SOLACTIVE
German Index Engineering

The Downside of Low Volatility

White Paper

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EXECUTIVE SUMMARY

- We introduce a new factor investing strategy in the index context: Low downside volatility. While standard deviation, as used in classic low volatility strategies, punishes positive and negative deviations from mean returns equally, downside volatility only considers negative returns when calculating an asset's risk.
- This paper compares low downside volatility to low volatility factor strategies. We form a tradable starting universe covering 85% of the Developed European stock market. Based on this, we run historical simulations using weighting schemes that build on downside volatility and volatility.
- Our results show that the low downside volatility outperforms the low volatility strategy by 0.84% per annum with a 2 percentage points lower annual standard deviation, maintaining a higher Sharpe ratio than the low volatility strategy.
- Using cross-sectional regression analysis, we complement these findings. We run the regression on market excess returns, value and size factors as well as our downside volatility factor. We show that there is a risk premium associated with downside volatility of 0.20% and unit factor exposure. That means that there is a positive relationship between having a low downside volatility and higher expected market excess returns.
- We conclude that low downside volatility is a valuable addition to a factor portfolio.

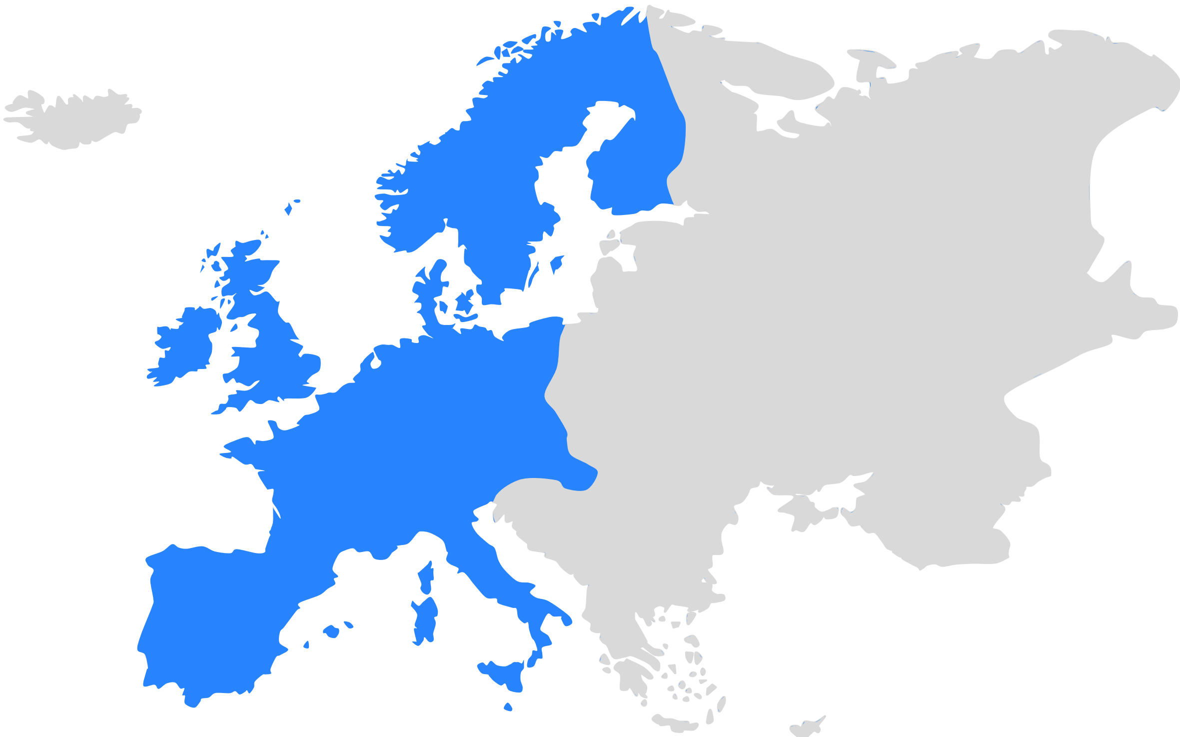
INTRODUCTION

Challenging established factor models that aim to explain stock returns using risk factors such as value or size is commonplace in the financial literature. Research aims at adding and/or removing risk factors to further explain stock returns. There practically exists a “zoo of new factors” (Cochrane (2011,1047)).

