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Exploring the Momentum Strategy

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Abstract

During different periods in history, buying past winners and selling past losers have proven a profitable strategy when applied to portfolios consisting of stocks. Naturally, if such an opportunity exists it should after a while disappear as arbitrageurs profit. The aim of this thesis is to further test this momentum strategy on the US large capitalized stock market to understand if the behavior is still there. By introducing dynamic holding periods to replace the more conventional fixed holding periods we also test if an adjusted momentum strategy yields similar results. The main result is that we fail to find momentum strategies that generate abnormal returns. Instead, some support of contrarian behavior is found.

"Market participants don't know whether to buy on the rumor and sell on the news,

do the opposite, do both, or do nothing,

depending on which way the wind is blowing."

Research note, Global Link

I. Introduction

TREND BEHAVIOR IN THE stock market has during the past decades been subject to extensive research and debate both in the academic world and on the trading floors. While academic papers have tried to explain and test these trends, or momentum of stock prices, investors have tried to take advantage of these price patterns to make money. Despite the possible uncertainty of using a trading strategy not fully understood, the success of many trend following portfolios continues to stir interest for this strategy. This same interest is the fundament of this thesis and we hope to show whether investors have been able to profit from the strategy after the effect became well known in the early 90´s.

With a momentum strategy, a trader tries to capture the future price spread between up-trending and down-trending securities, betting on historical top performing stocks to keep outperforming the historical underperformers. This is done by buying the stocks that performed best during a certain period and selling the worst performing ones. The portfolio is held for typically a half or one year and the process is then repeated. This straight forward method has made the strategy common for professional institutional investors as well as for smaller private investors.

In this thesis we do acknowledge the popularity of momentum strategies among smaller professional investors as well as private investors and thus the focus will be primarily on these kinds of market participants. The choice will affect transaction costs which may barely be affecting the trading of major banks, pension funds or asset managers but have a significant impact on the choice of portfolio strategy for investors trading smaller volumes. Our hypothesis is indeed that retail investors that have significant transaction costs will not be able to earn abnormal returns.

The momentum pioneers Jegadeesh and Titman (1993) try to utilize the spread that momentum behavior in the market seems to cause. They show that they could have earned abnormal returns by using the strategy. Ever since, a number of researchers have shown that the momentum strategy was working on different markets and asset types. The aim of this paper is firstly to replicate the methods used by Jegadeesh and Titman. Even if there are papers already showing this, not so many have included the time period with the recent financial crisis and it will be interesting to see how this may affect the results.

Second we will try to extend their model. This is accomplished by introducing what we call a dynamic holding period. In conventional momentum trading the holding period is fixed. The dynamic holding period is created by first assuming that the holding period is simply one day. This would imply that at each day, portfolios are ranked according to the performance during the ranking period. The best ones are then bought while the worst ones are sold. This process would lead to possible portfolio re-balancing taking place every day. For the small investor this would be unfeasible, since transaction costs would likely impact the trading result too much. To avoid this issue a threshold is established. To understand the process, consider the following example.

Assume that the ranking period has passed and long and short positions are initiated. The next day, if one stock that was not included in the long portfolio has a better ranking period performance than has the worst stock in said portfolio, it should be exchanged. Due to the threshold, however, the stock that now qualifies has to have a performance that is a specific amount of percentage points better than the worst stock that is already held. How much better the stock has to perform than the stock already included is given by the threshold. Thus if the threshold is 5%, and stock A is already held in the long portfolio and has a performance of 10%, while stock B that was not included in the long portfolio has a performance of 13%, stock B will not be included in the long portfolio. Not before stock B performs more than 5% (the threshold) better than stock A will it be included in the long portfolio. The selection of stocks to the short portfolio works in a similar way.

The reason for including this threshold is to have different holding periods for different stocks, depending on their individual momentum characteristics. Conventional momentum trading holds assets for a minimum time which may sometimes be quite long. With this dynamic holding period we hope to add some flexibility to the inclusion of stocks in the portfolios. Furthermore, the threshold also has the effect that a higher reading implies less frequent portfolio constituent changes, and thus less negative transaction cost effects.

Thereby it will be a tradeoff between changing portfolio constituents so that the ones with strongest momentum behavior is included but at the same time not to change the composition so often that transaction costs will make the strategy unprofitable. This is the main aim of this thesis. Thus besides the replication part where the conventional momentum strategy is tested, we hope to shed some new light on momentum strategies. We find this interesting since the knowledge of the existence of momentum strategies have been around since at least the 90´s when Jegadeesh and Titman (1993) published their groundbreaking paper. This implies that investors have had time to explore this market anomaly. Furthermore, the tendency that investing is getting more quantitative and is to a large extent driven by algorithmic trading should also have affected the profit opportunities. With this in mind, our hypothesis is that trading based on momentum strategies is likely to be less profitable (if profitable at all) on the sample time period compared to papers that have tested the strategy on earlier time periods.

This thesis focuses on a randomly selected subset of all US stocks that from January 1990 to December 2010 have belonged to the S&P 500 index. As has been highlighted, this data set will hopefully lead to some understanding of how momentum portfolios performed during the last two decades.

In brief, our results show that conventional momentum strategies do not yield positive significant results. We show that for our strategy with a threshold of zero the optimal ranking period is 13 months. Using this optimal ranking period we vary the threshold between 0 and 100 percentage points. The results show that optimal portfolios are formed with a ranking period of 13 months and a threshold of 80%. Such a high threshold is not implying active portfolio management, rather the opposite. With a threshold of 80% stocks are almost never exchanged and the process is very close to a *buy and hold* strategy. We test a more realistic formation with the threshold being 10% but this yields a significant negative abnormal return, alpha, of -18%.

