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Return Continuation at Stockholm Stock Exchange

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Abstract

This thesis show that stocks listed at Stockholm Stock Exchange display short- to medium-term return continuation. Over the 1993 to 2014 period past winners outperform past losers. Hence, trading strategies which short-sell past losers and use the proceeds to finance the purchase of past winners generate positive returns. Results are robust also after adjusting for commonly used risk factors. Results also indicate that a retail investor could earn abnormal returns by trading accordingly to momentum trading rules. These results should although be interpreted with some caution, mainly due to limitations in the estimation of transaction costs.

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I. Introduction

In 1953 Maurice Kendall published his work, "The Analysis of Economic Time Series". He found, to his surprise[1], that there was no predictable pattern in stock prices. Stock prices were as likely to go up as down regardless of past performance. Kendall´s work in addition with the work of many other researchers, for example, Fama (1970)[2], have resulted in the today well-known and established "efficient market hypothesis". It states that stock prices reflect all available information and that they are random and unpredictable, Bodie (2011).

In direct disparity to "efficient market hypothesis" are the findings of Jegadeesh and Titman (1993). They concluded that stocks which have a strong past[3] performance outperform, over the following 3-12 months, stocks which have a weak past performance. In other words, they found evidence of predictability in stock returns. This outcome is often referred to as momentum effect or return continuation. Other papers[4] have reached similar conclusions, this have in turn caused a lot of debate in the financial and academic world. How can such an anomaly exist in markets that by many are considered to be efficient?

Conventional risk factors have not been successful in explaining return continuation, hence, many have looked for alternative explanations. The relatively new research field called behavioral finance is one such explanation, see for example Jegadeesh and Titman (2001). Conventional finance theory often assumes that investors are rational, something that is questioned by researchers within behavioral finance. If investors make irrational decisions then that is something that could open up for non-efficient markets. Others have argued that momentum profits are the result of data snooping. Today financial data is easily accessible and computing power is cheap. At the same time the potential reward for the discovery of a trading strategy that generates abnormal returns is huge. This has resulted in that many practitioners and researchers have tested a large number of trading strategies in the hunt of a working model. Indeed, if you process large amounts of data and search over many different alternatives it is likely that one will find a profitable trading strategy. However, it is far from clear that the finding of a profitable trading strategy will generate persistent and statistical significant abnormal returns. The documented returns could be the result of historical

[1] At the time the general view was that a predictable pattern in stock returns existed, Bodie (2011), Conrad and Kaul (1998).
[2] Fama concluded, with a few exceptions, that markets are efficient.
[3] 3-12 months.
[4] Fama and French (1996), Rouwenhorst (1998) and Lui et al. (1999), among others.

circumstances or trading patterns that is not likely to occur again. Jegadeesh and Titman followed up their work from 1993 with Jegadeesh and Titman (2001). They concluded that momentum profits documented during the original sample period, 1965-1989, continued in an out of sample test, 1990-1998. This, of course, raises the question even further about the effectiveness of stock markets. Return continuation, persistent over time, in stock markets around the world implies a serious controversy with conventional finance theory.

The remainder of this thesis is organized as follows. Section two presents research questions. In section three the results from previous studies, regarding return continuation and other relevant topics, are presented. Section four describes the methodology and data. Section five presents the results and an extensive analysis of those results. Finally, section six concludes the thesis.

II. Research Questions

The main purpose of this thesis is to investigate the presence of return continuation, on the short- to medium-term[5], at Stockholm Stock Exchange between 1993 and 2014. To do this a framework which follows previous literature on the subject will be developed. This also addresses the data snooping critique discussed in the introduction. The use of a methodology which is well-accepted and established limits the room for critique regarding data snooping.

The result section is divided into two parts. As shown in section III: literature review, return continuation in a friction free market has been proven to be robust many times. Return continuation in a friction free market are also the lion´s share of this thesis. That is, it will be assumed that no transaction costs or trading limitations exists. However, the author feels that it would be interesting to make an attempt to investigate if it is possible for a retail investor to exploit return continuation. Therefore, the second part of the result section will consider return continuation from the perspective of a retail investor, thus taking both transaction costs and trading limitations into consideration. The magnitude of transaction costs will not be decided with the use of historical data. Instead an estimation, based on research and previous literature, is performed. This is of course a major limitation of this thesis. To collect and process the data needed to calculate historical transaction costs were by the author judged to be far too time consuming within the scope of a master thesis. Nevertheless the author feels that the "retail" part of the result section is an interesting contribution. The amount of research on momentum effects

[5] 1-12 months.

in a non-friction free environment is limited in comparison to research on momentum effects in a friction free market.

Further, the amount of research with respect to the Swedish stock market is, of course, limited compared to momentum research undertaken on the US stock market. Thus, it is interesting to see if characteristics regarding return continuation found in the US also are relevant for the Swedish market. Two research questions can be formulated:

> **Do return continuation exist, on the short- to medium-term, at Stockholm Stock Exchange between 1993 and 2014?**
>
> **If return continuation is documented, is it possible for a retail investor to exploit this effect, taking transaction costs and trading limitations into consideration?**

III. Literature Review

Vast amounts of research have been performed on the existence of return continuation. This section will try to summarize the most important studies as well as research on other relevant topics.

Jegadeesh and Titman (1993) is a paper that can be viewed as pioneering regarding research on return continuation[6]. Their framework for investigating momentum effects has been replicated many times. The basic idea is to create a "loser portfolio" of historically badly performing stocks which then is sold short. The capital from the short selling are then used to finance the "winner-portfolio" which consists of stocks which historically have a strong performance. Jegadeesh and Titman found evidence of short- to medium-term return continuation in the US stock market during their sample period, 1965-1989. That is, the winner-portfolio outperformed the loser-portfolio. Returns were robust also after adjusting for systematic risk. They concluded that the evidence were "consistent with delayed price reactions to firm-specific information". In other words, stocks consistently underreacted to new firm specific information.

They followed up their work with Jegadeesh and Titman (2001). This time, with the same methodology, they examined the presence of momentum effects between 1990

[6] Earlier studies have been done, for example, Levy (1967). He showed that buying stocks which have a current price higher than their past average price will generate abnormal returns. However, Jensen and Bennington (1970) pointed out that Levy went through 68 different trading strategies before finding a working model.

and 1998. Again, they concluded that momentum strategies generated abnormal profits. One important difference compared to their work in the early nineties was the tools used to risk adjust the returns. In the late nineties the Fama-French three-factor model, TFM, had been presented and accepted. Jegadeesh and Titman concluded that returns were robust also after risk adjustment with the above model. Together the two papers present conclusive evidence towards a US stock market not being entirely efficient.

The three factor model is also used to risk adjust returns in this thesis. The model, presented in Fama and French (1993), is today common when it comes to risk adjusting returns. TFM consists of two risk variables[7], SMB and HML. SMB stands for "small minus big" and is meant to capture risk arising from investing in companies of different size[8]. HML stands for "high book-to-market ratio minus low book-to-market ratio" and is meant to capture risk arising from investing in companies of different book-to-market ratios. Fama and French have chosen these variables because they have a strong predictability with regards to stock return deviations from fair CAPM levels, Bodie (2011). That is, the variables are chosen based on empirical research. They argue that the variables themselves may not be clear risk factors but they may be proxy variables for other unknown more fundamental risk factors, Bodie (2011). Nevertheless it can be valuable to provide some intuition behind how financial risk is associated with SMB and HML. For example, one can argue that small companies are more exposed to changes in market conditions and thus carry higher risk. Further, accordingly to Fama and French, stocks which have a high book to market ratio[9] are more likely to be in financial distress and thus associated with a higher risk.

TFM has been successful in predicting stock returns in various time periods and in markets all around the world. This is a strong reason to the popularity of the model, it is simply hard to find other risk variables that are easily quantified with higher predicting power. In other words, it is hard to specify a model, meant to predict security returns, which generates a higher R^2. Fama and French (1996) show that many of the anomalies which CAPM fails to explain disappear in the three factor model. One example[10] is return reversals or contrarian strategies as discussed by Bondt and Thaler (1985). While return continuation often is interpreted as a sign of under-reaction, return reversals are frequently interpreted as a sign of over-reaction. If stocks, over time, overreact to good news they will become overvalued.

[7] Market risk is, measured as beta, is also included in the model.
[8] Size is measured as market capitalization.
[9] Often referred to as value stocks.
[10] Other examples of anomalies are earnings/price and past sales growth.

Bondt and Thaler (1985) shows that a portfolio of past[11] winners underperform, over the following 3-5 years, when compared to a portfolio of past losers. It might seem strange that return continuation and return reversal can exist simultaneously when they imply complete opposite actions. One can though argue that these two trading strategies can coexist since they operate on different time horizons, momentum strategies on short- to medium-term and contrarian strategies on long-term. More interestingly, with regard to this thesis, Fama and French (1996) show that return reversals "disappear" in the TFM but return continuation is left unexplained.

Research on momentum effects outside the US is more limited. Still, Rouwenhorst (1998) brings an interesting contribution. He investigates return continuation in a European context[12]. Rouwenhorst argues that if momentum effects, in markets outside US, are absent or captured by commonly used risk factors then momentum effects might be caused by characteristics unique to the US market. On the contrary, documented momentum effects in markets around world would point towards a misspecification of models commonly used for risk adjustment, or towards a general propensity for markets to underreact to information. Rouwenhorst concludes that a "winner-portfolio", diversified between the 12 countries outperforms a "loser-portfolio" diversified in the same way. Thus, he presents evidence on momentum effects in large parts of Europe.

Since this thesis has its focus on Stockholm Stock Exchange it is interesting to zoom in on Rouwenhorst´s findings regarding the Swedish market. On average across the 12 countries the "winner-portfolio" outperforms the "loser-portfolio" with 0.93% per month. Interestingly the same figure for Sweden is 0.16%. Sweden is also the only country with a return not significantly different from zero. That is, Sweden is the only country, of the 12 examined, that not show significant short to medium term return continuation. However, Rouwenhorst´s sample period ends approximately were the sample period used in this thesis starts. Thus, comparing the findings of Rouwenhorst (1998) with the results of this thesis could highlight changes in the existence of return continuation and consequently the efficiency of the Swedish stock market.

Lui et al. (1999) investigates return continuation at Europe's largest stock exchange, London Stock Exchange. Using a sample consisting of 4182 stocks between 1977 and 1996 they present conclusive evidence of return continuation. Further, they argue,

[11] 3-5 years.
[12] Countries included in the sample, 1978-1995: Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland and United Kingdom.

in line with research discussed above, that stock prices show a delayed reaction to industry- or firm-specific information.

In general, previous research point towards the presence of momentum effects and that returns are robust also after risk adjusting. The evidence holds for various time periods and markets around the world. If momentum effects are caused by a general inefficiency in stock markets or by some not yet discovered risk factor is unclear.

IV. Data and Methodology

Data

The dataset used in this thesis consists of monthly return data from 1993 up until 2014 for stocks traded at Stockholm Stock Exchange, SSE. The dataset consists of stocks traded anytime during the sample period, thus also including delisted companies. Only companies that have its main listing on SSE are included, that is, no secondary listings or depositary receipts are allowed in the dataset[13]. When a company has listed more than one stock-class the most liquid class has been chosen. More specifically the data represents a monthly total return index for any given stock[14]. The data is equal to the index level at the closing of the last trading day in each month. A total return index is often assumed to be a fair measurement of returns since it accounts for all equity actions, such as splits and reversed splits, and assumes that dividends are reinvested in the stock at question. The above return-data as well as all other data used in this thesis were collected from Thomson Reuter DataStream[15].

