



An Assessment of Volatility-Managed Performance on Single Investment Factors and Mean-Variance-Efficient Portfolios

Is volatility timing in the context of
a global health crisis beneficial ?

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Abstract

This paper analyzes if volatility-managed investing strategies outperform traditional buy-and-hold approaches focusing on a time span of 1926 until 2021. Volatility managed portfolios produce positive and mostly significant alphas for all single factors checked in our analysis. We document this for the market, value, momentum, profitability, investment, Earnings-to-Price ratio, Return-on-Equity, and cash flow volatility. A multifactor approach for volatility management improves the Sharpe Ratio for all the combinations of factors most of the time. This paper differentiates from others due to the fact that it focuses also on the effect of global crises like the COVID-19 pandemic and assesses additional factors of excess return. Although our strategy takes on average less risk than the unmanaged one, our OOS results show that does not necessarily result when compared to the regular one. Nevertheless, we believe that our paper can give insightful information about other volatility-managed combinations.

1. Introduction

Existing literature on the impact of volatility-timing on returns has proven that volatility-timing, if applied correctly, has the potential to thrive investment returns while volatility remains unchanged compared to a non-managed portfolio. A market environment coined by instability of financial and labor markets like during a global health crisis as the COVID-19 pandemic justifies an extension of this analysis to see how a volatility-timed investment strategy had performed in a time frame that includes such crisis.

In order to test this, we follow a similar approach like Moreira and Muir (2017) but extend our study by supplemental investment factors and extend the period of observation by including the timespan n of 2015 until 2021 and hence take the core phase of the COVID-19 pandemic into account. Our data sample consists of daily and monthly returns retrieved from Fama and French as well as from Jensen, Kelly, and Pedersen (JKP) and ranges in a timeframe of 1926 until 2021. Similar to Moreira and Muir (2017) we created a volatility-managed portfolio by scaling monthly returns by the inverse of the previous month's realized variance to diminish the burden of risk if the latest variance was high and enhance it if the recent variance was low. Both the volatility-managed portfolio as well as the unmanaged traditional buy-and-hold portfolio strategy are compared to determine whether the volatility-managed investment has the potential to outperform non-managed strategies and improves Sharpe Ratios.

Our paper performs an In-Sample (IS) analysis for a single-factor and a multifactor scenario and an Out-Of-Sample (OOS) analysis of one multifactor portfolio to study the effects of a volatility-timed investment approach. Like most research papers on volatility-timing, we use the five factors of Fama and French (Mkt, SMB, HML, RMW, CMA). For the single-factor analysis, we supplemented our data set by Momentum (Mom) also taken from Fama and French, and Return on Equity (ROE), Earnings-to-Price (E/P), and Cash Flow volatility (CF Vol), all extracted

from Jensen, Kelly, Pedersen. The latter three were selected to gain additional insights on factors that are worth investigating for volatility-timing. The multifactor analysis is conducted by applying several combinations of the three Fama and French factors (FF3), the five Fama and French factors (FF5), Momentum, and the JKP factors. We obtained the relative optimal weights for each factor by satisfying mean-variance efficiency for the unmanaged portfolio and apply the resulting relative factor weights on the managed portfolio. In order to gain nuanced results, we additionally divide our sample in three subsamples (1926 – 1966, 1966 – 1991, 1991 – 2021) and analyze the respective outcome.

For the single-factor and multi-factor analysis, we obtained predominantly positive alphas, which indicates that the managed-volatility factors and portfolios produce elevated IS Sharpe ratios compared to the unmanaged portfolio. This implies that, considering the in-sample analysis the investor should time volatility rather than investing traditional, considering the in-sample analysis the investor should time volatility rather than investing traditional buy-and hold portfolios.

As a last step, we perform an OOS analysis in order to test the IS results for robustness and check if they also produce favorable investment returns if actively performed during the period of observation.