Our results hold whether or not transaction costs are accounted for. This highlights the fact that for a large investor for which transaction costs can be neglected, contrarian strategies have been profitable. These results are in line with our hypothesis that momentum effects have diminished during the last decade for retail investors and for professional investors as well.

A possible extension of this topic would be to analyze how larger investors perform using the strategy tested. This would imply significantly lower transaction costs. Furthermore it would be interesting to see whether the framework would perform better if being tested on other asset classes.

The remainder of the thesis is organized as follows. In Section II, we introduce and discuss previous research. In Section III, we present the methodology of the tests, as well as limitations of the framework. Section IV presents the results and Section V the implications and concluding remarks.

II. Previous Research

In 1900 Louis Bachelier presented his paper *Théorie de la Spéculation*. It was one of the first academic writings that described the movement of stock prices in a mathematical way. According to his work stock prices moved according to a random walk and because of this they should be impossible to predict as well as make money on. In other words, past stock prices could not be used to predict future prices. Thus if stock prices actually moved randomly investors could simply flip a coin to select assets instead of investing in funds. In essence the theory is in contrast with a large part of today´s finance industry which claims that abnormal returns can be achieved.

Contrarian Strategies

Contrarian strategies are in many ways the opposite of momentum strategies. Instead of buying past winners and selling the losers you buy the losers and sell the winners. This was first tested by de Bondt and Thaler (1995) who showed that historically, past losers actually outperformed past winners. The explanation for this anomaly was according to the authors the overreaction of investors. This stands out as a contrast to the extrapolating ideas corresponding to momentum trading. However, the holding periods used by de Bondt and Thaler are significantly longer (one to five years) compared to what is used when testing momentum strategies. Thus there doesn´t have to be a direct conflict between the strategies.

Contrarian strategies have been broadly tested. Except for the famous paper by de Bondt and Thaler (1995), Antoniou et al (2006) tested contrarian strategies on the London Stock Exchange and showed that it generated abnormal returns. De Jongh Jr. et al (2008) show that contrarian strategies work on exchange traded funds if the ranking and holding periods are properly chosen and Wang et al (2009) reached the same conclusion when testing the strategy intraday on stocks on the Taiwan Stock Exchange.

It is important to highlight and understand contrarian strategies since results of momentum strategies often show that for certain choices of settings contrarian effects dominate momentum effects.

Momentum Strategies

Among the first to test a momentum strategy was Levy (1973) who used his findings as a way to show that stock prices did not follow a random walk. The results however got some criticism from Jensen and Bennington (1970) who indicated that Levy had studied scores of models and eventually chosen the one that yielded satisfying results. Attempts to show that momentum was taking place in the markets did nonetheless not stop here. Jegadeesh and Titman (1993) showed that buying past winners and selling past losers yielded positive returns over a 3- to 12-month holding period. Furthermore they showed that their results were not due to systematic risk or delayed reactions to common factors.

Different explanations have been used to explain the market anomaly that momentum symbolizes. Bradford de Long et al (1990) suggest that the effect exists because traders buy when stock prices go up and sell when they go down. This is known as positive feedback trading. Hirschleifer and Subrahmanyam (1988) proposed overconfidence and self biased self-attribution as a possible explanation. In brief, they first argue that investors trust themselves too much and value their own ideas and information too highly. Second, market participants´ confidence changes in a biased fashion as they experience success and setback. This irrational behavior explanation of momentum has furthermore been questioned by Crombez (2001) who argues that rational investors could follow momentum strategies. Another popular explanation is that momentum is due to delayed overreaction (Jegadeesh and Titman, 2001) and Moskowitz and Grinblatt (1999) attributed the effect to the momentum in the underlying industry and not the stock itself.

Today the fact that the momentum effect exists is rather well-documented. As outlined above, so are the reasons for the existence of this observable fact. The trading strategy described in this thesis is to be seen as an extension and development of momentum trading. By adding some features to the already existing methods we want to examine whether we can create a strategy that is profitable and more attractive to investors than plain momentum investing. A similar framework was developed by Agyei-Ampomah (2006) who examined if momentum strategies can be enhanced by including information about stock volume.

III. Methodology

The testing and implementation of momentum strategies have to a large extent been shaped by the work of Jegadeesh and Titman (1993). Thus the way we test and construct winner and loser portfolios is similar to theirs. We will start by explaining how the conventional momentum portfolios are created and tested and continue by explaining how we have tried to extend the model.

The Momentum framework

In the first part of the empirical testing of momentum strategies we replicate the momentum framework used by Jegadeesh and Titman (1993). The main difference however is that we analyze a different time period. In our analysis ranking periods of 3, 6, 9 and 12 months are used. Consequently, the holding periods are of similar length. This forms a total of 16 portfolios.

Assume the current month is t and that there is a ranking period J and holding period K. The stock returns over the period t-J and t are calculated and the stocks ranked thereafter. The best performing stocks in the highest decile are then bought while the worst performing stocks in the lowest decile are sold. The positions are held for K months after which the actual returns are realized. It is important to note that the winner and loser portfolios are equally weighted and thus the winner minus loser portfolio will be a zero-cost portfolio.

To make the results more robust we use overlapping holding periods. A holding period of for example three months will by this method create sixty different time series; one for each market day included in the holding period. This ensures that the portfolios will be less sensitive to market timing. Furthermore this makes the starting period of our analysis less relevant. Thus the results obtained from the above example will contain equal portions of all sixty time series.