The dataset consists of 504 companies in total and the average number of companies traded at any time is 229. Stocks with a valid trading history of at least 6 months are included in the dataset[16]. Up until July 2000 Stockholm Stock Exchange consisted of three lists, A-, O- and OTC-list. The OTC-list and the O-list were merged in 2000 (SSE). After 2000 SSE consisted of only the A-list and O-list before

[13] Classification in DataStream, Exchange=Stockholm, Market=Sweden, Currency=Swedish krona, Type= equity or closed end fund.

[14] Explanation of the total return index from DataStream manual: "a theoretical growth in value of a shareholding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date".
The index is calculated as follows: $RI_t = RI_{t-1} * \frac{P_t+D_t}{P_{t-1}}$ where RI represents the index level at month t, P the price for the stock and D any dividend payment.

[15] Except for the risk-free rate which was collected from the statistical archive at the homepage of Sweden´s Central Bank (Sveriges Riksbank)

[16] The "smallest" trading strategy in terms of ranking- and holding-periods is 3/3. Therefore a minimum of 6 months trading history is needed.

the current classification, Large-, Small- and Mid-cap was presented in 2006. Beyond SSE a number of smaller exchanges for trading stocks have existed/exists in Sweden, some are classified as a formal exchange and some are not. In common for all of these smaller exchanges is that they are made up of small highly volatile growth stocks. In order to avoid very small stocks and stocks with low or almost no liquidity only stocks listed on SSE are included in the dataset.

The dataset was constructed with the use of fact books provided by SSE. An alternative is to use constituent lists provided by DataStream. However, there is a potential problem with that approach. If you, for example, use a constituent list from DataStream called OMXS which include all stocks, presently listed and "dead", at SSE you will also automatically include return data from other exchanges. The problem occurs because many of the stocks traded at SSE initially are listed on a smaller exchange and then at some later point in time, when the company fulfills listing-requirements, transferred to SSE. DataStream includes both return data from SSE and return data from smaller stock exchanges in their constituent list, OMXS. It is possible that this problem occurs because the author lacks the knowledge to correctly set up DataStream. However, a considerably amount of time were used to analyze and trying to find a solution to the problem. The choice was then made to work with firsthand information from SSE. A list consisting of companies traded at SSE anytime during the sample period were created. This list also included information about during which time periods the various stocks were traded at SSE. Return data were then downloaded from DataStream and adjusted to only include data from correct time periods. Although a more work intensive approach, it is considered to be worth the efforts in order to get an accurate dataset.

Analyzing the dataset raises questions of further limitations. Small stocks with a relatively low trading volume can also be found at the OTC-list or Small Cap list. One of the major reasons for imposing restrictions on size or/and liquidity is to mitigate problems with short-sale constraints. That is, small and illiquid stocks are often not possible to short-sale. At the Swedish stock market and specifically for a retail investor it is only possible to short-sale the very most liquid stocks[17]. This implies that any size- or liquidity-restrictions has to be huge in order to have a meaningful effect. An institutional investor might have more extensive possibilities to short-sale stocks but if such investor has access to all stocks traded in terms of short-sale is unclear. Jegadeesh and Titman (2001) excluded the lowest decile in terms of market capitalization and all stocks priced under 5 USD. They did that to make sure that the results not primarily were driven by small and illiquid stocks.

[17] For example, in April 2014 at Avanza, one of the largest stock brokers in Sweden, it was only possible to short-sell 43 stocks of the 253 traded, (Avanza).

However, their main results are the same with or without the restrictions. Based on the above discussion and for simplicity no restrictions in terms of stock-price, market-capitalization or trading volume will be used in this thesis.

The sample period, 1993-2014, was chosen mainly for two reasons. Firstly, in 1992 the Swedish Central Bank gave up its fixed exchange rate regime and adapted a floating exchange rate. This in turn caused a large depreciation of the Swedish Krona. In some sense this can be viewed as the start of a "new" economy in Sweden. The depreciation of the Krona caused, for example, a boom for the very important export oriented industry sector. Secondly, the time period in question includes several business cycles. For example, the IT-bubble in the early 2000, the more recent financial crises and periods of steady increases of the general value of companies traded at SSE.

Other data collected for the purpose of this thesis is presented below:

> **Risk-free rate.** Sweden Treasury Bill 90 day, monthly average.
>
> **Market-index/benchmark-portfolio.** MSCI-Sweden total return index (MSCI). The MSCI index is well established and well trusted among professionals around the world. It is a broad value weighted index which covers 85% of the total equity traded at SSE.
>
> **Market capitalization and book-to-market equity.** In order to perform Fama-French three factor model regressions this data is needed. The market-cap is calculated as number of ordinary shares in issue times the share-price. The book-to-market equity is calculated as the inverse of the market-to-book equity which is given directly by DataStream.

Portfolio Formation

The portfolio formation process will follow Jegadeesh and Titman (1993) and Fama and French (1996). 17 different trading strategies will be evaluated. The ranking periods, henceforth called J, are 3, 6, 9 and 12 months. The holding periods, henceforth called K, are 1, 3, 6, 9, and 12 months. For instance, a J/K strategy called 3/3 is equal to a ranking period of 3 months and a holding period of 3 months.

The portfolio formation procedure starts by calculating monthly returns for every company in the dataset. Based on the cumulative return during the ranking period two different portfolios are created. The top decile of stocks, in terms of cumulative return, goes into the winner portfolio and the bottom decile goes into the loser portfolio. The basic idea is then to short-sell the loser portfolio in order to finance the winner portfolio, hence, creating a zero investment portfolio[18]. If the winner portfolio then outperforms the loser portfolio, profits will be created. Following Jegadeesh and Titman (1993), and all major literature on the subject, return averages are arithmetic averages. The market environment is assumed to be friction free, that is, no transaction costs exist.

In order to increase the statistical significance of the results overlapping portfolios are used. At the start of a given month, using the 3/3 strategy in figure 1 as an example, the total position will consist of three equally sized portfolios: One portfolio with a holding period of one month remaining, one portfolio with a holding period of two months remaining and one portfolio were the three month holding period just started[19]. Thus, at the end of each month $\frac{1}{k}$ of the total position is liquidated and invested in a new portfolio. The only exception is in the beginning of the sample period when implementation of a new J/K strategy just started. Again using figure 1 as example, at the start of month 4 one will be 100% invested in portfolio 1, in month 5 one will be 50/50 invested in portfolio 1 and 2. In month 6 the total position will, naturally, consist of 1/3 in portfolio 1, 1/3 in portfolio 2 and 1/3 in portfolio 3.

Between the ranking period and the holding period there is a 1 month waiting period or gap. This means that for a 3/3 strategy as illustrated in figure 1 the ranking period ends after 2 months and at that point the winner- and loser-decile is decided. One month later the trade is executed, short-selling the loser portfolio and buying the winner portfolio. The motivation for the one month gap is to avoid the short term reversal effect as documented by Jegadeesh (1990). A main conclusion from Jegadeesh (1990) is that contrarian strategies which pick stocks based on their returns in the previous month generate abnormal returns. In other words, a stock that has performed good (poor) in the previous month will have a poor (good) performance in the following month. When controlling for this effect in the dataset used in this thesis it seem to exist. One of the most successful strategies is 12/1, when the holding period follows directly after the ranking period the return for the WL portfolio drops from 1.7% per month to 1.3% per month.

The winner- and loser-portfolios are equally weighted. They are also rebalanced each month to maintain equal weights, both between the portfolios held in a given trading strategy and within an individual portfolio. Jegadeesh and Titman (1993) investigated both buy and hold portfolios and portfolios that were re-balanced each

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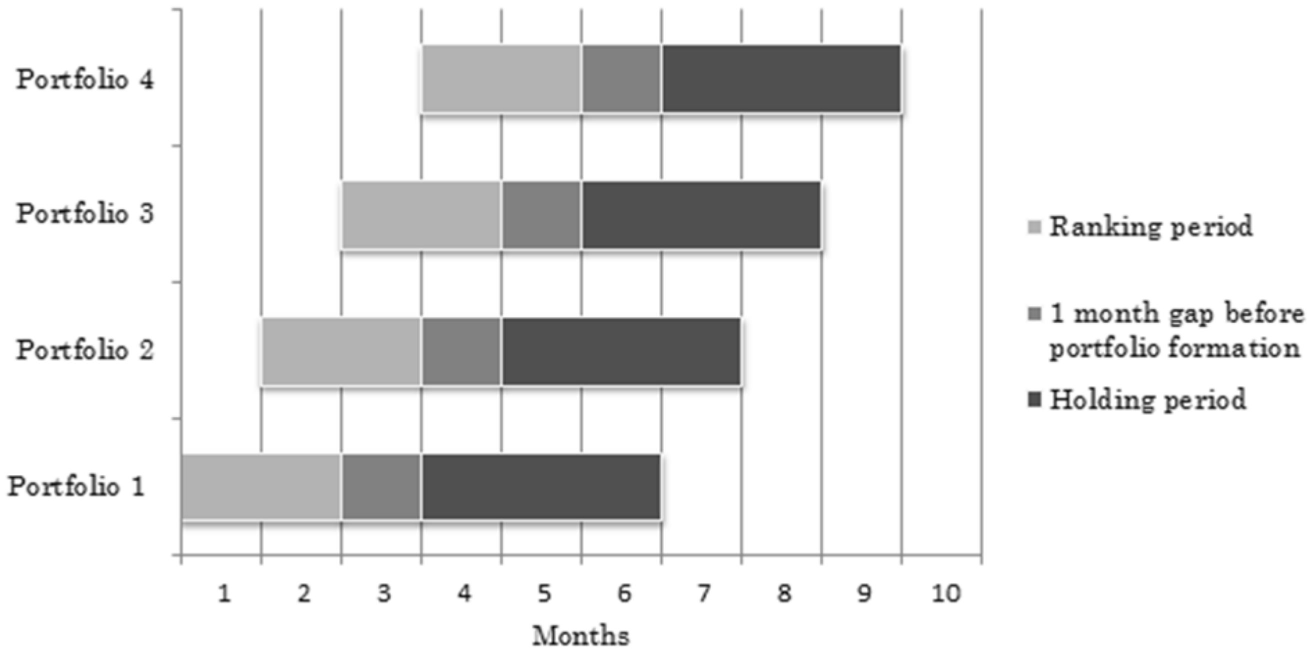
[18] Called WL portfolio (Winner-Loser)

[19] To clarify further, the total position for a trading strategy will in a given month equal K portfolios.

month to maintain equal weights. The results showed that the returns were very similar for both methods[20].

Figure 1. Portfolio Formation Process[21]



To calculate returns for all seventeenth strategies, in total over 8000 winner- and loser-portfolios, Excel were used. Several manual calculations have been performed to make sure that formulas used in Excel are set to generate correct results. All regressions and statistical tests are performed in statistical software package Stata.

When performing return calculations for the various momentum strategies it is clear that in some cases a stock is delisted during the holding period. In other cases it is not possible to buy/sell a stock in the winner or loser portfolio at the portfolio formation date[22]. The question is then how to deal with these situations. The value of the position could for example be invested in the risk-free rate, the benchmark portfolio or equally spread over the rest of the stocks in the winner/loser portfolio. Further analysis of the dataset shows that the above situations are relatively uncommon. In addition, the frequency seems to be approximately the same for stocks in the winner- and loser-portfolio. Based on the former discussion and for simplicity the author have chosen to not reinvest the funds at all. The consequence

[20] The buy and hold portfolios yielded a slightly higher return. Jegadeesh and Titman (1993) presented only the returns for the rebalanced portfolios.
[21] Figure generated by the author.
[22] In some cases a stock is delisted during the one month waiting period.

should be lower returns from winner- and loser-portfolios but returns from WL portfolios, and therefore the main results of this thesis, should be unaffected.