Blitz and van Vliet (2007), among others, present empirical evidence that stocks with low volatility achieve high risk adjusted returns. They provide evidence that the low volatility effect cannot be explained by established factors such as value and size. In line with Frazzini and Pedersen (2014), Blitz and Van Vliet (2007) attribute the low volatility effect partially to restrictions in leveraging stocks that affect investors investment decisions. In order to increase their expected returns, investors bid up more risky stocks that are commonly associated with higher risk premia. Thus, they create a demand shock that affects this risk-return relationship. Frazzini and Pedersen (2014) analyze the holdings of Berkshire Hathaway and find that Warren Buffett, as an unconstrained investor, is conceptually using this phenomenon by leveraging low risk stocks. However, they conclude that even investors that face leverage constraints could exploit the demand shock by including low risk stocks into their factor investing strategies.

Yet, the question remains how we define the risk of a stock. Often, this is done using the standard deviation of a stock. However, when using plain volatility, one considers both negative and positive deviations from the mean returns equally. Yet, a rational investor would not consider deviations to the upside as risk but as potential. Investing in factor strategies that aim to exploit the low risk effect using a low volatility strategy inherently limit this upside due to the nature of how standard deviation is being calculated. Using a measure that describes the volatility of the negative returns can help to avoid this drawback. Downside volatility is such a measure. To show the distinction consider two portfolios realizing the following sets of returns: A = [-10% -10% -10%] and B = [2% 10% 3%]. The respective volatilities are 0% and 4%, i.e. portfolio A is considered the less risky investment by the classic standard deviation framework. Thus, a plain low volatility factor strategy would select stock A over B. The downside volatility, on the other hand, suggests that portfolio B is the less risky investment, as the resulting downside volatilities are 10% and 0%, respectively. A low downside volatility factor strategy would select B over A. This result is more in line with what a rational investor would prefer.

The purpose of this study is to compare the two competing risk measures. For this purpose, we run historical simulations for both strategies since 2002. We further run cross-sectional regressions using the competing risk measures to compare their explanatory power.



BACKTESTING

To analyze the historical characteristics of the downside volatility strategy we run backtests on the European stock market. First, we create a selection pool of eligible stocks that serves as the starting universe of our analysis. Then, we run historical simulations based on the starting universe to illustrate the hypothetical historical performance of the two competing strategies, namely low downside volatility versus low volatility factor investing.

Initially, we build the selection pool that covers the Developed European stock market starting in February 2002. To do so, we consider stocks primary listed in 15 countries, i.e. the United Kingdom, France, Germany, Sweden, Spain, Norway, Netherlands, Denmark, Italy, Belgium, Switzerland, Portugal, Austria, Ireland and Finland. The resulting starting universe covers 85% of the entire market capitalization in those countries. In order to ensure basic tradability, an Average-Daily-Value-Traded (ADVT) over the last six months of at least EUR 100,000 is applied. As of September 2017, there are 525 stocks in the universe. Table 1 contains statistics concerning the historical performance of the constructed starting universe.

Based on the starting universe we now run historical simulations using indices that reflect the two competing strategies.

Table 1 Performance Measures Solactive Developed Europe Selection Pool. Measures are per annum.