Extending the momentum framework: including a dynamic holding period

The framework for momentum trading described above is the traditional way of using the strategy. Our aim however is to adjust the model slightly and see whether this could improve the results. Consider the following strategy. A ranking period J is used to rank the stocks according to their period returns in the same way as outlined above. Also, assume the rather extreme case when the holding period is only one day. This would imply that each day the portfolio is re-balanced so that it includes the stocks that were best performers during the previous J months. To some extent this is a rather realistic method, since if a stock has rallied and another one has dropped out of the top decile the holdings will be changed immediately and not after a *K* month holding period.

The obvious downside however is the fact that transaction costs will be large if stocks in the portfolio are going to be changed every day. To deal with this we create a threshold *T* which tells us how much higher return a stock needs to achieve in the ranking period compared to a stock that is already held, in order to be included in the winner portfolio. For example, consider a stock universe of 100 stocks where we after a holding period have a winner portfolio with the 10 stocks that performed best during the last *J* months. At time *J+1(day)* we rank the stocks again according to their performance in the period from 1(day) to *J+1(day)*. Now consider the case that at date *J+1(day)* one stock that was previously not among the top ten performers is now a top ten performer. Without a threshold this would mean that the new stock would be added to the portfolio and another one would be removed. However, due to the threshold we require that for the stock to be added, the performance must be *T* percentage points higher than the ranking period return of the worst performing stock that is already held. The loser portfolio works in a similar fashion where the distinction lies in the fact that the threshold *T* is always negative.

The reason why we have removed the classical holding period and replaced it with the threshold *T* is that we believe that a dynamic holding period, the result of including the switching threshold, is a more realistic way of building and re-balancing portfolios. For example, if a stock has performed well during the ranking period but whose price now is falling rapidly, traditional momentum trading would still keep the stock in the portfolio. With the dynamic holding period however, the stock would be excluded as soon as another stock has performed *T* percentage points better, which is likely to happen quickly if the fall is significant. Thus with a dynamic holding period stocks will be held in the portfolio for different lengths of time.

Risk and Return

To give the reader a introduction to how risk and return has been calculated in the thesis we briefly discuss it in this part. For a practitioner risk and return is often associated with annual return and volatility. In academia risk and return are more rigorously defined and often associated with the possibility to achieve a significant abnormal return. Our aim is to include both parts. Previous academic research mentioned in earlier chapters often focus on the latter option which is the rigorous method.

We shall start by discussing some common ways of measuring risks and returns well known and important in the industry and then proceed to discuss more rigorous methods. The arithmetic return over a period where V_i is the initial value of an asset and V_f is the final value is defined as

$$r = \frac{V_f - V_i}{V_f}$$

The arithmetic average return is expressed as

$$\bar{r} = \sum_{i=1}^{n} \frac{1}{n} r$$

There are also a risk measure that will be mentioned later in the text. The most common one being standard deviation, or volatility

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (r_i - \bar{r})^2}$$

These measures are enough to do the most basic hypothesis tests on the results of the different strategies. We test the null hypothesis

$$\begin{cases} H0 : \bar{r} = 0 \\ H1 : \bar{r} \neq 0 \end{cases}$$

The emphasis will be on the t-statistics relating to the zero-cost portfolios, since these are the ones that in theory shall have a zero return. The measures described above are often used by practitioners to assess the performance of a strategy. However, to rigorously show if a strategy consistently can generate abnormal returns other methods have to be used.

A well-known and recognized way of measuring risk and return is by using a multi-factor model. We have chosen to work with the Fama and French three factor model since it is one of the most recognized asset pricing models even if it has come under a lot of criticism, which shall also be mentioned. However, to understand the model it is easier to start from the beginning when CAPM (Capital Asset Pricing Model) was the leading explanatory asset pricing model.

The aim with this part is not to look into the details of the derivations and proofs of CAPM or the Fama French model but instead try to outline some of their important results. According to the CAPM there are systematic risk and idiosyncratic risk. Idiosyncratic risk are specific to a certain stock. An airline company may for example be sensitive to price fluctuations in jet fuel. Thus volatility in the fuel price is considered an idiosyncratic risk since it only affects that particular stock and not the market as a whole. Other risks such as market crashes and nature catastrophes may affect all stocks to some extent and is thus considered systematic risk. The important assumption of CAPM is that investors will only be rewarded for carrying systematic risk, since idiosyncratic risk can be diversified away by holding a large enough portfolio.

This implies that the only factor affecting stock prices should be their systematic risk, which is measured by beta

$$\beta = \frac{Cov(r_i, r_m)}{Var(r_m)}$$

r_m is the market return and r_i is the return on a single stock i. Thus the CAPM formula for the expected stock return given a certain beta is,

$$E(r_i) = r_f + \beta\left[E(r_m) - r_f\right]$$

where r_f is the risk free rate of return[1]. However this model is rather simplistic and it was quickly realized that more factors were needed to better capture the drivers behind stock returns. In 1992 Fama and French published their famous paper arguing for two additional factors; a size factor and a book to market factor. They realized that small stocks as well as stocks with high book-to-market ratio had higher historical returns than other stocks. Thus adding these two factors and keeping the excess market return factor from the CAPM the result will be the Fama French three factor model.

$$r_i = r_f + \beta_m\left[r_m - r_f\right] + \beta_s SMB + \beta_h HML$$

Back-testing the conventional momentum strategy as well as our own developed version we will be able to test whether the strategies can generate alpha. This is done by running the regression

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{m,i}\left[E(r_{m,i}) - r_f\right] + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \varepsilon_i$$

If the Fama French model is correct the returns should be fully explained by the factors. That implies that if the constant α is significantly larger than zero the strategy can generate significant abnormal returns. Thus we will test the hypothesis

[1] We will use the treasury bill return found on French´s data webpage http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html as risk free return.

$$\begin{cases} H0:\alpha = 0 \\ H1:\alpha \neq 0 \end{cases}$$

It is important to mention that extensions of the three factor model with a fourth factor, a momentum factor, has been successfully implemented and tested (Carhart, 1997).

