Predicting Momentum Returns

Changes in the risk-free interest rate as a leading indicator

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Abstract

Momentum strategies have historically shown to yield positive returns with little systematic risk exposure. Although usually profitable over long time periods, momentum strategies have also shown to suffer from irregular but severe losses that effectively erode the strategies' attractiveness. By analysing a size-restricted sample of stocks listed on the Stockholm stock exchange between 1987 and 2013 we present how to predict and exploit these losses with the risk-free interest rate as a leading indicator. By incorporating a "switching rule" that alters between momentum and reversal portfolios conditional on changes in this leading indicator, we provide a self-financing strategy that yields a monthly alpha of 0.76%, and which risk-reward profile dominates that of the unconditional momentum strategy for two reasons; expected returns are higher and downside risk is lower.

Keywords: Dynamic, Momentum, Predictability, Reversal, Trading strategy

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We, the authors, have been students at the Stockholm School of Economics (SSE) for over four years, and we both earned our respective BSc degrees in Business and Economics in 2012. During our time at SSE we have studied the behaviour of stock markets and the characteristics of asset returns in various contexts both in and out of the academic environment. Our aggregate experience includes various commitments at multiple companies active in Stockholm's and London's finance and asset management industries. Although, this combination of academic and business experiences has provided the foundation of this thesis, it is predominantly our personal passions for investment strategies that have inspired us in our writings.

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1 Introduction

In context of the momentum literature there are two extensively documented, contradictive phenomena, each of which is argued to prevail in time series data of asset prices. One is the so called "momentum" effect, and refers to the tendency of an asset's value to continue to develop in the same direction as its historical performance, Jegadeesh and Titman (1993). The other is known as the "reversal" effect, and refers to the tendency of an asset's value to develop in the opposite direction as its historical performance, DeBondt and Thaler (1985) and Lehman (1990). On stand-alone bases, the existence of these effects have been shown in different stock markets and documented across various asset classes, Rouwenhorst (1998) and Asness et al (2013).

Depending on which of the effects, momentum or reversal, investors believe in, they can exploit it by constructing a self-financing portfolio that either buy past winners and sell past losers (exploiting the momentum effect), or buy past losers and sell past winners (exploiting the reversal effect). With extensive back-testing previous research argues that, if timed correctly, both of these strategies yield abnormal returns but also feature overhanging downside risk exposures, Daniel and Moskowitz (2011). Considering that the effects are each other's inverse, they are contradictive by nature and only one of them can prevail at a time. Accordingly, if investors wish to exploit any one of the effects, they will have to make two critical decisions. First, they will need to decide which of the investment strategies, momentum or reversal, to invest according to. Then, they will need to consider how to time the entry and exit of the chosen strategy.

In this thesis we combine theory with renowned empirical findings and our own primary research to address which of the strategies to invest according to, and how to time the investments. By doing so, the content herein adds value to the existing literature for at least three distinct reasons. First, we provide a model which effectively can be used to predict severe losses in momentum portfolios' returns. Second, the findings hold complementary value as our empirical research is carried out on Swedish stock market data, which is infrequently researched in this context. Third, we present a new investment technique that dynamically combines momentum and reversal portfolios, holding value both from a theoretical and practical perspective as it outperforms each of them on stand-alone bases.

Confirming the findings of Daniel and Moskowitz (2011), the conventional momentum strategy has been shown to provide investors with abnormal returns and little systematic risk exposure, Menkhoff et al (2011) and Moskowitz et al (2012). Simultaneously, the momentum strategy has been shown to feature a negatively skewed, leptokurtic return distribution that provides investors with irregular but severe losses, Fuertes et al (2009). In other words, evidence suggests that a conventional momentum portfolio features positive returns in most time periods, but occasionally when a tail event occurs, it suffers from large losses. Given the inverse relation between the momentum and the reversal effects it directly follows from this that the reversal portfolio features the opposite performance compared to the momentum portfolio, that is, it provides investors with frequent negative returns, but occasionally when a tail event occurs, it benefits from large positive returns.

By bringing this evidence together with findings from the predictability literature, including evidence suggesting that external variables such as the interest rate and fundamental valuation ratios have predictable features in future asset prices[1], we propose three pillars, which in combination provides the foundation for the findings presented later on in the thesis. They are:

1. Momentum returns follow a leptokurtic distribution with positive median and negative skew, implying that a momentum portfolio yields positive returns in most time periods, but occasionally, when a tail event occurs, suffers from sudden and severe losses.

2. Reversal returns follow a leptokurtic distribution with negative median and positive skew, implying that a reversal portfolio yields negative returns in most time periods, but occasionally, when a tail event occurs, gains from sudden and large profits.

3. Certain external variables can be looked upon as indicators of when it, in a relative sense, is more profitable to invest according to the momentum strategy rather than the reversal strategy, and vice versa.

In order to provide supportive evidence for these pillars, what we do in this thesis is essentially four things. First, by following the momentum evaluation technique as

[1] See for example Banz (1981), Rosenberg et al (1985), Lakonishok et al (1994), Estrella and Mishkin (1996), Pontiff and Schall (1998), and Asness et al (2000).

first suggested by Jegadeesh and Titman (1993), we investigate the distribution of momentum returns on a sample of Swedish stocks ranging from 1982 to 2013. Second, we repeat this procedure while incorporating a focus on implementation for momentum traders. Specifically, we impose a firm size-restriction to, in each time-period, only include the largest 25% of the stocks from the original sample. By doing so we mitigate issues related to size and value that inevitably are inherent in the original sample as it includes infrequently traded, small and illiquid stocks. Third, we employ a logistic regression to investigate the relationship between lagged changes in the risk-free interest rate and future momentum returns. Fourth, while continuing to work with the size-restricted sample, we take the conventional momentum portfolio and add a simple, yet strikingly effective "switching" feature to it, which performance attribution significantly improves the risk-reward profile of the conventional momentum strategy as it exploits a predictive relationship between the risk-free interest rate and future momentum returns.

In consistency with pillar 1 to 3 above, the additional switching feature is the use of lagged changes in the monthly average of the risk-free interest rate as an indicator of when to switch between momentum and reversal portfolios. Hereafter, this additional feature will be referred to as the "*Stenlund-Holmberg switching rule*" (SH-switching rule), and any portfolio that employs this rule will be referred to as a "*Stenlund-Holmberg switch portfolio*" (SH-switch portfolio).

From a macro perspective a decrease in the short-term interest rate works as a stimulus to the market, signalling insecurity about the future, Rigobon and Sack (2003) and Bernanke and Reinhart (2004). Furthermore, given momentum portfolios' tendencies to feature extreme value declines in times of financial crises or recessions, (implying equivalently sized gains for reversal portfolios), Fuertes et al (2009). Accordingly, we argue that investors should be investing in momentum portfolios conditional on observing an increase in the lagged monthly average of the risk-free interest rate, and that they should invest in reversal portfolios conditional on observing a decrease.

As discussed, we find that the performance of the SH-switching portfolio is superior to the momentum portfolio. Unambiguously, we find that the incorporation of the SH-switching rule succeeds in improving the risk-reward profile for all portfolios in a set of 16 different portfolios with varying evaluation and holding periods. Specifically, with either the same or lower standard deviation, and with lowered downside risk in all portfolios, arbitrary scalable monthly average returns for the SH-portfolios range from 0.23% to 1.04%, whereas the corresponding momentum portfolios range from -0.50% to 0.60%. In addition, 14 out of the 16 alphas are higher for the SH-portfolios than for the momentum portfolios.

The structure of the paper continues as follows. Section 2 provides a chronological review of existing momentum and predictability literature. Section 3 describes our data and its sources. Section 4 provides explanations of the methodologies applied in our research and section 5 summarises our empirical findings. Section 6 outlines our main conclusions, and finally, section 7 provides suggestions about future research.

2 Previous literature

2.1 Momentum literature – international context

Throughout the last decades the topic of momentum and reversal strategies has been thoroughly researched. As numerous momentum and reversal studies have reached publication status the emphasis of the phenomena has increased over time. The bulk of the existing literature suggests that momentum and reversal effects are widely present both geographically and across asset classes.[2]

The history of momentum and reversal documentation stretches back to early studies on the topic of relative strength strategies and market efficiency. For example, Levy (1967) showed that a strategy that bought equities with current prices that were substantially higher than their own historical 27-week average realised significant abnormal returns. Later, Jensen and Bennington (1970) criticised Levy's discoveries for being pinned-out from an ambitious analysis of 67 arbitrary strategies. By examining Levy's trading strategy over long out-of sample periods Jensen and Benington were able to decipher that Levy's strategy was outperformed by a simple buy-and-hold strategy. Thus, they proposed that Levy's abnormal returns were merely attributable to poor statistical application. Nonetheless, Levy's results remained of interest to many, and the years that followed provided several publications with supportive evidence of a momentum effect. Examples include papers by Shiller (1981) and DeBondt and Thaler (1985).

In the 1990's Lehmann (1990) and Jegadeesh (1990) shed light over contrarian (reversal) strategies with their respective papers which suggested that abnormal returns could be reaped by applying short-term reversal strategies that picked stocks based on their last-week or last-month performance. Jegadeesh and Titman (1993) built on these studies with their influential, and often cited paper "Returns to buying winners and selling losers: Implications for stock market efficiency". In this paper they showed that a trading strategy that bought equities that had performed well in the past and sold equities that had performed poorly in the past delivered positive abnormal returns over various holding periods ranging between one and four quarters.

Apart from the hereto mentioned studies, further examples include Bernard (1992), who showed that stocks tend to experience a "news conditional post-event

[2] See for example Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Asness et al (1997), Okunev and White (2003), Erb and Harvey (2006) and Asness et al (2013)

drift" in the same direction as suggest by the news. Based on these and similar findings, Barberis et al (1998) were able to provide a model that, based on physiological evidence, explained such post-event drift. Contrastingly, Hong and Stein (1999) provided further understanding in stocks' reaction tendencies as they provided empirical evidence suggesting that prices under-react in the short run, and that therefore "momentum traders" could profit by chasing short run trends.

If much of the first half of the 1990's focused on finding evidence of momentum and contrarian effects, the later parts involved a gradual shift towards explaining the effects rather than just proving their existence. For example, Moskowitz and Grinblatt (1999) first documented a strong and persistent momentum effect in the industry components of stock returns and then also analysed the phenomenon with factor attribution.

Literature from year 2000 and onwards is wide-ranging in its elaboration around momentum. For example, by examining American stock returns ranging back to 1926, Grundy and Martin (2001) studied the cross-section in momentum returns and found that common factor models can explain around 95% of return variability both for winners and losers, but cannot explain average returns. Daniel and Moskowitz (2011) further showed that return distributions from momentum strategies are skewed. They provided evidence of persistent strings of volatile and unpredictable return plunges, and furthermore, they concluded that these rapid declines (to some extent) can be forecasted as they follow market declines and are concurrent with sudden market rebounds. Finally, Asness et al (2013) documented that momentum effects exist across eight diverse markets and asset classes.

2.2 Momentum literature – Swedish context

Existing Swedish momentum literature principally include a PhD dissertation; Söderström (2008) and a few MSc and BSc theses; Blank and Hehenberger (1996), Söderström (2000), Hagwall and Lundén (2008) and Nyman and Siljeströmer (2011). Additionally, Rouwenhorst (1998) touched on the topic of momentum on the Swedish market, as it was included as one of twelve sample countries in an international momentum study.

The PhD dissertation by Söderberg (2008) contains three papers in the field of empirical finance which Söderström himself, in aggregate, refers to as a test of market efficiency. One of his papers, "Empirical Characteristics of Momentum Returns", is of relevance for this paper as it is a momentum-focused comparison of how strong the momentum effect has been in various parts of the world. With data from 40 countries, ranging from 1979 to 1999, Söderström found that the momentum effect in general has been strong in Europe and in the US, and that it has been weaker in other parts of the world and especially weak in South-East Asia. Moreover, he also pointed out non-normality in the momentum return distribution.

Blank and Hehenberger's research focused on 254 analyst-covered stocks and their performance in a nine-year sample from 1987 to 1996. With holding periods ranging from 6 to 12 months they showed that previous winners (top 20%) underperformed compared to previous losers (bottom 20%). That is, their findings argued for a contrarian rather than a momentum tendency among analyst-covered stocks.

With data ranging from 1979 to 1999, Söderström (2000) addressed the momentum topic in relation to the devaluation of the Swedish krona in 1992. Results from a pre-devaluation sample were compared to a post-devaluation sample, and as findings suggested greater momentum returns in the post-devaluation era, Söderberg concluded that markets had become less efficient post the devaluation.

After examining the existence of a momentum effect on a sample from 1987 to 2008, Hagwall and Lundén (2008) concluded, coherently with Söderström (2000), that a momentum effect has been present in the Swedish stock market. Moreover, after controlling for various common factors they were able to conclude that traditional models such as the capital asset pricing model ($CAPM$) and the Fama-French three-factor model only proved to explain momentum returns to some extent. Finally, results were only marginally improved when adding a coskewness factor that controlled for momentum returns' sudden and irregular price drops.

In addition to examining the momentum effect on Swedish data, the thesis by Nyman and Siljeströmer (2011) took an innovative approach to the conventional momentum research. By including a risk measure in the evaluation process they examined whether the conventional momentum strategy could be improved by analysing a sample from 1997 to 2010. More specifically, in addition to considering past returns when ranking stocks, past risk in the form of past Value at Risk (VaR) was also considered. Even though not always significant, their findings suggested that an evaluation methodology that includes both past returns and past risk should be superior to the conventional evaluation method that only considers historical returns.

Finally, as already mentioned, Rouwenhorst (1998) examined momentum on twelve international equity markets, one of which was the Swedish market. Although finding return continuation tendencies in all twelve markets, the Swedish market stood out as the only one in which the excess returns were not significantly different from zero.

