BI Norwegian Business School - campus Oslo

# GRA 19502

## Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Preliminary thesis

Navn: Lars Christian Haavik, Min Alexander Øvergaard

Start: 01.01.2018 09.00

Finish: 15.01.2018 12.00

# Risk-managed momentum in the Norwegian stock market

Study programme: MSc Finance

Supervisor: Geir Bjønnes

## Abstract

The concept of managing the risk of momentum trading has rendered the notion of momentum portfolios more appealing to investors, as it addresses the potential for devastating losses during periods of financial distress. While this has been well researched on larger stock exchanges, smaller ones have thus far been largely ignored. We examine the performance of the risk-managed momentum strategy as developed by Barroso & Santa-Clara (2015) on the Norwegian market, implicitly assessing the contested hypothesis relating to the profitability of momentum strategies in markets with varying degrees of liquidity.

# Contents

# 1. Introduction

The persistent pricing anomaly incurring abnormal returns to buying winners and selling losers as observed by Jegadeesh & Titman (1993), among others, has since been widely researched and documented. An extension of this is the risk-managed momentum strategy as conducted by Barroso & Santa-Clara (2015), a popular trading strategy which has documented success internationally. This strategy works especially well in times of turbulence (crisis), and historically has improved the Sharpe-ratio of the plain momentum portfolio significantly when applied in France, Germany, Japan and the UK. We apply this strategy to the Norwegian market (Oslo Stock Exchange), a much smaller and less liquid exchange than all of the above. This is to see whether the abnormal profits will persist in a less liquid market, and the relative extent to which managing the risk contributes to increasing the profitability of plain momentum.

Annerstedt & Schönström (2006) have demonstrated the profitability of plain momentum strategies in the Nordic market, and suggested further research into ways of increasing profitability and testing a different time period. We use the risk-managed momentum strategy in order to increase profitability, with particular emphasis on its performance during the financial crisis which follows immediately where they left off, as well as during the Norway-specific banking crisis of 1987-1992. In all of the Nordic market they observe positive momentum returns for most of the portfolios they constructed within a 3-12 month investment horizon, which is in line with Jegadeesh and Titman's findings. Other than this, strategies over a one month horizon incurred large, negative returns, and investment horizons beyond 12 months see decreasing returns which mostly dissipate by the time the holding period reaches 24 months.

Barroso & Santa Clara (2015) identified the risk of momentum to be highly volatile yet predictable. They estimate this risk by the realized variance of daily returns, and scale the long-short portfolio by its realized volatility over the past six months, obtaining a strategy with constant volatility. We will confirm that momentum is a viable trading strategy in the Norwegian market by constructing a winner-minus-losers portfolio and observing the returns, then implement Barroso & Santa Clara's risk-managed version to observe how this impacts the profitability of momentum, with particular emphasis on its performance during recessions. Our data spans a much shorter time period than the data Barroso & Santa-Clara employed. However, they went back as far as 1926 in order to include the Great Depression which had only a minor impact on Norway, thus it is not particularly interesting for the purposes of our analysis.

Chordia, Subrahmanyam & Tong (2014) hypothesized that increased liquidity with consequent reduced trading costs would lead to increased arbitrage activity, inhibiting the sort of pricing anomalies that render momentum trading a profitable strategy. Avramov, Cheng & Hameed (2016) contest this, finding that momentum strategies perform better in liquid market states. Determining the performance of momentum strategies in the case of Norway sheds some light on this topic. Moreover, the added level of managing the risk allows us to observe whether this proves proportionally more or less lucrative relative to in a more liquid market state.

Following is a review of the literature surrounding this topic, revolving the anomalies that drive momentum profits and its poor performance during recessions, and how managing the risk curbs the extensive losses that puts many investors off pursuing momentum strategies. We also review momentum's performance in terms of relative stock market liquidity along with an examination of the liquidity of the Oslo Stock Exchange. Then follows the theory and associated methodology we employ along with a description of the data used. This is followed by our results and analysis, and subsequent concluding remarks.

