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The performance of (risk-managed) momentum strategies during the Covid-19 pandemic

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Abstract

There is extensive literature available on momentum strategies, the ability of these strategies to realize an excess return and the vulnerability of the strategies to 'momentum crashes'. Risk-managed momentum strategies aim at making traditional momentum portfolios more robust and preventing these momentum crashes. This paper studies the performance of (risk-managed) momentum strategies in the period from 1972-2020 within the US stock market. With special attention to the period surrounding the recent market crashed caused by the uncertainty that the Covid-19 pandemic introduced into the markets. Alterations are presented that aim to improve on the risk-managed momentum strategies originally introduced by Barosso & Santa-Clara (2015). Over the full sample period four out of five traditional momentum portfolios and all twelve of the risk-managed momentum portfolios realize a significant excess return over the market index. Risk-managed momentum strategies realize an excess return over their traditional momentum counterparts over the full sample period. The risk-managed momentum strategies still outperform their traditional momentum counterparts during the Covid-19 period, but the excess return was not significantly impacted by the pandemic. The performance of risk-managed momentum can be improved by reducing the lookback period to three months. This lookback period is used to scale the portfolios exposure to the market. The reduction of the lookback period results in a more dynamic strategy which realizes an excess return over the original risk-managed momentum strategy with a six-month lookback period.

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1 Introduction

The momentum anomaly was first introduced by Jegadeesh & Titman (1993). In their paper *'Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency'* they report on a trading strategy with a positive risk-adjusted return that uses the past performance of stocks to predict future performance. By looking at the at the past twelve-month return of different stocks they conclude that prior winners outperform prior losers. Strategies that use the phenomenon that recent winners outperform recent losers generate returns in excess of the market. This is described as the momentum anomaly. The momentum anomaly has become one of the most prominent anomalies found in financial markets. The main reason that the momentum anomaly has gotten such a high level of attention within financial literature is the fact that it directly violates the efficient market hypothesis (EMH) introduced by Eugene F. Fama (1970). Under the EMH all available information is incorporated in an assets price immediately. Therefore, it is impossible for past prices to have any predicting value on future price developments under this assumption. The information that these past prices contain is already incorporated into the price. Therefore, finding positive risk-adjusted returns realized by a strategy that uses that exact phenomenon directly challenges the EMH.

Traditionally in finance it was assumed that markets and the majority of the economic agents active in it behave in a rational way. Meaning, economic agents are unbiased and make the best possible decisions for themselves (Baltussen, 2009). But over the past 20 years using behavioural sciences to understand financial markets has gained popularity. Behavioural biases are seen as the driver behind the underreaction of prices. This underreaction of prices lies at the foundation of the momentum anomaly (Jegadeesh & Titman, 1993). The underreaction of prices can partly be explained by the anchoring and representativeness bias (Barberis, Shleifer, & Vishny, 1998). When prices initially underreact to a certain type of information this makes for predictable price developments. Predictability of prices allow for a profitable trading strategy.

However, momentum strategies are known to endure the occasional crash (Daniel & Moskowitz, 2016). These crashes mainly occur during periods when market volatility is extremely high. These momentum crashes eliminate a big part of the excess returns realized by momentum portfolios and cause many investors to deem momentum strategies too risky. In February 2020 the market endured a crash due to the economic uncertainty caused by the worldwide Covid-19 pandemic. This situation strongly represents the high volatility panic state of the market in which conventional momentum strategies experience crashes and realize negative returns.

Barosso & Santa-Clara (2015) introduce a trading strategy that aims at being more robust to momentum crashes. Their findings indicate that the occasional crashes traditional momentum strategies endure are predictable. They present a risk-managed momentum strategy that uses the forecasted volatility to scale the portfolios exposure to the market. This should make the strategies more robust during a market crash like the most recent one caused by the Covid-19 pandemic. The volatility is forecasted using a six-month lookback period. This means that the returns from the past six-months are used to estimate the future volatility. The volatility forecast is then used to scale the portfolios exposure to the market. In practice this means that when a high level of volatility is forecasted stocks are sold and the exposure to the market is reduced. On the contrary, if a low volatility is forecasted more stock is bought to increase market exposure. If the strategy functions as intended, the volatility forecast picks up on spikes in market volatility and reduces the portfolios exposure to the market before a traditional momentum portfolio would have endured a crash.

The aim of this paper is to answer the following two main research questions about (risk-managed) momentum strategies:

- '*How did (risk-managed) momentum strategies perform in the period from 1972 to 2020?'* and
- *'How did (risk-managed) momentum strategies perform during the Covid-19 pandemic period that included the market crash induced by the uncertainty that Covid-19 introduced into the economy?'*

To answer these questions this study will assess the performance of both the conventional and risk-managed momentum strategies. Is it possible to realize returns in excess of the market during the 1972 to 2020 sample period? And how does the performance of risk-managed momentum strategies during the corona pandemic compare to the performance of conventional momentum strategies during this period? By comparing traditional- to risk-managed momentum portfolios the ability of risk-managed momentum strategies to reduce the crash sensitivity of momentum strategies can be tested.

Moreover, this study aims to extend on the paper by Barosso & Santa-Clara (2015) by altering the risk-managed momentum strategy introduced in their paper. The goal is to study the effects of these alterations and see if overall improvement of the strategy is possible. By performing these alterations this paper intents to answer the following sub-questions that further support the main research questions:

- *'How does increasing the target volatility of the original risk-managed momentum strategy impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'*
- *'How does using a different lookback periods to forecast volatility impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'*

To answer these questions alterations are made to both the lookback period and target volatility of the original risk-managed momentum strategy. Changing the lookback period influences the period of past returns used for forecasting future volatility. Extending this period results in a more conservative forecast while reducing this period makes the forecast more dynamic. The adjustments to the target volatility influence the way the volatility forecasts are translated to market exposure.

For the full sample period, 1972-2020 the results of this paper indicate that momentum strategies still produce positive risk-adjusted excess returns within the US stock market. For the 1972-2020 period the factor portfolio reports the highest significant annualized excess return of 9.2%. During the full sample period the risk-managed momentum portfolios achieve their goal of reducing momentum crashes leading to these portfolios outperforming the traditional momentum portfolios. A time-series regression model shows that the risk-managed momentum portfolios realize excess returns ranging between 1.5% and 6.6% over their traditional momentum counterparts.

The Covid-19 pandemic period does not significantly change the excess returns compared to the pre-Covid period. However, the results found do provide proof that during the Covid-19 period the risk-managed momentum portfolios also realize an excess return over their traditional momentum counterparts.

This paper intends to improve the risk-managed momentum strategy. Alterations are made to both the target volatility used for scaling market exposure, and the lookback period that is used to forecast the future volatility. The alterations to the lookback period are made to improve the volatility forecast while the alteration to the target volatility changes how this volatility forecast is used. The strategy with a reduced lookback periods achieves the goal of improved performance. The reduction of the lookback period results in a more dynamic strategy. This strategy reacts faster to changes in the market conditions resulting in a better overall return.

The possibility of improvement on an already strong performing momentum portfolio is a further challenge to the EMH.

The upcoming sections are structured as follows: in section 2 the relevant literature is discussed, and the hypotheses are introduced. Thereafter in section 3, the data, portfolio construction, and the methodology are discussed. In section 4 the results are analyzed. Section 5 contains the discussion. Finally, in section 6 the conclusion is presented.

2 Literature Review

In this section relevant literature, the research questions that this study aims answer, and the hypothesis that are going to be tested are discussed. First, the Efficient market hypothesis form traditional finance is introduced in section 2.1. Thereafter, section 2.2 discusses the literature on behavioural finance. This is followed by the relevant literature on (risk-managed) momentum in sections 2.3 and 2.4. Finally, in section 2.5 the hypotheses are introduced and the motivation for the selection of the research questions and hypotheses is discussed.

2.1 Efficient market hypothesis

The efficient market hypothesis (EMH) was introduced by Eugene F. Fama (1970) and quickly became one of the most widely accepted financial theories. This hypothesis states that in an efficient market prices fully reflect all available information (Fama, 1970). In a situation where all information is incorporated into prices immediately, prices follow a random walk (Malkiel, 2003; Samuelson 1965). Prices immediately adjust to new information and the arrival of new information is unpredictable. Meaning that the change of price from tomorrow is only influenced by new information that arises tomorrow and is independent of the change in price of today. The unpredictability of new information causes prices to develop randomly. Under this assumption it is impossible research stocks and use the gathered information to find assets that are undervalued. The main consequence of market efficiency is that 'prices are right'. This has strong consequences and would mean that under the efficient market hypothesis it is impossible for trading strategies that are only based on information currently available to realize returns in excess of the market, also described as no free lunch (Barberis & Thaler, 2002; Fama, 1970).

The efficient market hypothesis exists in three forms that differ in the amount of information that is deemed available to all investors. This distinction was introduced in an unpublished paper by Harry Roberts (1967). In the weak form, the set of available information only includes historical prices. For the semi-strong form, also publicly available information, like earnings announcements are common knowledge and therefore are incorporated in the price. The strong form states that prices reflect all information, both public and private. Between these three forms, the difference in information that is deemed to be available to investors influences the ability for an investor to realize excess returns over the market. Under the strong form all information is included, and no level of research or inside-knowledge can help the investor predict price movements and realize an excess return over the market. For the semi strong form of the EMH private information is not immediately included in the prices. An investor that has access to information not readily available to the public can use this information to raise their returns above those of the market. Under the weak form EMH only the information from historical prices in immediately included into the market prices. Meaning that an investor that performs research and uses information like fundamentals or earnings announcements can realize an excess return over the market.

Under the assumptions of the efficient market hypothesis market prices contain all available information and rational agents work together to correct mispricing's present in the market. Rational agents correct mispricing's in the market through arbitrage. Arbitrage is defined as the simultaneously purchasing and selling two equal or essentially equal assets for different prices in a way that results in immediate profit for the investor (Sharpe & Alexander, 1990). The most straightforward example of arbitrage is when a stock is priced differently in two different markets. An investor can buy the stock in the market with the lower price and sell the same stock in the market where the stock price is higher for an immediate and risk-free profit. When multiple investors use an arbitrage opportunity this causes prices to return to the 'correct' value.

In traditional finance these assumptions are used to try and gain an understanding of financial markets. But when taking a critical look at these assumptions it can be observed that they often do not hold. A possible way to reject the efficient market hypothesis is to find a wrongfully priced asset in the market. This would violate the hypothesis since mispricing's should not persist under the EMH. Even though it is difficult to prove a mispricing there are examples where a clear violation of the law of one price is found. This can for example be seen in dual listed stocks that have different prices on the two exchanges or equity carve-outs that lead to a negative stub[1] (Lamont & Thaler, 2003). The assumptions of the efficient market hypothesis also imply that economic agents are rational, process new information correctly and make normatively acceptable decisions (Barbaris & Thaler, 2003). These assumptions are strongly challenged in the field of behavioural economics.

Even though the efficient market hypothesis has been extremely important in the development of financial theory it is becoming increasingly controversial. Both the theoretical and empirical evidence is being challenged by an increasing number of authors. Sewel (2011) performed an extensive literature review on the history of the EMH and concluded that more

[1] The definition of a negative stub is the situation where stock A, that gives you the right to stock B, is priced lower than stock B itself. This might happen in the case of a spin-off or different type of corporate restructuring.

than half of the papers reviewed don't support the EMH with the majority of the papers critical towards the EMH written after 1990. Schleifer (2000) concludes that the key mechanisms that are supposed to reach efficiency, like arbitrage are probably much weaker than they are according to the traditional efficient market theorist.

2.2 Behavioural Explanations

Over the past two decades the paradigm has shifted towards using behavioural sciences to understand the financial markets. As described by Tversky & Kahneman (1974, 1979) people face different types of limitations. For example, the preferences of people differ from rational agents and individuals fail to update their beliefs correctly. People's preferences don't always follow the predictions of expected utility theory and people form their beliefs about probabilities using certain heuristics. This leads to a variety of behavioural biases. The fact that investors suffer from a variety of biases causes irregularities on financial markets with under- and overreaction of prices being the most prominent. Previous research has shown an underreaction of prices in a 1-12 month horizon (Chan, Jegadeesh & Lakonishok, 1995; Grinblatt & Han, 2005; Jegadeesh & Titman, 1993) which could be caused by anchoring and the conservativeness bias (Barberis, Shleifer, & Vishny, 1998). The conservativeness bias causes investors to stick to what they belief about an asset and update their beliefs to slowly when new evidence presents itself. A different reason that is brought forward for the initial underreaction is the slow diffusion of news (Hong & Stein, 1999). EMH has the assumption that new information is incorporated into prices immediately. In reality it takes time for information to reach all investors through a variety of channels. Also, the disposition effect is mentioned as a possible cause of the underreaction of prices to new information (Frazzini, 2006; Odean, 1998). The disposition effect is the tendency of investors to hold on to stocks on which have lost value and sell stocks which have increased in value. When positive news about an asset is released and this asset increases in value investors want to sell the asset, this temporarily depresses the price. Following the same logic, if bad news about an asset is released the asset will decrease in value which causes investors to be reluctant to sell. The reluctance to sell initially slows down the decrease of the assets price.