Data

The data chosen when testing the above illustrated strategies is based on daily dividend- and split adjusted returns on the S&P 500 stock constituents. It was obtained via Wharton University of Pennsylvania and attributes to the database The Center for Research in Security Prices (CRSP), which contains security prices, returns, and volume data for the NYSE, AMEX and NASDAQ. To avoid any significant amount of so called survivorship bias, all constituents that since 1990 have belonged to the S&P 500 index are included in the data sample. Due to practical reasons the number of stocks were then narrowed down to 190; the selection fully randomized. Further, periods where these companies had a too small market capitalization to belong to the index were not included in the sample. In other words, the for stocks applicable critique by Elton et al (1996) that almost all earlier studies on mutual funds had a large portion of survivorship bias has been considered.

As a next step to further add quality to the sample false Saturdays and Sundays were removed since no stock listed on the NYSE, AMEX and NASDAQ are traded on weekends. For those stocks that sporadically missed data on regular trading days the share price quoted the day before was used as a proxy. However, since this thesis emphasizes whatever realism can be gathered in trading strategy back testing, a trade ban was pertained for these days, affecting only the stocks with proxy share price data. With this method no trade in the back testing will occur on a day when the stock indeed did not trade historically. Lastly, if the share price did not change for a minimum of ten days, the time series split to be treated as two stocks instead of one. The reason for this method is not to pollute the back-testing with wrongly calculated ranking- and holding periods that extend over too many days where the stock did not trade.

Transaction Costs

Further elements of realism were added with regards to the portfolio exposure to transaction costs. Taking brokerage fees, the bid-ask spread and slippage into account when changing a stock in the portfolio, the cost amounts to approximately 0.7% of the capital moved. The number is backed by a professional participant in the long-equity segment of the hedge fund industry. These transaction costs will impact on what optimal switching threshold will be used in the back testing.

A note of clarification with regards to these transaction costs concerns how they affect different type of portfolios. As the strategies outlined above take a market neutral position by buying and short-selling stocks at the same time, these transaction costs must be used with caution. A thoughtless tester might run a long-only back test on a proposed winner- as well as on a looser portfolio, thinking the difference in return is the theoretical spread. This conclusion is wrong since the transaction costs acquired when restructuring the looser portfolio after a holding period must have the opposite effect on the portfolio value from what is commonly used for long portfolios. By inverting the transaction costs, making them negative for short-sold portfolios, the setting is right and the spread between the long and short positions can correctly be calculated.

Limitations of the Framework

Before presenting the results it is important that the limitations and the possible issues with the momentum trading strategy are covered. These may be topics that are not at first considered until the trading strategy is tested in the market. Doing this we hope to shed a more realistic light on the results and better understand the limitations of the whole framework.

How traders operate in the market often depends on what kind of investor you are. Conditions will vary for example depending on whether you are a private investor, a buy side investor or a sell side investor. As a private investor transaction costs and bid-ask spreads will definitely be more significant. Thus it may not be optimal for the individual investor to re-balance her portfolio as often as the professional investor since this induces a significant cost. The professional investor is closer to the market, trades larger volumes and may have more and better access to data and information. This is indeed supported by the paper of Pettengill et al (2006) which concludes that momentum strategies are too short-term for individual investors and that profits will be significantly lower than for professionals.

On the contrary the individual may be able to invest more long-term. While institutional investors may be pushed to perform within each quarter, adjust the books due to balance sheet publications and respect the risk restrictions, the individual investors enjoy more freedom.

Furthermore, there are plenty of details in relation to short selling which when back-testing are hard to model. When shorting stocks the investor contacts her broker and instructs her to sell the stocks and put the money into her account. The investor will in general not earn interest on the money or on any profits made. Investors are also likely forced to put cash into a margin account where money will be withdrawn or added depending on price movements of the underlying stocks. This mark to market mechanism reduces the effects of default. However, institutional investors such as banks may be able to borrow stocks directly from their investors, thus reducing the costs of short-selling. The fact that short-selling works in a different way than buying are not considered in our trading. Instead, short-selling is seen as the opposite of buying. Besides, during the financial crisis of 2008-2009 short-selling was partly forbidden to calm the sell-offs and restore some confidence in the markets. Moreover, short-selling of smaller stocks may be limited and will thus be more costly. These implications are often well known by practitioners but are very hard to account for in a back-testing framework.

Another issue is related to liquidity. Stocks that are liquid traded usually have low bid-ask spreads while smaller, less liquid stocks often have higher bid-ask spreads. Bettmann et al (2010) show in a study of the Australian stock market that momentum strategies yielded significant negative returns for illiquid stocks and significant positive returns for liquid stocks. Since we use stocks from the S&P 500 they are among the 500 largest traded companies in the US, yet there are still vast differences in liquidity. For example, the three month average volume of Apple is about 16 million while the same number for Clorox Company is about one million. Volume is to some extent a proxy for the bid-ask spread and thus the spread will be significantly different for the two companies[2]. In our framework we deal indirectly with bid-ask spreads by assuming rather high transaction costs. However, since this cost is the same no matter which stock is traded we have not accounted for liquidity differences between stocks; differences that in reality have an effect on the trading performance.

