enhance the model with varying betas on different factors (making directional bets), but we limit ourselves here.
Market	Swedish Stocks	Equity is the most accessible asset class when it comes to data-availability and literature on arbitrage. It also has the most interesting prospects in terms of risk-return profile. The exclusion of derivatives is a limitation from our side. Swedish data is used for limitation and availability reasons.

odology – Signal Generation and Risk Control).

3.3 Technical Specification of the Computer Program

The computer program, which took us 6 months to develop, functions as a simulation platform. With it we can, using data stored in the Microsoft Access database format, simulate virtually any trading strategy with a few adjustments in the program. We have built in functions to automatically analyze any interesting statistical property of a user-specified model executed in the program.

The programming environment employed is Sun's Java. Among the reasons for this choice are Java's relative robustness, its scalability, its position among financial computer systems in general, its object oriented nature, and its platform independence. The choice of programming system is not critical, but it is convenient to be able to use it under different operating systems (Windows, Linux, MacOS and so on). Java 1.4 is the latest version and therefore probably the better choice when it comes to speed of execution and richness in features, but the larger installed base of software made Java 1.3 the final choice.

This section requires some understanding of object oriented design, but it should be enough to note that a program written in a language such as Java or C++ consists of several classes with different duties and relations among themselves. The main goals in the development phase were robustness, ease-of-use, speed, and scalability. The program is based on a scalable plugin architecture, where the plugins are different sets of rules (see Section 5) that are to be applied to the underlying data (such as price or volume). Implementationwise, this means that each set of rules is its own class. One minor goal has been to minimize the coding effort needed to add a new rule. In the current version of the program, it is enough to write one main function for each plugin and some small methods for determining what kind of data the plugin needs. Without going in too deep on object oriented design, the rest of the

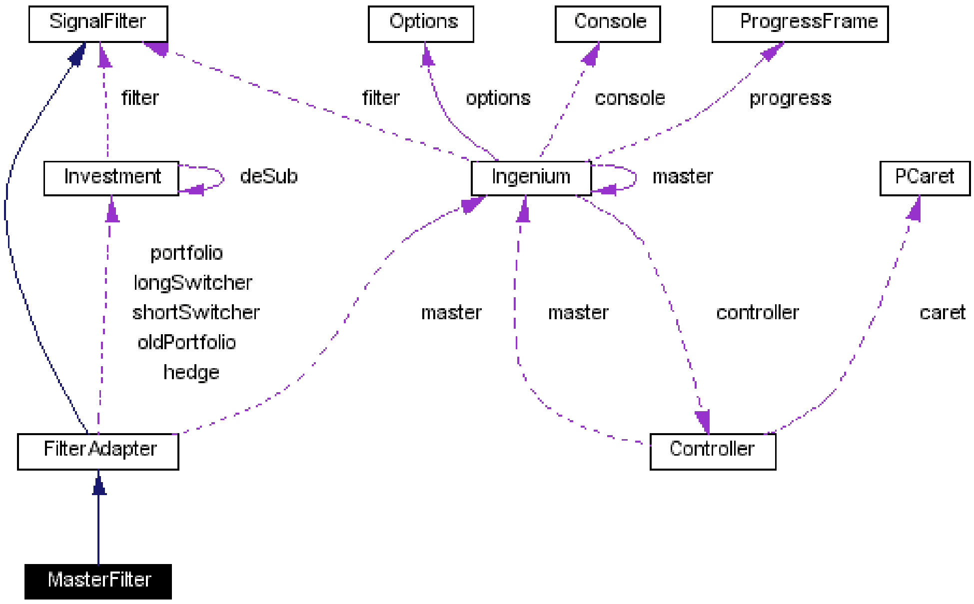

Figure 5. Conceptual view of the computer system.

functions reside in the superclass. The conceptual design of the system is depicted in Figure 5. In the diagram, one can view the filter (abstraction for trading rule) MasterFilter and its relationship to the rest of the system, particularly the core (Ingenium). The collaboration and hierarchy of different classes are illustrated using arrows. As is hopefully evident, the modularity of the system makes it an easy task to write a new filter.

A part of the graphical user interface of the system is depicted in Figure 9 in Appendix A.3. Ease-of-use has been the goal in this area, as well as clarity in design. Robustness and numerical stability in calculations have been checked using Microsoft Excel XP. In Appendix A.4, we display an example of what kind of data the simulation platform can generate in a day of trading.

The source code amounts to more than one megabyte of sheer text, which is approximately equivalent to 220 pages of text (assuming 4500 characters per page). 270 classes have been produced from the code.

4 Data

The data was electronically retrieved from the international database Datastream and the Swedish Trust.

4.1 Description of the Data

We have used closing prices for the most liquid Swedish stocks. The stocks are all from OM's liquidity classes A and B, and have been adjusted for splits and dividends.[12] The Swedish stock prices were retrieved from Trust. Moreover, data on traded volume, market value, market-to-book and predicted cash flow for the Swedish stocks were retrieved from Datastream. See further Tables 10 and 11.

Table 10. Number of companies for which there exist various fundamental data at the beginning and end of the test period.

	M/B	Market Value	Volume	Predicted Cash Flow
95-06-30	69	91	98	65
01-11-06	111	155	150	143

The stocks have been divided into 10 different sectors, based on "Veckans Affärers Industriindex", see Table 15 for specification.[13] To get a reasonable number of foreign stocks in each respective market, we set the market capitalization limit to 4.9 billion SKr. The non-Swedish stocks were downloaded from Datastream. The reason for looking at non-Swedish stocks is to make out-of-sample tests to ensure that the effects we are studying are not isolated to the Swedish market. Further details can be seen in Table 11. For a list of the stocks used please see Table 23 in Appendix A.5.

Table 11. The stocks used in the model.

Country	Number of Stocks	Time Period
France	110-181	900101 - 011106
Germany	110-167	900101 - 011106
Sweden	101-175	950101 - 011106
U K	192-202	900101 - 011106

Apart from the data on stocks, daily quotes of the Swedish one-year rates from 1990-01-02 through 2001-12-21 have been used. For the calculations of β-values, "Affärsvärldens Generalindex" ranging from 1979-12-31 – 2001-11-14 has been used.

Missing data has been approximated as a weighted average of the two closest neighbors.

[12] The criteria for the A-group are that the stocks should be traded every day, have an average turnover exceeding MSkr 4 and a spread under 1%. The B-class of stocks requires that the proportion of trading days exceeds 50%, that the average daily turnover exceeds Skr 200 000 and that the spread is below 5%. From these classes we have taken the 175 most liquid stocks.

[13] The data is from 1982-09-13 - 2001-11-05 and was downloaded from EcoWin.

5 Methodology – Signal Generation and Risk Control

We will in this chapter give a non-technical and non-detailed description of how we have constructed the algorithms of our trading model (also called default trading model), which is based on Swedish data and incorporates all trading rules. For the non-Swedish markets, we have only got the price variable and hence only used a subset of the rules that are applied to the Swedish market.

A stock in the portfolio can be dropped for two reasons; it hits the stop-loss limit, or it reaches the end of the holding period when the momentum effect is believed to fade away. This means that the stocks in the portfolio quickly will move out of phase. In 95% of the days in our model (see Section 6) there are 0 - 3 trades (sell one & buy another) executed, with an average of one stock traded every third day. Since we always keep 10 stocks in the long and 10 stocks in the short portfolio, a dropped stock needs to be replaced immediately (we have tested the effects of delayed execution in our robustness tests in Appendix A.1.2). And every time a stock is bought (or shorted), the program needs to evaluate all stocks available and rank them according to a scheme and then pick a stock from the top (or bottom if it is a short stock that needs to be added) if it fits the portfolio risk criteria.

We have thus divided this process into two steps. First, the model uses the data and different algorithms to rank all the stocks according to expected strength and direction in future momentum, and a "master list" is created. We have called this step *Signal Generation*. Next, we let the program go through the top candidates. For example, if we need a long (short) stock, the program checks the first 4 stocks (the last 4 stocks) on the master list for certain properties. The one that best meets our risk criteria is chosen. We have called this step *Risk Control*.

5.1 Signal Generation

The purpose of this part of the model is to produce an optimal master list of momentum stocks. In Sections 2.4 and 2.1 we have found a few guidelines on where to look for good momentum stocks, which are illustrated in Table 12. For these 5 dimensions, we have

Table 12. Our momentum-proxies.

Characteristics of strong momentum stocks	**Our Proxy**
Large increase/decrease in price last 6 months, momentum persists for 4 months	Stock price 6 months back compared with today, with an extra weight to the last week to sort out declining stocks: 20% weight to the last week and 80% weight to the rest.
Low analyst coverage (long portfolio)/ High analyst coverage (short portfolio)	Low market cap for long, high market cap for short portfolio.
More susceptible to sentiment changes, i.e. growth stocks	High M/B
Positive/negative sentiment in trading	Large changes in price during increase in volume
Fundamental strength/weakness Positive/negative sentiment of analysts	Large changes in analyst expectations of Cash Flow one year ahead

constructed mathematical rules to rank the stocks in accordance with their expected future momentum. The most important variable is as stated before price, i.e. the rule that ranks stocks by performance the last 6 months and keeps them for 4 months (although we have modified this rule somewhat by giving extra weight to the last week). This rule is thus almost the same as in the simplistic strategy. But by combining this simple rule with others we have constructed a more advanced and hopefully more effective strategy.

5.2 Risk Control

An investor wants, given the return, as low volatility and low correlation with other assets as possible. The correlation with the market (or beta) measures this exposure assuming that the investor holds a diversified portfolio. In a market neutral portfolio such as ours, the market risk will be rather low (see Section 6). But there are other risks that are not correlated with the market. These risks stem from the fact that the long and short portfolios may contain stocks that belong to groups of stocks that are negatively correlated. A decrease in the price of the long portfolio and a simultaneous increase in the stock prices of the short portfolio will result in a large loss. It is therefore important to neutralize these risks.

The most obvious risk is that the long and short portfolios end up with a large exposure to different industries that tend to move in the opposite direction of each other. This frequently happens when one ranks stocks on price changes alone, where one industry is located on the top of the chart and another industry close to the bottom. If there is a turnaround in the economy, both the long and short portfolio will start to lose money at the same time.

Other categorizations of stocks that tend to move in cycles are growth versus value stocks and large cap versus small cap stocks. The growth category is overweight in both the long and short portfolios and will as such not pose a large threat to the stability of the portfolio. The relative small overweight of large caps in the short and small caps in the long portfolio also does not seem to create a systematic risk exposure of great importance (see correlations with industry index below in Section 6.1), in line with our observations in Section 2.1.

What we basically have then is a problem of covariance within the portfolio. Our main solution is that we test the best 4 candidates for inclusion in the portfolio by calculating the sum of the variance-covariance matrix, one at a time, and then pick the stock that results in the lowest portfolio risk. By testing 4 candidates, one will increase the chance of finding a stock that has strong momentum but also a beneficial volatility structure.