## 2. Literature review

### 2.1 Momentum performance

Momentum is possible due to weak form inefficient pricing. De Bondt & Thaler (1985) identified that this is due to stock prices overreacting to information. But while they used this notion in support of contrarian momentum strategies (buying past losers and selling past winners), Jegadeesh & Titman (1993) attribute its apparent success to short term price pressures and illiquidity, opting for buying winners and selling losers over the medium term investment horizon of 3-12 months. They found that this strategy generated significant abnormal profits. The best performing strategy, which selects stocks based on the return over the past 6 months with a 6 month holding period, realized on average 12.01% annually between 1965 and 1989.

Skjeltorp (2000) applied chaos theory and fractals to the US and Norwegian stock markets in an attempt to explain the dynamics of stock prices, and discovered a fractal scaling behavior inconsistent with what that of a random walk would produce. This confirms that there are patterns in the prices of the Norwegian stock market over time, echoing the fact that an active trading strategy such a momentum can be used to exploit price patterns and earn abnormal returns also in the Norwegian stock market.

### 2.2 Momentum performance during crashes

Outline how momentum crashes come about as per Daniel & Moskowitz (2016), and also how this leads to momentum reversals and the consequences of this.

### 2.3 Risk-managed momentum

A discussion of Barroso & Santa-Clara's (2015) method of measuring volatility followed by a broader discussion on how to take advantage of the volatility of returns as put forth by Moreira & Muir (2017).

### 2.4 The Oslo Stock Exchange

As previously mentioned, Barroso & Santa-Clara (2015) tested their risk-managed strategy on some of the largest and most liquid stock exchanges in the world. Since all of them displayed promising results for this strategy, it is only natural to extend the analysis to a more isolated, less liquid exchange to further test its robustness. Despite the Oslo Stock Exchange being relatively small by international standards, it has experienced an increase in size and liquidity since 1980. This is evident from the increase in listed companies and number of stocks traded, as well as the substantial increase in market value. There is however also a cyclical component to stock market liquidity, as it has been shown to fluctuate with the business cycle (Næs, Skjeltorp & Ødegaard, 2011). When economic activity slows, transaction costs (the relative spread) increase, but there has been a clear overall upward trend since 1980.

Næs, Skjeltorp & Ødegaard (2008) attribute some of this development to structural changes such as the change from an open outcry system to an electronic trading platform in 1988, which allowed for continuous trading. Subsequently, in 1999, this became a fully automated computerized trading system similar to the stock market structures in Paris, Stockholm and Toronto (Næs, Skjeltorp & Ødegaard, 2008: p.7). They go on to consider four main indicators of liquidity; the cost of executing a trade, the quantity that can be traded, the time it takes to execute a trade, and how big of a price impact a trade of a given size has along with how long it takes for the price to revert back to its true value. The development of these indicators shows that there was an increase in liquidity during the sample period, however there is still a long way to go to rival other exchanges in size and liquidity.

As well as a change in liquidity over time, there is also a difference in liquidity within the sectors represented on the Oslo Stock Exchange. Firms in the energy industry are more linked to international economic activity, hence are more prone to the state of the global economy as opposed to just the Norwegian business cycle. In this sense stock market fluctuations will become increasingly homogeneous as trade becomes more globalised. So far Norway has remained relatively shielded from the brunt of global financial crises, and thus conceivably appears more attractive to momentum investors seeing as the main argument against momentum trading is the potential losses during recessions. However, being a smaller, less liquid exchange implies higher transaction costs, which is expensive for an active trading strategy such as momentum. The profits from the risk-managed momentum strategy must be great enough so as to justify its application in an exchange with a relatively higher spread, while also taking into account the reduced downside risk of smaller crashes.

### 2.5 Momentum and liquidity

A discussion of the debate concerning to what extent momentum strategies are appropriate in liquid/illiquid stock markets as put forth by Chordia et al (2014) versus Avramov et al (2016).

## 3. Theory

The main focus of our thesis is to study the performance of the momentum trading strategy within the Norwegian stock market, and implementing the risk-managed momentum trading strategy. To empower our findings and the robustness of the strategy our research we will also include the strategy’s performance in other stock markets during the relevant period of 1991 until the end of 2017.

