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Managing the risk of momentum on the Oslo Stock Exchange

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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 in the aftermath of 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. This involves using an estimate of momentum risk to scale exposure to the strategy, targeting constant risk over time. Maintaining constant volatility when conducting a long-short strategy reflects what real investors and hedge funds attempt to do, as opposed to maintaining constant amounts invested in the long and short legs (Barroso & Santa-Clara, 2015). Implicit in our research is a contribution to the contested hypothesis regarding the relative profitability of momentum strategies in markets with varying degrees of liquidity. We find that although managing the risk successfully ïmproves the momentum strategy's statistical properties as promised, the momentum effect in Norway is very weak. Another caveat is that the highly predictable risk of momentum that Barroso & Santa-Clara (2015) identified on the larger stock exchanges is considerably less so on the Oslo Stock Exchange, making the strategy more difficult to implement in Norway based on ex ante information.

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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 seeks to lessen the consequential, devastating impact that times of financial turbulence can have on the portfolio, 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 Oslo Stock Exchange (OSE), 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 attempt to reaffirm that momentum is a viable trading strategy in the Norwegian market by employing a winner-minus-loser portfolio and observing the cumulative returns. This is followed by implementing Barroso & Santa Clara's (2015) risk-managed version to observe how this impacts the profitability of momentum, with particular emphasis on its performance during periods directly following recessions. Our data spans a much shorter time period than the data Barroso & Santa-Clara (2015) employed. However, they went back as far as 1926 in order to include the Great Depression. Although we would have liked to do the same, the data we were able to acquire on the OSE only stretches as far back as 1980. But considering the fact that the OSE was a mere 5 percent of GDP in 1980 and grew to over 90 percent by 2007 (Næs, Skjeltorp & Ødegaard, 2008: p. 4), data prior to 1980 is not particularly crucial for the purposes of our analysis.

Chordia, Subrahmanyam & Tong (2014) show 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, pertaining to the factors that drive momentum profits and its poor performance during recessions, and how managing its risk serves to curb the extensive losses that puts many investors off pursuing momentum strategies. In addition, we review momentum's performance in terms of relative stock market liquidity along with a closer examination of the liquidity of the OSE. Subsequently, we provide a description of the data used along with the limitations of said data. We then establish the current state of affairs for momentum relative to other risk factors in Norway through an empirical analysis. Then follows an explanation of the methodology we employ. This is followed by our results and analysis, and subsequent concluding remarks.

2. Literature review

2.1 Sources of momentum

The momentum effect refers to trends in the prices of securities. It is a pricing anomaly so persistent that Carhart (1997) devised a new risk factor to account for it. This is due to the fact that conventional asset pricing models were unable to explain momentum profits. For instance, Jegadeesh & Titman (1993) found that the strategy's profitability is not due to its exposure to systematic risk when applying the CAPM. Similarly, Fama & French (1996) were unable to explain continuations in short term returns using their three-factor model. Rational investors would identify predictable patterns and trade on them, hence eliminate them. Despite a considerable amount of momentum traders, this is not the case, and momentum profits prevail. Therefore, the leading explanations for momentum are behavioural.

One behavioural explanation concerns investor overconfidence about the precision of private information along with biased self-attribution (Daniel, Hirshleifer & Subrahmanyam, 1998). Investor overconfidence about the precision of private information is based on the empirically documented premise that individuals tend to overestimate their own abilities (De Bondt & Thaler, 1995). Investors overweight their private signals relative to public information, and underestimate their forecast errors. This causes the price to overreact and deviate from a rational level, leading to excessive return volatility. As more public information becomes available the deviation tends toward correction. Biased self-attribution concerns investors' tendency to attribute successes to personal skills and failures to factors beyond their control (Daniel et al, 1998). It draws from attribution theory as presented by Bem (1965). When private signals are validated by subsequent public information, the overreaction is perpetuated and potentially made worse. On the other hand, invalidated private signals fail to discourage the investor. This causes a momentum effect in security prices, which is eventually reversed as more public information arrives and gradually corrects them to their true value.

However, Moskowitz, Ooi & Pedersen (2012) challenge behavioural models with their finding that price continuations are present in a range of asset classes, such as country equity indices, currencies, commodities and sovereign bonds. Although this is in line with behavioural models in that it contradicts the random walk hypothesis and remains unexplained by conventional asset pricing models, the fact that momentum persists in so many different asset classes with so many different types of investors suggests that an underlying source of momentum has yet to be discovered. Andrei & Cujean (2017) introduce a rational expectations model which suggests that word-of-mouth communication serves as a mechanism that spreads rumours that lead to price run-ups and reversals.

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's performance

De Bondt & Thaler (1985) were the ones who identified that the momentum effect 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.

A clear obstacle to momentum becoming a consistently successful investment strategy is its performance following financial turbulence. Momentum crashes occur in the immediate aftermath of financial crises, when volatility is high and the market is rebounding. It is a result of the short side 'crashing up' due to a strong momentum reversal while the winner bracket appreciates to a much lesser degree (Daniel & Moskowitz, 2016). Over the course of their 1927-2013 US equity sample, Daniel & Moskowitz (2016) identified the two worst performing months for a momentum strategy which buys the top decile of past 12-month winners and shorts the bottom decile of past 12-month losers to be consecutive; in July and August of 1932 (Daniel & Moskowitz, 2016). These two months saw a past-loser decile return of 232 percent while the past-winner decile produced a meagre 32 percent (Daniel & Moskowitz, 2016: p. 221). More recently, from March to May of 2009, the returns to the past-loser and past-winner deciles were 163 percent and 8 percent, respectively.

In conjunction with this, Daniel & Moskowitz (2016) observe a dramatic increase in beta, i.e. a stock's volatility relative to the market, for the loser portfolio during such volatile, bear market periods. On the other hand, they find that the winner portfolio beta slightly decreases. Grundy & Martin (2001) provide the intuition that this is a result of past-return sorted portfolios' time-varying exposure to systematic factors, first identified by Kothari & Shanken (1992). When the market falls during the formation period of a momentum portfolio, the stocks that fall with it are likely to have a high beta, while the best performers likely have a low beta as they do not follow the market's downward trajectory. Thus, the momentum portfolio will be long stocks with a low beta and short stocks with a high beta. The issue arises when the market then promptly rebounds while the momentum portfolio has a significant, negative beta bet on the market. In line with this, Daniel & Moskowitz (2016) found that the past-loser decile beta can rise above 3 while the past-winner decile beta can fall below 0.5 following bear markets.

2.3 Volatility management

When implementing their volatility-scaled strategy, Barroso & Santa-Clara (2015) were able to almost double the Sharpe ratio of the plain momentum strategy. Because there is negligible correlation between lagged volatility and average returns, but a strong correlation between lagged volatility and current volatility (Moreira & Muir, 2017), significant risk-adjusted returns can be gained from taking on more risk when volatility is low, and lowering exposure when volatility is high. This is the basis of volatility-managed portfolios, going against conventional financial theory which encourages either maintaining current exposure or even taking on more, since expected returns are higher during periods of high volatility (Fama & French, 1989).

Barroso & Santa-Clara's (2015) constant volatility scaling approach is one of two competing volatility-scaled methods in recent momentum literature. The other is the dynamic volatility scaling approach put forth by Daniel & Moskowitz (2016). They attempt to maximize the unconditional Sharpe ratio by scaling the weights of the WML at each particular time to make the strategy's conditional volatility proportional to the strategy's conditional Sharpe ratio (Daniel & Moskowitz, 2016). The weights are essentially dependent on the ratio between expected market return and realized volatility, rather than the ratio between a target constant volatility and realized variance as is the case in Barroso & Santa-Clara (2015). Their divergence stems from what the two pairs of authors attribute the major sources of the risk of momentum to. Barroso & Santa-Clara (2015) primarily attribute it to the systematic risk, that which is specific to the strategy. On the other hand, Daniel & Moskowitz (2016) attribute it to the time-varying betas of the winner and loser portfolios. So far it is unclear whether one approach can be considered superior to the other.

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 OSE still being relatively small by international standards, it has experienced a considerable increase in size and liquidity since 1980. This is evident just 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 Næs, Skjeltorp & Ødegaard (2008) found that there was a clear overall increase in liquidity in their study of the period 1980-2007.

Næs et al (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 et al, 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 terms of 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 OSE. 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 in the aftermath of 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.

When analysing the Norwegian stock market, the price of oil will inevitably emerge as a prominent variable that must be considered. Bjørnland (2009) identifies two ways in which higher oil prices affect the economy of an oil exporting country such as Norway; through positive income and wealth effects in that there is a transfer of wealth from oil importers to oil exporters, and through a negative trade effect due to the oil importers demanding less of the exporters' goods in general. She found that a 10 percent increase in the oil price leads to an immediate 2.5 percent increase in stock returns in the case of Norway, but that this effect eventually subsides following a peak of 3.6 percent after 14-15 months. In fact, oil price shocks account for almost 20 percent of the variation in the Oslo Stock Exchange Benchmark Index (OSEBX) in the short run (6 months), an index which comprises a representative selection of the most traded stocks.

The relationship between the oil price and the stock market is relevant to our study in light of Moskowitz & Grinblatt (1999), who found that momentum profits are largely driven by industry momentum, and that the strategy is significantly less profitable when controlling for this. Another important feature to note about the OSE is its heavy concentration in a few very large firms. For instance, in 2006 the three state majority-owned companies Equinor (Statoil at the time), Norsk Hydro and Telenor alone amounted to over 53 percent of aggregate market value (Næs, Skjeltorp & Ødegaard, 2009: p. 9). So not only is the OSE dominated by certain industries, it is dominated by just a few companies within those industries.

2.5 Momentum and liquidity

The effect of liquidity on momentum profits remains inconclusive, with for instance Chordia et al (2014) and Avramov et al (2016) coming to opposing conclusions. This is mainly due to their fundamentally different methods.

Chordia et al (2014) investigated whether capital market anomalies such as momentum have been depleting as a consequence of increases in liquidity. This occurs through for instance changing trading infrastructure and growing trading volume, which facilitates arbitrage that should promote market efficiency and eliminate anomalies. With this underlying hypothesis in mind, they look at the impact of hedge fund assets under management, aggregate short interest and share turnover on momentum profitability, as these proxy for arbitrage activity. In addition, they also analyse how momentum profits were affected by decimalization in 2001, when U.S. security prices went from being quoted in fractions to decimals. This process led to tighter spreads as it allowed for smaller incremental price movements. Thus, they argue that decimalization proxies for lower trading costs, which in turn influences greater arbitrage activity. They found that the switch to decimalization, along with increases in the above arbitrage proxies, correspond with declining momentum profitability in their 1976-2011 sample of NYSE/AMEX stocks and 1983-2011 sample of Nasdaq stocks.

Avramov et al (2016) on the other hand, found that momentum performs better in liquid market states. Contrary to Chordia et al (2014), they investigate how the relationship between market liquidity and momentum profits vary over time. On the premise that changes in momentum profits are a result of changing arbitrage constraints, one would expect momentum profits and market liquidity to have a positive correlation. Avramov et al (2016) found the opposite to be true. They use the same sample of all common stocks listed on NYSE, AMEX and Nasdaq as Chordia et al (2014) did, but over an extended period of 1928-2011. Note that Chordia et al (2014) limited their study to the post mid-1970s due to the fact that deregulation of brokerage commissions in the mid-1970s is what led to the reduced trading costs which they argued incited the arbitrage activity that would eliminate anomalies, and that prior to this trading costs were relatively stable. Indeed, when they tested their hypothesis on a 1950-1975 sample they did not find any reduction in anomaly profits.

Avramov et al (2016) base their analysis on the illiquidity measure ILLIQ developed by Amihud (2002), which is “the daily ratio of absolute stock return to its dollar volume” (Amihud, 2002: p. 32). It represents the daily price response to a dollar of trading volume, hence is considered a proxy for price impact. Over the course of their 1928-2011 sample, Avramov et al (2016) find that a standard deviation increase in market illiquidity decreases momentum profits by 0.87 percent per month. Even after decimalization was imposed in 2001, they found that monthly momentum profits increased from -0.69 percent during illiquid markets to 1.09 percent during liquid markets.

Both Chordia et al (2014) and Avramov et al (2016) investigate U.S. stock exchanges, so their findings are hardly applicable to the OSE, which is on a much smaller scale to begin with. Although it is clear that the OSE goes through liquid and illiquid phases as well, an illiquid NYSE is more than likely to be considerably more liquid than the OSE at any given time, so it is not a fair comparison. But the fact that research on the topic points both ways suggests that we are far from a consensus on the matter. It also means we do not quite know what to expect to see in terms of the evolution of momentum in the Norwegian market, and by extension, the evolution of risk-managed momentum.

3. Data

3.1 Data description

Our data is obtained from Oslo Børs Informasjon AS/BI’s database. The momentum portfolios we use were constructed by Professor Bernt Arne Ødegaard at the University of Stavanger using raw data comprised of daily observations of stock market data obtained from the Oslo Stock Exchange Data Service, consolidated with accounting data from Datastream from 2010 and on as the Oslo Stock Exchange Data Service discontinued their provision of accounts in 2010. They are based on returns from January 1980 to December 2017, one with stocks equally-weighted and one with stocks value-weighted (weighted by the equity size of the firms), for both daily and monthly data. The momentum strategy is a strategy that bases the investment decision on a market trend. One is essentially calculating the past performance of a list of securities in a certain stock market, which is used as an indicator to establish a trend. Based on the established trend, the argument is that the trend is likely to continue in the same direction rather than developing a new path. By initiating a long position on the past, best performing securities while at the same time shorting the worst performing securities, the momentum strategy is in effect. Our paper focuses mainly on two types of momentum strategies in the Norwegian market, each with a different structure but both follow the same concept.

The value-weighted, ten-portfolio WML momentum strategy is a portfolio that ranks the stocks ascendingly in deciles based on their previous eleven-month returns, lagged one month (t-12 to t-2) to account for the issue of short-term reversal identified by Jegadeesh (1990). This concerns the tendency of stocks with strong gains or strong losses to reverse over a short time frame, considered to be a result of investors' overreaction to past information followed by a swift correction. The resulting WML portfolio is then constructed by subtracting the bottom decile from the top decile, representing the worst performing stocks and the best performing stocks, respectively.

The equal-weighted, three-portfolio Carhart PR1YR factor on the other hand is a momentum strategy that arranges the past performance of the securities in a similar fashion. However, the PR1YR factor initiates a long position on the average of the top 30 percent past performing stocks while shorting the average of the bottom 30 percent. We employ the value-weighted WML as it is the strategy that Barroso & Santa-Clara (2015) employed, but we also include the PR1YR in order to observe how adding more stocks and equally weighting them influences the output. However, as the momentum strategy invests in both the best and worst performing stocks in the whole market, using value-weighted rather than equally-weighted indices is more appropriate for the purposes of our study (Ødegaard, 2018: p.19). Therefore, we choose to focus more on the value-weighted WML in this paper.

The forward looking daily and monthly interest rates we use in our calculations primarily stem from the monthly Norwegian Interbank Offered Rate (NIBOR) which is available from 1986 and on. Prior to this, Professor Ødegaard employs the overnight NIBOR rate as an imperfect proxy for the monthly risk free rate between 1982 and 1986 (Ødegaard, 2018: p. 55). Another, more significant, drawback of the dataset lies in the fact that certain stocks were excluded in the construction of the momentum portfolios. Stocks included in the sample were required to have a minimum of 20 trading days, have a price above 10 NOK and a total value outstanding of at least 1 million NOK (Ødegaard, 2018: p. 17). This was done to minimise the distortion caused by stocks that are seldom traded and which have exaggerated returns, and resulted in an annual exclusion of 75 stocks on average between 1980 and 2017. Such filtering is common practice when conducting asset pricing investigations as it makes for more representative results, but it constrains an already limited sample of firms considering the average number of listed securities from 1980 to 2017 is only 209 stocks (Ødegaard, 2018: p. 18). A downside to this for the purposes of our analysis is the fact that the liquidity of the OSE will be overstated as the most illiquid stocks are excluded from the sample, somewhat undermining our goal of assessing the effect of relative stock market liquidity on momentum profits.