Relevant research papers analyze similar topics concerning volatility-managed portfolios and in most cases also take the paper of Moreira and Muir (2017) as a theoretical basis. For instance, Cederburg et al. (2019) collected a dataset of 103 equity strategies to analyze if volatility-managed portfolios outperform traditional buy-and-hold portfolios. They generate positive alphas but poor out-of-sample results implying structural instability in the regression as well as impossible implementation in real time. Recent literature Wang and Yan (2021) as well as Qiao et al. (2020) focus on analysing the performance of a downside volatility strategy towards a total respectively an upside volatility investment approach, coming to the result that the downside volatility investments generate higher returns. Guo and Liu (2019) however present a series of contradictions to the Moreira and Muir (2017) approach by showing that the volatility-managed portfolio alphas aren't guaranteed to be positive due to an arbitrariness of the constant c . Finally, Barroso and Detzel (2021) analyze if transaction costs, arbitrage risk, and short-sale impediments might be the reason for the abnormal returns of volatility-managed equity portfolios. Considering these three effects managed portfolios only delivered high profits if sentiment is high implying investors underreact to volatility.

Our paper is structured as follows: Section 2 describes our data and methodology. Section 3 presents results for the single factor and multifactor approach as well as for the out-of-sample analysis. Section 4 shows relevant limitations and Section 5 concludes.

2. Data and Methodology

2.1. Data Description

Daily and monthly factor excess returns are collected from the Kenneth French database, which again relies on stock returns as indicated by CRSP database. Factor excess returns are computed on market excess return (Mkt), size (SMB), value (HML), momentum (Mom), profitability (RMW), and investment (CMA). Because previous literature has proven Momentum to be highly predictable and manageable, we additionally include the momentum factor as a strategy that goes long on winners of the preceding period and short on losers. Moreover, we retrieve daily and monthly data from the Global Factor Data website, whose factor data is composed of results generated in “Is There a Replication Crisis in Finance?” (Jensen, T., Kelly, B., and Pedersen, L.?) and includes factor excess returns for Return on Equity (ROE), Earnings-to-Price (E/P) and Cash Flow Volatility (CF Vol). Analogously to the 3FF and 5FF plus Momentum factor data, the data retrieved for ROE, E/P and Cash Flow Volatility are retrieved for the US. Data is retrieved for the period 1926-2021 for FF3, 1927-2021 for Momentum, 1963-2021 for 5FF, 1950-2021 for ROE and E/P and 1965-2021 for Cash Flow volatility.

2.2. Methodology

In the following paragraph we define how we constructed our volatility-managed portfolio as well as model underlying our regression. We structure our volatility-managed factors and portfolios by weighting the buy-and-hold excess return of one or more factors by the inverse of its conditional variance, for which we use a proxy for simplicity. Our portfolio’s risk exposure fluctuates each month according to the variation in our measure of conditional variance.

We define the volatility-managed strategy as follows:

$$f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}_t^2(f)} f_{t+1} \quad (1)$$

Here f_{t+1} represents the excess return of a non-managed or buy-and-hold strategy of any given asset whereas $\hat{\sigma}_t^2(f)$ is our strategy's conditional variance in the preceding month. The constant "c" is estimated so that realized variance of the of the non-managed strategy equals realized variance of the managed strategy, either for the entire sample (IS) or for a rolling window of 10-years (OOS). In order to simplify portfolio formation, we determine "c" in a way that managed and non-managed strategy have the same realized variance for the preceding month, which serves as a proxy for unconditional variance here. An alternating approach would be to define a desired target level of variance or volatility and use this as a constant to scale returns. For the multifactor portfolio formation, we perform portfolio optimization according to Markowitz and determine respective factor loadings that maximize the IS Sharpe Ratio. The risk-return trade-off, given by, $w_t^* \propto \frac{E_t[f_{t+1}]}{\hat{\sigma}_t^2(f)}$, is thus proportional to the optimal weights determined in the previous step. We just apply this equation the multifactor case when the factors are approximately uncorrelated.