V. Results and Analysis

Returns from Momentum Trading Strategies

Table 1 report returns from the 17 trading strategies. Following Jegadeesh and Titman (1993) all returns are calculated as simple averages over the sample period. The winner-, loser- as well as the WL-portfolios are presented. In parenthesis t-statistics for WL portfolios are stated. The t-statistics were calculated accordingly to equation 1. Where $\bar{x}$ is equal to the simple average return of a WL portfolio, μ is equal to expected return for an investment in a WL portfolio[23], σ is the standard deviation for a WL portfolio and n is the number of observations in a given momentum strategy.

$$t = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \tag{1}$$

When conducting hypothesis testing using simple t-statistics it is important that the data is normally distributed. The number of observations, for a given WL strategy, ranges from 240 to 2922[24]. In order to investigate the normality of the data, returns from WL portfolios are plotted in histograms[25]. Accordingly to the histograms, the return data show some deviation from normal distribution. Skewness- and kurtosis-coefficients also points towards deviation from normality. All WL portfolios have negative Skewness-coefficients which indicate that the distribution is skewed to the left, Newbold (2010). From the histograms it is clear that negative extreme values are more common than positive extreme values, a possible explanation for the skewed distribution. Further, all WL portfolios have kurtosis-coefficients between 7 and 11. The kurtosis-coefficient measures the "peakedness" of the distribution, Hill et al. (2011). Values above 3 indicate a distribution which is more peaked compared to normal distribution. On the contrary a value below 3 indicates a flatter distribution. A formal Skewness-Kurtosis test rejects the null hypothesis of normality for all 17 strategies.

[23] The upfront investment for a WL portfolio is zero which implies that the expected return from a WL portfolio also is zero. Thus, μ in equation 1 is set to zero.
[24] 240 for J/K strategy 12/1, 2922 for J/K strategy 3/12.
[25] See appendix B, figure 5 for histograms over the 6 best performing WL-portfolios.

T-values obtained from equation 1 tell us if returns from WL-portfolios are separated from zero. The critical t-value for fulfilling a significance level of 1%, for a single sided test, is 2.33 which all strategies clear with ease. That is, with a certainty of 99%, returns for all 17 WL portfolios are larger than zero. Still, based on the normality analysis it might be wise to interpret the t-statistics with some caution.

In general the most profitable strategies include a ranking period of 6-12 months and a holding period of 1-6 months with 12/1 and 6/3 being the two most successful strategies. These results are in line with Jegadeesh and Titman (1993) who also found that longer ranking periods in combination with shorter holding periods are preferable. The size of the raw returns are also in line with Jegadeesh and Titman (1993)[26]. In all strategies the winner portfolio outperforms the loser portfolio, thus, all WL strategies are profitable. In combination with the strong significance of the strategies, momentum effects seem to exist on Stockholm Stock Exchange. That is, stocks consistently underreact to information so that stocks which performed well/poor will keep performing well/poor. To set the WL returns in perspective the benchmark portfolio[27] has an average monthly return of 1.29% over the sample period. However, when comparing WL portfolios with the benchmark portfolio one must remember that WL portfolios require no initial investment. The winner portfolio in a WL strategy is therefore more interesting to compare with the benchmark-portfolio. The winner portfolio will be treated more closely in the part about implementing a momentum strategy. An important remark at this point is that the returns discussed are not risk-adjusted. Although having concluded that WL strategies generate positive returns it is not possible to say that WL portfolios generate abnormal returns. That is, commonly used risk factors might be able to explain the observed return patterns.

[26] With the exception of 6/3 which in this thesis is a "top" strategy. In Jegadeesh and Titman (1993) it is only the fifth best strategy.
[27] MSCI-Sweden, total return index.

Table 1. Monthly returns from the 17 momentum trading strategies. All returns are calculated as simple averages over the sample period. The Winner-, Loser-, and WL-portfolio are presented. J is equal to the ranking period, K is equal to the holding period. T-statistics for the WL-portfolio in parenthesis.

J		K=	1	3	6	9	12
	Winner			0.0182	0.0180	0.0168	0.0162
3	Loser			0.0071	0.0080	0.0103	0.0099
	W-L			**0.0111**	**0.0100**	**0.0065**	**0.0063**
				(3.87)	(5.24)	(4.42)	(5.28)
	Winner			0.0221	0.0197	0.0179	0.0163
6	Loser			0.0060	0.0081	0.0087	0.0089
	W-L			**0.0161**	**0.0116**	**0.0093**	**0.0074**
				(4.60)	(4.96)	(5.22)	(5.08)
	Winner			0.0191	0.0169	0.0149	0.0135
9	Loser			0.0066	0.0072	0.0079	0.0080
	W-L			**0.0126**	**0.0098**	**0.0071**	**0.0055**
				(3.75)	(4.68)	(4.50)	(4.37)
	Winner		0.0207	0.0176	0.0154	0.0137	0.0125
12	Loser		0.0041	0.0056	0.0065	0.0072	0.0065
	W-L		**0.0166**	**0.0120**	**0.0090**	**0.0065**	**0.0059**
			(2.82)	(3.76)	(4.13)	(3.92)	(3.54)

Risk Adjusted Returns from Momentum Strategies

Because the initial investment for a WL strategy is zero the expected return is also zero, this means that μ will be set to zero in equation 1. However, an expected return equal to zero does not imply that a momentum strategy is risk-free. If the loser portfolio increases more in value compared to the winner portfolio an investor will suffer from losses. Indeed, there are several months during the sample period were the loser portfolio heavily outperforms the winner portfolio. For example, in November 2002, the 12/1 loser portfolio increases 63% whereas the 12/1 winner portfolio increases 9%. WL strategies are especially sensitive to market turnarounds. Under such circumstances the loser portfolio consists to large parts of high beta stocks which have suffered from large losses during a previously market decline. On the contrary the winner portfolio consists of low beta stocks which, in general, have a better resistance to market declines. When the market bounces up, in general, high beta stocks will increase more in value compared to low beta stocks. Hence, WL portfolios are likely to generate negative returns. This effect is documented by Daniel and Moskowitz (2013) in a working paper about hedging a WL strategy. They show that by implementing a dynamic momentum strategy it is possible to achieve considerably higher returns compared to a non-dynamic strategy. Their results are in line with this thesis, many of the "worst" months for a given WL strategy are concentrated around market turnarounds. For example, in 2009 the Swedish stock market "bounced" back after a severe decline due to the outburst of the financial crisis in 2008. SSE had, during 2009, a monthly average return of 3.64%. During the same time period the 6/3 WL-portfolio had a monthly average return of -3.36%. Returns in 2003, which is a recovery year after the burst of the IT-bubble, show similar characteristics.

This effect is also illustrated in figure 2. Over shorter time-periods it is clear that the 6/3 WL-portfolio displays a very different return pattern compared to the benchmark portfolio. Indeed, the correlation between the 6/3 WL-portfolio and the benchmark portfolio is -0.33 which not could be considered as strong. Return movements of the 6/3 WL-portfolio is further illustrated in figure 3. The 6/3 WL-portfolio shows, at several occasions, a very poor performance with one month losses getting close to 40 percent. The benchmark portfolio has no single loss over 1 month which exceeds 20 percent. For more descriptive statistics regarding SSE- and WL 6/3-returns see appendix A, table 11 and 12.

Above discussed potential losses naturally move the question to return measurements that accounts for risk. One very popular way of quantifying risk is to use the single index model[28]. Results from single index model regressions are presented in table 2. The model is specified in equation 2 where r_{WL} is the return from a WL portfolio, r_f is the risk free rate, r_m is the return of the benchmark portfolio and ϵ_{WL} is a residual term. The slope coefficient of the model, ß, is equal to the level of systematic risk associated with, in this case, a WL portfolio.

$$r_{WL} - r_f = \alpha_{WL} + \beta_{WL}(r_m - r_f) + \epsilon_{WL} \tag{2}$$

By definition the market has a beta of 1, thus, any value larger than 1 implies a higher risk compared to the market. An investor should then be compensated for this risk with a higher than market return. The intercept, α, is thought of as abnormal return generated by a security or a portfolio of securities. That is, when

[28] First suggested by Sharpe (1963).

alpha is positive, an investor will receive some extra return on top of the return associated with the level of systematic risk. Further, if the explanatory variable, $(r_m - r_f)$, in the single index model "captures" returns from a security then the intercept of the model will be equal to zero. Thus, if the single index model explains returns from the WL-portfolios then alphas from the 17 portfolios should be equal to zero.

Figure 2. Cumulative return from June 1993 up until January 2014 for a 1 dollar investment in the 6/3 WL-portfolio and the benchmark portfolio, respectively. Logarithmic scale is used.