Another consequence with regard to the filtering criteria is that, once one moves past the very smallest stocks, the profitability of momentum strategies declines sharply with firm size (Hong, Lim, & Stein, 2000). This relates to the notion that smaller firms have less analyst coverage, leading to information getting out slower. The cost of this information acquisition can be seen as an opportunity cost to investors who would rather focus their energy on analysing stocks they can take larger positions in. Thus, it takes longer for the price of the smallest capitalization stocks to get corrected, and price continuations will be more persistent. As these stocks have been filtered out of our dataset, the momentum effect in Norway will more than likely be understated.

Finally, an issue with regard to the construction of the WML portfolio is the evolution of the number of stocks included in the winner and loser brackets. The number of stocks on the OSE has fluctuated dramatically over the course of our sample period due to new listings, delistings, mergers and demergers. At times the number of stocks has been dramatically low, limited further by the filtering criteria. Between 1980 and 2017 it ranged from a minimum of 33 to a maximum of 223 stocks, averaging 134 throughout the period (Ødegaard, 2018; p. 18). This implies that the number of stocks included in the decile portfolios has ranged from around 3 to 22 at any given time, averaging 13. Meanwhile, the NYSE comprises thousands of stocks. The problem with this discrepancy is that the portfolios we are working with are not always well-diversified. Ødegaard (2018) investigated how many stocks ought to be included in order to ensure a well-diversified portfolio on the OSE. He was surprised to find that a reasonably well diversified portfolio is attained after 10-15 stocks, similar to that of the NYSE, despite the difference in size and concentration (Ødegaard, 2018: p. 41). Nevertheless, our portfolios are not necessarily limited to systematic risk, as some idiosyncratic risk is inherent in their construction due to the constrained investment universe.

Furthermore, we have also obtained the dataset which was employed by Barroso & Santa-Clara (2015). This we have used to replicate their strategy in order 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[1], which includes data from 1991 till the present day. We also use data from other stock markets to compare to the Norwegian market in order to empower our findings. Kenneth French's data library provides data for the Japanese, European, US and global stock markets over the same time period as for the Fama French risk factors (1991-2017).

3.2 Benchmark

In order to track the performance of the momentum strategy we need to pick a benchmark from the same market which is suitable to use as comparison to the momentum strategy itself. For instance, Barroso & Santa-Clara (2015) used the following Fama French risk factors; value (HML), size (SMB) and the market

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

excess return (RMRF) to control for the risk exposure. We will proceed in the same fashion with the data from the OSE obtained from professor Bernt Arne Ødegaard's online data library. The market excess return will be displayed in our graphical illustrations as the main index used to compare with the momentum strategies.

Two commonly used indices for representing market return in the Norwegian stock market is the Oslo Børs All Share Index (OSEAX) and the Total Return Index (OBX), which is also referred to as the main index. The OSEAX comprises all the shares listed on the OSE. The index is adjusted for corporate actions on a daily basis, and the total amount of shares outstanding per index constituent is represented in the index (Oslo Børs, 2018). It is also adjusted for dividends. The OBX index on the other hand is comprised of the 25 most liquid stocks as measured by the past six-month performance, and is adjusted for dividends every six months (in July and December). An issue we face is with regard to the availability of the return data. The online data library produced by professor Bernt Arne Ødegaard has data on the Fama French factors spanning 1980 to the end of 2017. The return on the OSEAX on the other hand is available from January 1983, while return on OBX is available from January 1987. This is considerably less than the availability of return on the momentum strategies which ranges from January 1980 till December 2017.

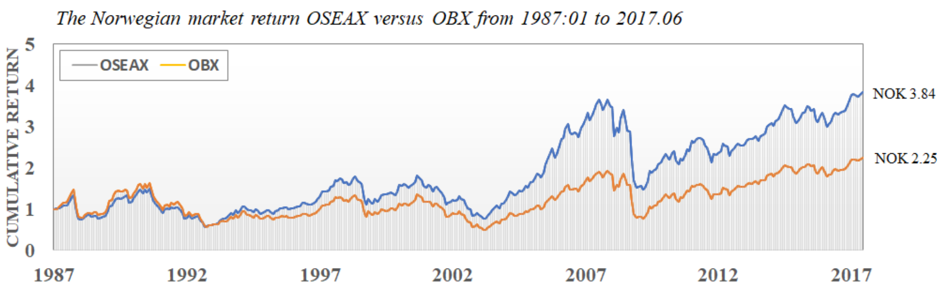

Figure 1: Norwegian stock market indices. The cumulative return of the Oslo Børs All Share Index (OSEAX) and the Total Return Index (OBX) from 1987:01 to 2017:06.

The OSEAX and OBX have very similar features both visually as seen in figure 1 and in terms of descriptive statistics. For instance, they each have annualized standard deviations of 21.3 percent and 22.79 percent, and average returns of 0.56 percent and 0.44 percent, respectively. The correlation between the two indices is as high as 98.34 percent. We illustrate their rolling correlation with the risk factors on the OSE in figure 18 in the appendix.

Considering the fact that momentum strategies do not only focus on the upside of the stock market (the long positions on the best performing stocks), but also on the downside (the short positions on the worst performing stocks), it is important to include as many stocks in the Norwegian market as possible. Furthermore, as a higher number of observations is crucial to produce a reliable result and hopefully a clearer conclusion, choosing a benchmark with a comparably long time horizon as the momentum strategy is important. Finally, taking into account that there should be similarities in terms of the risk characteristics of the benchmark and momentum strategy, we find that the OSEAX is the most appropriate benchmark to use as well as it being the most representative of the market return in the Norwegian market.

3.3 Replication of the strategy

As mentioned in the previous section, we have fully replicated the results from Barroso & Santa-Clara (2015). For the sake of accuracy we replicated the results both manually in Excel and with programming in Matlab. This we in turn adapted to the data obtained on the OSE. The graphical illustrations and tables featured in our paper are based on the code created in Matlab. When implementing the strategy in Matlab we use data from the value-weighted momentum portfolio (mom_daily_ose.mat), the Carhart factor PR1YR (pr1yr_dayli_ose.mat), the Fama French factors (data_ose.mat) and the market return (oseaxrf_daily.mat). The data_ose.mat file includes both daily and monthly returns for the Fama French factors RMRF(oseax-rf & obx-rf), SMB, HML, and also includes WML and the risk-free rate RF.

4. Empirical analysis

4.1 Historical performance

Taking a long position on the past top 10 percent best performing stocks (winners) while shorting the past bottom 10 percent worst performing stocks (losers), has delivered an abnormally high excess return to investors in many markets worldwide. However, the abnormally high excess return does not come without costs. The empirical data of the WML strategy, obtained from the Kenneth French data library[2], has shown that the large upside comes with the price of a high excess kurtosis of 18.24 and a left skewness of -2.47 (Barroso & Santa-Clara, 2015; p. 113), which indicate a crash risk that may take decades to recover form. However, considering the large potential upside of the strategy it is worth investigating momentum also in the Norwegian stock market.

Table 1: Descriptive statistics.

Descriptive statistics from the Norwegian stock market data, where the excess return of the market is calculated from OSEAX less the risk-free rate. The size (SMB), value (HML) and momentum (WML) factors are calculated in accordance with the Fama French methodology. The UMD is a six-portfolio momentum strategy and the PR1YR is the Carhart three-portfolio momentum strategy. Each factor is calculated from monthly returns. The table reports the mean excess return (annualized), standard deviation (annualized), excess kurtosis, skewness, Sharpe ratio (annualized) and the maximum and minimum monthly returns observed over the course of the sample period from 1983:01 to 2017:06.

Table 1 Descriptive statistics from period 1983:01 to 2017:06

Portfolios	Mean	Standard deviation	Kurtosis	Skewness	Sharpe ratio	Max	Min
OSEAX-rf	7,69 %	21,28 %	2,59	-0,89	0,36	16,51 %	-28,69 %
SMB	9,69 %	15,03 %	3,44	0,47	0,64	22,22 %	-17,08 %
HML	3,98 %	16,82 %	1,26	-0,12	0,24	18,44 %	-16,65 %
WML	0,17 %	29,76 %	2,81	0,29	0,01	47,85 %	-26,77 %
UMD	7,35 %	19,62 %	1,91	-0,20	0,37	25,48 %	-24,27 %
PR1YR	9,50 %	16,87 %	1,30	-0,40	0,56	15,43 %	-16,78 %

From the OSE data displayed in table 1 above we see that the momentum strategy has delivered a negligible average return of 0.17 percent per year from 1983.01 to 2017.06, far less than the average excess return of the market of 7.69 percent per year. Taking into account the maximum and minimum values in conjunction with the standard deviation of monthly returns, the WML is clearly the most volatile strategy with an annualized standard deviation of 29.76 percent. The WML reached a maximum upside of 47.85 percent, which is almost 3 times higher than the maximum excess return from the market. However, the WML strategy is the strategy with the lowest Sharpe ratio compared to the other factors in the table. The most interesting result is the positive skewness of the WML strategy, which indicates very low or almost no crash risk. As mentioned previously, underperforming momentum is a result of

[2] The WML from Kenneth French's data library is a ten-portfolio momentum strategy which is constructed each month, and includes NYSE, AMEX, and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of month t-1), a stock must have a price for the end of month t-13 and a good return for month t-2. In addition, any missing returns from t-12 to t-3 must be -99.0, CRSP's code for a missing price.

the short side outperforming the winners, and this is no exception. Figure 20 in the appendix shows the evolution of the return to winners and losers on the OSE.

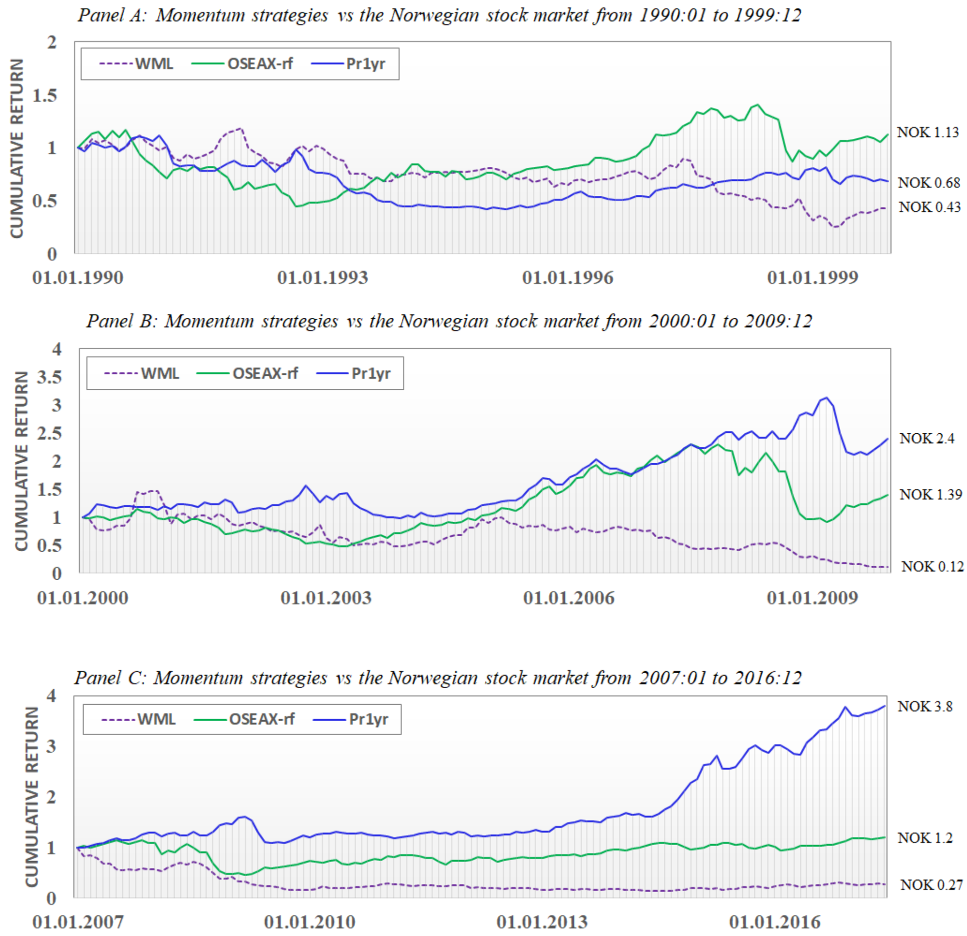

Figure 2: Cumulative return to momentum strategies vs the market on the OSE. The two momentum strategies are WML and PR1YR, which are compared to the market excess return from 1990:01 to 1999:12 in panel A, 2000:01 to 2009:12 in panel B and 2007:01 to 2016:12 in panel C.

Figure 2 shows the factor performances spanning the most relevant time periods between 1983:01 to 2017:06. The Carhart PR1YR factor is the only momentum strategy that beats the market over the course of the last 34 years, with an annualized average return of 9.5 percent. However, there is still no evidence of a significantly high crash risk in the Norwegian stock market in comparison to the WML strategy from Kenneth French's data library. The question is then whether implementing the risk-managed strategy will create value to investors despite there being little evidence of momentum crashes, and whether the strategy would work in the event of a momentum crash in the near future.

4.2 Momentum in the Norwegian stock market in the long run

From January 1983 to June 2017 the WML momentum strategy on the OSE has essentially delivered zero return. We examine this further by controlling the momentum strategy for the Fama French risk factors, which includes the market excess return (OSEAX-rf), value (HML) and size (SMB). We run an ordinary least squares (OLS) regression of the WML of the Norwegian stock market on the Fama French factors, which are computed by Professor Bernt Arne Ødegaard from the stocks from the same market. The results are as follows (t-statistics are in parentheses):

$$\underset{}{r_{WML,t}} = \underset{(-0.48)}{-0.00218} + \underset{(1.69)}{0.12759}\, r_{RMRF,t} + \underset{(0.94)}{0.10067}\, r_{SMB,t} - \underset{(-0.01)}{0.00094}\, r_{HML,t}$$

$$r_{Pr1yr,t} = \underset{(3.21)}{0.00811} - \underset{(-1.64)}{0.0699}\, r_{RMRF,t} + \underset{(1.59)}{0.09567}\, r_{SMB,t} - \underset{(-0.82)}{0.0405}\, r_{HML,t}$$

In annualized terms, the WML strategy has delivered a negative return of 2.6 percent after controlling for its exposure to the other risk factors. The WML strategy has large, positive loadings on both the market excess return and size factors, and a small, negative loading on the value factor. PR1YR on the other hand has an annualized, abnormal return of 9.7 percent, which is significantly higher than that of the WML strategy. The PR1YR has negative loadings on the market and value factors, which implies diversification, and quite a large, positive loading on the size factor. However, note that, aside from the PR1YR alpha, none of the coefficients are statistically significant. Hence, we cannot reject the null hypothesis that they are equal to zero.

4.3 Momentum's time-varying risk

To answer whether momentum crashes are predictable, we start by investigating the excess kurtosis implied by momentum's historical performance in the Norwegian stock market. One possible cause of the excess kurtosis is the time-varying risk 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).

