UiA University of Agder

Master

Return Premiums in Volatility-Managed Portfolios

Empirical evidence from Norway and international equity markets.

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Abstract

We scale portfolios by the inverse of their previous month’s realized variance to create volatility-managed portfolios. Our managed portfolios reduce market exposure when volatility is high and vice versa. We analyse the strategy's performance on portfolios constructed on various risk factors in the Norwegian and U.S. stock markets. Our results show that volatility-managing lead to improved returns for six out of eight portfolios. The strategy significantly reduces drawdowns during market turmoil while also amplifying returns through increased market exposure during calm markets. Volatility-managing performs well during most economic crises. However, the strategy shows ambiguous performance in the aftermath of the COVID-19 market crash, as only half of the portfolios outperform their unmanaged counterparts. We also provide international evidence of return premiums when applying the strategy to portfolios constructed on momentum. The superior risk-adjusted returns challenge the linear risk-return relationship in the capital asset pricing model.

Key words: Volatility-managing portfolios, market crashes

JEL classification: G11

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Simen Lilletvedt Årsland

Sindre Alme

Table of Contents

List of Figures

List of Tables

1. Introduction

Traditional financial theory assumes a positive relationship between risk and return that economists try to model accurately. The capital asset pricing model (CAPM) was introduced by William F. Sharpe in 1964 and marked the birth of asset pricing theory. His model is based on the idea that individual investments contain two types of risk: systematic risk tied to the market and unsystematic risk related to individual stocks. The first type is undiversifiable, and examples include changes in interest rates, recessions, and wars. Unsystematic risk represents the component of a stock's return that is not correlated with general market moves. Modern portfolio theory shows that specific risks can be removed, or at least minimized, through portfolio diversification. The expected return of a security is the risk-free rate plus the beta of the security times the excess return on the market. Beta is the measure of a stock's risk relative to the market. Stocks, or portfolios, with higher betas than one, are rewarded with proportionally increased returns. This leads to the main takeaway from the capital asset pricing model: the only way an investor should earn more, on average, is by investing in riskier stocks or portfolios. There is a positive linear relationship between risk and return in the CAPM.

Contrary to the expectation of a positive relationship between risk and return, Black (1976) argues that sometimes the relationship between volatility and return is negative, especially when volatility suddenly spikes. Figure 1 plots the average monthly volatility sorted in five bins with the corresponding average excess return. It shows a negative relationship between volatility and returns on the Oslo Stock Exchange. The mean excess returns are lower in the months with higher realized volatility. In the fifth quantile, the monthly volatility is accompanied by a negative mean excess return. The graph demonstrates the occasional negative relationship discovered by Black.

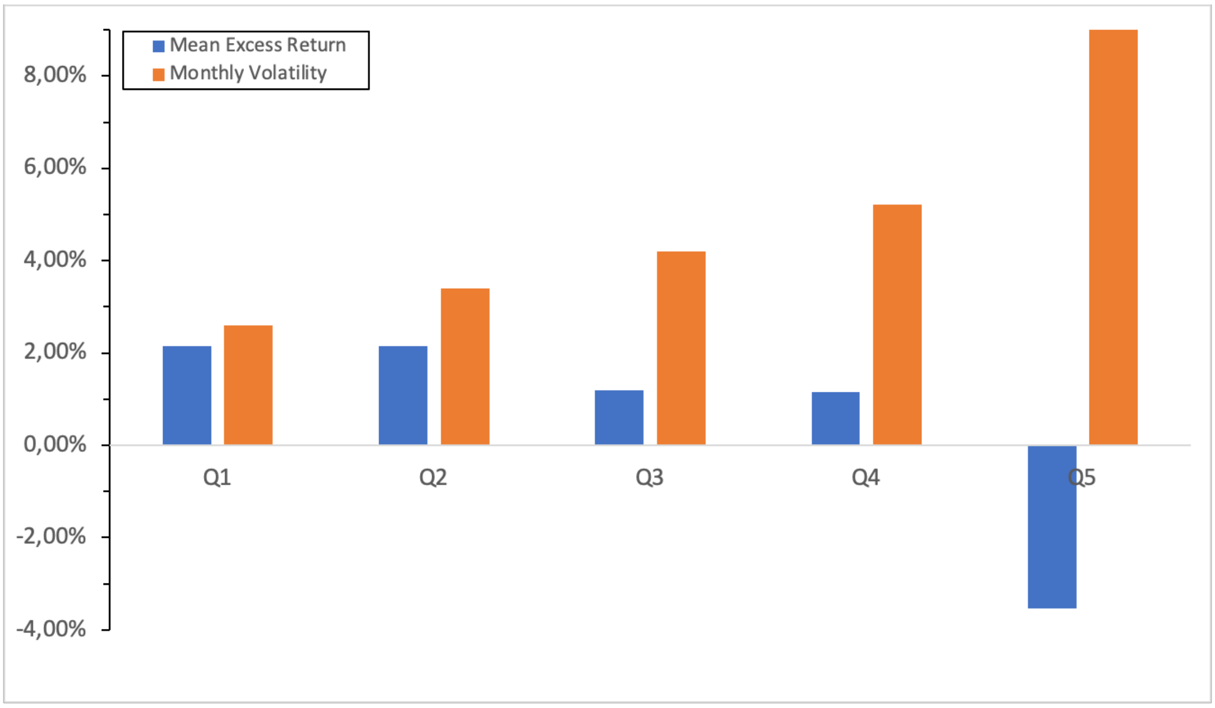

Figure 1: Mean excess return and average monthly realized volatility of the Oslo Stock Exchange (OSEAX) from 1983 to 2019. We use daily returns to calculate the monthly volatility. They are sorted into five quintiles, ordered from the lowest monthly volatility (Q1) to the highest monthly volatility (Q5).

Engle (1982) developed statistical models for variance forecasting and found that the past provides information about the one-period forecast variance. The variance is, to some extent, predictable in the near future. Moreira and Muir (2017) suggest that an investor can exploit the predictability of variance and its relationship with returns by employing a volatility-managing strategy. The goal of volatility-managing is to achieve higher returns without taking more risk. We follow their methodology to examine the relationship between risk and return by constructing volatility-managed portfolios that adjust market exposure according to the previous month's volatility. Our managed portfolios are constructed by scaling portfolios by the inverse of their previous month's realized variance. When the realized variance is higher than the unconditional variance over the entire sample, an investor allocates a proportion of his portfolio to the risk-free asset. If the realized variance is lower, he borrows money at a risk-free rate to increase exposure. We calculate the realized variance using the daily returns of the previous month; thus, the strategy is easy to implement for an investor.

We run predictive regressions of the volatility-managed portfolios on the unmanaged counterparts to evaluate the strategy's performance. We observe improved returns at the same level of unconditional variance for six out of eight portfolios in the Norwegian and U.S. markets from 1981 to 2019. The managed momentum portfolios report the most significant improvements.

The primary motivation behind the strategy is to avoid large drawdowns during market crashes. This leads to an important contribution to our thesis: we compare the performance of volatility-managed Norwegian and U.S. portfolios during the COVID-19 pandemic. The market collapse following the outbreak in China is, unlike other market crashes that the strategy has been tested on, not of economic origin. Our results demonstrate how some characteristics, such as the rapid recovery from the crash, reduce its viability. The market exposure is significantly reduced after a month of high volatility. Our managed portfolios miss out on a significant portion of the upward movement in the months following the crash. Nevertheless, the strategy reports promising results when applied to portfolios constructed on momentum.

The managed momentum portfolios deserve further investigation because of their strong performance during the 1981 to 2019 period and the COVID-19 pandemic. Therefore, we expand our empirical analysis of volatility-managed momentum portfolios to a broader selection of international equity markets. We find that the strategy performs remarkably well on portfolios constructed on momentum.

This paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology used in our paper. In section 4, we present the empirical results of volatility-managing portfolios in the Norwegian and U.S stock markets from 1981 to 2019. Section 5 discusses the strategy's performance during the COVID-19 pandemic and the empirical results from volatility-managing momentum portfolios in international equity markets. Finally, section 6 presents our conclusions.

2. Literature Review

Black (1976) discovered a positive relationship between risk and return under normal circumstances. However, in some extreme cases, the opposite is true. When volatility spikes, the increased risk is often accompanied by negative returns. It highlights that the conditional expected return and volatility may be negatively correlated.

Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) processes. His empirical paper has been vital for studies exploring volatility, as it suggests that the past provides information about the one-period forecast variance. Moreover, because volatility is time-varying, it is to some extent predictable in the near future.

Andersen and Bollerslev (1998) further explored volatility forecasting. Their study suggests that stochastic volatility models, such as the ARCH model, produce accurate intraday volatility predictions. Andersen, Bollerslev, Diebold, and Labys (2003) progressed the volatility forecasting literature five years later. They found that realized volatility is an unbiased and highly efficient estimator of near-future return volatility.

Busse (1999) examined the daily return data of 230 equity funds. The funds' market exposure is reduced when the market volatility is high and vice versa. The volatility-timing strategy leads to improved fund performance, especially during periods of high conditional volatility.

Fleming, Kirby, and Ostdiek (2001) employ a GARCH model to test the effectiveness of volatility-timing assets such as gold, cash, stocks, and bonds. Their results suggest that the volatility-timing strategies outperform their unmanaged counterparts. In 2003, they expanded their research on volatility-timing. The study implements a realized variance approach to predict the variance. It concludes that the strategy leads to improved performances given timelines of up to a year.

Albeverio, Steblovskaya and Wallbaum (2013) study the long-term performance of volatility-targeting portfolios versus pure equity index investments. Their results show that their volatility-targeting strategy improves the risk-return ratio. It performs well in rising markets with low volatility and declining markets accompanied by high volatility levels. However, investors might suffer losses in non-standard market environments, such as sudden downfalls during calm markets. The paper concludes that the strategy could be improved by combining it with other strategies.

Moreira and Muir (2017) test the effectiveness of volatility-managing portfolios constructed on various risk factors through a realized variance approach. The managed portfolios outperformed their unmanaged counterparts from 1926 to 2015. Their results show improved Sharpe ratios, positive alphas, and higher utility gains. Furthermore, it highlights that an investor can time equity risk by using the previous month's realized variance as a predictor of future variance.

Cederburg, Doherty, Wang, and Yan (2019) examine if volatility management is beneficial by analysing 103 equity trading strategies. Their results suggest that volatility-managed portfolios fail to earn higher Sharpe ratios than their unmanaged counterparts. Liu, Tang, and Zhou (2019) also investigate volatility-timing strategies and find them difficult to apply to investors because the strategies suffer from look-ahead bias[1].

Barroso and Santa-Clara (2015) apply volatility-timing to portfolios constructed on momentum in four major markets. The performance is improved when the portfolios are scaled by their realized volatility from the previous six months. More specifically, the managed portfolios report improved Sharpe ratios and reduced crash risk. Daniel and Moskowitz (2016) suggest that the momentum crashes are partly forecastable, as they often appear during market turmoil. Their study finds that applying a volatility-timing strategy may double the Sharpe ratios compared to their unmanaged counterparts.

Claudio Borio (2020) studied the nature of economic crises and argued that the COVID-19 pandemic was different from other market crashes in recent history. The COVID-19 market

[1] Look-ahead bias means using information that would have not been known or available at the time.

crash had a non-economic origin. It was also a global crisis with unprecedented policy responses in terms of monetary and fiscal policies.

While the literature on volatility-timing portfolios in the U.S. stock market is extensive, there is limited research on the Norwegian market. Our empirical study applies volatility-managing to portfolios constructed on various risk factors in the Norwegian market and compares the strategy's performance with results from the U.S. market. Furthermore, we supply current literature with an analysis of the strategy's performance during the market crash following the COVID-19 pandemic. Lastly, we complement existing literature on volatility-managing portfolios constructed on momentum by investigating time series from Norway and six major stock markets.

3. Data and Methodology

3.1 Factor Portfolios

The data used in this paper is primarily daily and monthly returns of portfolios constructed on risk factors. These factors include the three original Fama-French factors and one factor from the extended five-factor model (Fama and French, 2014). The first portfolio represents the excess return on the market (MKT). The second portfolio is constructed on the size factor (small-minus-big, SMB). It assumes that small companies outperform larger companies in the long run. It is constructed by shorting large companies while going long on small companies. Furthermore, the high-minus-low (HML) portfolio is created by going long on value stocks while shorting smaller companies. Lastly, we apply volatility-managing to portfolios constructed on momentum. The manager takes a long position on stocks with upwards momentum and a short position on stocks with negative momentum (MOM/UMD). Odegaard (2021) has constructed factor portfolios as calculated by Fama and French using Norwegian data. The factor portfolios are chosen because their returns are weakly correlated. Therefore, they represent different areas of risk in the market. It enables discussion of the strategy's effectiveness on different types of portfolios.

We analyse factor portfolios in the Norwegian and U.S. stock markets from 1981 to 2019. For the Norwegian market portfolio, the data is only available from 1983 to 2019. Furthermore, we compare the performance of Norwegian and U.S. momentum portfolios with corresponding portfolios from five major economies in Europe. Specifically, the period from 1986 to 2019 is examined for the following countries: France, Italy, Spain, Great Britain, and Germany. One of the main motivations behind volatility-managing is to outperform the unmanaged portfolio by reducing drawdowns during market crashes. Therefore, we further analyse the Norwegian and U.S. factor portfolios during the market crash following the COVID-19 outbreak in China (Jan. 2020 to Dec. 2020).

Data on the Norwegian portfolios are available from Odegaard's website[2], U.S. data is available on Ken French's website[3], and global factor data is available on Jensen, Kelly, and Pedersen's website[4]. In-depth descriptions of the construction of the factor portfolios are available on the respective websites.

3.2 Volatility-Managed Portfolios

The background of volatility-managing stems from two realizations. Volatility is predictable to some degree, and high volatility does not consistently compensate for increased expected returns (Moreira and Muir, 2019). This implies that an active strategy where an investor increases market exposure when volatility is low, and vice versa, will generate higher returns than a passive approach.

Our volatility-managed portfolios follow the methodology presented by Moreira and Muir (2017). By scaling the excess return by the inverse of its conditional variance, the strategy increases or decreases risk exposure to the portfolio based on the variation of conditional variance. The return of the managed portfolio is computed as follows:

$$f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}^2(f)} * f_{t+1}, \tag{1}$$

where f_{t+1}^{σ} is the managed portfolio excess return, f_{t+1} is the unmanaged portfolio excess return, $\hat{\sigma}^2(f)$ is a proxy for the portfolio's conditional variance, and the constant c controls the average exposure of the strategy. We choose c so that the managed portfolio has the same unconditional standard deviation as the original portfolio to simplify the interpretation of its

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[2] The daily and monthly returns of the factor portfolios are found on the following website: https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html

[3] Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] Global factor data: https://jkpfactors.com/

performance (if the portfolios have different returns at the same levels of risk, they have different Sharpe ratios) [5].

We use the previous month's realized variance as our proxy for the conditional variance:

$$\hat{\sigma}_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1}\left(f_{t+d} - \frac{\sum_{d=\frac{1}{22}}^{1} f_{t+d}}{22}\right)^2 \qquad (2)$$

We also estimate a predictive regression model with the ordinary least squares (OLS) approach, using the returns of the managed and unmanaged portfolios as the dependent and independent variables, respectively. The regression is computed following this equation:

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}, \qquad (3)$$

where the intercept is represented by the alpha (α). In the context of our regression, the alpha is interpreted as follows; a positive value implies that volatility-managing leads to increased returns and higher Sharpe ratios relative to the unmanaged portfolio. It can be explained as the expected return of the volatility-managed portfolio when the return of the original portfolio is zero. The error term, ϵ_{t+1}, represents the difference between the predicted value, given the parameters α and β, and the actual value f_{t+1}^{σ}.