We have three more categories of risk control; the stop-loss rule, a low price cut-off and an indicator of extreme valuations. We do not trade when the stock price is under 3 SKr. These stocks often move in large discrete steps in an unpredictable manner. The stop-loss rule is set to 20% of the maximum value during the holding period. Interpreting the 20% stop-loss as a contrarian signal motivates this rule, since expected momentum profits diminish with contradictory signals (since the basis for momentum is return continuation). When a stock hits the stop-loss limit, it is banned from entering the portfolio for 15 trading days (3 weeks). And when 4 stop-losses are executed within one month and industry (as defined by correlation with AFGX indices 6 months back), the whole industry is banned from entering the portfolio for one month and an opposite position is taken within the industry relative to the original position. This rule remedies situations where an industry has had a strong momentum for a long time and suddenly turns around. This industry will be overweight in the long (or short) portfolio, and some signals will still indicate momentum in the old direction before the turnaround.

The indicator for extreme valuations is also targeted to challenge the problem of turnarounds. The rule bans industry sectors on the long (short) side where the M/B has doubled (halved) the last year for more than 4 stocks in the sector. When valuations deviate too much from fundamental value, prices start to converge again. In the words of Shiller (2000), irrational exuberance can not hold forever.

5.3 Assumptions in Our Simulations

In all of our simulations, we let the program use three separate accounts to make the simulations as realistic as possible. These are:

1. The Long Portfolio
2. The Short Portfolio
3. The Transaction Account (TA)

We start out with an equal value of the long and short position (consisting of 10 long, 10 short stocks respectively) and a blank Transaction Account, where the transaction costs for taking the initial positions are subtracted at the end of the first day. When a long position is sold it is booked in the TA, and when a long position is bought, money is withdrawn from the TA. All the transaction costs for both the long and short portfolios are booked in the TA. Except for the transaction costs, the short portfolio (which is a zero net investment) will affect the TA every time one closes a position, leading to a net profit or loss. In essence, the structure of the accounts and the transactions between them should mimic the real world situation.

The following definitions have been made:

- Value of Total Portfolio(t) = [Value of Long Position(t)]+[Value of Net Short Position(t)]+ [Value of Transaction Account(t)]
- Total Return(t) = log[Value of Total Portfolio(t)/Value of Total Portfolio($t-1$)]

5.3.1 Basic Assumptions of Our Trading Model

These are all true unless otherwise stated.

- We have 10 short and 10 long positions at all times. This is of course a variable that could be changed in a better model. But it is a reasonable limitation from our side considering that our sample of less than 175 stocks would cause less profitability on the margin if one includes many more stocks, and that fewer stocks would make the portfolio too undiversified.
- Our default trading model is run from 1995-06-30 through 2001-11-06. We had to work with this limitation due to our restricted access to good fundamental data.
- Transaction costs are set to 0.3% for both long and short trades. This should not be an understatement of the costs for an investor with more than 1 million SKr to invest. These figures are from Germer (2002).
- When a new position is entered, the basic rule is to make it 10% of the total value of the long and short portfolios, respectively. This will keep the portfolios from deviating too much from equal weighting (ten long and ten short positions).
- The Transaction Account, which is initially set to zero, will increase as profitable short positions are closed and decrease with transaction costs and unprofitable short positions. We have put two limits on the size of this account; the lower limit being -3% of Total Portfolio Value, and a higher limit of +3%. The reason is that a too large negative balance would yield interest rates, and that a too large positive balance would not effectively use the capital. If it exceeds the positive limit, positions on the long stocks are increased. Similarly, if the TA exceeds the negative limit, long positions are trimmed to bring back the account balance to zero. It would be preferable to shift

weight during rebalancing to the stocks with the most expected momentum left. However, since we only have +10 -10 stocks and a small sample to pick from, the portfolio turns out to be very undiversified in these simulations.

- All trades are made at closing prices, and all changes in the portfolio are made within the day. For example, if a long position exceeds the stop-loss limit, it will be sold at a worse price than the set limit (the closing price), and a new stock will be added that day at that day's closing price.
- The portfolios are rebalanced (in terms of total weight of long and short portfolios) every time the long or the short portfolio exceeds the other with more than 25%, in order to keep market neutrality (see Tables 6 and 7). If the long portfolio outgrows the short, the short portfolio is increased in value by adding to existing positions. The same process is applied if the short portfolio outgrows the long, which happens rarely. However, this assumption leads to a small asymmetry between the portfolios where the short portfolio on average is worth less than the long. This is not the case in the (less realistic) classical methodology with CAR where an equal money amount is assumed when the portfolio is periodically rebalanced.
- Interest earned on the proceeds from the shorting of stocks (which is used as a security by the broker) is set to 0%. This would in real life be somewhat less than the risk-free interest rate. Interest rate on the TA is also set to zero.
- Fees on entering short positions are set to 0%. This would be less than 0.5% on an annual basis for the more liquid stocks, but over 10% for illiquid stocks that are drastically declining in price for longer periods (this happens rarely according to Germer (2002)). Not including these fees, and the interest rate on the Transaction Account, is however more than offset on average by not including the interest rates earned on the security deposits described above.
- We start each simulation with a nominal value of 10 million SKr. The absolute starting level is however irrelevant for the statistical analysis since everything is expressed in relative terms and there are no fixed costs assumed.

6 Results - Portfolio Simulations

6.1 Results of Our Trading Model

The idea now is to apply a battery of descriptive statistical tests to evaluate the performance of our model. These are described in Table 13. We believe that all of these measures are necessary complements to each other, although not all are discussed in this thesis. The futility of using only CAR and a t-statistic when evaluating trading strategies is evident. Unfortunately, it is very common.

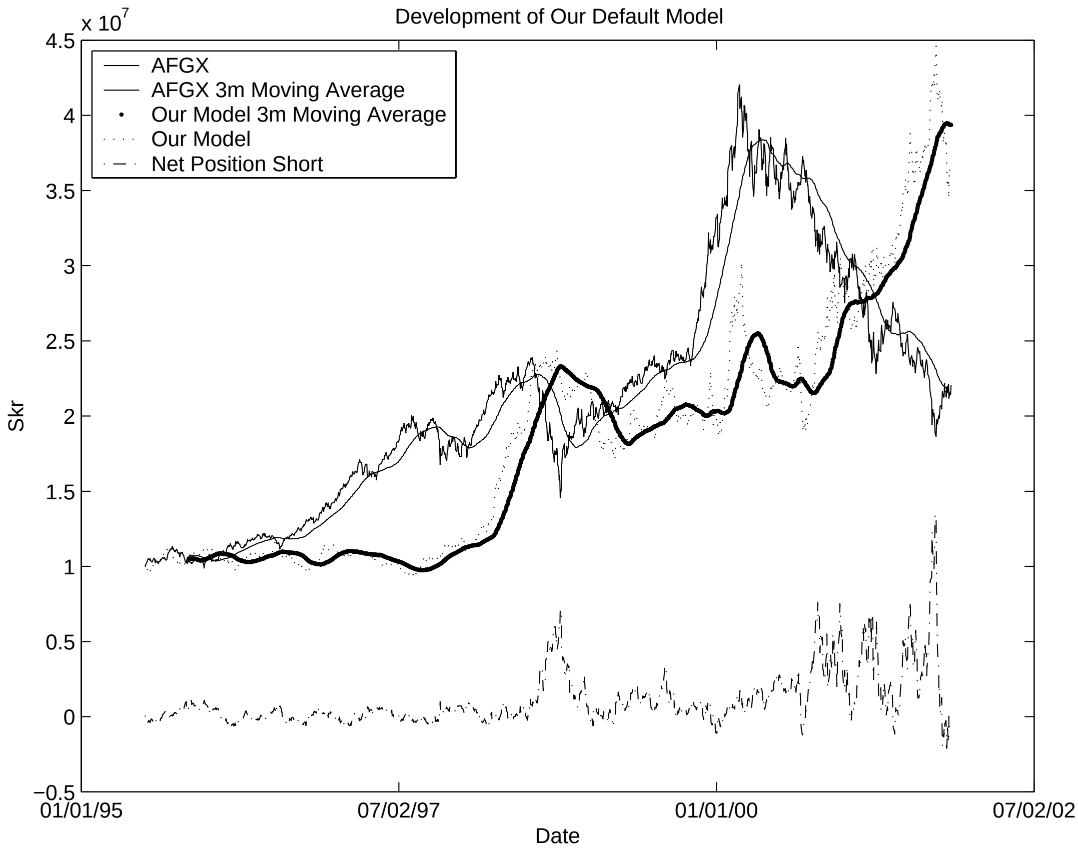

Figure 6. A diagram over the development of our model, compared with the same investment in AFGX.

Table 13. Evaluation variables.

Evaluation Variable	Mathematical Definition	Comment on variable
Annualized Return (1st moment)	$\left(\frac{\text{Total Value}_{t=T}}{\text{Total Value}_{t=0}}\right)^{1/T}$, T = number of years since inception.	How much money can this strategy produce per year?
Daily Return day t	$R = \log(\frac{\text{Total Value}_{t+1}}{\text{Total Value}_{t}})$, t = day	
Annualized standard deviation (2nd central moment)	(monthly standard deviation)$\sqrt{12}$	We have used months as a base for calculating annualized standard deviation since the trading horizon is a few months. Standard deviation alone do not however give a correct picture of a portfolio's risk characteristics. Also, there are many ways to measure standard deviation, which makes it susceptible to manipulation. Had we used 3 months averaged portfolio value as a basis for calculating std, the Sharpe ratio would be over 5!
Skewness (3rd moment)	See Appendix	This measure and kurtosis is based on daily values. Negative skewness is less attractive than positive.
Kurtosis (4th moment)	See Appendix	The lower kurtosis, the better, since that will mean less exposure to extreme events.
Sharpe ($r_f = 4\%$)	$\frac{\text{Annualized Return}-4\%}{\text{Annualized Std}}$	We have used 4% as the risk-free interest rate. This measure is rather blunt for our kind of strategy since it does not consider correlations or distinguish between positive or negative (return) contributions to volatility. However, as a comparison tool for similar simulations it is excellent.
VaR 1 day (worst, 1%, 5%, 10%)		The Value at Risk measure can be used to get a feeling for the negative end of the distribution of returns.
Worst 1 day, 1 week, 1 month, 1 year)		A good way to establish how bad bad can get.
Worst/Best	$\log\left(\frac{S_T}{S_t}\right)$	Date given is starting date for period. Note that the returns are logged, which e.g. means that the continuous return one year can be below -100% (or -63.2% $=e^{-1}-1$ simple return).
Downside Risk	$\sum_{t=0}^{t=T}(\min(0, \text{daily return}_t - r_f))^2$, t = day	This measure gives a value to the aggregate returns below the risk-free rate (averaged yearly risk-free rate in Sweden).
Beta (AFGX)	See Appendix	Comovement with market. A low β provides insurance which is valuable to investors.
Autocorrelation total return (1 day, 1 week 1 month)	See Appendix	The return's correlation with itself yields an indication of whether the portfolio is prone to trend.
Accumulated transaction costs divided by final total portfolio value		This measure quantifies total transaction costs. One should divide with time elapsed since inception and also consider the dependence of ending total value to make this number comparable across simulations.
Total return from short positions and total return from long positions		This non-normalized measure before transaction costs (total sum of percentage return of all positions) tells us the relative decomposition of returns from the long and short portfolio. The short portfolio will lose money on average and can be interpreted as the price to be paid for lower risk and beta.

The results of our model is displayed in Table 14. In Figures 7 and 8 the distribution of returns is depicted.