2.3 Predictability literature

For many years economist and statisticians though of the log of a stock price to be following a "random walk", that is, to be totally unpredictable, implying zero value for any method designed to predict stock returns, Fama (1965). Moreover, evidence presented by Fama and French (1989) suggested that time variation and fluctuations in the required rate of return seemed to be related to the business cycle. The 80's and 90's also included a number of publications suggesting the existence of a certain set of financial variables that feature predictability in future asset returns. Predominantly, these variables included volatility, yields and yield spreads, and ratios of fundamental valuation in relation to market prices, such as the price-earnings ratio, dividend-to-price ratio, and the book-to-market ratio.[3]

Apart from the above mentioned research, influential literature on predictability also include Campbell and Shiller (1988a, 1988b), Fama and French (1989), Campbell (1991), Hodrick (1992) and Poterba and Summers (1988). The aggregate message from these papers is that historical information for variables such as lagged returns, interest rates, yield spreads, valuation ratios and default premia do, at least to some extent, feature predictability in future asset returns. Even though the bulk of the above mentioned studies are carried out on US data, international findings point in the same direction. For example, Harvey (1991, 1995) and Ferson and Harvey (1993) provided evidence of predictability in stock returns both in developed and emerging markets. Furthermore, Kandel and Stambaugh (1996) showed that even minute predictability tendencies seem to have substantial impact on the asset allocation decision.

[3]See for example Banz (1981), Rosenberg et al (1985), Lakonishok et al (1994), Estrella and Mishkin (1996), Asness et al (1997) and Pontiff and Schall (1998).

3 Data

In this section we describe the data used for constructing our sample and a size-restricted sub-sample, followed by a description of the market (R_m) and risk-free interest rate (R_f) approximations.

3.1 Sample construction – "full sample"

The data used in this study includes all stocks listed on the Stockholm stock exchange with available price level, market capitalisation and price-earnings ratio data between February 1982 and September 2013.[4] The observations are collected on the first day of each month, and in total the sample consists of 626 stocks (including stocks that have been delisted, defaulted and suspended) over a sample period of 380 months, Datastream (2013). We later refer to this sample as the "*full sample*". The sample covers several economic cycles and market conditions like the devaluation of the Swedish krona in 1992, the IT-era from the late 90's to the beginning of the 00's and the financial crisis of the late 00's.

In context of the momentum literature, bankruptcies and delistings can be handled in numerous ways, for example by reinvesting any remaining amount of the stock in the risk-free interest rate or in the market, or by simply treating the remaining amount as cash. We have chosen the third technique which is time invariant rather than any of the other approaches which, due to their dependence on external variables, are varying over time.

3.2 Sub-sample construction – "large cap sample"

We form a size-restricted sub-sample which only includes the largest quartile (25%) of all stocks in each time period. We refer to this size-restricted sub-sample as the "*large cap sample*" since it is comparable to the OMX Stockholm large cap[5] list over time. The characteristics of the stocks included in the large cap sample entail that a practitioner will not be hindered by short-sale constraints, liquidity issues or be able to affect the share price by trading, which are problems that would be more likely to appear if smaller stocks were included in the sample.

[4]Since the examined strategies requires lagged return data over 23 months before a full evaluation can be done the first full calendar year for which we could examine the portfolio's returns is 1984.

[5]OMX Stockholm large share cap is an index issued by Nasdaq OMX group, Inc. and includes shares listed on Nasdaq OMX Stockholm with a market capitalisation above one billion euro (EUR 1,000,000,000).

From the sub-sample formation follows that we lose the first 90 months due to an insufficient number of stocks[6] in the first years of the full sample period. Consequently, we have 243 stocks in the large cap sample over the time period June 1987 to September 2013.

Table I

Summary statistics for the number of observations (stocks) over time in the full sample and the large cap sample

	Full sample	Large cap sample
Total*	626	243
Min	36	27
Max	404	111
Mean	240	71
Median	287	79
Time period	Feb 1982 to Sep 2013	Jun 1987 to Sep 2013

*The number of stocks are varying over time.

3.3 Market and risk-free interest rate approximations

The *OMX Stockholm all share cap general index* is used to calculate a proxy of the market return (R_m). The index is value weighted and consists of all shares listed on Nasdaq OMX Stockholm stock exchange, and is issued daily by the Nasdaq OMX Group, Incorporated. We retrieve monthly values for the price level of the index for the same time period as for the full sample, Datastream (2013).

We use *SE 3M*, a market based three-month treasury bill issued by Riksgälden (the Swedish national debt office), as a proxy of the risk-free interest rate (R_f). Data of SE 3M is retrieved from the Swedish central bank, Riksbanken (2013), for each month of the full sample period.

[6] The momentum strategy requires at least 20 stocks in each time period.

4 Methodology

In this section we provide an explanation of the methods employed in our research. We begin by discussing the underlying logic behind working with the *large cap sample*. Second, we define how to calculate returns for long-only and zero net-investment (self-financing) portfolios, followed by an explanation of how to construct the momentum portfolios. Then, we describe the underlying logic of the logistic regression model set-ups used for prediction of momentum returns. Finally the section provides an explanation on how to exploit this predictive relationship with the use of Stenlund-Holmberg switch portfolios.

4.1 Adjusting the sample for market imperfections

Inspired by the methodology employed by Jegadeesh and Titman (1993) we form a size-restricted sample in order to mitigate size and liquidity issues inherent in our full sample.

By cutting off the 10% smallest stocks based on market capitalisation, Jegadeesh and Titman (1993) adjusted their sample to only include stocks with "well behaving" characteristics. Building on this reasoning, and in order to present a thesis that takes an "investor friendly perspective", our sample is cut-off to include only the largest quartile (25%) of all stocks from the full sample. The reason for cutting-off a larger proportion of the stocks lies in the size and liquidity differences between the US and the Swedish stock markets; since the Swedish market is smaller than the US market, a larger proportion of stocks needs to be cut-off in order to get a sample that for example feature short-sale opportunities.

Accordingly, the bulk of the research in this paper is conducted on this "large cap sample". Although we investigate momentum returns in the full sample, we merely do so to examine how the momentum effect changes as we restrict the sample. We work exclusively with the size-restricted data when forming the SH-portfolios, and all findings related to the SH-portfolios are based on the large cap sample.

4.2 Return definition

In consistency with the way of calculating returns in the existing momentum literature we define returns as the simple return from time t to $t + T$ as follows:

$$R_{T,t} = \frac{V_T}{V_t} - 1 \tag{1}$$

where V_t is the initial value at time t and V_T is the final value adjusted for corporate actions such as dividends and splits at time $t+T$. Simple net returns for self-financing portfolios apply the simple return definition, equation (1), but are in addition formed as follows:

$$R_{T,t} = \left(\frac{V_T^{long}}{V_t^{long}} - 1\right) - \left(\frac{V_T^{short}}{V_t^{short}} - 1\right) \tag{2}$$

where V^{long} is the value of the long position and V^{short} is the value of the short position. From equation (2) follows that the zero-net investment returns are normalised to the long side of the investment.

4.3 Momentum portfolios

When constructing the momentum portfolio we closely follow the method first employed by Jegadeesh and Titman (1993). Below we describe a detailed step-by-step guide of the methodology used.

4.3.1 Construction of the winner portfolios and loser portfolios

As previously noted in the introduction, the momentum theory states that past winners will continue to perform well in the future and that past losers will continue to perform poorly in the future. Hence, the intuitive way to exploit this anomaly is to buy (long) previous winners and sell (short) previous losers. To efficiently satisfy this objective, the first step in forming these portfolios is to rank all stocks in the sample in ascending order based on each individual stock's lagged return for some historical evaluation period. The second step is to separate the best and worst performing stocks.

To investigate the persistency of the momentum effect we analyse multiple combinations of evaluation periods (J) and holding periods (K). More specifically, in each month the stocks are ranked in ascending order, four times, based on their historical simple returns over the past 1, 2, 3 and 4 quarters (J–quarters lagged returns). The loser portfolios are then formed of the equally weighted stocks in the bottom decile. The winner portfolios are correspondingly formed of the equally weighted stocks in the top decile. Once these groups are constructed, they are held for holding periods of 1, 2, 3 and 4 quarters (K–quarters evaluation period). This procedure yields a total of 16 loser and winner portfolios as it takes into account all possible combinations of evaluation periods and holding periods ($J \times K = 4 \times 4$).

As a direct implication, the momentum portfolios' exposure to idiosyncratic risk increases as the sample-size decreases. Even though this was not an issue for Jegadeesh and Titman's (1993) (considering the large number of listed stocks on the US stock market), this has been something we have needed to consider since the earliest years of our sample merely constitute some 30 stocks. To alleviate this problem, if the number of stocks in the sample is less than 100 in any time period, our strategy adjusts the cut-off boundaries so that at least 10 stocks are included in each of the winner and the loser portfolios.

4.3.2 Construction of the momentum portfolios

To exploit the momentum effect using the above outlined winner and loser portfolios one should short-sell the loser portfolio and use the proceeds to invest in the winner portfolio. In each month the momentum strategy buys the winner portfolio and sells short an equally sized position in the loser portfolio, and holds these positions for K-quarters. In other words, the momentum portfolio is a zero net-investment as the short side of the investment finance the long side. This implies that no initial investment, aside from transaction costs and eventual collateral is required to pursue the strategy. With the same J-quarters evaluation periods and K-quarters holding periods as outlined for the winner and loser portfolios above, we once again get a total of 16 different combinations of "momentum portfolios".

4.4 Predicting momentum returns

In the previous subsection we explained how to set-up the momentum portfolio through its parts (the winner and loser portfolios). In this section we build on this as we outline the methodology we use to predict the momentum portfolio's return, namely, the logistic regression.

Given some set of observations, the logistic regression provides an answer to what the conditional probability of a certain event's occurrence is. Similar to the ordinary least square (OLS) regression, a logistics regression is designed to measure the relationship between a dependent variable (Y) and one or more independent variables (x). However, unlike the OLS regression, a logistic regression is used to predict only discrete (binary) outcomes of the dependent variable. Usually, the outcome is coded with a "1" for a success and "0" for a failure.

In this study we first employ a single factor logistic regression model in which we let the independent variable (x) be changes in the monthly average of the risk-free interest rate from the month beginning in $t-2$ to the month beginning in $t-1$, and the dependent variable (Y) be the simple return for a momentum portfolio held from t to $t+K$. Zero or positive returns of the momentum portfolio are categorised as "1" and negative returns are categorised as "0". This design enables us to construct a model which output can be used to make inferences regarding which strategy, momentum or reversal, that is most likely to be the best performing strategy in the following time period.

We also set-up a second single factor logistic regression model in which we categorise the top 4/5 of all returns as "1", and the bottom 1/5 of all returns as '0", using the same definition of the independent variable and investment horizon as above. Effectively, this means that we evaluate whether lagged changes in the risk-free interest rate can be used to predict in which periods the bottom 20% of the momentum portfolio's returns will occur.

Specifically, in both settings we have a binary output variable (Y), and wish to model the conditional probability: $P(Y = 1|X = x)$ as a function of x. The conceptual problem solved by the logistic regression is how to transform these binary properties of Y into a continuous, bounded function, ranging between 0 and 1, that is suitable for probability interpretation. It can be shown mathematically that Y can be transformed into a continuous variable with these properties via a "logistic transformation" of the odds, which means taking the natural logarithm of the odds for a successful trial:

$$log\left(\frac{p(x)}{1-p(x)}\right) \tag{3}$$

This expression can be linearly related to x, and the logistic regression is set-up as follows:

$$log\left(\frac{p(x)}{1-p(x)}\right) = a + b \times x \tag{4}$$

By solving for $p(x)$ this expression becomes:

$$p(x) = \frac{e^{a+b\times x}}{1+e^{a+b\times x}} = \frac{1}{1+e^{-(a+b\times x)}} \tag{5}$$

where p is the probability of observing a Y=1 in the following time period, and x is the observed lagged change in the risk-free interest rate.

For the first model, this means that given the observed x, if $p > 0.5$ ($p < 0.5$) it is more likely than not that the simple holding period (K) return of the momentum portfolio (reversal portfolio) is expected to be the, relatively speaking, best performing portfolio. This first logistic regression model does not only provide a 50/50 cut-off value for the x-variable (lagged changes in the risk-free interest rate) that suggests where the probability of positive and negative momentum returns are equal, but does also state that the probability of observing a positive momentum return is dependent on how far away from the 50/50 cut-off boundary the actual x-observation is. More specifically, the further above (below) the boundary the observed x-value is, the higher is the probability of observing a positive (negative) return in the momentum portfolio.

The interpretation of the second model is similar, but instead of predicting the the likelihood of observing a positive or a negative momentum return in the future time period, it predicts the likelihood of observing a return in the bottom quintile (20%) of the momentum portfolio's return distribution.

4.5 Stenlund-Holmberg switch portfolios

In this section we describe the economic intuition behind how the conditional probabilities from the logistic regression is incorporated with momentum portfolios and reversal portfolios to form what we call Stenlund-Holmberg switch portfolios. After providing the economic intuition behind the SH-portfolios the section explains how to construct them conditional on changes in the risk-free interest rate as a leading indicator for expectations about future momentum returns.

4.5.1 Economic intuition

The SH-portfolio has its intuition in a combination of historical findings from the momentum and the predictability literature. In particular, there are three pillars which the SH-portfolio rests upon:

1. Momentum returns follow a leptokurtic distribution with positive median and negative skew, implying that a momentum portfolio yields positive returns in most time periods, but occasionally, when a tail event occurs, suffers from sudden and severe losses.