3.3 Sharpe Ratio

The Sharpe ratio (SR), developed by William F. Sharpe (1966), is a tool investors use to evaluate portfolio performance. It describes the return of an investment compared to its risk by measuring the average return earned in excess of the risk-free rate per unit of volatility:

[5] The value of c does not affect the Sharpe ratio because returns are amplified as the unconditional variance is changed. This amplification is proportional to the increase or decrease in volatility, hence, the Sharpe ratio stays the same.

$$SR = \frac{E\left[r_p - r_f\right]}{\sigma_p}, \tag{4}$$

where r_p is the return on a portfolio p, r_f is the return on a risk-free asset, $E\left[r_p - r_f\right]$ is the expected (or realized) excess return, and σ_p is the standard deviation of the portfolio. The measurement is used to compare the performance of two or more portfolios; a higher Sharpe ratio translates to a better performing portfolio. To determine whether there is a significant difference between the portfolio's Sharpe ratios, we apply the test formulated by Jobsen and Korkie (1981), further improved by Memmel (2003). The following are the null and alternative hypotheses:

$$H_0\colon SR_a = SR_p \; and \; H_1\colon SR_a > SR_p, \tag{5}$$

where SR_a and SR_p is the Sharpe ratios of the managed and unmanaged portfolios, respectively. We can test the null hypothesis by applying the following test statistic:

$$z = \frac{SR_a - SR_p}{\sqrt{\frac{1}{T}\left[2(1-\rho) + \frac{1}{2}\left(SR_a{}^2 + SR_p{}^2 - 2SR_aSR_p\rho^2\right)\right]}}, \tag{6}$$

where ρ denotes the estimated correlation coefficient between returns over the sample size, the T represents the number of observations (months), and the z is asymptotically distributed with the standard normal distribution.

4. Empirical Results

This section analyses the descriptive and performance statistics of the unmanaged and managed portfolios in Norway and the USA from 1981 to 2019.

4.1 Descriptive Statistics

Table 1 shows a weak correlation between the returns of the Norwegian portfolios. The portfolios that exhibit the strongest negative correlation in Norway are MKT and SMB, with a correlation of (0.43). The same is observed amongst the portfolios on the U.S. market, as the HML and MKT portfolios reveal the strongest negative correlation of (0.24)[6]. Because the portfolios are weakly correlated, they capture different dimensions of risk in the market.

Table 1: Correlation between the monthly returns of the Norwegian factor portfolios from 1981 to 2019.

	SMB	**HML**	**UMD**	**MKT**
SMB	1.00	(0.19)	0.05	**(0.43)**
HML	-	1.00	(0.04)	0.08
UMD	-	-	1.00	(0.05)
MKT	-	-	-	1.00

In table 2, the Norwegian momentum portfolio reports the most significant one-month return of 25.53%. The market portfolio discloses the largest single-month drawdown of (27.39%) and the highest mean return of 1.11%. Similarly, the U.S. market portfolio also reports the highest monthly excess mean return of 0.67%. The SMB portfolio shows the most significant single-month return of 18.38%, and the momentum portfolio experiences the

[6] Table 9 in the appendix shows the correlation between the monthly returns of the U.S. factor portfolios.

biggest one-month drop of (34.30%). Our results show that momentum portfolios experience more significant downfalls than other factor portfolios[7].

Table 2: Summary statistics of monthly returns from 1981 to 2019.

NORWAY

	SMB	HML	UMD	MKT
Max. (%)	21.05	22.22	25.53	17.37
Min. (%)	(16.62)	(19.57)	(24.29)	(27.39)
Mean (%)	0.68	0.43	0.82	1.11
Obs.	462	462	462	443

USA

	SMB	HML	MOM	MKT
Max. (%)	18.38	12.48	18.20	12.47
Min. (%)	(15.39)	(11.11)	(34.30)	(23.24)
Mean (%)	0.06	0.25	0.55	0.67
Obs.	462	462	462	462

4.2 Performance Statistics

Table 3 reports the results of the predictive regressions of the volatility-managed portfolios on their unmanaged counterparts. The alpha is a measure of the abnormal return of an investment. A positive alpha implies that the strategy stretches the mean-variance efficient frontier. In other words, the expected return is improved for a defined level of risk. Most managed Norwegian portfolios report positive alphas. The largest is for the momentum portfolio, disclosing an annualized alpha of 8.69%. The managed HML portfolio reports a negative alpha of (4.18%), which is statistically significant at a 95% confidence level. It implies that the managed version underperforms compared to its unmanaged counterpart. The

[7] Barroso and Santa-Clara (2015) find that momentum portfolios are accompanied by the largest occasional crashes.

positive alphas are statistically significant at the 5% level for the momentum and the market portfolios and at the 10% level for the SMB portfolio.

Three out of four managed U.S. portfolios report improved returns. These three are the HML, MOM, and MKT portfolios. Consistent with the findings from the Norwegian market, the managed momentum portfolio reveals the highest alpha. It outperforms its benchmark with an annual abnormal return of 9.37%. The alphas of the momentum and market portfolios are positive, statistically significant at 95% confidence levels. For an investor seeking gains by applying the strategy, the Norwegian and U.S. market portfolios offer abnormal returns of 5.67% and 3.59%, respectively. Our results show that managing momentum and market portfolios would increase returns in both markets. For the other factor portfolios, the strategy reports ambiguous performances.

Table 3: Predictive OLS regressions of equation (3). Our sample runs from 1981 to 2019 (1983 to 2019 for the Norwegian market portfolio). Alpha estimates are annualized by multiplying monthly values by 12.

NORWAY

	SMB^{σ}	**HML^{σ}**	**UMD^{σ}**	**MKT^{σ}**
α	2.90%	(4.18%)	8.69%	5.67%
β	0.76	0.77	0.76	0.77
p-value	0.08	0.03	0.00	0.01
Obs.	461	461	461	442
R^2	0.58	0.58	0.58	0.57
RMSE	35.65	40.63	44.41	47.58

USA

	SMB^{σ}	**HML^{σ}**	**MOM^{σ}**	**MKT^{σ}**
α	(1.27%)	0.47%	9.37%	3.59%
β	0.79	0.65	(0.02)	0.72
p-value	0.20	0.71	0.00	0.04
Obs.	461	461	461	461
R^2	0.62	0.39	0.00	0.49
RMSE	21.22	27.07	52.58	37.43

Table 4 presents the unmanaged and managed Sharpe ratios and the Modigliani-Modigliani measures. The Sharpe ratio of the managed Norwegian market portfolio increases from 0.37 to 0.51. The risk-return ratio improves from 0.49 for the unmanaged momentum to 0.81 for its managed version. Moreover, managing the SMB portfolio also leads to an improved Sharpe ratio. However, the Sharpe ratio is reduced from 0.27 for the unmanaged HML portfolio to (0.01) for its managed version.

Table 4: The unmanaged and managed Sharpe ratios, p-values from Memmel's test, and the annualized Modigliani-Modigliani measures of the portfolios from 1981 to 2019.

NORWAY

	SMB	**HML**	**UMD**	**MKT**
Unmanaged SR	0.57	0.27	0.49	0.37
	SMB^{σ}	**HML^{σ}**	**UMD^{σ}**	**MKT^{σ}**
Managed SR	0.63	(0.01)	0.81	0.51
p-value	0.06	N/A	0.00	0.00
M^2 (%)	0.91	(5.12)	6.25	2.88

USA

	SMB	**HML**	**MOM**	**MKT**
Unmanaged SR	0.07	0.30	0.43	0.53
	SMB^{σ}	**HML^{σ}**	**MOM^{σ}**	**MKT^{σ}**
Managed SR	(0.06)	0.24	1.01	0.61
p-value	N/A	N/A	0.00	0.02
M^2 (%)	(1.69)	0.03	8.94	0.76

Two out of four managed U.S. portfolios reveal reduced Sharpe ratios. The largest decline is reported by the SMB portfolio, with a reduction of 0.13. We also observe a lower risk-return ratio when managing the HML portfolio. The remaining portfolios show improvements. The most significant difference is realized with the managed momentum portfolio, where the Sharpe ratio has increased by 0.58. Managing the market portfolio increases its Sharpe ratio from 0.53 to 0.61.

We use Memmel's (2003) test to determine whether the improved Sharpe ratios of the managed portfolios are statistically significantly better than those of their unmanaged counterparts. The p-values in table 4 represent the standard score obtained from the test. Our results show that the following managed Norwegian portfolios exhibit statistically significant Sharpe ratio improvements at 95% confidence levels: UMD and MKT. In addition, the improvement in the managed SMB portfolio is statistically significant at the 10% level. Since applying the strategy to the HML portfolio reduces its Sharpe ratio, it is not tested for improvement. Similarly, results from the U.S. market show statistically significant improvements in the Sharpe ratios at the 5% level for the momentum and market portfolios. We do not apply the test to the remaining managed portfolios because their risk-return ratios are reduced.

The Modigliani and Modigliani (1997) metric measures if the managed portfolio out- or underperforms its unmanaged version on a risk-adjusted basis. Bodie, Kane, and Marcus (2007) explain that when two portfolios have the same standard deviation, the metric is expressed as:

$$M^2 = r_p - r_M, \tag{7}$$

where M^2 is the Modigliani-Modigliani measure, r_p is the return of the managed portfolio, and r_M is the return of the unmanaged portfolio.

Our results show that the managed Norwegian and U.S. momentum portfolios outperform their counterparts by 6.25% and 8.94%, respectively. The managed market portfolios also outperform their unmanaged versions. In Norway, the market portfolio outperforms by 2.88%, while in the U.S., the managed version provides a positive gain of 0.76%. The managed U.S. HML portfolio reports a positive M^2 measure of 0.03%, while the managed Norwegian HML portfolio underperforms by 5.12%. The managed SMB portfolio performs well (up 0.91%) in Norway and poorly in the U.S (down 1.69%). The strategy's overall performance is similar, as three out of four factor portfolios outperform their unmanaged counterparts in the respective countries.

Figure 2 plots the cumulative excess returns of the managed and unmanaged Norwegian market portfolios. An investor would increase returns by applying the strategy to the market portfolio. Investing one dollar in 1983 would accumulate to $20.32 in 2019 for the managed version versus $6.76 for its unmanaged counterpart. Furthermore, we observe that the managed portfolio avoids significant drawdowns before, during, and after the financial crisis in 2008-2009, in which the unmanaged version realizes its most significant drawdowns. This showcases one of the strategy's biggest strengths: avoiding large market declines in times of crisis. Another strength of volatility-managing is the ability to increase leverage during periods of low volatility and positive returns. This was observed from 1997 to 1998 and from 2014 to 2015, when the returns of the managed portfolio were higher than the unmanaged counterpart.

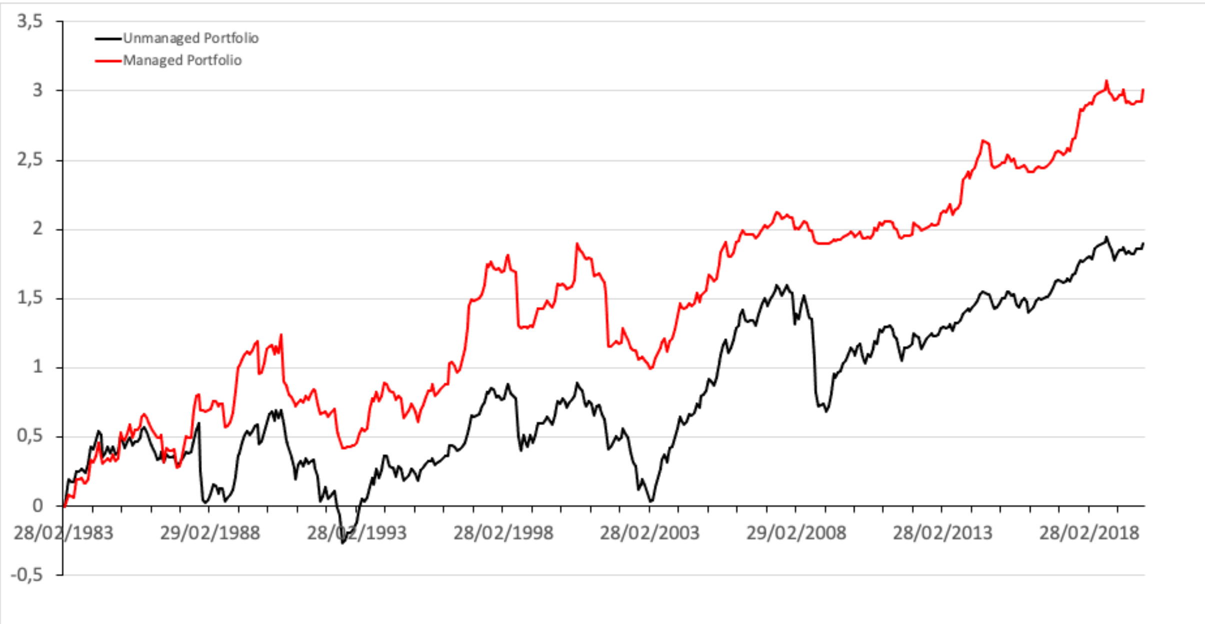

Figure 2: Cumulative excess returns for the managed and unmanaged Norwegian market portfolios from 1983 to 2019. Both portfolios have the same unconditional standard deviation. The y-axis is expressed on a log scale, and the x-axis represents the timeline.

Managing the Norwegian portfolios leads to positive excess returns in most cases. For the HML portfolio, an investor would benefit from holding on to the unmanaged version throughout our sample instead of continuously adjusting market exposure. Figure 3 shows a sharp upswing in the market after the economic crisis in the early 1990s. The managed portfolio misses a portion of the upward movement because the exposure has been reduced following a period of high volatility. This weak performance is not consistent with the performance of the other portfolios. Most managed portfolios (e.g., the market portfolio) outperform their counterparts during periods of high volatility, such as during the Black Monday crash in 1987, the dot-com bubble in 2000-2002 and the global financial crisis in 2008-2009.

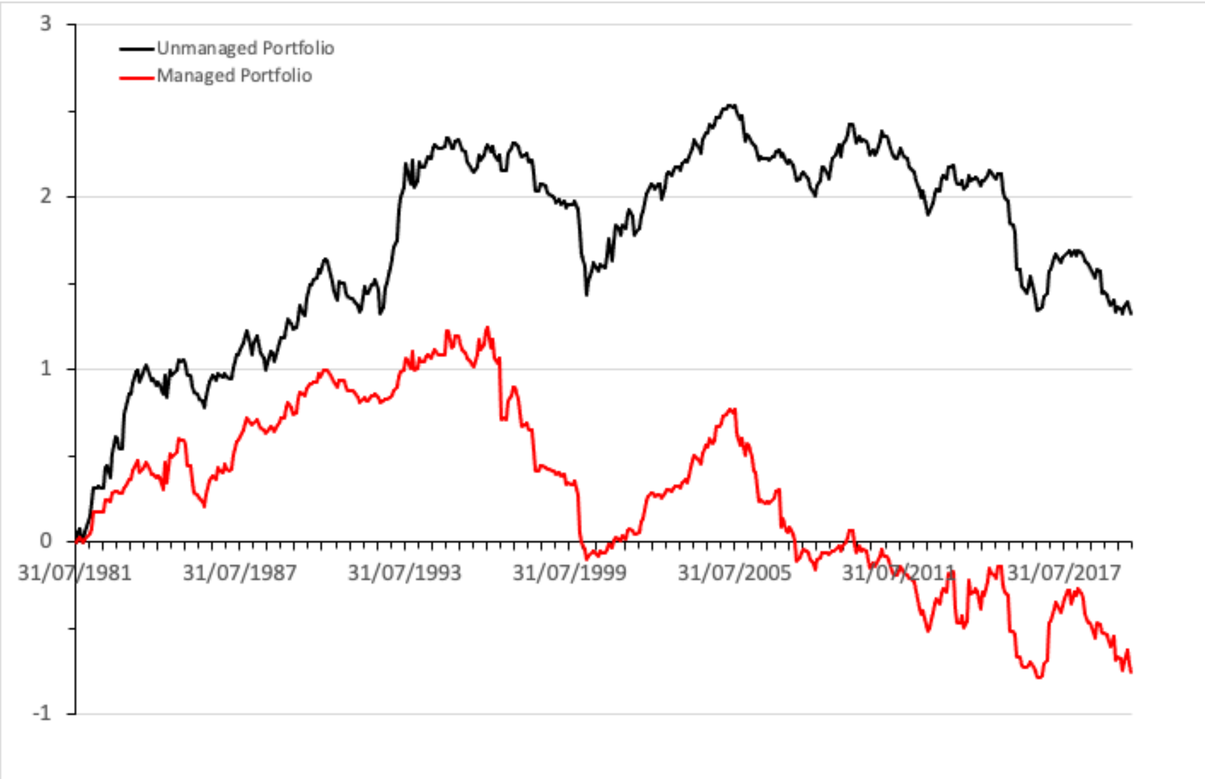

Figure 3: Cumulative excess returns for the managed and unmanaged Norwegian HML portfolios from 1981 to 2019. Both portfolios have the same unconditional standard deviation. The y-axis is expressed on a log scale, and the x-axis represents the timeline.

