



Master Thesis Financial Economics

Downside volatility, the future of the low volatility anomaly

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Abstract

Academic literature challenges the theoretical security market line, and finds that the empirical relation between risk and return is too flat. In this paper we investigate the performance of portfolios sorted downside volatility or negative semi-variance. Negative semi-variance can better predict future volatility. Consequently, negative semi-variance might better capture the low volatility anomaly as it can better predict the future volatility of a stock. We find a significant alpha in the long-short portfolio for the downside volatility risk measure. Moreover, we show that the alpha is significantly higher than the alpha of the low volatility sort. Further, we show that the alpha is robust to different data intervals, data frequencies, and the known factors (size, value and momentum). Additionally, we find a significant alpha for the sector-neutral portfolio.

Contents

1 Introduction	3
2 Methodology	8
2.1 Risk Measures	8
2.2 Performance measures	9
2.3 Robustness Tests	10
3 Data	12
4 Results	14
4.1 Other risk measures	17
4.2 Data frequency and intervals	19
4.3 Sub-period analyses	20
4.3.1 Up- and down market behavior	20
4.3.2 Dot-com bubble	21
4.3.3 Financial crisis	22
4.3.4 Corona crisis	23
4.4 Controlling for size, value and momentum	25
4.4.1 Fama-French corrected alpha's	25
4.4.2 Double sorted portfolio's	26
4.5 Performance within sectors	30
5 Conclusion	32
A Results other sorting mechanisms	34
A.1 Upside volatility	34
A.2 Extreme value sorts	35
A.2.1 Decile returns extreme value sorts	35
A.2.2 Regression on VaRs	36
A.3 Size, value and momentum	38
B Results downside volatility: one tracking year	40
C Sector Results	42

1 Introduction

Institutional and retail investors try to outperform the market. In their search of outperformance a lot of different strategies have been proposed. In economic theory the CAPM model is central, and mostly a starting point of each proposed strategy. Academic literature finds that the empirical relation between risk and return is too flat in comparison to the modelled relation of the CAPM model, e.g. [Fama and MacBeth \(1973\)](#). Alterations of this model have been proposed to explain this flat risk return relation. In this research we do not question the flat risk return relation, but try to compose a strategy that can profit from this relation. We hypothesize that the solution can be found by looking at the (assymmetric) volatility of an asset.

We base this hypothesis on a comprehensive overview of the possible explanations why the empirical relation does not hold, based on the violation of the CAPM assumptions that [Blitz et al. \(2014\)](#) provide. [Blitz et al. \(2014\)](#) categorize violations of the CAPM model into five different categories or assumptions. Three of these violation categories explain why high volatility stocks could be overpriced. The first assumption is that there are no constraints (e.g. on leverage and short-selling). In practice this assumption does not hold, as leverage is restricted by for example margin rules, and also short selling is restricted in practice. Furthermore, regulatory constraints such as Basel and Solvency II consider only the total amount invested in stocks. Therefore, investors are drawn to the high-volatility segment as it gives most equity exposure per unit of capital charge. [Frazzini and Pedersen \(2014\)](#) attribute the volatility effect to leverage constraints. In addition to examining the cross-sectional risk–return relation, they also provide time-series evidence by showing that when funding constraints tighten, betas tend to be compressed toward one and the risk–return relation becomes flatter. The second assumption is that investors are risk averse, maximize the expected utility of absolute wealth, and care only about the mean and variance of return. However, people tend to find relative wealth as compared to others more important than their absolute wealth. This changes the utility function of investors, and could explain a flatter (or flat) relation between risk and return. Relative utility is also apparent in the asset management industry, as portfolio managers are not judged on their absolute performance in terms of return and risk. Portfolio managers are focused on benchmark-relative returns, and benchmark-relative risk. Moreover, investment professionals try to optimize the value of their option-like contracts. Consequently, they do not necessarily behave in a risk-averse manner for their clients. Another explanation is that investors have a skewness preference which again changes their utility function. This new function rewards risk-seeking behavior and thus draws investors with this preference towards the high volatility stock segment. Further, it is well known that investors have a certain degree of crash aversion. Consequently, the concern of investors might shift from total risk

to downside risk. [Bali et al. \(2009\)](#) investigates the relation between Value-at-Risk (VaR), Expected Shortfall (ES), and Tail Risk (TR), and returns. They find a positive relation between these measures and return with a regression analysis. They explain this positive empirical relation between these measures and return with the notion that investors prefer assets with positive skewness, and low kurtosis, such that negative skewness and high kurtosis should command higher expected returns. The third violated assumption is that information is complete and rationally processed. Four examples of biases that violate this assumption are; attention-grabbing stocks (behavioral bias) which are mostly high volatility, and overpriced as they are traded more. Secondly, representativeness bias, that is people rely more on appealing anecdotes of companies or stories in the news, than on stock statistics. Highly volatile stocks generate a lot more favorable anecdotes. Thirdly, mental accounting, that is people tend to invest in 2 types of portfolios, a low aspiration layer (designed to avoid poverty) and high aspiration layer (shot at riches). Lastly, overconfidence bias, if manager believes he is more skilled he will be more active in high-volatility segment, as that segment offers the largest reward to skill. The other (violated) assumptions are that there is only one period, and markets are perfect.

The theoretical security market line can be challenged by finding simple investment strategies that have returns similar to the market, but at systematically lower risk. Multiple studies focus on constructing investment portfolios based on different types of risk measures to accomplish these higher risk adjusted returns. [Blitz et al. \(2014\)](#) explain that high volatility stocks might be overpriced, moreover they give examples why investors tend to focus on downside risk measures. Therefore, we focus in this research on portfolios constructed based on the measure downside volatility, an asymmetric risk measure. We replicate the research of [Blitz and Van Vliet \(2007\)](#), however we sort on downside volatility instead of volatility. We compare the performance of the downside volatility decile portfolios to other downside risk measures. We consider downside beta, VaR, ES, and TR of assets. Furthermore, we also compare the downside volatility portfolios to portfolios constructed based on volatility. The decile portfolios we construct from sorts on each respective measure are compared on their respective Sharpe ratios, excess returns, and alphas. We also consider the performance of the (downside) volatility portfolios within the Global Industry Classification Standard (GICS) sectors. Furthermore, we also consider sector-neutral portfolios.

With our approach as described above we answer the main research question if portfolios sorted on negative semi-variance are able to outperform portfolios sorted on low volatility. Moreover, we aim to compare the portfolios to other downside risk measures. Lastly, we investigate if the low volatility anomaly can be explained by sector weights, and if the anomaly also holds within sectors.

With the answers of these research questions we aim to add to the literature that challenges the theoretical market line by using risk as a portfolio construction mechanism. The risk of an asset can be measured in several manners. For example, risk can be measured by the CAPM beta, variance, or negative semi-variance. [Black et al. \(1972\)](#) show that low beta stocks actually contain positive alpha. [Frazzini and Pedersen \(2014\)](#) introduce betting against beta as a way to profit from this effect. They construct portfolios based on the CAPM beta, and report a significantly positive return on a portfolio long in low beta, and short in high beta assets. The beta of an asset is of course highly correlated with the volatility of an asset. Other recent studies therefore look at the volatility of an asset as risk measure instead of considering the beta. These studies find anomalously high returns on low volatility assets. [Clarke et al. \(2006\)](#) propose minimum variance portfolios, as then no assumption has to be made on the expected or forecasted return, and only the variance is optimized. For the construction of the portfolios they consider the 1.000 largest US stocks. However, they use only a limited amount of time series observations, namely 60 or 250. This leads to two problems in the the sample covariance matrix: it is non-invertible, and it contains a lot of pairwise estimates which leads to estimation outliers that can dominate the optimized portfolio (error maximization). They propose two different methods to solve these two problems: Principal Component Analysis, or Bayesian Shrinkage. They find outperformance of the market. This outperformance is persistent also when they adjust for factors, however now the absolute return is similar. If they control for the factors size, value and momentum, they find that the minimum variance portfolios constructed from the 1.000 largest US stocks deliver comparable average returns to the market portfolio, while reducing volatility with approximately 25%. Further, they note that the Bayesian shrinkage method works better, as in PCA still the total risk is preserved in the estimated covariance matrix, such that the maximum weight constrained of 3% becomes leading. [Blitz and Van Vliet \(2007\)](#) build upon this by constructing portfolios based on the individual volatility of an asset. Therefore, they differ from [Clarke et al. \(2006\)](#) as they do not need to estimate the covariance matrix. In a large investment space this needs less computing power, and also ensures lower estimation risk. They again find significantly higher risk-adjusted returns on the low volatility portfolios. Furthermore, they show that the low volatility portfolio contains more alpha than the low beta portfolios. However, they do not find much evidence of anomalous behavior if the simple return perspective is used. Further, they compare the volatility effect with the classic size, value, and momentum strategies and control for these effects. In order to disentangle the volatility effect from those other effects they use global and local Fama and French regressions and apply a double sorting methodology. The anomaly is persistent when controlling for these effects. They further show that (as expected) the low risk portfolio's underperform in up market months, and outperform during down months. The underperformance is considerably smaller than the outperformance, this

effect is however countered partly by there being more up than down market months.

[Blitz and Van Vliet \(2007\)](#) look at the total volatility of an asset. However, in economic theory it is well known that investors are more concerned with capital losses than upside gain. As volatility is a symmetric measure it can not capture this. [Markowitz \(1959\)](#) therefore advocates using negative semi-variance as a measure of risk. We define negative semi-variance as the squared negative returns of an asset. [Barndorff-Nielsen et al. \(2008\)](#) find that negative semi-variance in high frequency data is more informative when used in non-leverage based GARCH models, than the usual realised variance statistic. Thus, they conclude that negative semi-variance can better predict future volatility of a stock. [Patton and Sheppard \(2015\)](#) also show that future volatility is more closely related to negative semi-variance than positive semi-variance, using a simple autoregressive model. Consequently, negative semi-variance might better capture the low volatility anomaly as it can better predict the future volatility of a stock. [Wang and Yan \(2021\)](#) investigate downside volatility managed portfolios as compared to volatility managed portfolios. They construct these respective portfolios by scaling them based on volatility and negative semi-variance. They scale their portfolios using a constant which equalizes the full-sample volatility of the investment position which is unknown to the investor, and is a measure of leverage. As the constant can not be obtained by an investor, and in practice leverage is constrained this constant limits practical implications. Therefore, we do not use such a measure. [Wang and Yan \(2021\)](#) find that downside-volatility managed portfolios perform better than low volatility managed portfolios. They use a decomposition analysis to decompose the enhanced performance of downside volatility-managed portfolios, and find that downside volatility negatively predicts future returns. Therefore, we believe that negative semi-variance can potentially be a better forward looking measure for the construction of low volatility portfolios. As semi-variance can better predict volatility and thus might better capture the low volatility anomaly, we expect to find higher risk adjusted returns for portfolios sorted on low negative semi-variance than for portfolios sorted on low volatility.

We compare the downside volatility decile portfolios also to the other asymmetric risk measures. We consider the measures of [Bali et al. \(2009\)](#). Furthermore, we consider downside beta, a measure introduced in [Ang et al. \(2006\)](#). They compute downside and upside betas and show that the downside risk premium is about 6% per annum. They show this on individual stock level, using a series of one-year periods with daily data. Lastly, we also control for the effect that sector weights might have on the performance of the (downside) volatility constructed portfolios. [Bellone and Carvalho \(2020\)](#) find that low volatility portfolios outperform high volatility portfolios in every sector. We replicate their approach and test if we find similar results for low downside volatility portfolios. We differ from the research of [Bellone and Carvalho \(2020\)](#) by considering a larger time-period and we include only

US stocks, while they use the MSCI World Index.