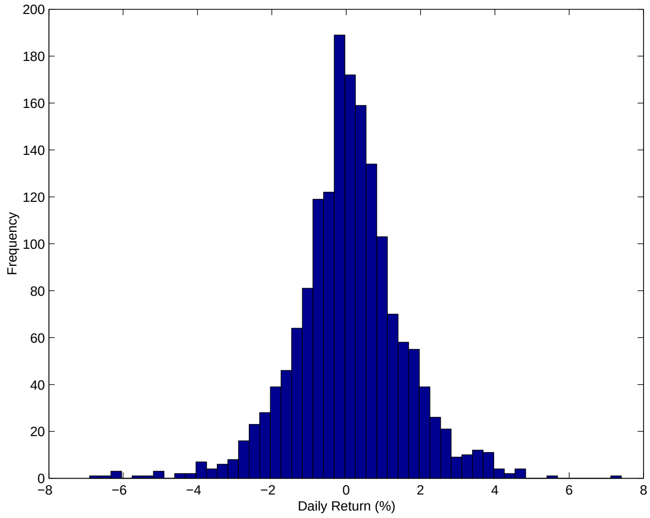

Figure 7. Histogram describing the distribution of the daily returns of our model.

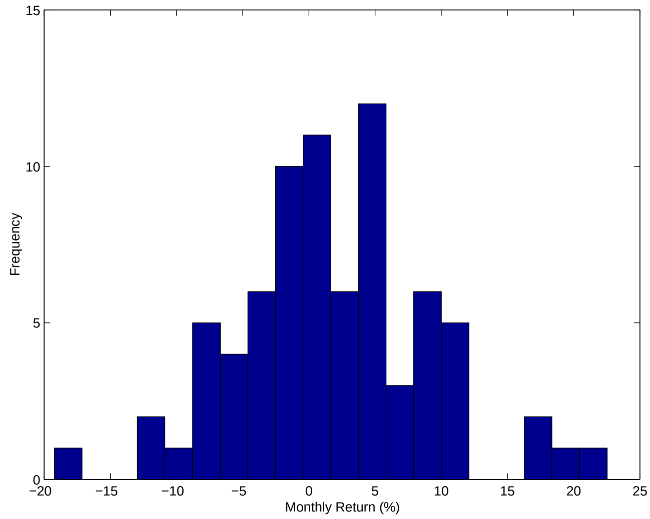

Figure 8. Histogram describing the distribution of the monthly returns of our model.

Table 14. Results of our trading model.

	Sweden
Number of stocks	94-175
Time period	19950630-20011106
Annualized Return	21.8%
Daily Std	1.46%
Annualized Std	25.6%
Downside Risk	4.33%
Beta	-0.011
Skewness	-0.154
Kurtosis	2.20
VaR (daily)	
Worst	-6.90%
1%	-3.95%
5%	-2.26%
10%	-1.57%
Autocorrelation	
One day	0.0981
One week	0.0248
One month	-0.0307
Sharpe ($r_f = 4\%$)	0.71
Acc. Tr. Costs/Total Value end	13.6%
Acc. Return Long	2181
Acc. Return Short	-159
No. of short/long investments/run	344/272
Worst annual returns	1996-06-30: -7.15%
	1998-06-30: -0.705%
	1995-06-30: 9.44%
	1999-06-30: 17.9%
	2000-06-30: 41.4%
Worst monthly returns	1998-12-28: -19.2%
	2001-09-28: -12.1%
	1998-09-28: -11.8%
	2000-04-28: -8.96%
	1999-08-28: -8.44%
Best annual returns	1997-06-30: 64.4%
	2000-06-30: 41.4%
	1999-06-30: 17.9%
	1995-06-30: 9.44%
	1998-06-30: -0.705%

Table 15. Correlations of our trading model with different industries.

Industry	**Correlation with our model**	**Correlation with our model from 980101**
Bank and financial	0.01653	-0.02286
Forestry	-0.03130	-0.03283
IT	N/A	0.00353
Manufacturer	-0.01962	0.01270
Miscellaneous	0.00669	0.03007
Retail	0.01143	0.03245
Chemicals and pharma	-0.02407	-0.09324
Investment companies	-0.01788	0.00585
Real estate and constr	-0.00729	0.01093
Shipping and transportation	-0.02769	-0.00090

6.1.1 Comments on the Results of Our Model

The stock market in Sweden between 1995 and 2001 is characterized by a relatively calm period followed by a boom-bust cycle, which should be a favorable environment for momentum traders that manage to time the turnaround in the market. As one can see in the Appendix, without risk control, our momentum strategy produces returns close to 40% per year in this period. But it is not entirely straightforward to objectively compare the merits of different strategies, and return is certainly not the only (or even most important) measure of performance.

To establish the optimal balance between return, risk structure and correlations, one would need to specify a utility function, which we have not done due to the inherent subjectivity and difficulties in doing that. Instead, we have simply set out that we would like to produce returns that are comparable to the naïve momentum strategies while avoiding large losses and sustained periods with negative returns. But we have only roughly optimized the model; we could for example have fine-tuned the sector ban rules to strike in the beginning of March 2000 and hence produced better results.

The basic problem we have had with our strategy is that the model at times bans up to 40% of an already small sample. We have chosen to accept this flaw and recognize that results would be smoother and more diversified in a larger market with more stocks to choose from. Also, as we stated earlier in Section 4, the fundamental data is of poor quality before 1997. Other than that, the result depicted in Table 14 is rather representative of our kind of strategy.

Before 1998, the market moves sideways and the model has a hard time finding profitable positions in stocks with momentum. Return picks up in 1998 until the Russian crisis shakes the markets. Then comes a period of rather poor performance where there are no clear trends in the market. Our risk control rules ban most of the stocks that skyrocketed in 1999 from entering the long portfolio (more than doubled M/B in 6 months). In the beginning of 2000, some of these technology stocks have entered the portfolio, only to start losing money in March. And from the summer of 2000 to the last trading day, a lot of value is created from short positions in dwindling stocks in the bust tech sector. In summary, we can see the importance of clear trends and volatility in the underlying market for the profitability of our strategy.

All things considered, our strategy has performed very well in this period, delivering both high returns and a low correlation with the market index.

6.1.2 Comparison with the Simplistic Momentum Strategy

The simplistic strategy (see also Appendix A.6 for a definition) common in academic papers on the momentum effect means basically a static rebalancing after a fixed interval and ranking based purely on the price variable. In this strategy, we change all stocks every 4th month and go long (short) in the 10 stocks that have exhibited the biggest increase (decrease) in price the last 6 months. This is thus the strategy we set out to compare our own model with as stated in the purpose of this thesis, and also the strategy that usually has the best performance in academic research (see Section 2.4). We want to find out how an inclusion of transaction costs and more advanced trading rules affect performance. (Our emulated simplistic strategy still differs somewhat from the strategies in Section 2.4, due to our use of the Transaction Account and rebalancing rules. This is however of minor importance.)

It is important to note that we have already assumed, based on theoretical and empirical evidence, the existence of a momentum effect. Our goal here is merely an assessment of how performance is affected when introducing the added realism of transaction costs and more advanced trading rules in relation to a simplistic strategy. For a discussion of the strength of this underlying assumption, see our analysis of robustness with respect to our sample in Appendix A.1.

The robustness of the *relationship* between our own model and the simplistic strategy is however another question. The inclusion of transaction costs always lowers returns while keeping risk virtually unchanged. The use of more advanced trading rules always lowers risk in approximately the same magnitude as evident here, and some return is of course also sacrificed. This conclusion is supported both by theoretical arguments and statistical tests of our simulations (see Appendix A.2). The robustness of this relationship is therefore stronger than that of the model itself, which strengthens our conclusions.

Looking at Table 16 and comparing it with Table 14, we can see that even before including transaction costs, the Sharpe measure is about the same (0.68 compared with 0.71). Sharpe incorporates the two first moments of return and is hence a good indicator of relative performance. The rest of the statistics tells the story why this is so and should not come as a surprise. The risk characteristic of the simplistic strategy is dramatically worse than in our model. All the risk measures; standard deviation, downside risk, VaR, are worse. In Appendix A.2, we find that the standard deviation of monthly returns is indeed significantly lower in our model. Returns on a monthly basis are not significantly different however, with or without transaction costs, leaving Sharpe virtually unchanged. Although we do see some tendencies of lower return in our model with transaction costs compared with the simplistic model without transcation costs, these tendencies are not as statistically significant as the improvement in risk.

The use of more advanced trading rules in our model have thus paid off, and the bulk of improved performance is apparent on the risk side. We do give up some upside potential when controlling risk, but this and the effect of transaction costs is compensated for by the much better risk profile in terms of risk-return tradeoff. There are many things that can be said about the relative performance, but these facts are the most important.

We can thus conclude that, when assessing the feasibility of a simplistic no transaction cost momentum strategy commonly depicted in academic research in a real-life setting, performance loss when introducing transaction costs may be less than the improvement from more advanced trading rules. In our case and in this sample, assuming any risk-averse utility function, the attractiveness of the risk-return profile has actually improved a lot due to the lower risk.

Table 16. Results of simplistic momentum strategy.

	Simplistic price momentum without transaction costs (replication of earlier studies)	**Simplistic price momentum with transaction costs**
Number of stocks	101-175	101-175
Time period	19950602-20011106	19950602-20011106
Annualized Return	30.4%	19.8%
Daily Std	2.52%	2.47%
Annualized Std	39.1%	40.9%
Downside Risk	7.93%	8.91%
Beta	-0.062	-0.076
Skewness	-0.707	-2.07
Kurtosis	22.5	34.5
VaR (daily)		
Worst	-26.1%	-29.7%
1%	-7.30%	-7.00%
5%	-3.57%	-3.29%
10%	-2.07%	-1.96%
Autocorrelation		
One day	0.194	0.171
One week	0.012	-0.019
One month	0.147	0.157
Sharpe ($r_f = 4\%$)	0.68	0.39
Acc. Tr. Costs/Total Value end	0%	11.4%
Acc. Return Long	2887	2887
Acc. Return Short	-274	-274
No. of short/long investments/run	200/200	200/200
Worst annual returns	1999-06-30: 8.68%	1999-06-30: -32.1%
	1995-06-30: 13.1%	1995-06-30: 9.91%
	1998-06-30: 16.9%	1998-06-30: 15.1%
	1996-06-30: 18.7%	1996-06-30: 16.3%
	2000-06-30: 29.7%	2000-06-30: 31.9%
Worst monthly returns	2000-12-28: -46.2%	2000-12-28: -45.9%
	1999-12-28: -27.3%	1999-12-28: -44.3%
	2001-09-28: -19.8%	2001-09-28: -21.6%
	1999-02-28: -14.7%	2000-01-28: -13.8%
	2001-04-28: -13.6%	2000-04-28: -12.9%
Best annual returns	1997-06-30: 72.8%	1997-06-30: 69.8%
	2000-06-30: 29.7%	2000-06-30: 31.9%
	1996-06-30: 18.7%	1996-06-30: 16.3%
	1998-06-30: 16.9%	1998-06-30: 15.1%
	1995-06-30: 13.1%	1995-06-30: 9.91%

7 Conclusions

There is both theoretical and empirical support for the existence of the momentum effect. But any good quantifications of what performance actually can be achieved in a real trading strategy are hard to get by. Results presented in most academic journals are not based on a methodology realistic enough to measure the performance really available to investors.