In figure 4, we observe the managed momentum (UMD) portfolio performing remarkably well. An investment of $1 in the managed version in July 1981 provides an impressive $205.82 in December 2019 versus $17.23 for the unmanaged portfolio. We observe an even more substantial growth when managing the momentum portfolio in the U.S., as the portfolio accounts for $236.71 in 2019 after investing $1 in 1981. These improvements highlight the strategy's effectiveness on portfolios constructed on momentum. Figure 4 shows that the unmanaged momentum portfolio provides higher returns than its counterpart until 1992. From there on, the managed version excels in all market environments, including both bull and bear markets. Because of the significant outperformance in Norway and the U.S., the momentum portfolios deserve further investigation. We expand our empirical analysis of portfolios formed on momentum in section 5.

Figure 4: Cumulative excess returns for the managed and unmanaged Norwegian momentum portfolios from 1981 to 2019. Both portfolios have the same unconditional standard deviation. The y-axis is expressed on a log scale, and the x-axis represents the timeline.

Figure 5 plots the cumulative excess return of the unmanaged U.S market portfolio and its managed counterpart. There is a significant increase in returns when the strategy is applied to the market portfolio. Investing one dollar in 1981 would grow to 22.75 dollars in 2019, compared to 14.28 dollars for the unmanaged version. The graph illustrates the strength of the strategy, showing less significant drawdowns during market turmoil, such as during the dot-com bubble in 2000-2002 and the financial crisis in 2008-2009.

Figure 5: Cumulative excess returns for the managed and unmanaged U.S. market portfolios from 1981 to 2019. Both portfolios have the same unconditional standard deviation. The y-axis is expressed on a log scale, and the x-axis represents the timeline.

The maximum drawdown (MDD) is calculated by taking the difference between the current peak value and the lowest value of the portfolio before a new peak is reached. Then, the difference is divided by the previous peak's value. According to Magdon-Ismail and Atiya (2004), MDD is a common risk measure among investors. It captures the portfolio's downside risk during a specific period. The volatility-managed portfolios report less significant drawdowns than their unmanaged versions. The reduced downfalls from managing portfolios highlight one of the most important features of the strategy: reducing the market exposure during market turmoil. In figure 6, we observe a higher frequency of significant drawdowns for the unmanaged Norwegian market portfolio. The large downfalls mainly occur during market turmoil. More specifically, the strategy successfully hedges against substantial drawdowns during the Black Monday crash in 1987 and the global financial crisis in 2008-2009.

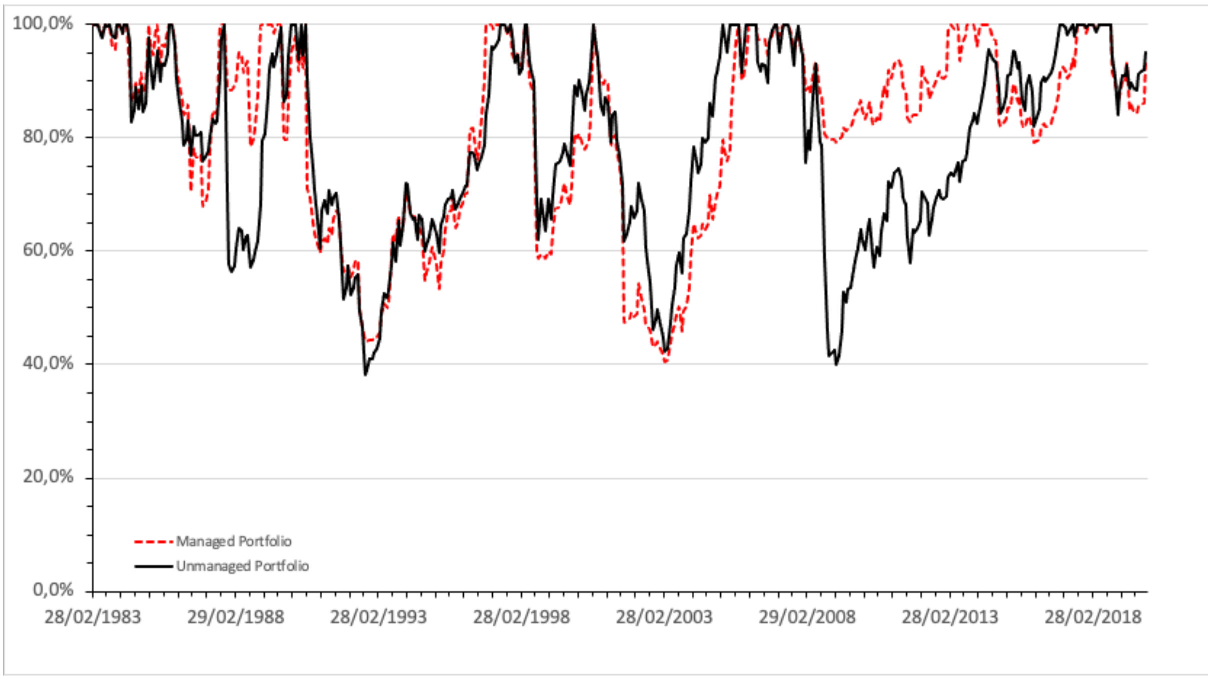

Figure 6: Drawdowns for the managed and unmanaged Norwegian market portfolios from 1983 to 2019.

Figure 7 displays that the managed U.S. market portfolio suffers from less significant drawdowns during the worst market crashes in our sample. Similarly to the performance of the managed Norwegian market portfolio, the managed U.S. version also excelled during the financial crisis in 2008-2009. Drawdowns of about 55% were reduced to a mere 20%. The maximum drawdown for the unmanaged portfolio is 54.44%, and the equivalent measure for the managed counterpart shows a downfall of 37.67%. Interestingly, the highest drawdown for the managed portfolio occurs during a period of relatively low volatility (from 2017 to 2019). It suggests that the strategy may struggle when minor falls during calm markets are magnified by high leverage.

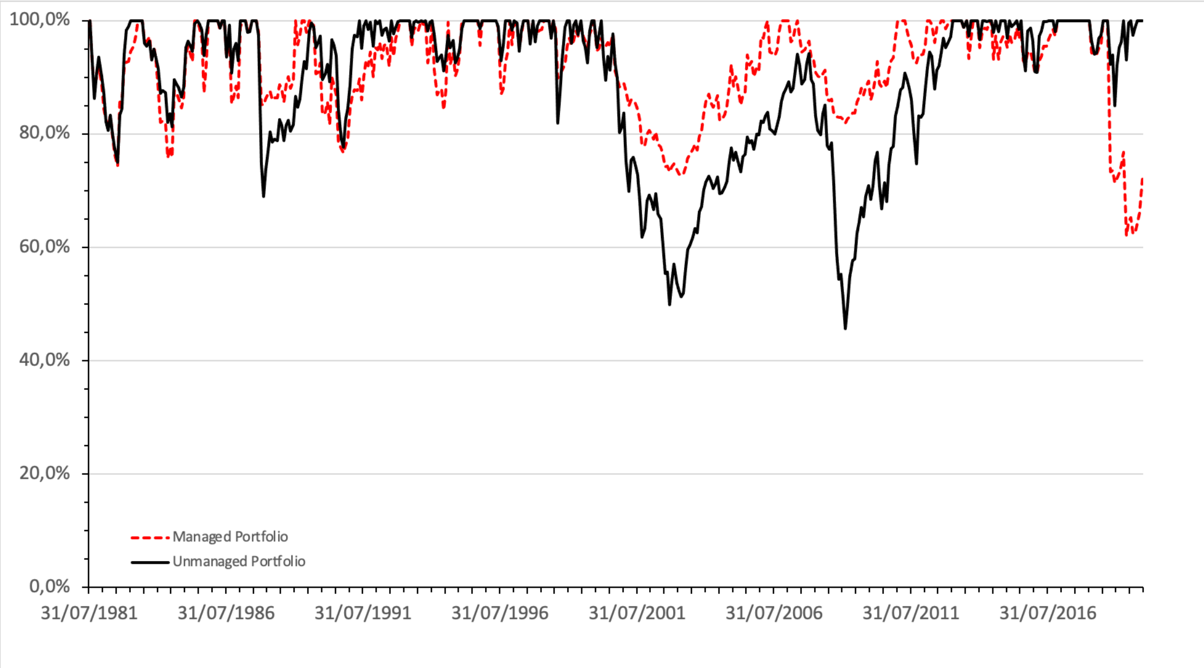

Figure 7: Drawdowns for the managed and unmanaged U.S. market portfolios from 1981 to 2019.

The maximum drawdown of unmanaged Norwegian momentum is 66.78% versus 47.56% for its managed version. In the U.S., the managed portfolio reveals a downfall of 19.31% versus 57.56% for the unmanaged counterpart[8]. Figure 8 demonstrates how the Norwegian momentum portfolio struggles to recover after a significant drop in 1990. It takes 16 years for the unmanaged portfolio to recoup its old peak from 1990. One of the reasons might be the occasional large crashes that come with momentum, as shown by the minimum one-month return of (24.29%) in Norway. In comparison, the managed version discloses a minimum one-month return of (15.90%). In addition, it only spends six years before reaching the same level as prior to the collapse in 1990. The managed version also experiences less significant drawdowns, especially during economic downturns such as the Black Monday crash in 1987, the early 1990s recession, the dot-com bubble in 2000-2002, and the global financial crisis in 2008-2009. An important benefit of volatility-managing momentum comes from the reduction in crash risk.

[8] The drawdowns of the unmanaged and managed U.S. momentum portfolios from 1981 to 2019 are plotted in figure 14 in the appendix.

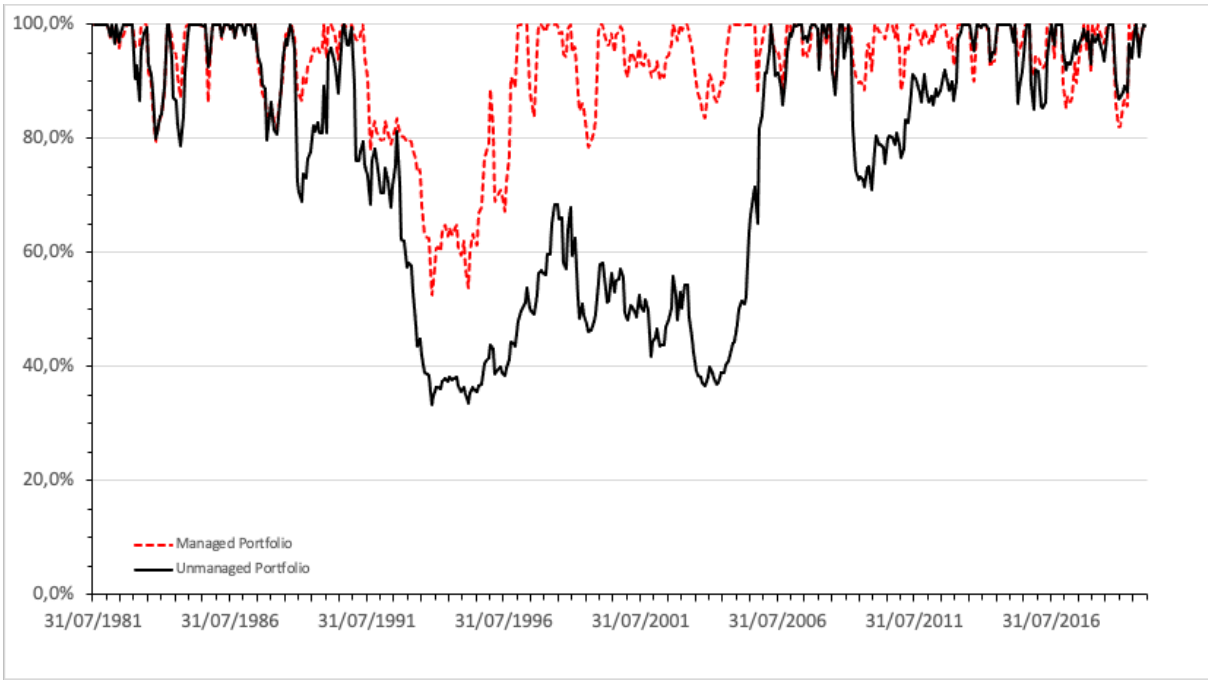

Figure 8: Drawdowns for the managed and unmanaged Norwegian momentum portfolios from 1981 to 2019.

The volatility-managing strategy reports improved returns for six out of eight portfolios. Our results show that the strategy exceeds during market crashes and excels at managing portfolios constructed on momentum. We theorize explanations for our findings in the next section.

5. Further Discussion

We examine the strategy's performance during financial crises of the past, followed by an analysis of its viability during the COVID-19 pandemic. Lastly, we investigate the performance of volatility-managed momentum portfolios.

5.1 Volatility-Managed Portfolios in Times of Crises

We realize that the strategy is most relevant to the market portfolio because an investor may adjust the exposure to a market-tracking ETF with little effort. Hence, the performance of the volatility-managing strategy on the market portfolios is of utmost interest to an investor. Therefore, we analyse the market portfolios in the respective markets. Figure 9 displays the market exposure in the months before, during, and after the market crashes in 1987, 2008, and 2020. The strategy successfully hedges against significant losses during the worst market crash in our sample. In October 1987, the Norwegian market recorded a downfall of 28.70%, and the U.S. market dropped 23.24%. The leverage levels are reduced to 0.39 and 0.56 for the Norwegian and U.S. market portfolios, respectively. The reduced exposure effectively cuts the losses in half in both markets. Furthermore, the following month after the crash is accompanied by negative returns of 19.13% in Norway and 7.77% in the U.S. The leverage ratio of the adjusted portfolios on both markets is a mere 0.02 this month. Therefore, the strategy managed to avoid an impressive 98.03% of the downfall in November 1987. Our results show that the strategy successfully reduces the largest collapses and most of the minor drawbacks in the aftermaths of other market crashes in our sample - resulting in higher cumulative returns.