Our results are in line with the literature and our expectations as we find that the long-short portfolio based on negative semi-variance contains a significant alpha. Further, the downside volatility effect significantly outperforms the low volatility anomaly. We find that these results are robust to the data frequency and interval that is used to construct the decile portfolios. Furthermore, the effect is also robust to the known factors size, value, and momentum. In addition, we find that a sector-neutral long-short portfolio still contains significant positive alpha. However, the alpha is significantly lower compared to the long-short portfolio not controlled for sector weights. Thus, sector weights seem to partly explain the low volatility anomaly, but are not able to fully explain the anomaly.

The research is structured as follows, in Section 2 we introduce the different risk measures we use to construct the decile portfolios. Further, we explain how we intend to compare the different strategies, and their robustness. Thereafter, we discuss which stock data we use, how we clean the data, and what the descriptive statistics are in Section 3. The results of our research are discussed in Section 4. Lastly, we draw conclusions from our results in Section 5.

2 Methodology

2.1 Risk Measures

To answer the question if there is a relation between downside volatility and returns we construct decile portfolios based on negative semi-variance. To further investigate downside volatility we compare the constructed downside volatility decile portfolios to other portfolios based on different risk measure types. We consider: low volatility, negative beta, VaR, ES, and TR. The decile portfolios are constructed from individual stock selection based on the respective criteria. We also construct a long-short portfolio which has a long position in the first decile portfolio and a short position in the tenth decile portfolio. All portfolios are constructed to be equally weighted portfolios.

Negative semi-variance sort

We calculate negative semi-variance or downside volatility in a similar manner as [Feunou et al. \(2013\)](#). They define downside volatility as follows,

$$\sigma_{down}^2 = \sum_{i=1}^n r_i^2 I_{[r_i < 0]},$$

where r_i is defined as the return on the considered asset in period i , and n the number of returns. Thus, negative semi-variance is calculated as the squared sum of negative returns. The measure can be constructed using several time frequencies, such as daily and weekly. Also, multiple time periods can be used, such as a year, or multiple years. If the number of negative returns is lower than three in time period t , then downside volatility is measured using both period t and $t-1$. The decile portfolios are sorted, such that the first decile portfolio contains the stocks with the lowest downside volatility.

Low volatility sort

We construct the decile portfolios for the low volatility anomaly in a similar manner as [Blitz and Van Vliet \(2007\)](#). We calculate the volatility of the stocks weekly returns over the past three years, where we account for the mean return,

$$\sigma_{low}^2 = \frac{1}{n} \sum_{i=1}^n (\tilde{r}_i^2 - \mu)^2,$$

where \tilde{r}_i is defined as the excess return of the considered asset in period i . Further, μ denotes the average return in the considered period. In line with downside volatility, the first decile portfolio contains the stocks with the lowest volatility.

Downside beta sort

We calculate the downside beta following the methodology as described by [Ang et al. \(2006\)](#). They calculate downside beta, denoted by β^- , as introduced by [Bawa and Lindenberg \(1977\)](#),

$$\beta^- = \frac{\text{cov}(\tilde{r}_i, \tilde{r}_m | \tilde{r}_m < \mu_m)}{\text{var}(\tilde{r}_m | \tilde{r}_m < \mu_m)}.$$

The tilde denotes that the considered returns are excess returns. Further, μ_m denotes the average market excess return. They consider a 1-year horizon with weekly returns. However, the 1-year returns are evaluated at a monthly frequency. Consequently, there is an eleven month overlap in the metric. Thus, by construction there is serial correlation. To adjust for this in the t-statistics we make use of the HAC variance-covariance estimator as proposed by [Newey and West \(1986\)](#). The first decile portfolio contains the stock with the highest β^- .

Extreme value sorts

We consider three different extreme value measures, namely Value-at-Risk (VaR), Expected Shortfall (ES), and Tail Risk (TR). [Bali et al. \(2009\)](#) describes the calculation of these measures. They define the measures with confidence intervals $100(1 - \alpha\%)$ as follows,

$$\begin{aligned}\text{VaR}_\alpha(r_t) &= F_Y^{-1}(1 - \alpha), \\ \text{ES}_\alpha(r_t) &= E(r_t | r_t \leq \text{VaR}_\alpha(r_t)), \\ \text{TR}_\alpha(r_t) &= E[(r_t - \text{ES}_\alpha(r_t))^2 | r_t \leq \text{VaR}_\alpha(r_t)],\end{aligned}$$

Thus, ES is defined as the mean of returns lower than the VaR, and TR as the variance of returns lower than the VaR. [Bali et al. \(2009\)](#) consider the VaR computed from the past 1 to 6 months of daily data. One month is assumed to have 21 trading days. They always use the lowest return during this period. Such that the 6 month VaR would be the $\text{VaR}_{99.04\%}$. The ES and TR are calculated on the 2.5% and 5% level using the past 100 observations. To be consistent, and make comparison easier we consider only the measures computed from the last 5 months of returns (105 days) on the 2.5% level. [Bali et al. \(2009\)](#) find that for shorter periods the positive relation between VaR and return is stronger. However, for ES and TR a minimum sample size is required to be able to find a mean and variance of extreme observations beyond de VaR threshold. They find a positive relation between the measures and return, thus the first decile portfolio contains the stocks with the highest respective extreme value measure.

2.2 Performance measures

To test the existence of a downside volatility anomaly and compare the other sorting methods to downside volatility we follow the approach used by [Blitz and Van Vliet \(2007\)](#). For each sorting mechanism described in Section 2.1 we calculate the excess return, standard deviation, Sharpe Ratio, beta

and alpha. The alpha and beta of each decile portfolio follow from the CAPM regression. For both the alpha and Sharpe ratio we also show their respective t-statistics. For alpha this follows from the CAPM regression. The statistic for the Sharpe ratio is calculated using the [Jobson and Korkie \(1981\)](#) test with the [Mommel \(2003\)](#) correction. The test statistic is calculated as follows,

$$z = \frac{SR_1 - SR_2}{\sqrt{\frac{1}{T}[2(1 - \rho_{1,2}) + \frac{1}{2}(SR_1^2 + SR_2^2 - SR_1 SR_2(1 + \rho_{1,2}^2))]}}, \quad (1)$$

where SR_i is the Sharpe ratio of portfolio i , $\rho_{i,j}$ refers to the correlation between portfolios i and j , and T is the number of time periods.

We compare downside volatility not only to other risk measures, but also to other known investment strategies. We consider: Size, Value and Momentum.

2.3 Robustness Tests

We perform several robustness tests. Firstly, we consider two different time periods in which the downside volatility is calculated. We consider one and three tracking years. Additionally, we use three different data frequencies: daily, weekly, and monthly data. Thus, this results in six different frequency, and period combinations. For all six combinations we again consider the performance measures as described in [2.2](#).

Secondly, we evaluate the performance of downside volatility in different sub-periods. We first analyse the performance of the decile portfolio as compared to the market in bullish- and bearish market periods. We define a bullish market as a month with a positive market return and vice versa. [Blitz and Van Vliet \(2007\)](#) also use this definition, and find that low volatility outperforms in down markets and underperforms in up markets as compared to the market. We investigate if also find this for downside volatility and if this effect strengthens. Further, we consider three different market events as sub-periods and analyse the decile portfolios in these periods. More specifically, we consider the dot-com bubble (2000-2003), the Financial Crisis (2007-2010), and the Corona Crisis (2019-2021).

Thirdly, we control for the Fama-French factors size and value, and the momentum factor as proposed by [Jegadeesh and Titman \(1993\)](#). We consider two different methods to control for these factors. The first method is a double sort on one of the three factors and downside volatility respectively. In this method first five quintile portfolios are created by sorting the stocks on size, value, or momentum respectively. Thereafter, each quintile of the respective measure is again sorted into five quintiles on downside volatility. Then, the top volatility quintile portfolios from within the size, value and momentum quintiles are combined to a neutral top volatility quintile (and similarly for the other quintile portfolios). Additionally, we use regression approach for which we report the alphas. We compare

the magnitude and significance of the uncorrected alpha of the long-short portfolio to the corrected alpha to investigate how much of the alpha spread can be attributed to the considered factors.

Lastly, we also evaluate the performance of downside volatility in sectors. To evaluate this we first consider sorting stocks into quintile portfolios per sector individually. To identify to which sector a stock belongs we use the GICS sector codes. For each sector we compare the Sharpe ratio of the sector to that of the market, however the Sharpe ratios of the constructed quintile portfolios are compared to the sector-specific Sharpe ratio. We also consider the performance of sector-neutral portfolios. These sector-neutral portfolios are constructed by combining each volatility quintile of the individual sectors into a sector-neutral volatility quintile.

3 Data

To construct the portfolios we make use of daily data from the Center for Research in Security Prices (CRSP) from 1990 until 2021. Such that, we can examine the portfolios in the dot-com bubble, the Financial Crisis, and Corona crisis. Moreover, we examine a long time period to ensure the volatility effect is not driven by a specific time period. The assets universe is restricted to common stocks listed on the NYSE, AMEX and NASDAQ, which are the securities in the CRSP database with share type code 10 or 11. This is consistent with the choice of [Ang et al. \(2006\)](#), [Jarrow et al. \(2021\)](#), and [Wang and Yan \(2021\)](#). We define the stock universe per month as the top thousand stocks ranked on market capitalization. Consequently, we ensure results are not driven by small, or illiquid stocks. We define the market as the capitalization weighted portfolio of the aforementioned thousand stocks.

To construct the value deciles we use the book value data of Compustat. Returns are reported in excess of the risk free rate. For the risk free rate we use the 4-week Treasury Bill rate in the CRSP database. The yield is defined as the promised daily yield based on the nominal price.

The main results of this paper are based on a three year backward looking measure. Thus, the first three years of the dataset are not included in the returns, because to construct the volatility measure 3 years of past returns are used. Furthermore, the stock universe per month consists of the top thousand stocks ranked on market capitalization. However, these stocks do not always have 3 years of past returns, or book value data in Compustat. Such stocks are not considered as we cannot compute all measures for these stocks in that particular month. Such that the number of stocks considered per month varies between 643 and 923 and is 843 on average.

In [Table 1](#) the descriptive statistics of the stocks included in the data set are shown. In [Figure 1](#) the density of the excess return is shown. From the table and figure it follows that the median of the excess returns is lower than the average excess returns. This shows that the distribution of the returns is slightly right skewed, as confirmed by the skewness of 0.65. Further, we notice that the distribution is quite pointy and fat-tailed.

Table 1: Descriptive statistics

Number of stocks	3016
Excess Return	0.05%
Std. Dev.	2.64%
Skewness	0.65
Kurtosis	63.06

In the table the average excess return, the standard deviation, skewness, and kurtosis are given. These statistics are calculated using the daily stock returns of the stocks included in the stock universe.

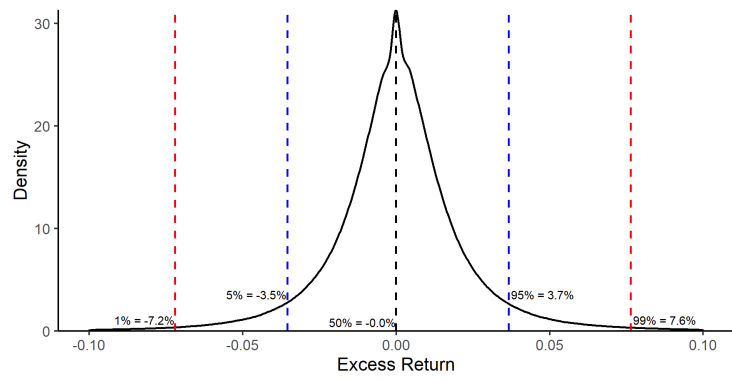


Figure 1: Density excess returns

4 Results

The downside volatility anomaly is existent in the dataset. The results for the decile portfolios spanning from 1993 to 2021 are shown in Table 2.