To keep it simple we use the previous month's realized variance as a proxy for the conditional variance, but do unlike other research on the topic not demean our observation of realized variance, which might cause our results to deviate slightly from those of other authors:

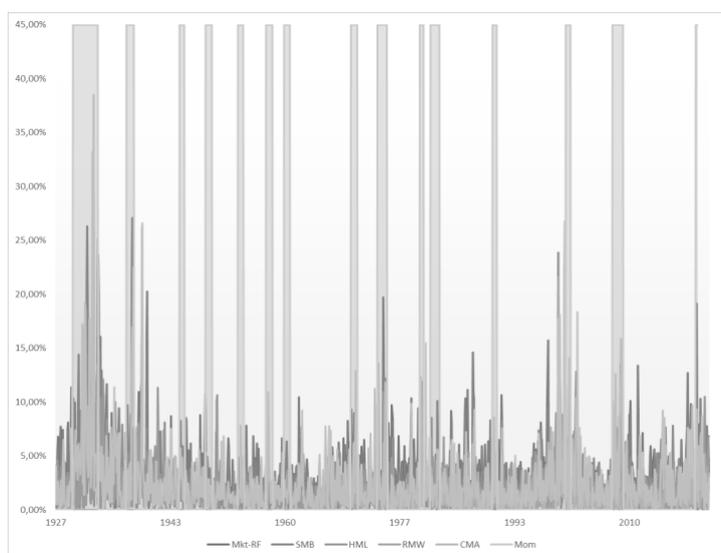


Figure 1. Realized volatility by factor across time. This figure plots the time series of monthly volatility of each individual factor. We can see that volatility commonly increases for all factors in recessions.

After estimating scaled returns of single- and multi-factor portfolios, we run a time-series regression of the volatility-managed portfolio on unmanaged single- and multi-factors.

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \varepsilon_{t+1} \quad (3)$$

One of the most important findings in our regressions is the intercept (α) which represents the ability of the strategy to beat the non-managed portfolio. Following this rationale, a positive α can lead us to the conclusion that volatility timing increases the Sharpe Ratios relative to the non-managed portfolio.

Each one of our factors represents a different explanation for excess returns and summarizes different pricing figures regarding several cross-section of assets. Taking this into consideration we can state that a positive alpha suggests that our managed portfolio expands the mean-variance frontier - a movement to the left side of the plot as suggested by asset pricing literature.

3. Results

3.1. Results for single-factor regression

As a first step, we perform an analysis for each individual factor in order to discover if the factor profits from using a volatility-managed investment strategy and significantly outperforms the results for the buy-and-hold approach. The main component impacting our results is the relationship between risk and return in our sample, as the scaled portfolio's return is directly affected by the realized variance in the preceding month.

In general, we are able to substantially interpret the produced alpha values if the different factors present a reasonable overview of the investor's choices. Each factor should investigate another aspect of risk, individually not being correlated with each other.

We show the results of running a univariate regression of the volatility-managed factors on the unmanaged factors in Table 1. Overall, our intercepts (α 's) are positive except for the SMB factor. We further find significant alphas for Mkt-Rf, HML, RMW, Mom and E/P, while our results for SMB, CMA, ROE and CF Vol do not suffice the 95% confidence interval requirement. Similar to the results of Moreira and Muir (2017) the volatility-managed market portfolio continues to produce significant alphas over the non-managed Portfolio (+4.38% p.a.). As mentioned above, most of the factors present strong and positive alphas with emphasis on the momentum factor which shows an alpha of 12.22%. The results for Momentum are consistent with Barroso and Santa-Clara's (2015) research, who exhibits that when we hedge momentum volatility to avoid large downturns it performs extremely well. Furthermore, noteworthy is the elevated performance of HML-factor based investment, which improved its alpha by 1.5% compared to the research done by Moreira and Muir (2017). As this factor is value focused, it seems reasonable to attribute the increase to the strong impact the pandemic had on value-based volatility management.

Moreover, we control alphas to the FF3 factors on the non-managed factors in every regression. Generally, the results do not change significantly, however, for the Momentum, CMA, and E/P strategies, we observe interesting changes. For instance, Momentum alpha improved its value by 3.79% p.a. continuing to be in line with the results shown by the paper mentioned above. Furthermore, CMA and E/P alphas improved substantially from 0.08% p.a. to 3.13% p.a. and from 4.32% p.a. to 7.25% p.a., respectively.

Lastly, we would like to point out that our results confirm previous work done on the topic, which is why we believe that the extension considering the JKP factors as well as an extended sample period is valid and insightful.