The momentum strategy, WML[1], is a strategy that aims to base the investment decision on a market trend. One is essentially calculating the past performance of a list of securities in the chosen stock market and use this as an indicator to establish a trend. Based on the established trend, the argument is that the trend will be more likely to continue in the same direction than to develop a new path. In order to analytically study the performance of the strategy we do not only look into the main drivers behind this strategy and try to explain how the strategy works, but also study the performance of the strategy over time. We identify the weaknesses of the plain momentum strategy along with how we can perform even better than the plain strategy by employing the strategy conceived by Barroso & Santa Clara (2015).

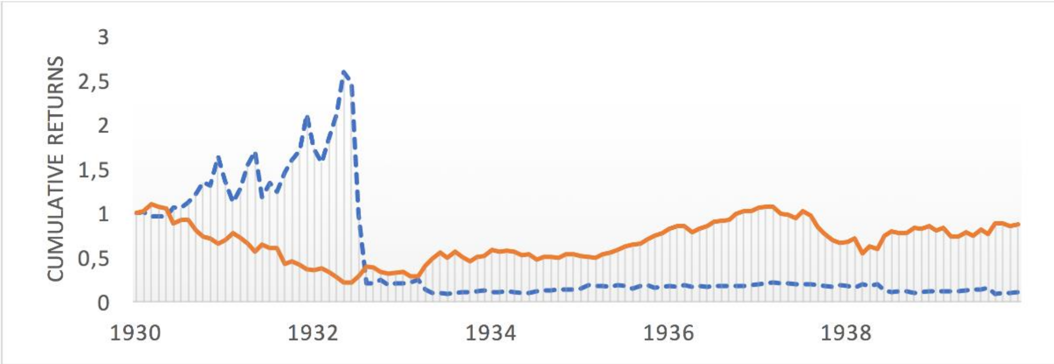
# 4. Methodology

## 4.1 Historical performance

In the previous section, we mentioned how the WML momentum strategy is able to create abnormally high excess returns to investors over time. However, Daniel and Moskowitz (2016) found that the high excess return of the momentum strategy does not come without costs. The dark side that comes with the strategy is an inelegant statistical performance with an extremely high excess kurtosis of 18.24 and a left skew of -2.47. The combination of these descriptive statistics implies that the WML has a fat left tail, indicating a very high level of crash risk of return which can potentially take decades to recover from.

[1] WML (winners minus losers) is a momentum trading strategy which involves past six-month performance with a holding period of six months. At the end of each period each security in the portfolio is ranked ascendingly based on the past period's cumulative returns. This way, each security is ranked and categorized for each period according to the top 10%, 20% and 30% best performing securities and are assigned to the winners' categories. On the other hand, the worst performing securities are assigned to the losers' categories after their rank of 10%, 20% and 30% worst performing securities.

*Panel A: Plain momentum (WML) and the market (RMRF): 1930:01 to 1939:12*




*Panel B: Plain momentum (WML) and the market (RMRF): 2000:01 to 2009:12*

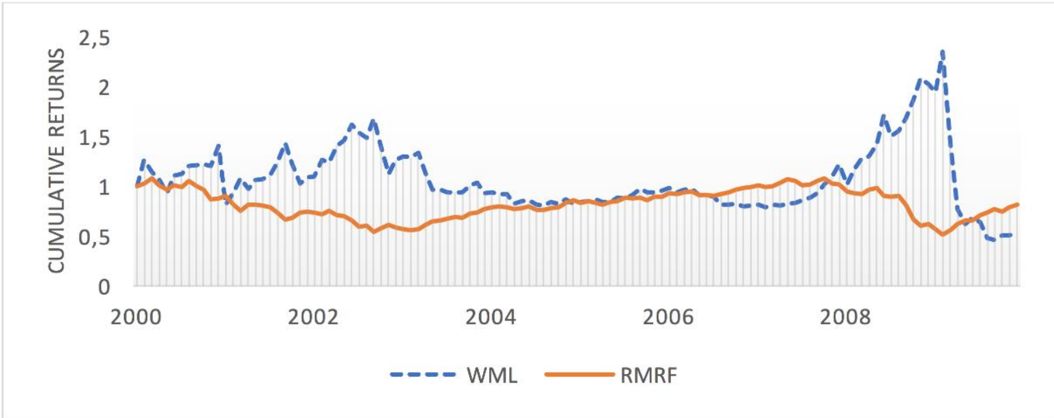



**Figure 1: WML performance** (replicated from Barroso & Santa-Clara, 2015: Fig. 1 using the same data from Kenneth French data library[1])