On the contrary, when looking at a 3-5 year horizon, overreaction of prices is observed (De Bondt & Thaler, 1985). This can be attributed towards overconfidence, the confirmation bias (Daniel, Hirshleifer, & Subrahmanyam, 1998) and the representativeness bias. Overconfidence causes people to overestimate their ability to gather and interpret information. The confirmation bias causes people to interpret or favor information that supports their own personal beliefs. The combination of overconfidence and the confirmation bias causes the overreaction in stock prices. Overconfident investors overreact to initial new information about a stock and overweigh new information that confirms this high valuation causing stock prices to overreact. The representativeness bias causes people to see trends in random data. Investors will mistake an upward return history as a trend and therefore expect the value of an asset to continue to grow. For this reason, investors assign a higher value to that certain asset which causes the price to overreact (Barberis, Shleifer, & Vishny, A model of investor sentiment, 1998). In a more general sense, investor sentiment can also be the cause of overreaction (Baker & Wurgler, 2007). If a large group of investors is optimistic about a stock this drives the price above its fundamental value.

The mispricing's created by irrational investors can persist due to limits to arbitrage. In theory arbitrage strategies should be risk-free. In practice, strategies designed to arbitrage mispriced assets are both risky and costly. This is caused by the presence of fundamental risk, noise trader risk, short-sale constraints, and transaction costs (Barberis & Thaler, 2003: Shleifer & Vishny, 1997). Arbitrageurs protect themselves against negative news about the fundamentals of a stock they buy by shorting a substitute stock. Fundamental risk arises because for most mispriced securities there is no perfect substitute. This makes it impossible to build a risk-free long-short arbitrage portfolio. Noise trader risks refers to the phenomenon where traders buy a stock because the stock is rising in price and getting attention. This drives the price of an asset even further away from its fundamental value. This could lead to the arbitrageur having to cancel the short position at a loss. Short-sale constraints include the fact that there must be investors willing to lend out their shares. On top of that, there can be legal constraints preventing certain assets so be sold short. The transaction costs are relevant because on top of the normal transaction costs an extra cost for borrowing a stock might be incurred. For these reasons, this type of strategy is only conducted by a small number of specialized investors (Jones & Lamont, 2001; Lamont, 2012; Ljungqvist 2014). In extreme market conditions when mispricing's are the largest, the limits to arbitrage are the biggest. When volatility is high, and prices are driven far away from there fundamental values, the chance that an arbitrageur has to liquidate his position at a loss increases. Therefore, arbitrageurs who should correct these mispricing's are unable or unwilling to do so.

The irrational agents, affected by a variety of heuristics and biases, in combination with limits to arbitrage can be seen as a reason the efficient market hypothesis does not hold. This is supported by the fact that there are many anomalies reported in financial markets. Over the past years research has reported a high number of anomalies present in financial markets. Many of these anomalies are unable to be explained when using traditional asset pricing models as the Capital Asset Pricing Model (CAPM) or the three-factor model introduced by Fama and French (Chen, Novy-Marx, & Zhang, 2010)

2.3 Momentum

The momentum anomaly is one of the most prominent anomalies found in the financial markets. The momentum anomaly entails the relationship between an assets historical and future return. Due to this relationship the historical returns of an asset have predictive power over the asset's future returns. The reason that this anomaly has drawn such a high level of academic effort and attention is the fact that it directly violates the weakest form of the efficient market hypothesis. In the weak form of the EMH information about historical prices is immediately included into prices. If asset prices respond to new information immediately and with the right amount then past returns should not be able to predict future performance (Ehsani & Linnainmaa, 2019) and can't be used to build a trading strategy realizing excess returns over the market (Subrahmanyam, 2018).

The momentum anomaly was first reported on by Jegadeesh & Titman (2013). The authors study monthly return data from CRSP on US stock over the 1965-1989 period. With this data a variety of portfolios are constructed with a holding periods that vary between three and twelve months. To measure 'momentum' each stock is assigned a momentum statistic. This momentum statistic defined as the returns over the past twelve months. This statistic is then used to rank the stocks from relatively good past performance to relatively bad past performance. They find that strategies that buy stocks with a good past performance and sell stocks with poor past performance generate significant positive risk-adjusted returns. In the period following this paper momentum returns have been proven over a broad variety of periods and asset classes. At first most studies focused on momentum within the US stock market. But later, significant positive risk adjusted momentum returns were also found within different asset classes and geographic regions (Asness, Moskowitz, & Pedersen, 2013). Asness et al. (2013) find positive momentum return premia for five asset classes: global individual stocks, global equity indices, currencies, and commodity futures. These results are found for a broad range of regions like the United States, continental Europe, the United Kingdom and Japan. More recent papers also still report on the possibility to realize excess risk-adjusted return by using momentum strategies. (Baltussen, Swinkels, & Vliet, 2020). Baltussen et al. (2020) incorporate statistical measures to account for p-hacking and still finds significant excess returns using a very extensive dataset over the period from 1800 to 2016.

An important distinction to make when writing about momentum is the distinction between cross-sectional and time-series momentum. Time series momentum was introduced by Moskowitz, Ooi & Pedersen (2012). Time series momentum is related to the more traditional cross-sectional momentum, but it is a different phenomenon. Where cross-sectional momentum focusses on the performance of an asset relative to other related assets, time series momentum solely focuses on an asset's own past return. The excess returns realized by using a time series momentum strategy have been at the core of the efficient market debate. It can be argued that time series momentum matches the predictions of many prominent behavioural asset pricing theories (Moskowitz, Ooi, & Pedersen, 2012). Most of these theories focus on a single asset and can therefore be directly linked to time series momentum instead of cross-sectional momentum. However, the strategies discussed in this paper rank stocks based on their relative performance and are therefore associated to the cross-sectional momentum anomaly.

2.4 Risk-managed momentum

The exceptional performance of momentum strategies does come with an occasional large portfolio drawdown (Daniel & Moskowitz, 2016). A portfolios drawdown is defined as the percentual difference between a portfolios peak value and subsequent lowest value before a new peak is reached. In 2009 a momentum high-minus-low portfolio realized a negative return of -73.42% in a period of just three months. Such large crashes can't be compensated by the exceptional returns realized over other periods and scare away investors with any kind of risk aversion (Barosso & Santa-Clara, 2015). These exceptional drawdowns occur during the market recovery following a market crash. There have been different authors that have tried to account for this crash risk and build a more robust strategy. It is argued that introducing a total return momentum strategy, where the time varying market exposure of momentum strategies is hedged produces more stable momentum returns (Grundy & Martin, 2001). The total return strategy differs from the traditional momentum strategy in the way 'winners' and 'losers' are defined. Stocks are ranked on their cumulative return in excess of the risk-free rate instead of their total return. However, a later study by Daniel & Moskowitz (2016) has shown that this method does not avoid momentum strategy crashes. A paper containing a more successful attempt of making momentum strategies more robust to momentum crashes was written by

Barosso & Santa-Clara (2015). They find that the crash risk of momentum strategies is highly variable over time and can be predicted. The past realized volatility of a portfolio can be used to forecast future volatility. Since momentum crashes occur at the times that the market is highly volatile this prediction can be used to protect the portfolio from those crashes. In their paper they analyze High-minus-low momentum portfolios by using the risk factors introduced by Fama & French (1992). By looking at the realized variance in relation to volatility, annual return, and Sharpe ratio they conclude that the variance can be used as a predictor of momentum crash risk. While there isn't a clear trade-off between risk and return for the market (Ghysels, Santa-Clara, & Volkanov, 2005) there is a negative relation between risk and return for momentum. Due to this relation this risk can be used as a predictor for the momentum crashes. Barosso & Santa-Clara (2015) do this by forecasting variance and using this forecast to scale the portfolios exposure to momentum. The variance is forecasted using a lookback period of 126 trading days. The average of the returns over these 126 days are used to calculate the variance forecast. This variance forecast in combination with a target volatility is then used to scale the market exposure of the risk-managed momentum strategies. When the forecasted volatility is relatively high the exposure to the market is decreased, meaning that stocks are sold. Vice versa, when the forecasted volatility is relatively low the exposure to the market is increased meaning more stock is bought. The aim of this procedure is to create portfolio returns with a more constant volatility over-time. The results of Barosso & Santa-Clara (2015) show that risk-managed momentum strategies almost completely eliminate crash risk and practically double the Sharpe ratio of traditional momentum strategies. These results are confirmed using international evidence. While the transaction costs are not taken into account in the results of this paper the authors do conclude that these costs need to be 40% higher than for traditional momentum to remove the significance of the results. The results of the paper by Barosso & Santa-Clara (2015) pose a new challenge to theories attempting to explain momentum returns. Their findings and the extraordinary returns the strategy they created realizes are even more puzzling than those of traditional momentum strategies.

2.5 Hypotheses

In this section the hypotheses associated to the research questions are introduced. This research aims to answer two main research questions about the performance of (risk-managed) momentum strategies in general combined with sub-questions that extend on the risk-managed momentum strategy introduced by Barosso & Santa-Clara (2015). Momentum strategies have proven to underperform in the period following a market crash. During the ongoing Covid-19 pandemic the market has endured a quick crash followed by a rapid recovery. These are the exact circumstances in which momentum strategies have proven to underperform in the past. This paper aims at answering the following two main research questions:

- '*How did (risk-managed) momentum strategies perform in the period from 1972 to 2020'*
- *'How did (risk-managed) momentum strategies perform during the Covid-19 pandemic period that included the market crash induced by the uncertainty that Covid-19 introduced into the economy?'*

By answering these two questions this research extends on the many papers that analyze momentum strategies and test their profitability across multiple periods, regions, and asset classes. This research will extend the period up until the present and see if a positive risk-adjusted return is still found.

The second question is aimed at studying whether the general findings on momentum strategies combined with the findings of Barosso & Santa-Clara (2015) still hold during the corona pandemic market crash. The goal is to find out whether risk-managed momentum strategies performed better and experienced smaller drawdowns during this period of extreme volatility when compared to traditional momentum strategies. To answer these questions the definition of the Covid-19 period is important. There is no exact date that can be put on the start of the Covid-19 pandemic and the date chosen will always be arbitrary. For this research the timeline from the World Health Organization (WHO) is used to determine the start of the pandemic and the above mentioned 'Covid-19 period'. The first report by the WHO of the novel coronavirus outbreak in China dates from January 9th, 2020. This date is chosen as the start of the pandemic period. Since at the time of writing the pandemic is still ongoing the end date is equal to the end date of the full sample period, 31-12-2020.

The two main research questions will be assessed using the following four hypotheses.
Hypothesis 1: Momentum strategies are able to generate a positive excess return compared to the S&P 500 benchmark market index the period 1972-2020.
Hypothesis 2: Risk-managed momentum strategies are able to generate a positive excess return compared to the S&P 500 benchmark market index in the period 1972-2020.
Hypothesis 3: Risk-managed momentum strategies generate a positive excess return compared to using traditional momentum strategies during the pre-Covid period. (1972-2019)

Hypothesis 4: The excess return of Risk-managed momentum strategies over traditional momentum strategies increases in the period of the Covid-19 pandemic. (2020)

This research will use the following sub-questions to further support the main research questions and extend on risk-managed momentum strategies. These sub-questions are aimed at studying different ways of improving a risk-managed momentum strategy and are formulated as follows:

- *'How does increasing the target volatility of the original risk-managed momentum strategy impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'*
- *'How does using a different lookback periods to forecast volatility impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'*

For the above-mentioned sub-questions, the strategy originally introduced by Barosso & Santa-Clara (2015) is altered in ways that make it react differently to changes in market volatility.

The first alteration is made to the target volatility. The change in target volatility causes the strategy to make bigger adjustments in market exposure following changes in forecasted volatility. In practice this results in more stocks being bought or sold following a change in the market conditions. This way the strategy allows for a higher portfolio volatility. The relation between volatility and return has often been described as difficult to estimate (Glosten, Jagannathan, & Runkle, 1993). But there are studies reporting on a negative relation between volatility and return for individual stocks (Blitz & Vliet, 2007). Since this strategy adjustment will impact both the domain of gains and losses it is interesting to study what will happen to overall portfolio performance. It will be especially interesting to see how this will interact with the second strategy adjustment, changing the lookback period to forecast volatility.

To answer the final sub-question the lookback period, used for forecasting volatility, is adjusted. Traditionally, the lookback period is 126 days. For this study both the effect of extending and decreasing the length of this lookback period is of interest. When extending the lookback period, the forecasted variance is calculated using the average realized return over a longer period than before. This results in a more conservative forecast that is less dynamic. Since the average over a longer period is taken the most recent observations have a smaller effect on the total estimation. This causes the scaling weights to lag behind the weights of the traditional risk-managed momentum strategy and move over a narrower scale. On the contrary, when decreasing the lookback period, the forecasted variance is calculated using the average realized return over a shorter period than before. This results in a more extreme forecast that is more dynamic. Since the average over a shorter period is taken the most recent observations have a bigger effect on the total estimation. This causes the scaling weights to adjust faster to the changing market conditions than the weights of the traditional risk-managed momentum strategy and cause the weights to move over a broader scale.