In Panel A in Table 1, after scaling each one of our factors for timing volatility, we run a univariate time-series regression for each one of the scaled factors, $f_t^\sigma = \alpha + \beta f_t + \varepsilon_t$, to comprehend how this managed strategy behaved through time. In Panel B, we controlled the alphas for the Fama-French three factors to understand if there are substantial changes on the alpha values. For the 3FF Model and Momentum we use monthly data from 1926 to 2021. For RMW and CMA (the additional two factors used in

5FF Model) we consider monthly data from 1963 to 2021. Lastly, for the factors we retrieve from Global Factor Data we also use monthly data from 1950 to 2021 for ROE and E/P and 1965 to 2021 for CF volatility factor.

Panel A: Univariate Regression									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mkt-Rf	SMB	HML	RMW	CMA	MOM	ROE	E/P	CF Vol.
Mkt-Rf	0,62								
SMB		0,63							
HML			0,56						
RMW				0,58					
CMA					0,70				
MOM						0,47			
ROE							0,54		
E/P								0,48	
CF Vol.									0,58
Alpha	4,38 (1,5)	-0,78 (0,87)	3,47 (1,04)	2,23 (0,82)	0,08 (0,65)	12,22 (1,49)	1,35 (0,92)	4,32 (1,41)	0,77 (0,97)
N	1142	1142	1142	703	703	1142	850	850	667
R2	0,38	0,40	0,31	0,34	0,49	0,22	0,30	0,23	0,34
RMSE	50,38	29,46	35,12	21,57	17,16	49,90	26,60	40,79	24,85
Panel B: Alphas Controlling for Fama-French Three Factors									
Alpha	4,08 (1,51)	-0,91 (0,88)	3,16 (1,05)	4,35 (0,99)	3,13 (0,9)	16,01 (1,69)	0,27 (1,09)	7,25 (1,61)	2,78 (1,11)

Table 1. Standard errors are in parentheses, adjust for heteroskedasticity and are annualized in percent per year by multiplying by square root of 12. All factors are annualized in percent per year by multiplying monthly factors by 12.

Figure 2 outlines the cumulative returns of a traditional buy-and-hold approach in comparison to a volatility-managed strategy for market excess returns. This graph illustrates that our managed strategy outperforms the buy-and-hold approach. We can also derive from the graph that, despite the good performance of the managed portfolio, this strategy would have had some significant crashes after 2018, indicated by severe downswings in cumulative returns. An investor who decides to follow this strategy has to be patient and not too much averse to risk, otherwise he could lose an important part of the investment. With the aim of deriving the annualized managed factor excess return (Appraisal ratio) calculated by $\frac{\alpha}{\sigma_e} * \sqrt{12}$, we include in all tables the

root mean squared error. This ratio represents a measure of the influence that this trading strategy has on the slope of the mean-variance efficient frontier.

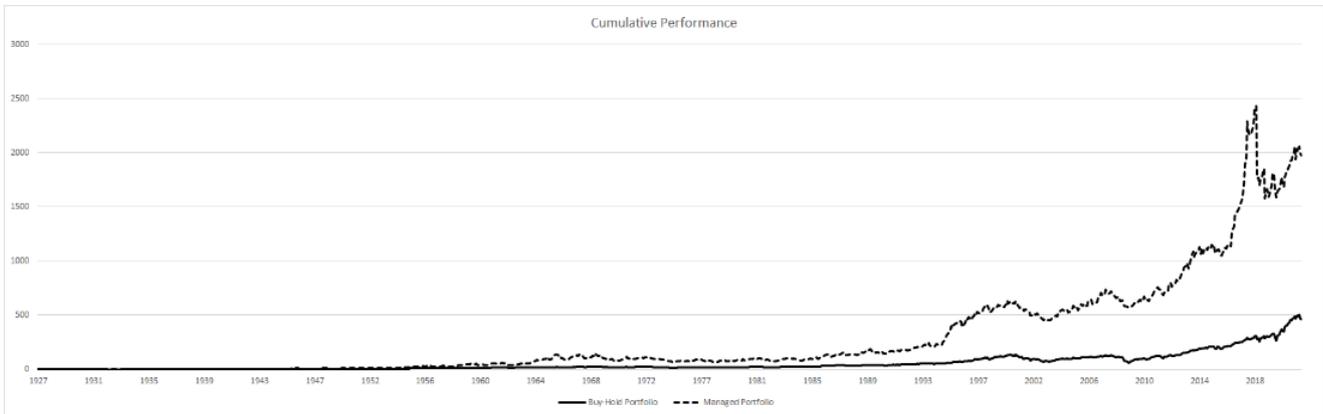


Figure 2 Comparison of buy-and-hold and volatility-managed cumulative returns for the market portfolio. This figure compares the cumulative returns of a buy-and-hold approach and a volatility-managed strategy for the Mkt Portfolio from 1926 to 2021.