To assess the dynamics of the risk implied by the momentum strategy, we start 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 as the sum of squared daily returns, as expressed in the following formula:

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

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:

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

Figure 3 shows a graphical representation of the monthly volatility of the WML momentum strategy from January 1983 to June 2017. It displays a high variability over time, ranging from a minimum of 0.96 percent to a maximum of 82.2 percent, annualized.

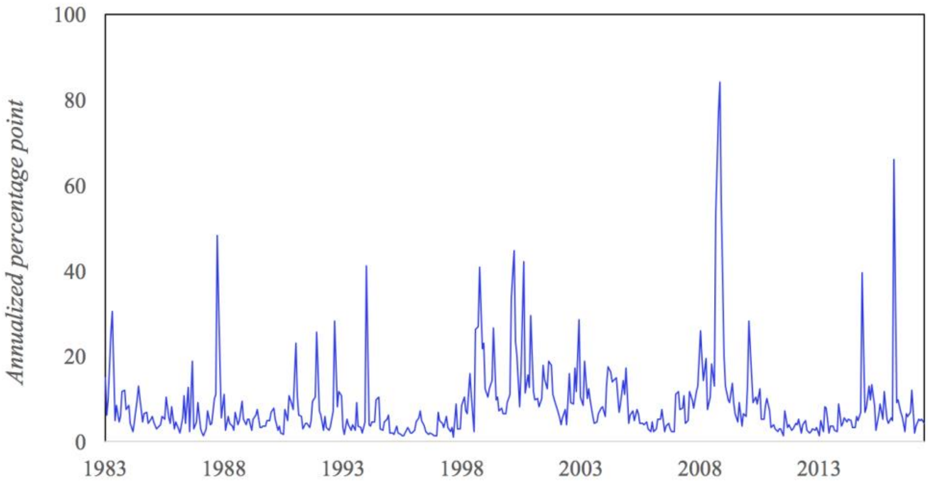

Figure 3: Monthly realized variances in annualized percentage points. The realized variance is obtained by taking the sum of squared returns in the past 21 days, rolled from 1983:01 to 2017:06.

Table 2: AR(1) of one-month realized variances.

The realized variance is obtained by taking the sum of squared returns in the past 21 days rolled from 1983:01 to 2017:06. The AR(1) regresses the non-overlapping realized variance of each of the momentum (WML), market excess return (OSEAX-rf), value (HML) and size (SMB) factors of each month on their own previous value for the previous month, and a constant. The regression also uses an expanding window of observations to regress an out-of-sample (OOS) set, where the OOS R-squared is calculated using the first 120 months to run the regression that produces the OOS forecast.

AR(1) of one-month realized variance

Variable	α (t-statatistic)	ρ (t-statatistic)	R^2	R^2_{OOS}	$\bar{\sigma}$	σ_ε
OSEAX-rf	0,0014	0,6148	37,78	47,92	17,94	10,23
	(4,91)	(15,78)				
SMB	0,0006	0,7657	59,00	56,67	16,12	7,89
	(4,15)	(24,29)				
HML	0,0011	0,5968	37,72	36,31	16,70	7,30
	(7,27)	(15,76)				
WML	0,0030	0,5632	31,74	32,38	26,27	11,81
	(7,08)	(13,82)				
PR1YR	0,0016	0,4760	22,69	39,12	17,12	8,35
	(7,21)	(10,98)				

The autoregression in table 2 produced a very similar level of risk for each factor except for the WML, which is the most volatile strategy with an average standard deviation of 26.27 percent. This is even higher than the average standard deviation of the WML from Kenneth French's data library. The WML strategy also has the highest idiosyncratic risk of 11.81 percent, which is higher than the market's idiosyncratic risk of 10.23 percent. However, the low coefficient of 0.5632 implied by the one-month realized variance of the WML means that it is the least persistent factor, 0.5 less than that of the market.

Furthermore, we want to control for the predictability of risk with respect to the out-of-sample (OOS) data. We use a sample of 120 months (approximately one third of the data set) to run an initial autoregressive model of order one, then use the estimated coefficient along with the last observation of realized variance to forecast the realized variance in the next month. For each month an expanding window of observations is used to produce OOS forecasts that are to be compared to the mean of the historical, realized variance at a particular point in time. To test whether the model fits the actual data we proceed by calculating the OOS R-squared as follows:

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

where S is the OOS initial sample and $\hat{\alpha}_t$, $\hat{\rho}_t$ and $\overline{RV}_{i,t}$ denote the estimates computed using data available up to time t. The OOS R-squared from table 2 shows that the predictability of the market is actually higher than of both of the momentum strategies in the Norwegian stock market. This contradicts Barroso & Santa-Clara's (2015) finding that the WML they obtained from Kenneth French's data library was more predictable than the market. Although the predictability of the market is higher when regressing an AR(1) on the OOS set, the predictability of the momentum strategies is still somewhat high with 32.5 and 39 percent for the WML and PR1YR, respectively.

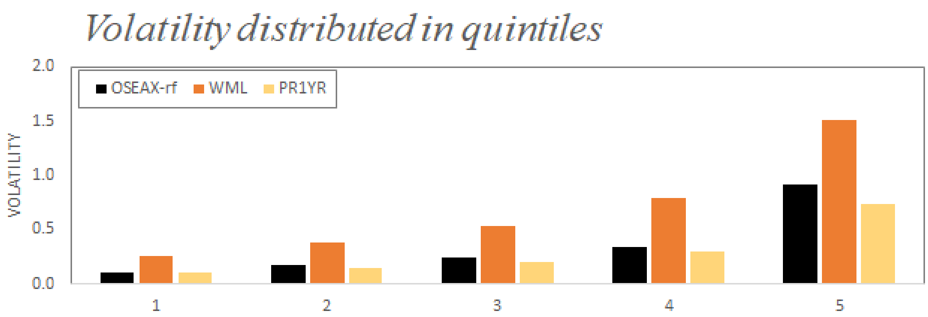

Figure 4: Factor performance sorted by volatility. The factors' performances are distributed into quintiles conditional on their previous six-month volatility from 1983:07 to 2017:06.

Figure 4 above displays the volatility distributed in quintiles. Quintile 1 represents the months with the lowest volatility while quintile 5 represents the months with the highest volatility. It illustrates how higher risk precedes higher risk going forward. We can see that this relationship is stronger for the WML than for the market, with the PR1YR showing a weaker relationship than both of the other factors.

5. Methodology

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:

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

where $\hat{\sigma}^2$ is the variance estimated from the past six months of daily returns, while $\{r_{WML,d}\}_{d=1}^{D}$ and $\{d\}_{t=1}^{T}$ 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:

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

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 σ_{target} corresponds to the targeted variance which is a constant. Since the strategy is a zero-investment strategy and self-financing, it is possible to scale it without any constraints. We use the same target volatility of 12 percent[3] (annualized) that Barroso & Santa-Clara (2015) used to scale their momentum strategy. Changing the target volatility between 10 and 18 percent yields marginally different outputs.

Since the main ingredient of the risk-managed strategy is the realized volatility, implementing the strategy would result in an output starting six months after January 1983. As the Fama French factors and the market excess return (OSEAX-rf) are all available from January 1983, we want an estimate from the risk-managed strategy to start on the same date rather than six months later (July 1983). We solve this by extending the daily return data of the plain momentum strategies by six additional months (126 days), such that the risk-managed strategy can also be observed from January 1983 and on[4].

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[3] The annualized standard deviation of the WML and PR1YR calculated from monthly returns are both higher than 12%. Since the volatility of the WML on the OSE is at a similar level to that of the WML obtained from Kenneth French's data library, we picked the same target volatility that Barroso & Santa-Clara (2015) use.

[4] The methodology behind this calculation is shown in figures 21 and 22 in the appendix.

6. Results

Figure 5 below illustrates the evolution of the weights of the risk-managed momentum strategies on the OSE from January 1983 to June 2017.

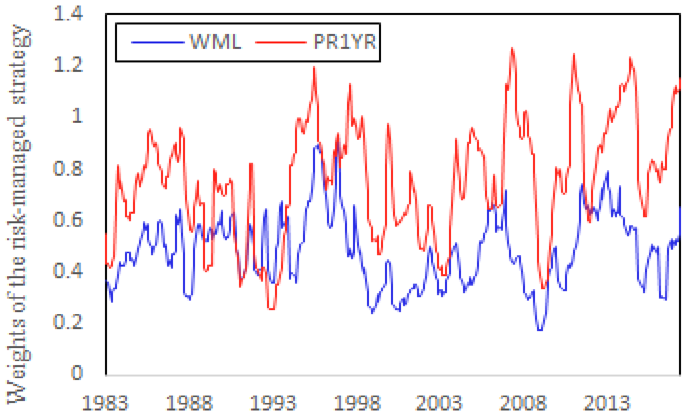


Figure 5: Weights of the risk-managed WML and PR1YR momentum strategies from 1983:01 to 2017:06.

Weights of the PR1YR generally exceed that of the WML, reaching its highest point of 1.27 while the WML did not go higher than 0.93. The mechanism of the scaled strategy automatically changes the holding position using a target annualized volatility. As the volatility of the momentum strategy increases beyond the targeted volatility, the scaled strategy automatically reduces the exposure. On the other hand, as the annualized volatility decreases, the exposure increases. The higher weight of the PR1YR is due to the fact that the annualized standard deviation of the Carhart PR1YR factor is almost half of that of the WML.

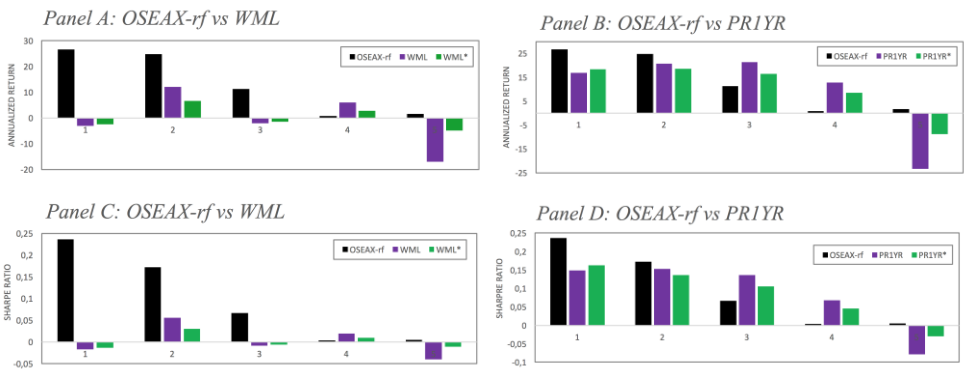


Figure 6: Factor performance of the market (OSEAX-rf) and momentum conditional on the past six-month realized volatility, distributed in quintiles. The plain momentum strategies are denoted by WML and PR1YR while the risk-managed strategies are denoted by WML* and PR1YR*. The quintile distribution distributes the data set into five equal parts ranging from the lowest to the highest value. Panels A and B show the annualized return (monthly return times 12) conditional on the past six-month volatility. Panels C and D display the quintile distribution of the annualized Sharpe ratios conditional on past six-month volatility.

In figure 6 above we can clearly see that, conditional on the volatility, there is no obvious trend in the relation between the risk and return of the momentum strategies. However, one thing both momentum strategies have in common is that they are more likely to fail when volatility is high, as illustrated in the fifth quintile of panels A and B. As a consequence, the Sharpe ratio in panels C and D varies considerably conditional on its past volatility. The risk-managed versions curb the downside considerably. In section 7.1, we examine the properties of the risk of momentum and return in more detail, and show how risk management can be useful in order to create and preserve the value of the plain momentum strategy.

Table 3: Descriptive statistics of the plain vs. risk-managed momentum strategies.

Risk managed vs plain momentum (31.01.1983 to 30.06.2017)

Portfolios	Mean	Standard deviation	Kurtosis	Skewness	Sharpe ratio	Max	Min
WML	0,17 %	29,76 %	2,81	0,29	0,01	47,85 %	-26,77 %
WML*	0,51 %	13,00 %	1,76	0,18	0,04	18,10 %	-12,87 %
PR1YR	9,50 %	16,87 %	1,30	-0,40	0,56	15,43 %	-16,78 %
PR1YR*	10,58 %	11,38 %	0,66	0,26	0,93	14,16 %	-10,90 %

Table 3 displays the performance of both the plain and risk-managed strategies from January 1983 to June 2017. Clearly, the risk-managed strategy creates a lot of value. The average return of the WML tripled while the Carhart PR1YR factor increased by 1.08 percent, annually. Annualized volatility decreased to near the targeted volatility of 12 percent, which drastically improved the Sharpe ratio. Risk management works particularly well on higher-order risk, which is evident from the reduction of the excess kurtosis and the improvement of the skewness, which even turned positive for the PR1YR. In practice, this means that we have almost eliminated the crash risk. Panels C and D of figure 6 support this argument, as we can clearly see that there is a significantly high improvement in Sharpe ratio especially in the fifth quintile, where the volatility is at its highest (highest crash risk). This stands in contrast to the other quintiles, where the gap between the risk and return is less significant. Figure 7 below features a graphical representation of the density of the plain momentum strategies and the risk-managed versions.

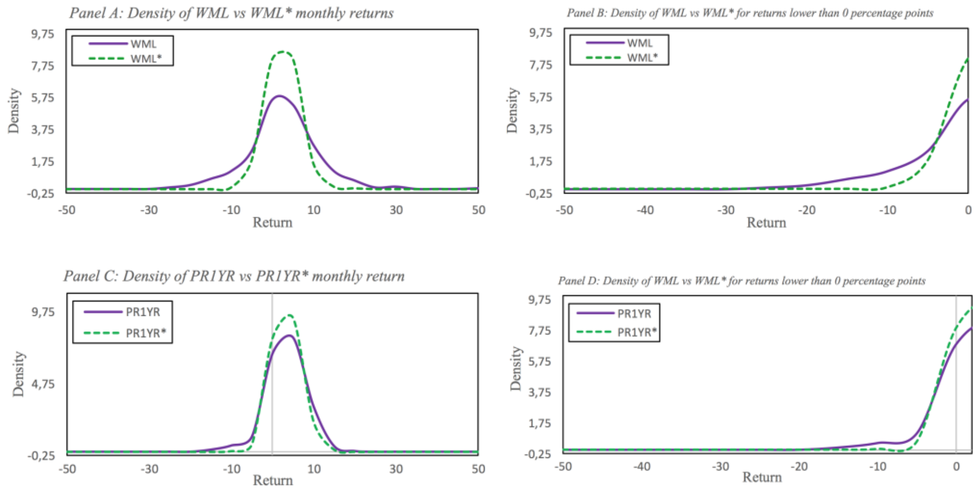
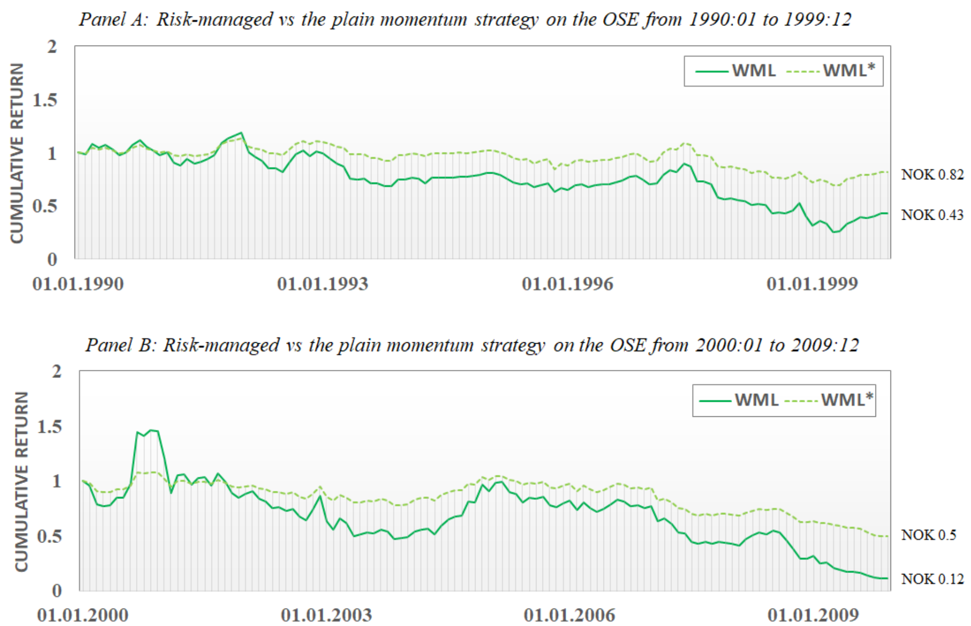


Figure 7: The density of monthly returns of the raw momentum strategies compared to the risk-managed momentum strategies from 1983:01 to 2017:06. Panels A and B display the density of the plain WML vs the risk-managed version, WML*. Panels C and D show the density of the plain Carhart PR1YR factor vs the risk-managed version, PR1YR*. Panels B and D display the density below zero. We added graphical illustrations of the density with a higher frequency of intervals in figure 19 in the appendix.