The changes made to answer these research questions change the dynamics of the risk-managed momentum strategies and intended to further increase overall portfolio performance. The strategy with a shorter lookback period is more dynamic and reacts faster and more extreme to changing market conditions. For these reasons it can in theory better serve the goal of risk-managed momentum strategies. Reducing the market crash sensitivity of the original momentum strategy.

The strategy with a longer lookback period uses more information to forecast the market volatility and could therefore be more accurate. A more accurate market volatility forecast could in theory improve the protection of the portfolio against momentum crashes.

The sub-questions discussed above will be answered by testing the following hypotheses.

Hypothesis 5: Using a shorter, 3-month, lookback period in a risk-managed momentum strategy will generate an excess return over using the traditional 6-month lookback period for forecasting volatility.

Hypothesis 5B: The excess return of the risk-managed momentum strategy with a 3-month lookback over the risk-managed momentum strategy with the traditional 6-month lookback period increases during the Covid-19 period. (2020)

Hypothesis 6: Using a longer, 12-month, lookback period in a risk-managed momentum strategy will generate an excess return over using the traditional six-month lookback period for forecasting volatility.

Hypothesis 6B: The excess return of the risk-managed momentum strategy with a 12-month lookback over the risk-managed momentum strategy with the traditional 6-month lookback period increases during the Covid-19 period. (2020)

3 Data and Methodology

3.1 Data

For this research observational data is used. The US stock data is retrieved from the Center for Research in Security Prices (CRSP). The CRSP is known for being the most comprehensive database for research on the US stock market. Before any data analysis can be done it is important to determine the ‘stock universe’. The stock universe defines which securities are used in this research. It is important to clearly define the stock universe to be able to retrieve the correct data and to perform proper analysis. For this research a highly liquid stock universe is constructed using the methodology from Asness et al. (2013). Their procedure is almost identical to the way MSCI defines their stock universe for global stock indices. To start, only stocks with share codes 10 or 11 are used. This way the universe is restricted to common stock. This means that closed-end funds, foreign stocks, real estate investment trusts (REITs), financials and American Depositary receipts (ADR’s) are excluded. This is done to ensure the liquidity of the stocks within the stock universe. Trading foreign stocks for an investor operating within the United States has several downsides. Amongst others, these include possible double taxation, more difficult to participate in the market, currency risk and higher transaction fees. ADR’s represent shares of a foreign (non-US) company but are traded on united states stock markets just as regular shares would. This does make it easier for US investors to trade them and eliminates the possibility of higher transaction fees. However, investors might still incur currency conversion fees and the possibility of double taxation remains. REITs also have disadvantages compared to normal Stocks. REITs have low growth potential and are taxed more heavily. For these reasons these specific types of stocks are excluded. Including them could lead to a distortion of the results.

On top of that, at the beginning of each month penny stocks, stocks with a share price lower than $1 are dropped from the sample. Often there is a limited amount of financial information available on the companies represented by these penny stocks making them riskier and more prone to bankruptcy or fraud. This causes there to be less buyers/sellers in the market for these types of stock making them less liquid. Using a highly liquid stock universe is important when back testing trading strategies. This ensures that the strategies tested could actually have been implemented at a certain point in time in the past. Prior research has shown that using a liquid sample of larger companies causes the results found to be more conservative because the momentum effect is smaller for these larger companies. (Stein, Hong, & Lim, 1998)

Using these criteria, the US stock universe consists of daily time-series data from the period 1972-2020. At the beginning of the sample period there are 1120 companies in the sample. In total the stock universe contains 5186 unique companies, and the stock universe contains 1804 companies on average. Further descriptive statistics can be found in appendix 1.

Variables used to perform the stock selection, portfolio construction and the analysis of the portfolio performance are daily and monthly stock closing price, the number of shares outstanding, delisting price, delisting return and share code. These variables will be used to calculate a variety of statistics like returns, market capitalization and past twelve-month return.

As the market index the S&P 500 is used. The S&P 500 contains the 500 largest Companies listed in the United States measured by market capitalization. The S&P 500 is a value weighted index, this way the largest companies have a bigger influence on the total index value. This gives a reliable representation of the situation on the US stock market. For these reasons it is deemed appropriate to use as a proxy for the market within this study. For the risk-free rate the one-month treasury bill yield is used. Treasury bills are considered to be essentialy risk-free since they are backed by the U.S. government

The following section describes how the data will be used to implement the strategies, construct investment portfolios, and analyze their performance.

3.2 Portfolio construction

For the aim of this research 17 portfolios are created. The portfolios are constructed following the methodology from Asness et al. (2013). The momentum measure is constructed following the methodology from the paper by Jegadeesh & titman (2013) that is regarded as the first paper reporting on the profitability of momentum strategies. As the momentum measure, the past 12-month return, is used. To avoid the 1-month reversal effect return of the most recent month is skipped.[2]

Using the momentum measure, the companies within the stock universe are divided into three groups using the 33rd and 66th percentile as breakpoints. This results in three portfolios: low momentum, medium momentum, and high momentum. The stocks within these three portfolios are value weighted using their beginning of the month market capitalization in relation to the total market capitalization. This way the stocks of the larger companies count

[2] a well-documented anomaly that describes a phenomenon where stocks that realize a relatively low (high) return over the last month realize an excess positive (negative) return the following month. This could be caused by liquidity issues (Jegadeesh, Evidence of Predictable Behavior of Security Returns, 1990).

more towards the monthly return. While the stock selection already ensures a liquid set of stocks within our stock universe, value weighting further increases liquidity. Since larger companies are more broadly known there is more supply and demand for these types of stocks making these stocks more liquid. The low- and high momentum portfolios are then used to construct a high-minus-low (HML) spread portfolio. This portfolio represents the spread in returns between the group of companies with relatively high momentum statistics, the group above the 66th percentile, compared to the companies with relatively low momentum statistic, the group below the 33rd percentile. The results of this portfolio can be seen as the result of a long-short strategy where long positions are taken in the high momentum stocks and the low momentum stocks are sold short. Finally, following the methodology of Asness et al. (2013) zero-cost long-short factor portfolios are constructed. In general, factor portfolios are well diversified portfolios that include a broad spectrum of stocks with a varying exposure to a certain risk. In this case, the factor portfolios use all available stocks within the stock universe. This results in a portfolio including stocks with both low and high past twelve-month return. The stocks are ranked using the momentum statistic using the following formula:

$$w_{i,t} = c_t(rank(M_{i,t}) - \sum_i rank(M_{i,t})/N) \quad (1)$$

Where $w_{i,t}$ is the weight of a stock at a certain point in time, c_t is a scaling factor which makes sure the final portfolio is one dollar long and one dollar short and $rank(M_{i,t})$ is the overall rank of the momentum signal from stock i. This results in a portfolio where the sum of all the weights in the universe is equal to zero. This way the portfolio represents a dollar-neutral long short portfolio. Meaning that the amount of money in long and short positions is equal. The return of these portfolios is calculated as follows:

$$r_i = \sum_i w_{i,t} * r_{it} \quad (2)$$

Where r_i is the weighted return of a stock within the factor portfolio, $w_{i,t}$ the weight calculated in formula 1 and r_{it} the return of the stock on a certain point in time.

The risk-managed momentum portfolios are constructed using the methodology from the paper by Barosso & Santa-Clara (2015) that introduces this strategy. The momentum measure used for the risk-managed portfolios is the same as for the traditional momentum portfolio, the past twelve-month return skipping the return of the most recent month. The portfolios differ in the sense that for the risk-managed momentum strategies the forecasted volatility is used to estimate risk and scale the exposure of the portfolios to momentum. The goal of a risk-managed momentum strategy is to make the portfolio more robust during momentum crashes. This is done by estimating momentum risk using a volatility forecast and adjusting the portfolios exposure to momentum accordingly. The authors of the traditional risk-managed momentum paper found a negative relation between past volatility and future Sharpe ratio. Meaning that low performance of momentum strategies can be predicted by using the past volatility to forecast future volatility. The volatility is forecasted using the following formula:

$$\sigma_{for}^2 = 21 \sum_{j=0}^{125} r_{HML}^2 /126 \quad (3)$$

Where σ_{for}^2 is the forecasted monthly variance, and r_{HML}^2 is the return realized by the traditional momentum portfolio squared. The variance forecast is based on the daily returns from the past six trading months. The Average of the returns within this lookback period is used to estimate future volatility. Formula 3 uses a lookback period of 126 days, half a trading year to forecast the volatility. One of the goals of this paper is to study whether using a different lookback period improves the performance of risk-managed momentum strategies. As an extension on the original paper the formula is altered to accommodate for different lookback periods. Formula 3 is altered into the following two formulas:

$$\sigma_{for}^2 = 21 \sum_{j=0}^{62} r_{WMl}^2 /63 \quad (4)$$

$$\sigma_{for}^2 = 21 \sum_{j=0}^{251} r_{WMl}^2 /252 \quad (5)$$

These formulas are identical to the formula from the original paper except for the fact that they take the average over a different period, 3- and 12-months respectively.

After the volatility is forecasted, this forecast is used to scale the exposure to momentum. The goal of the risk-managed momentum strategy is to have constant risk over time instead of the highly variable levels of risk of traditional momentum. To achieve constant risk the exposure to momentum of risk-managed momentum portfolios is scaled using a target volatility. In the traditional methodology a target volatility of 12% is used. Meaning that the exposure to momentum is scaled in a way to result in a future annualized volatility of 12%. Scaling can be done without constrains since both the HML and factor portfolios are zero-cost long short portfolios. Scaling the returns is done by using the following formula:

$$r = \frac{\sigma_{target}}{\sigma_{wml}} \quad (6)$$

Where σ_{target} is the target volatility and σ_{wml} the volatility of the unscaled momentum portfolio. For the construction of the risk-managed momentum portfolios two target volatilities are used. 12% as in the original paper by Barosso and Santa-clara (2015) and 25% as an extension, to allow for a higher volatility. To put these numbers into perspective, the average annualized volatility of the S&P 500 is 15% and the volatility generally stays within the range of 10% to 20%. Using this as a benchmark, the strategies with a 12% target volatility can be seen as a more conservative strategy, with below average volatility. The strategies with a 25% target volatility are regarded as a relatively risky, with above average volatility.

These steps described above result in a total of 17 different portfolios. Five traditional momentum portfolios, HML, factor, Low, medium, and high momentum. And 12 risk-managed momentum portfolios. A factor- and HML portfolio for three lookback periods and two target volatilities, producing 2*3*2 = 12 risk-managed momentum portfolios.

The procedures described above result in multiple daily series of weights for each asset within the different types of portfolios. For this study the portfolios are rebalanced monthly. Meaning that the daily returns are used to calculate the monthly returns and only the portfolio weights for the first day of each month are used. Momentum strategies are known for their complexity and high turnover. Monthly rebalancing is done to ensure that the strategies studied in this paper could have realistically been reproduced without extreme management or turnover cost.

3.3 Performance analysis

The performance of the constructed portfolios over the two different time periods is analyzed in a variety of ways. Multiple regressions are performed to study whether (risk-managed) momentum strategies realize an excess return over the market index. The main variable of interest resulting from these regression are the intercepts. The intercept, generally known as alpha, is defined as the excess return above a benchmark index. To further compare the performance of the (risk-managed) strategies among each other the Sharpe ratios and realized returns of the HML and factor portfolios are compared.

As mentioned above, the realized returns from the low momentum group (the losers) are subtracted from the realized returns from the high momentum group (the winners). This can be seen as a high minus low (HML) long-short strategy. The HML portfolio is studied because it is able to measure the difference in performance between the low- and high momentum portfolios. The factor portfolio has a similar purpose but takes all the stocks within the universe into account. The HML and factor portfolios will also be used to compare the traditional momentum strategies to the risk-managed momentum strategies and to compare the different risk-managed momentum strategies among each other.

The alphas reported are calculated using a time-series regression of the returns realized by the portfolios build using the different strategies, on the market index return (For this research the S&P 500 index is used). The regression formula used is as follows:

$$R_{i,t} - R_{rf,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{rf,t}\right) + \epsilon_{i,t} \quad (7)$$

Where $R_{i,t}$ is the portfolio return series, $R_{rf,t}$ is the risk free rate, α_i is the portfolios alpha, β_i the portfolios beta and $R_{m,t}$ is the market index return series. By using this formula, we get the alpha and beta statistics which identify the performance of a portfolio compared to the market index. The alpha can be defined as the excess return over the market index. The beta contains information about the relation between the portfolio and the benchmark index. A beta of 1 means that the benchmark index and the portfolio follow the same direction with the same volatility. High beta stocks, with a beta higher than 1, are considered riskier since their movements are bigger than the those of the market. This is desirable when the market goes up but means bigger losses when the market goes down. Contrarily low beta stocks, with a beta below 1, are considered less risky and are less volatile than the market.

The beta is especially interesting for this study since momentum portfolio generally have a significant negative beta following bear markets (Grundy & Maritin, 2001). Following a bear market, the high momentum portfolio of a momentum strategy contains low-beta stock while the low momentum portfolio contains high beta stock. Therefore, a momentum HML strategy will go long in low beta stock and short high beta stock. This results in an overall negative beta bet on the market. This can be seen as one the reasons for the momentum crashes during a period where the market rebounds after a crash. The results found in this paper will try and confirm this theory.