Then, this new Sharpe Ratio is defined as:

$$SR_{New} = \sqrt{SR_{Old}^2 + \left(\frac{\alpha}{\sigma_\epsilon}\right)^2} \quad (4)$$

Where SR_{Old} is the SR given by the original factors (non-scaled) and the second term is the Appraisal Ratio squared.

In general, most of our scaled factors show favourable results regarding the Appraisal Ratio (AR). The momentum factor was the one with the vastest improvement, with an AR of 0.85. On the other hand, the SMB factor showed a negative AR (-0.092), but we must keep in mind that the intercept for this single strategy is not significant.

On top of these measures, we also add another economic measure to try to quantify the gains for the mean-variance investor by computing the utility gain:

$$\Delta U_{MV}(\%) = \frac{SR_{New}^2 - SR_{Old}^2}{SR_{Old}^2} \quad (5)$$

We used Campbell and Thompson (2008) results as a benchmark to our estimates. They showed that the utility gain of timing expected returns is 35%. When we compare this value with the ones that we get, we see that our volatility timing strategies have on average, good utility gains. For example, the Momentum Strategy revealed a utility gain of 111.41% showing an improvement of more than 75% against

the normal expected return. Overall, all our managed single portfolios have interesting utility gains showing that volatility-timing generates high level of returns and works across multiple factors.

	Mkt-Rf	Scaled Mkt-Rf	SMB	Scaled SMB	HML	Scaled HML	RMW	Scaled RMW	CMA	Scaled CMA
Mean return (%)	8,18	9,44	2,65	0,89	3,97	5,70	3,27	4,13	3,42	2,47
t-stat	4,31	4,97	2,35	0,79	3,16	4,54	3,26	4,13	3,77	2,72
p-value	0,00	0,00	0,02	0,43	0,00	0,00	0,00	0,00	0,00	0,01
St. Dev. (%)	18,52	18,52	10,99	10,99	12,24	12,24	7,67	7,67	6,94	6,93
Sharpe ratio	0,44	0,510	0,24	0,08	0,32	0,47	0,43	0,54	0,49	0,36
RMSE		50,38		29,46		35,12		21,57		17,16
SR new (as suggested by Moreira and Muir)		0,531		0,177		0,452		0,534		0,497
Appraisal Ratio		0,301		-0,092		0,343		0,358		0,016
Utility gain (MV-Investor)		44,59%		-45,87%		94,12%		56,76%		1,87%

	Momentum	Scaled Momentum	ROE	Scaled ROE	E/P	Scaled E/P	CF Vol	Scaled CF Vol
Mean return (%)	7,64	15,79	2,68	2,80	4,47	6,48	1,51	1,65
t-stat	4,57	9,45	2,46	2,58	2,79	4,05	1,28	1,39
p-value	0,00	0,00	0,01	0,01	0,01	0,00	0,20	0,16
St. Dev. (%)	16,30	16,30	9,16	9,16	13,47	13,47	8,82	8,82
Sharpe ratio	0,47	0,97	0,29	0,31	0,33	0,48	0,17	0,19
RMSE		49,90		26,60		40,79		24,85
SR new (as suggested by Moreira and Muir)		0,682		0,369		0,465		0,246
Appraisal Ratio		0,849		0,175		0,367		0,108
Utility gain (MV-Investor)		111,41%		59,10%		96,28%		106,39%