We have found that, when introducing transaction costs and more advanced trading rules using Swedish data from 1995 to 2001, performance as measured by e.g. Sharpe does not deteriorate in relation to a simplistic strategy (with static rebalancing, no transaction costs, only price as input variable and no other trading rules). The negative impact on return when introducing transaction costs (0.3% per trade) is outweighed by the much lower risk attainable with our model that uses a variety of data and rules to optimize performance.

In fact, the improved risk characteristics of our more realistic model infer that exploiting the momentum effect might be even more attractive as a trading strategy than have been suggested in academic research.

Having stated this conclusion, we would like to emphasize once again that the real importance of this thesis lies in the use of the simulation platform, which took us 6 months to develop. But it now takes us only 5 seconds to run a 10-year simulation, a few minutes to adjust the parameters and test an alternative hypothesis, and a few hours to download new data and test *any other trading strategy*. And all this is done in a way that is more realistic than the use of for example CAR.

If the finance departments at business schools were to adopt an introduction to simulation platforms in their methodology courses, maybe someday one would not have to look up the impact of transaction costs in a footnote in the Appendix.

A Appendices

A.1 Robustness

A.1.1 Four Criteria of Robustness

We will here discuss the robustness of our model and the momentum effect with the help of simulations from Germany, France, UK and Sweden.

We will use four conditions of robustness to evaluate our trading model. These conditions have implications for the profitability in a real life setting, and whether the strategy benefits investors in a way that is at least as good as in the historical simulations. These four stipulations are as follows:

1. Liquid Markets

One of the theoretical explanations for the existence of the momentum effect is illiquid markets, or limits to arbitrage with respect to the short side. We have assumed that all the stocks in the sample can be shorted without delay, and that there always is someone willing to lend us stocks. This is not a realistic assumption indeed, but we believe that these constraints will not impede the results if the investor is big enough to have good relationships with brokers, but small enough not to drain the market or affect prices.

For the simulations on the Swedish markets, where the lowest volume stocks in our sample have a turnover of about 1 million SKr per day, it is evident that a portfolio bigger than 10 million SKr would not allow immediate execution as assumed in this thesis, see below for further discussion. In the foreign countries, where we have stocks based on market capitalization (>4.9 billion SKr), the liquidity is better. For example, the daily turnover of the 200 UK stocks we have in our sample is above 90 million SKr. But in France, there are a few high capitalization, low volume stocks that one realistically could not trade in. We have commented on this in the simulations below.

To test the robustness of our default model in Sweden (where we have daily data on volume), we exclude the 10% stocks with the lowest volume, and do a simulation where these stocks are included, but subjected to delayed execution and higher transaction costs.

2. Trading rules based on sound empirical and theoretical evidence

We have seen that it is a trivial task to construct very profitable strategies. Try using this rule starting 1992: buy large cap Finnish companies that begin with the letter "N". This is obviously an ex post constructed rule, that is not based on a theory why it should outperform the market. We have to have some kind of reason to believe that a certain strategy will continue to work, and we have found that support in the theoretical and empirical findings of behavioral finance. And the best way of checking for the potential of any sample specific bias is to compare the results with previous studies and to do out-of-sample tests of the model.

We have done this on German, French and UK data, by replicating the methodology (only using price as momentum signal) of previous empirical studies and comparing the results with randomly generated signals. For these countries, we have almost 12 years of data, and the time consistency of performance can also be studied. In Sweden, we have rather few stocks (for a 20 stock momentum portfolio) between 1990 and 1995. When we run simulations using rules that can ban stocks or industries, it can happen that the portfolio almost runs out of stocks to consider including. In general, assuming that 5-10% of the market at any given moment exhibit momentum characteristics, including more than that in a portfolio is likely to produce bad results. Hence, these simulations should be interpreted with care.

But the biggest threat for an absolute return manager that believes that there are real arbitrage profits to be made is however new entrants. Theory describes a gloomy scenario in the case of too many investors chasing too little momentum: markets will be more volatile and it will be much harder to catch the momentum in time. The Catch 22 is this; one want to have good and solid research to build your strategy on, but one does not want anyone else to know about it. We have not tested for this problem but can only note that momentum strategies appear profitable up to date and that behavioral inefficiencies are likely to persist.

3. Correct assessment of risk, especially extreme events
Historical data is a poor judge when deciding upon the merits of a model's protection towards extreme events. The negative tails are stochastic and hard to estimate correctly. We believe that our default model is reasonably crash-proof if unleveraged, at least on the catastrophic scale. Changes in the volatility structure of the market may lead to periods of worse performance, but not sudden crashes. But we can never be certain. For the naïve strategies without risk control, big drops in value are common however. One can look at the VaR table to get a feeling for the bad side of the return distribution. This requires that one has long data series.

4. Correct assessments of costs incurred
We have included transaction costs, and made in our view assumptions on fees and interest rate charged and earned that lower returns in our simulations. However, costs like getting information, setting up computers and office space, taxes, and so forth are not included. In one of the simulations below, we check for the sensitivity of the default model when increasing transaction costs.

A.1.2 Tables of Results for Robustness

Since we only have the price variable for the German, UK, and French markets, we primarily use this data to check for the momentum effect with roughly the same methodology as indicated in Section 2.4. We just turn off all risk control, and let the model rank the stocks according to price change the last 6 months. The holding period is set to 4 months. This means that all stocks will be replaced simultaneously every 4th month.

The results presented in Table 17 are clearly consistent with previous studies, e.g. the study on the German market by D. Schiereck and Weber (1999). An abnormal return of a little bit less than 1% per month, together with a risky volatility structure with large and sudden drops in value.

Without risk control, this naïve strategy is not very interesting for an investor, even before considering transaction costs. But for academic purposes, the results strengthen the hypothesis that there is return continuation in the medium term.

There are two problems with the data presented here, one is the few stocks in the beginning of the Swedish sample, and one is the existence of thinly traded stocks in the French sample. One exceptional example of a winning position is noticeable on the first of August 2000 when a stock called Look Voyages increases from 3 to over 40 franc in one day (which helps explain the large skewness for French stocks). The company is a 97% majority owned travel group. This experience is also a hint for a rule that bans short positions in stocks that are not widely held. If we exclude the four French stocks that have increased or decreased more than 50% in one day, the annual return stops at 2.55% and annual standard deviation is 33.2%. In Sweden, where the devaluation of the currency shook up the economy in 1992-93, this momentum strategy lost over 70% (simple return) in one year (see Section 2.4).

Due to these problems, we would like to consider the UK and German simulations to have the most reliable samples.

Table 17. Replication of earlier studies. Settings: No transaction costs, no risk control, ranking based on last 6 month price change (not weighted), rebalancing every fourth month.

	Germany	**UK**	**France**	**Sweden**
Number of stocks	110-167	192- 202	110-181	90-175
Time period	19900702-20011106	19900702-20011106	19900702-20011106	19900702-20011106
Annualized Return	8.25%	10.9%	7.42%	13.9%
Daily Std	1.22%	1.32%	2.24%	2.57%
Annualized Std	22.5%	27.7%	42.7%	44.9%
Downside Risk				10.6%
Beta				-0.095
Skewness	-0.266	-1.19	18	-0.346
Kurtosis	4.36	9.94	6.89	22.66
VaR (daily)				
Worst	-15.5%	-11.4%	-24.0%	-32.9%
1%	-3.36%	-4.20%	-4.88%	-7.39%
5%	-1.82%	-2.09%	-2.19%	-3.16%
10%	-1.21%	-1.39%	-1.56%	-2.09%
Autocorrelation				
One day	0.0427	0.2040	0.0168	0.0875
One week	0.0118	0.0394	0.0166	-0.0155
One month	0.0139	0.0072	0.0013	0.0116
Acc. Tr. Costs/Total Value end	0%	0%	0%	0%
Sharpe (rf =4%)	0.19	0.25	0.08	0.22
No. of short/long investments	350/350	350/350	350/350	350/350
Acc. Return Long	1854	2717	3104	2887
Acc. Return Short	-716	-1057	-1505	-274
Worst annual returns	1992-07-02: -24.3%	1998-07-02: -38.3%	1998-07-02: -53.7%	1992-07-02: -161%
	1998-07-02: -6.95%	1999-07-02: -31.3%	1992-07-02: -46.5%	1999-07-02: -37.9%
	1991-07-02: -2.09%	1992-07-02: -13.9%	1990-07-02: -42.0%	1990-07-02: 8.19%
	1990-07-02: -1.83%	1993-07-02: -1.07%	1993-07-02: -12.4%	1995-07-02: 10.4%
	1997-07-02: 3.11%	1990-07-02: 5.09%	1997-07-02: 9.84%	1994-07-02: 14.4%
Worst monthly returns	2001-04-02: -19.1%	2000-05-02: -33.2%	2000-03-02: -30.5%	1992-11-02: -65.1%
	2000-03-02: -16.7%	2000-03-02: -32.2%	2001-10-02: -25.1%	1993-02-02: -62.1%
	2001-10-02: -15.9%	1999-04-02: -24.3%	2001-04-02: -24.9%	2000-03-02: -36.5%
	1998-05-02: -12.9%	2001-10-02: -17.3%	2000-05-02: -23.8%	2001-10-02: -31.5%
	1997-05-02: -12.9%	1991-02-02: -17.2%	1993-02-02: -23.3%	2000-05-02: -31.4%
Best annual returns	1995-07-02: 37.2%	1991-07-02: 53.1%	2000-07-02: 112%	1997-07-02: 99.5%
	2000-07-02: 28.8%	2000-07-02: 46.0%	1999-07-02: 39.2%	2000-07-02: 68.8%
	1999-07-02: 21.4%	1995-07-02: 37.9%	1995-07-02: 32.5%	1991-07-02: 68.4%
	1994-07-02: 14.7%	1997-07-02: 23.7%	1996-07-02: 31.6%	1998-07-02: 38.2%
	1993-07-02: 14.5%	1996-07-02: 17.2%	1994-07-02: 22.8%	1996-07-02: 19.5%

The significance of the momentum effect is clearly evident when comparing Table 17 with Table 18, where we have ranked the stocks randomly. The average return is centered slightly below zero due to the asymmetry between the long and short positions (see Section 5.3.1). Returns are not as volatile here because of the lower correlations within the portfolios.

Table 18. Random rankings (median of 50 runs). Settings: No transaction costs, no risk control, ranking based on a random number generator, rebalancing every fourth month.