Table 2 show that the excess returns of the decile portfolios do not differ significantly. The standard deviation increases over the decile portfolios. With an almost constant return the standard deviation therefore is the main driver of the differences in Sharpe ratios. The Sharpe ratios are compared to that of the market using the test statistic defined in Equation 1. The t-value of this test is given under the Sharpe ratio values. As expected the Sharpe Ratio of the low downside volatility deciles is significantly higher than the market, and significantly lower for the high downside volatility deciles respectively. In addition, the low downside volatility deciles, and long-short portfolio contain a significant positive alpha. As expected we observe that the CAPM beta increases with downside volatility.

Table 2: Decile returns downside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.79	11.35	12.20	13.31	12.45	12.02	11.89	10.88	11.77	10.21	0.58	11.23
Std Dev (%)	10.96	12.48	13.66	14.87	16.17	17.21	18.33	20.18	25.41	33.49	31.38	14.59
SR	0.98	0.91	0.89	0.90	0.77	0.70	0.65	0.54	0.46	0.30		0.77
(t-value)	4.32	3.87	4.01	4.49	0.00	-2.80	-4.96	-8.32	-9.04	-12.18		
Beta	0.51	0.71	0.82	0.92	1.00	1.08	1.16	1.24	1.48	1.88	-1.37	
Alpha (%)	4.83	3.19	2.77	2.75	1.14	-0.09	-1.06	-2.92	-4.62	-10.36	15.19	
(t-value)	3.16	2.42	2.24	2.24	0.85	-0.07	-0.78	-1.75	-1.81	-2.84	3.31	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

In Figure 2 a graphical representation of the downside volatility is given. From the graphs follows that the empirical relation between risk and return is slightly negative, contrary to economic theory. However, this (flattened) empirical relation has been shown in earlier literature.

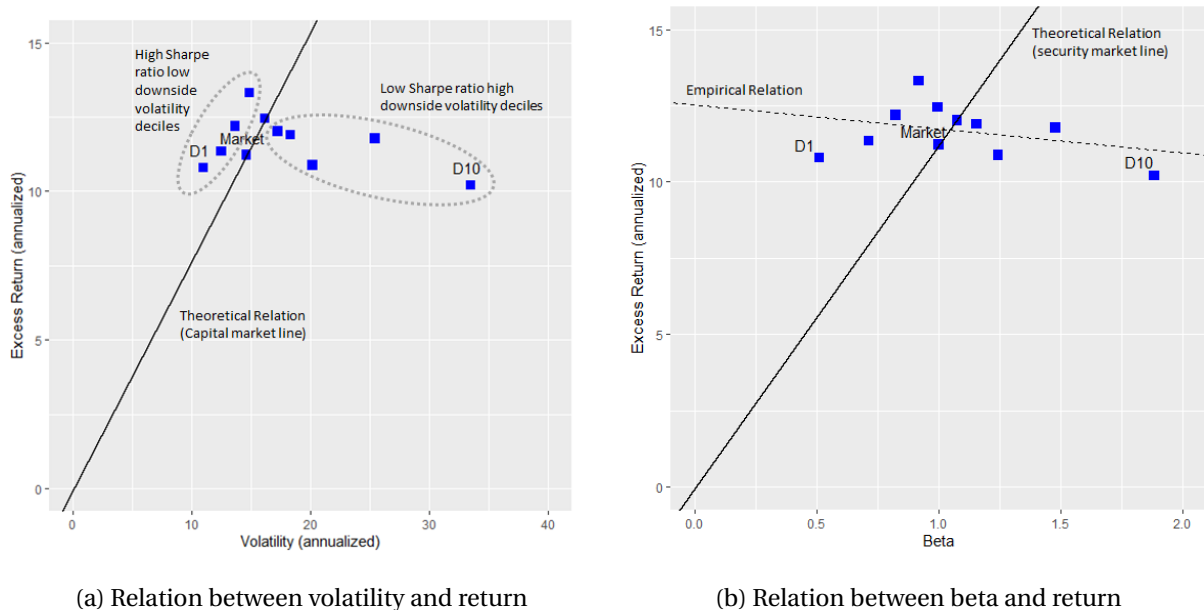


Figure 2: Relation between risk and return

When we sort on low volatility we notice a slight decrease in performance. The results of the sort on low volatility are shown in Table 3. The returns are rather similar, but we notice a slight decrease in the Sharpe ratios and alpha's in the low volatility deciles as compared to downside volatility. Moreover, the alpha of the long short portfolio is 1.5% lower. Although the differences in Sharpe ratios is small for the low volatility deciles, it is significant for the first and fourth decile. Other deciles do not differ significantly. The t-values of the comparison are given in Table 4.

Thus, this confirms that there is a significant relation between expected returns and downside volatility. Furthermore, it advocates the use of negative semi-variance instead of total volatility as measure as the performance is better. This is in line with the findings of Wang and Yan (2021) who also find that downside volatility-managed portfolios perform better than volatility-managed portfolios.

Table 3: Decile returns low volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.43	11.11	12.54	12.11	12.15	11.85	12.15	10.54	13.34	10.69	-0.26	11.23
Std Dev (%)	11.19	12.50	14.09	15.39	16.28	17.25	18.34	20.20	25.60	33.50	31.93	14.59
SR	0.93	0.89	0.89	0.79	0.75	0.69	0.66	0.52	0.52	0.32		0.77
(t-value)	3.24	3.35	3.80	0.61	-0.85	-3.12	-4.48	-9.00	-7.41	-11.14		
Beta	0.51	0.71	0.84	0.94	1.01	1.07	1.16	1.25	1.49	1.81	-1.30	
Alpha (%)	4.51	2.95	2.88	1.44	0.78	-0.18	-0.87	-3.29	-3.31	-9.17	13.68	
(t-value)	2.84	2.25	2.19	1.08	0.58	-0.13	-0.65	-1.99	-1.28	-2.35	2.80	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 4: Comparison Sharpe Ratio's low volatility versus downside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
SR Neg. Vol.	0.98	0.91	0.89	0.90	0.77	0.70	0.65	0.54	0.46	0.30
SR Low Vol.	0.93	0.89	0.89	0.79	0.75	0.69	0.66	0.52	0.52	0.32
(t-value)	4.96	0.65	0.08	2.58	0.52	0.24	-0.27	0.32	-0.96	-0.23

In the table the Sharpe ratios of the decile portfolios shown in Table 2 and 3 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

We also consider the performance of the decile portfolios which are sorted towards the CAPM beta in Table 5. We notice that the difference in excess return between the decile portfolios is quite small. The standard deviation behaves as expected, and is positively correlated with beta. The Sharpe ratio is increases as the beta becomes lower, with the exception of the tenth decile. Thus, again standard deviation is the main driver of the Sharpe ratio. These results are consistent with the almost flat security market line depicted in Figure 2.

Table 5: Decile returns CAPM beta

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	11.57	11.10	12.00	12.64	12.64	12.40	11.00	11.62	12.29	9.15	2.41	11.23
Std Dev (%)	33.00	24.87	20.20	18.67	16.14	15.37	14.79	13.33	12.39	11.61	31.04	14.59
SR	0.35	0.45	0.59	0.68	0.78	0.81	0.74	0.87	0.99	0.79		0.77
(t-value)	-11.80	-10.61	-7.44	-3.84	0.57	1.39	-0.91	3.27	5.53	0.36		
Beta	1.91	1.51	1.28	1.18	1.02	0.95	0.90	0.80	0.68	0.49	1.42	
Alpha (%)	-9.41	-5.52	-2.33	-0.63	1.05	1.58	0.82	2.51	4.39	3.60	-13.01	
(t-value)	-2.80	-2.50	-1.62	-0.46	0.89	1.26	0.64	2.03	3.11	2.06	-2.97	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

For completeness we also looked at sorting on only positive semi-variance (or upside volatility). These results are shown in Appendix A, in Table 28. As expected we see a decrease in performance, which is again significant in the first decile (Table 29).

4.1 Other risk measures

We also considered downside beta, and several extreme value measures to sort into decile portfolios. In Table 6 the properties of the downside beta decile portfolios are shown, and in Table 7 the results are shown for the $\text{VaR}_{2.5\%}$ are shown. In both tables we observe that the first decile portfolio underperforms as compared to the market and even the tenth decile portfolio considering the Sharpe ratio. The downside beta and VaR decile portfolios are sorted from high measure values to low values. Both the risk measures are positively correlated with the standard deviation of the underlying portfolio. In the results of the downside and low volatility sort we noticed that the Sharpe ratio is driven by the standard deviation. Again we notice that returns of all decile portfolios are rather similar. Thus, the Sharpe ratio is again driven by the standard deviation, and as in the top decile portfolios the low beta or VaR stocks are present their standard deviation is lower, so the Sharpe ratios are higher. Similar results are found for the ES and TR sort, which are shown in Appendix A in Table 31, and 32. The results of downside beta are not in line with Ang et al. (2006) who find higher returns for higher downside beta. We do not find higher returns for a higher downside beta. A possible explanation could be the difference in underlying data, as they look at data from 1962 to 2001. Moreover, they do not include standard deviation and Sharpe ratio in their results. Thus, it might be that returns were higher, but the risk-adjusted return, or Sharpe ratio were not significantly better for higher downside betas. Con-

sidering the VaR sort, [Bali et al. \(2009\)](#) do not consider portfolio sorts and individual stock returns, but regress the market return on the VaR of the market and lagged market return. When we perform these regressions we also find a positive relation, however whereas [Bali et al. \(2009\)](#) find a significant positive relation for all 1- to 6-month rolling window we only find a significant relation for the 2-month rolling window. This difference in significance might again be related to the underlying data, and also the data interval we chose. The regression results are shown in Appendix A in Tables 33, 34, 35, 36, 37, and 38. Note that the reported z- and p-values are Newey-West adjusted. Concluding, the VaR measure as used by [Bali et al. \(2009\)](#) can possibly explain future market returns, but does not yield this relation to individual stock returns.

Table 6: Decile returns downside beta

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.02	10.52	13.67	12.68	11.53	13.11	11.57	11.63	11.25	10.75	-0.72	11.23
Std Dev (%)	28.78	22.69	19.37	17.63	15.92	15.45	14.43	13.94	13.37	14.18	22.21	14.59
SR	0.35	0.46	0.71	0.72	0.72	0.85	0.80	0.83	0.84	0.76		0.77
(t-value)	-11.96	-11.74	-2.81	-2.18	-1.87	3.04	1.19	2.12	2.19	-0.31		
Beta	1.67	1.43	1.23	1.12	1.00	0.97	0.89	0.84	0.78	0.80	0.88	
Alpha (%)	-8.28	-5.23	-0.31	0.03	0.24	2.07	1.47	2.09	2.32	1.75	-10.03	
(t-value)	-2.58	-3.23	-0.21	0.02	0.12	1.00	0.87	1.18	1.34	0.85	-2.29	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 7: Decile returns extreme value sort $\text{VaR}_{2.5\%}$

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.40	12.27	11.51	11.74	12.59	12.82	13.00	11.62	10.12	10.55	-0.15	11.23
Std Dev (%)	32.31	24.94	20.60	18.02	17.26	15.86	14.51	13.69	12.49	10.97	29.80	14.59
SR	0.32	0.49	0.56	0.65	0.73	0.81	0.90	0.85	0.81	0.96		0.77
(t-value)	-11.72	-8.62	-8.32	-4.78	-1.56	1.41	4.39	2.56	1.14	4.08		
Beta	1.81	1.48	1.29	1.13	1.08	0.98	0.89	0.82	0.71	0.54	1.27	
Alpha (%)	-9.40	-4.14	-2.89	-0.95	0.42	1.69	2.77	2.29	2.10	4.35	-13.75	
(t-value)	-2.66	-1.73	-1.84	-0.70	0.31	1.27	2.25	1.80	1.58	2.97	-3.11	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

We also constructed the results for size, value and momentum. These results are shown in Appendix A, in Table 39, 40, and 41 respectively.