Figure 1 above shows the cumulative return from momentum in the US during the two most financially turbulent periods to date, the Great Depression in the 1930s in Panel A and the financial crises of the 2000s in Panel B. The most devastating losses for each took place in 1932 and 2009, incurring cumulative losses of 91.59% and 73.42%, respectively. Barroso & Santa-Clara (2015) provide the example that had one invested an amount of money in 1932 according to the WML strategy, it would take up to 31 years to recover the position and breakeven in 1963 (Barroso & Santa-Clara, 2015: p. 113). The question then becomes whether such a crash can be predicted, which would aid investors in hedging their investment against momentum crashes.

### 4.2 Momentum's time-varying risk

To answer whether momentum crashes can be predicted, we must start by investigating the reasons for the large excess kurtosis implied by the historical performance. One possible cause is the time-varying risk of the strategy as

[1] Kenneth French data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

suggested by Bollerslev (1987), whose findings supported previous research that "speculative price changes […] are approximately uncorrelated over time but characterized by tranquil and volatile periods" (Bollerslev, 1987: p. 546). We therefore need to study the dynamics of the risk of the momentum strategy, starting by computing the realized variance of daily returns for the past 21 days (the total trading days of one month). The realized variance can be computed by the following formula for factor i in month t:

$$RV_{i,t} = \sum_{j=0}^{20} r_{i,d_t-j}^2$$

where $\{r_d\}_{d=1}^{D}$ denotes the daily returns and $\{d_t\}_{t=1}^{T}$ denotes the time series of the last trading date of each month, resulting in an AR(1) expression of:

$$RV_{i,t} = \alpha + \rho \times RV_{i,t-1} + \varepsilon_t$$

Compared to the market portfolio, the momentum strategy has historically twice as high excess kurtosis. This provides motivation for controlling for other risk factors such as the Fama and French risk factors of market (RMRF), size (SMB) and value (HML).

Barroso & Santa-Clara (2015) suggest that the predictability of the risk should be controlled with an out-of-sample (OOS) data set. We will therefore be controlling for the predictability in a similar fashion with a training sample of 1/3 of our data set expressed in months, where we will use the AR(1) process to predict the next month's realized variance based on the previous months' realized variance. The OOS forecast will then be compared to the mean realized variance $\overline{RV}_{i,t}$. The OOS R-squared is then computed to measure the goodness of fit of the model according to the following formula:

$$R_{i,OOS}^2 = 1 - \frac{\sum_{t=S}^{T-1}(\hat{\alpha}_t + \hat{\rho}_t \times RV_{i,t} - RV_{i,t+1})^2}{\sum_{t=S}^{T-1}(\overline{RV}_{i,t} - RV_{i,t+1})^2}$$

where S is the OOS initial sample and $\hat{\alpha}_t, \hat{\rho}_t, and\ \overline{RV}_{i,t}$ denote the estimates of the observations available up to time t.

### 4.3 Risk-managed momentum

The risk-managed momentum strategy devised by Barroso & Santa-Clara (2015) is a strategy that addresses the problem of time-varying risk. The strategy was borne from the idea that the risk of the momentum strategy has been empirically proven to be "highly predictable" (Barroso & Santa Clara, 2015: p. 112). The forecasted variance is then used to scale the exposure of the strategy such that the risk becomes constant over time.

The estimated variance is given by the following formula:

$$\hat{\sigma}^2 = 21 \sum_{j=0}^{125} r_{WML,d_{t-1}}^2 / 126$$

where $\hat{\sigma}^2$ is the variance estimated from the past six months of daily returns, while $\{r_{WML,d}\}_{d=1}^{D}$ and $\{d_t\}_{t=1}^{T}$ denote the daily return and the time series of the last trading date of each month, respectively. The estimated variance is then used to scale the return as follows:

$$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} \times r_{WML,t}$$

where $r_{WML,t}$ is the return of the unscaled momentum return and $r_{WML^*,t}$ denotes the scaled risk-managed momentum return at time t. The $\sigma_{target}$ corresponds to the targeted variance which is a constant[2]. Since the strategy is a zero-investment strategy and self-financing, it is possible to scale it without any constraints.