A similar regression model is used to compare the performance of the different (risk-managed) momentum strategies with each other. For this comparison the following regression formula is used:

$$R_{i,t}^{RM} - R_{rf} = \alpha_i + \beta_1 * D_{i,t} + \beta_2 * (R_{i,t}^{M} - R_{rf}) + \epsilon_{i,t} \quad (8)$$

Where $R_{i,t}^{RM}$ and $R_{i,t}^{M}$ are the return series of the two (risk-managed) momentum portfolios that are compared. $D_{i,t}$ is the period dummy with the value of 1 from the moment defined as the start of the pandemic, 9th of January 2020, until the end of the sample period and 0 otherwise. The alpha in this regression can be defined as the excess return of the portfolio that has its returns as the dependent variable over the portfolio with its returns as the independent variable during the pre-covid period. $D_{i,t}$ is a dummy variable that has the value of 0 during the pre-covid period and the value of one in the Covid period. For this reason, the $\beta_1$measures the difference in excess return between the pre-Covid and Covid period.

Another statistic that will be used to compare the performance of the different portfolio's is the Sharpe ratio. This ratio was introduced by William F. Sharpe (1966) and has since then gained considerable popularity. A big part the Sharpe ratio's popularity is due to its simplicity. The measure is mainly used to measure the performance of a portfolio and make the comparison between different portfolios. The Sharpe ratio is calculated using the following formula.

$$S(X) = \frac{R_x - R_{rf}}{\sigma_x} \quad (9)$$

Where S(X) is the Sharpe ratio for portfolio X, R_x is the average return of portfolio x, R_{rf} is the risk-free rate and σ_x is the standard deviation of the return of portfolio X. The Sharpe ratio is designed to measure the expected return per unit of risk (Sharpe W. F., 1994). Due to the way the Sharpe ratio is calculated the higher the Sharpe ratio, the better the portfolio performance.

One of the important elements within this study is protecting momentum strategies from the momentum crashes they occasionally occur. The (maximum) drawdown gives insights into the crashes a portfolio has endured and will be taken into consideration for the comparison of portfolio performance. A drawdown is defined as the percentual difference between the subsequential peak value and lowest value of a portfolio. For example, if a portfolio has a peak value of 100$ and the lowest value it reaches before the portfolio surpasses the previous peak 100$ valuation is 80$ the drawdown over this period was 20%. Big drawdowns can have an extremely negative impact on overall strategy performance. Important to keep in mind is that to offset a 10% loss in portfolio value an 11% gain is necessary, but for a 25% loss in value a 34% gain is necessary. This effect only gets more extreme the bigger the initial percentual value lost. The maximum portfolio drawdowns reported in the results table is the biggest drawdown that each portfolio has endured during the full period on which that table reports.

For the average return in excess of the risk-free rate, and the different coefficients following from the regression the t-statistic will be reported to show significance level.

4 Results

4.1 General performance of (risk-managed) momentum

The first two hypotheses relate to the overall performance of the (risk-managed) momentum strategies in relation to the market index. These hypotheses will be assessed using the results reported in the first section of table 1. Table 1 reports on the low, medium, and high momentum portfolios as well as the traditional momentum- HML and factor portfolios. Reported are the monthly mean returns in excess of the risk-free rate, standard deviation, annualized return, Sharpe ratio and the statistics resulting from the time-series regression model alpha and beta.

For the sample period of 1972-2020 the high momentum portfolio outperforms the low momentum portfolio when looking at the average returns with the mean annualized returns in excess of the risk-free rate being 19.1% and 17.8% respectively. Also, when looking at the Sharpe ratios, which next to returns also incorporates risks, the high momentum portfolio outperforms the low momentum portfolio. The zero-investment factor portfolio reports the highest monthly return of 4.7%. The variable of interest for the first hypothesis is alpha. Alpha is used to compare a portfolios performance to a benchmark. For this study the S&P 500 is used as the benchmark index. Alpha is the regressions intercept and can be seen as the excess return. Especially interesting are the alphas of the HML, factor and high momentum portfolios since those portfolios make use of high momentum stocks. With results ranging from 3.6% to 9.2% all the alphas are positive and only the alpha for the HML portfolio is not significant at the 5% level. Since the alphas for the low, medium, high and factor momentum portfolios are significant the evidence supports the first hypothesis '*Momentum strategies were able to generate a positive excess return compared to a benchmark index in the period 1972-2020.*' with regard to those portfolios. Because the alphas for these portfolios are positive the claim can be made that they generate an excess return over the S&P 500 market index over the full sample period. However, the alpha for the high-minus-low spread portfolio is positive but small. On average, the difference in monthly return in excess of the risk-free rate between the low and high momentum portfolio is just 0.1%. This causes the returns realized by the long-short strategy to be low and the Alpha to be insignificant. The small difference between the low- and high momentum portfolio could mean that the momentum effect is not that strong within this stock universe during the full sample period. The comparable return of the low momentum portfolio does come with a relatively high standard deviation. This could mean that, despite the focus one a liquid stock universe, the low momentum portfolio consists of more small high-risk companies that have a good performance over the full sample period.

Table 1, momentum portfolio performance

This table reports the performance of the low, medium, and high momentum portfolios. These portfolios are constructed by using the momentum statistic, the past twelve-month return, to divide the stocks within the stock universe used in this research into three equal groups. The stocks within these groups are value weighted and the portfolios are rebalanced monthly. The performance of the high-minus-low and factor portfolios are also reported. This is done for the two periods of interest. The full sample period and the Covid-19 period. Reported are the mean monthly returns in excess of the risk-free rate, t-statistics of these returns, standard deviation of the returns, annualized returns, annualized Sharpe ratio and the alphas and beta's following from the regression of the portfolio returns on the market index (S&P 500). The t-statistics for these coefficients are also reported. (* = significant on the 10% level, ** = 5% level and *** = 1% level)

		Momentum portfolios				
		L	**M**	**H**	**HML**	**Factor**
01-01-1972 - 31-12-2020	**Mean**	1.5%	1.1%	1.6%	0.1%	4.7%
	(T-statistic)	5.77***	6.15***	7.92***	0.53	2.20
	St dev	6.2%	4.4%	4.8%	4.8%	5.2%
	Return	17.8%	13.4%	19.1%	1.3%	5.7%
	Sharpe	0.83	0.89	1.14	0.08	0.31
	Alpha	4.4%	2.7%	7.8%	3.6%	9.2%
	(T-statistic)	2.59***	3.97***	7.25***	1.46	3.61***
	Beta	1.17	0.94	0.98	-0.20	-0.31
	(T-statistic)	37.5***	74.8***	48.3***	4.45***	6.62***
01-01-2020 - 31-12-2020	**Mean**	3.9%	2.6%	3.5%	-0.3%	-0.8%
	(T-statistic)	1.23	1.28	1.85*	0.19	0.32
	St dev	10.9%	7.1%	6.6%	6.2%	8.9%
	Return	46.7%	31.6%	42.6%	-4.1%	-10.0%
	Sharpe	1.23	1.28	1.85	-0.41	0.26
	Alpha	19.0%	12.5%	24.5%	5.5%	9.0%
	(T-statistic)	1.11	1.67	4.34***	0.29	0.41
	Beta	1.32	0.91	0.87	-0.46	-0.91
	(T-statistic)	6.87***	10.7***	13.5***	2.12*	3.72***

The betas of the low-, medium- and high momentum portfolios, found in table 1, are also interesting to discuss. These portfolios all have significant positive betas with values around 1. The low momentum portfolio contains the stocks with the relatively worse past performance and has a beta of 1.17. This means it can be considered as being 17% more volatile than the market. The high momentum portfolio has the second highest beta followed by the medium momentum portfolios with a beta of 0.94. This is in line with the findings of Jegadeesh & Titman (1993) who also report higher betas for the outmost momentum categories. This can partly be explained by the fact that those categories contain relatively more small companies. With the low momentum portfolio containing the most small companies. Small companies are generally known for being riskier and having higher a beta.

The negative betas reported for both the HML, and factor portfolios can be explained by the differences in beta for the low-, medium- and high momentum portfolios. These strategies both short the low momentum stocks and have long positions in high momentum stocks. Since the low momentum stocks have a higher beta than the low momentum stocks this results in a portfolio that reacts inversely to the market index. The absolute value of the HML and factor portfolio beta are close to zero. This can be explained by the fact that these portfolios both have long- and short positions. These positions cancel out each other. Appendix 2 further visualizes the negative beta of the traditional HML portfolio. Reported are the monthly returns of both the S&P 500 and the HML portfolio. Especially during extreme market conditions, the realized returns move in the opposite direction.

The negative beta for the HML and factor portfolios are seen as one of the reasons momentum strategies experience crashes in periods of rapid market recovery after a market crash (Grundy & Martin, 2001). The betas found for the traditional momentum portfolios confirm the general notion about momentum betas and it will be especially interesting to compare with the betas of the risk-managed momentum strategies.

The performance measures for the risk-managed momentum strategies for the full sample period are reported in table 2. This table includes the results for both the two traditional momentum portfolios and the 12 risk-managed momentum portfolios. Reported are the mean monthly return in excess of the risk-free rate, annualized standard deviation, Sharpe ratio, the alpha and beta following from a time series regression, maximum monthly return, minimum monthly return and the maximum drawdown the portfolio has endured.

The HML portfolio that uses the original risk-managed momentum strategy, a target volatility of 12% and a lookback period of 126 trading days, reports an average annualized return of 2.1%. All the strategies that allow for more volatility by using a target volatility of 25% report even higher average annualized returns. For all the risk-managed factor and risk-managed HML portfolios it holds that they realize a significant positive excess return (alpha) meaning that the results found support hypothesis 2 *'Risk-managed momentum strategies were able to generate a positive excess return compared to a benchmark index in the period 1972-2021'*. Opposed to traditional momentum, the risk-managed momentum portfolios do succeed in generating a significant excess return for the HML portfolio. The Risk-managed HML portfolio uses the same high- and low momentum portfolio as the traditional momentum HML portfolio. The fact that the risk-managed version of the HML does realize an excess return, while the traditional version does not, already shows that scaling the exposure to momentum using forecasted volatility has a positive effect on performance. Further comparison between the traditional- and risk-managed momentum portfolios is made in the following section.

4.2 Risk-managed vs traditional momentum

Table 2 shows the results for all the (risk-managed) momentum portfolios over the full sample period. When comparing the traditional momentum factor and HML portfolios to the variety of risk-managed momentum portfolios the different statistics reported show that the risk-managed momentum strategies outperform the portfolios composed using the traditional momentum strategy.

The annualized return of every risk-managed HML portfolio exceeds the 1.3% annualized return of the traditional momentum portfolio. The risk-managed portfolio that uses a lookback period of three months and a target volatility of 25% to scale the exposure to momentum performs best when solely looking at returns with the average annualized return being 4.7%.

For the factor portfolios a different observation must be made. The risk-managed factor portfolios only outperform the traditional factor portfolios on the aspect of annualized return when a target volatility of 25% is used. The factor portfolio with a three-month lookback period realizes the highest annualized return of 9.7%. The Sharpe ratio can be used to make a comparison that also takes volatility into account. By looking at the Sharpe ratio it can be concluded that all varieties of the risk-managed strategies for both the HML and factor portfolios perform better than the portfolios using the traditional momentum strategy.

Table 2, (risk-managed) momentum portfolio performance, 1972-2020

The performance of the traditional momentum portfolios is compared with the performance of the different risk-managed momentum portfolios. The risk-managed momentum portfolios use the past volatility from the traditional momentum portfolio to determine a volatility forecast. This forecast is then used to scale the portfolios exposure towards momentum. The risk-managed momentum portfolios differ in both the lookback period (six-months, three-months* and a year**) and the target volatility (respectively 12% and 25%). Reported are the mean monthly returns, t-statistics of these returns, standard deviation of the returns, annualized return, annualized Sharpe ratio, the alphas and beta's following from the regression of the portfolio returns on the market index (S&P 500). Including their t-statistics, maximum, minimum monthly returns and the maximum drawdown. (* = significant on the 10% level, ** = 5% level and *** = 1% level)

	Traditional momentum		**Risk-Managed Momentum**											
	HML	**Factor**	**HML (6-Month)**		**Factor (6-Month)**		**HML (3-Month)**		**Factor (3-Month)**		**HML (12-Month)**		**Factor (12-Month)**	
Mean	0.1%	0.5%	0.17%	0.37%	0.35%	0.73%	0.19%	0.39%	0.37%	0.775	0.15%	0.32%	0.33%	0.68%
T-stat	0.53	2.20**	3.14***	3.14***	5.80***	5.80***	3.40***	3.40***	6.29***	6.29***	2.65***	2.65***	5.24***	5.24***
St dev	16.8%	17.9%	1.36%	2.82%	1.33%	3.00%	1.32%	2.75%	1.41%	2.94%	1.38%	2.88%	1.50%	3.12%
Return	1.3%	5.7%	2.1%	4.4%	4.2%	8.7%	2.2%	4.7%	4.5%	9.3%	1.8%	3.8%	3.9%	8.1%
Sharpe	0.08	0.32	0.45	0.45	0.84	0.84	0.49	0.49	0.91	0.91	0.38	0.38	0.76	0.76
Alpha	3.6%	9.2%	2.5%	5.2%	4.7%	9.9%	2.6%	5.4%	5.0%	10.4%	2.2%	4.6%	4.5%	9.5%
T-stat	1.46	3.62***	3.61***	3.61***	6.48***	6.48***	3.89***	3.89***	6.96***	6.96***	3.16***	3.16***	6.00***	6.00***
Beta	-0.20	-0.31	-0.03	-0.07	-0.05	-0.10	-0.03	-0.07	-0.05	-0.1	-0.03	-0.07	-0.05	-0.11
T-stat	4.56***	6.62***	2.50**	2.50**	3.53***	3.53***	2.61***	2.61***	3.52***	3.52***	2.65***	2.65***	3.84***	3.84***
Max	20.2%	21.7%	4.9%	10.3%	4.9%	10.3%	4.1%	8.6%	4.7%	9.8%	4.4%	9.1%	5.0%	10.5%
Min	-30.1%	-34.7%	-5.2%	-10.8%	-5.6%	-11.7%	-4.4%	-9.1%	-4.8%	-10%	-6.1%	-12.7%	-7.1%	-14.9%
DD	-66.6%	-70.4%	-13.6%	-27.7%	-14.4%	-20.9%	-13.0%	-26.8%	-10.8%	-21.3%	-14.2%	-28.5%	-13.1%	-25.9%

As an addition to return and Sharpe ratio, table 2 contains more statistics that allow for comparing traditional momentum to risk-managed momentum.