The risk characteristics of the momentum strategy in the Norwegian market are not indicative of a significant crash risk. Therefore, we choose to focus on the most relevant time periods between January 1983 and June 2017 that include the most significant economic events. That is, when the WML drops to its lowest monthly return of negative NOK 0.24 in 1993, and immediately following the financial crisis in 2009. Figure 8 below displays the cumulative return of both the plain and risk-managed WML strategies during the most relevant time periods between January 1983 and June 2017.



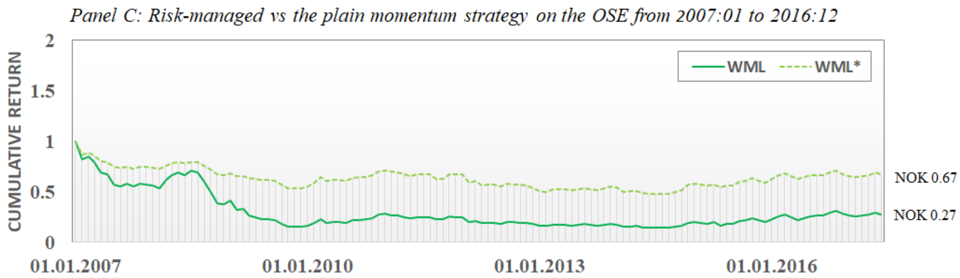


Figure 8: Cumulative return of the raw momentum strategy, WML, versus the risk-managed momentum strategy, WML*, where panel A shows the period from 1990:01 to 1999:12, panel B shows the period from 2000:01 to 2009:12 and panel C shows the period from 2007:01 to 2016:12. The risk-managed strategy uses the forecasted realized variance to scale the exposure to have constant volatility. The equivalent illustrations corresponding to the Carhart PR1YR factor are displayed in figure 16 in the appendix.

Managing the risk of momentum creates significant value. In cumulative terms, if one had invested NOK 1 in January 1983, one would have ended up with NOK 0.95 in June 2017 rather than NOK 0.26 as in the case of the plain WML strategy[5]. On the other hand, the Carhart PR1YR[6] factor appreciated to as much as NOK 31 in June 2017 rather than the NOK 18 its plain version had accumulated. The return to the risk-managed PR1YR cumulatively beats the market's NOK 5.57 by more than 6 times from January 1983 to June 2017[7]. Panel C of figure 8 displays the cumulative return over 10 years between January 2007 and December 2017, which includes the financial crisis. Instead of declining and wiping out decades worth of return starting in August 2008, the scaled strategy was able to preserve and stabilize the value of the investment throughout the whole period, till December 2017.

7. Analysis

7.1 Breaking down the anatomy of the risk of momentum

Since the scaled variance is the main ingredient in the risk-managed momentum strategy, the ability to assess the properties of the strategy's risk is crucial. In this section we explain why there are such strong gains to be made through managing the risk of momentum. In order to assess the properties of the momentum strategy, we decompose the risk of momentum into individual components for market risk and strategy-specific risk:

[5] Potential reasons for the negative return are explained in section 7.2:Contributing factors to WML's poor performance

[6] The graphical representation of cumulative return of the Carhart factor is displayed in figure 16 in the appendix

[7] See figure 15 in the appendix for the cumulative return of the whole period, 1983:01 to 2017:06.

$$RV_{wml,t} = \beta_t^2 RV_{rmrf,t} + \sigma_{e,t}^2.$$

We then conduct a first-order autoregression on each of the individual components to ascertain their level of predictability. The variance, beta and idiosyncratic risk are estimated from the past six months of non-overlapping monthly returns of the WML in the Norwegian stock market.

Table 4: Risk decomposition.

Each row is estimated by regressing an AR(1) process on the past six-month realized variance. Panel A displays the result when estimated with six-month, non-overlapping realized variance and panel B displays the result of the three-month, non-overlapping variance of the WML and the PR1YR from 1983:07 to 2017:06. Each of the components are separated by rows and the statistical variables are sorted by columns. The three first variables correspond to the realized variance of the plain WML strategy, the plain PR1YR strategy and the market excess return (OSEAX-rf), respectively. The third and fourth rows are the squared betas of the two momentum strategies. The fifth and sixth rows display the systematic component of the risk of momentum, and the last two rows include the idiosyncratic risk of the two momentum strategies. The OOS R-squared is calculated using an expanding window of observations after the initial in-the-sample period of 20 years for both the six-month and three-month non-overlapping periods. Running the model on a different number of observations yields marginally different outputs.

Panel A: Risk decomposition model using 6-months realized variance from 1983:07 to 2017:06

Variable	α (t-statatistic)	ρ (t-statatistic)	R^2	R^2_{OOS}
σ^2_{WML}	0,0052	0,2486	6,20 %	-5,02 %
	(4,74)	(2,07)		
σ^2_{PR1YR}	0,0018	0,3843	14,84 %	10,26 %
	(3,81)	(3,37)		
σ^2_{rmrf}	0,0030	0,1696	2,87 %	-0,49 %
	(4,17)	(1,39)		
β^2_{WML}	0,0978	0,4089	16,75 %	-33,45 %
	(2,59)	(3,62)		
β^2_{PR1YR}	0,0847	0,2669	7,12 %	3,59 %
	(4,06)	(2,23)		
$\beta^2_{WML}\sigma^2_{rmrf}$	0,0006	0,1528	2,34 %	-515,06 %
	(1,84)	(1,25)		
$\beta^2_{PR1YR}\sigma^2_{rmrf}$	0,0003	0,2889	8,32 %	-45,65 %
	(3,19)	(2,43)		
$\sigma^2_{\varepsilon,WML}$	0,0044	0,2893	8,48 %	4,48 %
	(4,91)	(2,45)		
$\sigma^2_{\varepsilon,PR1YR}$	0,0015	0,4189	17,76 %	32,70 %
	(3,65)	(3,75)		

Panel B: Risk decomposition model using 3-months realized variance from 1983:07 to 2017:06

Variable	α (t-statatistic)	ρ (t-statatistic)	R^2	R^2_{OOS}
σ^2_{WML}	0,0019	0,7268	52,92 %	48,62 %
	(3,55)	(12,23)		
σ^2_{PR1YR}	0,0007	0,7577	57,58 %	52,51 %
	(3,00)	(13,44)		
σ^2_{rmrf}	0,0010	0,7325	53,54 %	49,08 %
	(2,90)	(12,38)		
β^2_{WML}	0,0720	0,5864	34,40 %	-3,90 %
	(2,61)	(8,35)		
β^2_{PR1YR}	0,0465	0,6042	36,35 %	33,22 %
	(3,59)	(8,72)		
$\beta^2_{WML}\sigma^2_{rmrf}$	0,0002	0,6449	41,59 %	-31,87 %
	(1,60)	(9,73)		
$\beta^2_{PR1YR}\sigma^2_{rmrf}$	0,0002	0,6286	39,43 %	31,80 %
	(2,79)	(9,30)		
$\sigma^2_{\varepsilon,WML}$	0,0019	0,6844	47,15 %	45,51 %
	(4,12)	(10,89)		
$\sigma^2_{\varepsilon,PR1YR}$	0,0005	0,7781	61,01 %	56,44 %
	(2,88)	(14,42)		

Panel A of table 4 displays the results of the AR(1) process on the past six-month, non-overlapping realized variance. The result is underwhelming as it yields a relatively low predictability for every component. In terms of the WML strategy, the component with the highest R-squared is the squared beta. This contradicts Barroso & Santa-Clara (2015), who found that the beta was the least predictable component in the case of the WML strategy obtained from Kenneth French’s data library. This is not the case for the Carhart PR1YR factor. The beta of PR1YR is the second least predictable variable with an R-squared of 7.12 percent, the least predictable being the volatility of the market with an R-squared of 2.87 percent. These characteristics mean that the PR1YR factor is closer to the WML that Barroso & Santa-Clara (2015) obtained from Kenneth French's data library. In the last 34 years the market risk component $\beta_i^2 \sigma_{RMRF}^2$ only accounts for 2.34 and 8.32 percent of the risk within the WML and PR1YR strategies, respectively, which leaves over 90 percent of the risk specific to the strategies.

Due to the low or negligible predictability of almost every component for both the in-sample and out-of sample sets, further analysis is required in order to provide a better understanding of the poor output. We compare the results from the AR(1) processes obtained from the momentum strategies in the Norwegian market to that of the WML used by Barroso & Santa-Clara (2015) between 1983:07 and 2011:12.

Table 5: Comparison of risk components.

This table compares the risk components of the WML and the market excess return used by Barroso & Santa-Clara (2015) to the momentum strategies of the Norwegian market. The components are regressed by an AR(1) on the past six-month, non-overlapping realized variance and follows the same computation as in table 4 in the previous section.

Comparison to the WML strategy from Kenneth French library from 1983:07 to 2011:12

Variables		α	(t-stats)	ρ	(t-stats)	R^2	R^2_{OOS}
σ_i^2	WML	0,0020	(1,58)	0,6258	(5,90)	39,17 %	-16,67 %
	rmrf	0,0018	(3,03)	0,3104	(2,40)	9,64 %	8,27 %
	WML (NO)	0,0055	(4,32)	0,2370	(1,79)	5,57 %	-6,57 %
	PR1YR	0,0020	(3,60)	0,3607	(2,84)	13,03 %	4,44 %
	oseax-rf	0,0031	(3,78)	0,1638	(1,22)	2,68 %	-0,90 %
β_i^2	WML	0,3697	(3,55)	0,1194	(0,88)	1,42 %	-9,21 %
	WML (NO)	0,1021	(2,30)	0,4129	(3,33)	17,04 %	-34,71 %
	PR1YR	0,0956	(3,86)	0,2418	(1,83)	5,81 %	1,66 %
$\beta_i^2 \sigma_{RMRF}^2$	WML	0,0011	(1,54)	0,4127	(3,33)	17,03 %	-98,13 %
	WML (NO)	0,0006	(1,74)	0,1484	(1,10)	2,20 %	-519,21 %
	PR1YR	0,0004	(3,14)	0,2573	(1,95)	6,60 %	-51,61 %
$\sigma_{\varepsilon,i}^2$	WML	0,0009	(1,47)	0,7440	(8,19)	55,38 %	38,68 %
	WML (NO)	0,0047	(4,48)	0,2793	(2,13)	7,77 %	3,24 %
	PR1YR	0,0016	(3,39)	0,4053	(3,27)	16,57 %	31,57 %

Table 5 displays the results of the AR(1) regressions on the risk components of the momentum strategies. The WML used by Barroso & Santa-Clara (2015) shows far more predictable risk components than those of the WML of the Norwegian stock market. In addition, the predictability of the market excess return (OSEAX-rf) is much lower than that of the excess return retrieved from the US stock market. This could be a result of the aforementioned drastic changes that the OSE has undergone between 1983 and 2011 in terms of increases in size and trading volume, as well as varying degrees of concentration. Due to the extent of the structural changes to the exchange from year to year, it is reasonable to expect the realized volatility to be highly unpredictable. By contrast, the market proxy from Kenneth French's data library is based on the NYSE/AMEX and Nasdaq stock exchanges, which are the largest in the world in terms of the number of listings and trading volume. They were already well established by 1983 and have not faced the same structural changes that the OSE has during the period in question, and thus can reasonably be expected to have more a stable and predictable realized volatility. The PR1YR seems to be the only strategy comparable to Barroso & Santa-Clara's (2015) WML with respect to the degree of predictability of its risk components.

Having compared the results of the strategies, we believe it is worth examining how the result would change if we decreased the non-overlapping periods from six months to three months. Panel B of table 4 displays the results of the AR(1) on the risk components based on three-month, non-overlapping periods, for the momentum strategies in the Norwegian stock market during the period of July 1983 to June 2017. This time the R-squared of every component increases dramatically. This could be due to the shorter jumps between the non-overlapping periods, and the fact that the number of observations has doubled by using three-month instead of six-month, non-overlapping periods.

The most surprising result is that the R-squared of the beta squared now became the least predictable risk component for both strategies, even turning negative, or zero predictability, in the case of the OOS-R-squared of the WML. The market risk $\beta_i^2 \sigma_{RMRF}^2$ accounts for 42 and 39 percent for the WML and PR1YR, respectively, while the OOS R-squared shows -32 and 32 percent. The WML variable with the highest level of predictability is now the strategy-specific risk, σ_{WML}^2 , with an OOS R-squared of 48.62 percent. This is almost at the same level as its idiosyncratic risk of 45.51 percent. It is also the case for the Carhart PR1YR factor, of which the idiosyncratic risk is the most predictable variable.

However, due to the rebalancing constraint which occurs every six months, the conclusion must be drawn from the initial results from panel A. From panel A, the beta squared is the most predictable variable in the data sample for the WML strategy. The OOS R-squared of beta squared on the other hand is negative 33.45 percent, which can be interpreted as zero predictability. For the combined market and beta squared variables the model produced a much worse outcome, with an OOS R-squared of negative 516.55 percent. The idiosyncratic risk became the most predictable component with an OOS R-squared of 4.88 percent. In addition to the WML, we should also take into account the fact that the Carhart factor, PR1YR, almost has the same structure as the WML from Kenneth French's data library. Our findings are in line with what Barroso & Santa-Clara (2015) found in that hedging the market risk alone fails because most of the risk is left out.

7.2 Contributing factors to WML's poor performance

It is clear that, over the course of the latter half of our sample period, the WML portfolio steadily declines, eventually fizzling out completely by the time the financial crisis hits. This naturally limits the success of the risk-managed strategy. We now seek to explain this poor performance by highlighting certain characteristics exhibited by the OSE during this period, which historically have contributed to negate the WML strategy. One of a few likely culprits is the oil price drop of 1997 in conjunction with the heavy concentration in the energy sector within the Norwegian stock market.