There are a couple of other minor issues where we have to make assumptions. For instance, we assume that if we buy stocks we don´t move the market. That is, our trading volume is small compared to the daily volume being traded. Moreover, we assume that we can buy and sell the whole amount at a current market price. This is in general not the case since orders tend to be split up and bought for different price in case there are not enough sellers selling at the desired price. Furthermore, in order to test if returns are significantly different from zero we have to assume that the log returns are normally distributed.

Besides the practical issues that were mentioned above there are also some debate regarding the models that will be used in this thesis. First and foremost the Fama French three factor model has really been developed into the benchmark model with which assets can be priced. Using the model we will later be able to show whether our trading strategy can generate abnormal returns. This term itself needs a bit of explanation.

[2] Data from Yahoo finance.

The abnormal return is the excess return of an asset or trading strategy that is not explained by the three Fama French factors. In the regression above that would be α. By testing if α is significantly larger than zero, we can show whether our model generates a higher return than what is explained by the three factors. In essence, if that can be shown we have succeeded with developing a profitable trading strategy. Thus the assumption will be that the Fama French model holds. However, there are other asset pricing models that have added or replaced factors in order to better explain asset returns. Since momentum has been widely tested and proved generating abnormal returns under the Fama French model some papers have argued that it is simply a problem with the pricing model being used. For example, L´Her et al (2004) has shown that a four factor model, extending the Fama French model with a momentum factor does explain stock returns better than the original model, on the Canadian stock market. This suggests that the Fama French model is not complete and should be extended.

Moreover, it is important to highlight some of the common critique of the pricing model. Kothari et al (1995) argue that the standard error of the beta coefficient from Fama and French´s original results is large and it is thus hard to interpret the results. Thus basically they argue that the data is too noisy and the results not enough to prove that the model is better than the CAPM.

Jagannathan and Wang (1993) criticize the use of the size factor since the fraction of small firms in these tests is in general small. They split stocks in 100 groups and show that firms in the largest 40 percent of the groups account for 90 percent of the market value. Other critique deal with the collection of data and survivorship bias that makes the book-to-market factor much stronger than it should be.

Thus by no means is the Fama French model the complete one but it is probably the most widely used asset pricing model. However, it is important to understand the limitations and historical critique of the framework in order to better be able to interpret our results.

What have been discussed in this part are market frictions. There are plenty which will affect the daily trading portfolio but in a back-test it is hard if not impossible to take into account all of them. Instead we have made certain assumptions and simplifications. These, however, we believe will have minor impact on the final results. Thus our findings can nevertheless be interpreted and considered for practical purposes.

IV. Results

This section is organized in the following way. The first part deals with the replication of the conventional momentum strategy along the lines of Jegadeesh and Titman (1993). We aim to present the results from the back-testing with different ranking- and holding periods. Even though this is a replication it will shed some light on how momentum strategies have performed during the last twenty years. These results will also be important as a benchmark when our trading strategy with dynamic holding period is tested.

Second, the results of our momentum framework are presented. Initially we test different ranking periods with a switching threshold of zero in order to choose the optimal ranking period. This will be done both with and without transaction costs in order to separate the effects on transaction costs from the possible underlying momentum effects. Furthermore, when the optimal ranking period is selected we hold it constant and vary the threshold to determine what level of threshold is best capturing the future price spread. Finally, the optimal settings; the ranking period and threshold are selected and we test whether abnormal returns can be generated.

Momentum Strategy Replication

As outlined above, Table I is a replication of the strategies used by Jegadeesh and Titman (1993). The main difference doesn´t lie in how the different portfolios are created, but in what data sample is used. While Jegadeesh and Titman on a broad index of US stocks test for the period January 1965 to December 1989, we test for the later period January 1990 to December 2010. Here the purpose is to see if Jegadeesh and Titman's results still hold for this later sample time period as well as for the selected portion of S&P 500 stocks.

In contrast to the results this table tries to replicate, it can be seen that momentum strategies like those of Jegadeesh and Titman are not working well on our data sample. While none of Jegadeesh and Titman's original zero-cost portfolios show negative returns, all but one of ours do. With a ranking period of 9 months and a holding period of 12 months our zero-cost portfolio returns 0.68% per year, yet this is not statistically significant on any conventional level. Three of our zero-cost portfolios are statistically significant on a 10% level and they all show negative annual returns.

Table I

Returns of momentum strategies with fixed holding periods

The portfolios are formed based on *J* months past returns and held for *K* months. The values for *J* and *K* are shown in the first column and first row, respectively. By ranking the stocks in ascending order based on *J* months past returns, two equally-weighted portfolios are created. The winner portfolio consists of bought stocks in the highest decile while the looser portfolio consists of short-sold stocks in the lowest decile. The annual returns of these portfolios are presented in this table. The t-statistics are reported in parentheses. All portfolios are constructed with transaction costs taken into account and the sample period is January 1990 to December 2010. One star (*) means the return is significant on the 10% level. Two stars (**) mean the return is significant on the 5% level. Three stars (***) mean the return is significant on the 1% level.