Table 2 Main Statistics for the volatility-managed Single Factors

3.2. Results for Multi-factor regression

To extend our study, we analyze a multifactor setting and build several portfolios as a combination of the following factors: Mkt, FF3, FF5, Momentum and Jensen, Kelly, Pedersen (JKP). As a next step we select the weights that our portfolio is mean variance efficient (MVE) for the respective factor set. The weights for these multifactor MVE portfolio are calculated as the ones maximizing the Sharpe Ratio for the respective combination of factors in an In-Sample (IS) analysis. As we construct Portfolios for FF3, FF5 and JPK, individually extended by Momentum, we construct a total of six MVE strategies, whose weights tend to vary severely from another. Therefore, a positive MVE alpha for a managed Portfolio on the un-managed Portfolio indicates that volatility timing generally improves the Sharpe Ratios compared to pursuing the best buy-and-hold strategy with access to the several factors. Our MVE portfolio is built of a vector for factor returns (F_{t+1}) and the variable b representing the static weights that ensure the in-sample Sharpe ratio to be maximized. Defining this in an equation we get:

$$f_{t+1}^{MVE} = b' F_{t+1} \quad (6)$$

Thereby we construct the respective multi-factor MVE portfolio as:

$$f_{t+1}^{MVE,\sigma} = \frac{c}{\sigma_t^2(f_{t+1}^{MVE})} f_{t+1}^{MVE} \quad (7)$$

Again, c represents a constant that normalizes the realized variance of the volatility-managed MVE portfolio to be equal to the non-managed MVE portfolio. Therefore, our approach to estimate returns of a volatility-managed Portfolio is essentially the same. Differences arise in the computation of realized variance in the preceding month as we are not only taking one factor but multiple into account. In order to construct the different multifactor portfolios, we developed the optimal weights for the unmanaged portfolio and applied these weights on the volatility managed portfolio.

In Table 3 we show our results for this multifactor approach. The combinations of factors we created are designed as follows: Market, FF3, FF3 with Momentum, FF5, FF5 with Momentum, JKP and JKP with Momentum. Taking into consideration both managed and non-managed MVE portfolios we only achieve positive values for alpha for every combination of the factors implying higher Sharpe ratios. Appraisal ratios show promising positive values ranging between 0.26 and 0.97.

To account for time-induced anomalies as they might occur in different financial eras, we have split our sample into three subsamples, ranging from 1927-1966, 1966-1991 and 1992-2021 respectively. The first subsample only contains regression results for FF3 and Mom due to the non-availability of the other factors but shows significant alphas (6.15% and 3.56% p.a. for FF3 and FF3 Mom respectively). In the following period (1966-1991) only the JKP and JKP Mom strategy showed significant positive alphas (6.16% and 6.61% p.a. respectively) while other strategies only indicated insignificant or even negative alphas. The third subsample (1992-2021), which contains financial and COVID-19 crisis, has shown significant positive alphas for FF3, FF3 Mom, FF5 Mom and JKP Mom, which again lead us to believe that the inclusion of Momentum in a volatility-management context influences the return of the entire portfolio positively.

Panel A: Mean-Variance Efficient Portfolios (Full Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mkt	FF3	FF3 Mom	FF5	FF5 Mom	JKP	JKP Mom
Alpha	4,38 (1,5)	3,78 (0,94)	2,86 (0,52)	0,64 (0,34)	1,11 (33,16)	5,53 (1,35)	7,33 (1,04)
Observations	1143	1143	1137	699	699	664	664
R2	0,34	0,46	0,52	0,47	0,47	0,21	0,27
RMSE	50,38	31,41	16,87	8,53	8,80	34,53	26,25
Original Sharpe	0,44	0,51	0,96	1,08	1,26	0,34	0,68
Vol-Managed Sharpe	0,53	0,64	1,08	0,96	1,18	0,65	1,18
Appraisal Ratio	0,30	0,42	0,59	0,26	0,44	0,55	0,97

Panel B: Subsample Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mkt	FF3	FF3 Mom	FF5	FF5 Mom	JKP	JKP Mom
Subsample 1 (1926-1966)		6,15 (1,83)	3,56 (0,97)				
Subsample 2 (1966-1991)		-0,09 (1,23)	0,53 (0,79)	-0,10 (0,43)	0,38 (0,47)	6,16 (1,67)	6,61 (1,65)
Subsample 3 (1992-2021)		2,47 (1,05)	3,16 (0,67)	0,72 (0,39)	1,11 (0,36)	0,47 (1,34)	3,40 (0,85)