4.2 Data frequency and intervals

The results in Table 2 use three tracking years and a weekly data frequency to construct the downside volatility measure, which is in line with the volatility measure introduced by Blitz and Van Vliet (2007). To check the robustness of the downside volatility measure we also consider daily, and monthly data. Additionally, we use one tracking year to construct the downside volatility measure.

In Table 8 the decile properties of the decile portfolio constructed with daily data are given. Table 9 contains the properties for the monthly data respectively. In both tables we again notice that the low volatility decile portfolios outperform the market and the high volatility portfolios underperform. We also notice that the performance of the long-short portfolio of monthly data is worst. If we consider one tracking year we see similar results, the anomaly is again apparent, but seems less strong considering monthly data. The deterioration of the performance using monthly data might be linked to the definition of downside volatility. It is defined as squared negative returns, if we use monthly returns the mean and median are far above zero. Thus, negative returns occur less often. This might reduce the estimation accuracy of the true negative semi-variance of a stock. Nevertheless, the anomaly is significant for each combination of tracking years, and data frequency. The results for the decile portfolios constructed using one tracking year are shown in Appendix B in Table 42, 43, and 44.

Table 8: Decile returns downside volatility constructed with daily data tracking 3 years

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.01	12.11	11.78	12.51	11.85	11.58	12.20	11.03	11.88	10.89	-0.80	11.23
Std Dev (%)	11.35	12.58	14.17	15.57	16.26	17.48	18.06	19.67	24.67	33.05	31.59	14.59
SR	0.88	0.96	0.83	0.80	0.73	0.66	0.68	0.56	0.48	0.33		0.77
(t-value)	2.18	5.39	1.98	1.19	-1.57	-4.18	-3.94	-7.89	-8.72	-11.10		
Beta	0.50	0.72	0.84	0.95	1.01	1.09	1.14	1.22	1.45	1.81	-1.31	
Alpha (%)	4.25	3.75	2.17	1.67	0.44	-0.65	-0.64	-2.58	-4.19	-8.94	13.19	
(t-value)	2.56	2.89	1.63	1.25	0.34	-0.47	-0.48	-1.65	-1.73	-2.36	2.76	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 9: Decile returns downside volatility constructed with monthly data tracking 3 years

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	9.89	11.01	12.19	12.53	11.96	11.69	12.87	10.93	10.69	11.81	-1.74	11.23
Std Dev (%)	11.26	12.46	13.78	15.28	16.18	17.60	18.37	20.22	24.19	32.16	30.47	14.59
SR	0.88	0.88	0.88	0.82	0.74	0.66	0.70	0.54	0.44	0.37		0.77
(t-value)	2.24	3.40	3.90	1.84	-1.12	-4.19	-2.84	-8.79	-10.12	-10.10		
Beta	0.53	0.73	0.84	0.94	1.00	1.10	1.16	1.26	1.44	1.74	-1.22	
Alpha (%)	3.82	2.70	2.58	1.80	0.66	-0.68	-0.20	-3.09	-5.14	-7.42	11.24	
(t-value)	2.45	2.19	2.15	1.42	0.50	-0.50	-0.15	-1.97	-2.23	-1.98	2.39	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

4.3 Sub-period analyses

In the sub-period analyses we analyse the performance of downside volatility in up- and down markets. Further, we consider three market events in the past 30 years: the dot-com bubble, the financial crisis, and the corona crisis.

The outperformance in down markets and underperformance in up markets of the low volatility strategy as described by [Blitz and Van Vliet \(2007\)](#) is again confirmed in our dataset, and is also apparent for downside volatility. If we look into the performance of both measures during the three market events the low volatility deciles only clearly outperforms within the dot-com bubble. In the financial crisis this is not apparent, moreover in the corona crisis the high volatility portfolios have a return almost twice as high. The underlying sector weights of the decile portfolios could be the explaining factor of these results. For example, in the dot-com bubble the technology sector crashed while it surged in the corona crisis. This could explain the out-/underperformance of the high volatility deciles in these periods, as the high volatility deciles are weighted towards the tech sector, while low volatility deciles contain none to only a few tech stocks.

4.3.1 Up- and down market behavior

In Table 10 the average return of the low volatility decile portfolios as compared to the market return is shown. The decile portfolios containing low volatility stocks underperform the market in bullish periods, and outperform the market in bearish periods. This is to be expected as the low volatility deciles also have a low beta.

Just as [Blitz and Van Vliet \(2007\)](#) we find that the outperformance in bearish markets is larger than

in the up market. This outperformance is partly compromised by the fact that up market months are more frequent than down market months. Nevertheless, this behavior can partly explain the outperformance of the low- and downside volatility strategy as compared to the market.

Table 10: Up- and down market performance low volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Up market	-1.26	-0.78	-0.39	-0.22	-0.12	-0.04	0.22	0.26	0.98	1.53	-2.79	0.00
Down market	1.93	1.09	0.60	0.14	-0.07	-0.30	-0.79	-1.25	-2.12	-3.89	5.82	0.00
VaR _{95%}	-4.55	-5.02	-5.61	-6.44	-7.05	-7.79	-8.52	-8.71	-10.81	-15.33	-12.75	-6.73

In the table average return of the low volatility decile portfolios, and long-short portfolio as shown in Table 3 relative to the market return are given. The up market, and down market are defined as a month with a positive or negative market return, respectively. Additionally, the VaR on the 5% level is calculated for each decile portfolio, the long-short portfolio, and market portfolio.

Table 11 shows the results for the downside volatility decile portfolios. We again find the same behavior as for the low volatility portfolios. However, the Value-at-Risk values of the decile portfolios are higher on average for the downside volatility portfolio.

Table 11: Up- and down market performance downside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Up market	-1.21	-0.78	-0.45	-0.17	-0.12	0.00	0.17	0.29	0.80	1.65	-2.86	0.00
Down market	1.90	1.14	0.65	0.31	-0.00	-0.36	-0.75	-1.23	-2.10	-4.26	6.16	0.00
VaR _{95%}	-4.70	-5.16	-5.86	-6.62	-7.12	-7.93	-8.86	-9.04	-11.04	-14.59	-13.86	-6.73

In the table average return of the downside volatility decile portfolios, and long-short portfolio as shown in Table 2 relative to the market return are given. The up market, and down market are defined as a month with a positive or negative market return, respectively. Additionally, the VaR on the 5% level is calculated for each decile portfolio, the long-short portfolio, and market portfolio.

4.3.2 Dot-com bubble

We define the dot-com bubble sub-period from January 2000 until December 2003. In Table 13 the results are shown for the low volatility sort. Striking is that almost all Sharpe ratios are significantly better than the market. This can partly be explained by the fact that the market performs really bad, as in 2000 the market factor was largely weighted to the information technology sector. This is also visible in the 10th decile portfolios return, which has a weight between 60-75% towards the information technology sector during this period. In the dot-com bubble mainly this sector was hit, while other more traditional sectors only took a minor hit. This is also visible as the in the returns of the low volatility decile portfolios with significantly higher returns, as they are weighted more towards these 'stable' sectors. In Table 12 the results are shown for the downside volatility sort. This shows similar results as for the low volatility sort.

Table 12: Decile returns downside volatility dot-com bubble

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	11.03	11.82	7.46	10.38	12.16	9.37	4.65	-1.59	3.88	-13.35	24.37	-3.67
Std Dev (%)	12.88	14.99	15.91	16.38	16.10	17.32	21.45	24.35	40.07	55.04	55.95	17.71
SR	0.86	0.79	0.47	0.63	0.76	0.54	0.22	-0.07	0.10	-0.24		-0.21
(t-value)	5.70	6.11	5.04	6.38	7.13	7.02	5.53	1.68	2.89	-0.39		
Beta	0.30	0.49	0.60	0.69	0.71	0.84	1.09	1.15	1.71	2.50	-2.20	
Alpha (%)	11.62	13.07	9.46	12.49	14.17	12.13	8.63	2.69	10.19	-4.92	16.54	
(t-value)	1.95	2.12	1.58	2.26	2.77	2.71	1.84	0.40	0.77	-0.30	0.81	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2000 until December 2003. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 13: Decile returns low volatility dot-com bubble

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	13.92	9.44	9.90	9.90	9.63	11.00	5.27	1.51	-0.51	-14.03	27.95	-3.67
Std Dev (%)	13.00	15.43	17.21	16.38	17.35	17.80	20.54	25.26	40.47	57.24	59.02	17.71
SR	1.07	0.61	0.58	0.60	0.56	0.62	0.26	0.06	-0.01	-0.25		-0.21
(t-value)	6.42	5.30	5.42	6.08	6.20	7.01	6.11	3.30	1.89	-0.36		
Beta	0.30	0.50	0.62	0.67	0.76	0.83	1.06	1.23	1.73	2.38	-2.08	
Alpha (%)	14.23	10.92	11.78	11.97	12.05	13.58	9.10	6.07	5.93	-6.13	20.36	
(t-value)	2.37	1.71	1.75	2.09	2.16	2.68	2.15	0.93	0.44	-0.31	0.87	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2000 until December 2003. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

4.3.3 Financial crisis

We define the financial crisis sub-period from January 2007 until December 2010. In Table 14 and 15 the results are shown for the downside- and low volatility sort respectively. In contrast to the dot-com bubble now the low decile portfolios do not outperform the market. Yet, the mid- to high volatility portfolios do outperform the market. This holds for both mechanisms. Again, this seems to be related to the underlying sector weights of the decile portfolios, as the low volatility deciles are mostly weighted towards financials. This sector was mainly punished in this crisis.

Table 14: Decile returns downside volatility financial crisis

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	2.76	0.77	4.45	5.82	1.62	3.43	6.92	8.92	6.57	6.15	-3.39	2.19
Std Dev (%)	12.84	15.55	18.40	19.66	21.84	25.30	25.92	27.69	31.07	39.41	31.16	19.33
SR	0.22	0.05	0.24	0.30	0.07	0.14	0.27	0.32	0.21	0.16		0.11
(t-value)	1.49	-1.48	3.69	5.09	-1.08	0.60	3.89	4.01	1.94	0.75		
Beta	0.59	0.77	0.93	0.99	1.09	1.27	1.30	1.36	1.51	1.88	-1.29	
Alpha (%)	1.44	-0.91	2.34	3.51	-0.77	0.62	3.88	5.63	3.09	1.89	-0.45	
(t-value)	0.49	-0.39	1.14	1.69	-0.28	0.19	1.20	1.25	0.59	0.25	-0.05	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2007 until December 2010. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 15: Decile returns low volatility financial crisis

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	1.84	1.36	2.92	5.40	3.71	0.95	6.42	8.14	12.69	4.14	-2.30	2.19
Std Dev (%)	13.16	16.10	18.39	20.89	23.15	25.17	24.66	27.67	30.66	37.82	29.24	19.33
SR	0.14	0.08	0.16	0.26	0.16	0.04	0.26	0.29	0.41	0.11		0.11
(t-value)	0.40	-0.72	1.14	3.99	1.17	-2.29	3.54	3.46	5.45	-0.07		
Beta	0.61	0.80	0.92	1.05	1.15	1.27	1.23	1.35	1.51	1.80	-1.19	
Alpha (%)	0.50	-0.39	0.89	2.98	1.15	-1.82	3.56	4.92	8.73	0.15	0.35	
(t-value)	0.17	-0.17	0.36	1.25	0.36	-0.64	1.08	1.06	1.82	0.02	0.04	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2007 until December 2010. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

4.3.4 Corona crisis

We define the corona crisis sub-period from January 2019 until December 2021. The results for the downside and low volatility portfolios are shown in Table 16, and 17, respectively. In contrast to the other sub-periods this major market event was not induced by a financial shock, but a health care shock. One of the properties of this event was that the downturn was relatively short, and thereafter the stock market gained a lot of value following the large amounts of money pumped into the economy by governments and central banks. Furthermore, due to the lockdowns in this crisis people needed to be able to work from home which in turn led to a large increase in value for technology

companies. This sector is usually the most negatively effected in economic downturns, however in this crisis the opposite was true. This is also apparent in the returns of the decile portfolios. The high volatility portfolios have very high returns, as these are mostly weighted to the information technology sector which is relatively volatile compared to other sectors. In short, this crisis led investors to re-evaluate what measures risk. Moreover, some risk-premia might have changed, such as an increase in premium for bankruptcy risk. In our results we see a market with a high Sharpe ratio, as compared to the full period and other periods. This leads us to believe that the risk premium on stocks increased. Furthermore, we notice a large difference in return between the portfolios, which might point to a change in how risk is valued. We leave a more in-depth analysis of the change in risk premia and measures for further research.