Ranking period (J)	Strategy	Holding period (K)			
		3	6	9	12
3	W	6.54%	5.88%	6.25%	6.07%
	L	-10.90%	-8.19%	-8.25%	-6.99%
	W+L	-4.36%***	-2.32%	-2.00%	-0.92%
	t-stat	-3.31	-1.67	-0.88	-0.36
6	W	5.10%	5.24%	5.32%	6.35%
	L	-10.07%	-8.55%	-6.36%	-6.63%
	W+L	-4.98%***	-3.31%	-1.04%	-0.28%
	t-stat	-3.46	-1.17	-0.53	0.10
9	W	5.91%	6.37%	5.97%	6.20%
	L	-8.82%	-7.10%	-6.35%	-5.52%
	W+L	-2.92%*	-0.73%	-0.38%	0.68%
	t-stat	-1.87	-0.35	-0.15	0.34
12	W	6.29%	5.82%	5.87%	4.82%
	L	-8.35%	-7.39%	-7.12%	-5.68%
	W+L	-2.06%	-1.57%	-1.25%	-0.86%
	t-stat	-1.06	-0.73	-0.49	-0.38

Momentum Strategy Enhancement

The first test of our own strategy consists of selecting a suitable ranking period. This will be done by varying the ranking period and holding the threshold fixed at the level of zero. To better understand the effects of transaction costs, as well as the actual market behavior, this will first be done without transaction costs and later with transaction costs under consideration. The latter test will suggest which ranking period to use when we test for the optimal threshold. When the most favorable ranking period and threshold is selected we have found the desirable settings for our strategy.

Table II

Returns of momentum portfolios without transaction costs

The portfolios are formed based on *J* months past returns and are then held dynamically. By ranking the stocks in ascending order based on *J* months past returns, two equally-weighted portfolios are created. The winner portfolio consists of bought stocks in the highest decile while the looser portfolio consists of short-sold stocks in the lowest decile. The annual returns of these portfolios are presented in this table. The sample period is January 1990 to December 2010. The t-statistics are reported in parentheses. One star (*) means the return is significant on the 10% level. Two stars (**) mean the return is significant on the 5% level. Three stars (***) mean the return is significant on the 1% level.

Strategy	Ranking period (J)					
	1	2	3	4	5	6
W	-2.18%	-0.15%	2.36%	5.26%	4.21%	3.59%
L	-19.55%	-18.29%	-14.87%	-20.51%	-16.62%	-16.08%
W+L	-21.73%***	-18.44%***	-12.51%***	-15.25%***	12.41%**	-12.49%***
t-stat	-109.12	-78.70	-55.00	-48.64	-51.40	-49.84

Strategy	Ranking period (J)					
	7	8	9	10	11	12
W	4.27%	3.47%	3.60%	3.47%	4.64%	5.13%
L	-14.73%	-15.90%	-13.75%	-11.55%	-13.09%	-13.77%
W+L	-10.46%***	-12.43%***	-10.15%***	-8.08%***	-8.45%***	-8.64%***
t-stat	-28.31	-37.91	-31.70	-28.59	-23.61	-20.75

Strategy	Ranking period (J)					
	13	14	15	16	17	18
W	5.39%	4.56%	4.43%	4.54%	4.67%	4.57%
L	-10.82%	-13.22%	-17.33%	-15.94%	-13.90%	-14.47%
W+L	-5.43%***	-8.66%***	-12.90%***	-11.40%***	-9.23%***	-9.90***
t-stat	-11.25	-17.46	-21.18	-23.33	-22.32	-18.47

Table II shows some interesting results in the sense of market behavior. All zero-cost portfolios' annual returns are negative and significant on the 1% level. This suggests contrarian characteristics in the stock price movements. The most significant result we find when stocks are ranked on their past month return. With that setting, investing in the top decile of performers would return -2.18% annually. Short-selling the bottom decile of performers would instead return -19.55% annually. The best performing winner portfolio is found when the ranking period is 13 months. Interestingly, the worst performing looser portfolio is found in the same setting, making the zero-cost portfolio the obvious winner when compared to all other zero-cost portfolios.

Table III

Returns of momentum portfolios with transaction costs

The portfolios are formed based on *J* months past returns and are then held dynamically. By ranking the stocks in ascending order based on *J* months past returns, two equally-weighted portfolios are created. The winner portfolio consists of bought stocks in the highest decile while the looser portfolio consists of short-sold stocks in the lowest decile. The annual returns of these portfolios are presented in this table. Transaction costs are taken under condideration. The sample period is January 1990 to December 2010. One star (*) means the return is significant on the 10% level. Two stars (**) mean the return is significant on the 5% level. Three stars (***) mean the return is significant on the 1% level.

Strategy	Ranking period (J)					
	1	2	3	4	5	6
W	-17.96%	-13.21%	-9.48%	-5.51%	-5.58%	-5.28%
L	-53.65%	-41.06%	-32.79%	-37.18%	-31.08%	-28.98%
W+L	-71.6%***	-54.26%***	-42.27%***	-42.68%***	-36.66%***	-34.25%***
t-stat	-210.68	-181.11	-136.50	-102.76	-113.41	-106.98

Strategy	Ranking period (J)					
	7	8	9	10	11	12
W	-4.45%	-4.64%	-4.30%	-3.85%	-2.58%	-2.11%
L	-26.33%	-27.27%	-24.15%	-20.39%	-22.34%	-22.72%
W+L	-30.78%***	-31.91%***	-28.45%***	-24.23%***	-24.91%***	-24.83%***
t-stat	-66.64	-79.29	-72.95	-71.52	-57.90	-52.78

Strategy	Ranking period (J)					
	13	14	15	16	17	18
W	-1.35%	-2.10%	-1.84%	-1.63%	-1.44%	-1.20%
L	-18.37%	-20.66%	-25.14%	-24.26%	-21.61%	-21.01%
W+L	-19.71%***	-22.76%***	-26.98%***	-25.88%***	-23.04%***	-22.21%***
t-stat	-35.68	-42.24	-40.07	-45.98	-50.25	-39.22

Table III uses the findings in Table II but takes transaction costs into consideration. All 18 zero-cost portfolios are still significant on all conventional levels; not surprisingly since transaction costs push the returns down even further. The best winner portfolio yields an annual return of -

1.20% and is no longer found when using a 13 month but a 18 month ranking period. The best looser portfolio returns of -18.37% and is found when using a ranking period of 13 month. The best zero-cost portfolio is still the one constructed with a 13 month ranking period. It returns -19.71%.