2. Reversal returns follow a leptokurtic distribution with negative median and positive skew, implying that a reversal portfolio yields negative returns in most time periods, but occasionally, when a tail event occurs, gains from sudden and large profits.

3. Certain external variables can be looked upon as indicators of when it, in a relative sense, is more profitable to invest according to the momentum strategy rather than the reversal strategy, and vice versa.

Building on pillar 1 and 2, it follows that momentum portfolio investors want to harvest the frequent and positive returns, but want to avoid the sudden and severe losses. Likewise, reversal portfolio investors want to avoid the frequent and negative returns while still being able to harvest the sudden and large profits. We argue that these objectives, to some extent, can be realised by incorporating pillar 3 with pillar 1 and 2.

As outlined in the introduction, the Stenlund-Holmberg switch portfolio is a time varying combination of the momentum portfolio and the reversal portfolio, which underlying logic rests upon two fundamental ideas about the dynamics of the momentum effect. The first being that the momentum and the reversal effect is not static, and the other being that certain external variables can be looked upon to gain information that allows investors to predict which of the effects that is likely to dominate the other in coming time periods.

In practice, if pillar 1 and 2 hold were to hold, but not pillar 3, that is, if the return distributions of the momentum strategy and the reversal strategy were known, but the future is unpredictable, investors will be forced to arbitrarily choose between the two strategies, and make uninformed guesses about when to enter and when to exit the chosen strategy.

If pillar 3 also were to hold, that is, if some external variable feature predictive power in the future momentum performance, we have a scenario in which investors will benefit from acting according to this information. It will, from an expected value perspective, always be superior to follow the external variable's predictions rather than holding on to any of the strategies statically. In other words, given the existence of a predictor the optimal strategy will be a *dynamic* combination of the momentum and the reversal portfolios; the SH-portfolio.

4.5.2 Construction of the Stenlund-Holmberg switch portfolios

The SH-portfolio looks at lagged changes in the risk-free interest rate with the aim to identify forthcoming time periods when it, in a relative sense, is more profitable to invest according to the momentum strategy rather than the reversal strategy, and vice versa.

From a macro perspective a decrease in the short-term risk-free interest rate is a stimulus to the market that signals insecurity about the future, Rigobon and Sack (2003) and Bernanke and Reinhart (2004), and accordingly, we interpret an increase as a signal suggesting that momentum returns will be positive and a decrease as a signal suggesting that reversal returns will be positive. In short, our expectations are the following:

$$E\left(R^{Mom}_{(K,t)}\middle|\frac{\overline{R}_{f,(t-1)}}{\overline{R}_{f,(t-2)}}-1>0\right)>0 \tag{6}$$

and

$$E\left(R^{Mom}_{(K,t)}\middle|\frac{\overline{R}_{f,(t-1)}}{\overline{R}_{f,(t-2)}}-1<0\right)<0 \tag{7}$$

where $R^{Mom}_{(K,t)}$ is the return of the momentum portfolio from time t to $t+K$, as defined by equation (2) on page 13, and $\overline{R}_{f,t}$ is the monthly average of the three-month treasury bill for the month beginning in t.

Conditional on an observed increase in the monthly average of the short-term risk-free interest rate (from the month beginning in $t-2$ to the month beginning in $t-1$), our portfolio takes a momentum position (*momentum mode*) in time t and holds this investment until $t+K$, referring to the conditional expectations in equation (6). On the contrary, given a decrease in the monthly average of the short-term risk-free interest rate (from the month beginning in $t-2$ to the month beginning in $t-1$), our portfolio takes a reversal position (*reversal mode*) in month t and holds this investment until $t+K$, referring to the conditional expectations in equation (7).

This framework implies that for any time period t to $t+K$, if the SH-portfolio holds a momentum portfolio, it will provide returns identical to the plain momentum portfolio, and if the SH-portfolio holds is a reversal portfolio, it will provide returns identical to the pure reversal portfolio. However, given that pillar 3 from the previous subsection holds, the information advantage gained from acting according to the leading indicator's suggestion makes it likely that the SH-portfolio will deliver returns in excess of any of the momentum or the reversal portfolios on stand-alone bases over time.

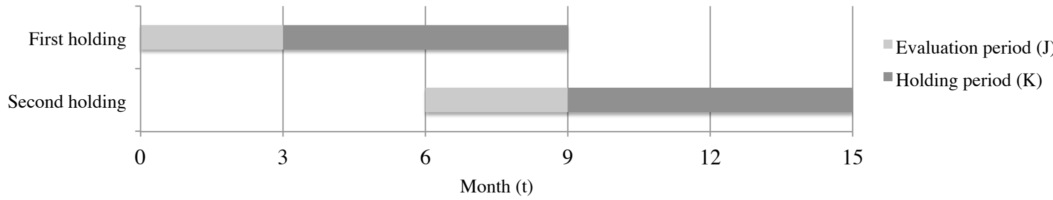
4.6 Portfolio evaluation

There are two conventional ways to evaluate the performance of a momentum strategy, both of which due to the similarities between the momentum portfolio and the Stenlund-Holmberg switch portfolio, are valid evaluation techniques also for the latter.

The first is a technique that in a consecutive manner, based on some evaluation period $t-J$ to t, takes a position in time t, and then holds this single investment until time $t+K$ (referred to as the "first holding"). In time $t+K$ the process repeats, that is, based on an evaluation period ranging from $t+K-J$ to $t+K$, a position referred to as the "second holding" is held until $t+K+K$. An example of this consecutive investment technique is illustrated in Figure I.

Figure I

Schematic overview of a consecutive portfolio with no overlapping holdings where J=1 and K=2

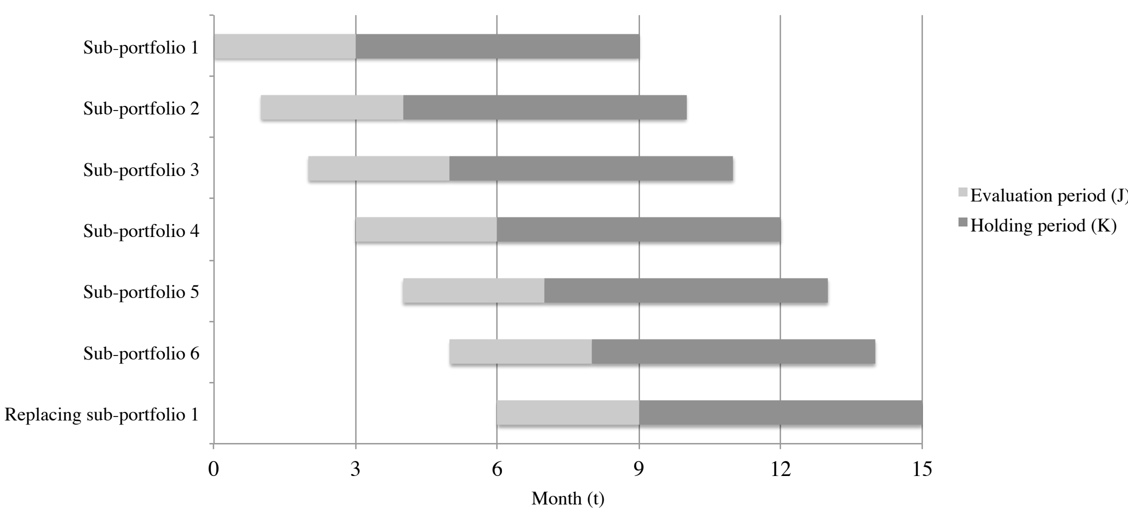


The second evaluation technique is more advanced than the first one because it is built with the application of overlapping sub-portfolios. This construction implies that positions in various winner and loser portfolios are held at a time. Figure II below shows an illustrative example of such an *overlapping* investment technique where $J = 1$ quarter and where $K = 2$ quarters.

By applying this latter approach we reallocate the weights of $(1/(K \times 3))$ of the securities of the entire portfolio in any given month and carry all other positions forward. The number of sub-portfolios will, at any given time, equal the number of months in the holding period $(K \times 3)$.

Figure II

Schematic overview of a portfolio with overlapping holdings where J=1 and K=2



When comparing the consecutive investment technique to the overlapping, it becomes evident that the first holding and the second holding of the consecutive technique are identical to sub-portfolio 1 and the sub-portfolio that replaces sub-portfolio 1 in the overlapping technique (the top and bottom sub-portfolios in Figure II). This implies that the information in sub-portfolio 2 to 6 in Figure II is lost whenever a consecutive investment technique is applied. Thus, one of the implications of applying the simpler technique is a reduced total number of observations that impacts statistical significance negatively. Furthermore, another deficiency is increased dependence on market timing. Conversely, both of these implications are arguments in favour of the overlapping technique.

With this being said, the overlapping method is the obvious choice for evaluating our portfolios. Nevertheless, by using overlapping holding periods a statistical problem arises; the time series data become exposed to heteroskedasticity and autocorrelation as the performance of each sub-portfolio will be dependent rather than independent of the performance of the adjacent sub-portfolios. This, in turn, has implications for the t-statistics of the risk adjusted coefficients. By applying a semi-definite, heteroskadasticity and autocorrelation consistent covariance matrix, as suggested by Newey and West (1987), we nevertheless calculate t-statistics that are adjusted for these properties.

4.7 Risk-adjustment of portfolio returns

In the previous two subsections we have outlined the SH-portfolios and explained how they are best put in use through the overlapping investment technique. In this section we explain how to evaluate (risk-adjust) the returns stemming from these and the conventional momentum portfolios according to the established capital asset pricing (CAPM) regression model and the Fama-French three-factor time series regression model.

In accordance with techniques used in previous studies we address the question of whether the observed returns of the examined trading strategies can be attributed to market exposure and conventional risk factors. In other words, to determine the strategies' risk-adjusted performance, we analyse their returns in a two-step procedure. First, we examine how much of the returns that can be attributed to market exposure (systematic risk), that is, we run a single factor OLS time series regression in which we let the market risk premium be the one and only risk factor, commonly known as the CAPM regression, Sharpe (1964). Second, to examine how much of the returns that can be attributed to the market factor and the two firm specific characteristics, "size" and "value", we run the three-factor time series regression, as first suggested by Fama and French (1993).

Technically, for the single factor OLS model the following regression is run:

$$R_{i,(K,t)} = a_i + b_i(R_{M,(K,t)} - R_{f,(K,t)}) + e_i \tag{8}$$

where $R_{i,(K,t)}$ equals the simple return of portfolio i, $R_{M,(K,t)}$ equals the simple return of the market, $R_{f,(K,t)}$ equals the simple return of the risk-free interest rate, all for the period t to $t+K$, and e_i is an error term. The left hand side of the equation is not reduced by $R_{f,(K,t)}$ as the portfolios are self-financing. For the multi-factor OLS model, the following regression is run:

$$R_{i,(K,t)} = a_i + b_i(R_{M,(K,t)} - R_{f,(K,t)}) + s_i SMB_{(K,t)} + v_i HML_{(K,t)} + e_i \tag{9}$$

where $R_{i,(K,t)}$, $R_{M,(K,t)}$, $R_{f,(K,t)}$, and e_i are defined as above. $SMB_{(K,t)}$ (Small Minus Big) is a factor controlling for returns attributable to size characteristics, and $HML_{(K,t)}$ (High Minus Low) is a factor controlling for returns attributable to value characteristics for the time period t to $t+K$.

For all regressions, we construct the $SMB_{(K,t)}$ and the $HML_{(K,t)}$ factors based on our own data. Below follows a presentation of the procedure for constructing each factor.

The market factor (the market risk premium) is constructed as $R_M - R_f$, where R_M is represented by OMX GI and where R_f is represented by the three-month treasury bill, SE 3M. The $SMB_{(K,t)}$ and the $HML_{(K,t)}$ factors are constructed each month by classifying the full sample into certain groups based on their size and value characteristics. First, based on market capitalisation, two sub-groups are created by letting the median observation be a cut-off point that separates "big" companies from "small" companies. To be precise, we get a group for the 50% largest companies and another one for the 50% smallest. Second, based on price-earnings ratios, we form three groups; one with the 30% highest valued stocks, another one with the 30% lowest valued stocks, and a group in between, containing the remaining, middle 40%. The intersection of these classifications provides us with a total of six groups, which enables us to calculate the size and value factors as follows:

$$SMB_{(K,t)} = \frac{R^{S/L}_{(K,t)} + R^{S/M}_{(K,t)} + R^{S/H}_{(K,t)}}{3} - \frac{R^{B/L}_{(K,t)} + R^{B/M}_{(K,t)} + R^{B/H}_{(K,t)}}{3} \tag{10}$$

and

$$HML_{(K,t)} = \frac{R^{S/H}_{(K,t)} + R^{B/H}_{(K,t)}}{2} - \frac{R^{S/L}_{(K,t)} + R^{B/L}_{(K,t)}}{2} \tag{11}$$

where $R_{(K,t)}$ is defined as equation (2). The $SMB_{(K,t)}$ factor can then be interpreted as the difference between the equally weighted average simple returns of the three groups with small stocks and the corresponding equally weighted average simple returns of the three groups of large stocks. Similarly, the interpretation of the $HML_{(K,t)}$ factor is the difference between the equally weighted average simple returns of the two groups containing the stocks with the highest price-earnings ratios and the equally weighted average simple returns of the two groups of stocks with the lowest price-earnings ratios.

5 Empirical findings

The empirical findings discovered from analysing our data according to the techniques and methods outlined in the methodology section are in this section presented and analysed in a six-step procedure. First, the section begins by providing an analysis of the summary statistics for the momentum portfolios' return distributions, which is then followed by a presentation and discussion of the predictability in momentum returns. Afterwards follows an analysis of the summary statistics for the Stenlund-Holmberg switch portfolios and an analysis of the Fama-French three-factor time series regression outputs. Last, a set of 16 different SH-portfolios are compared to their corresponding momentum portfolios in cumulative performance graphs, followed by a detailed decomposition of the SH-portfolios.