Table 16: Decile returns downside volatility corona crisis

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	16.38	23.38	19.43	24.00	24.79	22.62	29.44	33.36	25.23	31.74	-15.36	28.72
Std Dev (%)	14.18	16.31	18.20	19.38	23.57	22.96	23.37	24.25	29.47	34.62	29.19	17.89
SR	1.15	1.43	1.07	1.24	1.05	0.98	1.26	1.38	0.86	0.92		1.61
(t-value)	-3.28	-1.76	-5.29	-4.24	-5.30	-5.57	-3.84	-2.37	-5.75	-4.80		
Beta	0.67	0.84	0.95	1.03	1.23	1.19	1.23	1.25	1.48	1.65	-0.98	
Alpha (%)	-1.81	-0.26	-6.46	-4.52	-9.04	-9.82	-5.29	-2.84	-15.12	-14.11	12.30	
(t-value)	-0.37	-0.06	-1.61	-1.16	-1.69	-1.80	-1.06	-0.48	-1.85	-1.22	0.83	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2019 until December 2021. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 17: Decile returns low volatility corona crisis

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	16.78	18.79	23.26	21.83	24.31	23.55	30.30	31.37	24.80	36.28	-19.50	28.72
Std Dev (%)	14.74	16.39	18.30	21.25	22.09	23.68	24.15	24.72	29.67	31.72	26.81	17.89
SR	1.14	1.15	1.27	1.03	1.10	0.99	1.25	1.27	0.84	1.14		1.61
(t-value)	-3.43	-4.48	-3.74	-5.71	-5.15	-5.69	-3.55	-3.29	-5.92	-3.19		
Beta	0.70	0.85	0.96	1.12	1.16	1.24	1.25	1.27	1.50	1.46	-0.76	
Alpha (%)	-2.22	-4.34	-3.48	-8.70	-7.70	-10.27	-5.15	-4.82	-15.91	-5.88	3.66	
(t-value)	-0.45	-1.12	-0.89	-1.95	-1.62	-1.94	-0.89	-0.80	-1.98	-0.51	0.25	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given for the period January 2019 until December 2021. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

4.4 Controlling for size, value and momentum

To control for size, value and momentum we consider two different approaches. First, we show the results of the regression approach. The factor returns are constructed from the monthly stock universe (top 1000 stocks ranked on market capitalization). They are constructed in the same manner as the Fama-French factors¹. Thereafter, we show the results of the double sorted portfolio's.

4.4.1 Fama-French corrected alpha's

In Table 18 the corrected alpha's for the downside volatility are shown. The uncorrected alpha is also shown for comparison. We notice that the influence on the magnitude of the alpha for the factors alone is small, but in the full 4-factor model the alpha is affected more. The alpha of the long-short portfolio decreases with approximately 5.5%.

¹The construction of the factors is given on their site: <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>

Table 18: FF-corrected alpha's downside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Uncorrected	4.83	3.19	2.77	2.75	1.14	-0.09	-1.06	-2.92	-4.62	-10.36	15.19
Adj. Size	4.84	3.28	2.98	3.09	1.56	0.42	-0.51	-2.27	-3.83	-9.40	14.24
Adj. Value	4.68	3.03	2.61	2.61	0.98	-0.21	-1.10	-2.85	-4.40	-10.02	14.70
Adj. Mom	4.98	3.57	3.33	3.28	1.77	0.38	-0.91	-3.32	-5.38	-10.91	15.89
Adj. All	3.33	2.12	2.12	2.36	0.84	-0.20	-0.75	-2.12	-2.61	-6.27	9.60

In the table the uncorrected (CAPM) alpha and corrected alpha for the known factors Size, Value, and Momentum is shown for the downside volatility portfolios shown in Table 2. Further, the alpha corrected for all factors is shown. The alphas are obtained by regressing the decile portfolio, or long-short portfolio return on the market factor, and the respective factor(s) that are controlled for.

In Table 19 the corrected alpha's are given for the low volatility anomaly. Again we notice that the factors do not alter the alpha significantly if we consider them separately. When we consider the 4-factor model the magnitude of the alpha's is affected more. The alpha of the long-short portfolio decreases with approximately 5%, but stays significant. This decrease is lower than for the downside volatility anomaly, nonetheless the alpha of the downside volatility long-short portfolio is still 1% higher than for the low volatility anomaly.

Thus, both downside and low volatility can not be fully explained with the four-factor model. This is consistent with previous literature which also find that the four-factor model can not explain the low volatility anomaly.

Table 19: FF-corrected alpha's low volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Uncorrected	4.51	2.95	2.88	1.44	0.78	-0.18	-0.87	-3.29	-3.31	-9.17	13.68
Adj. Size	4.54	3.05	3.11	1.79	1.20	0.30	-0.29	-2.64	-2.56	-8.24	12.78
Adj. Value	4.34	2.78	2.69	1.26	0.62	-0.32	-0.91	-3.25	-3.06	-8.70	13.04
Adj. Mom	4.85	3.52	3.62	2.17	1.48	0.39	-0.77	-3.41	-4.29	-10.75	15.59
Adj. All	3.12	2.06	2.34	1.05	0.62	-0.35	-0.55	-2.45	-1.42	-5.52	8.64

In the table the uncorrected (CAPM) alpha and corrected alpha for the known factors Size, Value, and Momentum is shown for the downside volatility portfolios shown in Table 3. Further, the alpha corrected for all factors is shown. The alphas are obtained by regressing the decile portfolio, or long-short portfolio return on the market factor, and the respective factor(s) that are controlled for.

4.4.2 Double sorted portfolio's

To recap, here first all stocks are sorted into quintile portfolios based on Size, Value and Momentum respectively. Thereafter, the top volatility quintiles are sorted into one measure neutral top volatility quintile. For all other quintiles a similar technique is used.

Size

The results for the double sort on size, and downside, or low volatility are shown in Table 20 and 21 respectively. Consistent with the results in Section 4.4.1 the low volatility anomaly and downside volatility effect remain existent. Moreover, the outperformance of the downside volatility sort is still apparent, as the Sharpe ratio's of the first quintiles are higher. Furthermore, the long-short portfolio of low volatility results in an alpha of 9.65%, whereas for downside volatility this is 11.20%.

Table 20: Quantile returns downside volatility & size

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	11.25	12.61	12.13	11.35	11.04	11.23
Std Dev (%)	11.49	14.46	16.27	18.86	28.10	14.59
SR	0.98	0.87	0.75	0.60	0.39	0.77
(t-value)	4.99	3.54	-0.96	-6.77	-11.05	
Beta	0.61	0.88	1.02	1.19	1.64	
Alpha (%)	4.14	2.48	0.60	-1.89	-7.06	
(t-value)	3.03	2.00	0.48	-1.33	-2.54	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Size, and thereafter on the risk measure considered, downside volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 21: Quantile returns low volatility & size

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	10.90	11.92	12.53	10.97	12.04	11.23
Std Dev (%)	11.61	14.72	16.63	18.75	28.22	14.59
SR	0.94	0.81	0.75	0.58	0.43	0.77
(t-value)	4.09	1.37	-0.62	-7.62	-9.70	
Beta	0.62	0.89	1.03	1.19	1.62	
Alpha (%)	3.77	1.80	0.80	-2.23	-5.88	
(t-value)	2.72	1.37	0.61	-1.62	-2.00	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Size, and thereafter on the risk measure considered, low volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Value

The results for the double sort on value, and downside, or low volatility are shown in Table 22 and 23 respectively. Consistent with the results in Section 4.4.1 the low volatility anomaly and downside volatility effect remain existent. Again, the top quantile of the downside volatility sort outperforms the top quantile of the low volatility anomaly, and the alpha of the long-short portfolio of downside volatility is larger. However, in contrast to the double sort on size this outperformance is no longer apparent in the second quantile.

Table 22: Quantile returns downside volatility & value

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	11.75	12.46	12.47	12.34	9.86	11.23
Std Dev (%)	11.11	13.23	15.49	17.72	22.87	14.59
SR	1.06	0.94	0.80	0.70	0.43	0.77
(t-value)	7.58	6.59	1.51	-2.95	-11.19	
Beta	0.63	0.83	0.98	1.11	1.39	
Alpha (%)	4.40	2.91	1.30	-0.19	-5.43	
(t-value)	3.75	2.91	1.17	-0.14	-2.70	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Value, and thereafter on the risk measure considered, downside volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 23: Quintile returns low volatility & value

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	11.01	12.91	11.98	12.24	10.65	11.23
Std Dev (%)	11.03	13.25	15.59	17.64	23.02	14.59
SR	1.00	0.97	0.77	0.69	0.46	0.77
(t-value)	6.10	7.82	-0.04	-3.09	-10.01	
Beta	0.63	0.83	0.99	1.11	1.39	
Alpha (%)	3.78	3.28	0.77	-0.27	-4.68	
(t-value)	3.23	3.32	0.70	-0.20	-2.25	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Value, and thereafter on the risk measure considered, low volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Momentum

The results for the double sort on momentum, and low volatility, or downside volatility are shown in Table 25 and 24 respectively. Consistent with the results in Section 4.4.1 the low volatility anomaly and downside volatility effect remain existent. Again, the downside volatility sort outperforms the low volatility anomaly in Sharpe ratios and long-short alpha.

Table 24: Quintile returns downside volatility & momentum

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	11.73	12.65	11.48	10.67	10.15	11.23
Std Dev (%)	12.32	15.38	18.03	20.45	26.69	14.59
SR	0.95	0.82	0.64	0.52	0.38	0.77
(t-value)	4.97	1.84	-5.03	-9.64	-12.69	
Beta	0.70	0.94	1.12	1.28	1.63	
Alpha (%)	3.64	1.94	-1.04	-3.55	-7.68	
(t-value)	2.79	1.46	-0.71	-2.28	-3.31	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Momentum, and thereafter on the risk measure considered, downside volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 25: Quantile returns low volatility & momentum

	Q1	Q2	Q3	Q4	Q5	Univ
Ex. Return (%)	11.22	12.25	11.53	11.11	10.64	11.23
Std Dev (%)	12.38	15.51	18.25	20.23	26.49	14.59
SR	0.91	0.79	0.63	0.55	0.40	0.77
(t-value)	3.77	0.70	-5.28	-8.64	-12.20	
Beta	0.70	0.94	1.14	1.27	1.62	
Alpha (%)	3.18	1.54	-1.17	-2.99	-7.15	
(t-value)	2.41	1.13	-0.81	-1.94	-3.13	

In the table the characteristics of double sorted quintile portfolios are shown. These portfolios are constructed by first sorting on a known factor, Momentum, and thereafter on the risk measure considered, low volatility. The excess return and standard deviation of each quintile portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

4.5 Performance within sectors

In contrast to [Bellone and Carvalho \(2020\)](#) we do not find a significant low volatility. We only find a significant alpha for downside volatility in 6 of the 10 sectors: Health Care, Financials, Consumer Staples, Information Technology, Consumer Discretionary, and Industrials. Low volatility is only found in Health Care, Information Technology, and Industrials. The complete portfolio properties for each sector are shown in Appendix C.