First, the maximum and minimum values of the monthly return are important to consider when comparing traditional momentum to risk-managed momentum. The main goal of using risk-managed momentum is protecting the portfolio against sudden momentum crashes. The traditional momentum strategy is known for realizing an extreme negative return during these periods. This causes momentum strategies to lose their value since the big negative returns during those market crashes pose a big risk and possibly offset earlier realized excess returns.

As can be expected the lowest monthly return for the traditional momentum portfolios is much lower than for the risk-managed momentum portfolios. The traditional factor portfolio has a month in which it realizes a negative return as big as -34.7%. The biggest negative return realized by a risk-managed factor portfolio is -14.9%. These differences in return cause differences in the drawdowns the portfolios ultimately endure. As can be seen in table 2 the traditional HML and factor portfolios both endure big drawdowns of respectively -66.6% and -70.4%. This significantly reduces a portfolios long term performance since even larger percentual gains are needed to recover from these losses in portfolio value. For comparison, the largest drawdown recorded for a risk-managed momentum portfolio is 27.7% with many of the 12 risk-managed portfolios reporting maximum drawdowns that are significantly smaller than that.

These differences in drawdowns can also be linked to the differences in beta between traditional and risk-managed momentum portfolios. Table 2 shows that the absolute values of the betas of the traditional momentum HML and Factor portfolios are higher than the beta values of the risk-managed momentum portfolios. This means that the inverse reaction compared to the market of the traditional momentum portfolios is bigger than that of the risk-managed momentum portfolios. This can be used as proof for the fact that the momentum portfolios will endure smaller drawdowns in the periods of a market crash followed by a rapid market recovery.

For a statistical comparison between the risk-managed and traditional momentum portfolios the time-series regression is analyzed. The regressions performed have the return of a risk-managed momentum strategy as the dependent variable and its traditional momentum counterpart as the independent variable. This is done to determine if the risk-managed strategies have a significant excess return over their traditional momentum counterparts. The results of these regressions can be found in table 3.

Table 3, comparison between traditional momentum and risk-managed momentum portfolio performance.

The performance of the traditional momentum portfolios is compared to the performance of the risk-managed momentum portfolios by using a regression. Each of the regressions consist of 567 observations of the three variables included. For the top section the return series from traditional momentum HML portfolio is used as the independent variable. For the bottom section the return series from the traditional momentum factor portfolio is used as the independent variable. The columns indicate which risk-managed momentum portfolio is used as the dependent variable. The risk-managed momentum portfolios differ in both the lookback period (six-months, three-months and a year) and the target volatility (respectively 12% and 25%). Reported are both the alpha (intercept), the coefficient for the period dummy and the beta. The t-statistics for these coefficients are also reported to show for significance. (* = significant on the 10% level, ** = 5% level and *** = 1% level)

	HML (6-Month)		**HML (3-Month)**		**HML (12-Month)**	
Alpha	**1.8%**	**3.8%**	**1.9%**	**4.1%**	**1.5%**	**3.2%**
T-Stat	5.34***	5.34**	5.63**	5.63**	4.47**	4.47**
Dummy	**0.3%**	**0.7%**	**1.0%**	**2.1%**	**0.7%**	**1.3%**
T-stat	0.14	0.14	0.41	0.41	0.28	0.28
Beta	**0.24**	**0.50**	**0.23**	**0.49**	**0.25**	**0.52**
T-stat	41.1***	41.1***	39.1***	39.1***	42.8***	42.8***
	Factor (6-Month)		**Factor (3-Month)**		**Factor (12-Month)**	
Alpha	**2.9%**	**6.0%**	**3.2%**	**6.6%**	**2.5%**	**5.3%**
T-Stat	7.17**	7.17**	7.78**	7.78**	6.24**	6.24**
Dummy	**-0.1%**	**-0.2%**	**0.7%**	**1.4%**	**0.4%**	**0.7%**
T-stat	0.10	0.10	0.24	0.24	0.13	0.13
Beta	**0.23**	**0.48**	**0.22**	**0.47**	**0.24**	**0.51**
T-stat	36.2***	36.2***	34.0***	34.0***	37.1***	37.1***

Table 3 show that the annualized excess returns over the traditional momentum strategies range from 1.5% to 6.6% and are all positive. This means that all the risk-managed momentum portfolios generate a positive excess return over their traditional momentum counterpart. All the Alphas are significant. Therefore, the evidence supports hypothesis 3 '*Risk-managed momentum strategies generate a positive excess return when compared to using traditional momentum strategies during the pre-covid period*' for all the variations of the risk-managed momentum portfolios. Even the lowest excess return reported, 1.5%, has strong influence on portfolio value over time due to the compounding of returns.

Table 3 also shows that all the betas reported are significant and follow a similar pattern for the three different lookback periods used. The portfolios with a 12% target volatility report a beta ranging from 0.23 - 0.25. This implies that these portfolios are way less volatile than the traditional momentum portfolios. The portfolios that aim for 25% volatility have betas ranging between 0.48 - 0.52. This means these portfolios are about half as volatile as their traditional momentum counterparts. The goal of the risk-managed strategies is to reduce the average volatility of the momentum strategies over time. The significant betas serve as proof that his goal is achieved.

The regression results from table 3 are also used for the statistical comparison between the performance of the different (risk-managed) momentum strategies during the Covid pandemic period. The excess return of the risk-managed momentum strategies over their traditional momentum counterpart is given by alpha. The dummy variable is a time dummy that has the value 1 during the Covid-19 pandemic. Therefore, the alpha in combination with the coefficient for the dummy variable is the excess return of the risk-managed strategies during the Covid-19 pandemic. Almost all the dummy coefficients are positive meaning that the evidence implies that the excess return of the risk-managed momentum strategies is even higher during the corona pandemic compared to the rest of the sample period. However, the dummy coefficients are relatively small and insignificant. This means that the excess return (alpha) during the Covid-pandemic do not significantly differ from the alpha for the period before the Covid-19 pandemic. Therefore, the evidence does not support hypothesis 4 '*The excess returns of Risk-managed momentum strategies over traditional momentum strategies increases in the period of the Covid-19 pandemic (2020).*'

Since the dummy variable is insignificant but the alphas are all positive and significant the conclusion can be drawn that also during the Covid-19 period the risk-managed momentum strategies realized an excess return of the traditional momentum strategies. No conclusive evidence is found for a significantly stronger performance of risk-managed momentum strategies during the Covid-19 pandemic compared to risk-managed momentum strategies over the pre-Covid period.

Table 4 reports the performance measures used for studying the performance of the constructed portfolios during the Covid-19 period. This table includes the results for both the traditional HML and factor momentum portfolios as well as the and the 12 risk-managed momentum HML and factor portfolios. Reported are the monthly mean return in excess of the risk-free rate, standard deviation, annualized return, Sharpe ratio, the alpha and beta following from a time series regression, maximum monthly return, minimum monthly return and the maximum drawdown the portfolio has endured.

The HML portfolio composed using the traditional strategy has a negative annualized return of -4.1%. When comparing this to the HML portfolios that use a risk-managed momentum strategy it immediately stands out that these strategies have positive return. The risk-managed momentum strategy that uses the 12% target volatility and a 3-month lookback period reports the highest annualized return of 4.07%.

The traditional factor portfolio reports an annualized average return of -10%. When comparing this to the factor portfolios that use a risk-managed momentum strategy it is striking to see that these strategies realize a positive return. The Covid-19 period results for the factor portfolio differ from the results of the full period. For the full period it was the case that using the target volatility of 25% for scaling the momentum exposure caused the risk managed momentum portfolios generate a higher average annualized return compared to the traditional momentum portfolios. For the Covid-19 period not only the portfolios with a 25% target volatility, but also those with a 12% target volatility, outperform the traditional momentum strategies when looking at the annualized return.

Important to note is the fact that, for this period, the monthly (risk-managed) momentum portfolio returns in excess of the risk-free rate are low and insignificant. This can partly be explained by the fact that these returns are close to zero and are the returns for a shorter period. Therefore, they are constructed using far less datapoints compared to the full sample results from table 2. However, this insignificance can also be interpreted as the strategies not being able to generate a return in excess of the risk-free rate different from zero over the Covid-19 period. The strategies reported are all long-short strategies that use the momentum statistic to determine in which stock long- and short positions are taken. Thus, it can be concluded that during this period the (risk-managed) momentum strategies are unable to realize a significant monthly return using the momentum statistic for stock selection. The same holds for the alphas found. None of these excess returns are significant meaning that during the Covid-19 period the (risk-managed) factor- and HML portfolios were unable to generate excess return.

When looking at the performance measure that also takes volatility into account, the Sharpe ratio, almost all the risk-managed momentum portfolios outperform their traditional counterparts. Only the factor portfolio with a twelve-month lookback period reports a lower Sharpe ratio than its traditional momentum counterpart.

Table 4, (risk-managed) momentum portfolio perfromance, 2020

This table reports the same data as table 1. The differentiating factor of this table is that it reports on the Covid-19 period 01-01-2020 until 31-12-2020. This period is of interest for studying the Covid-19 pandemic, the market crash itself and the swift market recovery that followed. The performance of the traditional momentum portfolios is compared with the performance of the different risk-managed momentum portfolios. The risk-managed momentum portfolios use the past volatility from the traditional momentum portfolio to determine a volatility forecast. This forecast is then used to scale the portfolios exposure towards momentum. The risk-managed momentum portfolios differ in both the lookback period (six-months, three-months and a year) and the target volatility (respectively 12% and 25%). Reported are the mean monthly returns, t-statistics of these returns, standard deviation of the returns, annualized return, annualized Sharpe ratio, the alpha's and beta's following from the regression of the portfolio returns on the market index (S&P 500). Including their t-statistics, maximum, minimum monthly returns and the maximum drawdown. (* = significant on the 10% level, ** = 5% level and *** = 1% level)

	Traditional momentum		**Risk-Managed Momentum**											
	HML	**Factor**	**HML (6-Month)**		**Factor (6-Month)**		**HML (3-Month)**		**Factor (3-Month)**		**HML (12-Month)**		**Factor (12-Month)**	
Mean	-0.3%	-0.8%	0.09%	0.20%	0.04%	0.08%	0.16%	0.34%	0.13%	0.28%	0.09%	0.19%	0.04%	0.08%
t-stat	0.19	0.32	0.33	0.33	0.11	0.11	0.57	0.57	0.42	0.42	0.29	0.29	0.10	0.10
St dev	6.2%	8.9%	0.99%	2.06%	1.14%	2.38%	1.00%	2.07%	1.10%	2.29%	1.11%	2.30%	1.29%	2.68%
Return	-4.1%	-10.0%	1.10%	2.37%	0.43%	0.91%	1.95%	4.07%	1.61%	3.36%	1.12%	2.33%	0.46%	0.95%
Sharpe	-0.41	0.26	-0.33	-0.33	0.11	0.11	0.57	0.57	0.42	0.42	0.29	0.29	0.10	0.10
Alpha	5.5%	9.0%	2.87%	5.97%	2.96%	6.17%	3.46%	7.21%	3.98%	8.30%	2.96%	6.16%	3.25%	6.76%
t-stat	0.29	0.41	0.99	0.99	1.14	1.14	1.11	1.11	1.52	1.52	0.89	0.89	1.07	1.07
Beta	-0.46	-0.91	-0.08	-0.17	-0.12	-0.25	-0.07	-0.15	-0.11	-0.24	-0.09	-0.18	-0.13	-0.28
t-stat	2.12*	3.72***	2.54**	2.54**	4.12***	4.12***	2.04*	2.04*	3.84***	3.84***	2.35***	2.35***	3.90***	3.90***
Max	7.34%	11.2%	1.87%	3.89%	1.89%	3.95%	2.43%	5.06%	2.00%	4.16%	2.08%	4.34%	1.97%	4.11%
Min	-11.4%	-17.3%	-1.76%	-3.68%	-2.27%	-4.73%	-1.33%	-2.77%	-1.75%	-3.65%	-2.07%	-4.32%	-2.60%	-5.41%
DD	-18.1%	-30.8%	-2.41%	-5.02%	-3.66%	-7.55%	-2.01%	-4.18%	-2.91	-6.03%	-2.64%	-5.49%	-4.03%	-8.33%

A final observation, regarding the beta coefficients, can be made when comparing the full sample period results to the Covid-19 period results. All the beta coefficients found are significant at a 5% significance level. Table 1 shows that the difference in betas between the low and high momentum portfolios is bigger for the Covid-19 period compared to the full period. For the full sample periods these betas are 1.17 and 0.98 while for the Covid-19 period these betas are 1.41 and 0.82. The bigger difference in betas causes the betas for the HML and factor portfolio to be more negative, -0.58 and -0.97 respectively. This is in line with the theory about momentum strategy betas following a bear market and can, at least partly, explain the negative returns realized by the HML and factor portfolio during this period that contains the Covid-19 market crash. The betas for the risk-managed strategies over both periods can be found in tables 2 and 4. For the risk-managed momentum portfolios it also holds that the betas for the Covid-19 period are higher than the betas for the full sample period. However, it can be concluded that for both periods the risk-managed strategies succeed in lowering the absolute beta value. This confirms the conclusion that the risk-managed momentum strategies are less volatile and more robust during momentum crashes.