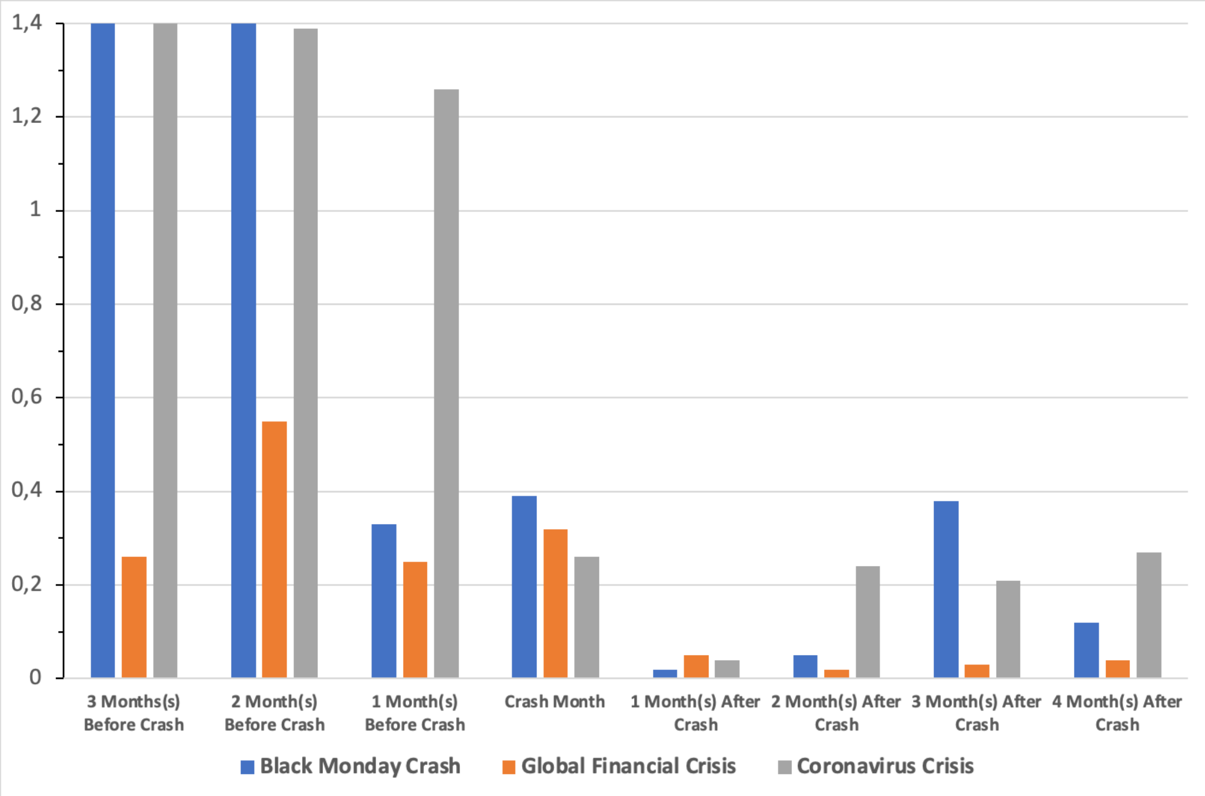

Figure 9: The leverage levels of the managed Norwegian market portfolio before, during and after market crashes.

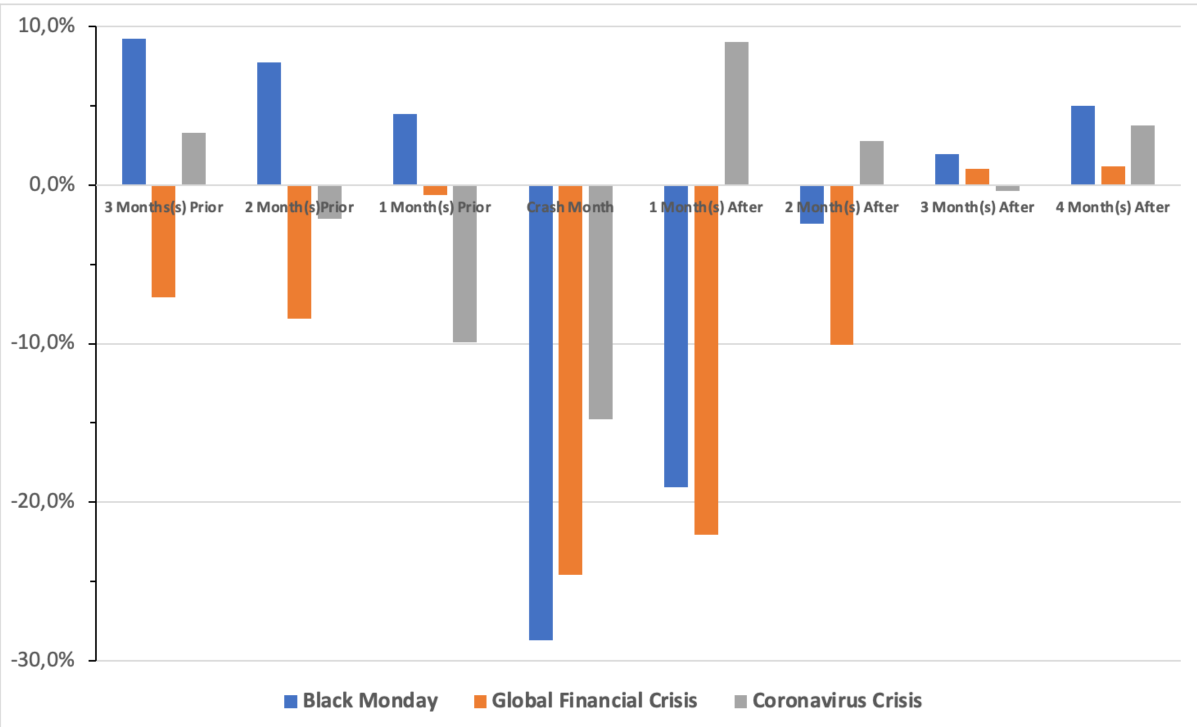

Figure 10: The monthly returns of the unmanaged Norwegian market portfolio before, during and after the market crashes.

The previous paragraph highlighted the strategy's effectiveness during market crashes. However, the strategy shows one of its weaknesses towards the end of our sample. In May 2019, the unmanaged U.S. market portfolio suffered a sudden decline of seven percentages during a period of low volatility. Because of the previous month's low realized volatility, the managed portfolio adjusted its leverage up to 2.7. This magnifies the decline, resulting in a drop in cumulative returns from 2426% to 1925%[9]. During the remaining six months, the portfolio fails to recover to its old peak and ends up with a cumulative return of 2264%. Its unmanaged counterpart performs better as it only spends two months before returning to a new peak level. This stresses that, while the strategy exceeds at reducing downfalls during market turmoil, the performance is poor when the market encounters drawbacks during periods of low volatility.

Next, we turn to the coronavirus crisis. We examine the performance of the volatility-managed factor portfolios during the outbreak period of the COVID-19 pandemic, Jan. 2020 to Dec. 2020.

Table 5 shows that investing $1 in the managed Norwegian and U.S. market portfolios accumulates to $0.87 and $0.92, respectively, in December 2020. An investor would be better off sticking to the unmanaged market portfolios, as they both provide higher returns than their managed versions. However, managing the Norwegian and U.S. momentum portfolios would increase gains by $0.23 and $0.04, respectively, compared to their counterparts. We find that the managed HML portfolios outperform their unmanaged versions in both countries. In the Norwegian and U.S. markets, an investor would expect an increase in accumulated wealth of $0.05 and $0.19, respectively. Lastly, the managed SMB portfolio reports ambiguous results. The final value of the portfolios remains the same in Norway. However, the value of the managed U.S. portfolio is significantly less than its counterpart.

[9] A dollar invested in the adjusted U.S. market portfolio accumulates to $25.26 in April 2019, giving a cumulative return of 2426%

Table 5: The final value of $1 invested in the managed and unmanaged factor portfolios from January 2020 to December 2020.

NORWAY

	SMB	**HML**	**UMD**	**MKT**
End value (Unmanaged)	$1.13	$0.81	$0.89	$0.98
End value (Managed)	$1.13	$0.86	$1.12	$0.87

USA

	SMB	**HML**	**MOM**	**MKT**
End value (Unmanaged)	$1.01	$0.71	$1.02	$1.18
End value (Managed)	$0.88	$0.90	$1.06	$0.92

The unmanaged and managed Norwegian market portfolios report their maximum drawdowns in March 2020. In figure 11, the unmanaged version discloses a downfall of 25.65% versus 18.54% for its managed counterpart. Interestingly, the managed market portfolio performs worse than its counterpart every month, excluding the crash month. The poor performance results from the quick rebound of the market in April (the month following the crash). Since the market exposure was reduced after a month of extreme volatility, it cancels out a large proportion of the upward movement. The managed portfolio struggles to recover from the significant market collapse.

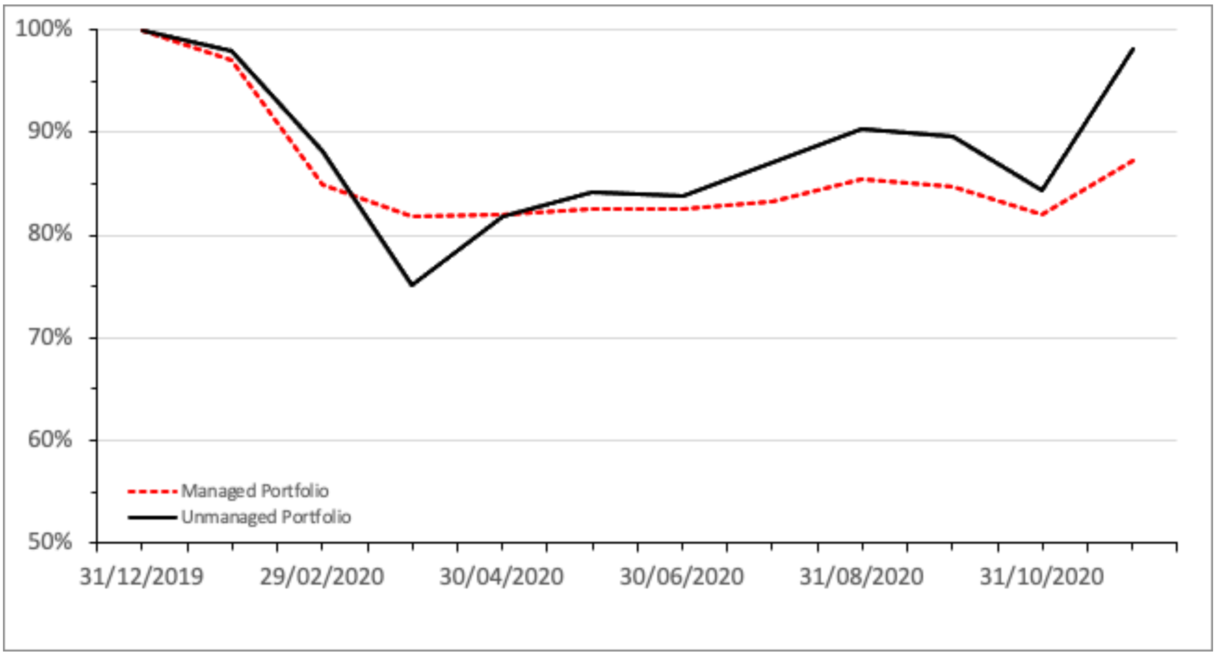

Figure 11: The drawdowns of the managed and unmanaged Norwegian market portfolios from Jan. 2020 to Dec. 2020.

Consistent with the performance of the managed portfolio in the Norwegian market, the managed U.S. market portfolio also avoids significant drawdowns (shown in figure 12). The unmanaged version reveals a maximum drawdown of 21.37%, while its counterpart reports a downfall of only 11.18%. Our results show that the strategy successfully hedged against large drawdowns during the pandemic. However, we note that the managed U.S. portfolio also struggled to recover after the initial market crash.

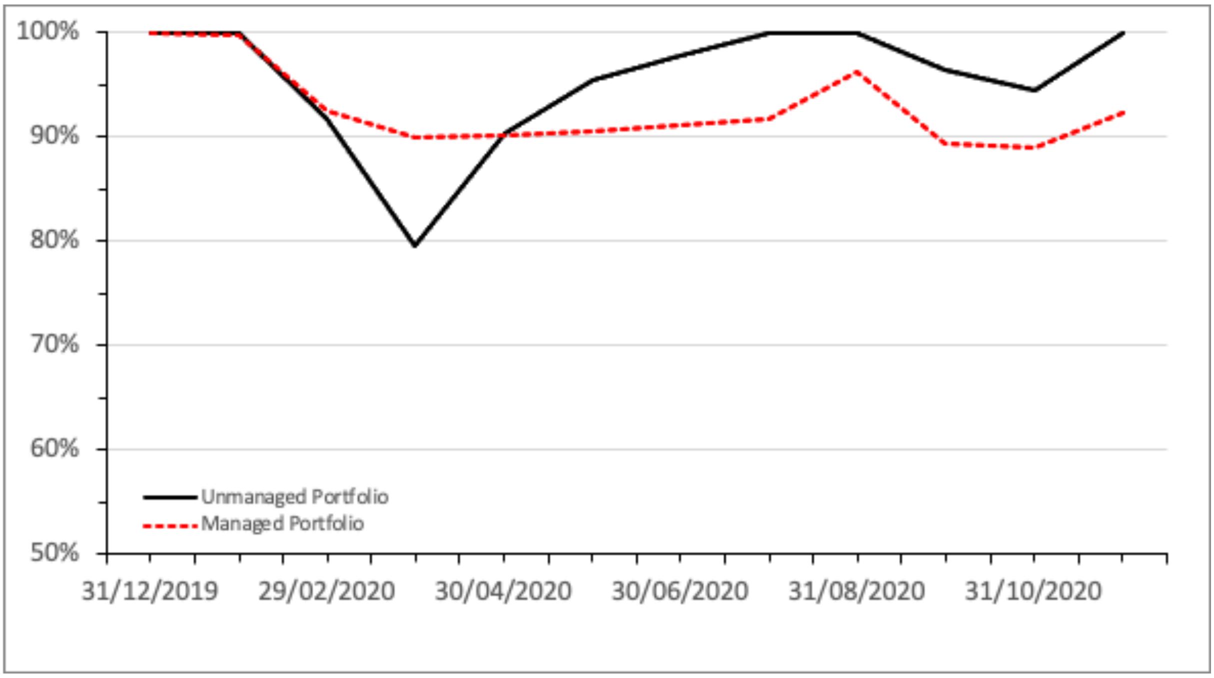

Figure 12: The drawdowns of the unmanaged and managed U.S. market portfolios from Jan. 2020 to Dec. 2020.

The volatility-managed market portfolios perform poorly during the pandemic. Finding a definite answer to the underperformance is left for future research. Nevertheless, we theorize a few possibilities. Our results show that, during the two worst market crashes in our sample, Black Monday in 1987 and the financial crisis in 2008-2009, the managed market portfolios avoid significant drawdowns. Bongaerts, Kang and van Dijk (2020) also find that volatility-managing is effective in times of extreme volatility because it manages to hedge against substantial declines. This is also the case for the coronavirus period. The strategy manages to reduce the initial drawdown; however, it suffers in the aftermath of the crash because its leverage is reduced. The following months after the crash exhibited relatively high levels of volatility (shown in figure 13). Therefore, the market exposure remains low. Unlike the other crashes in our sample, where the initial crash is followed by several months of negative returns, the market rebounds the months after the crash. The quick recovery is likely due to the rapid fiscal and monetary policy response, such as close-to-zero interest rates and government securities purchases (Chadha et al., 2021). The market reports mostly positive returns until September 2020, even reaching higher levels than pre-COVID. However, due to low leverage, our managed portfolios miss out on most of the gains from the upward movement.