Although not each sector has a significant alpha for the long-short portfolios the long-short sector-neutral portfolio does have a significant alpha for both downside volatility and low volatility. The results are shown in Table 26, and 27. However, the alphas about halve for both measures. For downside volatility the alpha decreases from 15.19% to 8.18%, and for low volatility in more than halves from 13.68% to 6.25%. Thus, the weighting of decile portfolios towards different sectors is able to explain a significant part of the anomaly. However, a significant alpha remains. Further, the outperformance of downside volatility as compared to low volatility remains.

Table 26: Quantile returns sector-neutral downside volatility

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Market
Ex. Return (%)	12.28	11.25	13.05	12.50	12.22	0.05	11.23
Std Dev (%)	11.79	13.87	15.79	18.72	24.69	16.98	14.59
SR	1.04	0.81	0.83	0.67	0.50		0.77
(t-value)	9.07	1.78	2.33	-4.18	-9.01		
Beta	0.73	0.88	1.00	1.18	1.49	-0.76	
Alpha (%)	3.87	1.27	1.68	-0.77	-4.31	8.18	
(t-value)	3.96	1.30	1.43	-0.55	-1.93	3.35	

In the table the characteristics of the sector-neutral quintile portfolios are shown. The excess return and standard deviation of each quintile portfolio, long-short portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, and long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 27: Quantile returns sector-neutral low volatility

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Market
Ex. Return (%)	11.58	11.90	11.90	12.90	13.26	-1.49	11.23
Std Dev (%)	12.08	14.08	16.02	18.63	24.18	16.58	14.59
SR	0.96	0.84	0.74	0.69	0.55		0.77
(t-value)	6.36	2.97	-1.10	-3.14	-7.50		
Beta	0.74	0.88	1.01	1.17	1.46	-0.73	
Alpha (%)	3.11	1.85	0.49	-0.33	-3.14	6.25	
(t-value)	3.00	1.72	0.41	-0.24	-1.46	2.58	

In the table the characteristics of the sector-neutral quintile portfolios are shown. The excess return and standard deviation of each quintile portfolio, long-short portfolio, and market portfolio are shown. The Sharpe Ratio (SR) is also calculated for the quintile portfolios and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, and long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

To summarize, in the results we find a significant alpha in the long-short portfolio for the downside volatility risk measure. Moreover, we show that the alpha is significantly higher than the alpha of the low volatility sort. Further, we show that the alpha is robust to different data intervals, data frequencies, and the known factors (size, value and momentum). Additionally, we find a significant alpha for the sector-neutral portfolio. However, we find that the alpha is not significant in the sub periods we consider.

5 Conclusion

In this paper we investigated the performance of downside volatility. We considered negative semi-variance as proposed by [Feunou et al. \(2013\)](#) as measure for downside volatility. To measure the performance we constructed decile, or quintile portfolios and inspected their properties. Additionally, we constructed a long-short portfolio and inspected its properties.

From our results it followed that for our dataset from 1993 to 2021 of large cap American stocks the downside volatility effect exists. The long-short strategy shows a significant positive alpha of 15.19%. Also, the low downside volatility contain significant positive alpha. We might be able to profit from this effect by investing in low downside volatility stocks as separate asset class, or leverage low volatility deciles to match market risk and utilize the alpha. However, we have not controlled for turnover, and in extension trading costs that might reduce performance.

The downside volatility effect is robust for chosen data frequencies and tracking years. However, the performance seems the decrease for larger data frequencies, such as monthly data. Additionally, we show that if we correct for the Fama-French factors size, and value, and the factor momentum the alpha of downside volatility remains significant. Further, we find that downside volatility is characterized by relatively small drawdowns, a low beta, and outperformance in down markets and underperformance in up markets, which has earlier been shown for the low volatility anomaly, ([Blitz and Van Vliet, 2007](#)). This is not surprising has the returns for both measures are of course highly correlated.

Although, the returns are highly correlated we find a outperformance of downside volatility as compared to low volatility. The alpha of the long-short low volatility portfolio is 1.5% lower than for downside volatility, and the Sharpe ratio of the lowest downside volatility decile is significantly higher than the lowest low volatility decile. We also find that positive volatility, as measured by positive semi-variance, underperforms as compared to low volatility. The outperformance of downside risk is in violation of economic theory. From theory it would follow that high downside risk should be rewarded with a higher premium. Also the behavioral argument that investors react more extreme to losses than profit would warrant a higher premium. However, in economic literature we find that negative semi-variance can better predict future volatility than variance, such that part of the effect might be explained by better capturing low volatility stocks. Moreover, in past literature is shown that downside volatility not only enhances volatility timing, but also negatively predicts future returns. The fact that positive semi-variance leads to lower returns as compared to low volatility, and negative semi-variance vice versa, might point to a skewness effect. More specifically, stocks with a low negative semi-variance have a smaller left than right tail, thus are right-skewed. The opposite holds for positive semi-variance. Investors should prefer right-skewed stocks to those that are left-skewed,

such that left-skewed stocks should warrant higher returns. However, the reverse seems to hold, as the low downside volatility portfolios outperform low volatility portfolios. While for low upside volatility underperform. However, we leave an investigation of this relation for further research.

Further, we investigated the performance of downside volatility in sectors. We find that the long-short portfolio of downside volatility does not have a significant positive alpha for every sector. However, when we construct a sector-neutral portfolio, we again find significant outperformance of the market. The alpha does, however, significantly decrease after controlling for sectors. Thus, sectors have a significant role in explaining the downside volatility effect, but are not able to explain the complete effect. We find a similar result for low volatility.

A Results other sorting mechanisms

A.1 Upside volatility

Table 28: Decile returns upside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	9.91	10.92	12.03	11.71	12.31	12.10	11.64	11.13	13.73	11.51	-1.60	11.23
Std Dev (%)	11.66	12.88	14.35	15.86	16.36	17.15	18.12	20.36	25.06	32.70	31.23	14.59
SR	0.85	0.85	0.84	0.74	0.75	0.71	0.64	0.55	0.55	0.35		0.77
(t-value)	1.66	2.20	2.26	-1.15	-0.64	-2.53	-5.22	-8.07	-6.65	-11.11		
Beta	0.53	0.74	0.86	0.96	1.01	1.07	1.13	1.27	1.46	1.75	-1.22	
Alpha (%)	3.77	2.50	2.22	0.86	0.91	-0.01	-1.06	-2.95	-2.67	-7.77	11.54	
(t-value)	2.29	1.87	1.68	0.61	0.66	-0.00	-0.76	-1.82	-1.07	-2.00	2.36	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 29: Comparison Sharpe Ratio's low volatility versus upside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
SR Pos. Vol.	0.85	0.85	0.84	0.74	0.75	0.71	0.64	0.55	0.55	0.35
SR Low Vol.	0.93	0.89	0.89	0.79	0.75	0.69	0.66	0.52	0.52	0.32
(t-value)	-8.47	-1.29	-1.29	-1.20	0.13	0.39	-0.39	0.46	0.44	0.51

In the table the Sharpe ratios of the decile portfolios shown in Table 28 and 3 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Table 30: FF-corrected alpha's upside volatility

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Uncorrected	3.77	2.50	2.22	0.86	0.91	-0.01	-1.06	-2.95	-2.67	-7.77	11.54
Adj. Size	3.84	2.66	2.50	1.18	1.33	0.48	-0.49	-2.31	-1.95	-6.89	10.73
Adj. Value	3.57	2.31	2.03	0.66	0.73	-0.14	-1.11	-2.88	-2.40	-7.26	10.83
Adj. Mom	4.32	3.24	3.11	1.72	1.71	0.53	-0.90	-3.28	-3.84	-9.75	14.08
Adj. All	2.51	1.83	1.94	0.42	0.78	-0.08	-0.78	-2.14	-0.96	-4.58	7.09

In the table the uncorrected (CAPM) alpha and corrected alpha for the known factors Size, Value, and Momentum is shown for the downside volatility portfolios shown in Table 28. Further, the alpha corrected for all factors is shown. The alphas are obtained by regressing the decile portfolio, or long-short portfolio return on the market factor, and the respective factor(s) that are controlled for.

A.2 Extreme value sorts

A.2.1 Decile returns extreme value sorts

Table 31: Decile returns extreme value sort $ES_{2.5\%}$

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	8.72	12.92	12.95	13.00	11.59	12.65	12.41	11.57	10.52	10.31	-1.59	11.23
Std Dev (%)	30.05	24.52	20.81	18.35	16.99	16.04	14.95	13.90	12.59	11.13	27.08	14.59
SR	0.29	0.53	0.62	0.71	0.68	0.79	0.83	0.83	0.84	0.93		0.77
(t-value)	-13.20	-7.75	-5.56	-2.45	-3.55	0.70	2.15	2.09	1.88	3.35		
Beta	1.74	1.46	1.29	1.15	1.07	0.99	0.92	0.84	0.72	0.54		1.19
Alpha (%)	-10.19	-3396.00	-1.56	-0.03	-0.40	1.40	1.95	2.04	2.33	4.04		-14.23
(t-value)	-3.33	-1.47	-0.92	-0.02	-0.31	1051.00	1.54	1.62	1.77	2.72		-3.61

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 32: Decile returns extreme value sort $TR_{2.5\%}$

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.01	12.91	11.28	12.91	12.90	11.36	11.87	10.75	11.41	11.25	-1.25	11.23
Std Dev (%)	22.00	19.63	18.30	17.23	17.05	16.26	15.55	15.02	15.00	14.59	12.81	14.59
SR	0.45	0.66	0.62	0.75	0.76	0.70	0.76	0.72	0.76	0.77		0.77
(t-value)	-10.69	-4.83	-6.21	-0.87	-0.58	-2.96	-0.27	-2.23	-0.36	0.07		
Beta	1.34	1.25	1.15	1.09	1.09	1.03	0.99	0.95	0.95	0.90		0.45
Alpha (%)	-4.80	-1.13	-1.58	0.51	0.58	-0.17	0.68	0.13	0.73	1.10		-5.89
(t-value)	-2.54	-0.81	-1.15	0.41	0.48	-0.14	0.62	0.11	0.66	0.91		-2.81

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

A.2.2 Regression on VaRs

Table 33: Regression on 1-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.17	0.87
VaR	0.50	0.36	1.39	0.16
R_{t-1}	0.05	0.09	0.54	0.59

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

Table 34: Regression on 2-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.61	0.54
VaR	0.56	0.28	2.00	0.05
R_{t-1}	0.03	0.08	0.36	0.72

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

Table 35: Regression on 3-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.27	0.79
VaR	0.41	0.28	1.48	0.14
R_{t-1}	0.01	0.07	0.07	0.94

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

Table 36: Regression on 4-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.57	0.57
VaR	0.47	0.24	1.93	0.05
R_{t-1}	0.00	0.07	0.06	0.95

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

Table 37: Regression on 5-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.33	0.74
VaR	0.38	0.27	1.43	0.15
R_{t-1}	-0.00	0.07	-0.04	0.97

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

Table 38: Regression on 6-month rolling window VaR

	Estimate	Std. Error	z-value	p-value
Intercept	-0.00	0.01	-0.20	0.84
VaR	0.32	0.24	1.34	0.18
R_{t-1}	-0.00	0.07	-0.04	0.97

In the table the coefficients of the regression of the market return on VaR, and one-month lagged market return are shown. The VaR is defined as the minimum return in the rolling window. The z-, and p-value of the coefficients are also shown, and bold if they the coefficient is significant on the 5% level.