4.3 Improving the risk-managed momentum strategies

For the final hypotheses the performance of different alterations to the risk-managed momentum portfolios traditionally introduced by Barossa & Satna-Clara (2015) is compared. The adjusted risk-managed momentum strategies differ in two ways. The lookback period used to forecast volatility and the target volatility used to determine the weights to scale momentum exposure. Both adjustments ultimately change the scaling weights given to the different portfolios through time causing them to perform differently.

To start, a visualisation is made of the effect of the alterations to the lookback period. Figure 1 shows what the forecasted variance over time looks like each of the three different lookback periods. Reported are the variance forecasts for the Factor portfolios. Peaks in the variance forecast are visible at moments of known market crashes, as for example the housing- and dot-com bubble. The comparison between the variance forecasts made using different lookback periods give the following insights. The effect of the alterations to the original 6-month lookback period are as can be expected. Reducing the lookback period cause a more volatile forecast which picks up spikes in volatility earlier. Extending the lookback period to 12 months has the opposite effect. Causing a more conservative forecast which follows the movement of the other forecasts with a delay. Also, the corona pandemic market crash can be observed as a peak in the variance forecasts. Interesting to note here is that for the variance forecast with a 12-month lookback period the forecast does not seem to have reached its peak yet.

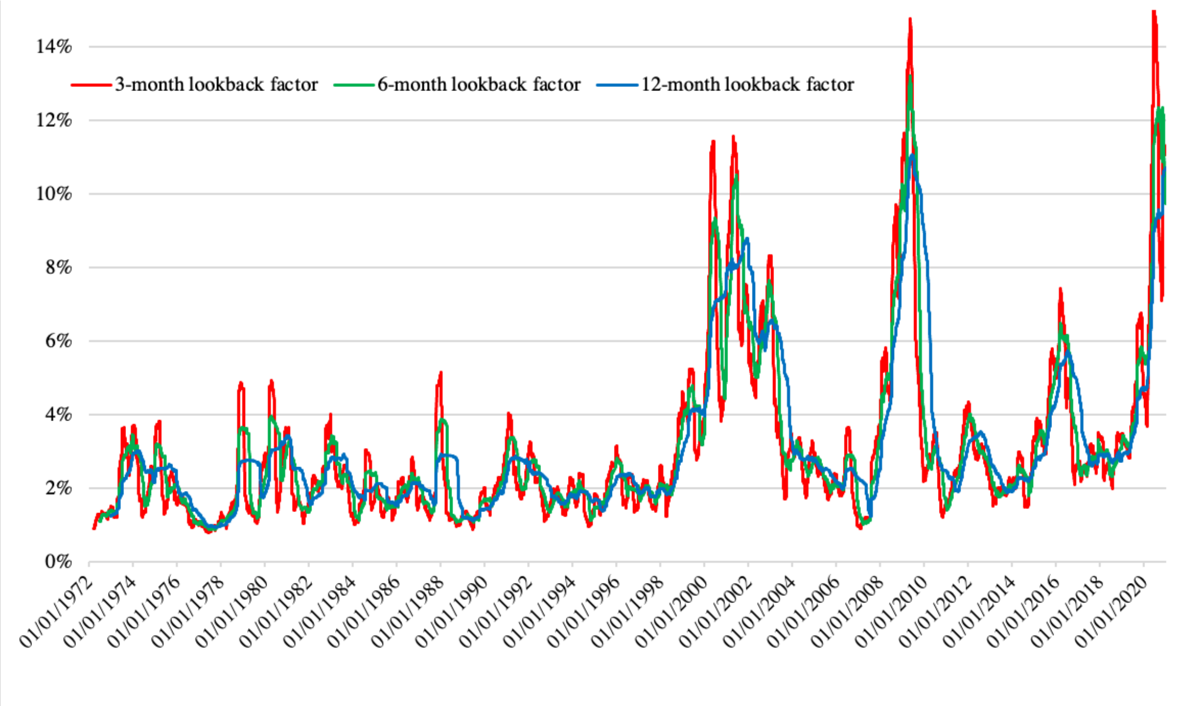

Figure 1, forecasted monthly variance.
(For clarity only the volatility forecast for the three factor portfolios are shown. See appendix 3 for the figure with the HML portfolio variance.)

These variance forecasts are subsequently used to calculate the weights necessary to scale a portfolios exposure to momentum. As previously described in the methodology, the weights are calculated by dividing the target volatility by the forecasted volatility. Figure 2 shows the resulting weights for the HML portfolio with the traditional lookback period of 6 months for both target volatilities used. As can be expected both lines follow the same pattern, but the weights scaled using the 25% target volatility move over a broader range and are always above the weights scaled using the traditional 12% target volatility. This is caused by scaling formula and the higher target volatility. Since the goal for the second strategy is a 25% volatility, more extreme weights are necessary. To reach this goal the scaling weights reach values up to 2. This happens during the periods where the forecasted volatility reaches the lowest values. Since scaling is used to try and keep volatility (risk) constant over time the weights have a value below one when the forecasted volatility is above the target volatility. The exposure to momentum necessary to reach a constant 12% volatility level is always lower than the exposure needed to reach a constant 25% volatility level. For this reason, the weights for the strategy with a 12% target volatility are always lower than the weights for the strategy with a 25% target volatility.

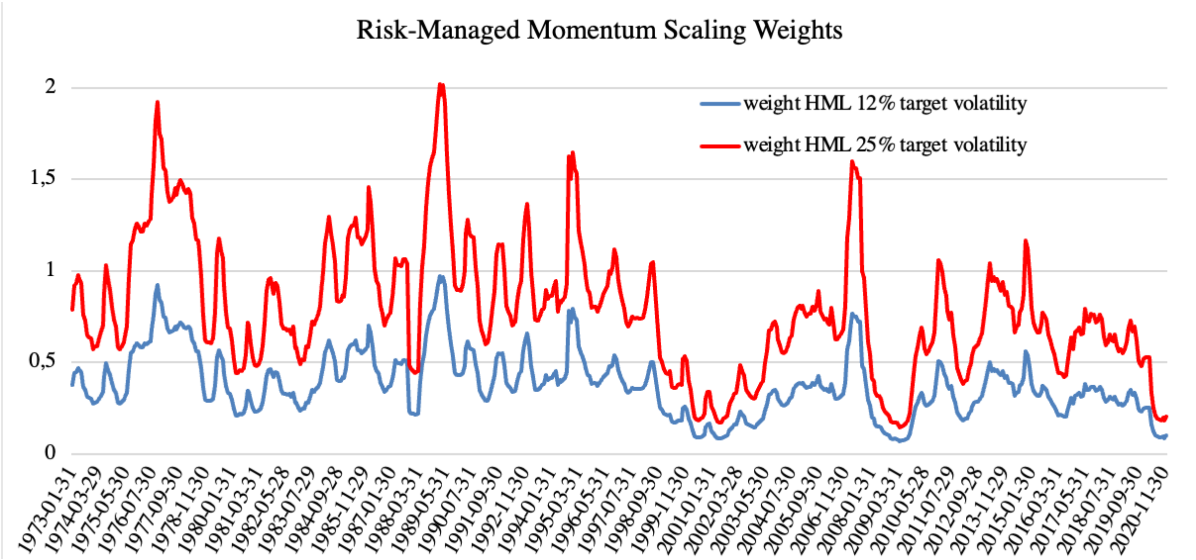

Figure 2, HML portfolio weights.
(For clarity only the weights of 2 HML portfolios that differ in target volatility but use the same lookback period to forecast volatility are shown. See appendix 4 for full figure.)

When analyzing the effect of changing the target volatility the comparison between two portfolios which are equal in all other aspects must be made. When comparing the original risk-managed momentum portfolio to its counterpart with adjusted target volatility interesting results can be found. As can be seen in table 2, the mean excess return more than doubles, going from 2.1% to 4.4%. But at the same time the volatility increases from 4.7% to 9.8%. Interesting to see is the fact that the Sharpe ratios are equal. This is caused by the interaction between the scaling formula and the calculation of the Sharpe ratio. The increase in return is offset by an increase in volatility. Equal results are found when comparing the other linked portfolios to each other. On top of that, it is impossible to compare the two strategies using a regression. Due to the way the scaling formula works the 12% and 25% target volatility portfolios have a strong correlation. For these reasons the difference in performance can't be statistically tested. To answer the question which portfolio performed better a different statistic must be used. The answer to the question which portfolio is more desirable will depend on investors personal preference. Between two portfolios that only differ in target volatility there is a clear trade-off between return and volatility/ turnover. An investor who is relatively risk-averse and/or does not like a high level of trading will prefer the 12% target volatility portfolio and vice versa.

For the final hypotheses the impact of changing the lookback period that is used for forecasting volatility is studied. Changing the lookback period causes the different risk managed momentum strategies to forecast a different level of volatility at the same point in time. First, shortening the lookback period is studied. To assess the effect of using a shorter lookback period the traditional risk-managed momentum HML and factor portfolios, with a six-month lookback period are compared to the portfolios that use a 3-month lookback period. As reported in table 2, using the traditional 6-month lookback period results in a Sharpe ratio of 0.11 for the HML portfolio compared to 0.18 for the strategy using a 3-month lookback period. For the factor portfolios the results are 0.64 and 0.72 respectively. For both portfolio types the more dynamic strategy with a 3-month lookback period outperforms the traditional risk-managed momentum strategy when looking at the Sharpe ratio.

The second way used to study the effect of changing the lookback period on performance is a regression model following from equation 8. This regression compares the performance of the portfolios that are equal except for their lookback period. Table 5 shows the regression results necessary to compare the different risk-managed momentum strategies with each other. Each sector of the table represents a cluster of portfolios of the same type (HML or Factor) and with the same target volatility (12% or 25%). Within each sector the portfolios only differ in lookback period.

The top section containins the HML portfolios with a 12% target volatility. For this portfolio type, the strategy using a three-month lookback period reports a significant excess-return over both the original strategy with a six-month lookback period as the twelve-month lookback period strategy introduced in this paper. The results for other types of portfolios, found in the remaining 3 sections of the table, report similar results. For these portfolios the shorter three-month lookback period also realizes an excess return over their counterparts with a longer lookback period. Therefore, the evidence found supports hypothesis 5 stating that '*Using a shorter, 3-month, lookback period in a risk-managed momentum strategy will generate an excess return over using the traditional 6-month lookback period for forecasting volatility.*'.