As alluded to earlier, with Norway being a net oil exporter with a substantial concentration in the energy industry, the Norwegian stock market is heavily influenced by oil price shocks. The energy sector constitutes an average of 23.7 percent of the fraction of value of the exchange over the course of our observation period, rising sharply from 9.9 percent in the 1980-1989 period to 42 percent in the 2000-2009 period (Ødegaard, 2018: p. 32). Therefore, considering the timing of it along with the importance of industry momentum to momentum strategies (Moskowitz & Grinblatt, 1999), the oil price drop was conceivably a catalyst that set WML off on its downward spiral. Figure 9 illustrates how the oil price and the cumulative return of the WML strategy has evolved over the course of our sample period. We can see that they are both relatively stable up until 1997 when they both suffered a sharp decline. However, while the oil price was quick to rebound, WML was unable to recover back to the level it was prior to the oil price shock throughout the remainder of the sample period.

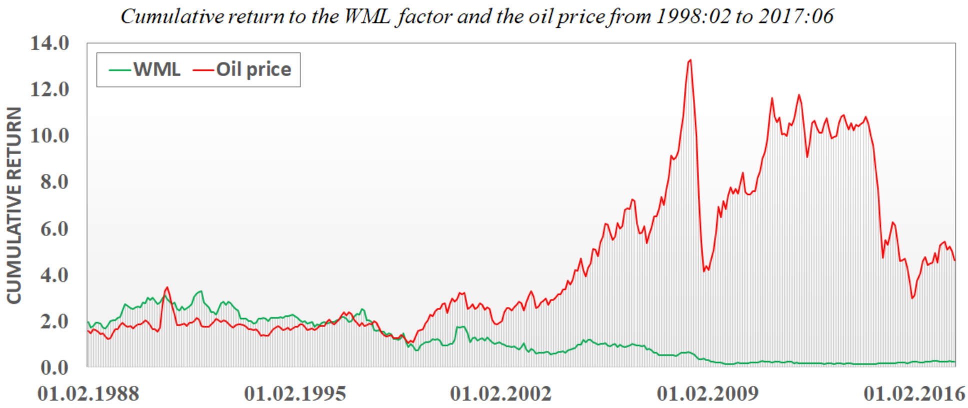


Figure 9: Cumulative return to the WML factor on the OSE and the oil price from 1988:02 to 2017:06. The oil price has been scaled down for illustrative purposes.

Another potential contributing factor is the low interest rate following said oil price crash. The interest rate was initially increased in light of the oil price drop as it coincided with a wage growth spike and international financial turbulence, all causing a depreciation of the NOK in mid-1998 (Norges Bank, 2000). This decrease reduced the pressures on the economy. However, at the start of 1999, in the face of a downturn, the interest rate was reduced again and has been kept at a relatively low level ever since, somewhat in line with the WML's gradually deteriorating performance. The interest rate is plotted alongside the WML's cumulative return in figure 10 below.

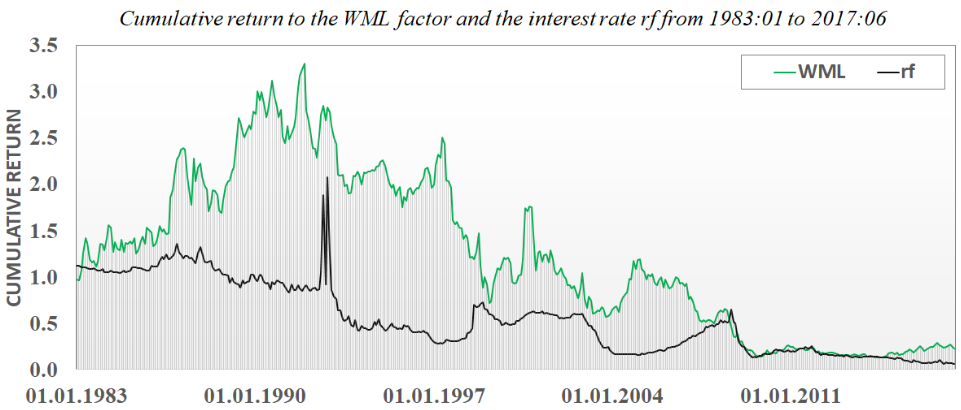


Figure 10: Cumulative return to the WML factor on the OSE and the interest rate, rf, from 1983:01 to 2017:06. The interest rate has been scaled up for illustrative purposes.

In an attempt to explain several CAPM anomalies, including that of long-term return reversal, Maio & Santa-Clara (2017) employ a 2-factor intertemporal CAPM model comprised of the market equity premium and an interest rate factor representing future aggregate investment opportunities. The interest rate factor is based on short-term interest rates, using the federal funds rate and 3-month Treasury bill rate as proxies. Their findings show that past long-term losers are more exposed to changes in the interest rate factor in that they have more negative loadings than is the case for past long-term winners. They attribute this in part to the fact that past loser firms tend to be in a poor financial position with modest growth expectations in terms of future cash flows. This renders them more vulnerable to rises in short-term interest rates which further constrain their access to external financing and investment in profitable projects that would lead to increases in firm value. Conversely, this indicates that a steady fall in interest rates as is observed over the course of our sample period in figure 10, should increase past loser return to a greater extent than for past winners, repressing the profitability of WML.

Amihud & Mendelson (1986) found that expected market illiquidity increases stock excess return, and Amihud (2002) shows that this effect also persists over time. Although this would indicate that the relatively less liquid loser firms should earn higher return than the relatively more liquid winner firms, Avramov et al (2016) found that the price trend anomaly dominates cross-sectional liquidity differences between winner and loser firms when the market is liquid, which leads to momentum profits. However, when the market is illiquid, this cross-sectional illiquidity gap aggravates momentum crashes as it amplifies loser firms' subsequent returns. Næs et al (2009) did in fact find that a portfolio formed of the 10 percent least liquid stocks, sorted based on the relative spread, had a consistently higher return than a portfolio of the 10 percent most liquid stocks on the OSE over the course of their sample period of 1980-2006.

They also constructed a liquidity risk factor to describe stock returns, where the relative spread is used as a proxy for liquidity. This was done by arranging the stocks into three portfolios based on their relative spread from the previous month, then subtracting the return of the most liquid portfolio from the return of the least liquid portfolio. The liquidity risk factor is plotted alongside the WML in figure 11. Note that its composition infers that as the liquidity series plotted in figure 11 increases, illiquid stocks are experiencing appreciating returns to a proportionally greater extent than for the liquid stocks. As the most liquid stocks are more likely to be part of the winner portfolio while the least liquid are more likely to be part of the loser portfolio (Avramov et al, 2016), the relationship between WML and Liquidity seen in the graph appears generally reasonable. The WML cumulative return is relatively higher as Liquidity is lower in the early 1990s, followed by a steadily decreasing WML cumulative return as Liquidity spiked and remained high from mid-1990s to early 2000s. However, the WML failed to mount a lasting recovery as Liquidity declined from 2004 and on.

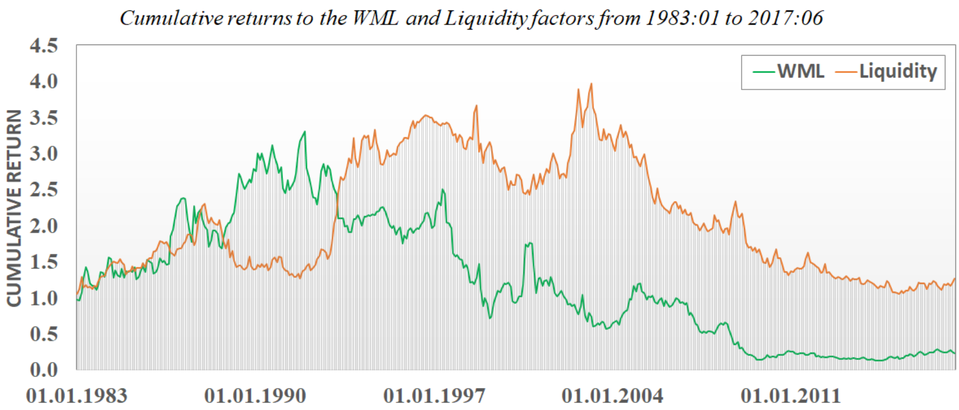


Figure 11: Cumulative returns to the WML and Liquidity factors on the OSE from 1983:01 to 2017:06.

Although we do not find a convincing, direct causal effect between the above factors and the WML's cumulative return due to the highly convoluted nature of their interrelationships, we do argue that these developments contributed to creating an economic environment which made it difficult for the WML strategy to thrive on the OSE. Chabot, Ghysels & Jagannathan (2014) established that momentum crashes were predictable in their study of the London Stock Exchange between 1867-1907 and the NYSE between 1926-2012. They found that momentum crashes were generally preceded by a period of strong momentum performance during both of their subsamples, low interest rates during their 1867-1907 subsample, and after having recently outperformed the market during their 1926-2012 subsample. In the case of our sample, all of the above apply as the WML started to decline considerably from 1997 and on, following several consecutive years of outperforming the market, amid low interest rates.

7.3 Contributing factors to WML's poor performance relative to UMD and PR1YR

Despite the poor performance of the WML portfolio, figure 12 below shows that both the UMD and PR1YR portfolios have enjoyed high returns over the same period during which the WML fails. This discrepancy is inherent in their construction which involves wider brackets than the WML's top and bottom deciles, providing some insulation from the above factors through industry diversification.

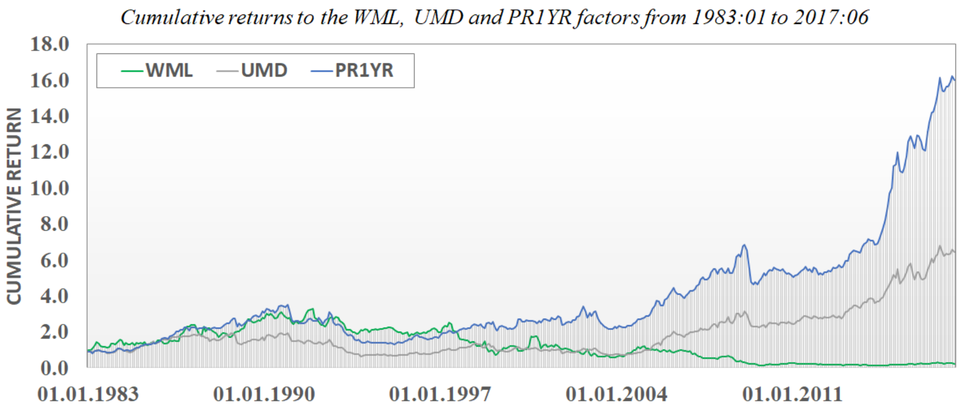


Figure 12: Cumulative returns to the WML, UMD and PR1YR factors on the OSE from 1983:01 to 2017:06.

In particular, we mentioned previously that Daniel & Moskowitz (2016) found a dramatic increase in beta for the loser portfolio during bear markets, while the winner portfolio beta slightly decreases. This effect on beta is more pronounced for outer deciles, indicating that being long the top decile and short the bottom decile exacerbates this issue. Figure 13 below illustrates how the betas of the winner and loser portfolios of the OSE have evolved over the last decade. We see that the winner beta has experienced some significant dips while the loser beta has appreciated, and substantially so over the last few years. By contrast, the UMD and PR1YR's wider brackets mitigate this problem. Similar arguments can be made in terms of the aforementioned more negative factor loading of the short-term interest rate on past losers as well as for the effect of the illiquidity gap inflating loser firms' returns. These phenomena will be more prevalent in the extreme deciles, repressing the WML while the UMD and PR1YR appear to avoid these issues altogether.

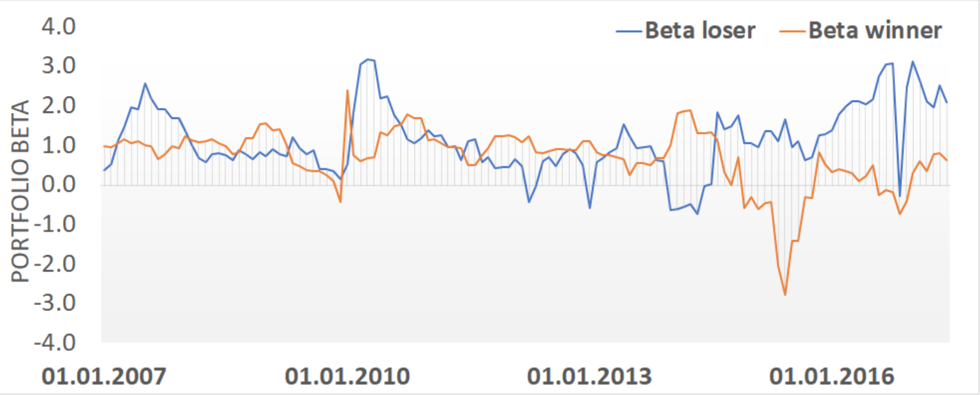


Figure 13: Evolution of beta for past winners and losers on the OSE from 2007 to 2017.

Also in relation to their wider brackets, a setback for the WML will be harder to recuperate from in terms of cumulative return than is the case for the UMD and PR1YR which can rely on more stocks to better shield them from drops and contribute to a quicker recovery. The larger brackets also reduce the idiosyncratic risk which the WML is more prone to. More specifically, considering the heavy concentration in oil related firms in conjunction with these likely being part of the winner portfolio more often than not, the top 10 percent bracket will likely be far more exposed to the negative oil price shock than the UMD and PR1YR, increasing the relative blow it experiences as well as the time it takes to recuperate the losses resulting from the price shock.

7.4 International evidence

Following our study of momentum in the Norwegian stock market we decided to extend our analysis to look at how the momentum strategy generally performs abroad. The international momentum evidence available to us is the PR1YR factor, which we obtained from Kenneth French's data library[8]. In order to get a clearer picture of how momentum works globally we consider momentum returns in the largest continents around the world, including Europe, Japan, the US and the global market overall. Figure 14 shows the performance of the momentum factors both in the Norwegian market and abroad.

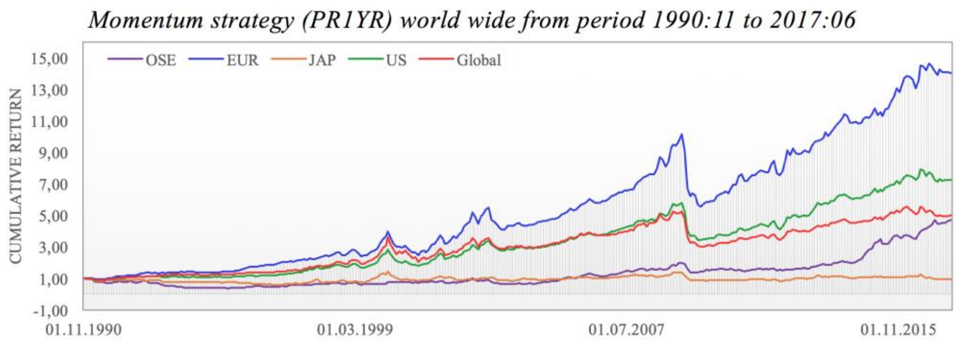


Figure 14: The cumulative returns to momentum worldwide. The return data is from 1990:11 to 2017:06.