5.1 Summary statistics – momentum portfolios

5.1.1 Winner and loser portfolios

In Table X (Appendix A on page 48) we display summary statistics for the return distributions of the winner and loser portfolios which have been used as the long and short sides of the momentum and Stenlund-Holmberg switch portfolios. The most important conclusions include, for both the full sample and the large cap sample, that the winner portfolios outperform the loser portfolios in the shorter holding periods (indicating momentum) but as the holding period increases the loser portfolios gain performance and eventually outperform the winner portfolios (indicating reversal). Further, as one might expect, the kurtoses and standard deviations for the portfolios formed on the large cap sample are lower than for those formed on the full sample. We also see that the maximum returns of the loser portfolios in many cases are substantially larger than the maximum returns of the corresponding winner portfolios, while the minimum returns of the two are comparable.

5.1.2 Momentum portfolios – full sample

Panel A in Table II on page 26 outlines summary statistics for the return distributions of the momentum portfolios constructed from the *full sample*. Looking at the mean returns and median returns we find that all combinations of J-quarters evaluation periods and K-quarters holding periods are expected to generate positive returns, with the exception of the J=4/K=4 portfolio. The self-financing momentum portfolios deliver monthly average returns between 0.10% and 0.80% over the sample period (J=4/K=4 set aside, -0.12%). This is interpreted as a weak form of proof for that the momentum effect is present in the full sample. Further takeaways from Panel A includes that the minimum values, in absolute terms, are larger that the maximum values, and that the kurtoses are relatively high, indicating that the negative extreme events outweighs the positive ones. This means that even though momentum portfolios are expected deliver positive returns in most time periods, the return distributions are leptokurtic, with overhanging downside risk, implying supportive evidence of pillar 1 and 2, as elaborated on in the "Stenlund-Holmberg switch portfolios" section on page 16.

5.1.3 Momentum portfolios – large cap sample

Moving on to Panel B in Table II, which presents summary statistics for the return distributions of the momentum portfolio constructed from the *large cap sample*, we see changes compared to the full sample momentum portfolios in Panel A. First, 11 out of the 16 mean returns are negative (compared to 1 out of 16), only the portfolios with the shortest holding periods remain positive. Second, the J=1/K=1 portfolio is the only portfolio which mean return has increased compared to its full sample equivalent. Third, as expected, the standard deviation, skewness and kurtosis are improved for the size restricted return distribution as the portfolios are no longer affected by the, from time to time, erratic behaviour of small stocks. Finally, the downside risk is outweighing the upside potential, although not as prominently as for the full sample portfolios.

5.1.4 Concluding remarks

In aggregate, the information presented in Table II indicates that a momentum effect is present in the full sample. However, in the large cap sample we find that the momentum effect is diminishing, and turns negative, as the holding period approaches four quarters, indication the presence of a reversal effect rather than a momentum effect.

Table II

Summary statistics for holding period (K) simple return distributions for the self-financing momentum and Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters.

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Momentum portfolios (long winner - short loser) – full sample																
Mean*(%)	0.49	0.80	0.39	0.47	0.73	0.55	0.49	0.28	0.54	0.38	0.27	0.10	0.50	0.22	0.24	-0.12
Mean	0.01	0.02	0.01	0.01	0.04	0.03	0.03	0.02	0.05	0.03	0.03	0.01	0.06	0.03	0.03	-0.01
t(Mean)	1.49	2.21	1.09	1.26	2.23	1.86	1.66	0.90	2.64	1.53	1.20	0.41	3.30	1.09	1.35	-0.51
Median	0.01	0.04	0.03	0.04	0.06	0.07	0.07	0.04	0.10	0.10	0.08	0.05	0.11	0.09	0.08	0.04
Std	0.19	0.21	0.20	0.21	0.37	0.34	0.33	0.35	0.35	0.42	0.38	0.40	0.35	0.47	0.40	0.50
Min	-1.11	-1.46	-1.38	-1.39	-2.99	-3.53	-3.89	-3.99	-2.26	-3.24	-3.38	-3.43	-1.72	-3.80	-3.11	-4.21
Max	1.08	0.79	0.54	0.79	3.55	0.72	0.69	0.91	1.82	1.57	0.58	0.68	1.19	0.81	0.77	0.76
Skewness	-0.27	-1.85	-2.32	-2.21	-0.35	-4.56	-5.50	-5.24	-1.75	-2.94	-3.34	-3.40	-1.51	-3.73	-2.29	-3.69
Kurtosis	13.29	15.00	13.85	15.41	44.39	40.79	58.15	53.72	14.02	19.30	23.45	24.05	7.82	26.70	14.55	24.73
Panel B: Momentum portfolios (long winner - short loser) – large cap sample																
Mean*(%)	0.60	0.53	0.32	0.21	0.07	-0.04	-0.08	-0.30	-0.13	-0.11	-0.27	-0.47	-0.06	-0.16	-0.43	-0.50
Mean	0.02	0.02	0.01	0.01	0.00	-0.00	-0.01	-0.02	-0.01	-0.01	-0.02	-0.04	-0.01	-0.02	-0.05	-0.06
t(Mean)	2.23	1.86	1.04	0.68	0.36	-0.19	-0.35	-1.17	-0.75	-0.52	-1.19	-1.92	-0.33	-0.80	-1.90	-2.16
Median	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.03	0.04	0.01	0.04	0.03	0.03	0.00
Std	0.14	0.15	0.16	0.16	0.21	0.23	0.25	0.26	0.26	0.31	0.34	0.36	0.34	0.40	0.44	0.45
Min	-0.56	-0.93	-0.91	-0.90	-0.88	-1.28	-1.31	-1.37	-1.38	-1.51	-1.44	-1.63	-2.15	-2.40	-2.22	-2.43
Max	0.87	0.48	0.42	0.42	0.68	0.57	0.48	0.58	0.72	0.65	0.63	0.74	0.76	0.82	0.76	0.99
Skewness	0.20	-1.47	-1.73	-1.70	-1.32	-1.82	-1.78	-1.77	-1.45	-1.82	-1.70	-1.59	-1.89	-1.81	-1.65	-1.45
Kurtosis	9.51	10.72	11.03	10.19	7.40	9.40	8.90	8.89	7.85	8.27	7.10	7.06	10.10	8.89	7.17	6.89

*Monthly mean return = $((1 + Mean)^{1/(K\times3)}) - 1$

5.2 Predicting the momentum portfolios' returns

As discussed in the methodology section, we suggest that it is advantageous for investors to base their choice of investment strategy (momentum or reversal) according to changes in the lagged average of the risk-free interest-rate as a leading indicator. In this section we analyse the proposed relationship between this external variable and future momentum returns in two specific model set-ups; a first model that predicts the likelihood of observing a positive or negative momentum return, and a second model that predicts the likelihood of experiencing one of the bottom quintile (20%) momentum returns.

5.2.1 Predicting the sign of the momentum portfolios' returns

Panel A in Table III below shows the outputs from the first logistic regressions set-up. The coefficients, both individually and collectively, indicate that there is a positive relationship between lagged change in the risk-free interest rate and the performance of the momentum portfolios. In detail this means that the probability of observing a positive (negative) return in a momentum portfolio is larger if there has been a increase (decrease) in the risk-free interest rate. This relationship is made evident in the positive value of all b's in Panel A, which in four cases are statistically significant at the five percent level.

To make more sense of the coefficients for someone who is unfamiliar with the logistic regression we, in Panel B, plot the conditional probabilities of observing a positive return in the momentum portfolios for a given set of lagged changes in the risk-free interest rate.[7] By following the columns from top to bottom, it is obvious that the probability of observing a positive return in a momentum portfolio is increasing with the lagged change in the risk-free interest rate.

Furthermore, we see that the probabilities are changing increasingly more for the portfolios with shorter holding periods compared to those with longer holding periods. This indicates that the predictive power is stronger for the portfolios with shorter holding periods compared to the ones with longer.

Table III

Logistic regressions predicting the sign of the momentum portfolios' returns

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters. The dependent variable is defined as "1" if the simple return for holding period (K) of the self-financing momentum portfolio is positive ("1" if $R_{i,(K,t)} > 0$). The dependent variable is defined as "0" if the simple return for holding period (K) of the self-financing momentum portfolio is negative ("0" if $R_{i,(K,t)} < 0$). The explanatory variable is defined as the lagged change in the monthly average interest rate $\overline{R}_f$ (SE 3M) from the month beginning in $t-2$ to the month beginning in $t-1$. The logistic regression outputs a_i and b_i can then be placed into the below equation together with the observed value of the lagged

[7] Note that the changes are relative and not percentage points. The given set of lagged changes corresponds to the observed changes in the risk-free interest rate in our sample.

change in the monthly average interest rate. The output p_i is the conditional probability of that the self-financing momentum portfolio i will yield a positive simple return over holding period t to $t+K$. Panel A displays the regression coefficients. Panel B displays the conditional probability of a positive return in the momentum portfolio given a certain lagged change in the risk-free interest rate (SE 3M).

$$p_i = \frac{1}{1+e^{-\left(a_i+b_i\left(\frac{\overline{R}_{f,(t-1)}}{\overline{R}_{f,(t-2)}}-1\right)\right)}}$$

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Logistic regression coefficients and t-statistics																
a	0.49	0.41	0.34	0.48	0.30	0.28	0.28	0.15	0.15	0.29	0.30	0.09	0.30	0.23	0.15	0.06
b	38.81	17.80	20.80	25.77	47.43	34.20	23.53	19.43	30.84	16.86	15.95	14.30	19.74	4.48	5.77	7.33
$t(a)$	3.98	3.42	2.86	3.92	2.46	2.29	2.36	1.28	1.27	2.39	2.50	0.72	2.48	1.93	1.22	0.51
$t(b)$	2.56	1.38	1.59	1.90	2.87	2.34	1.76	1.50	2.17	1.32	1.26	1.13	1.52	0.37	0.47	0.60
Panel B: Conditional probability of momentum returns being positive																
$\Delta\overline{R}_f$																
-7%	0.10	0.30	0.25	0.21	0.05	0.11	0.20	0.23	0.12	0.29	0.31	0.29	0.25	0.48	0.44	0.39
-6%	0.14	0.34	0.29	0.26	0.07	0.14	0.24	0.27	0.15	0.33	0.34	0.32	0.29	0.49	0.45	0.41
-5%	0.19	0.38	0.33	0.31	0.11	0.19	0.29	0.31	0.20	0.36	0.38	0.35	0.33	0.50	0.46	0.42
-4%	0.26	0.43	0.38	0.37	0.17	0.25	0.34	0.35	0.25	0.40	0.42	0.38	0.38	0.51	0.48	0.44
-3%	0.34	0.47	0.43	0.43	0.25	0.32	0.40	0.39	0.32	0.45	0.46	0.42	0.43	0.52	0.49	0.46
-2%	0.43	0.51	0.48	0.49	0.34	0.40	0.45	0.44	0.39	0.49	0.50	0.45	0.48	0.54	0.51	0.48
-1%	0.53	0.56	0.53	0.55	0.46	0.48	0.51	0.49	0.46	0.53	0.54	0.49	0.53	0.55	0.52	0.50
0%	0.62	0.60	0.58	0.62	0.57	0.57	0.57	0.54	0.54	0.57	0.58	0.52	0.57	0.56	0.54	0.52
1%	0.71	0.64	0.63	0.68	0.68	0.65	0.63	0.59	0.61	0.61	0.61	0.56	0.62	0.57	0.55	0.53
2%	0.78	0.68	0.68	0.73	0.78	0.72	0.68	0.63	0.68	0.65	0.65	0.59	0.67	0.58	0.57	0.55
3%	0.84	0.72	0.72	0.78	0.85	0.79	0.73	0.68	0.75	0.69	0.69	0.63	0.71	0.59	0.58	0.57
4%	0.89	0.75	0.76	0.82	0.90	0.84	0.77	0.72	0.80	0.72	0.72	0.66	0.75	0.60	0.59	0.59
5%	0.92	0.79	0.80	0.85	0.94	0.88	0.81	0.75	0.84	0.76	0.75	0.69	0.78	0.61	0.61	0.61

5.2.2 Predicting severe losses in the momentum portfolios' returns

As discussed in the introduction, one of the main flaws of the momentum portfolio is that it from time to time yields severe losses that effectively erodes its attractiveness to investors. Following on this, we examine if a statistical relationship can be established between our leading indicator, lagged changes in the risk-free interest rate, and the specific periods where the momentum portfolio experiences these losses (bottom quintile of the returns).

By looking at Table IV on page 29, where outputs for the logistic regressions are presented, it can be observed that the bottom 20% of the momentum returns can be predicted, with statistical significance at the five percent level or better, for all 16 portfolios.

Furthermore, turning to the conditional probabilities provided in Panel C, we see a divergence from the uninformed equilibrium of 0.80 when the change in the risk-free interest rate diverges from 0%. This implies that it can be predicted if there, conditional on an observed change in the risk-free interest rate, is an increased or decreased probability of observing a bottom 20% return in the following time period. This unambiguously suggests that pillar 3 as elaborated on in the "Stenlund-Holmberg switch portfolios" section on page 16 holds true.

5.2.3 Concluding remarks

To summarise Table III and IV, the main conclusion is that lagged changes in the risk-free interest rate gives indications of whether momentum returns will be positive or negative in next coming time period, and provides statistically significant probabilities that predict the likelihood of severe losses (bottom 20%). In short, this suggests an information advantage to investors who follows the SH-rule compared to investors that makes uninformed investment decisions. Moreover, as the relationship holds statistical significance for all portfolios, this further imply that the main flaw of momentum trading (the occurrence of irregular and sever losses) effectively can be exploited, giving merit to the underling logic of the Stenund-Holmberg switching rule.