Furthermore, we will also do research on the performance of the risk-managed momentum strategy compared to the plain momentum strategy, and provide a detailed report with both tables and figures.

## 5. Data

The main objective of our thesis is to implement the risk-managed momentum strategy on the Norwegian stock market. We will therefore be using the data set obtained from the Oslo Stock Exchange All Share Index (OSEAX), also called Oslo Børs All Share Index. The data set is of historical prices of all the shares listed on

[2] To determine the targeted variance of the momentum strategy, we will need to do further research and calculations on the WML return for the Norwegian stock market.

the index, including those securities that have been delisted. As a benchmark, we will be using the benchmark index of the Norwegian stock market, the Oslo Stock Exchange Benchmark Index (OSEBX) also called Oslo Børs Main index. The OSEBX will be used to calculate the market benchmark return.

In order to obtain the dataset, we have been using Datastream available at BI Norwegian Business School. We have encountered difficulties in finding a trustworthy dataset as well as difficulties in obtaining a satisfactory time horizon worth of data. The dataset we have obtained is historical prices of both OSEAX and OSEBX which reach back as far as 1997. However, we are still working on finding a set of historical prices which reaches back as far as 1987 in order to include the Norwegian Banking crisis of 1987-1992.

Furthermore, we have also obtained the dataset which was employed by Barroso & Santa Clara (2015). This we have used to replicate their strategy to improve our understanding of it. For the part of the research where we need to control for the risk factors RMRF, HML and SMB, we will be using a dataset obtained from Kenneth French’s data library, which includes data from 1991 through till today. We also plan to use data from other stock markets in order to empower our findings and compare to the Norwegian market. Kenneth French’s data library provides data for the Japanese, European, US and global stock markets for the same time period as the Fama French factors (1991-2017).

## 6. Results and analysis

## 7. Conclusion

## 8. Bibliography

Andrei, D., & Cujean, J. (2017). Information percolation, momentum and reversal. *Journal of Financial Economics, 123*(3), 617-645. doi:https://doi.org/10.1016/j.jfineco.2016.05.012

Annerstedt, P., & Schönström, A. (2006). Profitability of Momentum Strategies on the Nordic stock market. In.

Avramov, D., Cheng, S., & Hameed, A. (2016). Time-Varying Liquidity and Momentum Profits. *Journal of Financial and Quantitative Analysis, 51*(6), 1897-1923. doi:10.1017/S0022109016000764

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics, 116*(1), 111-120. doi:https://doi.org/10.1016/j.jfineco.2014.11.010

Bollerslev, T. (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics, 69*(3), 542-547.

Chabot, B., Ghysels, E., & Jagannathan, R. (2014). Momentum Trading, Return Chasing, and Predictable Crashes. *National Bureau of Economic Research Working Paper Series, No. 20660*. doi:10.3386/w20660

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting and Economics, 58*(1), 41-58. doi:https://doi.org/10.1016/j.jacceco.2014.06.001

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221-247. doi:https://doi.org/10.1016/j.jfineco.2015.12.002

De Bondt , W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805. doi:10.2307/2327804

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics, 105*(3), 457-472. doi:https://doi.org/10.1016/j.jfineco.2012.05.011

Grundy, B. D., & Martin, J. S. (2001). Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *The Review of Financial Studies, 14*(1), 29-78.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91. doi:10.2307/2328882

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance, 56*(2), 699-720. doi:10.1111/0022-1082.00342

Moreira, A., & Muir, T. (2017). Volatility-Managed Portfolios. *The Journal of Finance, 72*(4), 1611-1644. doi:10.1111/jofi.12513

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics, 104*(2), 228-250. doi:https://doi.org/10.1016/j.jfineco.2011.11.003

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2008). Liquidity at the Oslo Stock Exchange, Norges Bank. Available at https://dx.doi.org/10.2139/ssrn.1158410

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock Market Liquidity and the Business Cycle. *The Journal of Finance, 66*(1), 139-176. doi:10.1111/j.1540-6261.2010.01628.x

Skjeltorp, J. A. (2000). Scaling in the Norwegian stock market. *Physica A: Statistical Mechanics and its Applications, 283*(3), 486-528. doi:https://doi.org/10.1016/S0378-4371(00)00212-0