Aside from Japan, Norway has consistently had a lower cumulative return than the other regions. It is evident from the comparatively minor drop following the financial crisis that momentum on the OSE is shielded from the brunt of financial crises to some extent, as we mentioned previously. An obvious consequence of this is that Norway also then misses out on the same substantial upside that momentum in the other regions subsequently enjoyed. Moreover, Chan, Hameed & Tong (2000) show that return continuation is stronger following an increase in trading volume. Seeing as the other regions are significantly larger and more linked with one another, the OSE presumably cannot compete with the level of turnover on these exchanges. Trading activity on the OSE subsided considerably after 2008 and stabilized at a much lower

[8] The developed market factor of momentum uses the momentum breakpoints for the four regions to allocate the stocks of these regions to the global portfolios. The independent 2x3 sorts on size and momentum produce six value-weighted portfolios; SL, SN, SW, BL, BN, and BW where S and B indicate small and big while L, N, and W indicate losers, neutral and winners (bottom 30%, middle 40%, and top 30%), respectively. The factor is the equal-weighted average of the returns for the two winner portfolios for a region minus the average of the returns for the two loser portfolios, which can be found in Kenneth French's data library:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_developed_mom.html

level (Ødegaard, 2018: p. 8), which explains why the increase from that point on has been more gradual than for the other regions.

Table 6: Descriptive statistics of the plain- vs the risk-managed momentum strategies on the OSE and abroad.
The statistics are computed from the PR1YR momentum strategy, which is the only international evidence on momentum we have available. The PR1YR from the Norwegian stock market is obtained from Professor Bernt Arne Ødegaard's online data library. The rest of the momentum data is computed in the same fashion as the PR1YR, and is obtained from Kenneth French's data library. The average return, standard deviation, Sharpe ratio and information ratio are in annualized terms. The information ratio is computed using the plain momentum strategy as a benchmark. It does not depend on the targeted volatility of the risk-managed momentum strategy as it is divided by its respective standard deviation. The return data is from 1990:01 to 2017:06.

Statistics	OSE (Pr1yr)		Europe		Japan		Global ex-US		Global	
	Pr1yr	Pr1yr*	Pr1yr	Pr1yr*	Pr1yr	Pr1yr*	Pr1yr	Pr1yr*	Pr1yr	Pr1yr*
Maximum	15,00 %	12,73 %	14,00 %	25,46 %	15,00 %	14,85 %	13,00 %	19,60 %	18,00 %	16,66 %
Minimum	-16,00 %	-7,41 %	-26,00 %	-25,46 %	-20,00 %	-21,00 %	-23,00 %	-16,97 %	-24,00 %	-12,25 %
Mean	8,81 %	10,10 %	11,58 %	24,80 %	1,92 %	4,22 %	8,73 %	22,19 %	7,35 %	18,49 %
Standard deviation	16,40 %	11,06 %	13,92 %	17,72 %	15,56 %	15,55 %	12,42 %	18,11 %	13,61 %	16,85 %
Kurtosis	1,14	0,31	7,32	3,78	2,57	2,96	6,59	0,64	6,81	0,58
Skewness	-0,30	0,38	-1,23	-0,01	-0,39	-0,63	-1,04	0,07	-0,97	0,09
Sharpe ratio	0,54	0,91	0,83	1,40	0,12	0,27	0,70	1,23	0,54	1,10
Information ratio	NaN	1,13	NaN	0,78	NaN	0,30	NaN	0,81	NaN	0,92

Table 6 above displays descriptive statistics for the plain momentum strategy (PR1YR), and the risk-managed version (PR1YR*). As previously mentioned, this risk-managed strategy uses the realized variances from the previous six months to scale the exposure to the strategy in order to have constant volatility over time. We use the same target volatility of 12 percent as before. Implementing risk management significantly improved the average annualized return in every market, including on the OSE. The return doubled in every market and almost tripled in the US market. Standard deviation was reduced in the Norwegian and Japanese stock markets, while it increased in Europe, the US and globally. The risk and return tradeoff as measured by the Sharpe ratio improved significantly in every market when managing the risk. Risk management proves especially helpful when it comes to strategies with higher-order risk. Excess kurtosis improved significantly in every market except for in Japan, where the momentum strategy tends to be unsuccessful (Assness, 2011; Chaves, 2012). The plain momentum strategy usually has a negative skewness, indicating crash risk. However, when scaling the portfolio to have constant exposure to the strategy, skewness improved and even turned positive in almost all of the markets except for in Japan where it almost doubled, making it even worse.

8. Conclusion

Managing risk yields an overall improvement for strategies facing higher-order risk, such as the momentum strategy. Scaling the volatility to have constant risk over time has proven to work both abroad and in the relatively smaller Norwegian stock market. However, implementing the strategy in real time will be considerably more challenging in Norway, due to the unreliability of the ex ante information required. As mentioned in the discussion of our data, the OSE has evolved immensely over the course of our sample period. Changes in the composition of the exchange through inclusions and exclusions of stocks as well as the evolution of ownership concentration have a big impact on the resulting portfolios of the strategy when the exchange is small to begin with. The decile portfolios are particularly prone to being undiversified, hence the risk components of the WML strategy on the OSE are far more unpredictable than those of the PR1YR, whose wider brackets ensures a better chance of diversified portfolios. This rendered the results pertaining to the PR1YR more respectable and comparable to the WML that Barroso & Santa-Clara (2015) used.

The results of our study echo Barroso & Santa Clara's (2015) recognition of the fact that momentum has exhibited a very poor performance over the last decade or so. They attribute this to the high frequency of high-risk episodes that have occurred during this period, which serve to neutralize the momentum effect. However, the WML in the Norwegian stock market was already failing several years before the financial crisis even came to pass, thus it was more of a final nail in the coffin rather than a prominent reason for its initial degradation. The downward trajectory dates back to at least a decade prior, and the financial crisis appears to have merely kept it down as well as prevented it from rebounding. This makes it difficult to interpret our strategy's ability to withstand the crisis as there are clearly more factors at play. Future research should look to other stock exchanges of similar magnitude to the OSE in order to better determine whether the deteriorating performance of the WML portfolio can be attributed to the relatively illiquid nature of the stock exchange, rather than being a product of previously discussed characteristics particular to the OSE and the Norwegian economy at the time.

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Appendix

Cumulative return:

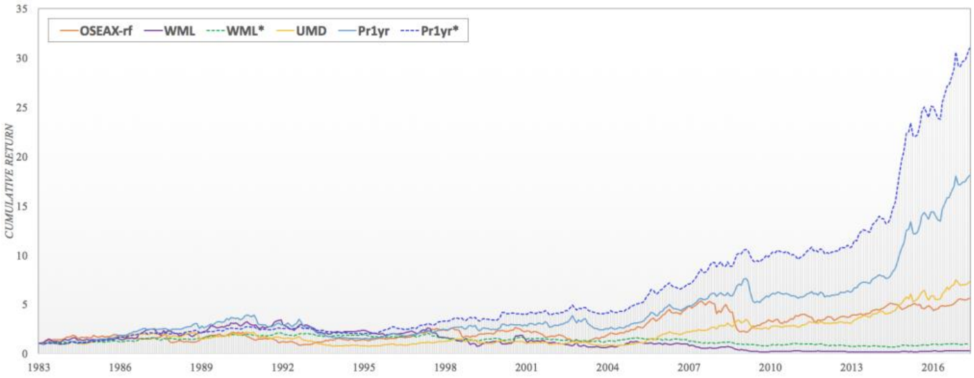


Figure 15: Cumulative return (incl. UMD) from 1983:01 to 2017:06.

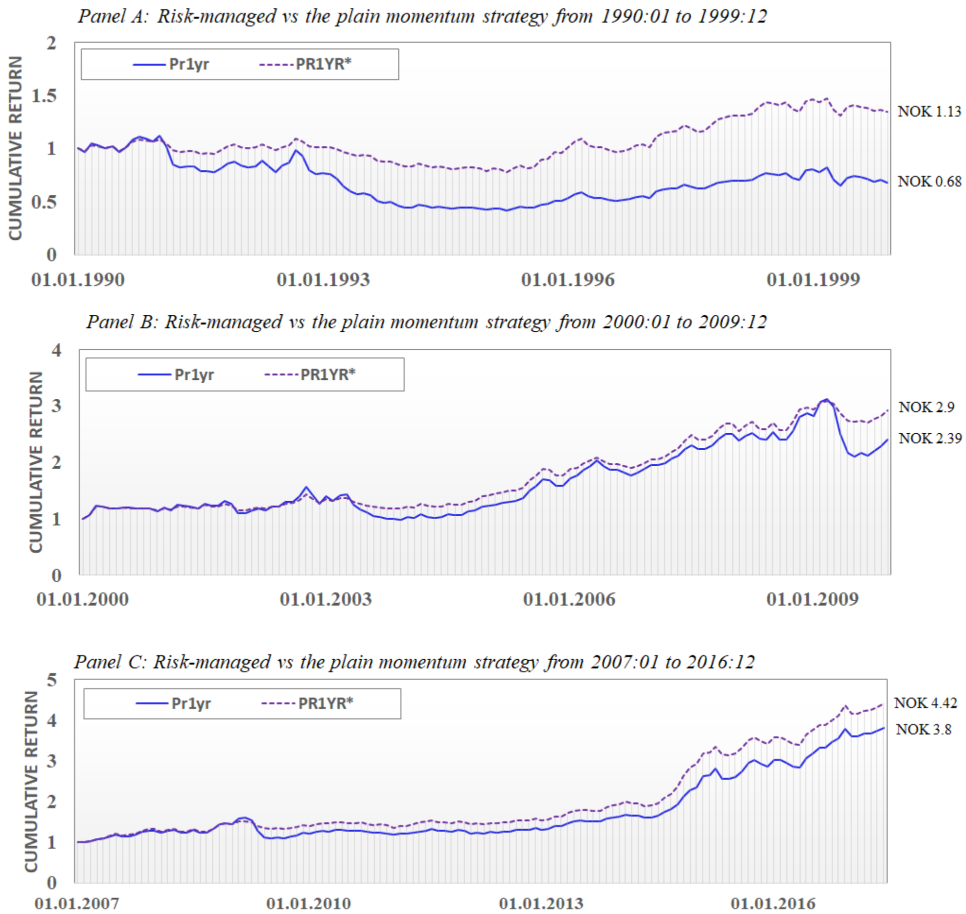
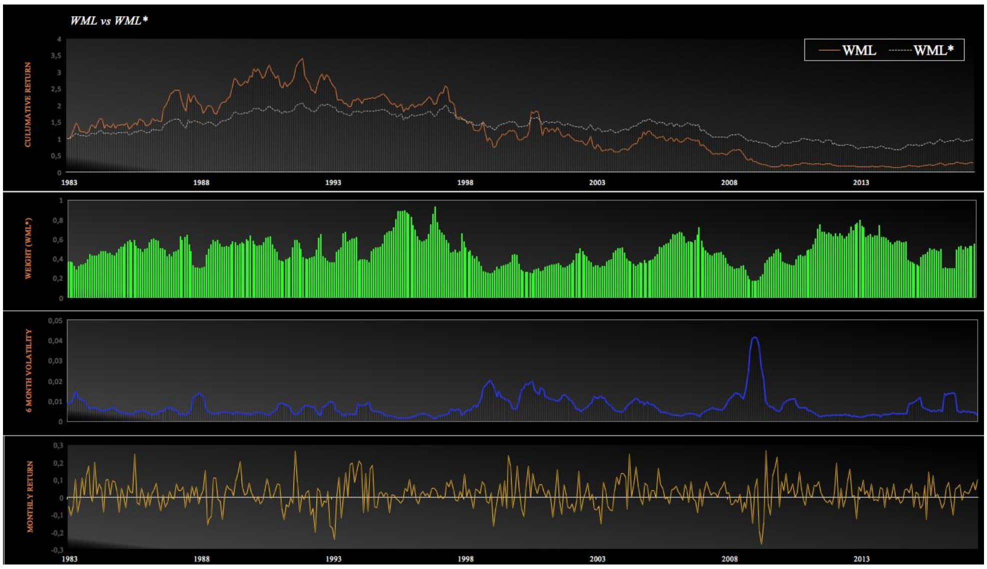


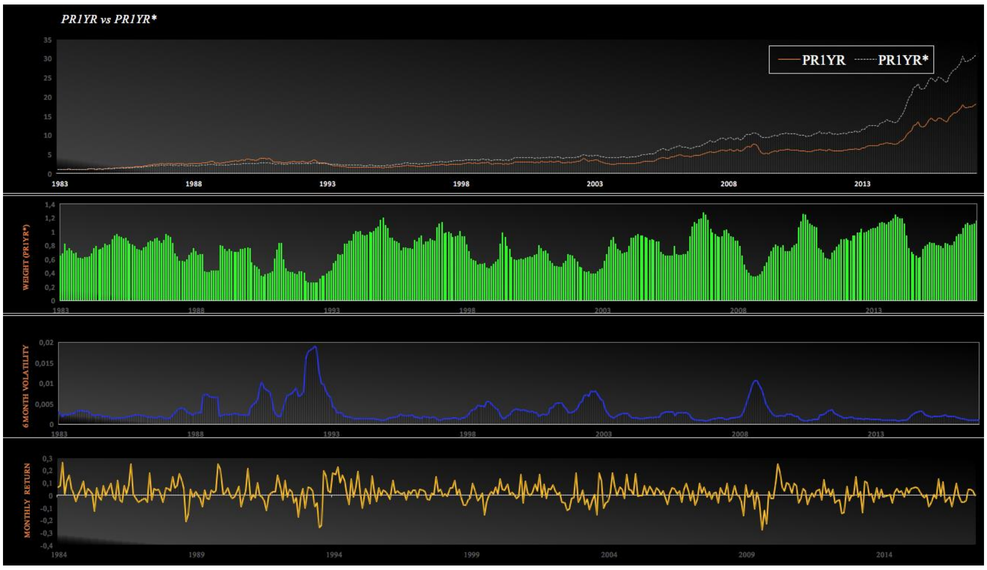
Figure 16: Cumulative return of the Carhart PR1YR factor versus the risk-managed version. The figure illustrates the cumulative return from the most relevant time periods. Panel A displays the period of 1990:01 to 1999:12, panel B shows 2000:01 to 2009:12 and panel C shows 2007:01 to 2016:12.

Overview of momentum strategies:

Panel A: *WML vs WML**



Panel B: *PR1YR vs PR1YR**



Figue 17: Momentum's performance from 1983:01 to 2017:06. The figure illustrates the performance of the momentum strategies. First off is a comparison of the plain momentum strategies and their risk-managed versions in terms of cumulative returns. The green chart illustrates the weights of the risk-managed strategies, which is followed by the six-month realized volatility of the plain momentum illustrated in blue. Finally, the yellow graph represents the monthly return. All the variables are in monthly terms.