Table IV

Logistic regressions predicting the bottom quintile of the momentum portfolios' returns

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters. The dependent variable is defined as "1" if the simple return for holding period (K) is larger than the observed 20^{th} percentile of the portfolios' returns ("1" if $R_{i,(K,t)}$ > "20^{th} percentile of all observed $R_{i,(K,t)}$"). The dependent variable is defined as "0" if the simple return for holding period (K) is smaller than the observed 20^{th} percentile of the portfolios' returns ("0" if $R_{i,(K,t)}$ < "20^{th} percentile of all observed $R_{i,(K,t)}$"). The explanatory variable is defined as the lagged change in the monthly average interest rate $\overline{R}_f$ (SE 3M) from the month beginning in $t-2$ to the month beginning in $t-1$. The logistic regression outputs a_i and b_i can be plugged into the below equation together with the observed value of the lagged change in the monthly average interest rate. The output p_i is the conditional probability of that the self-financing momentum portfolio i will yield a simple return over the holding period t to $t+K$ that is larger than the 20^{th} percentile of portfolio i's observed returns over the large cap sample period. Panel A shows the 20^{th} percentile of the observed simple returns of the momentum portfolios from the large cap sample. The value in Panel A has been used as a cut-off when classifying the dependent variable info binomial values. If the simple return for portfolio i has been larger than the value stated in Panel A it takes the value "1". If the simple return for portfolio i has been smaller than the value stated in Panel A it takes the value "0". Panel B displays the regression coefficients. Panel C displays the conditional probability of a return being larger than the observed 20^{th} percentile of returns, in the momentum portfolio, given a certain lagged change in the risk-free interest rate (SE 3M).

$$p_i = \frac{1}{1+e^{-\left(a_i+b_i\left(\frac{\overline{R}_{f,(t-1)}}{\overline{R}_{f,(t-2)}}-1\right)\right)}}$$

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Observed quintile return of the momentum portfolio (cut-off boundary)																
$R_{i,(K,t)}$	-0.06	-0.05	-0.07	-0.07	-0.09	-0.10	-0.12	-0.14	-0.14	-0.14	-0.18	-0.19	-0.18	-0.18	-0.21	-0.25
Panel B: Logistic regression coefficients and t-statistics																
a	1.59	1.49	1.49	1.47	1.48	1.45	1.45	1.46	1.44	1.41	1.41	1.40	1.42	1.39	1.39	1.40
b	107.7	60.3	60.4	53.6	66.0	50.4	51.2	56.3	50.8	38.0	35.3	31.8	48.8	33.5	35.7	37.6
$t(a)$	9.53	9.51	9.51	9.50	9.42	9.39	9.39	9.40	9.29	9.26	9.25	9.24	9.19	9.15	9.15	9.16
$t(b)$	4.05	3.26	3.26	3.08	3.39	2.98	3.01	3.16	2.99	2.48	2.34	2.15	2.92	2.25	2.36	2.46
Panel C: Conditional probability of momentum returns being above the bottom quintile																
$\Delta\overline{R}_f$																
-7%	0.00	0.06	0.06	0.09	0.04	0.11	0.11	0.08	0.11	0.22	0.26	0.30	0.12	0.28	0.25	0.22
-6%	0.01	0.11	0.11	0.15	0.08	0.17	0.17	0.13	0.17	0.30	0.33	0.38	0.18	0.35	0.32	0.30
-5%	0.02	0.18	0.18	0.23	0.14	0.26	0.25	0.21	0.25	0.38	0.41	0.45	0.27	0.43	0.40	0.38
-4%	0.06	0.28	0.28	0.34	0.24	0.36	0.36	0.31	0.36	0.47	0.50	0.53	0.37	0.51	0.49	0.47
-3%	0.16	0.42	0.42	0.47	0.38	0.48	0.48	0.44	0.48	0.57	0.59	0.61	0.49	0.59	0.58	0.57
-2%	0.36	0.57	0.57	0.60	0.54	0.61	0.61	0.58	0.60	0.66	0.67	0.68	0.61	0.67	0.66	0.66
-1%	0.62	0.71	0.71	0.72	0.70	0.72	0.72	0.71	0.72	0.74	0.74	0.75	0.72	0.74	0.74	0.74
0%	0.83	0.82	0.82	0.81	0.82	0.81	0.81	0.81	0.81	0.80	0.80	0.80	0.81	0.80	0.80	0.80
1%	0.93	0.89	0.89	0.88	0.90	0.88	0.88	0.88	0.88	0.86	0.85	0.85	0.87	0.85	0.85	0.85
2%	0.98	0.94	0.94	0.93	0.94	0.92	0.92	0.93	0.92	0.90	0.89	0.88	0.92	0.89	0.89	0.90
3%	0.99	0.96	0.96	0.96	0.97	0.95	0.95	0.96	0.95	0.93	0.92	0.91	0.95	0.92	0.92	0.93
4%	1.00	0.98	0.98	0.97	0.98	0.97	0.97	0.98	0.97	0.95	0.94	0.94	0.97	0.94	0.94	0.95
5%	1.00	0.99	0.99	0.98	0.99	0.98	0.98	0.99	0.98	0.96	0.96	0.95	0.98	0.96	0.96	0.96

5.3 Summary statistics – Stenlund-Holmberg switch portfolios

In Table V we show summary statistics for the return distributions of the Stenlund-Holmberg switch portfolios created using the *large cap sample*, which exploits the predictive relationship as outlined in the previous subsection. We see improvements in several aspects for all 16 portfolios when comparing to their corresponding momentum portfolios in Panel B of Table II. The mean returns are positive for all sixteen portfolios, ranging from 0.23% to 1.04% per month, and the minimum values have improved for all while the maximum values are either equal or higher. Moreover, the skew have improved and are positive for all SH-portfolios. These improvements have not been at the cost of worsened standard deviations or kurtoses, but there is a general slight decrease in median returns, though still positive for all but one portfolio.

Compiling the facts from Table II and V, we see that the SH-portfolios shift the return distributions' skew to the right as many of the extreme observations are moved from the negative to the positive side. Additionally, although the median returns of the SH-portfolios are slightly lower compared to the corresponding momentum portfolios, expected returns are substantially higher. In short, momentum investors are better off by investing in SH-portfolios rather than in plain momentum or reversal portfolios.

Table V

Summary statistics for holding period (K) simple return distributions for the self-financing Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$.

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Stenlund-Holmberg switch portfolios – large cap sample																
Mean*(%)	1.04	0.56	0.81	0.70	0.60	0.52	0.73	0.82	0.41	0.41	0.62	0.66	0.35	0.23	0.43	0.47
Mean	0.03	0.02	0.02	0.02	0.04	0.03	0.04	0.05	0.04	0.04	0.06	0.06	0.04	0.03	0.05	0.06
t(Mean)	3.93	1.98	2.69	2.31	3.04	2.33	3.12	3.37	2.47	2.02	2.89	2.88	2.11	1.19	1.99	2.15
Median	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.03	0.03	0.01	-0.03	0.01	0.02
Std	0.14	0.15	0.15	0.16	0.20	0.23	0.24	0.25	0.25	0.31	0.33	0.36	0.34	0.40	0.44	0.45
Min	-0.38	-0.39	-0.42	-0.49	-0.65	-0.72	-0.66	-0.80	-0.88	-0.89	-1.06	-1.24	-0.85	-0.99	-1.24	-1.39
Max	0.87	0.93	0.91	0.90	0.88	1.28	1.31	1.37	1.38	1.51	1.44	1.63	2.15	2.40	2.22	2.43
Skewness	1.11	1.40	1.50	1.28	1.06	1.38	1.51	1.39	1.11	1.42	1.22	1.12	1.50	1.51	1.21	1.02
Kurtosis	9.08	9.44	9.99	9.46	6.81	8.97	8.35	8.73	7.65	7.97	6.97	7.17	9.72	8.84	7.36	7.11

*Monthly mean return = $((1 + Mean)^{1/(K \times 3)}) - 1$

5.4 Fama-French three-factor time-series regression analysis

In this section we present an analysis of the risk exposures inherent in the SH-portfolios and their corresponding momentum portfolios. This is important as we explicitly are interested in examining whether the superior performance of the SH-portfolios tend to stem from any of the conventional risk factors (market exposure, size and value). Specifically, what we do in this section is to compare the SH-portfolios to their corresponding momentum portfolios by running the Fama-French three-factor model on both portfolios. For robustness reasons we also run CAPM regression and present its coefficients in Table XI (Appendix B on page 49).

5.4.1 Momentum portfolios – full sample

In consistency with the descriptive statistics, the outputs from the Fama-French three-factor time series regressions, presented in Panel A of Table VI on page 34, confirms that the momentum effect is present in our *full sample*. The sixteen portfolios are delivering alphas in the range of 0.05% to 1.00% per month, of which six are statistically significant at the five percent level. Moreover, the size of the alpha is decreasing as the length of the holding period increases, indicating that the momentum effect is strongest in the short-term.

5.4.2 Momentum portfolios – large cap sample

Panel B in Table VI shows regression outputs for the momentum portfolios constructed from the *large cap sample*. We observe statistically significant alphas for two of the portfolios, namely $J{=}1/K{=}1$ with an alpha of 0.76% per month and $J{=}1/K{=}2$ with 0.78%. Six of the portfolios with holding periods longer than one quarter are negative and none of them are statistically different from zero. Accordingly, the momentum effect is drastically reduced when the sample is restricted so that it only contains large cap stocks. Although this indicates that the momentum effect is "un-exploitable", it must not be misinterpreted as evidence suggesting a rejection of the existence of the momentum effect. These findings presented for the large cap momentum portfolios generally confirms the findings of Rouwenhorst (1998), who found no statistically significant momentum effect when examining a size restricted sample of the Stockholm stock exchange.

When it comes to risk-exposures we observe that the momentum portfolios almost exclusively have negative exposures to both the market factor, size factor and the value factor. However, since only the t-statistics for the loadings on the market factor and the value factor are significant for the shortest evaluation periods (and all other t-statistics are insignificant), we must conclude that it is difficult to fully explain momentum returns with conventional risk factors.

5.4.3 Stenlund-Holmberg switch portfolios – large cap sample

The regression coefficients for the Stenlund-Holmberg portfolios, presented in Panel C of Table VI, reveal improvements of the alphas in both relative and absolute terms compared to the corresponding momentum portfolios in Panel B. First, all alphas are positive, ranging from 0.21% to 0.76% per month. Second, all alphas but those for the portfolios J=1/K=1 and J=1/K=2 have improved compared to the alphas of the corresponding momentum portfolios. Moreover, six of the alphas are statistically significant at the five percent level, compared to two for the momentum portfolios.

For risk-exposures inherent in the SH-portfolios the only relevant conclusion to make, that is supported by Table VI, is that the SH-portfolios tend to feature the inverse factor loadings compared to those of the momentum portfolios. Generally, most signs for factor loadings have changed from negative to positive, however, the lack of significant t-statistics makes inference difficult.

5.4.4 Concluding remarks

The aggregate information from the regression outputs in Table VI confirms the findings presented in connection to the summary statistics, specifically, that there is a momentum effect observed in the full sample but not in the large cap sample. Furthermore, all Stenlund-Holmberg switch portfolios yields exclusively positive alphas, in 14 cases improved compared to the momentum portfolios, once again suggesting that they are superior to the momentum portfolios, even after risk-adjustments have been made.

Table VI

Fama-French three-factor time-series regression for holding period (K) simple return of the self-financing momentum and Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$. In the model specification; $R_{i,(K,t)}$ is the simple return for portfolio i, $R_{m(K,t)}$ is the simple return of OMX Stockholm General Index and $R_{f(K,t)}$ is the simple return of three month treasury bill (SE 3M). SMB and HML is formed as follows; at the end of each month all stocks in the full sample are allocated to two groups (small and big) based on whether their market capitalisation is above or below the median of the market capitalisation for the full sample. The stocks are then allocated into three independent value groups (low, medium or high) based on the breakpoints for the bottom 30%, middle 40% and top 30% of the values for Price/Earnings-ratio of the full sample. Six size-value portfolios (small/low, small/medium, small/big, big/low, big/medium and big/high) are defined as the intersections of the two size and three value groups. Value-weighted simple returns for these six portfolios are calculated from t to $t+K$. $SMB_{(K,t)}$ is the difference between the average simple return of the three *small* size portfolios and the three *big* size portfolios. $HML_{(K,t)}$ is the difference between the average simple return of the two *low* value portfolios and the two *high* value portfolios. To adjust for sample autocorrelation the t-statistics are calculated using Newey-West standard errors.

$$R_{i,(K,t)} = a_i + b_i(R_{M,(K,t)} - R_{f,(K,t)}) + s_i SMB_{(K,t)} + v_i HML_{(K,t)} + e_i$$