Measure	Value
Mean	5.07%
Standard Deviation	19.36%
Downside Deviation	13.65%
Max Drawdown	-58.17%
Sharpe Ratio	0.26
Sortino Ratio	0.37

Figure 1 Index Construction Logic

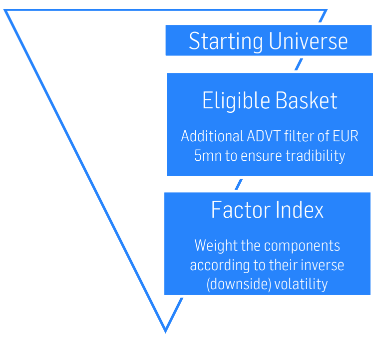


Figure 1 highlights the steps of the index construction that are carried out at every quarterly index rebalancing. First, as described above, the starting universe is defined. Second, an additional ADVT filter of EUR 5mn is applied to increase the liquidity of the index. Finally, all stocks are weighted according to the inverse of their (downside) volatility (see Formula 1). Formula 2 is applied to compute the downside volatility of every stock using a lookback period of 252 trading days. The low volatility index is built analogously using normal standard deviation.

$$w_i = \frac{\left(\sigma_i^D\right)^{-1}}{\sum_{i=1}^{n}\left(\sigma_i^D\right)^{-1}} \qquad (1)$$

$$\sigma_i^D = \sqrt{\frac{1}{T} \cdot \sum_{t=1}^{T}\left[Min(R_{it}, 0) \cdot Min(R_{it}, 0)\right]} \qquad (2)$$

T is the number of observations, R_{it} is the return of stock i at time t and n is the number of stocks in the eligible basket.

Figure 2 illustrates the backtests for the competing strategies. The corresponding performance measures are summarized in Table 2.

Table 2 Performance Measures Low Downside Volatility (DVol) and Low Volatility (Vol). Measures are per annum.

Measure	Low DVol	Low Vol
Mean Return	8.28%	7.44%
Standard Deviation	15.81%	17.82%
Downside Deviation	11.20%	12.64%
Max Drawdown	-55.00%	-58.54%
Sharpe Ratio	0.52	0.42
Sortino Ratio	0.74	0.59

Figure 2 Backtest Low Downside and Low Volatility Developed Europe

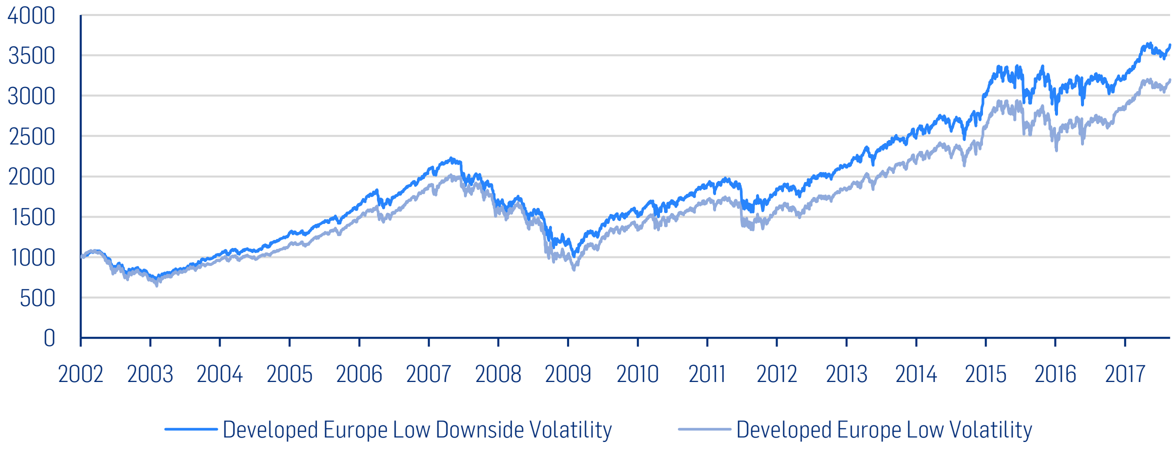
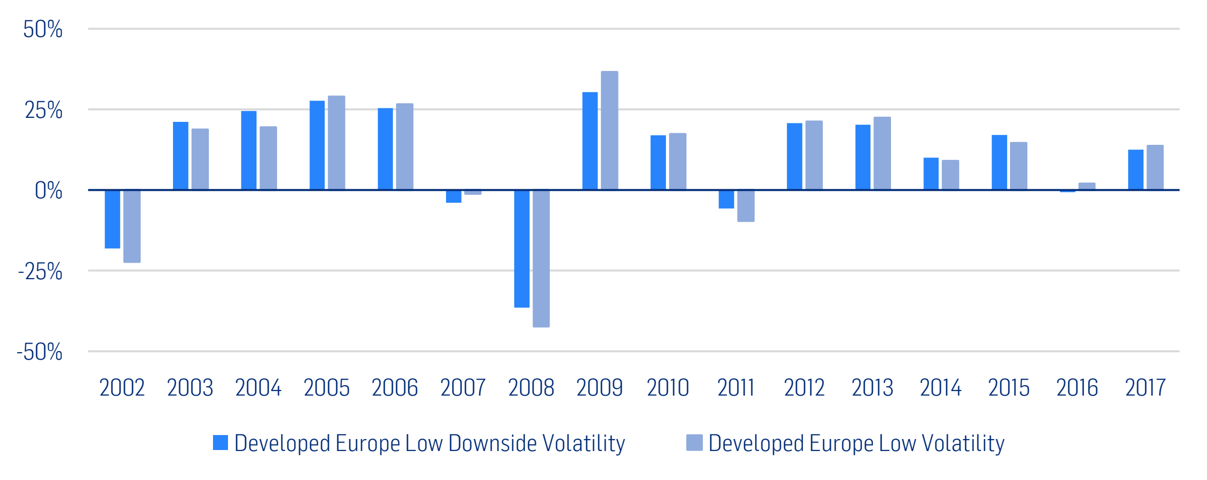