Table IV

Returns of momentum portfolios for different thresholds

Below the ranking period of 260 days (13 months) is kept fixed while the threshold *T* varied from 0 to 100 percentage points. Furthermore we also test an infinite threshold replicating a buy and hold strategy. The sample period is January 1990 to December 2010. One star (*) means that the return is significant on the 10% level. Two stars (**) mean that the return is significant on the 5% level. Three stars (***) mean that the return is significant on the 1% level.

Strategy	Threshold T					
	0	10	20	30	40	50
W	-2.69%	9.17%	13.37%	14.51%	22.23%	16.34%
L	-17.02%	-29.02%	-21.96%	-23.79%	-28.12%	-22.18%
W+L	-19.71%***	-19.85%***	-8.59%***	-9.28%***	-5.89%***	-5.84%***
t-stat	-35.68	-23.15	-12.58	-12.74	-9.10	-8.59

Strategy	Threshold T					
	60	70	80	90	100	1000
W	15.85%	15.71%	18.61%	17.20%	18.69%	14.41%
L	-18.54%	-18.56%	-18.64%	-18.01%	-17.08%	-15.20%
W+L	-2.69%***	-2.85%***	-0.03%	-0.81%*	1.61%***	-0.79%***
t-stat	-4.70	-5.84	-0.06	-1.66	3.86	-3.78

The effect this threshold has on portfolio performance is portrayed in Table IV. The threshold is varied from 0 to 100 percentage units. A buy and hold strategy is represented as well with an infinite threshold. We can see a general trend of better returns as the threshold is increased. The best winner portfolio is found when the threshold is 40. The best looser portfolio is found when the threshold is. Being the only one with positive annual returns, we find the best zero-cost portfolio when the threshold is 100. This is just slightly better than the buy-and-hold setting.

We continue to test the optimal zero-cost portfolio on the Fama-French three factor model. To put perspective on the results the zero-cost portfolio is first tested with no transaction costs considered. The results are portrayed in Table V. This test is done to increase the relevance of mainly the alpha coefficient, since taking transaction costs into account will put negative pressure on the alpha coefficient. By removing the transaction costs this negative pressure is removed as well.

Table V presents the regression results when transaction costs are not taken into account. The setting is that of a 13 month ranking period. We see that the negative alpha coefficient is significant on all conventional levels. None of the Fama-French factor slope coefficients are significant on the 10% level.

Table V

Test for alpha using three factor model without transaction costs

Below are the results of the test for alpha as described in the methodology. One star (*) means the return is significant on the 10% level. Two stars (**) mean the return is significant on the 5% level. Three stars (***) mean the return is significant on the 1% level.

	Alpha	Beta	SMB	HML
Coefficient	-5.50%***	-0.0024*	-0.0022	-0.0023
t-stat	-15.55	-1.81	-0.82	-0.91

Table VI presents the regression results when transaction costs are taken into account. The setting is that of a 13 month ranking period with a generic threshold of 20%. We see that the negative alpha coefficient is significant on all conventional levels. None of the Fama-French factor slope coefficients are significant on the 10% level.

Table VI

Test for alpha using three factor model

Below are the results of the test for alpha as described in the methodology. One star (*) means the return is significant on the 10% level. Two stars (**) mean the return is significant on the 5% level. Three stars (***) mean the return is significant on the 1% level.

	Alpha	Beta	SMB	HML
Coefficient	-9.08%***	-0.0012	-0.0021	-0.0013
t-stat	-27.18	-0.93	-0.83	-0.49

V. Implications & Conclusions

The most important implication in this study is the failure of tested momentum strategies to generate abnormal returns. This is in contrast to earlier findings and in line with our hypothesis that after discovered, any momentum effect would diminish as practitioners try to profit from the anomaly. The effect can be compared to the, after discovery, diminishing small firm effect mentioned earlier in the thesis.

The first test in the thesis proposed a replication of the testing done by Jegadeesh and Titman (1993), who could present results both abnormal and significant. Our zero-cost portfolios did on the contrary generate negative annual returns. The majority of these were not statistically significant, yet the dissimilarity from those they tried to replicate was considerable.

By introducing dynamic holding periods a more complete illustration could be portrayed of what kind of momentum behavior existed in the market during our sample period. Further, by starting the tests with no transaction costs, any pure stock behavior is even more accentuated in the output. Our results differ from earlier findings here as well. By investing in the stocks that had the worst performance during a ranking period an investor would have yielded much higher returns than had she instead invested in the top performing stocks. This behavior we consider contrarian rather than having tendencies of momentum. Of all zero-cost portfolios the largest t-value obtained was -11.25. This supports our hypothesis.

In further testing we found that when actually accounting for transaction costs they hinder almost any attempt to profit from a momentum strategy. This is in line with our hypothesis. The switching threshold, introduced with the momentum strategies of dynamic holding periods, does help to hamper the harm transaction costs inflict on the constructed portfolios. However, the results point to higher returns as the threshold increases. This implies an investor is better off pursuing a buy and hold strategy rather than any of the momentum strategies outlined in this study. What was also found in these tests was a general failure to generate higher returns by changing the fixed holding period strategies to dynamic holding period strategies.