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Momentum portfolios (long winner - short loser) – full sample																
$a^*(\%)$	0.60	1.00	0.80	0.75	0.89	0.83	0.83	0.57	0.67	0.60	0.52	0.33	0.59	0.39	0.41	0.05
$a(\%)$	1.80	3.02	2.43	2.26	5.44	5.11	5.08	3.49	6.20	5.54	4.80	2.99	7.31	4.77	5.04	0.58
b	-0.18	-0.22	-0.33	-0.21	-0.34	-0.48	-0.53	-0.43	-0.41	-0.63	-0.60	-0.53	-0.31	-0.62	-0.55	-0.57
s	0.16	-0.04	-0.43	-0.46	-0.05	-0.39	-0.62	-0.65	-0.04	-0.30	-0.54	-0.61	-0.21	-0.38	-0.45	-0.17
v	-0.63	-0.66	-0.67	-0.92	-0.44	-0.26	0.08	-0.15	-0.13	-0.33	0.27	0.07	0.13	-0.41	0.67	0.65
$t(a)$	1.75	2.33	1.89	1.78	3.01	2.19	2.08	1.40	2.56	1.63	1.25	0.82	2.59	1.10	1.15	0.12
$t(b)$	-1.03	-1.19	-2.31	-1.33	-1.62	-2.11	-2.47	-1.85	-1.59	-1.98	-1.83	-1.48	-1.65	-2.15	-1.77	-1.63
$t(s)$	0.72	-0.15	-2.57	-2.34	-0.18	-1.32	-2.04	-1.87	-0.18	-1.04	-1.94	-1.72	-0.86	-1.16	-1.43	-0.36
$t(v)$	-1.54	-1.47	-1.70	-2.10	-0.69	-0.41	0.15	-0.26	-0.18	-0.41	0.35	0.08	0.23	-0.41	0.72	0.64
R^2	0.04	0.04	0.10	0.08	0.02	0.04	0.07	0.05	0.02	0.04	0.05	0.05	0.01	0.03	0.04	0.02

Continued on next page

Table VI – ***continued***

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel B: Momentum portfolios (long winner - short loser) – large cap sample																
a*(%)	0.76	0.78	0.57	0.47	0.21	0.13	0.06	-0.18	0.00	0.05	-0.15	-0.36	0.09	-0.02	-0.30	-0.40
a(%)	2.31	2.37	1.71	1.42	1.29	0.79	0.33	-1.06	-0.01	0.46	-1.33	-3.17	1.13	-0.26	-3.56	-4.65
b	-0.29	-0.39	-0.38	-0.39	-0.43	-0.49	-0.42	-0.39	-0.51	-0.58	-0.44	-0.43	-0.73	-0.62	-0.54	-0.46
s	0.25	0.19	0.08	0.06	0.14	0.07	-0.09	-0.07	0.03	-0.23	-0.47	-0.34	-0.15	-0.39	-0.60	-0.35
v	-0.84	-0.83	-1.05	-1.03	-0.73	-0.72	-1.16	-1.39	-0.48	-0.42	-1.10	-1.21	0.19	0.41	-0.05	0.01
$t(a)$	2.48	2.40	1.49	1.14	0.89	0.40	0.13	-0.37	0.00	0.13	-0.31	-0.66	0.34	-0.05	-0.61	-0.78
$t(b)$	-2.10	-3.44	-2.94	-2.98	-2.70	-2.72	-2.17	-1.81	-2.29	-2.25	-1.59	-1.34	-2.49	-1.62	-1.43	-1.12
$t(s)$	1.14	1.24	0.63	0.52	0.70	0.37	-0.42	-0.28	0.10	-0.96	-1.26	-0.83	-0.53	-1.25	-1.38	-0.75
$t(v)$	-2.29	-2.13	-2.67	-2.64	-1.42	-1.10	-1.62	-1.74	-0.72	-0.50	-1.13	-1.04	0.21	0.36	-0.04	0.01
R^2	0.16	0.19	0.18	0.18	0.09	0.09	0.09	0.09	0.07	0.06	0.06	0.05	0.07	0.04	0.04	0.02
Panel C: Stenlund-Holmberg switch portfolios – large cap sample																
a*(%)	0.76	0.34	0.62	0.52	0.43	0.41	0.65	0.72	0.31	0.37	0.60	0.62	0.31	0.21	0.44	0.46
a(%)	2.29	1.02	1.86	1.56	2.58	2.46	3.97	4.40	2.86	3.37	5.50	5.76	3.78	2.59	5.35	5.67
b	0.28	0.23	0.21	0.23	0.38	0.24	0.20	0.29	0.32	0.14	0.11	0.21	0.19	0.10	0.00	0.13
s	0.28	0.13	0.18	0.17	0.22	0.13	0.28	0.28	0.27	0.17	0.40	0.37	0.14	0.13	0.33	0.32
v	-0.23	0.17	0.61	0.69	0.37	0.71	1.28	1.56	0.51	0.93	1.63	1.94	1.04	1.38	2.14	2.29
$t(a)$	2.74	1.14	1.92	1.53	2.01	1.75	2.51	2.42	1.84	1.66	2.48	2.34	1.78	0.98	1.77	1.86
$t(b)$	2.43	1.94	1.71	1.83	2.67	1.53	1.25	1.67	2.02	0.66	0.55	0.84	0.89	0.36	0.01	0.46
$t(s)$	1.72	0.90	1.89	2.12	1.35	0.63	1.80	1.84	1.47	0.65	1.52	1.47	0.60	0.39	0.93	0.99
$t(v)$	-0.71	0.41	1.56	1.88	0.78	1.13	2.28	2.47	1.03	1.23	2.27	2.20	1.49	1.55	2.34	2.29
R^2	0.10	0.05	0.07	0.08	0.07	0.04	0.07	0.10	0.04	0.02	0.05	0.06	0.02	0.02	0.04	0.05

*Monthly alpha = $((1+a)^{1/(K\times3)})-1$

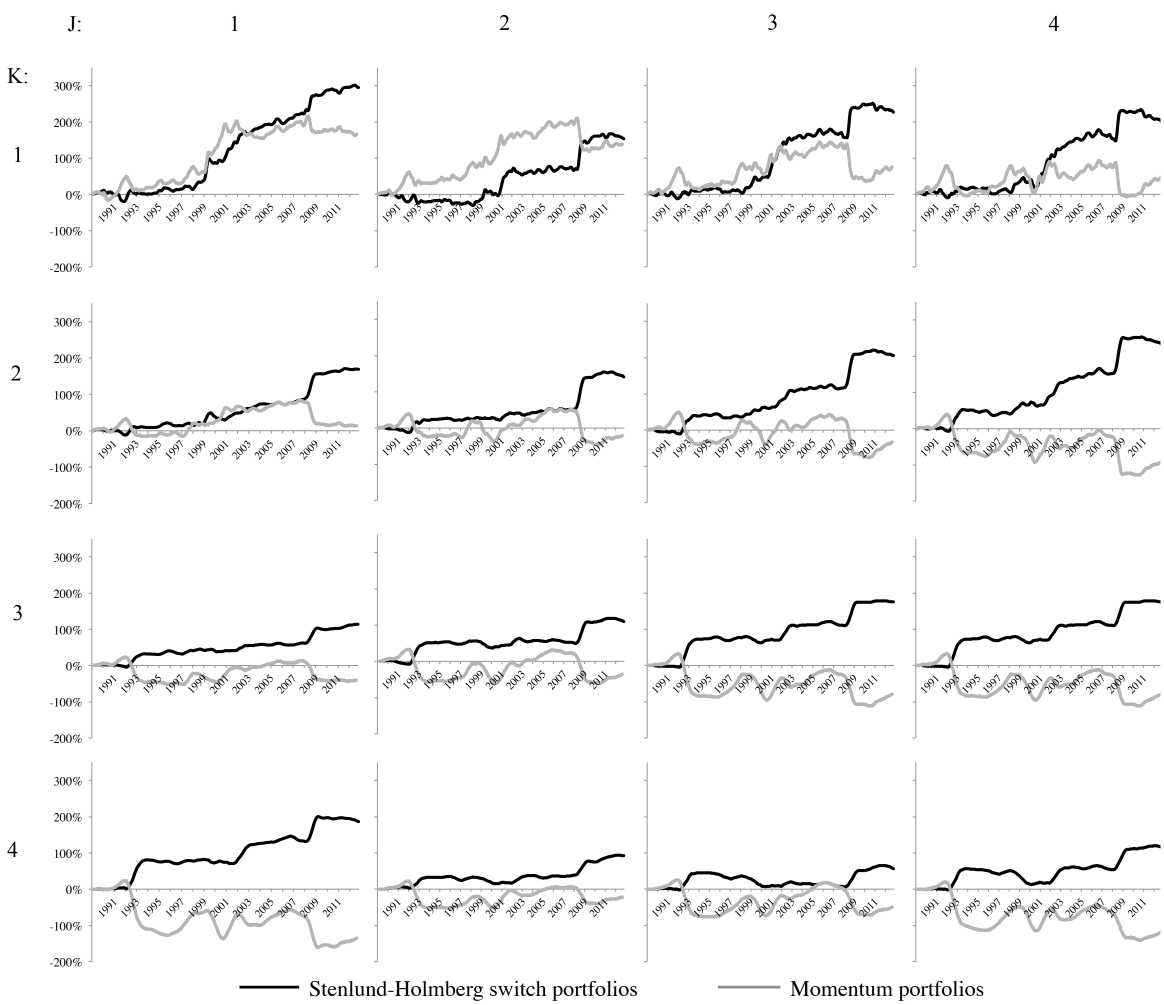
5.5 Cumulative performance evaluation

To visualise the Stenlund-Holmberg portfolios' dominance over the momentum portfolios, Figure III on page 36 shows cumulative performance graphs for all combinations of evaluation and holding periods using overlapping sub-portfolios. Regardless of which J/K-combination examined, the figure entails that all SH-portfolios outperform their corresponding momentum portfolio over the specific time-period. The prominent divergence observed in performance during short time periods highlight the advantage of investing according to the reversal strategy with proper timing. Furthermore, as shown by the consistently flat or positive development of the SH-portfolios, the downside volatility is substantially lower compared to the momentum portfolios. Moreover, a most interesting conclusion that can be inferred from Figure III is that the SH-portfolios tend to feature the opposite development as the momentum portfolios in time periods when the momentum portfolios suffer large losses.

Figure III

Cumulative performance graphs of the self-financing momentum and Stenlund-Holmberg switch portfolios with overlapping sub-portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$.



5.6 Stenlund-Holmberg switching rule evaluation

In a final evaluation of the SH-portfolios we provide information on the switching rule's behaviour over the sample period, and a thorough decomposition of the SH-portfolios' two legs (momentum investments and reversal investments) to better understand wherefrom the performance actually stem.

We begin this analysis by examining how many months of *momentum mode* and *reversal mode* that can be observed in our sample, where momentum (reversal) mode is a month where the SH-switch rule propose that the portfolio should take a momentum (reversal) position, following the expectations outlined in equation (6) and (7) on page 18. Figure IV visualises how the two modes are represented over the sample period and Table VII on page 38 summarises key statistics of the figure. The months are close to equally distributed between the two modes, and for both modes the number of consecutive months is usually one, two or three.

Figure IV

Schematic overview of the Stenlund-Holmberg switching rule behaviour

Conditional on an observed increase in the monthly average of the short-term risk-free interest rate, from the month beginning in $t-2$ to the month beginning in $t-1$, the SH-switching rule indicates *momentum mode*. On the contrary, given a decrease in the monthly average of the short-term risk-free interest rate, from the month beginning in $t-2$ to the month beginning in $t-1$, the SH-switching rule indicates *reversal mode*) in month t. The figure illustrates which mode the SH-switching rule has proposed over time, where white areas represent momentum mode and grey areas represent reversal mode.

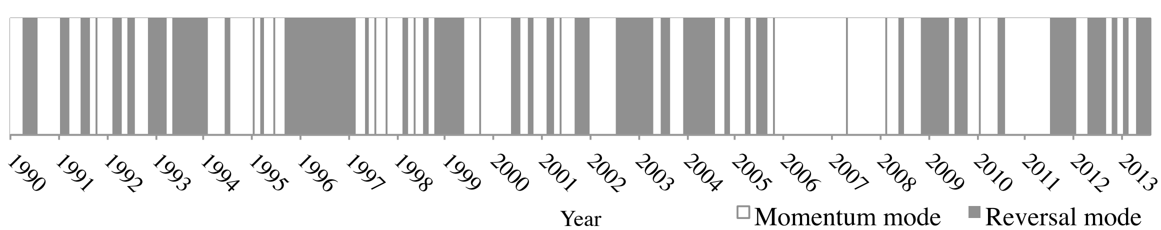


Table VII

Summary statistics for the behaviour of the Stenlund-Holmberg switching rule

Frequency table and summary statistics for the observed number of consecutive months of reversal mode and momentum mode. Conditional on an observed increase in the monthly average of the short-term risk-free interest rate, from the month beginning in $t-2$ to the month beginning in $t-1$, the SH-switching rule indicates *momentum mode*. On the contrary, given a decrease in the monthly average of the short-term risk-free interest rate, from the month beginning in $t-2$ to the month beginning in $t-1$, the SH-switching rule indicates *reversal mode*) in month t.

Consecutive months	Mode	
	Reversal	Momentum
1	17	15
2	10	10
3	6	8
4	3	3
5	2	3
6	-	1
7	2	1
8	2	-
9	1	-
10	1	-
11	-	1
17	-	1
18	1	-
Total	144	136
Mean	3	3
Median	2	2
Min	1	1
Max	18	17

5.6.1 Stenlund-Holmberg switch portfolios – momentum leg evaluation

Panel A in Table VIII shows summary statistics for the return distributions of the investments made by the Stenlund-Holmberg switch portfolios in *momentum mode*. The monthly mean returns are positive but decreasing with the length of the portfolios' holding periods. Compared to the momentum portfolios (see Panel B of Table II) we see that the mean and median returns, skew and minimum returns are all improved. This entails that, both in terms of downside risk and expected return, the momentum portfolios are performing better in months after an observed increase in the interest rate compared to how it performs in aggregate.

Furthermore, we find that the short side (loser portfolios in Panel B) of the investments with holding periods of one quarter has negative mean returns (-0.95% to -0.36% per month), while the corresponding long side (winner portfolios in Panel C) of the investments has positive mean returns (0.58% to 0.77% per month). From this follows a spread that the momentum portfolios exploit. However, as the holding period approaches four quarters, the mean returns are consistently worsened for the long side and improved for the short side, closing out potential momentum profits.