A.3 Size, value and momentum

Table 39: Decile returns size

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.51	11.87	12.64	11.90	12.73	11.86	11.90	12.14	10.17	10.85	-0.31	11.23
Std Dev (%)	19.05	18.61	17.62	17.84	18.15	17.31	16.37	15.61	15.02	14.49	10.52	14.59
SR	0.55	0.64	0.72	0.67	0.70	0.69	0.73	0.78	0.68	0.75		0.77
(t-value)	-7.41	-4.47	-1.94	-3.81	-2.80	-3.68	-2.04	0.38	-5.54	-1.91		
Beta	1.15	1.12	1.09	1.10	1.14	1.10	1.06	1.00	0.99	0.98	0.18	
Alpha (%)	-2.31	-0.74	0.33	-0.48	-0.18	-0.51	0.01	0.81	-0.87	-0.10	-2.20	
(t-value)	-1.37	-0.44	0.23	-0.33	-0.13	-0.42	0.01	0.77	-1.14	-0.21	-1.14	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 40: Decile returns value

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	13.75	11.93	11.55	11.02	10.87	10.65	10.66	11.34	11.39	13.75	0.00	11.23
Std Dev (%)	20.81	17.93	17.32	17.39	16.94	16.44	16.69	17.13	17.52	20.92	20.36	14.59
SR	0.66	0.67	0.67	0.63	0.64	0.65	0.64	0.66	0.65	0.66		0.77
(t-value)	-2.89	-3.27	-3.48	-5.04	-5.21	-5.47	-6.13	-4.44	-3.79	-2.85		
Beta	1.14	1.06	1.05	1.07	1.07	1.05	1.07	1.08	1.04	1.12	0.02	
Alpha (%)	0.72	0.03	-0.19	-0.98	-1.04	-1.08	-1.31	-0.76	-0.23	0.98	-0.26	
(t-value)	0.31	0.02	-0.12	-0.68	-0.81	-0.96	-1.21	-0.59	-0.14	0.39	-0.07	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 41: Decile returns momentum

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	14.79	13.51	10.96	10.49	11.39	11.63	10.52	11.88	10.77	10.72	3.71	11.23
Std Dev (%)	23.26	17.43	14.83	14.49	15.16	15.49	16.51	17.93	21.21	29.86	29.14	14.59
SR	0.64	0.78	0.74	0.72	0.75	0.75	0.64	0.66	0.51	0.36		0.77
(t-value)	-2.71	0.14	-1.08	-1.84	-0.69	-0.73	-5.11	-3.81	-8.56	-11.11		
Beta	1.04	0.93	0.90	0.91	0.94	0.97	1.03	1.10	1.27	1.69	-0.65	
Alpha (%)	2.76	2.79	0.79	0.30	0.77	0.69	-0.95	-0.44	-3.35	-7.85	10.62	
(t-value)	0.82	1.34	0.61	0.27	0.63	0.57	-0.73	-0.28	-1.73	-2.46	2.03	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

B Results downside volatility: one tracking year

Table 42: Decile returns downside volatility constructed with daily data tracking 1 year

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.72	11.53	12.29	11.04	12.49	11.92	12.13	10.77	11.00	9.41	1.20	11.23
Std Dev (%)	10.98	12.63	13.99	15.19	16.25	17.34	18.39	21.27	26.13	35.20	33.75	14.59
SR	0.98	0.91	0.88	0.73	0.77	0.69	0.66	0.51	0.42	0.27		0.77
(t-value)	4.11	4.13	3.58	-1.53	-0.04	-3.41	-4.51	-9.04	-9.72	-12.12		
Beta	0.51	0.73	0.84	0.93	1.01	1.10	1.16	1.30	1.49	1.89	-1.38	
Alpha (%)	4.80	3.15	2.63	0.59	1.04	-0.39	-0.88	-3.59	-5.43	-11.19	15.99	
(t-value)	3.11	2.45	2.08	0.45	0.80	-0.30	-0.64	-1.95	-1.97	-2.69	3.11	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 43: Decile returns downside volatility constructed with weekly data tracking 1 year

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.40	11.29	11.70	13.16	11.82	11.95	12.51	10.85	10.01	9.53	0.80	11.23
Std Dev (%)	10.99	12.19	13.82	15.19	16.37	17.23	18.35	20.80	26.03	35.12	33.36	14.59
SR	0.95	0.93	0.85	0.87	0.72	0.69	0.68	0.52	0.38	0.27		0.77
(t-value)	3.67	4.60	2.63	3.52	-1.88	-3.15	-3.56	-8.71	-11.00	-12.06		
Beta	0.52	0.71	0.84	0.94	1.02	1.09	1.15	1.28	1.51	1.89	-1.37	
Alpha (%)	4.33	3.13	2.14	2.39	0.28	-0.28	-0.48	-3.28	-6.54	-11.06	15.40	
(t-value)	2.89	2.58	1.76	1.92	0.22	-0.22	-0.35	-1.86	-2.47	-2.68	3.03	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 44: Decile returns downside volatility constructed with monthly data tracking 1 year

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10	Univ
Ex. Return (%)	10.66	10.96	11.89	12.43	12.75	12.35	11.82	10.15	8.90	10.96	-0.27	11.23
Std Dev (%)	11.57	12.23	13.85	14.86	16.26	17.21	18.81	20.75	25.54	33.08	30.90	14.59
SR	0.92	0.90	0.86	0.84	0.78	0.72	0.63	0.49	0.35	0.33		0.77
(t-value)	3.56	3.99	3.23	2.64	0.59	-2.20	-5.70	-10.28	-12.01	-10.66		
Beta	0.61	0.73	0.85	0.93	1.02	1.09	1.18	1.29	1.49	1.77	-1.16	
Alpha (%)	3.70	2.66	2.16	1.82	1.14	0.05	-1.42	-4.08	-7.33	-8.43	12.12	
(t-value)	2.60	2.32	1.88	1.60	0.92	0.04	-1.00	-2.45	-2.86	-2.14	2.47	

In the table the excess return and standard deviation of each decile portfolio, long-short portfolio, and market portfolio are given. The Sharpe Ratio (SR) is also calculated for the decile portfolios and market portfolio. The Sharpe ratios of the decile portfolios are compared to the market portfolio, and the t-value of the test in Equation 1 is shown. The t-value is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all decile portfolios, and the long-short portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

C Sector Results

Health Care

Table 45: Quantile returns low volatility in Health Care

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	15.42	16.21	15.57	12.67	10.74	4.26	13.99	11.23
Std Dev (%)	13.68	14.87	16.75	21.42	32.34	27.82	17.40	14.59
SR	1.13	1.09	0.93	0.59	0.33		0.80	0.77
(t-value)	7.38	7.42	4.30	-8.17	-13.96		0.82	
Beta	0.61	0.71	0.86	1.12	1.62	-1.01	0.90	
Alpha (%)	6.34	5.76	3.21	-2.81	-11.11	17.45	3.59	
(t-value)	3.90	3.66	2.25	-1.69	-3.70	4.24	1.64	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Health Care sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 46: Quantile returns downside volatility in Health Care

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	16.41	16.15	15.07	12.11	10.70	5.20	13.99	11.23
Std Dev (%)	13.34	14.78	16.81	21.26	31.20	25.87	17.40	14.59
SR	1.23	1.09	0.90	0.57	0.34		0.80	0.77
(t-value)	9.74	8.39	3.35	-9.11	-14.24		0.82	
Beta	0.61	0.74	0.87	1.12	1.59	-0.97	0.90	
Alpha (%)	7.20	5.35	2.63	-3.26	-10.70	17.90	3.59	
(t-value)	4.74	3.84	1.91	-2.02	-3.88	4.81	1.64	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Health Care sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 47: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	1.23	1.09	0.90	0.57	0.34
SR Low Vol.	1.13	1.09	0.93	0.59	0.33
(t-value)	5.55	0.13	-1.25	-1.10	0.66

In the table the Sharpe ratios of the quintile portfolios shown in Table 45 and 46 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Financials

Table 48: Quantile returns low volatility in Financials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	10.46	10.50	11.19	13.74	12.33	-1.68	11.55	11.23
Std Dev (%)	14.45	17.13	20.48	22.47	27.91	19.64	19.24	14.59
SR	0.72	0.61	0.55	0.61	0.44		0.60	0.77
(t-value)	5.01	0.72	-3.77	0.85	-6.87		-4.84	
Beta	0.69	0.85	1.03	1.14	1.34	-0.65	1.10	
Alpha (%)	2.44	0.68	-0.68	0.45	-3.02	5.46	-0.73	
(t-value)	2.23	0.71	-0.73	0.47	-1.50	1.92	-0.36	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Financials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 49: Quantile returns downside volatility in Financials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	10.60	9.74	13.13	12.36	12.48	-1.69	11.55	11.23
Std Dev (%)	14.32	16.71	19.93	23.27	28.43	20.14	19.24	14.59
SR	0.74	0.58	0.66	0.53	0.44		0.60	0.77
(t-value)	5.53	-0.91	3.94	-5.18	-7.11		-4.84	
Beta	0.68	0.82	1.00	1.18	1.37	-0.69	<i>1.10</i>	
Alpha (%)	2.66	0.31	1.38	-1.23	-3.21	5.87	<i>-0.73</i>	
(t-value)	2.41	0.30	1.48	-1.24	-1.59	2.06	<i>-0.36</i>	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Financials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 50: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.74	0.58	0.66	0.53	0.44
SR Low Vol.	0.72	0.61	0.55	0.61	0.44
(t-value)	1.68	-2.72	9.93	-7.30	-0.36

In the table the Sharpe ratios of the quintile portfolios shown in Table 48 and 49 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Consumer Staples

Table 51: Quantile returns low volatility in Consumer Staples

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	10.71	10.25	11.81	11.49	11.22	-0.46	11.53	11.23
Std Dev (%)	11.46	12.05	14.11	15.87	20.20	17.63	12.34	14.59
SR	0.93	0.85	0.84	0.72	0.56		0.93	0.77
(t-value)	0.00	-2.43	-3.41	-6.22	-9.56		3.70	
Beta	0.77	0.83	1.03	1.10	1.32	-0.55	0.63	
Alpha (%)	1.78	0.70	-0.04	-1.16	-3.81	5.59	4.26	
(t-value)	1.45	0.58	-0.03	-0.74	-1.66	1.79	2.71	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Consumer Staples sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 52: Quantile returns downside volatility in Consumer Staples

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	11.72	9.84	11.18	12.14	10.24	1.35	11.53	11.23
Std Dev (%)	11.16	12.56	13.93	15.48	20.25	17.95	12.34	14.59
SR	1.05	0.78	0.80	0.78	0.51		0.93	0.77
(t-value)	2.90	-4.52	-4.25	-5.13	-10.75		3.70	
Beta	0.73	0.88	0.99	1.12	1.33	-0.60	0.63	
Alpha (%)	3.10	-0.17	-0.23	-0.77	-4.78	7.88	4.26	
(t-value)	2.47	-0.14	-0.18	-0.58	-2.09	2.51	2.71	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Consumer Staples sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 53: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	1.05	0.78	0.80	0.78	0.51
SR Low Vol.	0.93	0.85	0.84	0.72	0.56
(t-value)	5.68	-2.55	-1.29	2.25	-2.78

In the table the Sharpe ratios of the quintile portfolios shown in Table 51 and 52 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Information Technology

Table 54: Quantile returns low volatility in Information Technology

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	15.50	16.21	16.39	20.27	16.33	-0.73	15.76	11.23
Std Dev (%)	17.86	23.90	29.77	33.07	40.52	28.50	29.19	14.59
SR	0.87	0.68	0.55	0.61	0.40		0.54	0.77
(t-value)	10.19	6.36	0.58	4.57	-8.20		-5.87	
Beta	0.53	0.76	0.97	1.09	1.33	-0.80	1.57	
Alpha (%)	6.62	3.85	1.04	2.54	-4.41	11.03	-2.10	
(t-value)	4.06	2.40	0.58	1.51	-2.08	3.58	-0.61	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Information Technology sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 55: Quantile returns downside volatility in Information Technology