Table 5, lookback period comparison regression

The performance of the 12 risk-managed momentum portfolios is compared by using a regression model. Each of the regressions consist of 567 observations of the three variables included. The portfolios are organized by type and target volatility resulting in 4 clusters of 3 portfolios. Therefore, within each section the portfolios only differ in the lookback period that is used to forecast volatility. The left column states which portfolio return series is used as the dependent variable. The top row states the portfolio return series that is used as the independent variable. Reported are the Alpha's and the coefficients for the period dummy variable. The alpha can be interpreted as the excess return of strategy used for the dependent variable over the other strategy. During the Covid-19 pandemic this excess return is represented by 'alpha + period dummy'. The t-statistics are reported to show for significance. (* = significant on the 10% level, ** = 5% level and *** = 1% level)

HML 12%	**Original risk-managed (6-month lookback)**	**(2) 12-month lookback**
(1) 3-month lookback (Alpha)	**0.18%**	**0.55%**
T-statistic	1.75*	3.05**
Period dummy	0.68%	0.38%
T-statistic	0.87	0.30
(2) 12-month lookback (Alpha)	**-0.31%**	
T-statistic	-2.43**	
Period dummy	0.29%	
T-statistic	0.32	
HML 25%	**Original risk-managed (6-month lookback)**	**(2) 12-month lookback**
(1) 3-month lookback (Alpha)	**0.38%**	**1.15%**
T-statistic	1.75*	3.05**
Period dummy	1.4%	0.78%
T-statistic	0.87	0.30
(2) 12-month lookback (Alpha)	**-0.65%**	
T-statistic	-2.43**	
Period dummy	0.60%	
T-statistic	0.32	
Factor 12%	**Original risk-managed (6-month lookback)**	**(2) 12-month lookback**
(1) 3-month lookback (Alpha)	**0.40%**	**0.90%**
T-statistic	2.85**	4.19**
Period dummy	0.78%	0.30%
T-statistic	0.84	0.21
(2) 12-month lookback (Alpha)	**-0.36%**	
T-statistic	2.41**	
Period dummy	0.37%	
T-statistic	0.37	
Factor 25%	**Original risk-managed (6-month lookback)**	**(2) 12-month lookback**
(1) 3-month lookback (Alhpa)	**0.84%**	**1.89%**
T-statistic	2.85*	4.19**
Period dummy	1.65%	0.62%
T-statistic	0.84	0.21
(2) 12-month lookback (Alpha)	**-0.74%**	
T-statistic	2.41**	
Period dummy	0.37%	
T-statistic	0.77%	

Sub-hypothesis 5b focuses on the effect of using a shorter lookback period during the COVID-19 pandemic. To study this effect a time dummy is introduced into the regression. This time dummy has the value of one from the start of the Covid-19 pandemic until the end of the sample period and the value of zero otherwise. Table 5 shows the coefficients for the dummy variables. For all the different types of portfolios the period-dummy coefficients are positive when comparing the three-month lookback portfolio to portfolios that use longer lookback periods. This positive coefficient implies that the excess return is even higher during the COVID-19 pandemic compared to the rest of the sample period. This could mean that during the Covid-19 pandemic the positive effect of shortening the lookback period of the risk-managed momentum portfolios is even bigger.

However, these coefficients are all insignificant and do not provide sufficient proof for a difference in excess return. For this reason, the evidence does not support hypothesis 5B stating that '*The excess return of the risk-managed momentum strategy with a 3-month lookback over the risk-managed momentum strategy with the traditional 6-month lookback period increases during the Covid-19 period. (2020)*'.

The fact that the period dummies are insignificant does not mean that the strategies with the shorter three-month lookback period do not realize an excess return over the similar portfolios with a longer lookback period during the Covid-19 period. Instead, the interpretation is that the excess return does not significantly differ from the excess return realized over the rest of the sample period. It can still be concluded that during the Covid-19 period the strategies with a shorter, three-month, lookback outperformed similar strategies with longer lookback periods.

For the final hypothesis the effect of extending the lookback period from six to twelve months is studied. As reported in table 2 above, using the traditional six-month lookback period results in a Sharpe ratio of 0.11 for the HML portfolio compared to 0.05 for the strategy using a twelve-month lookback period. For the factor portfolios the results are 0.64 and 0.59 respectively. For both portfolio types the more conservative strategy using a twelve-month lookback period performs worse compared to the traditional risk-managed momentum portfolio when using the Sharpe ratio as the performance measure. When looking at the regression results reported in table 5 the strategies using a twelve-month lookback period have significantly lower returns compared to the original risk-managed momentum strategy. Because all the risk-managed momentum portfolios that use a twelve-month lookback period report significantly lower returns the evidence does not support the final hypothesis '*Using a* *longer, 12-month, lookback period in a risk-managed momentum strategy will realize a higher return compared to using the traditional lookback period for forecasting volatility during the pre-Covid period'*. In fact, the evidence proves the opposite. Extending the lookback period significantly reduces the strategies return. The same holds for the sub-hypothesis concerning the effect of extending the lookback period during the time of the corona pandemic. The period dummies are positive. This could imply that the performance of the risk-managed strategies with an extended lookback period is relatively better during the Covid-19 pandemic compared to the rest of the sample period. However, the dummy coefficients are insignificant and do not give sufficient evidence to support this claim. This means that effect of extending the lookback period during the Covid-19 pandemic does not significantly differ from the rest of the sample period. Therefore, the results found do not support hypothesis 6B *'The excess return of the risk-managed momentum strategy with a 12-month lookback over the risk-managed momentum strategy with the traditional 6-month lookback period increases during the Covid-19 period. (2020)'*.

It can be concluded that during the Covid-19 pandemic, just as during the pre-Covid period, extending the lookback period decreases portfolio performance.

Overall, when comparing the different variations of the risk-managed momentum strategies the results are inconclusive about what target volatility generates the best performance. There is no difference in Sharpe ratio between the 12% and 25% target volatility strategies and the strong correlation makes a performance comparison using a regression impossible. For the variations in lookback period the results are more compelling. The strategy with the shorter 3-month lookback period outperforms the others when taking both the Sharpe ratio and regression results into consideration.

5 Discussion

The main goals of this research are studying the performance of (risk-managed) momentum strategies during the Covid-19 period and improving on the original risk-managed momentum strategy. This research is designed to achieve these goals as well as possible but does have its limitations. This section starts by discussing the two problems the Covid-19 period used in this paper raises. This is followed by a discussion relating the real-life implementation of the strategies. This topic involves portfolio turnover and has implications for the second goal of this paper, improving the risk-managed momentum strategy. Thereafter, some remarks on how this paper relates to the papers that stand at its foundation are made. Finally, possible extension that are relevant for future research are presented.

One of the main goals of this paper is linked to the Covid-19 pandemic period. This raises two problems. First, the data availability is a restricting factor within this research. At the time of writing the US stock data was available up to 31-12-2020. CRSP data gets released to students at the Erasmus University on a yearly basis. Return data on the year 2021 can only be retrieved starting from 01-01-2022. For this study both the market crash as well as the period following this crash are important. The fact that the data is limited to data up until 2020 restricts the period of interest. At the time of writing the Covid-19 pandemic is still ongoing. It would surely be interesting to repeat this research with a dataset that contains the full pandemic. On top of that, the restriction of the dataset, in combination with the use of monthly rebalanced returns, causes the analysis about the Covid-19 period to consists of a limited amount of datapoints which influences significance.

The second problem that arises when wanting to study the performance of investment strategies during the Covid-19 pandemic period is the determination of this period itself. There is no fixed date for the start of the pandemic. Therefore, the timeline of the WHO is followed for the fair determination of the start of the Covid-19 period. However, the determination of this period is still arbitrary but has a high influence on the results. On top of that, it could be argued that it does not make sense to test trading strategies using information that was not yet available at the time of the implementation of the strategy, in this case the information about the exact start and duration of the Covid-19 market crash. Comparing the performance of risk-managed momentum, a strategy designed to withstand market crashes, to traditional momentum using future information about when a crash will happen leads to unfair results that have no merit in the real world. For this study the methodology for the determination of this period is aimed at selecting a period that serves the goal of comparing traditional momentum to risk-managed momentum best. However, the chosen Covid-19 period and the results it provides definitely leaves room for discussion.

The next potential problem this research faces concerns the possibility for (retail) investors to implement the strategies discussed in this paper in real-life. While there have been many studies reporting strong risk-adjusted returns for momentum strategies across time and asset classes the investment strategy is not often used in practice, especially by retail investors. This is caused by the difficulty to implement, lack of knowledge and aversion towards shorting (Asness, Ilmanen, Israel, & Moskowitz, 2015). This could raise questions about the point of studying and improving on these strategies. However, great care is taken into making sure the strategies could in fact have been implemented and the positive risk-adjusted returns have interesting implications for the efficient market debate.

The difficulty to implement partly caused by the relatively high level of trading needed. This high level of trading also comes with another important consideration point, transaction costs. For this study the choice has been made to not take transaction costs and turnover into consideration. The profitability of traditional momentum strategies when transaction costs are being taken into consideration has been proven in many papers. Barosso & Santa-clara (2015) show that the turnover for risk-managed momentum is only slightly higher than the turnover for traditional momentum. This increased turnover does not offset the benefits of the risk-managed strategies.

For this research it would be especially interesting to take the turnover into account when comparing the different alterations to the risk-managed momentum strategy. The results imply that the strategy that uses an extended 252-day lookback period underperform compared to the strategies with shorter lookback periods. However, these results do not consider the fact that using a longer lookback periods causes more conservative volatility forecasts. These more conservative forecasts cause the scaling weights to move over a smaller range, which ultimately means less trading. A similar concern can be raised about the strategies using a shorter lookback period. The more dynamic variance forecast leads to more trading. It would be most interesting to see if the conclusions drawn about the different strategies performance still hold up when taking the difference in turnover into account.

The methodology of this paper is strongly based on the methodologies from Asness et al. (2013) and Barosso & Santa-Clara (2015). Great care is taken into duplicating their methods as precise as possible. However, this has proven to be difficult. The codes the authors used for their data-analysis are not publicly available and the written methodology does not fully cover all the information necessary. The determination of the stock universe for this paper is based the stock universe presented by Asness. Et al. (2013). However, the average amount of unique companies within the US stock universe in the reproduced paper is 724 compared to 1804 in this study. This is most likely caused by restricting factors that are not clearly presented. The more extensive dataset used for this paper is likely to produce results that are less conservative.

The first recommendation for further research is linked to the problems surrounding the Covid-19 period within this study. As already mentioned, at the time of writing the Covid-19 pandemic is still ongoing. Performing a similar research that includes the full Covid-19 period is a valuable extension that allows for a better analysis of the performance of (risk-managed) momentum strategies during the Covid-19 pandemic. A similar extension would be to also include different geographic regions to the dataset. Currently, only the US-stock market is considered. Within each region the pandemic developed in a different way. Also, the protective measures taken are different and have varying economic consequences. Studying these differences could lead to interesting results.

Transaction costs and portfolio turnover are not included in the analysis of this paper. However, these factors do influence the overall results and are especially important in the comparison of the different risk-managed momentum portfolios. Therefore, including the effects of turnover would make for a strong extension on this paper.

A final possible extension would be to change the way momentum exposure is calculated. This paper follows the original methodology of the paper introducing risk-managed momentum strategies by calculating the scaling weights used in equation 6. The research tests the effect of changing the input for target volatility from 12% to 25%. In essence this causes all the scaling weights to change with a certain factor. Interesting would be to see what happens when the formula for calculating the weights is altered and a formula that scales the weights between the values of zero and two is used. This results in weights that move over an even broader scale then the weights for the 25% target volatility strategy do now. Opposed to the extension tested in this paper the performance of this proposed alteration can be statistically tested trough a regression.

6 Conclusion

This study aimed at analyzing the performance of the well-documented momentum trading strategy up until the present and extending on the risk-managed momentum strategy introduced by Barosso & Santa-Clara (2015). The performance of the (risk-managed) momentum strategies are tested for the period 1972-2020 in combination with hypotheses focused specifically on the Covid-19 period. On top of that, alterations were made to the original risk-managed momentum strategy to see if further performance improvement was possible.

When looking at the results and the conclusions drawn about the first two hypothesis the research question '*How did (risk-managed) momentum strategies perform in the period from 1972 to 2020*' can be answered. The results found in this paper show that over the full sample period the low, medium, high and factor momentum portfolios generated positive excess returns. The factor portfolio reported the highest excess return of 9.2% which is significant at the 1% level. However, the HML portfolio does not report an excess return significantly different from zero. This leads to the conclusion that on average there is no difference in performance between the low and high momentum portfolios, containing stocks devided using the momentum statistic. All twelve risk-managed momentum portfolios report significant positive excess return. For the risk-managed momentum strategies it can be concluded that they realize excess risk-adjusted returns over the period from 1972-2020. This means that opposed to the traditional momentum HML portfolio, the risk-managed HML portfolios do report significant excess returns. This serves as evidence that on average the performance of the low- and high momentum portfolio don't differ, but when using varying market exposure trough risk-managed momentum a successful trading strategy with excess returns can be made.

More interesting is to compare the performance between traditional- and risk-managed momentum. All the risk-managed momentum strategies report a higher Sharpe ratio and realize an excess return over their traditional momentum counterparts. The differences in maximum portfolio drawdowns show that the risk-managed momentum strategies successfully achieve their goal of building portfolios that are more robust during momentum crashes.

Therefore, it can be concluded that risk-managed momentum strategies outperformed their traditional counterparts during the full sample period.

The second research question *'How did (risk-managed) momentum strategies perform during the Covid-19 pandemic period that included the market crash induced by the uncertainty that Covid-19 introduced into the economy?* focusses on the period of interest containing the Covid-19 pandemic market crash. Within this period the evidence shows that both traditional momentum portfolios are unable to realize significant excess returns. The evidence suggests a better performance for the risk-managed portfolios when looking at the Sharpe ratio and drawdown statistic. However, none of the risk-managed portfolios realize an significant excess return. This makes it hard to draw strong conclusions about the general performance of the momentum strategies during the Covid-19 period. The regressions, that compares the performance of risk-managed and traditional momentum shows no significant difference of alpha over the Covid-19 period. Meaning that the excess return during the Covid-19 period does not significantly differ from the excess return during the pre-Covid period. During the pre-Covid period all the risk-managed momentum strategies realized an excess return over their traditional momentum counterparts. This leads to the conclusion that also during the Covid-19 period risk-managed momentum strategies outperformed their traditional counterparts.