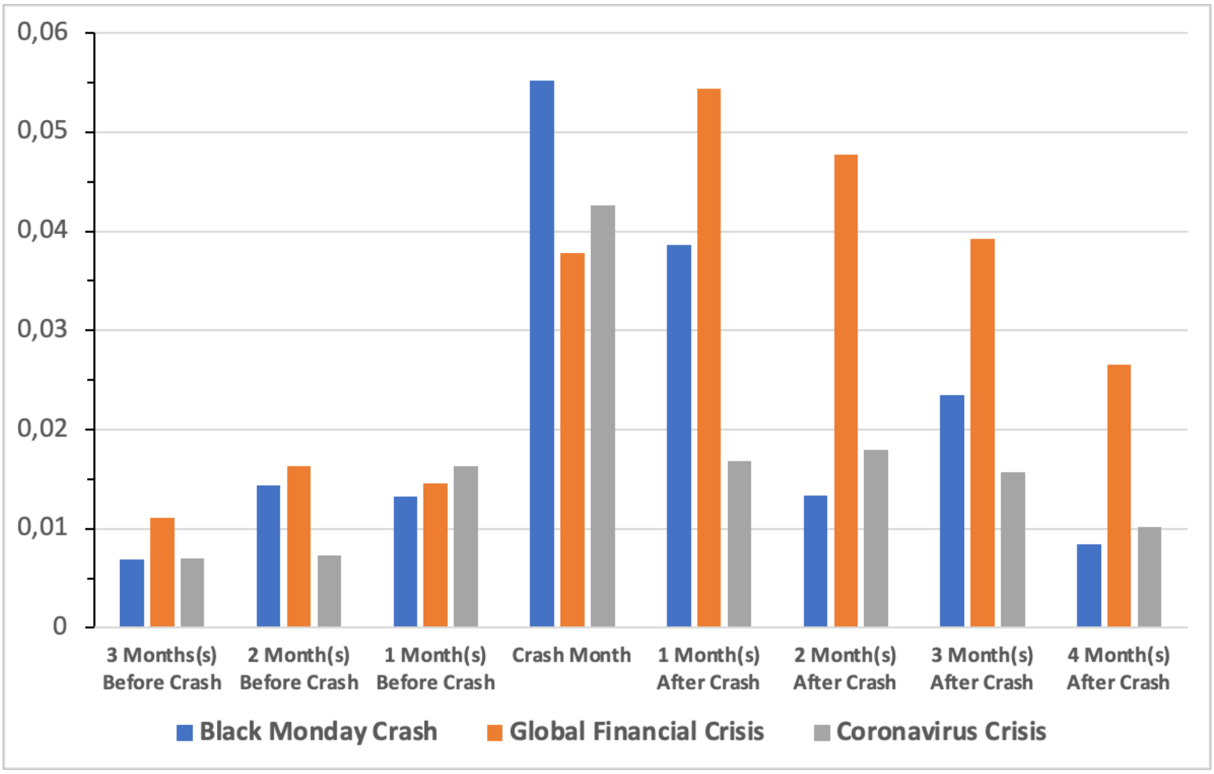

Figure 13: The volatility levels of the Norwegian market portfolio before, during, and after three economic downturns. For reference, the average standard deviation during the time sample is 0.011. The y-axis shows the realized volatility levels.

Cejnek and Muir (2021) present similar results in their empirical analysis of volatility-managed portfolios during the recovery period of the global financial crisis in 2008-2009. The managed portfolios perform poorly because they reduce their market exposure before a significant upswing. However, the two periods are not similar in terms of the time frame between the crash and the recovery period. The COVID-19 recovery starts the month following the crash, while the rebound from the collapse in 2008 begins in March 2009. However, the recovery periods are similar because volatility remains high after the crash. As a result of the high volatility, the low market exposure causes the investor to lose out on the recovery. The COVID-19 recovery period was not anticipated based on one of the fundamental assumptions behind the strategy; extreme volatility is often accompanied by negative returns. Therefore, it is different from the other recovery periods in our sample because the volatility remains high and accompanies positive returns. Exceptions to the general rule may cause issues for investors following the volatility-managing strategy.

5.2 Volatility-Managed Momentum Portfolios Across Europe

Our results highlight that managing the momentum portfolio in Norway and USA provides significant excess returns from 1981 to 2019 and during the pandemic. From 1981 to 2019, the Norwegian portfolio disclosed an annualized alpha of 8.69%, while the U.S. version reported an annual excess return of 9.37%. The cumulative growth highlights the remarkable performance of the managed momentum portfolios. Applying the strategy to the Norwegian version would accumulate to gains of 20489% at the end of our sample. The Norwegian market portfolio, widely used as a benchmark, only provides a return of 570% during the same period. It suggests that the strategy excels at portfolios constructed on momentum. With this realization in mind, we further investigate whether this is coincidental or consistent by analyzing the following five countries' momentum portfolios from 1986 to 2019: Italy (ITA), France (FRA), Spain (ESP), United Kingdom (GBR) and Germany (GER).

Table 6 reports positive, statistically significant alphas at the 5% level for all five portfolios. The largest return increase is for the Italian portfolio, which reveals an annualized abnormal return of 8.37%. Managing the French and the Spanish momentum portfolios significantly improves their Sharpe ratios. Spain shows the largest increase in the risk-return ratio, from 0.34 to 0.82. For the remaining three portfolios, the Sharpe ratio nearly doubles. The standard scores from Memmel's test highlight that the improvements in Sharpe ratios are statistically significant at 95% confidence levels. Consistent with an increased risk-return ratio, every managed portfolio shows a positive M^2 measure, ranging from 4.69% to 6.55%. The managed Spanish momentum portfolio also reveals the largest outperformance of 6.55% compared to its unmanaged counterpart. Our results show that the strategy consistently improves the cumulative returns of portfolios formed on momentum.

Table 6: Predictive OLS regressions of equation (3) on momentum portfolios. The time-series span from April 1986 to December 2019 for Italy, France, Spain, Great Britain and Germany, and from 1981 to 2019 for Norway and USA. The alpha is annualized, and the p-value describes the statistical significance of the alpha. The z-score is obtained from Memmel's test.

	ITA	FRA	ESP	GBR	GER	NOR	USA
α (%)	8.37	7.04	8.15	7.45	7.40	8.69	9.37
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Unmanaged SR	0.47	0.25	0.34	0.53	0.49	0.49	0.43
Managed SR	0.92	0.75	0.82	0.96	0.87	0.81	1.01
Z-score	8.25	9.52	9.27	7.20	6.75	8.54	7.78
M^2(%)	5.96	5.86	6.55	4.69	4.69	6.25	8.94
Obs.	405	405	405	405	405	461	461

Table 7 shows the final value of an investment in the managed and unmanaged momentum portfolios over the same period. The unmanaged Italian portfolio reveals an end value of \$6.62 versus \$46.67 for the managed counterpart. The next best investment is the managed French portfolio. Our results show that the initial investment of one dollar would provide a positive return of \$30.65. Despite having the largest alpha, the managed Spanish momentum portfolio reveals the lowest end value of \$15.21. Its unmanaged counterpart reports a final value of only \$2.21. The remaining portfolios disclose strong performances in terms of the end value; the managed GBR portfolio outperforms its counterpart by \$21.48, while the managed GER momentum portfolio reveals a positive return of \$28.05. Our results show return premiums when applying volatility-managing to momentum portfolios. All seven countries report significant outperformance compared to their unmanaged counterparts. In the following paragraphs, we seek to explain the strategy's strong performance on momentum portfolios.

Table 7: The final value of $1 invested in the managed and unmanaged momentum portfolios from April 1986 to December 2019 for Italy, France, Spain, Great Britain and Germany, and from 1981 to 2019 for Norway and the USA.

	ITA	FRA	ESP	GBR	GER	NOR	USA
End value (unman.)	$6.62	$3.79	$2.22	$5.55	$6.24	$17.36	$7.98
End value (man.)	$46.67	$31.65	$15.21	$27.03	$29.05	$205.89	$236.71

The research on momentum as a risk factor is robust and stable. Asness, Franzzini, Israel and Moskowitz (2014) show that the return premium of momentum is evident in 212 years of U.S. equity data. Their empirical paper suggests why the unmanaged momentum portfolios perform well. To our knowledge, there are only a few papers that investigate the consistently strong performances from managing portfolios constructed on momentum. Barroso and Santa-Clara (2015) suggest that it might be because momentum portfolios experience occasional large crashes. Due to the volatile nature of these portfolios, managing them mitigates the crash risk by reducing drawdowns. The strategy improves the Sharpe ratios and the returns. Daniel and Moskowitz (2016) find similar results when applying the strategy to portfolios constructed on momentum. The managed portfolios report positive alphas and improved risk-return ratios.

Table 8 shows the managed and unmanaged momentum portfolios' maximum drawdowns and minimum one-month returns. We observe significant differences in the maximum drawdowns, with the managed portfolio being superior in all seven countries. In addition, the strategy drastically reduces the negative minimum one-month returns. The minimum one-month return for unmanaged German momentum is (21.19%) versus (9.89%) for the managed version. Our results show that managing momentum portfolios reduces the crash risk. This is supported by Barroso and Santa-Clara's (2015) findings. As shown in table 6, we find positive alphas and improved Sharpe ratios. Our analysis point to the same conclusion as previous empirical papers; managing momentum portfolios produces positive alphas, improves the Sharpe ratios, and reduces crash risk.

Table 8: The maximum drawdowns and minimum one-month returns of the unmanaged and managed momentum portfolios from 1986 to 2019 for Italy, France, Spain, Great Britain and Germany, and 1981 to 2019 for Norway and the United States.

	ITA	FRA	ESP	GBR	GER	NOR	USA
Max. Draw. (%) (unman.)	33.96	35.93	39.71	35.25	33.59	66.78	57.65
Max. Draw. (%) (man.)	18.73	22.58	25.20	21.90	28.56	47.56	19.30
Min. Ret. (%) (unman.)	(16.66)	(17.73)	(23.80)	(17.04)	(21.19)	(24.29)	(34.30)
Min. Ret. (%) (man.)	(10.02)	(13.53)	(17.36)	(11.47)	(9.89)	(15.90)	(12.35)

There is robust evidence of a premium in unmanaged momentum portfolios. The results of multiple studies, including this one, show a possibility of achieving higher risk-adjusted returns by applying the strategy. We understand that investors want to replicate the strategy. To optimize volatility-managing, investors should seek exposure to the momentum portfolios at the lowest fees possible (Moskowitz, 2010). Our results do not account for transaction costs. However, the nature of the momentum portfolio makes continuous adjustment necessary, even without volatility management. Therefore, an application of the strategy might not impact the transaction costs that are already present. It is not clear that a managed momentum portfolio has significantly higher transaction costs than the unmanaged version. To conclude, our results show that volatility-managing momentum portfolios lead to improved returns.

6. Conclusion

In this thesis, we compare the performance of volatility-managing portfolios in the Norwegian and U.S. stock markets. We also analyse volatility-managed momentum portfolios from seven international equity markets. In all simplicity, the managed portfolios are constructed by scaling portfolios by the inverse of their previous month's realized variance.

Our results show that applying the strategy increases returns for six out of eight portfolios. The strategy provides a reduced crash risk through less significant drawdowns. This is complemented by amplified returns because of high market exposure during periods of low volatility and steady returns. The result is positive alphas, improved Sharpe ratios and increased cumulative returns.

The market crash following the COVID-19 pandemic is different from other market crashes in our sample because the upward movement starts the month after the collapse. We suggest that the quick rebound is caused by the rapid and extreme fiscal and monetary policy responses. The managed portfolios struggle to participate in the upswing due to their reduced market exposure after high volatility during the month of the crash. Our results show that four out of eight managed factor portfolios underperform compared to their unmanaged counterparts.

The strategy performs well on portfolios constructed on momentum because it mitigates the market crash risk. The managed portfolios show less significant drawdowns during market turmoil. The strategy's ability to increase the leverage during rising markets with low volatility leads to amplified returns. Our results from examining seven international stock markets show that volatility-managed momentum portfolios consistently outperform their unmanaged counterparts. The increased risk-adjusted returns challenge the linear risk-return relationship in the capital asset pricing model.

We conclude our paper by suggesting a few topics for future research. Our methodology assumes that next month´s volatility will be identical to the current month. This assumption simplifies the construction of the managed portfolios. However, it might not be the most accurate way to predict variance. A possible improvement to the strategy is to use a more sophisticated model to predict future variance. Specifically, the use of GARCH-modelling to predict volatility might improve the performance. Furthermore, the volatility-managing strategy employed in this paper adjusts the market exposure according to the previous month's volatility at the beginning of each month. Future studies may adjust their portfolios based on the previous week's volatility to investigate if a more frequent adjustment of market exposure generates improved results. Lastly, our results show great promise for volatility-managed momentum portfolios. Therefore, we suggest that academics analyse other international stock markets.

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Appendices

A Appendix

Table 9: Correlation between the monthly returns of the U.S factor portfolios from 1981 to 2019.

	SMB	HML	MKT	MOM
SMB	1.00	(0.13)	0.21	0.01
HML	-	1.00	(0.24)	(0.21)
MKT	-	-	1.00	(0.19)
MOM	-	-	-	1.00

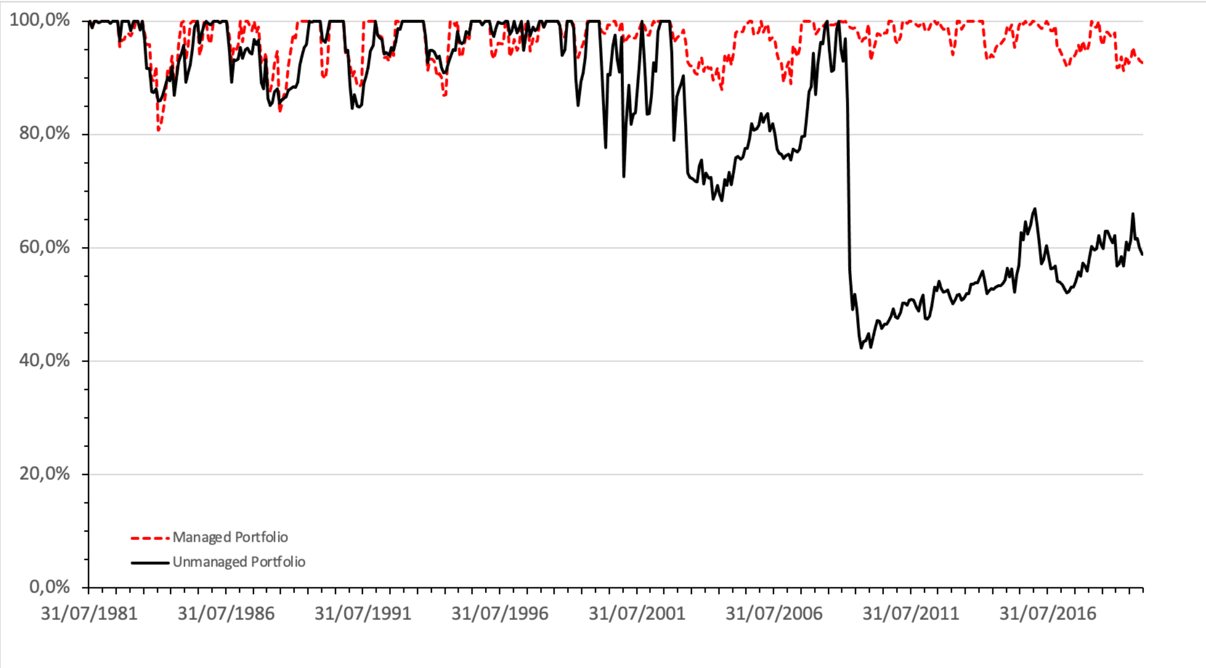

Figure 14: Drawdowns for the managed and unmanaged U.S. momentum portfolios during the 1981 to 2019 period.