Correlation with the market:

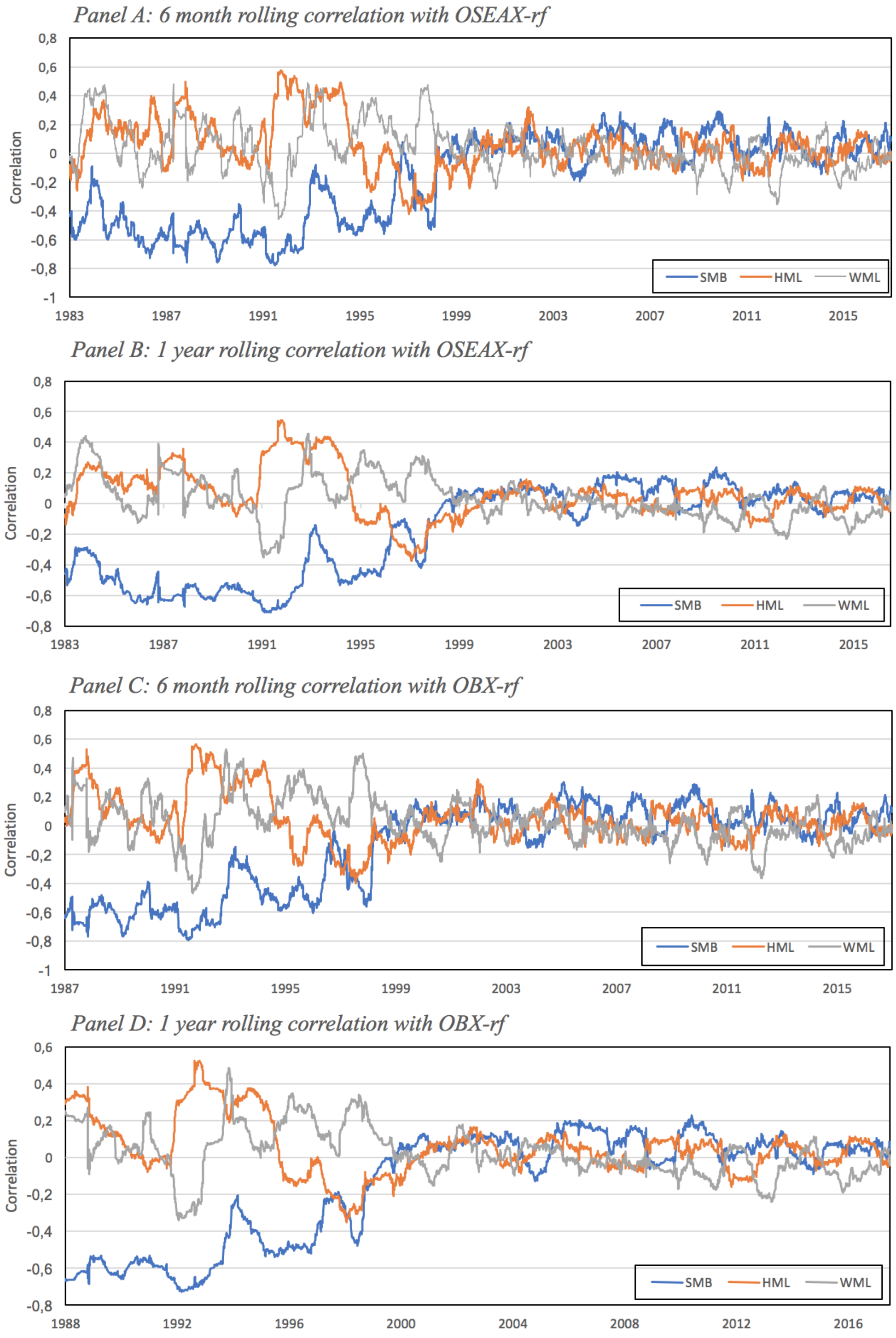


Figure 18: Rolling correlation with the market. Graphical illustration of the rolling correlations, where panels A and C display the six-month rolling correlation. Panels B and D display the one-year rolling correlation with the OSEAX and the OBX, respectively. The correlation of OSEAX-rf spans 1983:01 to 2017:06. The correlation of OBX-rf spans 1987:01 to 2017:06.

Density:

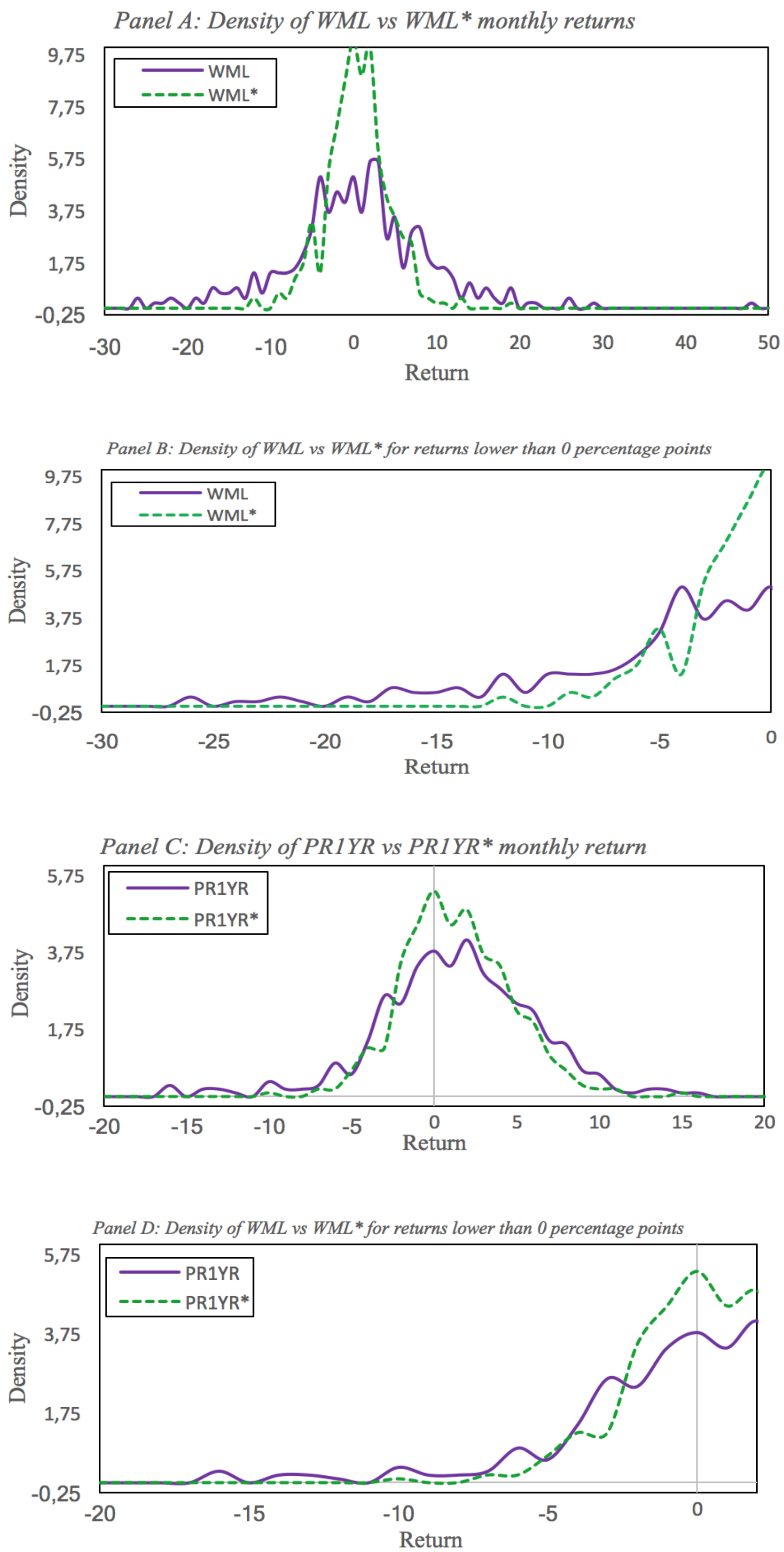


Figure 19: Density of the plain vs. risk-managed strategies. The figure represents the density of the plain vs. risk-managed strategies in more detail. The frequency between intervals is reduced from five (shown in figure xx in the paper) to, which gives us more detail of how the return is distributed. Panels A and C show the density of the WML and PR1YR, both plain and risk-managed versions. Panels B and D show the density of the WML and PR1YR below zero for both the plain and risk-managed versions.

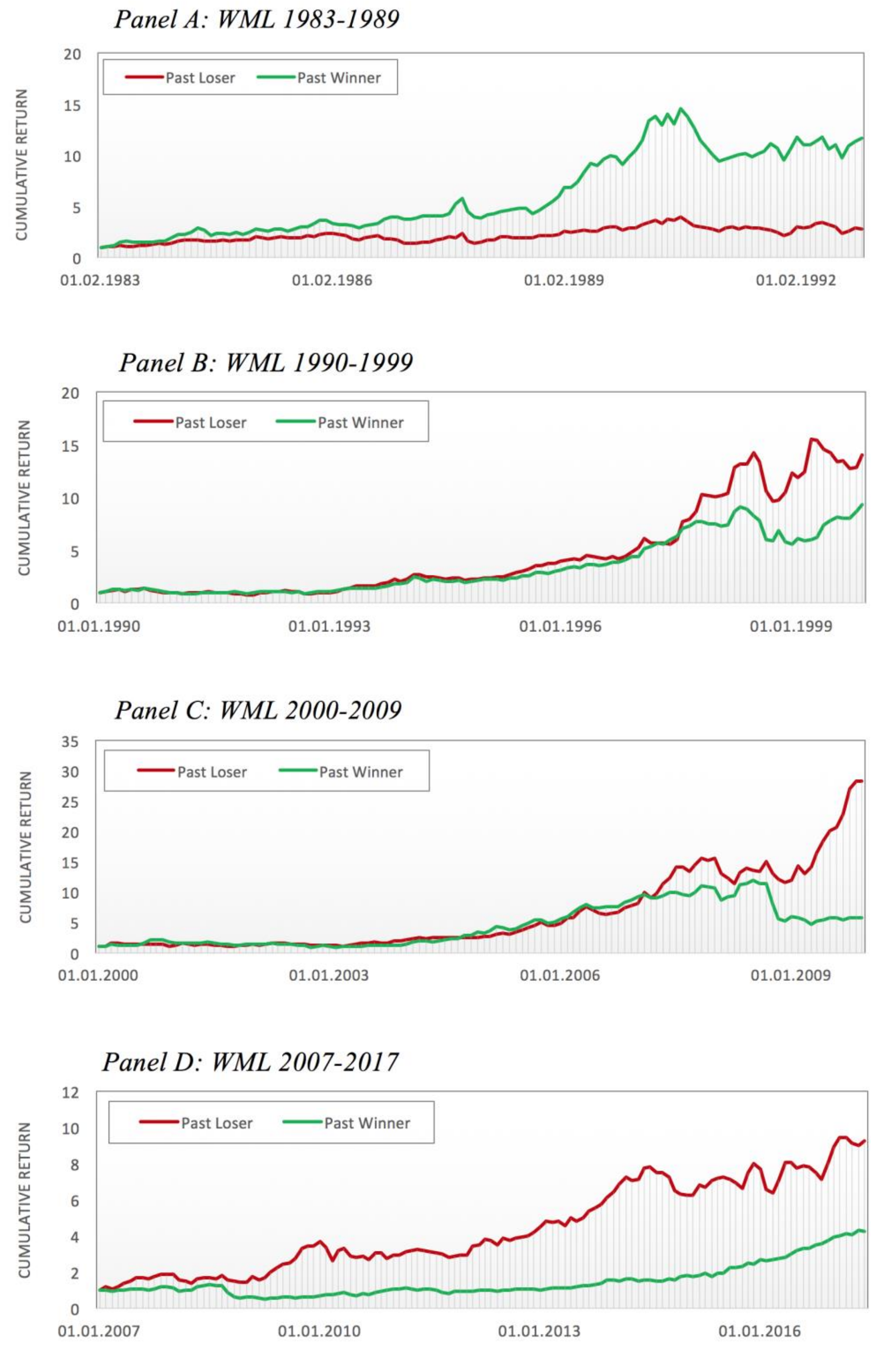


Figure 20: Cumulative performance of winners and losers from 1983:01 to 2017:06. Panel A shows the cumulative return from period 1983:01 to 1989:12, panel B shows from 1990:01 to 1999:12, panel C shows 2000:01 to 2009:12 and panel D shows 2007:01 to 2017:06.

Extended period

Because we want to compare the momentum strategy with the benchmark, they need to cover the same time period. Since the data of the benchmark is only available from 04.01.1983 to 30.06.2017, the plain momentum data has to be cut to match the same period. Hence, in the first section (0.1) of the code for the strategy we define our daily return matrix to include the date, oseax-rf, SMB, HML and the WML from 04.01.1983 to 30.06.2017. We do the same for the monthly return in section 0.2, where the data is given as the return on the last day of each month (31.01.1983 to 30.06.2017).

When running the code in matlab, Matlab produces “NaN” variables in periods three to seven, which shortens our data by an additional five observations. This is due to the fact that the monthly six-month rolling realized variance (RV_monthly_6M) is involved in the computation of the risk-managed momentum strategy (WML*). The momentum strategy requires an estimation of the daily six-month rolling realized variance (RV_daily_6M), which is calculated from the previous six months (126 trading days) of daily returns. This forces the RV_daily_6M variable to start at period 127 (07.07.1983), which in turn forces the RV_monthly_6M to be six months shorter, resulting in a five-period shorter WML*.

To solve this problem, we extend the data of the plain momentum strategy by 126 trading days in the mom_daily_ose.mat file, starting from 08.07.1982. When adding an additional 126 periods it is necessary to redefine our structuring of the daily and monthly return matrices in order for the strategy to be consistent. However, it is not necessary to add additional values for other variables such as oseax-rf, SMB, HML or RF because, contrary to WML, the other variables do not require any computation involving their own previous values. Hence, the redefined daily and monthly return matrices look as illustrated in figure 21 below.

Date	OSEAXRF	SMB	HML	WML
19820708	NaN	...	NaN	$x_{4,1}$
⋮	⋮	⋱	⋮	⋮
19830104	NaN	...	NaN	$x_{4,126}$
19830103	$x_{1,127}$	$x_{2,127}$	$x_{3,127}$	$x_{4,127}$
⋮	⋮	⋮	⋮	⋮
20170630	$x_{1,T}$	$x_{2,T}$	$x_{3,T}$	$x_{4,T}$

Date	OSEAXRF	SMB	HML	WML
19820731	NaN	...	NaN	$x_{4,1}$
⋮	⋮	⋱	⋮	⋮
19821231	NaN	...	NaN	$x_{4,6}$
19830131	$x_{1,7}$	$x_{2,7}$	$x_{3,7}$	$x_{4,7}$
⋮	⋮	⋮	⋮	⋮
20170630	$x_{1,T}$	$x_{2,T}$	$x_{3,T}$	$x_{4,T}$

Figure 21: Daily return matrix from section 0.1 and monthly return matrix from section 0.2 of the code for the strategy, where T represents the number of total observations which has increased from 8655 to 8781 days and from 414 to 420 months.

After adjusting the extended data to fit the return matrices, Matlab produces six additional values for RV_monthly_6M. This then results in six additional values for WML* which, when compared to the result before the extension of the data, is exactly the same as the value from period 14, corresponding to the same date as in the non-extended case as illustrated in figure 22 below. By extending the data we obtain six additional values, from row eight through to row thirteen, filling in the six missing months of the WML*.

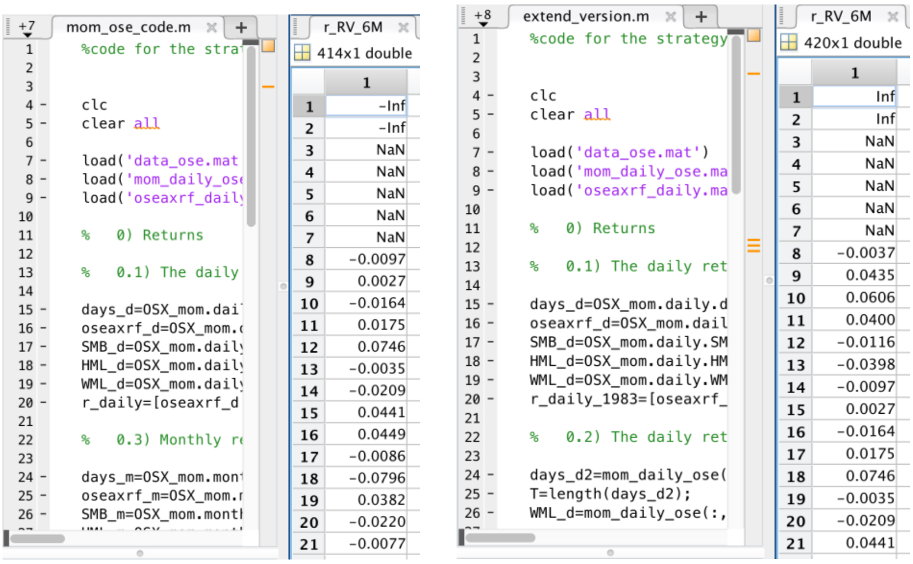


Figure 22: Comparison of the plain data set and the extended data set.