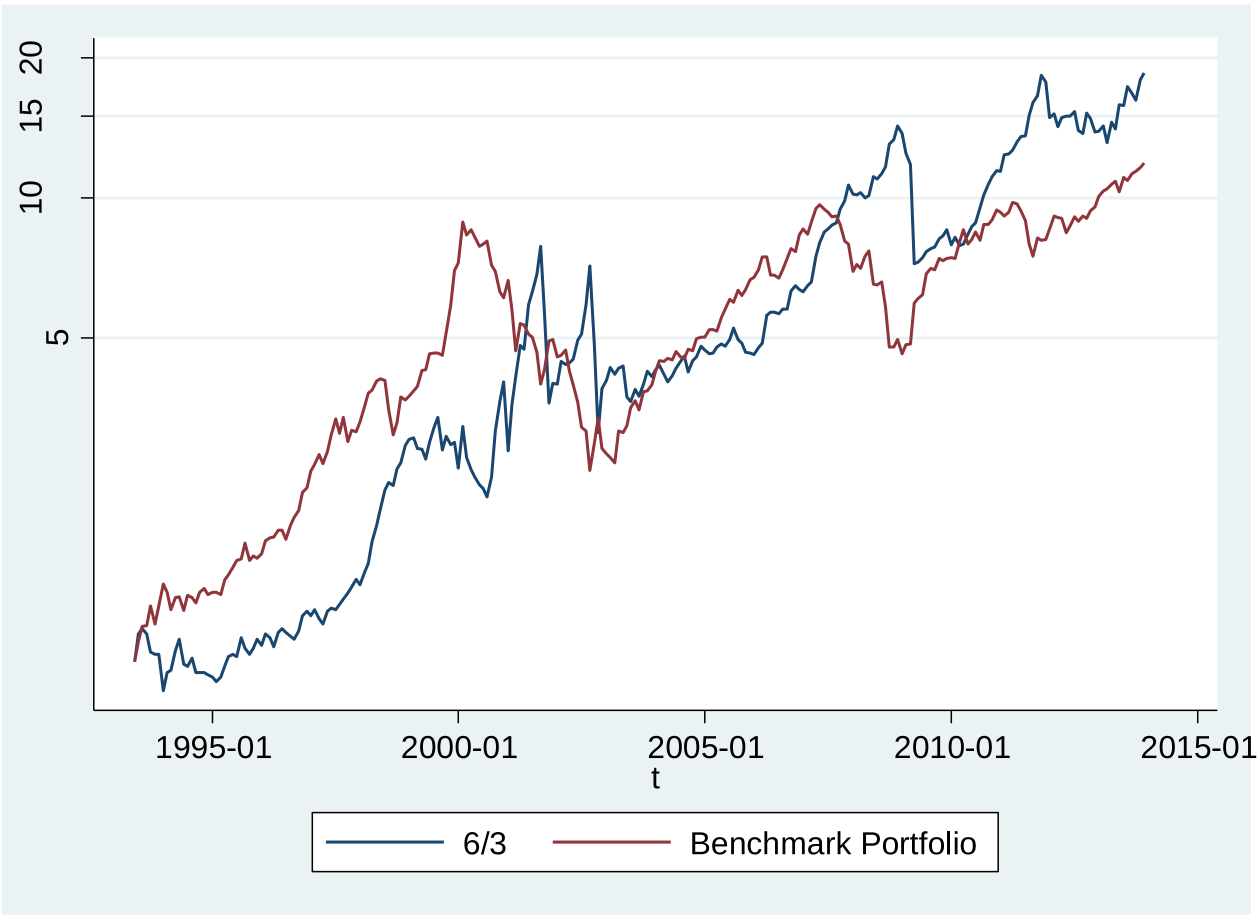
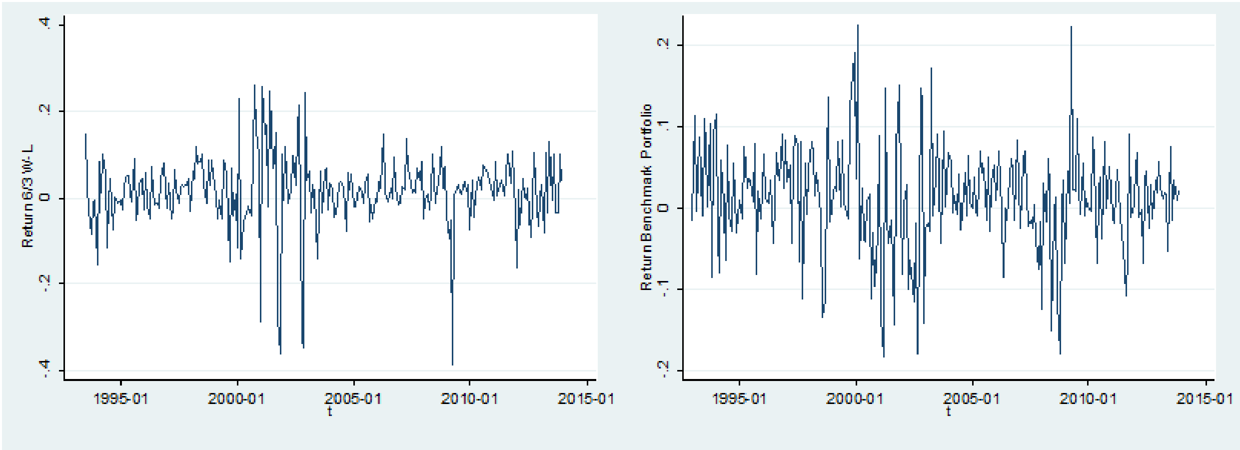


Figure 3. Monthly return plot for the 6/3 WL-portfolio and the benchmark portfolio.



In order to trust the results from the single index model it is important that underlying assumptions of OLS[29] regression are satisfied. Formal tests to check for autocorrelation[30] among the residuals and constant variance in the residual term, heteroscedasticity[31], were performed. As expected no autocorrelation was found but the presence of heteroscedasticity was documented. The short term volatility in stock returns often counteracts autocorrelation. In contrast, stock return data often has a problem with heteroscedasticity since the volatility of a stock market changes over time. Newey-West standard errors, which are robust to heteroscedasticity, were used for correction. Normally distributed residuals is another of the underlying assumptions for OLS regression, Hill et al. (2011). When testing the residuals with the Skewness-Kurtosis test the null hypothesis of normality was rejected for all 17 strategies. Further, residuals for the top 6 performing WL-portfolios are plotted in histograms, see appendix B, figure 6. Since returns from WL-portfolios showed deviation from normality it is no surprise that histograms of the residuals also show deviation from normality. Despite evidence of non-normal distributed residuals there is no need to panic, this assumption is often relaxed by text-books and not always considered as necessary in order to provide reliable results, Hill et al. (2011). Since the data is in the form of returns it is assumed to have no unit-root problem. Return data are mean-reverting in its nature and therefore the risk for a so called spurious regression is low. For a complete table over all statistical tests performed see appendix C, table 13.

[29] Ordinary Least Squares.
[30] Breusch-Godfrey test.
[31] Breusch-Pagan test.

Table 2. Alpha and beta values from single index model regressions.

J		K=	1	3	6	9	12
		α, β					
3	W-L			1.19%**, -0.38**	1.03%**, -0.33**	0.65%*, -0.30**	0.57%*, -0.23**
6	W-L			1.73%**, -0.44**	1.24%**, -0.39**	0.94%**, -0.32**	0.69%*, -0.26**
9	W-L			1.42%**, -0.50**	1.05%*, -0.40**	0.71%, -0.33**	0.50%, -0.27**
12	W-L		1.82%**, -0.51**	1.31%**, -0.46**	0.94%*, -0.38**	0.63%, -0.30**	0.48%, -0.20

* significant at the 5% level using Newey West std. errors

** significant at the 1% level using Newey West std. errors

When studying table 2 some issues are worth highlighting. Firstly, almost all alpha and beta values are significant at the 1% or 5% level. In line with the return pattern there are some strategies with longer holding periods with no significance. All strategies with holding periods of 3 or 6 months have significant alpha and beta values. Secondly, all strategies have negative beta values, suggesting that when the market portfolio increases in value the value of a WL portfolio should decrease. This is clearly not the case, all 17 strategies as well as the market generates positive returns over the sample period.

R^2 is a measure of the explanatory power of the independent variable/variables. It ranges from 3.9% to 15.4% with the 12/12 strategy having the lowest value and 3/9 the highest. In total, the evidence points towards that return continuation is something that is not explained by the single index model.

As mentioned before a positive alpha is a measurement of abnormal return. Table 2 then suggests that many of the WL portfolios are a superior investment compared to an investment in the benchmark portfolio. The largest alpha value of 1.82% is generated by the 12/1 strategy. An investor that followed the 12/1 strategy had a return that were 182 basis points higher per month than the fair compensation for the risk taken. However, it is not possible to say that 12/1 is a superior investment compared to, for example, 3/6 just because 12/1 has a higher alpha value. The level of systematic risk associated with the alpha in question must also be considered. Let´s consider two imaginary securities, security A with a high beta and a high alpha and Security B with a low beta and a low alpha. Security B could then be leveraged up to match the beta of security A and thus, maybe, also achieve a higher alpha. Table 2 does, however, show that the best performing WL-portfolios have somewhat similar betas. For example, 12/1 and 9/3 have almost identical betas. Hence, due to the higher alpha of 12/1 it is no doubt that 12/1, accordingly to single index model, is a superior investment compared to 9/3.

Having concluded that the single index model provides reliable evidence of abnormal returns a more complex model is considered. It could be the case that the single index model is too simplistic to capture return movements from momentum strategies. The Fama-French three factor model is a cornerstone in today's financial landscape when it comes to explaining security returns, Fama and French (1993). The model is specified in equation 3.

$$r_{WL} - r_f = \alpha_{WL} + \beta_{WL}(r_m - r_f) + S_{WL}(SMB) + H_{WL}(HML) + \epsilon_{WL} \tag{3}$$

The three factor model is basically the single index model expanded with two additional risk factors, SMB and HML. SMB stands for small minus big and is meant to capture risk arising from investing in companies of different size[32]. HML stands for high book-to-market ratio minus low book-to-market ratio and is meant to capture risk associated with investing in companies of different book-to-market ratios. The method for constructing SMB and HML follows Fama and French (1993), however, some differences are worth highlighting. Fama-French rebalances SMB- and HML-portfolios in June each year. In this thesis the portfolios are rebalanced in the beginning of every month. Further, Fama and French calculates value-weighted returns, in this thesis equally-weighted returns are used. The above method for return calculation, regarding the SMB- and HML-portfolio, is used in order to be in line with the methodology used when calculating returns from WL portfolios[33].

All stocks in the sample are dived in two equally large groups, small and big, based on whether their market value is above or below the median market value. Further, based on the book-to-market ratio three groups are formed, low, medium and high. The low group consists of the bottom 30%, the medium group of the middle 40% and the high group of the top 30%. Decided by the intersections of these groups six portfolios are formed, S/L, S/M, S/H, B/L, B/M, B/H. For example, the S/L portfolio contains small stocks which at the same time have a low book-to-market value. The SMB factor is then calculated as a simple average of the return from the three small stock portfolios minus a simple average of the return from the three large stock portfolios[34]. In a similar fashion the HML factor is calculated as a simple average of the two high book-to-market value portfolios minus the two low book-to-market value portfolios[35]. Fama and French (1993) suggest that the above methodology is

[32] Company size is defined as market capitalization.
[33] All WL portfolios are rebalanced monthly and all stocks in a WL portfolio have the same weight.
[34] $SMB = \frac{(S/L+S/M+S/H)}{3} - \frac{(B/L+B/M+B/H)}{3}$
[35] $HML = \frac{(S/H+B/H)}{2} - \frac{(S/L+B/L)}{2}$

used in order to reduce the correlation between SMB and HML[36]. That is, you want SMB to be free of influence from HML and vice versa[37]. If the explanatory variables in a multiple regression model is heavy correlated it is difficult to isolate their individual effect on the dependent variable even if the model as a whole is significant, Hill et al. (2011).

Monthly average return for the SMB- and HML-portfolio is, over the sample period, -0.14% and 1.38% respectively. This means that you have received a small negative premium for investing in small stocks but a rather large premium for investing in stocks with a high book-to-market value, often referred to as value stocks. These numbers can be compared with data from the homepage of Kenneth R. French. Over the same sample period but for Europe as a whole the return for the SMB- and HML-portfolio is 0.05% and 0.5% respectively (French). The HML factor is considerably larger in Sweden compared to Europe as whole. A possible explanation for this is the 1992 depreciation of the Swedish krona. At the time large export oriented companies had experienced sharp declines in their stock prices resulting in high book-to-market values. When the central bank of Sweden abandoned the fixed exchange rate the krona depreciated which in turn had a positive effect on the export sector. When checking for this effect in the data it seems to exist. For example, over the years 1993-1994 the HML portfolio generates a monthly return of 4.25%.

Table 3. Alpha values for the 17 strategies generated by Fama-French three factor model regressions.

J		K=	1	3	6	9	12
		α					
3	W-L			1.70%**	1.41%**	0.91%**	0.81%**
6	W-L			2.20%**	1.50%**	1.12%**	0.90%**
9	W-L			1.74%**	1.29%**	0.96%*	0.81%**
12	W-L		2.21%**	1.68%**	1.23%**	0.96%**	0.83%*

* significant at the 5% level using Newey West std. errors

** significant at the 1% level using Newey West std. errors

Alpha values from three factor model regressions are presented in table 3. All alpha values are positive and, except for the 12/12 and 9/9 strategy, significant at the 1%

[36] Compared to just using the difference between small and big and high and low. For example, to calculate HML the stocks in the sample would then simply be dived into two groups, high and low, and HML would be the difference between the two groups.

[37] The correlation between SMB and HML is -0.21.

level. The positive intercepts implies that TFM fails to explain returns from the WL-portfolios. In fact, alpha values from the three factor model are larger than both alpha values generated by the single index model and the raw return. This implies that after accounting for risk factors in the three factor model, momentum strategies look even more attractive. For example, the most successful strategy, 12/1, generates in terms a raw return 1.61% per month. The same strategy generates, according to the three factor model, an abnormal return of 2.21% per month. That is, you receive a monthly return that is 2.21% percentage points higher than the fair compensation for the risk taken. Jegadeesh and Titman (2001), in line with this thesis, also found that the alpha generated by the three factor model is larger than the single index model alpha and the raw return. R^2 values for the three factor model ranges from 28.9% to 41.9% with the 6/3 strategy having the lowest value and 3/12 the highest. As mentioned before, the highest R^2 obtained with the single index model were 15.4%, hence, three factor model shows a much stronger explanatory power. Still, apparently not strong enough since alphas, for all strategies, are positive and significant.