	Germany	UK	France	Sweden
Number of stocks	110-167	192-202	110- 181	90-175
Time period	19900702-20011106	19900702-20011106	19900702-20011106	19900702-20011106
Annualized Return	-0.75%	-1.81%	-1.31%	-0.65%
Daily Std	0.739%	0.813%	0.981%	1.32%
Annualized Std	11.5%	13.4%	14.4%	21.0%
Downside Risk				4.72%
Beta				-0.008
Skewness	-0.141	0.522	-0.796	1.02
Kurtosis	2.62	8.798	9.76	20.572
VaR (daily)				
Worst	-5.99%	-5.05%	-10.1%	-7.90%
1%	-1.86%	-2.18%	-2.67%	-3.53%
5%	-1.14%	-1.21%	-1.47%	-2.08%
10%	-0.86%	-0.913%	-1.06%	-1.51%
Autocorrelation				
One day	0.0249	0.0941	0.0080	0.0380
One week	0.0085	-0.0384	-0.0221	-0.0158
One month	0.0211	-0.0038	-0.0183	0.00822
Sharpe ($r_f = 4\%$)	-0.41	-0.43	-0.37	-0.22
Acc. Tr. Costs/Total Value end	0%	0%	0%	0%
Acc. Return Long	829	1845	871	1014
Acc. Return Short	-883	-1732	-1269	-1089
No. of short/long investments/run	350/350	350/350	350/350	350/350
Worst annual returns	1997-07-02: -24.4%	1991-07-02: -32.7%	1992-07-02: -16.5%	1999-07-02: -58.4%
	1995-07-02: -16.5%	1995-07-02: -13.3%	1990-07-02: -14.0%	1991-07-02: -30.9%
	1999-07-02: -2.62%	1996-07-02: -6.57%	1998-07-02: -11.1%	1994-07-02: -13.4%
	1996-07-02: 1.87%	1992-07-02: -5.10%	2000-07-02: -10.8%	1998-07-02: -3.19%
	1994-07-02: 2.39%	1990-07-02: -5.09%	1999-07-02: -9.36%	2000-07-02: 1.17%
Worst monthly returns	1999-01-02: -10.8%	1998-07-02: -12.7%	2000-02-02: -19.2%	2000-06-02: -19.0%
	2000-01-02: -10.1%	1995-09-02: -11.8%	2000-01-02: -15.1%	1999-11-02: -17.7%
	2001-10-02: -7.75%	1995-11-02: -9.28%	1999-12-02: -14.7%	1999-12-02: -14.2%
	1993-08-02: -7.64%	1992-02-02: -8.84%	1997-02-02: -9.05%	1999-10-02: -12.1%
	1998-02-02: -7.41%	1991-09-02: -8.46%	1990-10-02: -8.44%	1992-04-02: -11.8%
Best annual returns	1992-07-02: 14.8%	1998-07-02: 24.2%	1996-07-02: 10.5%	1993-07-02: 27.8%
	2000-07-02: 11.1%	1999-07-02: 9.11%	1994-07-02: 7.33%	1992-07-02: 25.9%
	1990-07-02: 8.99%	1993-07-02: 8.70%	1997-07-02: 3.17%	1997-07-02: 22.2%
	1991-07-02: 6.70%	2000-07-02: 7.43%	1991-07-02: 0.21%	1990-07-02: 16.1%
	1993-07-02: 3.65%	1994-07-02: 5.42%	1993-07-02: -0.24%	1996-07-02: 12.7%

In Table 19, we have introduced transaction costs and risk control with the price variable. The portfolio will now quickly move out of phase because of the stop-loss rule, and we can see that the turnover is higher. The returns still seem to be significantly different from zero after transaction costs have been subtracted. But the volatility has not come down much at all. Again, France has important outlier observations that affect the results, when we delete the 4 worst stocks, annualized return goes down to 6.05% and annual standard deviation to 26.9%. This makes the results across the European markets we have tested look very similar. The higher volatility in Sweden can be explained by the much smaller and more volatile stocks in the Swedish sample.

Table 19. Transaction costs and risk control based on price variable. Settings: 0.3% transaction costs, risk control (stop-loss 25% of maximum price, covariance matrix), ranking based on weighted return of 6 months price changes (last week: 20%, rest: 80%), stocks are held until stop-loss or 4 months pass.

	Germany	**UK**	**France**	**Sweden**
Number of stocks	110-167	192-202	110-181	90-175
Time period	19900702-20011106	19900702-20011106	19900702-20011106	19900702-20011106
Annualized Return	5.77%	7.75%	15.1%	11.2%
Daily Std	1.27%	1.25%	2.54%	2.00%
Annualized Std	24.5%	25.4%	43.9%	35.9%
Downside Risk				7.63%
Beta				-0.024
Skewness	-0.666	-0.0222	27.3	-0.613
Kurtosis	7.46	10.032	118	6.07
VaR (daily)				
Worst	-8.53%	-10.2%	-9.55%	-37.0%
1%	-3.86%	-3.92%	-4.22%	-5.69%
5%	-1.95%	-1.93%	-2.05%	-2.65%
10%	-1.38%	-1.30%	-1.44%	-1.83%
Autocorrelation				
One day	0.119	0.165	0.0439	0.119
One week	-0.0189	0.031	0.00822	0.0304
One month	-0.0309	0.003	-0.0048	0.0226
Sharpe (r_f = 4%)	0.07	0.15	0.25	0.20
Acc. Tr. Costs/Total Value end	22.3%	36.9%	11.3%	14.4%
Acc. Return Long	2029	2897	3731	2264
Acc. Return Short	-980	-1402	-1329	-471
No. of short/long investments/run	429/380	495/376	481/391	601/420
Worst annual returns	1990-07-02: -30.3%	1999-07-02: -25.1%	1990-07-02: -43.3%	1992-07-02: -33.1%
	1998-07-02: -15.2%	1993-07-02: -0.80%	1998-07-02: -38.9%	1990-07-02: -29.1%
	1996-07-02: -7.35%	1994-07-02: -0.67%	1992-07-02: -14.7%	1993-07-02: -23.1%
	1997-07-02: -6.51%	1997-07-02: -0.05%	1996-07-02: -4.37%	1998-07-02: -22.2%
	1992-07-02: -5.18%	1996-07-02: 0.460%	1994-07-02: 10.9%	1995-07-02: 2.35%
Worst monthly returns	2001-04-02: -26.2%	2001-10-02: -31.1%	2000-03-02: -28.9%	1992-01-02: -40.3%
	2000-03-02: -25.8%	2000-03-02: -22.0%	2001-10-02: -23.3%	1991-01-02: -34.1%
	1991-02-02: -16.6%	1997-08-02: -15.6%	2000-08-02: -20.8%	2000-03-02: -26.9%
	1999-04-02: -13.5%	2000-04-02: -14.1%	2000-05-02: -15.8%	1999-09-02: -20.6%
	2000-05-02: -12.4%	2000-05-02: -13.7%	1999-02-02: -14.6%	2000-08-02: -20.5%
Best annual returns	1995-07-02: 47.9%	1992-07-02: 41.1%	2000-07-02: 139%	1997-07-02: 68.5%
	2000-07-02: 38.7%	1991-07-02: 37.9%	1995-07-02: 34.1%	1999-07-02: 44.3%
	1993-07-02: 27.1%	1995-07-02: 32.5%	1991-07-02: 22.5%	2000-07-02: 41.6%
	1994-07-02: 8.16%	2000-07-02: 16.6%	1993-07-02: 21.8%	1991-07-02: 25.5%
	1991-07-02: 6.23%	1990-07-02: 4.41%	1999-07-02: 20.6%	1994-07-02: 21.4%

Looking only at the period used in our default model, we can see that the relationships between the different types of simulations persist. However, returns are about twice as high in this period, as evidenced by the data in Table 20.

Table 20. Simulations from 1995 in Sweden.

	Replication of earlier studies (Table 17)	**Random ranking (Table 18)**	**Transaction costs and risk control with price variable (Table 19)**
Number of stocks	101-175	101-175	101-175
Time period	19950602-20011106	19950602-20011106	19950602-20011106
Annualized Return	30.4%	-3.28%	24.0%
Daily Std	2.52%	1.23%	1.84%
Annualized Std	39.1%	17.3%	33.9%
Downside Risk	7.93%	3.18%	5.99%
Beta	-0.062	0.052	0.0064
Skewness	-0.707	1.02	-0.613
Kurtosis	22.5	20.6	6.07
VaR (daily)			
Worst	-26.1%	-7.53%	-10.6%
1%	-7.30%	-3.02%	-5.98%
5%	-3.57%	-1.89%	-2.78%
10%	-2.07%	-1.38%	-1.82%
Autocorrelation			
One day	0.194	-0.0113	0.158
One week	0.012	-0.0250	-0.005
One month	0.147	-0.0286	0.044
Sharpe (r_f = 4%)	0.68	-0.42	0.59
Acc. Tr. Costs/Total Value end	0%	0%	11.2%
Acc. Return Long	2887	1014	2264
Acc. Return Short	-274	-1089	-471
No. of short/long investments/run	200/200	200/200	200/200
Worst annual returns	1999-06-30: 8.68%	1998-06-30: -39.5%	1998-06-30: -29.5%
	1995-06-30: 13.1%	1995-06-30: -20.1%	1995-06-30: 0.195%
	1998-06-30: 16.9%	1997-06-30: -19.4%	1996-06-30: 20.1%
	1996-06-30: 18.7%	2000-06-30: 2.11%	1999-06-30: 41.1%
	2000-06-30: 29.7%	1996-06-30: 17.7%	2000-06-30: 44.2%
Worst monthly returns	2000-12-28: -46.2%	1998-11-28: -9.55%	1999-08-28: -21.9%
	1999-12-28: -27.3%	1998-07-28: -9.28%	1999-04-28: -16.5%
	2001-09-28: -19.8%	1999-02-28: -8.97%	1998-12-28: -16.3%
	1999-02-28: -14.7%	1998-04-28: -8.69%	2000-04-28: -16.0%
	2001-04-28: -13.6%	1995-10-30: -8.32%	2001-09-28: -15.0%
Best annual returns	1997-06-30: 72.8%	1999-06-30: 33.3%	1997-06-30: 54.5%
	2000-06-30: 29.7%	1996-06-30: 17.7%	2000-06-30: 44.2%
	1996-06-30: 18.7%	2000-06-30: 2.11%	1999-06-30: 41.1%
	1998-06-30: 16.9%	1997-06-30: -19.4%	1996-06-30: 20.1%
	1995-06-30: 13.1%	1995-06-30: -20.1%	1995-06-30: 0.195%

Finally, we look at alterations of our default model in Table 21. The results are expected, at least the direction of changes. No risk control yields a (much) higher return but also higher risk. We do not interpret the higher Sharpe ratio as this being a better model. Apart from worse risk characteristics, this profile seem to be rather time specific, considering the extremely profitable trades in connection with the rise and fall of the technology sector. Also, our method of banning stocks as a means for risk control in our default model is, as stated above, not very optimal in a small sample.

Transaction costs (TC) of 0.7% significantly lowers the return. Note that the model will not do the exact same trades as in the default model, when TC are altered. Much higher TC than 0.7% would in any way be critical to the profitability of the model. When we introduce delayed execution and higher TC for the 15 most illiquid stocks results are worse, but not much. In our simulations, the buy/sell order is postponed 1 day for these stocks. The effect of higher TC is thus more important in this case.

If we are restricted from trading in stocks with low volume, say the bottom 10% (less than about 1.5 million SKr/day), return drops. But this simulation points more to the importance of a large sample to start with rather than the importance of high volume, since there is not a big difference in daily turnover of the stocks at the bottom of the chart. If one takes away 10%, and these being mostly growth companies, from a small sample, performance will be severely hit.

An interesting simulation is if we just turn off the stop-loss rule (not tabulated). The model will rebalance all stocks simultaneously every 4th month and thus not trade in the same stocks as in the default model. We find that annual return is up to 30.9% and that the VaR and standard deviation (30.3%) are higher. Most of our simulations exhibit improved performance with the stop-loss rule. But these gains are most often on the risk side and are most significant in the presence of long sustained trends that diminish portfolio value.