B R-Script

The R-script shows the computations for the volatility-managed portfolios in the Norwegian market. We use the same computations when constructing the managed portfolios in the U.S. and international equity markets. We use the following code:

```
library(zoo)
library(tseries)
library(xts)
library(tidyverse)
library(lubridate)
library(PerformanceAnalytics)


# Importing the daily and monthly return data from the factor portfolios
FFmonthly1 = readxl::read_xlsx('~/Downloads/FFmonthly.xlsx')
FFdaily1 = readxl::read_xlsx('~/Downloads/FFxsl (1).xlsx') %>%
  mutate(date = ymd(date))


# Importing the returns from the Oslo All-Share index
MKT_monthly1 = readxl::read_xlsx('~/Downloads/Allshare_monthly.xlsx')
MKT_daily1 = readxl::read_xlsx('~/Documents/Masteroppgave/Portfolio Management/Excel
Files/Daily Market Returns.xlsx') %>%
  mutate(date = ymd(date))


# Importing the risk-free rate to subtract from all-share returns to get excess returns
RF = readxl::read_xlsx('~/Downloads/Risk-free_Monthly.xlsx')

RF = as.data.frame(RF)
MKT_monthly1$Allshare[37:491] = MKT_monthly1$Allshare[37:491] - RF[38:492,2]


# Groups returns into months and returns the daily variance of each factor for each month
FFSvar = FFdaily1 %>%
  group_by(Year=year(date),Month=month(date,label = T)) %>%
  summarise(SMB_var = var(SMB,na.rm = T) , HML_var = var(HML,na.rm = T), PR1YR_var =
var(PR1YR,na.rm = T), UMD_var = var(UMD,na.rm = T), LIQ_var = var(LIQ,na.rm = T))


# Groups returns into months and returns the daily std.dev. of each factor for each month
FFSd = FFdaily1 %>%
  group_by(Year=year(date),Month=month(date,label = T)) %>%
```

```
  summarise(SMB_sd = sd(SMB,na.rm = T) , HML_sd = sd(HML,na.rm = T), PR1YR_sd =
sd(PR1YR,na.rm = T), UMD_sd = sd(UMD,na.rm = T), LIQ_sd = sd(LIQ,na.rm = T))

# Groups all-share returns into months and returns daily st.dev and variance for each month
´
MKT_var = MKT_daily1 %>%
  group_by(Year=year(date),Month=month(date,label = T)) %>%
  summarise(Allshare_var = var(Allshare,na.rm = T))

MKT_sd = MKT_daily1[773:10265,] %>%
  group_by(Year=year(date),Month=month(date,label = T)) %>%
  summarise(Allshare_sd = sd(Allshare,na.rm = T))


# Converts vectors to data frames
FFSd = as.data.frame(FFSd)
FFvar = as.data.frame(FFSvar)
FFmonthly1 = as.data.frame(FFmonthly1)
FFdaily1 = as.data.frame(FFdaily1)

MKT_monthly1 = as.data.frame(MKT_monthly1[38:491,])
MKT_var = as.data.frame(MKT_var[38:491,])


#*********************
# This function adjusts the return of the original portfolios by the inverse of their previous
month's realized variance
# In other words: It creates the volatility-managed versions, based off the constant c, which
is given the value 1 (the value of c does not matter)
# The inputs are RV, realized variances, and FFmonthly, the monthly returns on each
portfolio.

create_sigma_uc = function(c,RV,FFmonthly){
  F_sigma_uc = c(rep(0,length(RV)))
  for (i in 2:length(RV)){{}
    F_sigma_uc[i] = ((c)/(RV[i-1]))*(FFmonthly[i])
  }
  std = sd(FFmonthly)
  stdsigma = sd(F_sigma_uc)
  csmb = std/stdsigma

  F_sigma_uc = c(rep(0,length(RV)))
  for (i in 2:length(RV)){{}
    F_sigma_uc[i] = ((csmb)/(RV[i-1]))*(FFmonthly[i])
  }
  return(F_sigma_uc)
}
```

```
# We run the algorithm to create the volatility-managed portfolios
F_sigma_smb = create_sigma_uc(1,FFvar$SMB_var, FFmonthly1$SMB)
F_sigma_hml = create_sigma_uc(1,FFvar$HML_var, FFmonthly1$HML)
F_sigma_umd = create_sigma_uc(1,FFvar$UMD_var, FFmonthly1$UMD)
F_sigma_liq = create_sigma_uc(1,FFvar$LIQ_var, FFmonthly1$LIQ)
F_sigma_mkt = create_sigma_uc(1, MKT_var$Allshare_var, MKT_monthly1$Allshare)


#************************
# We create a function that calculates the end value of two portfolios with the starting value of 1
# It returns a value for the managed version and a value for the unmanaged portfolio.
# The inputs are the returns of each portfolio for each month.

cumret = function(F_sigma, FFmonthly1){
 S = c(rep(0,length(FFmonthly1)))
 S[1] = 1
 for (i in 1:length(FFmonthly1)){
  S[i+1] = S[i] * (1+F_sigma[i+1])
 }

 S1 = c(rep(0,length(FFmonthly1)))
 S1[1] = 1
 for (i in 1:length(FFmonthly1)){
  S1[i+1] = S1[i] * (1+FFmonthly1[i])
 }
 returns = matrix(c(S1,S), length(S1))
 return(returns)
}


#********************
# Plotting the cumulative return - unmanaged vs managed portfolio
ysmb = cumret(F_sigma_smb[1:462],FFmonthly1$SMB[2:462])
plot(log(ysmb[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return",
main = "Cumulative Returns - Vol.Adj.Portfolio vs SMB Factor Portfolio", ylim = c(0,3.5))
lines(log(ysmb[,2]), type = 'l', col ='red')

yhml = cumret(F_sigma_hml[1:462], FFmonthly1$HML[2:462])
plot(log(yhml[,1]), type ='l', ylim = c(-1, 3), xlab = "Period of 1981 - 2020", ylab = "Logarithmic
Return", main = "Cumulative Returns - Vol.Adj.Portfolio vs HML Factor Portfolio")
lines(log(yhml[,2]), type = 'l', col ='red')

yumd = cumret(F_sigma_umd[1:462], FFmonthly1$UMD[2:462])
plot(log(yumd[,1]), type ='l',  xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return",
main = "Cumulative Returns - Vol.Adj.Portfolio vs UMD Factor Portfolio", ylim = c(0,5.5))
```

```
lines(log(yumd[,2]), type = 'l', col ='red')

yliq = cumret(F_sigma_liq[1:462], FFmonthly1$LIQ[2:462])
plot(log(yliq[,1]), type ='l', ylim = c(0,1.5), xlab = "Period of 1981 - 2020", ylab = "Logarithmic
Return", main = "Cumulative Returns - Vol.Adj.Portfolio vs LIQ Factor Portfolio")
lines(log(yliq[,2]), type = 'l', col ='red')

ymkt = cumret(F_sigma_mkt[1:443], MKT_monthly1$Allshare[2:443])
plot(log(ymkt[,1]), type ='l', xlab = "Period of 1983 - 2020", ylab = "Logarithmic Return", main
= "Cumulative Returns - Vol.Adj.Portfolio vs MKT Factor Portfolio", ylim = c(0,5))
lines(log(ymkt[,2]), type = 'l', col ='red')


#***********************************
# OLS predictive regressions - calculating the alphas.
regsmb = lm(F_sigma_smb[2:462] ~ FFmonthly1$SMB[2:462]);regsmb$coefficients
reghml = lm(F_sigma_hml[2:462] ~ FFmonthly1$HML[2:462]);reghml$coefficients
regumd = lm(F_sigma_umd[2:462] ~ FFmonthly1$UMD[2:462]);regumd$coefficients
regliq = lm(F_sigma_liq[2:462] ~ FFmonthly1$LIQ[2:462]);regliq$coefficients
regmkt = lm(F_sigma_mkt[2:443] ~ MKT_monthly1$Allshare[2:443]) ; regmkt$coefficients


# Summary function to find alpha, p-values, R-squared (adj), RMSE.
sumsmb = summary(regsmb);sumhml = summary(reghml);sumumd =
summary(regumd);sumliq = summary(regliq); summkt = summary(regmkt)


#*******************
# Reporting the performance statistics in a data frame
# Gathering alpha's
ADF = data.frame(cbind(asmb = sumsmb$coefficients[1,1]*12*100,ahml =
sumhml$coefficients[1,1]*12*100,aumd = sumumd$coefficients[1,1]*12*100,aliq =
sumliq$coefficients[1,1]*12*100, amkt = summkt$coefficients[1,1]*12*100))
# Reporting p-values
PDF = data.frame(cbind(psmb = sumsmb$coefficients[1,4], phml = sumhml$coefficients[1,4],
pumc = sumumd$coefficients[1,4],pliq = sumliq$coefficients[1,4],pmkt =
summkt$coefficients[1,4]))
# Calculating and reporting Appraisal Ratio
ARDF = data.frame(cbind(ARsmb = sqrt(12)*(sumsmb$coefficients[1,1])/(sumsmb$sigma)),
ARhml = sqrt(12)*(sumhml$coefficients[1,1])/(sumhml$sigma),ARumd =
sqrt(12)*(sumumd$coefficients[1,1])/(sumumd$sigma),ARliq =
sqrt(12)*(sumliq$coefficients[1,1])/(sumliq$sigma), ARmkt =
sqrt(12)*(summkt$coefficients[1,1])/(summkt$sigma))
# Gathering Adj. R-squared
RDF = data.frame(cbind(rsmb = sumsmb$r.squared, rhml = sumhml$r.squared, rumd =
sumumd$r.squared, rliq = sumliq$r.squared, rmkt = summkt$r.squared))
# Gathering RMSE
```

```
RMSEDF = data.frame(cbind(rmsmb = sumsmb$sigma*12*100, rmhml =
sumhml$sigma*(12)*100, rmumd = sumumd$sigma*12*100, rmliq = sumliq$sigma*12*100,
rmmkt = summkt$sigma*12*100))
# Reporting descriptive statistics
desc.stats = data.frame(SMB.Des.Stats = c(ADF$asmb, PDF$psmb, ARDF$ARsmb, RDF$rsmb,
RMSEDF$rmsmb), HML.Des.Stats = c(ADF$ahml, PDF$phml, ARDF$ARhml, RDF$rhml,
RMSEDF$rmhml), UMD.Des.Stats = c(ADF$aumd, PDF$pumc, ARDF$ARumd, RDF$rumd,
RMSEDF$rmumd), LIQ.Des.Stats = c(ADF$aliq, PDF$pliq, ARDF$ARliq, RDF$rliq,
RMSEDF$rmliq), MKT.Des.Stats = c(ADF$amkt, PDF$pmkt, ARDF$ARmkt, RDF$rmkt,
RMSEDF$rmmkt))
RWdesc.stats = c("alpha", "p-value", "AR", "R-squared", "RMSE")
rownames(desc.stats) = RWdesc.stats


#*************************
# Correlation based on daily and monthly observations between the unmananged portfolios
all_cor = cbind(FFmonthly1$SMB[20:462],FFmonthly1$HML[20:462],
FFmonthly1$UMD[20:462], FFmonthly1$LIQ[20:462], MKT_monthly1$Allshare[1:443])
all_cortable = cor(all_cor, method = c("spearman"))

fsigmonthlydf = cbind(FFmonthly1$SMB[1:462],FFmonthly1$HML[1:462],
FFmonthly1$UMD[1:462], FFmonthly1$LIQ[1:462])
cortable = cor(fsigmonthlydf, method = c("spearman"))
testtable = cbind(cortable, c(-0.42875353 , 0.07803353 ,-0.05468444 ,-0.57817873))
cortable = rbind(testtable, c(-0.42875353 , 0.07803353,-0.05468444 ,-0.57817873,1))
colnames(cortable) = c("SMB", "HML", "UMD", "LIQ", "MKT")
rownames(cortable) = c("SMB", "HML", "UMD", "LIQ", "MKT")
cortable # Table of all correlations 1981-2020, MKT with rest from 1983-2020


#*************************
# Calculating Sharpe ratio - unmanaged
SRDF = data.frame(cbind(SharpeRatio.SMB =
((mean(FFmonthly1$SMB[1:462]))/(sd(FFmonthly1$SMB[1:462])))*sqrt(12),SharpeRatioHML
= sqrt(12)*(mean(FFmonthly1$HML[1:462]))/(sd(FFmonthly1$HML[1:462]))),
SharpeRatioUMD =
sqrt(12)*(mean(FFmonthly1$UMD[1:462]))/(sd(FFmonthly1$UMD[1:462])), SharpeRatioLIQ
= sqrt(12)*(mean(FFmonthly1$LIQ[1:462]))/(sd(FFmonthly1$LIQ[1:462])), SharpeRatioMKT =
sqrt(12)*(mean(MKT_monthly1$Allshare[1:443])/sd(MKT_monthly1$Allshare[1:443])))
# Calculating Sharpe ratio - managed
SRNEWDF = data.frame(cbind(SRnewsmb =
sqrt(12)*(mean(F_sigma_smb[1:462]))/(sd(FFmonthly1$SMB[1:462])),SRnewhml =
sqrt(12)*mean(F_sigma_hml[1:462])/sd(FFmonthly1$HML[1:462]), SRnewumd =
sqrt(12)*mean(F_sigma_umd[1:462])/sd(FFmonthly1$UMD[1:462]),SRnewliq =
sqrt(12)*mean(F_sigma_liq[1:462])/sd(FFmonthly1$LIQ[1:462]), SRnewMKT =
sqrt(12)*(mean(F_sigma_mkt[1:443])/sd(MKT_monthly1$Allshare[1:443]))))
# Creating a function to execute Memmel´s test and get the test statistics
```

```
SRsignificance = function(SRnew, SRold, N_observations, p){
  z = (SRnew - SRold)/(sqrt((1/N_observations)*(2*(1-p)+0.5*(SRnew^2 + SRold^2 - 2 *
SRnew * SRold * p^2))))
  return(z)
}


# Running the test on the Sharpe ratios that are improved to see whether the improvement
is statistically significant
zsmb = SRsignificance(SRNEWDF$SRnewsmb, SRDF$SharpeRatio.SMB, 462,
cor(FFmonthly1$SMB[1:462], F_sigma_smb[1:462]))
zumd = SRsignificance(SRNEWDF$SRnewumd, SRDF$SharpeRatioUMD, 462,
cor(FFmonthly1$UMD[1:462], F_sigma_umd[1:462]))
zliq = SRsignificance(SRNEWDF$SRnewliq, SRDF$SharpeRatioLIQ, 462,
cor(FFmonthly1$LIQ[1:462], F_sigma_liq[1:462]))
zmkt = SRsignificance(SRNEWDF$SRnewMKT, SRDF$SharpeRatioMKT, 443,
cor(MKT_monthly1$Allshare[1:443], F_sigma_mkt[1:443]))

# Finding the p-value
pnorm(1.60);pnorm(8.14);pnorm(5.25);pnorm(3.87)

# Calculating the mean, max, minimum returns of the unmanaged portfolios
MEANDF = data.frame(cbind(meanSMB = mean(FFmonthly1$SMB[1:462]), meanHML =
mean(FFmonthly1$HML[1:462]), meanUMD = mean(FFmonthly1$UMD[1:462]), meanLIQ =
mean(FFmonthly1$LIQ[1:462]), meanMKT = mean(MKT_monthly1$Allshare[1:443])))
MAXDF = data.frame(cbind(MaxSMB = max(FFmonthly1$SMB[1:462]), MaxHML =
max(FFmonthly1$HML[1:462]), MaxUMD = max(FFmonthly1$UMD[1:462]), MaxLIQ =
max(FFmonthly1$LIQ[1:462]), MaxMKT = max(MKT_monthly1$Allshare[1:443])))
MINDF = data.frame(cbind(MinSMB = min(FFmonthly1$SMB[1:462]), MinHML =
min(FFmonthly1$HML[1:462]), MinUMD = min(FFmonthly1$UMD[1:462]), MinLIQ =
min(FFmonthly1$LIQ[1:462]), MinMKT = min(MKT_monthly1$Allshare[1:443])))
# Table with summary statistics
RWnames = c("Mean", "Max", "Min", "Non-Managed Sharpe Ratio", "Managed Sharpe
Ratio")
tableall = data.frame(SMB.Stats = c(MEANDF$meanSMB, MAXDF$MaxSMB,
MINDF$MinSMB, SRDF$SharpeRatio.SMB, SRNEWDF$SRnewsmb), HML.Stats =
c(MEANDF$meanHML, MAXDF$MaxHML ,MINDF$MinHML, SRDF$SharpeRatioHML,
SRNEWDF$SRnewhml), UMD.Stats = c(MEANDF$meanUMD, MAXDF$MaxUMD
,MINDF$MinUMD, SRDF$SharpeRatioUMD, SRNEWDF$SRnewumd), LIQ.Stats =
c(MEANDF$meanLIQ, MAXDF$MaxLIQ ,MINDF$MinLIQ, SRDF$SharpeRatioLIQ,
SRNEWDF$SRnewliq), MKT.Stats = c(MEANDF$meanMKT, MAXDF$MaxMKT,
MINDF$MinMKT, SRDF$SharpeRatioMKT, SRNEWDF$SRnewMKT))
rownames(tableall) = RWnames
```

```
#********************
# Calculating the M2 measure

m2smb = 100*((mean(F_sigma_smb[1:462])*12)-(mean(FFmonthly1$SMB[1:462])*12))
m2hml = 100*((mean(F_sigma_hml[1:462])*12)-(mean(FFmonthly1$HML[1:462])*12))
m2umd = 100*((mean(F_sigma_umd[1:462])*12)-(mean(FFmonthly1$UMD[1:462])*12))
m2liq = 100*((mean(F_sigma_liq[1:462])*12)-(mean(FFmonthly1$LIQ[1:462])*12))
m2mkt = 100*((mean(F_sigma_mkt[1:443])*12)-
(mean(MKT_monthly1$Allshare[1:443])*12))

#*******************************************
# The COVID-19 pandemic - Jan. 2020 - Dec. 2020.

# Calculating and plotting cumulative returns
csmb = cumret(F_sigma_smb[462:473],FFmonthly1$SMB[463:473])
plot(log(csmb[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return",
main = "Cumulative Returns - Vol.Adj.Portfolio vs SMB Factor Portfolio", ylim = c(0,0.25))
lines(log(csmb[,2]), type = 'l', col ='red')

chml = cumret(F_sigma_hml[462:473],FFmonthly1$HML[463:473])
plot(log(chml[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return", main
= "Cumulative Returns - Vol.Adj.Portfolio vs HML Factor Portfolio", ylim = c(-0.35, 0.1))
lines(log(chml[,2]), type = 'l', col ='red')

cumd = cumret(F_sigma_umd[462:473],FFmonthly1$UMD[463:473])
plot(log(cumd[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return",
main = "Cumulative Returns - Vol.Adj.Portfolio vs UMD Factor Portfolio", ylim = c(-0.15,0.2))
lines(log(cumd[,2]), type = 'l', col ='red')

cliq = cumret(F_sigma_liq[462:473],FFmonthly1$LIQ[463:473])
plot(log(cliq[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return", main
= "Cumulative Returns - Vol.Adj.Portfolio vs LIQ Factor Portfolio", ylim = c(0,0.25))
lines(log(cliq[,2]), type = 'l', col ='red')

cmkt = cumret(F_sigma_mkt[443:454],MKT_monthly1$Allshare[444:454])
plot(log(cmkt[,1]), type ='l', xlab = "Period of 1981 - 2020", ylab = "Logarithmic Return", main
= "Cumulative Returns - Vol.Adj.Portfolio vs MKT Factor Portfolio", ylim = c(-0.4,0))
lines(log(cmkt[,2]), type = 'l', col ='red')

#*******************
# Predictive Regression
covregsmb = lm(F_sigma_smb[462:473] ~
FFmonthly1$SMB[462:473]);covregsmb$coefficients
covreghml = lm(F_sigma_hml[462:473] ~
FFmonthly1$HML[462:473]);covreghml$coefficients
covregumd = lm(F_sigma_umd[462:473] ~
FFmonthly1$UMD[462:473]);covregumd$coefficients
```

```
covregliq = lm(F_sigma_liq[462:473] ~ FFmonthly1$LIQ[462:473]);covregliq$coefficients
covregmkt = lm(F_sigma_mkt[443:454] ~
MKT_monthly1$Allshare[443:454]);covregmkt$coefficients

# Calculating the alphas
covsumsmb = summary(covregsmb);covsumhml = summary(covreghml);covsumumd =
summary(covregumd);covsumliq = summary(covregliq);covsummkt = summary(covregmkt)

# Gathering alpha's
COVADF = data.frame(cbind(covasmb = covsumsmb$coefficients[1,1]*12*100,covahml =
covsumhml$coefficients[1,1]*12*100,covaumd =
covsumumd$coefficients[1,1]*12*100,covaliq = covsumliq$coefficients[1,1]*12*100,
covamkt = covsummkt$coefficients[1,1]*12*100))
# Reporting p-values
COVPDF = data.frame(cbind(covpsmb = covsumsmb$coefficients[1,4], covphml =
covsumhml$coefficients[1,4], covpumc = covsumumd$coefficients[1,4],covpliq =