Table 4. Regression results from Fama-French three factor model.

J		K= 1	3	6	9	12
	W-L					
	β		-0.43**	-0.36**	-0.33**	-0.26**
3	S		-0.82**	-0.78**	-0.73**	-0.63**
	H		-0.52**	-0.42**	-0.32**	-0.29**
	W-L					
	β		-0.50**	-0.43**	-0.35**	-0.29**
6	S		-1.04**	-1.02**	-0.87**	-0.79**
	H		-0.58**	-0.41*	-0.32**	-0.32*
	W-L					
	β		-0.57**	-0.46**	-0.39**	-0.33**
9	S		-1.25**	-1.13**	-1.06**	-1.01**
	H		-0.58**	-0.49**	-0.47**	-0.51**
	W-L					
	β	-0.60**	-0.54**	-0.45**	-0.38**	-0.27**
12	S	-1.30**	-1.28**	-1.24**	-1.18**	-1.07**
	H	-0.69**	-0.66**	-0.59**	-0.60**	-0.59**

* significant at the 5% level using Newey West std. errors

** significant at the 1% level using Newey West std. errors

Table 4 presents additional three factor model regression results. Regression coefficients for SMB and HML are significant at the 5% level in all 17 models. In all 17 strategies SMB and HML have a negative relationship with the WL portfolio. In line with the results from the single index model all ß-coefficients are negative and significant at the 1% level. The negative relation between SMB and a given WL-portfolio shows that loser portfolios are more heavily loaded on small stocks compared to winner portfolios. That is, when small stocks increase in value, gains in the loser portfolio will exceed gains in the winner portfolio. Hence, a W-L portfolio will suffer from losses. Further, negative HML coefficients show that the winner portfolios are concentrated on growth stocks and the loser portfolios on value stocks[38]. Therefore, in general, when value stocks increases in price a WL-portfolio will decrease in value and consequently when growth stocks increases in price a WL-portfolio will increase in value, causing the earlier mentioned negative relationship between HML and a WL portfolio.

The statistical tests used for the single index model were also used to check the validity of the results from the three factor model. As expected heteroscedasticity were found in all 17 models. Autocorrelation were only found in the 9/9 strategy. These problems were corrected by the use of Newey West standard errors which is robust to both heteroscedasticity and autocorrelation. All WL-portfolios fails the Skewness-Kurtosis test regarding normal distributed residuals. For a complete table over all statistical tests performed see appendix C, table 13. There is reliable evidence that abnormal returns from momentum strategies still exists after adjusting for risk factors in the three factor model.

To summarize, raw returns from the 17 strategies are positive and are all highly significant. Almost all of the 17 strategies have positive intercepts both from the single index model and the three factor model. Taken together, there is conclusive evidence on the presence of return continuation at Stockholm Stock Exchange over the 1993 to 2014 period. This stands in contrast of Rouwenhorst (1998) findings of a much more weak Swedish stock return continuation effect between 1978 and 1995. Hence, one can argue that the Swedish stock market seems to have developed towards being more inefficient.

Behavioral Finance as an Explanation to Return Continuation

Since neither the single index model nor the three factor model could explain returns generated by momentum strategies focus naturally moves to alternative causes. A common explanation amongst researchers is behavioral finance[39]. Models

[38] In general, growth stocks is stocks with a low book-to-market value and value stocks is stocks with a high book-to-market value.

[39] For example, (Jegadeesh and Titman, 2001) investigate behavioral models as an explanation to abnormal returns generated by momentum strategies.

like the single index model assume that investors are fully rational and always make well calculated and informed decisions. However, it is highly questionable if that really is the case. If investors from time to time make investment decisions that not are fully rational but instead based on emotions and other physiological factors, than that is something that would not show up in the earlier discussed models.

Investors are often assumed to be risk seeking when suffering from a not yet realized loss, they prefer not to realize the loss in hope of retrieving their investment. In other words the satisfaction of gaining a dollar is smaller than the dissatisfaction of losing a dollar. This effect was first introduced by Kahneman and Tversky (1979) and is referred to as prospect theory. Building on the work of Kahneman and Tversky (1979) is Shefrin and Statman (1985) whom investigate a general tendency of riding losses to long and realize gains to early, also called disposition effect. Further, many psychologists like Edwards in Kleinmuntz (1968) have identified an effect known as conservatism, this effect states that when individuals are faced with new facts they are slow to change their beliefs. Frazzini (2006) test the disposition effect and more specifically if investors have a tendency to underreact to new information and by that causing predictability in future returns.

Frazzini (2006) show that stocks trading at large capital gains tend to underreact to good news and that stocks trading at large capital losses tend to underreact to bad news. For example, when investors hold a stock which is currently trading at a capital loss they are unwilling to sell the stock and realize a loss, so when bad news about the company are presented the supply of stocks on the market will be limited. This in turn slows down the price decrease towards the stocks fundamental value. For stocks trading at capital gains investors is risk averse. Investors are selling stocks to realize gains which cause an excess supply. When good news is presented the excess supply hampers the price increase towards the stocks fundamental value.

Since stocks trading at large capital losses would turn up in the loser portfolio and stocks trading at large capital gains would turn up in the winner portfolio the above hypothesis could be a reasonable explanation to abnormal profits generated by momentum strategies. Frazzini (2006) also shows that a trading strategy based on this effect yield monthly alphas exceeding 2%, in line with the alphas generated by the most successful momentum strategies in this thesis. Although only scraping on the surface on the very vast research field of behavioral finance it seem like a possible explanation to momentum returns. However, this thesis presents no formal tests or evidence, much more in depth research would be needed to draw more certain conclusions.

Implementing Momentum Trading Strategies

The previous section was concerned with establishing evidence that past winners outperforms past losers. Engaged readers now, naturally, wonders if it is possible to profit from momentum strategies in real life. In theory the winner minus loser strategy seems very attractive. It generates large returns and since it is a zero investment strategy an investor could, in theory, use indefinite leverage. In sum, an investor pursuing the WL strategy has the potential to earn large profits very fast.

This section will take the perspective of a retail investor, an institutional investor have the ability to trade faster, cheaper and likely to short-sell a larger part of the stocks available on the market. The limited number of stocks that is possible to short sell, for a retail investor, is a major problem. As mentioned in the methodology part, in April 2014, only 43 of the 253 traded stocks were available for short selling[40]. In general it is large and liquid stocks that are available for short selling. However, TFM regression results showed that the loser portfolio is loaded on small stocks. If stocks that go into the loser-portfolio are unavailable for short-selling than that will, of course, counter the very core idea of the winner minus loser strategy. Also, when opening a new short position some collateral will be demanded, often around 30% of the value of the position[41]. This implies that not all proceeds from short-selling the loser portfolio could be used to finance the winner portfolio.

In addition, the transaction costs for a short position is considerable higher compared to long position in a given stock. For example, at Avanza, in April 2014, there is a fixed fee of 199 SEK and in addition a commission of 1.5% for short selling any of the 30 largest stocks and at least 3% for any other stock. Taken together, limitations regarding short-selling, for retail investors, are by the author considered so large that a winner minus loser strategy is very hard, if not impossible to implement. Therefore the focus shifts to the long leg of a momentum strategy, that is, the winner portfolio. Results from the previous section, table 1, show that the winner portfolio, for all strategies[42], outperforms the benchmark portfolio. This part of the thesis will investigate if these results still exist when adjusting for risk and transaction costs.

The formation of the winner portfolios follows the procedure described in the methodology part with three differences. Firstly, in the previous section value invested in stocks which were delisted during the holding period were not reinvested. This decision was made because it was assumed to have little effect on

[40] At Avanza, one of the largest internet broker in Sweden.
[41] For example, the margin requirement at Avanza was 30% in April 2014.
[42] Except 12/12.

the WL portfolio return. When pursuing a risky strategy like buying the winner portfolio it is not likely that a real life investor would just place any available funds at a broker- or bank-account. The optimal solution would be that funds which become available are reinvested in the rest of the stocks in the winner portfolio. However, that turned out to cause very cumbersome calculations when using the formula sheets set up in Excel. Therefore any funds that become available during a holding period are reinvested in the benchmark portfolio[43].

Secondly, compared to constructing a portfolio that will mimic a market index a momentum strategy is trading intensive. In the former result part the total position in a WL strategy were rebalanced every month. In this part and in order to reduce transaction costs buy and hold portfolios are investigated. That is, the winner portfolio is bought at the start of the holding period and then held without rebalancing until the end of the holding period.

Thirdly, in the previous section overlapping portfolios were used. For example, a 12/3 strategy held 3 WL portfolios simultaneously. In a buy and hold strategy, again to reduce transaction costs, only one portfolio at the time will be held. Based on the results from table 1 the 5 best performing winner portfolios were chosen. Returns for these 5 portfolios were then calculated. The other 11 winner portfolios were assumed to have too low raw returns in order to have a chance of generating significant results, after adjusting for risk and transaction costs[44]. Table 5 present returns, before transaction costs, for the 5 chosen buy and hold winner portfolios.

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[43] The difference between reinvesting funds, in the benchmark portfolio, or not is quite small. Between 5 -10 basis points per month for the different winner portfolios.

[44] This decision were taken early in the process of writing this thesis. Further research indicate that this probably were a bad decision. Results point to that all 17 buy and hold winner-portfolios, after deducting transaction costs, generate positive Fama-French three factor model alphas. Still, due to time limitations these results could not be fully included in this thesis.

Table 5. Monthly simple average returns from 5 momentum strategies in which only the winner portfolio is bought. The strategies use buy and hold, non-overlapping portfolios. All returns are before transaction costs. T-values in parenthesis. The t-values are calculated accordingly to equation 1. However, μ is not set to zero but instead equal to the average return of the benchmark portfolio. The benchmark portfolio yielded 1.29% per month, calculated as a simple average, over the sample period.

J		K=	1	3	6	9	12
3	Winner (buy and hold)			**0.0203**			
				(1.50)			
6	Winner (buy and hold)			**0.0222**	**0.0191**		
				(2.10)	(1.34)		
9	Winner (buy and hold)			**0.0186**			
				(1.32)			
12	Winner		**0.0208**				
			(1.92)				

As shown in table 5 a buy and hold winner strategy performs well, in terms of raw return, compared to a monthly rebalancing strategy, presented in table 1. The t-values are although negatively affected by the much fewer observations in a buy and hold strategy and that the expected return not is equal to zero but instead equal to the average return of the benchmark portfolio. 6/3 and 12/1 are the only strategies which generate significant results[45]. However, t-values are not the whole truth. T-values only measure the significance of raw return. It is possible that insignificant strategies generate positive and significant alphas from single index model- and three factor-model regressions. This would imply that they on a risk adjusted basis are attractive investments.