In a simulation where we only have used weighted price as a signal generator (not tabulated), ceteris paribus, the Sharpe ratio is down to 0.04. We have found that when the risk control rules are turned off, price is the most important signal generator, but if it is not turned off, it does not work very well alone.

If we let the default model start the simulation in 1997 (not tabulated), the portfolio is in essence the same as in a simulation where one starts in 1995 and cuts off the first two years. In this case, performance is somewhat better because of the flat performance between 1995 and 1997 in our default model.

Also, the model does remarkably well in 1992-93, where the simplistic momentum strategy lost over 70% simple return (see Table 17), even without access to fundamental data. Total value is down 2.5% in the corresponding year.

Table 21. Changes in our default model. Default settings: 0.3% transaction costs, all ranking signals and risk control rules

	No risk Control	**0.7% transaction costs**	**1 day delayed trades and 0.6% higher transaction costs for 10% most illiquid stocks**	**No trades in the 10% with lowest volume (<about 2 million SKr/day)**
Number of stocks	94-175	94-175	94-175	94-175
Time period	19950630-20011106	19950630-20011106	19950630-20011106	19950630-20011106
Annualized Return	39.8%	13.4%	12.9%	17.0%
Daily Std	1.94%	1.55%	1.42%	1.60%
Annualized Std	33.6%	31.5%	28.1%	31.6%
Downside Risk	5.82%	5.13%	5.56%	6.18%
Beta	0.0022	-0.014	-0.022	-0.053
Skewness	-0.524	-0.416	-0.279	-0.373
Kurtosis	5.95	4.79	5.97	5.52
VaR (daily)				
Worst	-14.9%	-10.9%	-11.5%	-11.8%
1%	-5.87%	-4.50%	-4.24%	-4.52%
5%	-2.79%	-2.26%	-2.11%	-2.39%
10%	-1.87%	-1.65%	-1.49%	-1.62%
Autocorrelation				
One day	0.0830	0.137	0.128	0.126
One week	0.0462	0.0313	0.0659	0.0481
One month	0.0423	-0.0271	0.00822	0.0177
Sharpe (r_f = 4%)	1.06	0.298	0.319	0.411
Acc. Tr. Costs/Total Value end	7.46%	49.7%	20.5%	15.9%
Acc. Return Long	2868	1952	2044	2436
Acc. Return Short	173	-314	-436	-505
No. of short/long investments/run	200/202	342/268	343/265	339/270
Worst annual returns	1998-06-30: 0.860%	1998-06-30: -19.1%	1999-06-30: -21.4%	1998-06-30: -25.4%
	1996-06-30: 9.78%	1996-06-30: -12.2%	1996-06-30: -6.99%	1996-06-30: 2.60%
	1995-06-30: 25.8%	1995-06-30: 3.85%	1998-06-30: 11.8%	1995-06-30: 7.93%
	1999-06-30: 36.9%	1999-06-30: 18.3%	1995-06-30: 17.7%	1999-06-30: 25.8%
	2000-06-30: 69.3%	2000-06-30: 33.2%	2000-06-30: 29.4%	2000-06-30: 26.7%
Worst monthly returns	2000-12-28 -28.1%	2000-02-28: -17.6%	2000-12-28: -23.1%	2000-12-28: -32.4%
	2001-09-28: -21.5%	1998-09-28: -15.9%	2000-02-28: -15.9%	2000-04-28: -17.1%
	2000-02-28: -19.6%	2000-03-28: -12.6%	2000-03-28: -14.4%	1999-01-28: -16.8%
	1999-01-28: -12.5%	2001-09-28: -12.6%	2000-04-28: -13.7%	2000-08-28: -13.6%
	2000-03-28: -9.67%	2000-07-28: -11.4%	2000-08-28: -13.2%	1998-12-28: -12.9%
Best annual returns	1997-06-30: 77.2%	1997-06-30: 59.8%	1997-06-30: 47.7%	1997-06-30: 62.2%
	2000-06-30: 69.3%	2000-06-30: 33.2%	2000-06-30: 29.4%	2000-06-30: 26.7%
	1999-06-30: 36.9%	1999-06-30: 18.3%	1995-06-30: 17.7%	1999-06-30: 25.8%
	1995-06-30: 25.8%	1995-06-30: 3.85%	1998-06-30: 11.8%	1995-06-30: 7.93%
	1996-06-30: 9.78%	1996-06-30: -12.2%	1996-06-30: -6.99%	1996-06-30: 2.60%

A.1.3 Discussion on the Robustness of Our Model

To reach a conclusive statement about robustness and other statistical properties of a trading model one needs extensive data from many countries and time series that are measured in decades. We have neither. But for the simplistic momentum strategy using only price as a variable, we can compare with earlier research and thus come to a more distinct conclusion.

Our results confirm other researchers' findings on the momentum effect. Results are similar for Sweden, UK, Germany and France and are consistent with both prior empirical evidence and contemporary theory. A market neutral momentum strategy in its most simple form can earn money. It is not a random walk. This conclusion holds true even after including transaction costs. But the performance is very volatile with long periods of good performance and sudden losses. This is why normal statistical methods to establish significance of results, such as the t-statistic, is afflicted with problems. Especially if the time period is too short and important extreme events are not captured in the sample.

One dimension of our analysis of robustness, the existence and similarity of the momentum effect across countries can thus be given an affirmative answer with respect to our sample.

As for our own self-made model, we can not draw any strong conclusions about the exact level of performance. Just over 6 years of data is simply too short, and there are no comparable studies. Considering that our model is a combination of many strategies, it is not either very likely that someone ever will test all possible permutations of these strategies. We can only tentatively state our conclusions and not accurately quantify future statistical properties of our strategy.

But we can be reasonably sure that our result is not a statistical fluke, since we have based our trading rules on established theoretical and empirical research, and not fine-tuned the model to fit a specific time-period. In conclusion, we find that the following things can be said about the robustness of results of our default model:

- On average, measured over a long time period, we believe that our model can produce economically significant results in the future. This conclusion is based on evidence from earlier research on the momentum effect and the relative stability of our model. However, the Swedish sample using only the price variable yields higher returns in the period where we have simulated our default model, than from 1990. It may be the case that one should expect an average return that relates in the same way to the results from 1995, i.e. only about half of the returns or 10% per year for the default model. The years around the turn of the millenium seem to have been favorable indeed for a momentum trader; first one long upward trend among especially high-tech growth companies, and then an equally persistent bearish trend. The fundamental determinant and limiting factor of profitability for a momentum strategy is the existence of persistent trends in the market. It is not hard to pick up on these trends in general once they show up, but it is a delicate task to spot the turnarounds that quickly diminish the value of the portfolio. How would our model have acted in earlier periods and, more importantly, how will it behave in the future? One can not exactly know the answer to that question.

- To implement our model on the Swedish market, one can not be too big. With a daily turnover of around 1-2 million SKr for the stocks with the lowest volume, we can with a rough estimation say that returns will be hit if total portfolio value exceeds about 30 million SKr. When we excluded the 10% lowest volume stocks, which would not be immediately executed in a 30 million SKr portfolio without price impact, returns dropped significantly. It is therefore imperative to diversify across many markets, not only to reduce risk, but also to gain access to more liquid stocks. Then it is possible to run a much larger portfolio. The size of the market one trades in is thus a limiting factor for performance.

- Transaction costs are critical determinants of profitability due to the high turnover of the portfolio. One needs to be big enough to avoid paying a fixed fee, and even if you can avoid this, average transaction costs most probably will exceed 0.3%. This limit, to reach 0.3%, is about 1 million SKr with an Internet broker today. Hence, we have both an upper and a lower limit to consider for the size of the portfolio. But these limits are obviously not critical for the interested momentum trader, who would seek out much larger and more liquid stock markets than the Swedish one.

A.2 Statistical Comparison of Our Model and the Simplistic Model

In this section we will compare the risk and return parameters of our trading model to the ones of the simplistic price momentum model including and excluding transaction costs, respectively. More specifically, we will try to test if our model performs worse than the other two strategies in two dimensions: standard deviation and return. Both tests are based on monthly figures, primarily to ensure large sample sizes and thereby more powerful tests. We have used monthly figures as they yield a large enough sample, and are closer to the trading horizon than figures on a daily basis. One could also test the equality of the Sharpe ratios, but the available tests have been criticized for their low power, see e.g. Jobson and Korkie (1981).

A.2.1 Volatility

At first sight, one would handle this topic by applying the standard procedure of testing the difference between two variances (the so called *variance ratio test*). According to Newbold (1995), "[t]hat test is valid when independent random samples from the two populations are available". However, in our case we are dealing with matched pairs (since we have run the simulations during the same time period during which the same set of stocks has been considered). Henceforth the parameter of our model will be denoted X, and the one of the model we compare to Y. The test procedure consists of a test for Zero Population Correlation (using Newbold's terminology), where one uses the fact that the correlation between $(X-Y)$ and $(X+Y)$ is zero if and only if σ_x^2 and σ_y^2 are equal. Our onesided test then looks like this:

$$H_0 : \sigma_x^2 = \sigma_y^2 \tag{11}$$

$$H_1 : \sigma_x^2 < \sigma_y^2 \tag{12}$$

Decision rule:

$$\text{Reject } H_0 \text{ if } \frac{r}{\sqrt{(1-r^2)(n-2)}} < -t_{n-2,\alpha}, \tag{13}$$

where r is the sample correlation, σ_x^2 is the variance of our model and σ_y^2 is the volatility of the simplistic model without transaction costs. n is the sample size (76 in all tests) and α is the significance level. $t_{n-2,\alpha}$ is the number for which

$$P(t_{n-2} > t_{n-2,\alpha}) = \alpha, \tag{14}$$

where the random variable t_{n-2} follows a Student's t distribution with $(n-2)$ degrees of freedom. Replace Y with Z to get the notation for the model with transaction costs. Comparing our model to the simplistic model without transaction costs, we find that the correlation is -0.454 and the corresponding test statistic is -4.39. The null hypothesis can thus (see Table 22) be rejected already at the five percent level, in favour of the hypothesis that our model has a lower variance, and thereby a lower volatility.

The correlation in the second test case is -0.466 yielding a test statistic of -4.53. The null hypothesis can once again be rejected at the five percent level, and the conclusions above apply here as well.

A.2.2 Return

Testing for the difference in returns is a simple matter of testing the differences between two means. In line with the standard deviation tests, we will use the matched pairs methodology presented in Newbold (1995). The test is set up as follows:

$$H_0 : \mu_x = \mu_y \tag{15}$$

$$H_1 : \mu_x < \mu_y \tag{16}$$

Decision rule:

$$\text{Reject } H_0 \text{ if } \frac{\bar{d}}{s_d/\sqrt{n}} < -t_{n-1,\alpha}, \tag{17}$$

where μ_x and μ_y are the average monthly returns of our model and the simplistic model without transaction costs, respectively. $\bar{d}$ is the sample mean of the difference between X and Y (here X and Y are the monthly return vectors). s_d is the sample standard deviation. Replace Y with Z to get the notation for the model with transaction costs.