When testing the momentum strategy on the three factor model introduced by Fama and French (1992); the only significant coefficients are the negative alphas. The relevance of the first regression amounts to the fact it is done with no transaction costs under consideration. The negative value of alpha suggests yet again contrarian tendencies in the market. However, what can be seen in the results of the second regression does not relate equally much to these tendencies. The large negative alpha is instead to be seen in relation to the first and the difference in size is to be interpreted as the effect transaction costs have on the momentum strategy outcome. These results are not only to be seen in separate lights. What further support the broad contrarian tendencies are the insignificant t-values of all slope coefficients in the two regressions. Since the capital is equally distributed between a long and a short portfolio in the tests, any significant slope coefficient t-value in the regression results would indicate that the constituents in the two portfolios do not share the same characteristics. Had this been the case one could draw the simplified conclusion that any contrarian behavior can be attributed to stock characteristics rather than to past period returns. Since we do not have any of these findings this suggests contrarian behavior.

The results are relevant for the smaller market participant. For the larger market participant transaction costs will probably have a smaller effect. Though the difference is probably not large enough to make the tested momentum strategies profitable even for larger market participants. We believe explanations for this underperformance of momentum strategies are many. The S&P 500 contains many of the world's largest companies. They are all well-known and are thus exposed to glamour effects where small non-professional investors buy them because they know about them through advertisement and news in different media. A tendency of reversal to their fundamental value may thus to some extent explain why momentum strategies don't seem to work on the S&P 500. Another explanation may be the increase of algorithmic trading, where any momentum pattern immediately are recognized by many of these systems. It does not, however, explain why our findings suggest contrarian behavior, since these patterns would be exploited by the algorithmic traders as well.

There are many paths open for further research on the subject of momentum. We recognize the shortcomings of not analyzing more stocks traded in the market. Using a random sample as proxy for the large capitalized US stock market, this encourages more robust testing for future papers. We also emphasize the need to adjust for any survivorship bias, making the tests more realistic and the results less prone to seem too optimistic. Further, we request more studies on contrarian behavior in different stock markets as our results imply that, for large US stocks at least, contrarian behavior is out there.

References

Agyei-Ampomah, S., 2006, On the Profitability of Volume-Augumented Momentum Trading Strategies: Evidence from the UK, *Investment Management and Financial Innovation* 3(3), 91-106.

Antoniou, A., Galariotis, C., Emilios, 2006, Short-term Contrarian Strategies in the London Stock Exchange: Are They Profitable? Which Factors Affect Them?, *Journal of Business Finance & Accounting* 33(5), 839-867.

Bachelier, L., 1900, Théorie de la Spéculation, *Annales Scientifiques de l'École Normale Supérieure* 3(17), 21-86.

Bettman, L. J., Sault, J., von Reibnitz, A. H., 2010, The Impact of Liquidity and Transaction Costs on the 52-week High Momentum Strategy in Australia, *Australian Journal of Management* 35(3), 227-244.

Bradford de Long, J., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *The Journal of Finance* 45(2), 379-395.

Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52(1), 57-82.

Crombez, J., 2001, Momentum, Rational Agents and Efficient Markets, *The Journal of Psychology and Financial Markets* 2, 189-199.

Daniel, K., Hirschleifer, D., Subrahmanyam, A., 1998, A Theory of Overconfidence, Self-Attribution, and Security Market Under and Over-reactions, *Journal of Finance* 53(6), 1839-1885.

De Bondt, W. F. M., Thaler, R., 1985, Does the Stock Market Overreact, *The Journal of Finance* 40(3), 793-805.

De Jong, J., C., Rhee, G., S., 2008, Abnormal returns with momentum/contrarian strategies using exchange traded funds, Journal *of Asset Management*, pp. 289-299.

Elton, E. J., Gruber, M. J., Blake, C. R., 1996, Survivorship Bias and Mutual Fund Performance, *The Review of Financial Studies* 9(4), 1097-1120.

Fama, E., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance* 25(2), 383-417.

Fama, E., French, R., 1992, The Cross Section of Expected Stock Returns, *Journal of Finance* 47(2), 427-465.

Jagannathan, R., Wang, Z., 1993, The CAPM is Alive and Well, *Research Department Staff Report* 165, Federal Reserve Bank Minneapolis.

Jeegadeesh, N., Titman, S., 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48(1), 65-91.

Jeegadeesh, N., Titman, S., 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56(2), 699-720.

Jensen, M., Bennington, G., 1970, Random Walks and Technical Theories: Some Additional Evidence, *Journal of Finance* 25, 69-482.

Kothari, S. P., Shanken, J., Sloan, R. G., 1995, Another Look at the Crossection of Expected Stock Returns, *Journal of Finance* 50, 185-224.

Levy, R. A., 1967, Relative Strength as a Criterion for Investment Selection, *The Journal of Finance* 22(4), 595 - 610.

L´Her, J-F., Masmoudi, T., Suret, J-M., 2004, Evidence to Support the Four-Factor Pricing Model fron the Canadian Stock Market, Jo*urnal of International Financial Markets, Institutions and money* 14(4), 313-328.

Moskowitz, T. J., Grinblatt, M., 1999, Do Industries Explain Momentum, *The Journal of Finance* 54(4), 1249-1290.

Pettengill, G. N., Edwards, S. M., Schmitt, D. E., 2006, Is Momentum Investing a Viable Strategy for Individual Investors?, *Financial Services Review* 15, 181-197.

Wang, K-Y., Peng, S-C., Huang, Y-S., 2009, The Intraday Performance of Contrarian Strategies: Evidence from the Taiwan Stock Exchange, *Review of Pacific Basin Financial Markets and Policies* 12(4), 655-674.