Transaction costs are divided into two major parts, broker commission and bid- ask spread. For both parts the magnitude is quite difficult to decide. Starting with the commission, which changes depending on the amount of capital invested. The larger trading volume the better terms one will have with its broker. Further, commission has changed over the years. The entry of internet brokers in the late 90ths has drastically reduced commission. It is decided to be overly time-consuming to research the average commission for the major brokers for different time periods, therefore an estimation will be conducted. Even harder to decide is the bid-ask spread. The bid price is the price a buyer of a stock is willing to pay. The ask price is the price a seller of a stock demands. The ask price is always higher than the bid price, that is, there is a spread between bid and ask. This means that an investor will receive, everything else equal, a lower selling price compared to the buying

[45] Using a significance level of 5% the critical value for a single sided test is 1.645.

price. The magnitude of the bid-ask spread is driven by the liquidity in a given stock. High liquidity implies a tight spread, low liquidity implies a wide spread. Liquidity on a stock market constantly changes, hence, the bid ask spread also constantly changes. The only way to determine the exact bid ask spread for every individual stock in the sample is to use higher frequency data. Since the use of more detailed data is beyond the scope of this thesis the bid-ask spread must be estimated[46].

Further transaction costs are often discussed amongst practitioners, such as slippage and market impact. With market impact one means that large orders may affect the price of the security in question, especially when buying stocks with low liquidity. However, this thesis assumes no market impact cost. Depending on the number of stocks traded at Stockholm Stock Exchange the winner portfolio consists of 14-26 different stocks during the sample period. With, for example, 20 stocks in the winner portfolio an investment of 1 million SEK would result in only 50 000 SEK in an individual stock. Hence, the market impact is considered to be fairly low. Slippage is the price difference between the expected price of a trade and the actual execution price. For example, if one uses market orders when trading then maybe the whole position is not possible to fill at the current price, instead a part of the order maybe will be filled at a higher price. Estimating slippage without higher frequency data is very hard and the author has therefore decided that it is beyond the scope of this thesis.

As discussed above the transaction costs used will be estimates. As a point of reference Jegadeesh and Titman (1993) use 0.5% as a one way transaction cost which they consider to conservative. Berkowitz et al. (1988) suggest a one way transaction cost equal to 0.23%, although for institutional investors. It is reasonable to assume that transaction costs have decreased since the late 80ths and early 90ths. Both competition among brokers and stock market liquidity have increased over the years. For example, in 1996 the annual turnover on SSE was equal to 139 billion USD, in 2012 the annual turnover was around 450 billion USD (Nasdaq-OMX). A tour among the list of prices for major internet brokers reveals that, depending on yearly trading volume, a reasonable commission today is between 0.03% and 0.1%. Since the sample period stretches from 1993 up until 2014 and the commission likely was higher in the beginning of the sample period, the commission, over the whole sample period, is estimated to be 0.1%.

When performing test checks on Stockholm Stock Exchange the most liquid stocks trade with a bid-ask spread of 0.1% and illiquid stocks trade with bid-ask spread of

[46] This thesis use close to close return data.

0.5-1.5 percent. Those figures are for July 2014, with only historical closing prices to work with there is no possibility to verify if these numbers are valid for different time periods during the sample period. As an estimate, although a crude one, an average bid-ask spread over the sample period of 1% will be used. Hence, the total, or two ways transaction cost is estimated to be 1.2% as specified in equation 4. Commission is paid twice in equation 4 since one is exposed to it both when selling and buying stocks. On the contrary it is assumed that one only is exposed to bid-ask spread when selling stocks, thus, it is only paid once in equation 4.

$$Total\ Transaction\ Cost = \big((commission \times 2) + bid\ ask\ spread\big) = \big((0.001 \times 2) + 0.01\big) = 0.012 \quad (4)$$

Lui et al. (1999) states that "some stocks retain their status as winners or losers over successive holding periods". This is also true for the dataset used in this thesis. The author estimates that for a holding period of 1 month 1/3 of the winner-portfolio must be rebalanced, for a holding period of 3 months 1/2 of the portfolio must be rebalanced. Finally, for a holding period of 6 months the whole portfolio must be rebalanced. For example, the total transaction cost for a strategy with a holding period of 3 months is then equal to 0.6% which is paid every 3 months[47]. Returns for the 5 strategies in question, after transaction costs have been deducted, are presented in table 6.

All 5 winner portfolios outperform the benchmark portfolio in terms of risk unadjusted returns. The t-values are further pressed down by the deduction of transaction costs. At the 5% level no strategy generates significant results. The 6/3 strategy is however very close and clearly significant at the 10% level[48]. When comparing monthly returns from the winner portfolios with the 1.29% per month that the benchmark portfolio generates they seem like attractive investments. Over long time periods the return difference between a winner portfolio and the benchmark portfolio will add up to large values. Figure 4 shows the cumulative return for a 1 dollar investment in the best performing strategy, 6/3, and the worst performing strategy, 9/3. For comparison the cumulative return for a 1 dollar investment in the benchmark portfolio is shown.

[47] $\big((commission \times 2) + bid\ ask\ spread\big) \times (proportion\ needed\ to\ rebalance) = \big((0.001 \times 2) + 0.01\big) \times 0.5 = 0.006$. It then follows that for a holding period of 1 month the transaction cost is equal to 0.4% which is paid every month and for a holding period of 6 month the transaction cost is equal to 1.2% which is paid every 6 month. When a strategy first is set up or closed out the transaction cost will be equal to 0.6% for all holding periods.

[48] At the 10% level the critical value for a single sided test is equal to 1.29.

Table 6. Monthly simple average returns from 5 momentum strategies in which only the winner portfolio is bought. The strategies use buy and hold, non-overlapping portfolios. All returns are after transaction costs. T-values in parenthesis. The t-values are calculated accordingly to equation 1. However, μ is not set to zero but instead equal to the average return of the benchmark portfolio. The benchmark portfolio yielded 1.29% per month, calculated as a simple average, over the sample period.

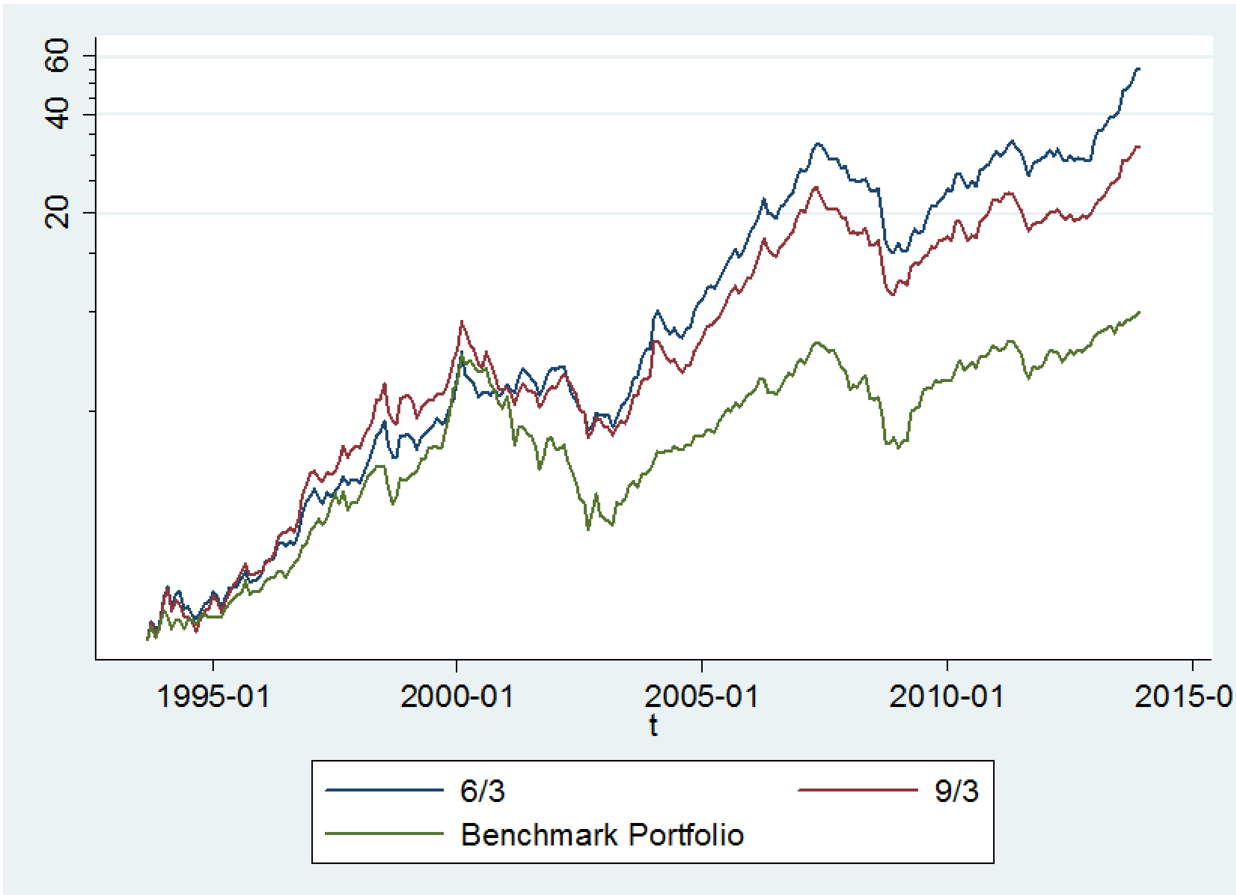
J		K=	1	3	6	9	12
3	Winner (buy and hold)			**0.0182** (1.08)			
6	Winner (buy and hold)			**0.0201** (1.62)	**0.0170** (0.89)		
9	Winner (buy and hold)			**0.0165** (0.84)			
12	Winner		**0.0167** (0.93)				

As displayed in figure 4, an investor who pursued the 6/3 strategy is considerably better-off compared to an investor which bought the benchmark portfolio. At the end of the sample period the 6/3 strategy has generated 55 dollars in cumulative return, or 21.8% per year as a geometric average. The cumulative return for the benchmark portfolio and the 9/3 strategy is 10- and 32-dollar respectively. Assuming that transaction costs estimates are fair, the results so far are quite clear, any of the 5 momentum winner portfolios is a superior investment compared to the benchmark portfolio. However, high returns could be the result of a high risk in the winner portfolios. To risk adjust the returns the same methods as in the previous section will be used, that is, single index model regressions and three factor model regressions.

Table 7 shows alpha and beta values from single index model regressions. All strategies except 3/3 have significant and positive alphas[49]. The beta values are all significant and ranges from 0.67 to 0.83 which in turn implies a lower systematic risk than the market. A lower systematic risk than the market in combination with a higher return is of course an attractive combination.

[49] Autocorrelation were found in 3/3 strategy, heteroscedasticity were found in 3/3, 6/3 and 6/6. These problems were corrected with the use of Newey West standard errors. All 5 portfolios fail the Skewness-Kurtosis test regarding normally distributed residuals. For a complete table over all statistical tests performed see appendix C, table 14. The alpha for the 3/3 strategy is very close to being significant with a p-value of 5.01%.

Figure 4. Cumulative returns from October 1993 up until January 2014 for a 1 dollar investment in 6/3 winner portfolio, 9/3 winner portfolio and the benchmark portfolio. Returns for the 6/3 winner portfolio and the 9/3 winner portfolio are after transaction costs. For the benchmark portfolio there is assumed to be no transaction costs. Logarithmic scale is used, every tick on the Y axis represents 5 dollar.



To further risk adjust the returns, three factor model regression results are presented in table 8[50]. Compared to the results from the single index model the 5 winner portfolios look even more attractive as an investment. All alphas are significant and for all 5 strategies higher than the alpha values obtained from the single index model. The 6/3 strategy, for example, offers a monthly return that is 1.18 percentage point higher than the fair compensation for the risk taken. All SMB coefficients are significant at the 5% level, however, the only significant HML coefficient are found in the 12/1 strategy. All beta coefficients are significant and ranges from 0.64 to 0.82. The 5 winner portfolios load positively on SMB and

[50] Autocorrelation were found in 3/3 strategy, heteroscedasticity were found in 3/3, 6/3, 6/6 and 9/3. These problems were corrected with the use of Newey West standard errors. All 5 portfolios fail the Skewness-Kurtosis test regarding normally distributed residuals. For a complete table over all statistical tests performed see appendix C, table 14.