covsumliq$coefficients[1,4],covpmkt = covsummkt$coefficients[1,4]))
# Gathering RMSE
COVRMSEDF = data.frame(cbind(covrmsmb = covsumsmb$sigma*12*100, covrmhml =
covsumhml$sigma*(12)*100, covrmumd = covsumumd$sigma*12*100, covrmliq =
covsumliq$sigma*12*100, covrmmkt = covsummkt$sigma*12*100))
# Calculating and Reporting Appraisal Ratio
COVARDF = data.frame(cbind(COVARsmb =
sqrt(12)*((COVADF$covasmb)/(COVRMSEDF$covrmsmb))), COVARhml =
sqrt(12)*(covsumhml$coefficients[1,1])/(covsumhml$sigma),COVARumd =
sqrt(12)*(covsumumd$coefficients[1,1])/(covsumumd$sigma),COVARliq =
sqrt(12)*(covsumliq$coefficients[1,1])/(covsumliq$sigma), COVARmkt =
sqrt(12)*(covsummkt$coefficients[1,1])/(covsummkt$sigma))
# Gathering Adj. R-squared
COVRDF = data.frame(cbind(covrsmb = covsumsmb$r.squared, covrhml =
covsumhml$r.squared, covrumd = covsumumd$r.squared, covrliq = covsumliq$r.squared,
covrmkt = covsummkt$r.squared))
# Reporting the performance statistics
COVdesc.stats = data.frame(COVSMB.Des.Stats = c(COVADF$covasmb, COVPDF$covpsmb,
COVARDF$COVARsmb, COVRDF$covrsmb, COVRMSEDF$covrmsmb), COVHML.Des.Stats =
c(COVADF$covahml, COVPDF$covphml, COVARDF$COVARhml, COVRDF$covrhml,
COVRMSEDF$covrmhml), COVUMD.Des.Stats = c(COVADF$covaumd, COVPDF$covpumc,
COVARDF$COVARumd, COVRDF$covrumd, COVRMSEDF$covrmumd), COVLIQ.Des.Stats =
c(COVADF$covaliq, COVPDF$covpliq, COVARDF$COVARliq, COVRDF$covrliq,
COVRMSEDF$covrmliq), COVMKT.Des.Stats = c(COVADF$covamkt, COVPDF$covpmkt,
COVARDF$COVARmkt, COVRDF$covrmkt, COVRMSEDF$covrmmkt))
RWdesc.stats = c("alpha", "p-value", "AR", "R-squared", "RMSE")
rownames(COVdesc.stats) = RWdesc.stats
```

```
#*************************
# Calculating Sharpe ratio - unmanaged
COVSRDF = data.frame(cbind(COVSharpeRatio.SMB =
sqrt(12)*(mean(FFmonthly1$SMB[462:473])/sd(FFmonthly1$SMB[462:473])),COVSharpeRat
io.HML = sqrt(12)*(mean(FFmonthly1$HML[462:473])/sd(FFmonthly1$HML[462:473])),
COVSharpeRatioUMD =
sqrt(12)*(mean(FFmonthly1$UMD[462:473])/sd(FFmonthly1$UMD[462:473])),
COVSharpeRatioLIQ =
sqrt(12)*(mean(FFmonthly1$LIQ[462:473])/sd(FFmonthly1$LIQ[462:473])),
COVSharpeRatioMKT =
sqrt(12)*(mean(MKT_monthly1$Allshare[443:454])/sd(MKT_monthly1$Allshare[443:454]))))
# Calculating Sharpe ratio - managed
COVSRNEWDF = data.frame(cbind(COVSRnewsmb =
sqrt(12)*(mean(F_sigma_smb[462:473])/sd(FFmonthly1$SMB[462:473])),COVSRnewhml =
sqrt(12)*(mean(F_sigma_hml[462:473])/sd(FFmonthly1$HML[462:473])), COVSRnewumd =
sqrt(12)*(mean(F_sigma_umd[462:473])/sd(FFmonthly1$UMD[462:473])),COVSRnewliq =
sqrt(12)*(mean(F_sigma_liq[462:473])/sd(FFmonthly1$LIQ[462:473])), COVSRnewMKT =
sqrt(12)*(mean(F_sigma_mkt[443:454])/sd(MKT_monthly1$Allshare[443:454]))))
# Creating a function to execute Memmel´s test and get the test statistics
zcovsmb = SRsignificance(COVSRNEWDF$COVSRnewsmb, COVSRDF$COVSharpeRatio.SMB,
11, cor(FFmonthly1$SMB[462:473], F_sigma_smb[462:473]))
zcovhml = SRsignificance(COVSRNEWDF$COVSRnewhml, COVSRDF$COVSharpeRatio.HML,
11, cor(FFmonthly1$HML[462:473], F_sigma_hml[462:473]))
zcovumd = SRsignificance(COVSRNEWDF$COVSRnewumd, COVSRDF$COVSharpeRatioUMD,
11, cor(FFmonthly1$UMD[462:473], F_sigma_umd[462:473]))
zcovliq = SRsignificance(COVSRNEWDF$COVSRnewliq, COVSRDF$COVSharpeRatioLIQ, 11,
cor(FFmonthly1$LIQ[462:473], F_sigma_liq[462:473]))


# Calculating the mean, maximum, minimum.
COVMEANDF = data.frame(cbind(COVmeanSMB = mean(FFmonthly1$SMB[462:473]),
COVmeanHML = mean(FFmonthly1$HML[462:473]), COVmeanUMD =
mean(FFmonthly1$UMD[462:473]), COVmeanLIQ = mean(FFmonthly1$LIQ[462:473]),
COVmeanMKT = mean(MKT_monthly1$Allshare[443:454])))
COVMAXDF = data.frame(cbind(COVMaxSMB = max(FFmonthly1$SMB[462:473]),
COVMaxHML = max(FFmonthly1$HML[462:473]), COVMaxUMD =
max(FFmonthly1$UMD[462:473]), COVMaxLIQ = max(FFmonthly1$LIQ[462:473]),
COVMaxMKT = max(MKT_monthly1$Allshare[443:454])))
COVMINDF = data.frame(cbind(COVMinSMB = min(FFmonthly1$SMB[462:473]),
COVMinHML = min(FFmonthly1$HML[462:473]), COVMinUMD =
min(FFmonthly1$UMD[462:473]), COVMinLIQ = min(FFmonthly1$LIQ[462:473]),
COVMinMKT = min(MKT_monthly1$Allshare[443:454])))
# The descriptive and performance statistics
RWnames = c("Mean", "Max", "Min", "Non-Managed Sharpe Ratio", "Managed Sharpe
Ratio")
COVtableall = data.frame(SMB.Stats = c(COVMEANDF$COVmeanSMB,
COVMAXDF$COVMaxSMB, COVMINDF$COVMinSMB, COVSRDF$COVSharpeRatio.SMB,
```

```
COVSRNEWDF$COVSRnewsmb), HML.Stats = c(COVMEANDF$COVmeanHML,
COVMAXDF$COVMaxHML,COVMINDF$COVMinHML, COVSRDF$COVSharpeRatio.HML,
COVSRNEWDF$COVSRnewhml), UMD.Stats = c(COVMEANDF$COVmeanUMD,
COVMAXDF$COVMaxUMD ,COVMINDF$COVMinUMD, COVSRDF$COVSharpeRatioUMD,
COVSRNEWDF$COVSRnewumd), LIQ.Stats = c(COVMEANDF$COVmeanLIQ,
COVMAXDF$COVMaxLIQ ,COVMINDF$COVMinLIQ, COVSRDF$COVSharpeRatioLIQ,
COVSRNEWDF$COVSRnewliq), MKT.Stats = c(COVMEANDF$COVmeanMKT,
COVMAXDF$COVMaxMKT, COVMINDF$COVMinMKT, COVSRDF$COVSharpeRatioMKT,
COVSRNEWDF$COVSRnewMKT))
rownames(COVtableall) = RWnames


# The M2 measure
m2covsmb = 100*((mean(F_sigma_smb[462:473])*12)-
(mean(FFmonthly1$SMB[462:473])*12))
m2covhml = 100*((mean(F_sigma_hml[462:473])*12)-
(mean(FFmonthly1$HML[462:473])*12))
m2covumd = 100*((mean(F_sigma_umd[462:473])*12)-
(mean(FFmonthly1$UMD[462:473])*12))
m2covliq = 100*((mean(F_sigma_liq[462:473])*12)-(mean(FFmonthly1$LIQ[462:473])*12))
m2covmkt = 100*((mean(F_sigma_mkt[443:454])*12)-
(mean(MKT_monthly1$Allshare[443:454])*12))
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C Discussion Paper - Sindre Alme

A crucial part of UIA's mission statement and vision is responsibility. This discussion paper will discuss how responsibility is applied in my master's thesis. Specifically, the paper is divided into three parts. The first part discusses the concept of writing responsibly. The second part outlines how I find responsible methodologies and statistical tools for my master's thesis. The third part aims to connect responsible investment and my master's thesis. Responsible investment is directly related to the topic of my master's thesis, portfolio management. Being responsible is not easy, as it comes with various ethical challenges. One must carefully think through what the consequences of your actions are. How do your actions impact the people around you, the environment you live in and the future generation? My discussion paper is organized as follows. First, I introduce the topic of my master thesis, followed by a discussion of the different concepts of responsibility. Finally, I conclude my discussion paper.

The volatility-managing strategy aims to achieve higher returns without taking more risk. The strategy follows the methodology by Moreira and Muir (2017). It examines the relationship between risk and return by constructing volatility-managed portfolios that adjust market exposure according to the previous month's volatility. The managed portfolios are scaled by the inverse of their previous month's realized variance. If the realized variance is higher than the unconditional variance over the entire sample, an investor allocates a proportion of the portfolio to the risk-free asset. However, when the realized variance is lower, the investor borrows money at a risk-free rate to increase exposure. In our study, we apply this strategy to investigate the performance of factor portfolios in the Norwegian and U.S. market from 1981 to 2019. We supply current literature with an analysis of volatility-managed momentum portfolios from international equity markets. Our results show that six out of eight managed portfolios report improved returns. Managing portfolios constructed on momentum lead to remarkable performances. They all produce positive alphas and improved Sharpe ratios.

There are contradictory findings on the relationship between risk and return. Merton (1980) argues that the relationship is positive. On the opposite side, Black (1976) argues that sometimes the relationship between volatility and return is negative. The relationship between the monthly volatility and average excess returns on the Oslo Stock Exchange is negative. When volatility is high, it is accompanied by a negative mean excess return. This supports Black's findings and contradicts Merton's results.

In this section, I discuss the first aspect of responsibility. Then, I will elaborate on how students can write responsibly. "Standing on the shoulders of giants" is a well-known concept in the academic world. It states the importance of crediting other researchers for the ideas that they have brought to life. The phrase was first introduced in 1675 by Isaac Newton. He expressed his humble acknowledgement to the researchers who contributed to making the scientific breakthrough possible (Schultz, 2019). This is important when students write academic papers. Luckily, the educational system is designed to punish researchers who take credit for others' work. As a writer of a master's thesis, I am obligated to give credit to the source of information. In my master's study, I even credit people's websites. When I constructed the managed factor portfolios, I used data from various websites. By citing the websites in my thesis, they get the credit they deserve. I also mention the source of information when I compare the results of my study with other studies' results. This is helpful because it complements the results of my paper. Most researchers spend years before they eventually publish their empirical papers. Their time and effort deserve to be recognized.

Massaro, Dumay, and Guthrie (2016) present a specific method for conducting a structured literature review (SLR). It helps examine literature more efficiently and develop critical reflections in a particular research field. Their findings suggest that when students applied SLR, they discovered articles and insights that they previously had not located. Using the SLR method will make it easier for researchers to understand previous studies and find relevant research questions to investigate. The main idea of the approach is to be respectful regarding previous literature and give credit to the person that first brought the finding or concept to life.

There are ethical challenges related to writing responsibly. Massaro et al. (2016) suggest that SLR is important in scientific disciplines dominated by quantitative approaches. My thesis is based on quantitative data. The data is gathered from the Norwegian and U.S. stock markets from 1981 to 2020. I also use data from five European countries from 1986 to 2019. The source of data is important as it determines the reliability of the study. I chose to use public data as the core of my master's thesis. The data is also cleaned and mined by well-known researchers. This strengthens the validity of the data. It increases the responsibility of my thesis.

I also evaluated the source that inspired the topic of my master's thesis. My paper supplies the already existing literature on volatility-managing. Well-known researchers carry out most literature on this topic. Their research upholds a high standard. Most of the papers are credited in respected journals. It enabled me to trust and rely on the sources that I cited in my paper. One of the challenges of writing responsibly is finding reliable, useful, and trustworthy sources. Before writing my paper, I obtained a good overview of the existing literature on volatility-timing strategies. The first paper to get recognized related to volatility-managing was in the late 1990s. Busse (1999) examined 230 equity funds and found that volatility-managing leads to improved performance. Fleming, Kirby, and Ostdiek (2001) tested the effectiveness of volatility-timing on assets such as gold, cash, stocks, and bonds. Their results suggest that the volatility-timing strategies outperform their unmanaged counterparts. After the global financial crisis of 2008-09, the research on the topic exploded (e.g., Tang et al. (2011) and Albeverio et al. (2013)). By reading reliable papers about volatility-managing, I improved my understanding of the topic. As a result, I found a way to supply the existing literature. My thesis focuses on volatility-managing portfolios in the Norwegian market. The paper also analyses the performance of portfolios from the Norwegian and U.S. market during the COVID-19 pandemic. Lastly, I analyse momentum portfolios from five European countries.

Another element to the meaning of "responsible" is related to the methodology and statistics. The volatility-managing strategy is dependent on the accuracy of the realized volatility approach. There are other methods that I could have used as a predictor of future variance. However, the literature on volatility forecasting and realized volatility are solid. Andersen et al. (2003) suggest that realized volatility is an unbiased and highly estimator of return volatility. Since my master's thesis is grounded in the literature heavily explored and supported by respected researchers, I could state that my master thesis is responsible.

In terms of the responsibility of the methodology, one could ask if the statistical toolbox is good enough to make predictions? Taleb (2005) states that we cannot make accurate predictions in the world of finance. This connects us to the topic of p-hacking. Stokes (2011) highlights that most researchers show favorable results in the hope of making an impact on the existing financial literature. The researchers have personal and economic incentives to produce revolutionary empirical papers. They make more money and increase their recognition. In an attempt to achieve that, they employ new and unproven statistical methodologies that could increase the significance level of their results. This is unhealthy for those whom it affects. The reader of the article bases their knowledge on fake results. The writer will struggle to cope with the pressure from others to prove that the methodology is reliable and valid. There is also an increasing danger that the writer will apply similar methods for future research.

My master thesis has its foundation in statistical processes that have been tested continuously for more than forty years. The realized variance estimator is based on the findings from Engle (1982) regarding the ARCH process. Andersen et al. (2003) progressed the literature on volatility forecasting. They found that realized variance is an efficient estimator for future variance. The strategy in my paper applies the realized variance estimator. It contributes to strengthening my results and validating the methodology I used.

The Sharpe ratio is a tool used to evaluate portfolio performance. It describes the return of an investment compared to its risk by measuring the average return earned in excess of the risk-free rate per unit of volatility. The metric was formulated by William F. Sharpe (1966). To determine whether the Sharpe ratio of the managed portfolio is significantly higher than the unmanaged counterpart, I applied the test by Jobsen and Korkie (1981), later improved by Memmel (2003). The hypothesis test determines if the null hypothesis can be rejected by evaluating if the p-value is lower than the chosen confidence level (usually $\alpha = 0.05$). The rejection indicates that the data generates sufficient evidence against the hypothesis that the Sharpe ratio of the two portfolios is similar. A hypothesis test needs to be conducted more than once to solidify and increase the robustness of the test. Since a significant result is the desired outcome of a study, researchers tend to perform p-hacking. This includes changing the test by shortening or extending the sample. My thesis analyses two different periods to determine if either period reveals statistically significant results. Taleb (2005) states that the more changes one performs on the sample, the higher likelihood of finding a rule that provides revolutionizing results. My study is based on the longest sample period available at the time of writing and is not changed.