The test statistic in the case where we compare the return of our model to the return of the simplistic model where the transaction costs are excluded is -0.398 which implies that the null hypothesis cannot be rejected (see Table 22). The corresponding statistic for the comparison between the returns of our model and the simplistic model excluding transaction costs is 0.155, and yet again we cannot reject the null hypothesis that the population means are equal. Thus, statistically speaking, one cannot say that performance in terms of risk and return deteriorates when one introduces transaction costs and the set of more advanced rules we have discussed in this thesis.

Table 22. A brief summary of the hypotheses tested above. x corresponds to our model, y to the simplistic model without transaction costs and z to the one with transaction costs.

H_0	H_1	**Test Statistic**	**Critical Value (5 %)**	**Result**
$\sigma_x^2 = \sigma_y^2$	$\sigma_x^2 < \sigma_y^2$	-4.39	-2.58	Reject H_0
$\sigma_x^2 = \sigma_z^2$	$\sigma_x^2 < \sigma_z^2$	-4.53	-2.58	Reject H_0
$\mu_x = \mu_y$	$\mu_x < \mu_y$	-0.398	-2.66	Cannot reject H_0
$\mu_x = \mu_z$	$\mu_x < \mu_z$	0.155	-2.66	Cannot reject H_0

A.3 Screenshot of the Program

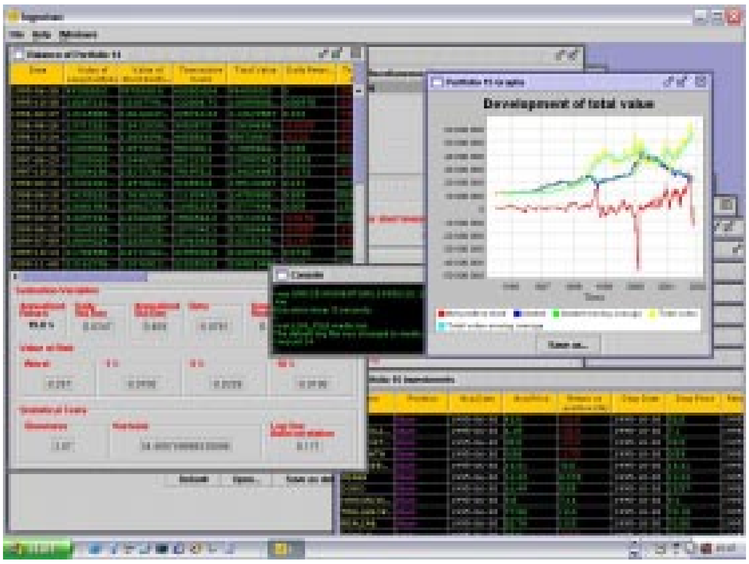

Figure 9. The program in action.

A.4 A Day of Trading

```
***New Trading Day***

1996-02-22 340
Transaction Account: 198889.75 (1.9625976 % of long portfolio).
The portfolio consists of the following stocks:
DORO (short) 1996-02-06.
SSABA (short) 1996-01-24.
ELEKTAB (long) 1995-11-23.
SANDVIK (short) 1996-02-02.
SKANDIA (long) 1995-10-30.
AKZONOBELSDB (short) 1995-11-14.
SKFB (short) 1996-02-02.
BERGMANBEVINGB (long) 1995-10-30.
HENNESMAURITZB (short) 1995-10-30.
TRELLEBORGB (short) 1995-10-30.
MUNKSJO (short) 1996-01-12.
ROTTNEROS (short) 1996-02-06.
SAS (long) 1996-01-30.
NOBELBIOCARE (long) 1996-02-19.
CUSTOSA (long) 1995-10-30.
NCCB (long) 1995-10-30.
ALLGONB (short) 1995-10-30.
FRONTECB (long) 1996-01-23.
OM (long) 1995-10-30.
IBSB (long) 1995-10-30.
Size of long: 1.0562329E7.
Size of short: 9329879.0
Time to divest HENNESMAURITZB (short).
Transaction Account before drop: 198889.75
Transaction Account after drop: 167891.78
Banned short stock HENNESMAURITZB
HENNESMAURITZB belongs to the sector: [retail$]
Divested the short stock HENNESMAURITZB at a price of 949319.06 SEK.
The Transaction Account is now 167891.78 SEK.
SCAB: Number of days between 1996-02-06 and 1996-02-22 is 16
SCAB is unbanned.
CONCORDIAMARITIMEB: Number of days between 1996-02-09 and 1996-02-22 is 13
HENNESMAURITZB: Number of days between 1996-02-22 and 1996-02-22 is 0
The following stocks are banned from the short portfolio:
CONCORDIAMARITIMEB
HENNESMAURITZB
Original candidate: NOKIASDBSEE
Considering the following stocks:
NOKIASDBSEE <=> 1.9383791E-5
KLIPPANS <=> 2.1233047E-5
TV4A <=> 2.2088336E-5
PRIF <=> 2.3530345E-5
At 1996-02-22 NOKIASDBSEE was shorted for 930188.9 SEK.
Size of long portfolio at end of trading day: 1.0562329E7
Size of short portfolio at end of trading day: 9310749.0
Total value decomposition:
lv (1.0562329E7) + nps (-339003.47) + transaction account (165092.81) = 1.0388419E7.
Checking development of market-to-book (1996-02-23).
Market-to-book for ACTIVEBIOTECHB has developed from 2.54 to 0.51 implying a ratio of 0.2007874.
ACTIVEBIOTECHB has therefore been banned from the short list.
Banned short stock ACTIVEBIOTECHB
```

A.5 A List of the Swedish Stocks Used

Table 23. Swedish stocks. The numbers in parentheses indicate the number of times the stock has entered the long and short portfolio in our default model, respectively.

ABBSEE (0, 0)	GORTHONLINES (1, 2)	PANDOX (2, 1)
ACTIVEBIOTECHB (3, 3)	GOTLANDREDERIB (4, 0)	PEABB (4, 3)
AGA A (1, 4)	GRANINGE (1, 0)	PERS B (2, 4)
AGA B (3, 3)	GUNNEBO (3, 0)	PHARMACIASDB (0, 3)
AKZONOBELSDB (1, 1)	HAGSTROMERQVIBERG (0, 0)	PIRE (3, 2)
ALFA (2, 4)	HALDEX (1, 5)	PLAT B (1, 2)
ALLGONB (0, 5)	HANDBKNHYPOTEKPREF (2, 0)	PLM (1, 1)
ALTH B (2, 4)	HENNESMAURITZB (0, 3)	PREVASB (1, 3)
ANGPANNEFORENINGENB (6, 1)	HEXAGONB (3, 1)	PRICERB (1, 2)
ASSAABLOYB (3, 1)	HLDISPLAYB (4, 2)	PRIF (1, 4)
ASSIDOMAN (1, 0)	HOGANASB (2, 2)	PROTECTDATA (3, 2)
ASTI (2, 0)	HOISTINTLB (4, 1)	RATOSB (2, 0)
ASTRAZENECASEE (0, 1)	HUFVUDSTADENA (0, 4)	REALIAB (1, 2)
ATLASCOPCOA (0, 0)	IBSB (1, 5)	RESCOB (1, 2)
AUTOLIVSDB (0, 2)	ICONMEDIALABINTL (2, 4)	ROTTNEROS (1, 3)
AVESTAPOLARITSEE (1, 0)	INDLFINLSYSB (2, 1)	SAABB (0, 0)
BERGMANBEVINGB (4, 3)	INDUSTRIVARDENA (0, 1)	SALUSANSVARB (0, 1)
BIACOREINTL (3, 3)	INTENTIAINTLB (1, 5)	SANDVIK (1, 3)
BILIAA (1, 3)	INVESTORB (0, 0)	SAPA (0, 0)
BIOGAIABIOLOGICSB (2, 0)	INVIKB (2, 1)	SARDUS (0, 0)
BIOPHAUSIAA (3, 1)	ITABINDUSTRIB (2, 0)	SAS (2, 4)
BIORA (2, 4)	JM (4, 0)	SCAB (0, 1)
BNNORDSJB (0, 4)	JPB B (0, 1)	SCANIAB (2, 4)
BONGSLJUNGDAHLB (5, 0)	KARLSHAMNS (1, 0)	SCRIBONAB (1, 3)
BPA B (3, 1)	KAROBIOB (1, 0)	SEBA (0, 4)
BROSTROM (2, 2)	KAROLINMACHINETOOL (0, 1)	SECOTOOLSB (2, 0)
BUREEQUITY (0, 3)	KINNEVIKINDB (0, 3)	SECURITASB (2, 1)
CARDO (0, 2)	KLIPPANS (3, 5)	SEMCON (2, 1)
CASTELLUM (1, 0)	KNOWIT (2, 3)	SHBA (0, 1)
CLOETTAFAZERB (2, 1)	LATOURINVESTMENTB (2, 1)	SIGMAB (0, 0)
COLU B (4, 1)	LEDSTIERNANB (0, 3)	SINTERCASTA (0, 0)
CONCORDIAMARITIMEB (3, 4)	LINDEX (0, 0)	SKANDIA (3, 3)
CONNOVA (1, 4)	LJUNGBERGGRUPPEN (4, 0)	SKANSKAB (0, 4)
CONSILIUMB (0, 1)	LUNDBERGSB (1, 0)	SKFB (1, 4)
CUSTOSA (2, 0)	MALD B (2, 2)	SOFTRONICB (4, 3)
DILI (1, 2)	MANDAMUS (2, 1)	SSABA (1, 2)
DORO (1, 4)	MAXIMPHARMSSEE (1, 3)	STORAENSORSEE (0, 1)
DROTTB (1, 0)	MEDITEAMDENTAL (2, 4)	STRALFORSB (1, 0)
ELANDERSB (3, 0)	MEDIVIRB (4, 5)	SVEDBERGSB (0, 0)
ELECTROLUXB (0, 3)	MODUL1DATA (6, 3)	SVENSKAORIENTB (0, 2)
ELEKTAB (6, 6)	MSCKONSULTB (0, 0)	SVOLDERB (0, 0)
ELEKTRONIKGRUPPENB (4, 2)	MUNKSJO (0, 1)	SWEDISHMATCH (1, 1)
ENAT (0, 1)	MUNTERS (2, 0)	SWITCHCORE (0, 4)
ENEADATA (4, 2)	NCCB (1, 2)	SYD C (1, 2)
ENTR A (3, 2)	NEFABB (4, 1)	TELE2B (2, 6)
ERICSSONB (0, 3)	NETINSIGHTB (0, 2)	TELELOGIC (0, 4)
ESSELTEA (1, 4)	NEWWAVEGROUPB (1, 0)	TELIA (0, 1)
EUROPOLITAN (4, 3)	NHNORDISKAB (1, 5)	TELIGENT (1, 3)
FAGERHULT (2, 1)	NOBELBIOCARE (7, 1)	TICKETTRAVEL (2, 0)
FGLD (0, 3)	NOKIASDBSEE (2, 5)	TORNETFASTIGHETSB (0, 0)
FINNVEDENB (1, 3)	NOLATOB (2, 4)	TRELLEBORGB (3, 5)
FNSPKA (0, 2)	NORDEA (0, 1)	TURNITB (2, 5)
FORC B (0, 2)	NORSKHYDROSDB (2, 0)	TV4A (3, 2)
FRAMTIDSFABRIKEN (1, 3)	OEMINTERNATIONALB (3, 0)	UTFORS (0, 2)
FRONTECB (2, 1)	OM (2, 4)	VOLVOB (0, 4)
GAMBROA (1, 3)	ORESUND (2, 1)	VOSTOKNAFTASDB (2, 2)
GETINGEINDUSTRIER (2, 2)	ORTIVUSB (3, 0)	WALLENSTAMB (1, 3)
GEVEKOB (3, 0)	OXIGENESEE (1, 2)	WIHLBORGSB (1, 1)
		WMDATAB (1, 4)

A.6 Some Basic Financial and Statistical Concepts

Adaptive Market Efficiency is a somewhat weaker form of market efficiency that allows for the appearance of profit opportunities in historical data, but requires these profit opportunities to dissipate when they become apparent.