Table 7. Alpha and beta values from single index model regressions. Buy and hold winner portfolios after transaction costs.

J		K=	1	3	6	9	12
		α, β					
3	W			0.73%, 0.83**			
6	W			1.04%**, 0.72**	0.69%*, 0.78**		
9	W			0.72%***, 0.74****			
12	W		0.80%****, 0.67****				

* significant at the 5% level using Newey West std. errors
** significant at the 1% level using Newey West std. errors
*** significant at the 5% level
****significant at the 1% level

negatively on HML. That is, the winner portfolios will increase in value when small stocks, relative to big stocks, increase in value. Hence, it is reasonable to assume that the winner portfolios to a large extent consist of small stocks. Further, an increase in the return of growth stocks indicates a positive effect on the winner portfolios, although this effect is not statistically robust.

Table 8. Regression results from Fama-French three factor model. Buy and hold winner portfolios after transaction costs.

J		K=	1	3	6	9	12
	W						
	α			0.97%*			
3	β			0.82**			
	S			0.67**			
	H			-0.07			
	W						
	α			1.18%**	0.88%**		
6	β			0.72**	0.77**		
	S			0.48**	0.59**		
	H			-0.01	-0.04		
	W						
	α			1.04%**			
9	β			0.71**			
	S			0.40**			
	H			-0.17			
	W						
	α		1.12%****				
12	β		0.64****				
	S		0.42****				
	H		-0.17***				

* significant at the 5% level using Newey West std. errors
** significant at the 1% level using Newey West std. errors
*** significant at the 5% level
****significant at the 1% level

As mentioned earlier it is not possible to rank securities accordingly to alpha values. One measurement that allows for securities to be ranked is the Treynor ratio which is specified in equation 5, Treynor (1965).

$$Treynor = \frac{r_{WL} - r_f}{\beta_{WL}} \tag{5}$$

Where r_{WL} is equal to the monthly average return for a WL-portfolio over the sample period, r_f is equal to the monthly risk free rate as an average over the sample period and β_{WL} is the beta value for a given WL-portfolio estimated from the earlier discussed single index model. The Treynor ratio can be interpreted as "excess return per unit of systematic risk", Bodie (2011). Table 9 presents Treynor ratios for the 5 winner portfolios.

Table 9. Treynor ratios for buy and hold winner portfolios after transaction costs.

J		**K=**	1	3	6
3	**W**			0.0183	
6	**W**			0.0238	0.0180
9	**W**			0.0183	
12	**W**		0.0205		

Accordingly to the Treynor ratio the best performing portfolio is 6/3. At the same level of systematic risk as the market the excess return for the 6/3 portfolio is equal to 2.38% per month compared to 1.26% per month for the benchmark portfolio. Outperforming the market with, on average, 112 basis points per month must be considered as a strong performance. All 5 portfolios outperform the market with the 6/6 portfolio having the weakest performance "only" outperforming the market with 54 basis points per month.

Standard deviation is often used as a fast and simple way to determine risk. Also, standard deviation incorporates total risk for an investment while single index model only measures systematic risk. The M^2 measurement allows us to compare performance between securities or portfolios of securities, Bodie (2011). M^2 is calculated by adjusting all winner portfolios so that they have the same standard deviation as the benchmark portfolio. That is, the winner portfolios are either leveraged up or down. M^2 is then interpreted as the extra return you get from holding a winner portfolio instead of the market index, Bodie (2011). Return, standard deviation and M^2 for the 5 winner portfolios are presented in table 10. For example, an investor which holds the adjusted 6/3 winner portfolio will receive a return which is 0.61 percentage points higher, per month, than the benchmark portfolio. Table 9 and 10 is conclusive in that among the 5 winner portfolios 6/3 is the best performing strategy.

Table 10. Monthly average return, monthly standard deviation and M^2 for buy and hold winner portfolios after transaction costs.

J	K=	1	3	6
	W			
	Return		0.0182	
3	Standard deviation		0.0789	
	M^2		0.0028	
	W			
	Return		0.0201	0.0170
6	Standard deviation		0.0700	0.0736
	M^2		0.0061	0.0027
	W			
	Return		0.0165	
9	Standard deviation		0.0682	
	M^2		0.0032	
	W			
	Return	0.0167		
12	Standard deviation	0.0642		
	M^2	0.0042		
	Benchmark portfolio			
	Return	0.0129		
	Standard deviation	0.0656		
	Risk free rate			
	Return	0.0030		

Despite low t-values for the 5 winner portfolios there is evidence that a winner-portfolio momentum strategy is profitable, also after adjustments for transaction costs and different risk factors. However, remember that the transactions costs only are estimates. If the estimates are too optimistic it is possible that the positive alphas don't really exist. It is though the opinion of the author that the estimates are reasonable, of course, they could deviate both up and down but not likely in such magnitude that the abnormal returns are wiped out. In fact, doubling the transaction costs will still leave all 5 winner-portfolios with positive and significant TFM alphas. For example, the 6/3 strategy gets a new alpha of 0.97% and the 9/3 strategy 0.82%. Further, it is also assumed that it is free to buy the benchmark portfolio, that is, it is free to buy a portfolio that mimics the market. In real life it is likely that there would be some transaction costs involved. This could, to some extent, compensate for a too low estimate of transaction costs. Finally, in order to get more statistically secure results, it would be interesting to expand on this work and with the use of higher frequency data to calculate more exact transaction costs for the various strategies.

VI. Conclusion

This thesis show that stocks listed at Stockholm Stock Exchange display short- to medium-term return continuation. Over the 1993 to 2014 period past winners outperform past losers. For example, a zero cost strategy[51] which select stocks based on their past 6 months performance and then holds them for 3 months generate a simple average monthly return of 1.61%. Strategies with evaluation periods of 6-12 months in combination with holding periods of 1-6 months are most profitable. Conventional risk factors are not successful in explaining returns from the various portfolios formed on past performance. Just as in the US stock market both single index model and the Fama-French three factor model leaves momentum returns intact. That is, systematic risk, company size or book-market-ratio cannot explain the observed return pattern.

Results in this thesis show resemblance to results from other work on return continuation. Similarities in momentum effects across different national stock markets and over different time periods suggest that results not likely are due to data-snooping. Further, predictions from behavioral models as an explanation to return continuation are discussed although no formal tests or evidence are presented. A third possible explanation to abnormal returns from momentum trading strategies, as pointed out by Fama and French (1996), is the possibility of explanatory power in additional risk factors beyond those included in the three factor model. The above three explanations are more or less plausible as a cause to return continuation. Still, the question why momentum effects exist on Stockholm Stock Exchange is by this thesis, to a large extent, left unanswered.

Impact from transactions costs and trading limitations on momentum profits are also investigated. Trading limitations, for a retail investor, mainly regarding access to short selling of stocks are large. In fact, they are considered so large that a zero cost strategy is close to impossible to implement. Thus, the focus shift to the long leg of a zero cost strategy, the past winners. Results show that strategies which buy past winners outperform the benchmark portfolio. For example, the best performing winner portfolio generate, after deduction of transaction costs, a monthly average return of 2.01% to be compared with 1.29% for the benchmark portfolio. Winner portfolios also look attractive on a risk adjusted basis. For instance, single index model regressions indicate a lower systematic risk than the market, at the same time all winner portfolios have a return higher than the market. Further, three factor model regressions produces positive and significant intercepts, suggesting that winner portfolios generate abnormal returns. These results should although be

[51] Past losers are sold short and the proceeds are then used to finance the purchase of past winners.

interpreted with some caution, mainly due to limitations in the estimation of transaction costs.

VII. Appendices

Appendix A. Descriptive Statistics

Table 11. Monthly average return and monthly standard deviation for SSE, during a given year, calculated from the benchmark index, MSCI-Sweden total return index. Also presented is the monthly average return and monthly standard deviation for WL-portfolio 6/3 under a given year.

Year	Return SSE	Standard Deviation SSE	Return 6/3	Standard Deviation 6/3
1993	4.31%	6.13%	NA	NA
1994	0.65%	5.76%	-0.55%	7.54%
1995	1.58%	4.09%	1.56%	3.92%
1996	3.03%	3.45%	1.24%	4.05%
1997	2.54%	6.44%	1.42%	3.21%
1998	1.61%	7.50%	5.75%	4.38%
1999	5.69%	6.31%	0.34%	6.50%
2000	-0.81%	8.33%	3.29%	12.74%
2001	-1.12%	10.69%	2.32%	20.57%
2002	-3.94%	9.80%	1.61%	17.76%
2003	2.84%	6.08%	0.68%	5.96%
2004	2.05%	3.17%	1.35%	4.00%
2005	2.47%	3.19%	-0.25%	3.10%
2006	1.93%	4.48%	2.77%	4.63%
2007	-0.27%	4.04%	4.48%	3.85%
2008	-3.53%	8.02%	2.58%	4.76%
2009	3.64%	6.92%	-3.36%	11.38%
2010	2.11%	4.47%	2.56%	4.19%
2011	-1.07%	4.91%	3.83%	4.22%
2012	1.39%	3.72%	-1.81%	6.72%
2013	1.88%	3.08%	2.67%	6.59%
All	1.29%	6.56%	1.62%	8.72%

Table 12. Maximum and minimum monthly return, during a given year, for MSCI-Sweden total return index and the 6/3 WL-portfolio.

Year	Maximum Return SSE	Maximum Return 6/3	Minimum Return SSE	Minimum Return 6/3
1993	11.36%	NA	-8.61%	NA
1994	11.47%	10.24%	-8.14%	-15.88%
1995	8.04%	8.97%	-8.15%	-5.26%
1996	9.17%	7.98%	-4.46%	-4.75%
1997	8.81%	6.60%	-11.16%	-4.79%
1998	13.69%	11.83%	-13.60%	-2.98%
1999	19.09%	8.78%	-1.34%	-15.01%
2000	22.54%	25.97%	-11.22%	-14.36%
2001	15.17%	25.84%	-18.42%	-36.06%
2002	14.74%	24.16%	-17.93%	-34.83%
2003	17.17%	6.94%	-4.38%	-14.23%
2004	6.89%	5.72%	-2.62%	-7.54%
2005	7.09%	5.60%	-2.75%	-5.40%
2006	8.35%	14.83%	-8.58%	-1.72%
2007	7.09%	13.69%	-7.69%	-1.13%
2008	6.18%	11.99%	-18.01%	-4.61%
2009	22.26%	3.92%	-6.91%	-38.88%
2010	8.67%	7.76%	-6.91%	-7.27%
2011	9.08%	10.74%	-10.92%	-3.27%
2012	6.93%	10.59%	-6.94%	-16.40%
2013	7.53%	12.81%	-5.31%	-8.01%
All	22.54%	25.97%	-18.42%	-38.88%

Appendix B. Histograms

Figure 5. Histograms of raw returns from the 6 best performing WL portfolios.