Table VIII

Summary statistics for holding period (K) simple return distributions of all momentum investments (and respective long and short side) taken by the self-financing Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$. Panel A displays summary statistics for holding period (K) simple returns of all momentum positions taken by the Stenlund-Holmberg portfolios. Summary statistics for holding period (K) simple return distributions of the short side (loser portfolio) and long side (winner portfolio) side of the reversal investments are displayed in Panel B and Panel C respectively.

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Stenlund-Holmberg switch portfolios in momentum mode																
Mean*(%)	1.69	1.10	1.14	0.94	0.67	0.46	0.65	0.53	0.28	0.30	0.36	0.22	0.28	0.05	0.00	-0.02
Mean	0.05	0.03	0.03	0.03	0.04	0.03	0.04	0.03	0.03	0.03	0.03	0.02	0.03	0.01	-0.00	-0.00
t(Mean)	4.47	3.23	3.30	2.54	3.14	1.90	2.67	2.00	1.39	1.34	1.61	0.84	1.48	0.24	0.00	-0.09
Median	0.04	0.03	0.04	0.04	0.03	0.03	0.03	0.02	0.03	0.04	0.06	0.06	0.04	0.00	0.03	0.03
Std	0.14	0.12	0.12	0.13	0.15	0.17	0.17	0.19	0.22	0.24	0.24	0.27	0.27	0.32	0.33	0.36
Min	-0.38	-0.39	-0.42	-0.49	-0.65	-0.72	-0.66	-0.80	-0.88	-0.89	-1.06	-1.24	-0.85	-0.99	-1.24	-1.39
Max	0.87	0.48	0.42	0.42	0.68	0.57	0.48	0.58	0.72	0.65	0.63	0.64	0.76	0.82	0.74	0.78
Skewness	1.42	0.23	-0.08	-0.55	-0.14	-0.77	-0.34	-0.73	-0.48	-0.74	-1.07	-1.01	-0.63	-0.59	-1.03	-0.91
Kurtosis	13.12	5.29	4.47	5.08	7.47	6.60	4.63	6.70	6.09	5.78	6.10	6.41	4.86	4.79	5.57	5.13

Continued on next page

Table VIII – *continued*

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel B: Loser portfolios (short side of Stenlund-Holmberg in momentum mode)																
Mean*(%)	-0.95	-0.42	-0.53	-0.36	0.16	0.40	0.21	0.36	0.31	0.33	0.26	0.41	0.25	0.41	0.48	0.49
Mean	-0.03	-0.01	-0.02	-0.01	0.01	0.02	0.01	0.02	0.03	0.03	0.02	0.04	0.03	0.05	0.06	0.06
t(Mean)	-2.13	-0.91	-1.19	-0.82	0.49	1.19	0.64	1.12	1.13	1.20	0.97	1.48	0.94	1.58	1.81	1.84
Median	-0.01	0.00	-0.01	0.00	0.02	0.02	0.02	0.04	0.03	0.02	0.01	0.05	0.00	0.04	0.05	0.05
Std	0.16	0.16	0.16	0.16	0.23	0.24	0.23	0.23	0.29	0.30	0.29	0.29	0.37	0.37	0.38	0.38
Min	-0.54	-0.53	-0.53	-0.51	-0.60	-0.60	-0.54	-0.57	-0.48	-0.52	-0.52	-0.62	-0.61	-0.63	-0.62	-0.64
Max	0.50	0.50	0.50	0.52	0.99	0.94	0.97	1.01	1.35	1.39	1.39	1.50	1.64	1.81	2.12	1.79
Skewness	-0.36	-0.44	-0.48	-0.35	0.40	0.70	0.39	0.38	1.14	1.18	1.20	1.13	1.27	1.56	1.84	1.44
Kurtosis	4.42	4.32	4.35	4.48	5.36	5.10	4.92	5.26	5.79	6.06	7.02	7.25	6.21	8.20	10.36	8.08
Panel C: Winner portfolios (long side of Stenlund-Holmberg in momentum mode)																
Mean*(%)	0.77	0.69	0.62	0.58	0.82	0.86	0.85	0.89	0.59	0.63	0.62	0.62	0.52	0.46	0.48	0.47
Mean	0.02	0.02	0.02	0.02	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06
t(Mean)	1.78	1.74	1.66	1.55	2.83	3.04	3.10	3.05	2.51	2.73	2.58	2.36	2.68	2.16	2.13	2.03
Median	0.03	0.03	0.03	0.04	0.05	0.04	0.04	0.05	0.05	0.06	0.08	0.06	0.08	0.06	0.06	0.07
Std	0.15	0.14	0.13	0.13	0.21	0.20	0.20	0.21	0.25	0.25	0.26	0.28	0.28	0.31	0.32	0.33
Min	-0.29	-0.36	-0.38	-0.39	-0.51	-0.54	-0.53	-0.49	-0.59	-0.58	-0.59	-0.68	-0.63	-0.63	-0.75	-0.75
Max	0.97	0.67	0.42	0.36	0.81	0.52	0.51	0.54	0.82	0.75	0.72	1.09	0.80	0.84	0.93	0.83
Skewness	1.89	0.60	0.03	-0.16	0.44	0.12	0.05	-0.01	0.11	-0.01	-0.09	0.07	-0.02	0.13	0.02	-0.03
Kurtosis	13.47	5.95	3.65	3.11	3.70	2.92	3.00	2.97	3.16	2.98	2.73	3.71	2.90	2.74	2.75	2.72

*Monthly mean return = $((1 + Mean)^{1/(K\times3)}) - 1$

5.6.2 Stenlund-Holmberg switch portfolios – reversal leg evaluation

Panel A of Table IX on page 41 shows summary statistics for the return distributions of the investments made by the SH-portfolios in *reversal mode*. The reversal mode investments have monthly mean returns ranging from 0.36% to 1.05%, with one exception which is the J=2/K=1 portfolio where the mean return is 0.00%. Different to what we see for the momentum mode investments, the size of the mean returns are generally not sensitive to the length of the holding period.

Examining the long and short side of the reversal mode investments closer, namely the loser portfolios in Panel B and winner portfolios in Panel C of Table IX, we find that both mean and median returns are larger compared to the momentum leg investments. The monthly mean returns range from 1.42% to 1.89% for the winner portfolios and from 1.84% to 2.40% for the loser portfolios (compared to 0.46% to 0.89% and -0.95% to 0.48%).

5.6.3 Concluding remarks

By combining the information from Table VIII and IX we find that the loser portfolios are expected to perform better than the winner portfolios in reversal mode (indicating the presence of a reversal effect) and that the opposite is true in momentum mode (indicating the presence of a momentum effect). Moreover, the reversal mode investments generally add performance to all 16 SH-portfolios, while the momentum mode investments add performance mainly to the portfolios with shorter holding periods.

Furthermore, although the switching rule provides a close to even distribution between momentum mode signals and reversal mode signals, it successfully identifies periods in which momentum returns will be positive or negative. Accordingly, the superior performance of the SH-portfolios stem from making better than uninformed guesses about future momentum returns.

Table IX

Summary statistics for holding period (K) simple return distributions of all reversal investments (and respective long and short side) taken by the self-financing Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$. Panel A displayssummary statistics for holding period (K) simple returns of all reversal positions taken by the Stenlund-Holmberg portfolios. Summary statistics for holding period (K) simple return distributions of the long side (loser portfolio) and short side (winner portfolio) side of the reversal investments are displayed in Panel B and Panel C respectively.

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Stenlund-Holmberg switch portfolios in reversal mode																
Mean*(%)	0.41	0.00	0.45	0.46	0.49	0.51	0.76	1.05	0.51	0.48	0.83	1.05	0.38	0.36	0.78	0.88
Mean	0.01	0.00	0.01	0.01	0.03	0.03	0.05	0.06	0.05	0.04	0.08	0.10	0.05	0.04	0.10	0.11
t(Mean)	1.12	0.01	0.93	0.97	1.50	1.41	1.94	2.63	1.96	1.46	2.34	2.83	1.41	1.12	2.24	2.54
Median	0.00	-0.03	-0.02	-0.01	-0.01	-0.01	-0.00	0.00	-0.00	-0.03	-0.01	0.02	-0.03	-0.05	-0.03	0.01
Std	0.14	0.16	0.18	0.18	0.24	0.27	0.29	0.30	0.29	0.37	0.40	0.42	0.39	0.47	0.52	0.53
Min	-0.34	-0.39	-0.36	-0.35	-0.44	-0.48	-0.44	-0.53	-0.55	-0.54	-0.62	-0.74	-0.53	-0.69	-0.76	-0.99
Max	0.56	0.93	0.91	0.90	0.88	1.28	1.31	1.37	1.38	1.51	1.44	1.63	2.15	2.40	2.22	2.43
Skewness	0.90	1.97	2.01	1.99	1.32	1.82	1.71	1.72	1.70	1.85	1.50	1.47	2.08	1.98	1.55	1.39
Kurtosis	5.55	10.67	10.43	10.22	5.68	7.85	7.02	7.20	7.23	6.88	5.38	5.62	9.44	8.09	5.85	5.93

Continued on next page

Table IX – ***continued***

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel B: Loser portfolios (long side of Stenlund-Holmberg in reversal mode)																
Mean*(%)	1.84	1.89	2.25	2.19	1.92	2.06	2.26	2.40	2.04	2.15	2.40	2.49	1.97	2.07	2.35	2.37
Mean	0.06	0.06	0.07	0.07	0.12	0.13	0.14	0.15	0.20	0.21	0.24	0.25	0.26	0.28	0.32	0.32
t(Mean)	3.52	3.44	3.93	3.93	4.51	4.70	4.94	5.36	6.05	5.86	6.19	6.51	6.30	6.24	6.71	7.03
Median	0.06	0.06	0.06	0.06	0.12	0.12	0.11	0.11	0.17	0.15	0.17	0.18	0.20	0.20	0.22	0.24
Std	0.20	0.21	0.22	0.21	0.33	0.34	0.35	0.35	0.40	0.44	0.47	0.46	0.50	0.54	0.57	0.55
Min	-0.46	-0.45	-0.42	-0.42	-0.57	-0.64	-0.54	-0.54	-0.54	-0.52	-0.54	-0.54	-0.65	-0.52	-0.59	-0.57
Max	0.82	1.09	1.08	0.99	1.31	1.48	1.53	1.51	1.96	1.89	1.85	1.88	3.03	3.35	3.21	3.10
Skewness	0.47	0.94	1.09	0.98	0.78	1.13	1.23	1.29	1.29	1.55	1.56	1.57	1.86	2.15	1.96	1.91
Kurtosis	5.01	7.36	7.27	7.07	4.70	5.56	5.60	5.76	6.21	6.48	5.90	6.03	9.45	10.78	8.35	8.19
Panel C: Winner portfolios (short side of Stenlund-Holmberg in reversal mode)																
Mean*(%)	1.45	1.89	1.82	1.74	1.46	1.59	1.55	1.42	1.60	1.73	1.67	1.56	1.66	1.77	1.69	1.62
Mean	0.04	0.06	0.06	0.05	0.09	0.10	0.10	0.09	0.15	0.17	0.16	0.15	0.22	0.23	0.22	0.21
t(Mean)	4.68	6.06	5.95	5.94	5.81	5.92	5.90	5.47	7.61	7.58	7.44	7.28	0.09	0.09	0.08	0.08
Median	0.06	0.06	0.07	0.07	0.09	0.11	0.13	0.10	0.11	0.15	0.17	0.16	0.16	0.21	0.20	0.22
Std	0.12	0.12	0.12	0.11	0.19	0.20	0.20	0.20	0.24	0.27	0.26	0.25	0.28	0.31	0.32	0.31
Min	-0.27	-0.33	-0.27	-0.27	-0.64	-0.68	-0.63	-0.59	-0.60	-0.64	-0.66	-0.63	-0.50	-0.58	-0.73	-0.70
Max	0.33	0.45	0.35	0.28	0.52	0.85	0.65	0.50	0.79	1.15	0.83	0.69	0.96	1.32	1.00	1.15
Skewness	-0.32	-0.35	-0.43	-0.54	-0.35	-0.07	-0.47	-0.61	0.09	0.33	-0.28	-0.65	0.28	0.22	-0.21	-0.36
Kurtosis	3.39	4.20	3.47	3.10	4.09	4.64	4.02	3.67	3.42	4.50	3.71	3.81	2.93	3.78	3.54	4.01

*Monthly mean return = $((1+Mean)^{1/(K\times 3)})-1$

6 Conclusions

The purpose of this study has been to examine the presence of a momentum effect in the Swedish stock market and to evaluate to what extent momentum returns can be predicted.

By employing the method as first suggested by Jegadeesh and Titman (1993), we show that a momentum effect is present in a comprehensive sample consisting of stocks listed on the Stockholm stock exchange. However, when market imperfections related to size and liquidity are considered by size-restricting the sample, we find that the momentum effect diminishes, confirming the findings of Rouwenhorst (1998). Furthermore, in-line with Daniel and Moskowitz (2011) we find that momentum portfolios feature leptokurtic return distributions with overhanging tail risk.

We show that changes in the risk-free interest rate works as a leading indicator for predicting momentum returns. Specifically, we find that changes in the risk-free interest rate give indications of whether momentum returns will be positive or negative, and provide statistically reliable probabilities of whether or not the next coming time period will feature a momentum return in the bottom quintile of the momentum portfolio's return distribution.

Three different methods; summary statistics analysis, regression analysis and cumulative performance evaluation all suggest that a dynamic portfolio that alters between momentum and reversal portfolios conditional on signals from the leading indicator outperforms the unconditional momentum portfolio as it benefits from the information advantage provided by the "predictor". To be precise, the dynamic portfolio manages to turn irregular and severe losses inherent in the momentum portfolio into equally sized profits by the use of well-timed investments in the reversal portfolio.