The second part of the research is concerned about improving the traditional momentum portfolio in general as well as during the Covid-19 pandemic induced market crash. To answer the third research question *'How does increasing the target volatility of the original risk-managed momentum strategy impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'* the target volatility that is used for scaling the exposure to momentum is altered. The alteration has a clear effect in both the returns and volatility a portfolio realizes. However, the performance measures chosen within this research do not provide evidence that helps in answering this specific research question. When comparing two portfolios that only differ in target volatility the reported Sharpe ratios are equal. Due to the way scaling for risk-managed momentum strategies work two strategies which only differ in target volatility have a strong correlation with each other. This makes comparison via a regression impossible. Further analysis using different performance measures, or a different volatility scaling formula is needed to conclusively answer this research question.

The final questions this research aims to answer is: *'How does using a different lookback periods to forecast volatility impact the performance of the risk-managed momentum strategy, and is this a possible way to further improve the strategy?'*. The answer to this research question can be found within the conclusions drawn for the last 2 hypotheses. For hypothesis 5(B) the lookback period is reduced from 126 to 63 days. This results in more dynamic strategies that react to changes in the market conditions faster. To start, the alteration causes in increase in performance measured by the Sharpe ratio. Also, the regression results show that this decrease in the lookback period increases strategy performance and causes an excess return over the portfolios with a longer lookback period during the pre-Covid period. When looking at the Covid-19 period the excess return over the strategies with longer lookback periods does not differ significantly from the excess return during rest of the sample period. This leads to the conclusion that decreasing the lookback period of the original risk-managed momentum strategy from 6 to 3 months increases returns and the Covid-19 pandemic did not significantly impact those returns.

The alteration made for hypothesis 6(B) is completely the opposite. The lookback period is extended from 126 to 252 days, a complete trading year. The result show that the increase in lookback period causes a decrease in portfolio performance. The strategies with shorter lookback report higher Sharpe ratios. The regressions confirm this conclusion. An excess return of the strategies with shorter lookback periods over the altered strategy with an extended lookback period is reported. When focusing on the Covid-19 pandemic the evidence shows that there is no significant difference in the effect of extending the lookback period compared the full sample period effect. Therefore, it can be concluded that extending the lookback period of the risk-managed momentum strategy from 6 to 12 months decreases returns and the Covid-19 pandemic does not have a significant effect on this decrease.

Overall, momentum strategies are still able to realize excess return in the period 1972-2020. Even though these strategies are vulnerable to market crashes the results found for these strategies are positive. When comparing the results of traditional momentum portfolios to risk-managed momentum portfolios the findings by Barrosso & Santa-Clara (2015) still hold. The risk-managed strategies are more robust during market crashes and outperform the traditional momentum portfolios. This has both theoretical and practical implications. The excess profitability found for the (risk-managed) momentum strategies is a direct violation of the EMH. This paper can be added to the vast body of literature challenging the EMH. For retail investors or fund managers the results show that the (risk-managed) momentum portfolios are a suitable way to create profitable investment portfolios. Especially the risk-managed momentum strategies report a strong and robust performance over the full sample period. For investors and fund managers that currently use momentum strategies the insights form this paper could support them in switching to risk-managed momentum strategies, protecting their portfolios from big drawdowns. Investors that initially found momentum strategies to risky the results presented can serve as evidence to implement the less risky risk-managed momentum strategies.

When solely looking at the Covid-19 pandemic period the same conclusions hold but the pandemic did not significantly impact the results. This serves as proof that also during the most recent market crash the risk-managed momentum strategies succeeded in protecting the portfolios from big drawdowns traditional momentum portfolios would have endured. For investors this shows that the risk-managed momentum strategies still achieve their goal and can be a relevant addition to their investment portfolios. From the different attempts to improve the risk-managed momentum strategies, reducing the lookback period was successful. This alteration results in a risk-managed momentum strategy that realizes even higher risk-adjusted returns than the traditional risk-managed momentum strategy while still serving the original purpose of this type of strategy: Reducing the vulnerability of momentum portfolios to market crashes.

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Appendix

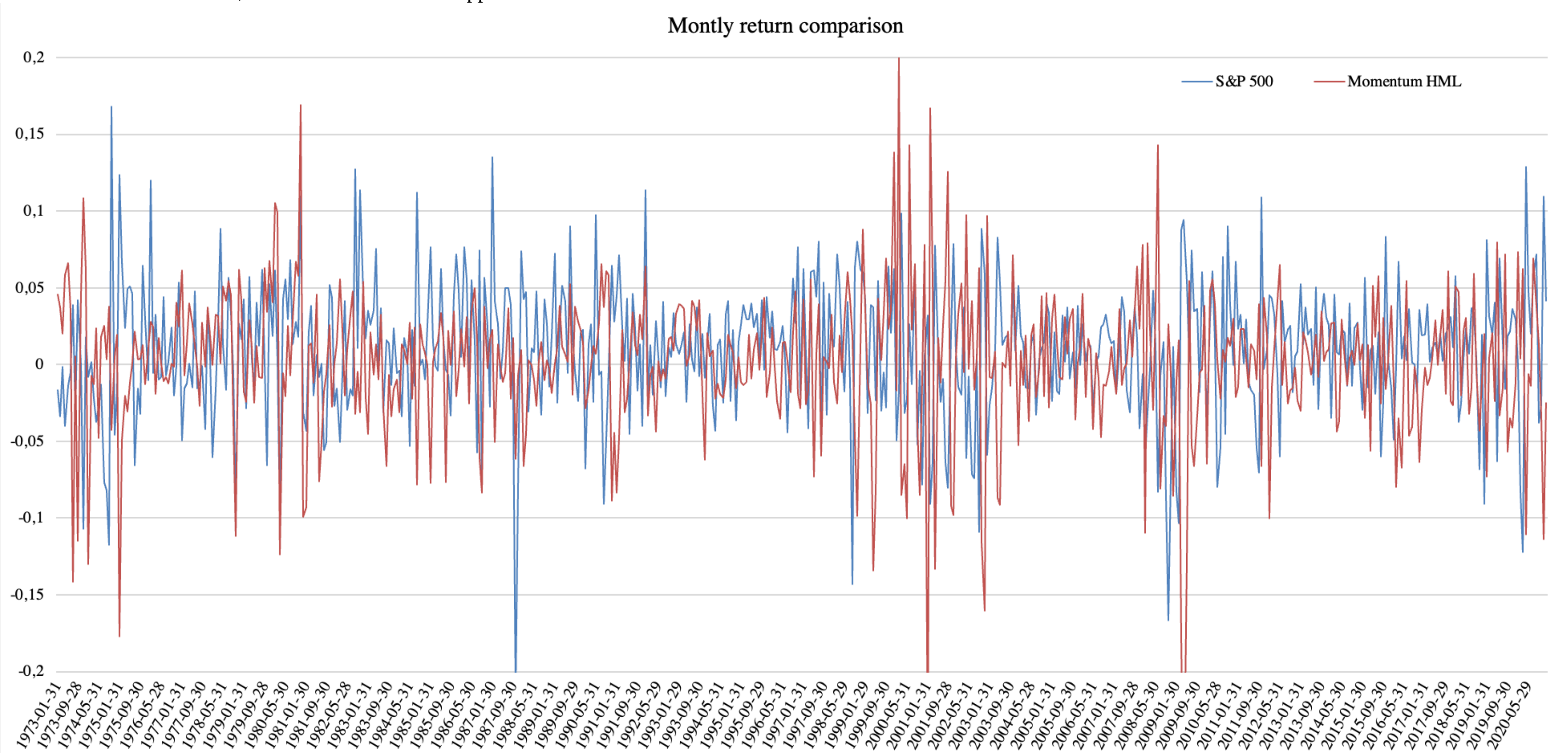
Descriptive statistics

Appendix 1, Descriptive statistics over the two periods of interest
This table includes the descriptive statistics of the dataset used over the two time periods that are studied in this paper. Reported are the average number of companies in the universe, the number of companies at the beginning of the period, the number of unique companies in the stock universe over the entire period, the average market value (X1000), total market cap of the entire stock universe and the average of the momentum statistic, the past 12-month return.

	# Companies average	# Companies start	# Companies unique	Market value	Market cap	Past 12-month return
1972-2020	**1804**	**1120**	**5123**	**5186**	**26.569.994**	**17.3%**
2020	**1263**	**1277**	**1312**	**24545**	**31.488.078**	**3.31%**

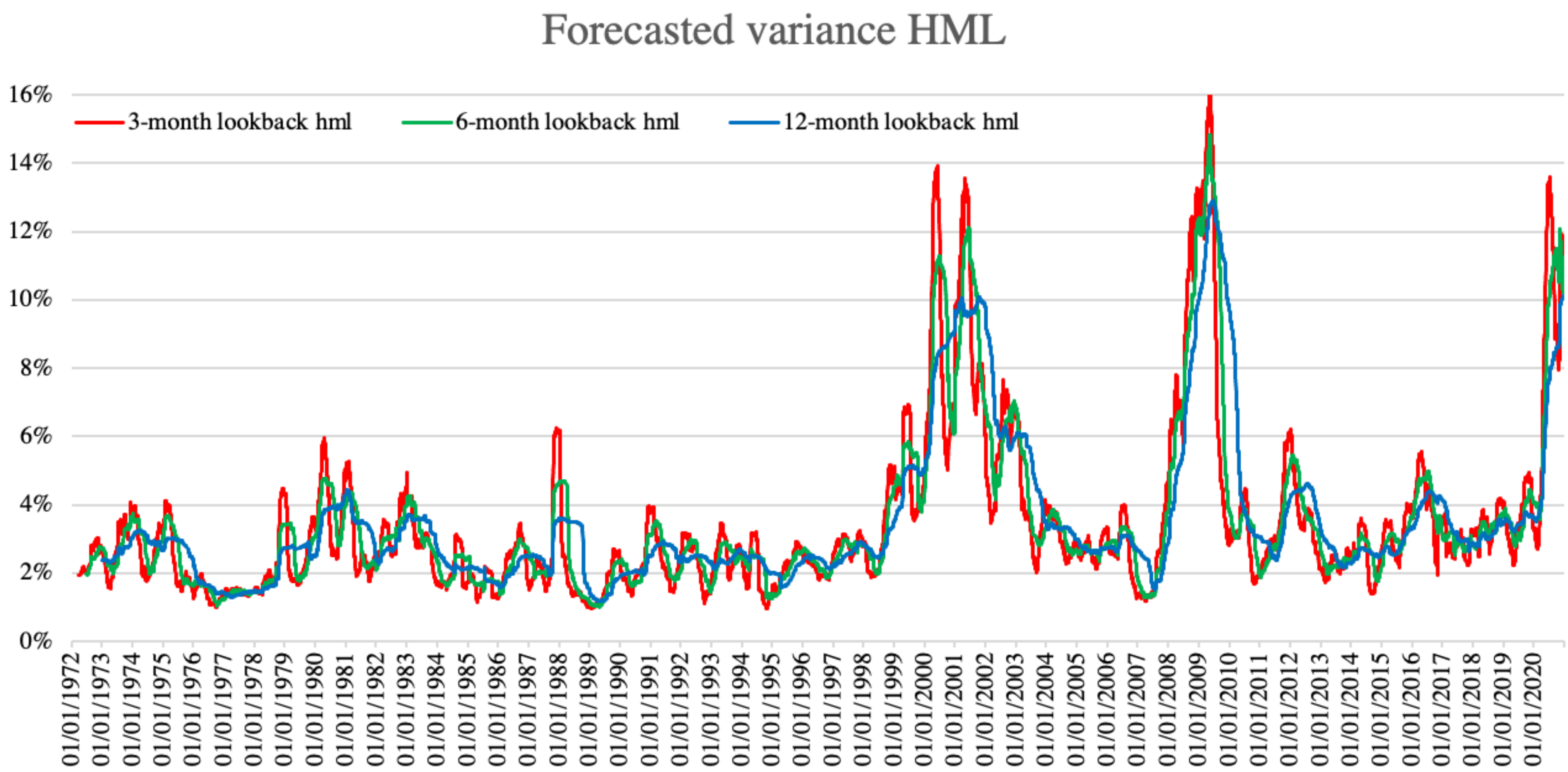
Appendix 2, Comparison between monthly returns

This figure compares the monthly return of the market index (S&P 500) to the monthly returns of the traditional momentum HML strategy over the full sample period. The goal of this figure is vizualizing the negative beta's following from the regression of momentum strategies on the marekt index. The main takeaway is the fact that, especialy in times of extreme returns, the returns move in the opposite direction.



Appendix 3, Forecasted variance fort the HML portfolios

Pictured are the variance forecasts for the HML portfolios over time. The lines differ in the lookback period used in estimating the forecast



Appendix 4, this table reports theweights of the different risk-managed momentum portfolio over time

Pictured ae the weights of all the risk-managed momentum portfolios over time. These weights are used to scale the exposure the exposure to momentum of each portfolio,