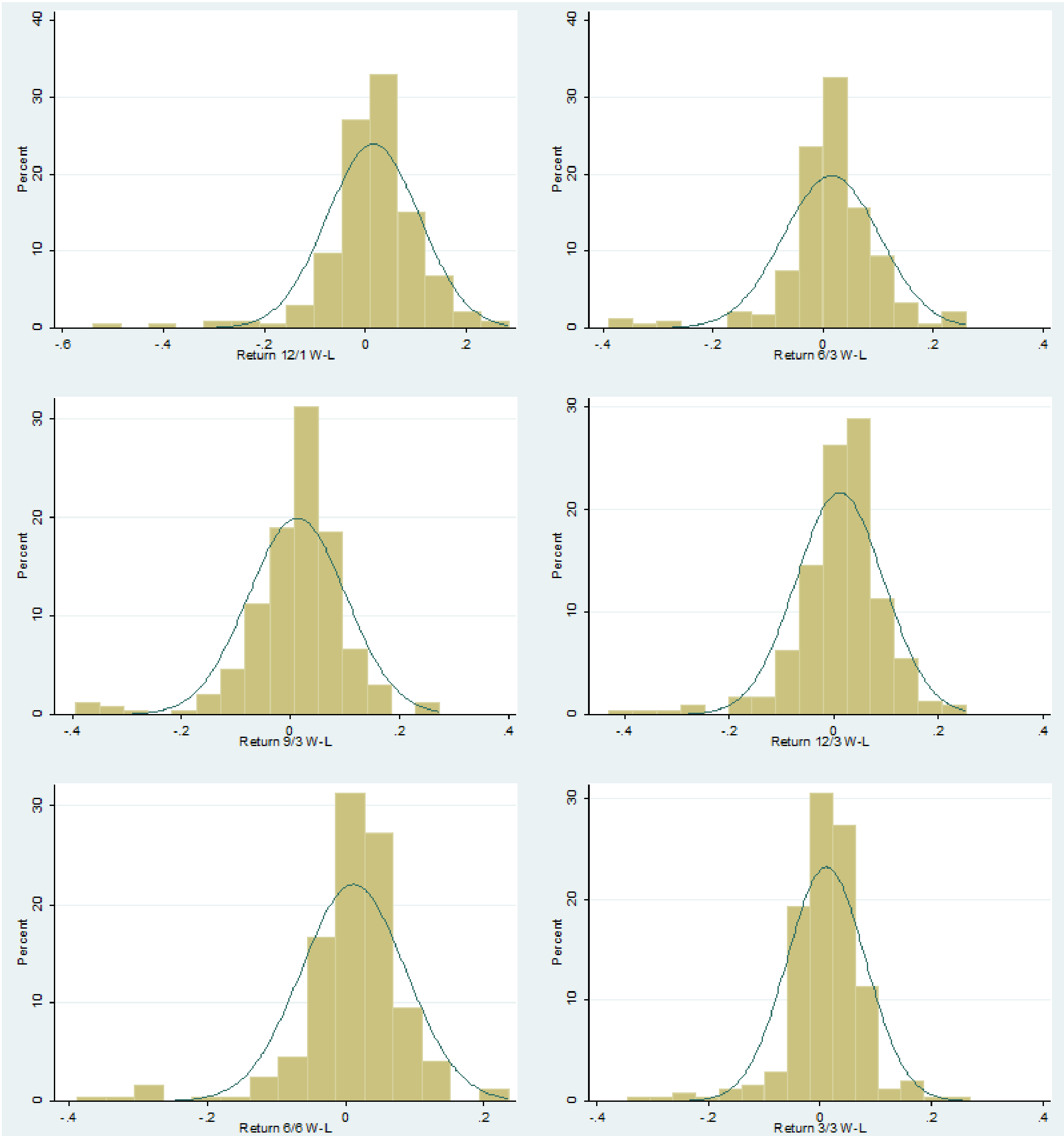
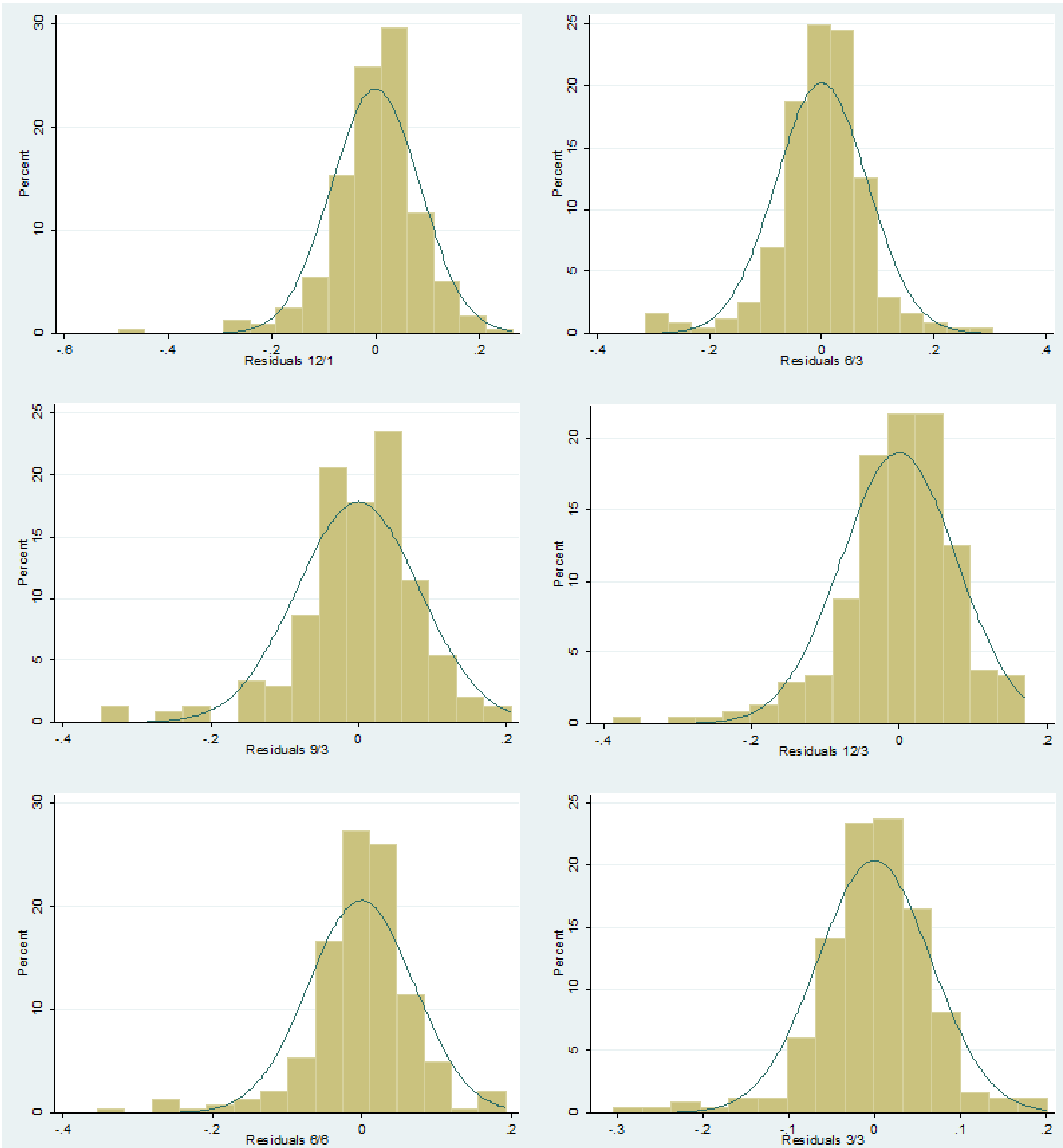


Figure 6. Histograms of residuals from Single Index Model regressions for the 6 best performing WL portfolios.



Appendix C. Statistical Tests

Table 13. P-values for Breusch-Godfrey-, Breusch-Pagan-, and Skewness-Kurtosis-test. The Skewness-Kurtosis test is performed with 1 lag. P-values bellow 0.05 are indicated in red. That is, any red number indicates a violation of the OLS assumptions. Breusch-Godfrey is a test for serial correlation in the residuals, Breusch-Pagan tests for constant variance in the residuals and Skewness-Kurtosis tests for normally distributed residuals.

J	K=	1	3	6	9	12
	Single index model					
	Breusch-Godfrey test		0.6080	0.7343	0.6254	0.9140
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0000
3	Skewness-Kurtosis test		0.0000	0.0000	0.0000	0.0000
	Three factor model					
	Breusch-Godfrey test		0.9170	0.5825	0.5185	0.1622
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0000
	Skewness-Kurtosis test		0.0000	0.0001	0.0000	0.0000
	Single index model					
	Breusch-Godfrey test		0.5782	0.8183	0.6701	0.3019
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0000
6	Skewness-Kurtosis test		0.0000	0.0000	0.0000	0.0000
	Three factor model					
	Breusch-Godfrey test		0.9023	0.6465	0.1790	0.0507
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0000
	Skewness-Kurtosis test		0.0000	0.0000	0.0000	0.0000
	Single index model					
	Breusch-Godfrey test		0.8305	0.5012	0.2301	0.3593
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0002
9	Skewness-Kurtosis test		0.0000	0.0000	0.0000	0.0000
	Three factor model					
	Breusch-Godfrey test		0.8761	0.1559	0.0463	0.1084
	Breusch-Pagan test		0.0000	0.0000	0.0000	0.0015
	Skewness-Kurtosis test		0.0003	0.0002	0.0000	0.0000
	Single index model					
	Breusch-Godfrey test	0.9720	0.6203	0.4377	0.5736	0.5327
	Breusch-Pagan test	0.0000	0.0000	0.0000	0.0004	0.0000
12	Skewness-Kurtosis test	0.0000	0.0000	0.0000	0.0000	0.0000
	Three factor model					
	Breusch-Godfrey test	0.3817	0.1352	0.0748	0.1388	0.0656
	Breusch-Pagan test	0.0000	0.0000	0.0001	0.0002	0.0000
	Skewness-Kurtosis test	0.0006	0.0007	0.0000	0.0000	0.0000

Table 14. P-values for Breusch-Godfrey-, Breusch-Pagan-, and Skewness-Kurtosis-tests. The Skewness-Kurtosis test is performed with 1 lag. P-values bellow 0.05 are indicated in red. That is, any red number indicates a violation of the OLS assumptions. Breusch-Godfrey is a test for serial correlation in the residuals, Breusch-Pagan tests for constant variance in the residuals and Skewness-Kurtosis tests for normally distributed residuals.

J	K=	1	3	6	9	12
	Single index model					
	Breusch-Godfrey test		0.0042			
	Breusch-Pagan test		0.0000			
3	Skewness-Kurtosis test		0.0000			
	Three factor model					
	Breusch-Godfrey test		0.0170			
	Breusch-Pagan test		0.0000			
	Skewness-Kurtosis test		0.0000			
	Single index model					
	Breusch-Godfrey test		0.9656	0.6869		
	Breusch-Pagan test		0.0015	0.0110		
6	Skewness-Kurtosis test		0.0000	0.0000		
	Three factor model					
	Breusch-Godfrey test		0.9406	0.4178		
	Breusch-Pagan test		0.0000	0.0000		
	Skewness-Kurtosis test		0.0000	0.0000		
	Single index model					
	Breusch-Godfrey test		0.6179			
	Breusch-Pagan test		0.1105			
9	Skewness-Kurtosis test		0.0000			
	Three factor model					
	Breusch-Godfrey test		0.5889			
	Breusch-Pagan test		0.0006			
	Skewness-Kurtosis test		0.0276			
	Single index model					
	Breusch-Godfrey test	0.1461				
	Breusch-Pagan test	0.2723				
12	Skewness-Kurtosis test	0.0003				
	Three factor model					
	Breusch-Godfrey test	0.0869				
	Breusch-Pagan test	0.1683				
	Skewness-Kurtosis test	0.0401				

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