Alpha According to the traditional capital asset pricing model, the expected rate of return for asset i can, in equilibrium, be expressed as:

$$E[r_i] = r_f + \beta_i(E[r_m] - r_f),$$

where r_i is the rate of return on asset i, β_i is defined as below, r_f is the risk-free rate of return, and r_m is the return on the market portfolio. Since r_f is assumed to be risk-free, it has zero variance, and can hence be handled as a constant, i.e. $E[r_f] = r_f$. If the expected rate of return exceeds this equilibrium value, then the asset is underpriced, and we would expect it to outperform the market, adjusted for risk. We cannot directly observe expectations, but we can infer them statistically from averages over historical data. If we regress $r_i - r_f$ against $r_m - r_f$, we assume that

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + \varepsilon_i, \tag{18}$$

where $\varepsilon_i \sim N(0, s^2)$ is the error term, and s^2 is the sample variance. Taking the expectation, we get

$$\alpha_i = E[r_i] - r_f - \beta_i(E[r_m] - r_f),$$

so we can estimate β_i as the slope coefficient in the regression, and we can interpret our estimate of the intercept α_i as an estimate of the amount by which the ith asset has outperformed the market (of course, if $\alpha_i < 0$, the security has underperformed in relation to the market).

Arbitrage Informally, arbitrage means that an agent can act in such a way that she is guaranteed a profit without exposure to risk, or with insignificant exposure. More formally we can define price as the vector $\{S_t; t = 0, 1\}$, if we assume that the market only exists at time $t = 0$ and at $t = 1$. A portfolio is in this context defined as $h = (h^1, \ldots, h^N)^T$. We can define the value process $V(h)$ as

$$V_t(h) = h^T S_t, \qquad t = 0, 1$$

The portfolio h is an arbitrage strategy if it satisfies

$$V_0(h) \leq 0, \qquad P(V_1(h) > 0) = 1$$

In the context of this thesis, an arbitrage opportunity emerges when a security for some reason is mispriced. That is for example the case with the double listings of the Royal Dutch/Shell stocks (they are listed both as Royal Dutch and as Shell, see e.g. Shleifer (2000) for a discussion).

Autocorrelation Given returns $R_1, R_2, \ldots, R_N$, the lag k autocorrelation function is defined as

$$r_k = \frac{\sum_1^N (R_i - \bar{R})(R_{i+k} - \bar{R})}{\sum_1^N (R_i - \bar{R})^2}$$

As one of our performance measures, we use $k = 1, 7, 30$ lag(s). In words, autocorrelation is the correlation between lagged realizations of a random variable.

Behavioral finance This attempt at explaining the movements of stock prices says that "investors can make systematic errors in forecasting cash flows or in setting the discount rate, and [that] these errors can push stock prices away from fundamental value for extended periods of time." This description is taken from Barberis (June 23 1997).

Beta β is a measure of the systematic risk in a security. The technical definition is

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2},$$

where β_i is the risk of security i, σ_{im} is the covariance between the security and the market, and σ_m^2 is the variance of the market.

CAR Abnormal return is the return on an asset in relation to some index. Cumulative abnormal return is of course the cumulation of abnormal returns of some period of time. In this thesis, we also use the acronym CAR as a reference for a simplistic methodology (see below) where a market neutral portfolio is created and evaluated.

Correlation The correlation coefficient ρ indicates the extent to which pairs of realizations of two stochastic variables lie on a straight line. For perfect linearity, $\rho = \pm 1$. If there is no linear trend at all – for example, if there is a random scatter of points – the value of ρ is close to zero. Points distributed evenly around a circle would also give a correlation of near zero, because there would be no overall linear trend. The correlation coefficient between the random variables X and Y is defined as

$$\rho = \frac{\sigma_{XY}}{\sigma_X \sigma_Y},$$

where σ_{XY} is the covariance between X and Y, and σ_X is the standard deviation of X.

Data mining The data mining method is intended to work on data without starting from a particular hypothesis or even a particular question. Essentially, it reverses the scientific method, starting from data and moving towards hypotheses instead of following the traditional order of the scientific method:

1. Define the problem
2. Generate hypotheses/models
3. Collect relevant data/conduct experiments to generate data
4. Test models against the data
5. Use the results to generate new hypotheses

The problems with this approach should be obvious to readers familiar with regression analysis.

Data-snooping is finding seemingly significant but in fact spurious patterns in data. Antonym for "our model".

Derivative instruments Contracts such as options and futures whose price is derived from the price of an underlying financial asset.

EMH (Efficient Market Hypothesis) This hypothesis says that the "price (of e.g. a stock) reflects fundamental value, defined as the best possible forecast, given available information, of a security's future cash flows, discounted at a rate that is appropriate for the risk of those cash flows".

Fat Tails If one uses the normal distribution to model stock returns, one will get too low probabilities for extreme events, i.e. the mass in the tails are too low. One way to get around this is to use e.g. hyperbolic distributions, which will render extreme events a larger likelihood.

Fundamental data Data that is objective in some sense, e.g. accounting data.

Glamour stock A glamour stock is characterized by a high P/E-ratio, high trading volume and long term positive earnings surprises. See Swaminathan and Lee (2000).

Growth stocks Companies that have a strong predicted growth in earnings, reflected in e.g. a high P/E-ratio. The opposite of growth stock is value stock.

Hedge Hedging is a way of reducing some of the risk involved in holding an investment. A hedge is a way of insuring an investment against risk.

Kurtosis Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. For the data $Y_1, Y_2, \ldots, Y_N$, the formula for kurtosis is

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4},$$

where $\bar{Y}$ is the mean, s is the standard deviation and N is the number of data points.

Leverage The use of debt financing to increase the return of an investment.

Long position To be long in a security means to actually own it.

Market neutral A market neutral strategy is neutral to market movements, i.e. its β is practically zero.

Markov Process A stochastic process $x(t)$ is a Markov process if

$$P(x(t_n) \leq x_n | x(t) \forall t \leq t_{n-1}) = P(x(t_n) \leq x_n | x(t_{n-1})) \qquad \forall n, t_1 < t_2 < \cdots < t_n$$

In words, "a Markov process models a situation in which where one is, is all one needs [to] predict the future – how one got there provides no further information" (Bingham and Kiesel, 1998).

Martingale A sequence of random variables $X_0, X_1, \ldots$ with finite means such that the conditional expectation of X_{n+1} given $X_0, X_1, \ldots, X_n$ is equal to X_n:

$$E[X_{n+1} | X_0, X_1, \ldots, X_n] = X_n$$

Momentum Here defined as persistence in returns of stocks over approximately three months to one year.

Neglected stock The opposite of 'glamour stock.

P/E ratio The ratio of price to earnings for a stock.

Proxy Stand-in or substitute. Proxy data is used in statistics when it is not possible to directly measure the object or phenomenon under observation.

Random Walk To get a mental picture of this concept, it is helpful to think about a moving particle. In one dimension (the space of interest in this thesis) the particle moves right with probability p and left with probability $q = 1-p$. The jumps are made independently of each other. A random walk is a martingale.

Risk Risk is subjective. In financial models, risk is often (e.g. in the mean-variance approach, CAPM etc) modelled with a quadratic utility function of the form $U(x) =$

$x - bx^2$, where U is the utility, x is a random wealth variable, and b is a positive parameter. But this is just one specification of the utility model, and there is an unlimited number of different specifications. The quadratic utility function models a risk-averse behavior, but there are also investors who are risk-lovers or risk-neutral, and their utility functions are of course of another form.

Risk Averse Investor Risk aversion implies that when facing choices with comparable returns, investors tend chose the less-risky alternative.

Risk Neutral Investor A risk neutral investor, choosing between different lotteries, picks the one that gives the highest expected monetary income.

Semi-deductive approach To simultaneously use both empirical data and theories to reach a conclusion about reality.

Sharpe ratio This ratio is defined as

$$S(X) = \frac{r_X - r_f}{\sigma_X},$$

where X is some investment, r_X is the average annual return on this investment, r_f is the best available return of a "risk-free" security and σ_X is the standard deviation of r_X.

Short position Taking a short position means that one sells securities which one does not own, and buys them back later, hopefully at a lower price than when one sold them.

Simplistic Methodology refers to the use of the classic CAR methodology. Stocks are ranked by price change the last X months, the best say 10-20% and worst 10-20% of the stocks available form the long and short portfolio respectively. These are equally weighted. Then these stocks are kept for Y months until the portfolio is rebalanced. Abnormal return in this market neutral portfolio is measured against 0% (which it should yield if markets where efficient, save transaction costs and interest rate received on the security deposit for the short positions). It is sufficient to use a program such as Excel to do these kinds of simulations.

Simplistic Strategy in this thesis refers to a strategy that emulates the simplistic methodology while using our simulation platform. We rank stocks after the price change the last 6 months, and hold them for 4 months until they are all replaced simultaneously. 10 stocks are always included in the long and short portfolios respectively. No transaction costs or other trading rules are used. The simulations with these parameter settings will yield the same kind of risk-return profile as those presented in the empirical section using CAR, as evidenced by our longer simulations in the Appendix.

Skewness For the data $Y_1, Y_2, \ldots, Y_N$, the formula for skewness is:

$$\text{skewness } = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)s^3},$$

where $\bar{Y}$ is the mean, s is the standard deviation and N is the number of data points. The skewness for a normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right. By skewed left, we mean that the left tail is heavier than the right tail. Similarly, skewed right means that the right tail is heavier than the left tail.

Trading horizon This is the end of the trading period, when the investment is assumed to pay off.

t-statistic The t statistic is used to test hypotheses about an unknown population mean μ in situations where the value of σ is unknown. Often used on e.g. monthly return or CAR when using the simplistic methodology, where the null hypothesis is that returns are zero. It is however afflicted with problems in our case since the return distribution of a market neutral momentum strategy has fatter tails than the one assumed when using the t-statistic. We believe that the performance measures used in this thesis give a better picture.

Utility Function Quoting from Luenberger (1998): "A utility function is a function U defined on the real numbers (representing possible wealth levels) and giving a real value. Once a utility function is defined, all alternative random wealth levels are ranked by evaluating their expected utility values." It is important to note that utility functions do not produce cardinal values, so their only significance is in relation to other utility scores. An important insight when reading this thesis is that a certain Sharpe value can have different utility values, depending on the level of risk aversion.

Value stocks Companies which earnings are not assumed to grow fast in the future, reflected in e.g. a low P/E-ratio.

Zero-cost investment An investment that does not require capital to be paid upfront. A margin (risk buffer) is however usually required. Going short in a stock is an example.

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