The implications of the predictive relationship challenge the efficiency of the Swedish stock market as one should not be able to harvest abnormal returns by acting on publicly available information. Furthermore, the findings imply that investors should consider changes in the risk-free interest rate when deciding which of the strategies, momentum or reversal, to invest according to, and when deciding how to time entry and exit of the investments.

7 Further research

Although this thesis presents new information on how to profit from the dynamics of the momentum effect and consequently provides answers to a few of the momentum literature's unanswered questions, the thesis as such opens up for further research.

For example, since the study is carried out with the use of Swedish stock market data it gives rise to the question whether the findings herein hold true for other markets than the Swedish. Furthermore, although changes in monthly averages of the risk-free interest rate is a successful predictor of momentum returns, it would be of great interest to investigate the performance of other predictors as well. Accordingly, further research could build on the findings presented in this thesis by examining whether more sophisticated switching rules could be created by combining signals from multiple leading indicators.

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Appendices

Appendix A

Table X

Summary statistics for holding period (K) simple return distributions for the long-only loser and winner portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile which are then held for K-quarters.

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Loser portfolios – full sample																
Mean*(%)	1.00	1.08	1.43	1.40	1.02	1.14	1.15	1.28	1.06	1.28	1.24	1.30	0.96	1.27	1.22	1.42
Mean	0.03	0.03	0.04	0.04	0.06	0.07	0.07	0.08	0.10	0.12	0.12	0.12	0.12	0.16	0.16	0.18
t(Mean)	2.44	2.39	3.01	2.95	2.54	2.94	3.01	3.30	3.46	3.93	3.96	4.28	3.94	4.42	4.73	4.93
Median	0.01	0.01	0.00	0.01	0.00	-0.01	0.01	0.00	0.02	-0.01	0.00	0.02	0.01	0.01	0.01	0.03
Std	0.23	0.26	0.27	0.27	0.46	0.45	0.44	0.45	0.54	0.58	0.55	0.54	0.57	0.69	0.62	0.69
Min	-0.46	-0.52	-0.46	-0.45	-0.58	-0.60	-0.60	-0.55	-0.65	-0.68	-0.64	-0.65	-0.70	-0.78	-0.76	-0.65
Max	1.36	1.81	1.68	1.65	4.80	4.32	4.61	4.63	4.13	4.11	4.08	3.97	3.74	4.78	4.18	5.13
Skewness	1.64	2.35	2.43	2.53	4.75	3.78	4.20	4.22	3.00	2.82	2.93	2.89	2.20	3.11	2.53	3.25
Kurtosis	9.24	14.32	12.87	13.84	41.63	28.75	36.21	35.16	17.16	14.79	16.16	16.05	10.94	17.44	13.16	18.63
Panel B: Winner portfolios – full sample																
Mean*(%)	1.47	1.86	1.81	1.85	1.71	1.66	1.61	1.54	1.55	1.63	1.48	1.39	1.42	1.47	1.43	1.32
Mean	0.04	0.06	0.06	0.06	0.11	0.10	0.10	0.10	0.15	0.16	0.14	0.13	0.18	0.19	0.19	0.17
t(Mean)	3.89	4.93	5.54	5.53	4.78	6.95	7.61	7.22	6.38	7.64	8.58	8.25	7.87	8.71	8.89	8.50
Median	0.02	0.04	0.05	0.05	0.06	0.07	0.08	0.08	0.07	0.10	0.11	0.13	0.12	0.14	0.16	0.17
Std	0.22	0.22	0.19	0.19	0.42	0.28	0.25	0.25	0.43	0.38	0.31	0.30	0.43	0.41	0.39	0.37
Min	-0.35	-0.39	-0.32	-0.34	-0.43	-0.46	-0.41	-0.50	-0.62	-0.64	-0.64	-0.62	-0.68	-0.74	-0.76	-0.75
Max	2.28	2.46	1.95	1.98	5.35	2.14	1.87	1.89	3.26	3.66	1.47	1.31	3.08	2.30	2.04	1.64
Skewness	4.48	4.96	3.71	3.69	6.65	2.05	1.48	1.47	3.17	3.02	0.92	0.42	1.78	1.37	1.05	0.63
Kurtosis	40.35	49.84	34.82	34.55	74.67	13.32	10.42	11.17	20.68	24.37	5.52	4.49	9.91	7.22	6.18	5.07
Panel C: Loser portfolios – large cap sample																
Mean*(%)	0.53	0.80	0.94	0.99	1.09	1.28	1.30	1.44	1.23	1.30	1.41	1.53	1.17	1.30	1.49	1.50
Mean	0.02	0.02	0.03	0.03	0.07	0.08	0.08	0.09	0.12	0.12	0.13	0.15	0.15	0.17	0.19	0.20
t(Mean)	1.48	2.17	2.50	2.67	3.95	4.48	4.41	5.01	5.43	5.40	5.61	6.11	5.49	5.89	6.40	6.63
Median	0.03	0.03	0.03	0.03	0.06	0.05	0.05	0.06	0.09	0.09	0.10	0.10	0.12	0.13	0.13	0.15
Std	0.18	0.19	0.19	0.19	0.29	0.30	0.31	0.30	0.36	0.39	0.40	0.40	0.46	0.48	0.51	0.49
Min	-0.54	-0.53	-0.53	-0.51	-0.60	-0.64	-0.54	-0.57	-0.54	-0.52	-0.54	-0.62	-0.65	-0.63	-0.62	-0.64
Max	0.82	1.09	1.08	0.99	1.31	1.48	1.53	1.51	1.96	1.89	1.85	1.88	3.03	3.35	3.21	3.10
Skewness	0.34	0.63	0.86	0.77	0.87	1.18	1.26	1.32	1.38	1.65	1.76	1.73	1.79	2.16	2.12	1.95
Kurtosis	5.24	7.22	7.69	7.32	5.57	6.28	6.68	6.95	6.76	7.57	7.63	7.67	9.53	11.67	10.09	9.41
Panel D: Winner portfolios – large cap sample																
Mean*(%)	1.12	1.32	1.25	1.19	1.16	1.24	1.22	1.16	1.12	1.21	1.17	1.11	1.12	1.16	1.12	1.08
Mean	0.03	0.04	0.04	0.04	0.07	0.08	0.08	0.07	0.11	0.11	0.11	0.10	0.14	0.15	0.14	0.14
t(Mean)	4.29	5.24	5.18	5.01	6.02	6.34	6.38	5.98	7.02	7.31	7.03	6.56	8.21	7.68	7.25	7.05
Median	0.04	0.05	0.05	0.06	0.07	0.07	0.08	0.08	0.09	0.11	0.12	0.12	0.13	0.15	0.15	0.15
Std	0.14	0.13	0.12	0.12	0.20	0.20	0.20	0.20	0.25	0.26	0.27	0.27	0.29	0.32	0.33	0.33
Min	-0.29	-0.36	-0.38	-0.39	-0.64	-0.68	-0.63	-0.59	-0.60	-0.64	-0.66	-0.68	-0.63	-0.63	-0.75	-0.75
Max	0.97	0.67	0.42	0.36	0.81	0.85	0.65	0.54	0.82	1.15	0.83	1.09	0.96	1.32	1.00	1.15
Skewness	1.14	0.15	-0.22	-0.38	0.06	0.02	-0.22	-0.31	0.07	0.22	-0.17	-0.29	0.13	0.17	-0.09	-0.22
Kurtosis	11.11	5.14	3.51	3.15	3.72	3.75	3.40	3.21	3.26	3.96	3.15	3.56	3.06	3.29	3.02	3.14

*Monthly mean return = $((1 + Mean)^{1/(K \times 3)}) - 1$

Appendix B

Table XI

CAPM time-series regressions for holding period (K) simple return of the self-financing momentum and Stenlund-Holmberg switch portfolios

The full sample contains 626 stocks listed on the Stockholm stock exchange, and ranges from January 1984 to September 2013. For each time period, the large cap sample consists of the largest 25% of the full sample's stocks. The large cap sample contains 243 stocks and ranges from June 1989 to September 2013. The stocks are ranked in ascending order based on J-quarters lagged returns. The loser (winner) portfolios consist of the equally weighted stocks in the bottom (top) decile. The momentum portfolio takes a long position in the winner portfolio and an equally sized short position in the loser portfolio and holds these positions for K-quarters. The Stenlund-Holmberg switch portfolio takes a *momentum* position (long position in the winner portfolio and an equally sized short position in the loser portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been positive from the month beginning in $t-2$ to the month beginning in $t-1$. The Stenlund-Holmberg switch portfolio takes a *reversal* position (long position in the loser portfolio and an equally sized short position in the winner portfolio) in month t if the change in the monthly average of the risk-free interest rate $\overline{R}_f$ (SE 3M) has been negative from the month beginning in $t-2$ to the month beginning in $t-1$. In the model specification; $R_{i,(K,t)}$ is the simple return for portfolio i, $R_{m(K,t)}$ is the simple return of OMX Stockholm General Index and $R_{f(K,t)}$ is the simple return of three month treasury bill (SE 3M). To adjust for sample autocorrelation the t-statistics are calculated using Newey-West standard errors.

$$R_{i,(K,t)} = a_i + b_i(R_{M,(K,t)} - R_{f,(K,t)}) + e_i$$

J	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
K	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
Panel A: Momentum portfolios (long winner - short loser) – full sample																
a*(%)	0.69	1.04	0.76	0.72	0.90	0.80	0.75	0.50	0.67	0.59	0.47	0.28	0.57	0.38	0.37	0.02
a(%)	2.07	3.16	2.29	2.16	5.53	4.89	4.60	3.05	6.20	5.42	4.32	2.52	7.11	4.62	4.51	0.26
b	-0.20	-0.25	-0.37	-0.25	-0.36	-0.51	-0.55	-0.46	-0.42	-0.65	-0.61	-0.55	-0.31	-0.64	-0.54	-0.55
$t(a)$	2.02	2.41	1.70	1.63	2.88	2.00	1.73	1.14	2.53	1.60	1.08	0.67	2.49	1.09	0.99	0.05
$t(b)$	-1.05	-1.30	-2.70	-1.73	-1.76	-2.33	-2.64	-2.08	-1.71	-2.19	-1.95	-1.62	-1.73	-2.35	-1.83	-1.69
R^2	0.02	0.02	0.05	0.02	0.01	0.03	0.04	0.02	0.02	0.03	0.04	0.03	0.01	0.03	0.03	0.02
Panel B: Momentum portfolios (long winner - short loser) – large cap sample																
a*(%)	0.85	0.86	0.66	0.56	0.25	0.17	0.11	-0.12	0.02	0.06	-0.13	-0.33	0.09	-0.04	-0.31	-0.40
a(%)	2.57	2.62	1.99	1.68	1.53	1.00	0.64	-0.69	0.14	0.52	-1.12	-2.90	1.04	-0.47	-3.66	-4.73
b	-0.31	-0.42	-0.42	-0.43	-0.45	-0.52	-0.47	-0.45	-0.52	-0.60	-0.51	-0.50	-0.73	-0.62	-0.57	-0.48
$t(a)$	2.86	2.75	1.79	1.38	1.11	0.53	0.26	-0.24	0.06	0.15	-0.27	-0.62	0.31	-0.10	-0.63	-0.80
$t(b)$	-1.84	-2.91	-2.72	-2.81	-2.53	-2.63	-2.19	-1.86	-2.36	-2.28	-1.74	-1.45	-2.63	-1.63	-1.51	-1.16
R^2	0.07	0.12	0.10	0.10	0.07	0.07	0.05	0.04	0.06	0.05	0.03	0.03	0.06	0.03	0.02	0.02
Panel C: Stenlund-Holmberg switch portfolios – large cap sample																
a*(%)	0.79	0.34	0.58	0.48	0.42	0.38	0.60	0.66	0.30	0.34	0.56	0.57	0.29	0.18	0.39	0.41
a(%)	2.40	1.01	1.75	1.43	2.53	2.29	3.68	4.03	2.78	3.15	5.12	5.28	3.49	2.19	4.77	5.03
b	0.28	0.24	0.24	0.26	0.40	0.28	0.26	0.36	0.35	0.18	0.20	0.30	0.24	0.16	0.10	0.24
$t(a)$	2.89	1.16	1.85	1.43	2.02	1.72	2.37	2.24	1.80	1.59	2.30	2.16	1.65	0.84	1.58	1.66
$t(b)$	2.21	1.86	1.74	1.88	2.66	1.53	1.40	1.76	2.17	0.79	0.85	1.06	1.12	0.54	0.35	0.75
R^2	0.06	0.04	0.04	0.04	0.06	0.02	0.02	0.03	0.03	0.01	0.01	0.01	0.01	0.00	0.00	0.00

*Monthly alpha $= ((1+a)^{1/(K\times 3)}) - 1$

Appendix C

C1 – Different length of full sample and large cap sample periods

In the data section we explain that the *full sample* ranges from January 1984 to September 2013 while the *large cap sample* ranges from June 1989 to September 2013. In order to confirm that the difference in the momentum effect between these two samples is not a result of the different sample periods, we have reproduced all calculations of the full sample for the corresponding sample period as for the large cap sample. These calculations confirm what we present in the thesis.

C2 – Choice of risk-free interest rate for risk evaluating regressions

For robustness reasons, we have tested our findings using the ten-year Swedish government bond as the risk-free interest rate, in the CAPM and Fama-French regressions, for the time period where it is available (1987-2013). The results are comparable to what is presented in this paper.

C3 – Critical evaluation of data sources

The two data sources used, Datastream (2013) and Riksbanken (2013), are both assessed to be credible and accurate. The sources are frequently used by academia and practitioners, and the probability of error in the data that would affect the findings of this thesis is therefore negligible.