Table 3 Multi-factor analysis of volatility-timed returns

Panel A: Mean variance efficient portfolio constructed as a combination of FF5, Mom, ROE, E/P and Cf. Vol and regressed on the respective non-managed factor. Again, a positive alpha implies an advantage of the managed over the non-managed strategy

Panel B: Subsample analysis of multi-factor portfolios

3.3 Results for Out-Of- Sample analysis (OOS)

When assessing the performance of a volatility-managed investment strategy in an OOS analysis, we find that its application would have led to a diminished performance then a plain buy-and-hold strategy for most decades under observation.

We performed an OOS analysis for the mean-variance efficient portfolio constructed with the FF3 factors extended by Momentum. Again, we computed the weights that had maximized the Sharpe Ratio in the non-management portfolio in an estimation window of the preceding ten years and repeated this procedure with 10-year rolling windows over the entire sample. For only three out of ten periods, a volatility-managed strategy would have resulted in an improved Sharpe Ratio, remarkable however is the increase in Sharpe Ratio in the 2008-2017 period.

Despite only assessing for one combination of factors, our findings are confirmed by supplemental research on the topic. Amongst others, Cederburg et. Al. find weak OOS performances of volatility-managed Portfolios. This must not necessarily hold for subparts of

these portfolios, as e.g. Barroso and Santa-Clara (2015) prove that volatility-managed investment following a Momentum strategy offers significant positive returns both IS and OOS.

	1927-1937	1938-1947	1948-1957	1958-1967	1968-1977	1978-1987	1988-1997	1998-2007	2008-2017	2018-2021
Original Sharpe Ratio	Estimation window	0,72	1,29	1,54	1,11	1,32	1,69	0,89	0,21	1,00
Managed Sharpe Ratio		0,78	1,15	1,44	1,23	0,84	1,37	0,79	0,87	0,89

Table 4 OOS Results for a FF3 Mom portfolio, constructed with a 10-year rolling window

4. Limitations

During our analysis, we found various limitations impacting our results. First, the geographical factor is a discriminating factor that should not be forgotten. Our analysis and research are based on US data, however there is no certainty that our results hold in security markets of other geographical areas such as Europe and Asia. The main problem is related to the calculation of market excess returns, which considers the American risk-free rate, which is historically one of the lowest in the world. This is because the level of solidity of the American economy is considered one of the best with a consequently low level of default risk. Considering the literature review we can highlight further limitations. It has been demonstrated that the structural instability in the regression parameters constitutes a limitation for real-time changing portfolios (Cederburg et al., 2019). Furthermore, if we take into consideration compounded returns, it has been demonstrated that the arbitrariness of the constant “C” does no longer hold, in this case, it’s rare for volatility managed portfolios to have statistically significant alpha (Guo and Liu, 2020).

5. Conclusion and outlook

In summary, we find significant positive alphas for an In-sample volatility-managed investment strategy for five out of nine factors under observation. While most alphas on the aforementioned single investment factors remained rather unchanged in an extended window of observation, e.g. the alpha on an HML-based investment strategy improved significantly during times of the COVID-19 crisis. An obvious inference here would be that during the global health crisis, a volatility-managed investment strategy focused on value had performed remarkably better than a non-managed value strategy

and had elevated its performance more than other factors. Equally remarkable here is the strong performance of a volatility-managed E/P factor.

For a mean-variance efficient investor, we find that volatility-managed portfolio formation is favourable for alternating approaches of combinations but not for portfolios that involve 5FF factors. In this regard, the extension for the years of the COVID-19 pandemic led to a diminished IS performance which had not been detected priorly. Noteworthy are the significant alphas in portfolios containing the three JKP factors which had, in this constellation, also not been researched before.

Our OOS results lead to the conclusion that volatility management in practice does not necessarily result in favourable returns compared to a non-managed approach. As this assessment was due to reasons of time and scope only performed for a FF3 Mom combination, research on other combinations might be insightful and, in our opinion, has the potential to identify combinations that allow to perform volatility-management efficiently.

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