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	15.97	15.89	17.85	19.35	15.47	0.44	15.76	11.23
Std Dev (%)	17.95	24.30	29.50	33.45	39.80	27.90	29.19	14.59
SR	0.89	0.65	0.61	0.58	0.39		0.54	0.77
(t-value)	10.51	5.85	3.70	2.31	-8.50		-5.87	
Beta	0.53	0.79	0.96	1.10	1.30	-0.77	1.57	
Alpha (%)	7.05	3.23	2.33	1.64	-4.71	11.75	-2.10	
(t-value)	4.20	2.19	1.41	0.92	-2.13	3.77	-0.61	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Information Technology sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 56: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.89	0.65	0.61	0.58	0.39
SR Low Vol.	0.87	0.68	0.55	0.61	0.40
(t-value)	1.65	-1.71	3.88	-2.56	-1.42

In the table the Sharpe ratios of the quintile portfolios shown in Table 54 and 55 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Consumer Discretionary

Table 57: Quantile returns low volatility in Consumer Discretionary

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	12.44	11.66	11.98	9.00	14.90	-2.17	10.80	11.23
Std Dev (%)	15.43	18.08	21.39	24.59	30.81	22.19	20.76	14.59
SR	0.81	0.64	0.56	0.37	0.48		0.52	0.77
(t-value)	9.35	5.99	2.03	-8.21	-1.77		-7.68	
Beta	0.66	0.82	0.97	1.12	1.39	-0.73	1.22	
Alpha (%)	5.04	2.67	1.39	-2.93	-0.31	5.35	-2.76	
(t-value)	3.67	2.27	1.02	-2.02	-0.15	1.76	-1.36	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Consumer Discretionary sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 58: Quantile returns downside volatility in Consumer Discretionary

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	13.36	12.38	11.76	10.80	11.22	1.93	10.80	11.23
Std Dev (%)	14.84	18.19	20.66	24.32	31.61	22.35	20.76	14.59
SR	0.90	0.68	0.57	0.44	0.36		0.52	0.77
(t-value)	12.37	6.91	2.70	-4.61	-8.31		-7.68	
Beta	0.64	0.81	0.95	1.12	1.44	-0.80	1.22	
Alpha (%)	6.01	3.38	1.44	-1.26	-4.11	10.11	-2.76	
(t-value)	4.84	2.61	1.19	-0.97	-2.08	3.58	-1.36	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Consumer Discretionary sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 59: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.90	0.68	0.57	0.44	0.36
SR Low Vol.	0.81	0.64	0.56	0.37	0.48
(t-value)	6.33	2.00	0.56	5.52	-11.23

In the table the Sharpe ratios of the quintile portfolios shown in Table 57 and 58 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Utilities

Table 60: Quantile returns low volatility in Utilities

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	9.53	9.93	10.52	8.10	9.69	-0.15	9.20	11.23
Std Dev (%)	13.66	14.63	15.12	15.29	21.50	18.02	14.39	14.59
SR	0.70	0.68	0.70	0.53	0.45		0.64	0.77
(t-value)	2.32	1.78	2.99	-5.48	-5.09		-2.15	
Beta	0.87	0.94	1.00	1.00	1.19	-0.32	0.46	
Alpha (%)	1.49	1.16	1.23	-1.04	-1.22	2.71	3.96	
(t-value)	1.40	1.14	1.38	-1.08	-0.49	0.82	1.63	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Utilities sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 61: Quantile returns downside volatility in Utilities

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	9.04	9.16	11.21	8.77	9.52	-0.44	9.20	11.23
Std Dev (%)	13.06	14.17	15.13	15.90	21.41	17.67	14.39	14.59
SR	0.69	0.65	0.74	0.55	0.44		0.64	0.77
(t-value)	2.17	0.32	5.28	-4.82	-5.37		-2.15	
Beta	0.83	0.92	1.00	1.05	1.20	-0.37	0.46	
Alpha (%)	1.35	0.70	1.85	-0.86	-1.46	2.81	3.96	
(t-value)	1.36	0.72	2.07	-942.00	-0.61	0.88	1.63	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Utilities sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 62: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.69	0.65	0.74	0.55	0.44
SR Low Vol.	0.70	0.68	0.70	0.53	0.45
(t-value)	-0.34	-1.91	2.71	1.34	-0.49

In the table the Sharpe ratios of the quintile portfolios shown in Table 60 and 61 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Industrials

Table 63: Quantile returns low volatility in Industrials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	11.64	13.37	13.49	12.92	9.67	1.81	12.07	11.23
Std Dev (%)	15.35	17.61	19.33	20.90	26.79	16.88	18.88	14.59
SR	0.76	0.76	0.70	0.62	0.36		0.64	0.77
(t-value)	5.14	7.05	3.51	-1.43	-12.46		-4.11	
Beta	0.75	0.90	0.98	1.07	1.33	-0.58	1.11	
Alpha (%)	2.44	2.34	1.45	-0.07	-5.99	8.43	-0.46	
(t-value)	2.24	2.58	1.44	-0.07	-3.45	3.47	-0.25	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Industrials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 64: Quantile returns downside volatility in Industrials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	12.65	12.40	14.37	13.22	8.58	3.78	12.07	11.23
Std Dev (%)	14.90	17.78	18.75	21.85	26.92	17.53	18.88	14.59
SR	0.85	0.70	0.77	0.60	0.32		0.64	0.77
(t-value)	8.55	3.47	7.05	-2.21	-13.75		-4.11	
Beta	0.73	0.90	0.95	1.12	1.34	-0.61	1.11	
Alpha (%)	3.61	1.38	2.62	-0.31	-7.04	10.65	-0.46	
(t-value)	3.39	1.49	2.56	-0.28	-3.98	4.25	-0.25	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Industrials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 65: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.85	0.70	0.77	0.60	0.32
SR Low Vol.	0.76	0.76	0.70	0.62	0.36
(t-value)	7.46	-4.37	4.21	-0.91	-4.48

In the table the Sharpe ratios of the quintile portfolios shown in Table 63 and 64 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Materials

Table 66: Quantile returns low volatility in Materials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	10.21	11.58	10.01	11.06	14.29	-3.61	11.21	11.23
Std Dev (%)	16.01	18.85	20.94	25.35	32.53	25.01	20.47	14.59
SR	0.64	0.61	0.48	0.44	0.44		0.55	0.77
(t-value)	3.00	2.79	-3.28	-5.73	-4.03		-6.05	
Beta	0.68	0.84	0.95	1.17	1.41	-0.74	1.14	
Alpha (%)	2.53	2.01	-0.59	-1.94	-1.66	4.19	-1.53	
(t-value)	1.68	1.41	-0.41	-1.23	-0.60	1.12	-0.68	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Materials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 67: Quintile returns downside volatility in Materials

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	11.92	10.48	11.35	9.16	14.10	-1.93	11.21	11.23
Std Dev (%)	15.17	17.81	21.18	25.06	34.15	26.48	20.47	14.59
SR	0.79	0.59	0.54	0.37	0.41		0.55	0.77
(t-value)	7.55	1.79	-0.58	-9.46	-5.26		-6.05	
Beta	0.64	0.80	0.97	1.16	1.50	-0.86	<i>1.14</i>	
Alpha (%)	4.46	1.46	0.43	-3.60	-2.78	7.23	<i>-1.53</i>	
(t-value)	3.14	1.12	0.31	-2.42	-1.00	1.95	<i>-0.68</i>	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Materials sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 68: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.79	0.59	0.54	0.37	0.41
SR Low Vol.	0.64	0.61	0.48	0.44	0.44
(t-value)	9.00	-1.23	2.85	-4.45	-2.32

In the table the Sharpe ratios of the quintile portfolios shown in Table 66 and 67 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Energy

Table 69: Quantile returns low volatility in Energy

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	10.39	11.36	12.01	15.09	15.63	-4.58	12.48	11.23
Std Dev (%)	20.17	27.37	30.07	37.55	44.63	31.54	30.08	14.59
SR	0.51	0.41	0.40	0.40	0.35		0.41	0.77
(t-value)	4.20	0.01	-0.93	-0.96	-3.26		-6.85	
Beta	0.61	0.87	0.96	1.21	1.39	-0.78	1.27	
Alpha (%)	2.70	0.54	0.10	-0.19	-1.82	4.52	-1.74	
(t-value)	1.74	0.36	0.06	-0.11	-0.62	1.14	-0.38	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Energy sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 70: Quantile returns downside volatility in Energy

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	11.89	8.99	13.56	14.57	15.33	-3.01	12.48	11.23
Std Dev (%)	20.14	26.78	30.73	37.37	45.31	32.54	30.08	14.59
SR	0.59	0.34	0.44	0.39	0.34		0.41	0.77
(t-value)	7.08	-4.37	1.64	-1.76	-3.70		-6.85	
Beta	0.61	0.84	0.98	1.20	1.40	-0.79	1.27	
Alpha (%)	4.08	-1.33	1.22	-0.53	-2.24	6.32	-1.74	
(t-value)	2.63	-0.84	0.74	-0.30	-0.73	1.53	-0.38	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Energy sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 71: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.59	0.34	0.44	0.39	0.34
SR Low Vol.	0.51	0.41	0.40	0.40	0.35
(t-value)	9.25	-7.24	3.05	-1.08	-1.55

In the table the Sharpe ratios of the quintile portfolios shown in Table 69 and 70 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

Communication Services

Table 72: Quantile returns low volatility in Communication Services

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	9.69	8.15	6.36	15.11	18.09	-7.21	11.13	11.23
Std Dev (%)	15.33	18.62	20.22	25.34	42.62	40.48	20.22	14.59
SR	0.63	0.44	0.31	0.60	0.42		0.55	0.77
(t-value)	1.82	-3.17	-7.86	1.52	-3.35		-6.51	
Beta	0.53	0.74	0.87	1.08	1.65	-1.12	1.17	
Alpha (%)	3.69	0.01	-3.02	2.70	-0.71	4.40	-1.92	
(t-value)	1.78	0.01	-1.60	1.12	-0.14	0.70	-0.93	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Communication Services sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 73: Quantile returns downside volatility in Communication Services

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Sector	Market
Ex. Return (%)	9.45	7.72	11.19	12.86	14.82	-4.73	11.13	11.23
Std Dev (%)	15.17	18.97	19.55	24.63	43.83	41.60	20.22	14.59
SR	0.62	0.41	0.57	0.52	0.34		0.55	0.77
(t-value)	1.63	-4.11	0.72	-0.97	-5.71		-6.51	
Beta	0.52	0.76	0.83	1.06	1.71	-1.19	1.17	
Alpha (%)	3.53	-0.62	1.89	0.92	-4.21	7.75	-1.92	
(t-value)	1.73	-0.30	0.99	0.40	-0.83	1.21	-0.93	

In the table the excess return and standard deviation of each quintile portfolio, long-short portfolio, sector portfolio and market portfolio are given for the Communication Services sector. The Sharpe Ratio (SR) is also calculated for the quintile portfolios, sector portfolio and market portfolio. The Sharpe ratios of the quintile portfolios are compared to the sector portfolio, and the t-value of the test in Equation 1 is shown. The Sharpe ratio of the sector portfolio is compared to the market portfolio. The t-value of the Sharpe ratio test is bold if it is significant on the 5% level. Additionally, a CAPM regression is run for all quintile portfolios, long-short portfolio, and sector portfolio. The t-value for the alpha is shown, and is again bold if it is significant on the 5% level.

Table 74: Comparison Sharpe ratios downside volatility and low volatility

	Q1	Q2	Q3	Q4	Q5
SR Neg. Vol.	0.62	0.41	0.57	0.52	0.34
SR Low Vol.	0.63	0.44	0.31	0.60	0.42
(t-value)	-0.42	-1.45	10.29	-3.14	-5.20

In the table the Sharpe ratios of the quintile portfolios shown in Table 72 and 73 compared to each other. The t-value of the test in Equation 1 is calculated. The t-value is bold if it is significant on the 5% level.

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