Matlab

1. Code for the strategy:

```
%code for the strategy
clc
clear all

load('data_ose.mat')
load('pr1yr_daily_ose.mat')
load('mom_daily_ose.mat')
load('oseaxrf_daily.mat')


%   0) Returns:
%   0.1) The daily returns

days_d=OSX_mom.daily.date;
oseaxrf_d=OSX_mom.daily.oseaxrf;
SMB_d=OSX_mom.daily.SMB;
HML_d=OSX_mom.daily.HML;
WML_d=OSX_mom.daily.WML;
pr1yr_d=OSX_mom.daily.PR1YR;

r_daily_1983=[oseaxrf_d SMB_d HML_d WML_d pr1yr_d]; r_daily_1983=[days_d r_daily_1983];

%   0.2) The daily returns

days_d2=mom_daily_ose(:,1);
T=length(days_d2);
WML_d=mom_daily_ose(:,11)-mom_daily_ose(:,2);
pr1yr_d=pr1yr_daily_ose(:,2);

r_daily=NaN(T,6);
start=127;
r_daily(start:T,:)=r_daily_1983;
r_daily(:,5)=WML_d;r_daily(:,6)=pr1yr_d;r_daily(:,1)=days_d2;

%   0.3) Monthly returns

days_m=OSX_mom.monthly.date;
L=6+414;
oseaxrf_m=NaN(L,1);
starts=7;

oseaxrf_m(starts:L,1)=OSX_mom.monthly.oseaxrf;
SMB_m=OSX_mom.monthly.SMB;
HML_m=OSX_mom.monthly.HML;
WML_m=OSX_mom.monthly.WML;
pr1yr_m=OSX_mom.monthly.PR1YR;
rf_m=OSX_mom.monthly.RF;
r_monthly=[oseaxrf_m SMB_m HML_m WML_m pr1yr_m]; r_monthly=[days_m r_monthly];

control_reg_WML=regstats(WML_m(7:420,1),[oseaxrf_m(7:420,1) SMB_m(7:420,1) HML_m(7:420,1)]);
control_reg_pr1yr=regstats(pr1yr_m(7:420,1),[oseaxrf_m(7:420,1) SMB_m(7:420,1) HML_m(7:420,1)]);


%   1) Beta and realized variances

RV_daily_1M=NaN(length(days_d2),6); RV_daily_1M(:,1)=days_d2;
RV_daily_3M=NaN(length(days_d2),6); RV_daily_3M(:,1)=days_d2;
RV_daily_6M=NaN(length(days_d2),6); RV_daily_6M(:,1)=days_d2;
Beta_daily_6M=zeros(length(days_d2),3); Beta_daily_6M(:,1)=days_d2;


%1.1.) The rolling window Realized Variances (RV) and beta
for n=127:length(days_d2)
   RV_daily_1M(n,2:6)=sum(r_daily(n-21:n-1,2:6).^2);
   RV_daily_3M(n,2:6)=sum(r_daily(n-63:n-1,2:6).^2)/3;
```

```
    RV_daily_6M(n,2:6)=sum(r_daily(n-126:n-1,2:6).^2)/6;

end
for n=127+126:length(days_d2)
    %WML
    b_WML=regress(r_daily(n-126:n,5),[ones(127,1) r_daily(n-126:n,2)]);
    Beta_daily_6M(n,2)=b_WML(2);
    %Pr1yr
    b_pr1yr=regress(r_daily(n-126:n,6),[ones(127,1) r_daily(n-126:n,2)]);
    Beta_daily_6M(n,3)=b_pr1yr(2);
end

%1.2.) monthly frequency
LL=length(days_m);
RV_monthly_1M=zeros(LL,6); RV_monthly_1M(:,1)=days_m;
RV_monthly_3M=zeros(LL,6); RV_monthly_3M(:,1)=days_m;
RV_monthly_6M=zeros(LL,6); RV_monthly_6M(:,1)=days_m;
Beta_monthly_6M=zeros(LL,3); Beta_monthly_6M(:,1)=days_m;

for n=1:length(days_m)
    Beta_monthly_6M(n,:)=Beta_daily_6M(find(days_d2<=days_m(n),1,'last'),:);
    RV_monthly_1M(n,:)=RV_daily_1M(find(days_d2<=days_m(n),1,'last'),:);
    RV_monthly_3M(n,:)=RV_daily_3M(find(days_d2<=days_m(n),1,'last'),:);
    RV_monthly_6M(n,:)=RV_daily_6M(find(days_d2<=days_m(n),1,'last'),:);
end

%   2) The scaled portfolio (targeted volatility at 12% annualized)

r_RV_6M_WML=0.12*r_monthly(:,5)./sqrt(12*[0;RV_monthly_6M(1:419,5)]);
r_RV_6M_pr1yr=0.12*r_monthly(:,6)./sqrt(12*[0;RV_monthly_6M(1:419,6)]);
r_RV_6M=[days_m r_RV_6M_WML r_RV_6M_pr1yr];

%   3) Table 1 summary statistic
 F=14:420; %starts from obs.14...
 %(31.01.1987 is the first observation available wrt. past volatility WML)
table1=NaN(5,7);

 for n=1:5
    x=r_monthly(F,n+1);
    x=summary(x);
    table1(n,:)=x(1:7);
 end

 %   4) Runs the AR(1) on realized variances (table 2 )

table_AR1=zeros(5,8);

 for n=1:5
    k=find(RV_monthly_1M(:,1)==19830228,1,'first');
    x=RV_monthly_1M(k:420,n+1);x_=RV_monthly_1M(k-1:419,n+1);
    a=regstats(x,x_);
    table_AR1(n,1)=a.beta(1);table_AR1(n,3)=a.beta(2);
    table_AR1(n,2)=a.tstat.t(1);table_AR1(n,4)=a.tstat.t(2);
    table_AR1(n,5)=a.rsquare*100;
    table_AR1(n,6)=OOS_r2_mom(x,x_,120)*100;
    table_AR1(n,7)=mean(sqrt(12*RV_monthly_1M(k:420,n+1)))*100;
    table_AR1(n,8)=std(sqrt(12*RV_monthly_1M(k:420,n+1)))*100;
 end

 %  5) Table 3 economic performance

 A=[r_monthly(:,5) r_RV_6M(:,2) r_monthly(:,6) r_RV_6M(:,3)];
 IR=@(x,y)sqrt(12)*mean(x-y)/std(x-y);%function to get the information ratio

 table3=NaN(9,4);
 table3(1:8,1)=summary(A(F,1));
 table3(1:8,2)=summary(A(F,2));
 table3(1:8,3)=summary(A(F,3));
 table3(1:8,4)=summary(A(F,4));
 table3(9,2)=IR(A(F,2)/std(A(F,2)),A(F,1)/std(A(F,1)));
```

```
table3(9,4)=IR(A(F,4)/std(A(F,4)),A(F,3)/std(A(F,3)));

 %  6) Table 4 the risk decomposition
%6.1 Panel A: using 6-months realized variance (68 obs)
row=@(x)[x.beta(1) x.tstat.t(1) x.beta(2) x.tstat.t(2) x.rsquare];
F={RV_monthly_6M(13:6:420,5) RV_monthly_6M(13:6:420,6) RV_monthly_6M(13:6:420,2) ...
   Beta_monthly_6M(13:6:420,2).^2 ...
   Beta_monthly_6M(13:6:420,3).^2 ...
   (Beta_monthly_6M(13:6:420,2).^2).*RV_monthly_6M(13:6:420,2) ...
   (Beta_monthly_6M(13:6:420,3).^2).*RV_monthly_6M(13:6:420,2) ...
   RV_monthly_6M(13:6:420,5)-...
   (Beta_monthly_6M(13:6:420,2).^2).*RV_monthly_6M(13:6:420,2)...
   RV_monthly_6M(13:6:420,6)-...
   (Beta_monthly_6M(13:6:420,3).^2).*RV_monthly_6M(13:6:420,2)};

table4_A=NaN(9,6);

for n=1:9
   x=F{n};
   a=regstats(x(2:length(x)),x(1:length(x)-1));
   r_oos=OOS_r2_mom(x(2:length(x)),x(1:length(x)-1),20);
   table4_A(n,:)=[row(a) r_oos];
end

%6.2 Panel B: Using 3-months realized variance (176 obs)
row=@(x)[x.beta(1) x.tstat.t(1) x.beta(2) x.tstat.t(2) x.rsquare];
G={RV_monthly_6M(13:3:420,5) RV_monthly_6M(13:3:420,6) RV_monthly_6M(13:3:420,2) ...
   Beta_monthly_6M(13:3:420,2).^2 ...
   Beta_monthly_6M(13:3:420,3).^2 ...
   (Beta_monthly_6M(13:3:420,2).^2).*RV_monthly_6M(13:3:420,2) ...
   (Beta_monthly_6M(13:3:420,3).^2).*RV_monthly_6M(13:3:420,2) ...
   RV_monthly_6M(13:3:420,5)-...
   (Beta_monthly_6M(13:3:420,2).^2).*RV_monthly_6M(13:3:420,2)...
   RV_monthly_6M(13:3:420,6)-...
   (Beta_monthly_6M(13:3:420,3).^2).*RV_monthly_6M(13:3:420,2)};

table4_B=NaN(9,6);

for n=1:9
   x=G{n};
   a=regstats(x(2:length(x)),x(1:length(x)-1));
   r_oos=OOS_r2_mom(x(2:length(x)),x(1:length(x)-1),20);
   table4_B(n,:)=[row(a) r_oos];
end

% Tabel 5 1983:07 to 2011:12 (to match with the data from Barroso & Santa
% Clara) runn the replication of B&S to get their result from the same
% period*****
row=@(x)[x.beta(1) x.tstat.t(1) x.beta(2) x.tstat.t(2) x.rsquare];
F={RV_monthly_6M(13:6:354,5) RV_monthly_6M(13:6:354,6) RV_monthly_6M(13:6:354,2) ...
   Beta_monthly_6M(13:6:354,2).^2 ...
   Beta_monthly_6M(13:6:354,3).^2 ...
   (Beta_monthly_6M(13:6:354,2).^2).*RV_monthly_6M(13:6:354,2) ...
   (Beta_monthly_6M(13:6:354,3).^2).*RV_monthly_6M(13:6:354,2) ...
   RV_monthly_6M(13:6:354,5)-...
   (Beta_monthly_6M(13:6:354,2).^2).*RV_monthly_6M(13:6:354,2)...
   RV_monthly_6M(13:6:354,6)-...
   (Beta_monthly_6M(13:6:354,3).^2).*RV_monthly_6M(13:6:354,2)};

table4_A=NaN(9,6);

for n=1:9
   x=F{n};
   a=regstats(x(2:length(x)),x(1:length(x)-1));
   r_oos=OOS_r2_mom(x(2:length(x)),x(1:length(x)-1),20);
   table4_A(n,:)=[row(a) r_oos];
end
```

1.1 Summary statistics:

```
%Produces a 1-by-8 vector of summary statistics for a series of monthly
%excess returns. Set option to 1 if the data is annual

function b=summary(x,option)
b=zeros(1,8);
x=x(isnan(x)==0);

if nargin<2
    option=0;
    b(1,1)=max(x)*100;
    b(1,2)=min(x)*100;
    b(1,3)=mean(x)*1200;
    b(1,4)=std(x)*sqrt(12)*100;
    b(1,5)=kurtosis(x)-3;
    b(1,6)=skewness(x);
    b(1,7)=b(1,3)/b(1,4);
    b(1,8)=length(x);
end

if option==1
    b(1,1)=max(x)*100;
    b(1,2)=min(x)*100;
    b(1,3)=mean(x)*100;
    b(1,4)=std(x)*100;
    b(1,5)=kurtosis(x)-3;
    b(1,6)=skewness(x);
    b(1,7)=b(1,3)/b(1,4);
    b(1,8)=length(x);
end
```

1.2 OOS R-squared:

```
%This function returns the OOS R square for a regression of y on x and an
%in sample period of k observations.

function r=OOS_r2_mom(y,x,k)
n=length(y);
x=[ones(length(x),1) x];
meansq_error=zeros(length(x),1);
regsq_error=zeros(length(x),1);

for z=k:length(x)
    b=regress(y(1:z-1),x(1:z-1,:));
    y_hat=x(z,:)*b;
    avg=mean(y(1:z-1));
    meansq_error(z)=(y(z)-avg)^2;
    regsq_error(z)=(y(z)-y_hat)^2;
end
MSE=sum(meansq_error(k:n));
RSE=sum(regsq_error(k:n));

r=1-RSE/MSE;
```

1.3 Table 6, International evidence:

```
%Computes the results shown in table  of the paper 'Managing the risk of momentum on the Oslo stocks exchange’
clear all
clc

load('mom_daily_org.mat')%daily momentum returns
load('mom_monthly_org.mat')%monthly momentum returns

%1)Get the realized variance for each country

T_days=length(mom_daily_org);
```

```
RV_6=NaN(size(mom_daily_org));

%Performs corrections on probable:

for n=127:T_days
    a=mom_daily_org(n-126:n,:);
    a=a.^2;
    b=nansum(a)/6;
    RV_6(n,:)=b;
end

RV_6(:,1)=mom_daily_org(:,1);

clear n a

%2)Organize and get scaled returns

YYYYMM=mom_monthly_org(:,1);
YYYYMM_days=floor(RV_6(:,1)/100);

    %Note: Daily data starts at 1980:01 while monthly data starts at
    %1971:01

    r_norm=mom_monthly_org;
    RV_6_M=NaN(size(r_norm));
    T_months=length(r_norm);

for n=1:T_months
    k=find(YYYYMM_days==YYYYMM(n),1,'last');
    RV_6_M(n,:)=RV_6(k,:);
end

r_scaled=0.12*r_norm./sqrt(12*[zeros(1,size(r_norm,2));RV_6_M(1:T_months-1,:)]);
r_scaled(:,1)=r_norm(:,1);

%3) Organize performance report

table1_performance_normal=zeros(7,8);
table1_performance_scaled=zeros(7,8);

r_scaled(r_scaled==Inf)=NaN;
r_scaled(r_scaled==-Inf)=NaN;
%This is because of missing data and to avoid NaN in final results

IR=@(x,y)sqrt(12)*nanmean(x-y)/nanstd(x-y);%function to get the information ratio
table_IR=NaN(8,1);

for n=2:6
    a=isnan(r_scaled(:,n));
    start=find(a==0,1,'first');
    a=summary(r_norm(start:T_months,n));
    table1_performance_normal(n,:)=a;

    b=summary(r_scaled(start:T_months,n));
    table1_performance_scaled(n,:)=b;


table_IR(n,1)=IR(r_scaled(start:T_months,n)/nanstd(r_scaled(start:T_months,n)),r_norm(start:T_months,n)/nanstd(r_nor
m(start:T_months,n)));
end

% Table performance of just the 5 major markets

table5=NaN(10,8);
table5(1:2:10,1:7)=table1_performance_normal(2:6,1:7);
table5(2:2:10,1:7)=table1_performance_scaled(2:6,1:7);
table5(2:2:10,8)=table_IR(2:6,1);
```