The last element of “responsibility” is responsible investment. The volatility-managing strategy adjusts the exposure based on volatility levels in the stock market. I allow for unrestricted leverage levels. Moreira and Muir (2017) show that the strategy reports significant results when allowing and avoiding restrictions. However, Hallerbach (2012) point out that limiting the leverage result in lower Sharpe ratios. On the opposite side, being a responsible investor involves making decisions that would not harm the global economy. This includes reducing the leverage levels of investors’ portfolios. Investment managers and financial institutions should be aware of the leverage they use to minimize the risk of harming the global economy in case an unexpected decline occurs. On the other hand, the strategy I apply in my thesis is grounded in risk management because the investor adjusts its market exposure according to the previous month’s realized volatility. If the market crashes, the strategy reduces the market exposure. This leads to reduced drawdowns. My results show that the strategy successfully hedges against downfalls during market turmoil. In other words, the volatility-managing strategy manages the risk of portfolios, which is responsible.

The discussion paper discusses how “responsibility” relates to my master thesis. I described how important it is to cite your references and give them credit for their findings. I also evaluated the reliability of my sources. Furthermore, I presented how responsible my methodology and statistical processes are, followed by a discussion of its validity. Lastly, I elaborated on the connection between my master’s thesis and responsible investment. Volatility-managing reduces crash risk through less significant drawdowns. Risk management is one of the main strengths of the strategy. It helps stabilise the financial market through lower downfalls. However, the strategy could also hurt the economy with its unrestricted leverage level. After analyzing the different aspects of responsibility concerning my master’s thesis, I became more aware and proud of the fundamentals of my paper.

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D Discussion paper - Simen Lilletvedt Årsland

A crucial part of the University of Adger's mission statement and vision is the concept "International". In this discussion paper, I discuss how the important the concept is for the university and how it relates to the master's thesis. My discussion paper is organized as follows. First, I explain how the University of Agder focuses on being an international university. Then, I introduce the topic of my master thesis, followed by a discussion of the concept of "International". Lastly, I conclude my discussion paper.

One of the University of Agder's focuses is to be an international university. On the masters' level the University of Agder offers most classes in English, to maintain the international focus. By providing education in English, it becomes easier for students graduating to work abroad after finishing their degree. In addition, the advantage of practicing your course in English is that you know most terms used in international context. An understanding of important vocabularies will be helpful when aiming to understand and participate in conversations and discussions. This will also be beneficial for socializing and becoming friends with people from other countries. If you want to work abroad, establishing international contacts are important.

Being an international university involves hiring English-speaking professors. The University of Agder has hired professors from all over the world. This contributes to a more diverse organizational culture. As a student, you will get insights of how the various professors teach their course. This will increase your adaptability and flexibility, as you need to adapt to the various techniques and tests the professors provide. Getting to know people and professors from various countries can increase your cultural understanding and improve your international network of people. Another example of the internationality of the University of Agder is the various exchange-programmes it offers. The university offers the possibility for their students to go abroad to study and work. In exchange, they offer students from partnership universities to attend their university. By doing so, one could get to know people from all over the world. The international students will attend the same courses as you. This offers the opportunity to expand your network. In addition, getting an understanding of how it is living and studying in other countries is very beneficial for your future life.

Cultural understanding is offered to you if you choose to study abroad. The University of Agder offers students to study abroad in countries like the United States, New Zealand, Switzerland, China and many more. Studying abroad will increase your cultural understanding and provide you a new perspective of how it is to study, live and work in other countries than your own. This could be very helpful when applying for future jobs, as it shows that you are willing to challenge yourself and go out of your comfort zone. It will also make it easier for you in international settings, as people will notice your deep understanding and respect for various cultures and countries.

Personally, I've taken advantage of the opportunity provided by the University of Agder by embarking on an exchange semester in Prague. This journey first and foremost let me travel to and experience Czech culture, nature and food, but it also let me make friends from all over the world. Another benefit is that it allowed me to take subjects not offered by my home university. Prague University of Economics and Business provided a wide range of subjects, some directed at finance, but also other subjects with great relevance. A subject especially relevant for my career was about "Communication and Presentation of Information". This subject was taught by a professor from Afghanistan and taught us about verbal and non-verbal communication between people in formal and informal settings. There was also special attention paid to intercultural communication, as this kind of communication often has some issues attached to it. People of different cultures have different ways of communicating and certain things, like the simple thumbs-up, may mean the complete opposite and be offensive in some cultures. The extra knowledge of communication has already been useful and will be even more helpful when I start working in an international company after my masters' degree. I have already had some contacts with different cultural backgrounds and have learned a lot about making intercultural friends. Working together with foreign people of different cultures will definitely be easier after my experience in Prague.

The benefit of studying courses in English, is that you will be able to write your master thesis in English. This is beneficial if you want your work to be published internationally and recognized by the well-known journals. It will make it easier for people from abroad to understand your work. When you apply for international jobs, your master thesis can play a big part in getting the job, especially since it is written in English. If it would have been written in Norwegian, you would have to explain it or translate it. This is not as effective as if your potential future organization can read and understand it themselves. Students writing and understanding their English master thesis have a better chance of getting a job abroad.

Our thesis examines the performance of the volatility-targeting strategy developed by Moreira and Muir (2017). Volatility-managed portfolios are constructed by scaling the return of unmanaged portfolios by the inverse of their past month's realized variance. We apply this strategy to portfolios constructed on four risk factors on U.S. and Norwegian stock markets. After realizing that the strategy performs remarkably well on portfolios constructed on momentum, we extend our analysis to five additional European economies. Our results show that results are consistent for momentum portfolios across Italy, France, Germany, Great Britain and Spain. The large and statistically significant alphas in our results show great promise for real life application of the volatility-managing strategy presented in this paper. An investor can utilize the strategy by continuously adjusting his/hers exposure to a market-tracking instrument such as the SPY S&P 500 index, or even an exchange traded fund (ETF) constructed on the momentum risk factor such as the iShares MSCI USA Momentum Factor ETF (MTUM) administered by BlackRock, the largest investment management firm in the world. Similar alternatives that focus on specific, international stock markets are available for investors that may not have access to the U.S. market. In other words: volatility-timing strategies, such as the one presented in this paper, are not limited by borders and are applicable on any stock market where prices are updated at a minimum of a daily frequency.

Globalization is a keyword often mentioned when the concept of modern internationality is discussed. The stock markets, as we know them today, are a great example of a system that continuously follows the trends we describe as globalization. When first stock market was introduced in the early 1600s in the Netherlands, nobody could imagine the state of the market today. The internationality of the markets has truly accelerated the last decades, with the first intercontinental securities opening when the NASDAQ joined forces with the International Stock Exchange based in London (Hwang, 2021). Today, investors from all over the world have access to international stock markets where they can buy shares of companies located worldwide. The continuous globalization is highly relevant for the evolution of financial theory in general. Researchers of today have close to unlimited data available on the world wide web where international sources continuously upload information. This availability of data makes research much more efficient as economists, like us, can find and download the data needed within a few minutes with the help of Google. In addition to the abundance of knowledge and raw data available, the internet also lets researchers share their ideas with, and receive feedback from, international academics. Social networks, like ResearchGate[10], allows academics to easily share ideas, ask and answer questions.

In the context of this thesis, the concept "International" is highly relevant. We analyse the performance of a volatility-targeting strategy on Norwegian, U.S. and five EU markets. The strategy has been developed and tested on the U.S. market by two American economists. Since the original article is published and available on the internet, it is easy for researchers worldwide to replicate their strategy to test whether it proves effective on other markets. Volatility-forecasting and timing-strategies have been a topic for debate for quite some years already and the debate has drawn interest among economists from different countries. To name a few, we use knowledge from Danish economists Andersen and Bollerslev (1998) that write about the accuracy of volatility-forecasting models. American economist Fischer Black (1976) investigates the relationship between stock volatility and return. Lastly, Norwegian economist Bernt Arne Ødegård (2021) has constructed portfolios on the original Fama-French risk factors (Fama, E. F. & French, K. R., 1993) as well as other risk factors, such as the momentum portfolio we analyse on the Norwegian stock market. This shows the importance of having an international scientific community to progress financial literature. The volatility-timing strategy presented in this paper would not have been possible to establish without existing literature and empirical studies by academics from other countries. Since our thesis

[10] Www.researchgate.net

is published on the University of Agder's website it is also possible for students all over the world to find our thesis and replicate the study to see whether the strategy is effective for portfolios formed on their own countries' stock markets.

Another feature of globalization that ties closely to the stock markets is the fact that companies have realized that countries have a wide range of policies regarding taxation and other regulations of companies. Ireland has, with its low company tax rate of 12.5%, become one of the main places for companies to move their headquarters in order to avoid taxes (Barrera & Bustamante, 2017). A consequence of this is that the gross domestic product (GDP) of Ireland has increased from 100 billion USD in 2000 to 425 billion USD in 2020 (OECD, 2022), truly an astonishing growth. This growth was possible only because major multinational companies such as Apple, Google, Amazon, Facebook, and several others have shifted their profits there. The movement of headquarters to tax havens also has consequences for the origin countries of the companies. Since they register in tax havens, they manage to avoid paying company taxes in their home countries. The situation is difficult to solve as the low tax rates offered by countries such as Ireland, Gibraltar, and Cyprus force companies to move their headquarters to stay competitive with competitors that have already moved. It can also pressure governments into lowering their tax rates in an attempt to keep their companies' headquarters on domestic soil.

In summary, the international focus of the University of Agder has given me the opportunity to take my degree in English. This has prepared me for a career in international companies by giving me experiences working with people of different cultural backgrounds. It has also given me the opportunity to partake on an exchange-program provided by the school. Given this, and the knowledge provided by my professors at my home university, and in Prague, I have been able to use research papers and data available on the internet to write my Masters' thesis. My master thesis is based on international sources which makes it more attractive for international academics and researchers to read it. It is written in English and in academic language to increase the likelihood of it being included in journals. My master thesis is also of great interest to others because it investigates international equity markets such as the U.S., German, and French stock markets. To my knowledge, it supplies to the current international literature on volatility-managing. Specifically, it adds to the literature surrounding the momentum risk factor. Hopefully, my master thesis will be of great interest and help to international academics and researchers.

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