Figure 3 Year on Year Returns

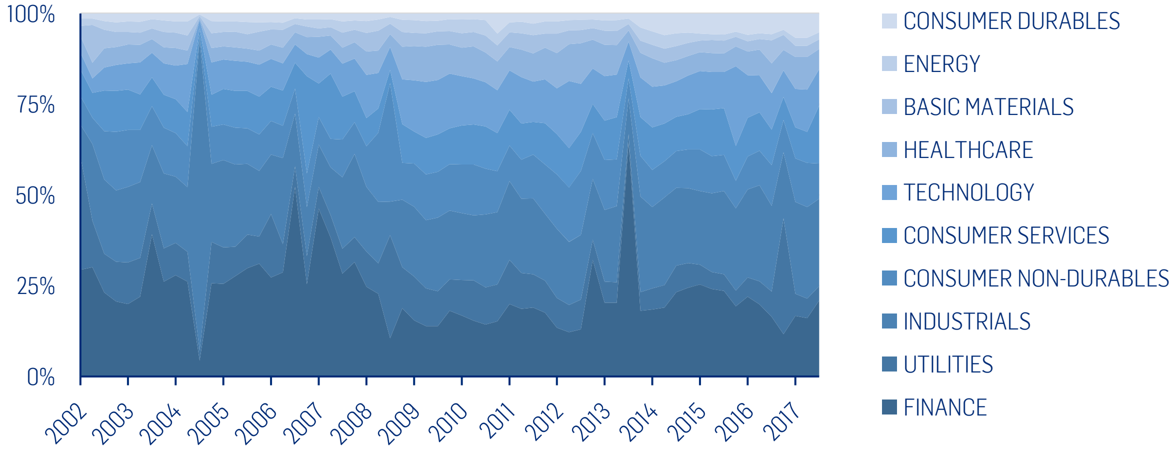


The historical simulations reveal that the low downside volatility strategy achieves a higher annual mean return than the low volatility strategy. As Figure 3 illustrates, this outperformance can also be attributed to the lower losses realized in the turmoil periods of 2002, 2008 and 2011. Additionally, the downside volatility strategy produces lower measures regarding both standard and downside deviation. Consequently, the risk profile, as measured by the Sharpe and the Sortino ratio, improves when the downside volatility is the considered risk measure.

Figure 4 illustrates the historical sector allocation of the low downside volatility strategy. We can observe that the weighting scheme considerably decreases the allocation to the financial sector before the year 2008 coinciding with the relative outperformance against the low volatility strategy.

An analysis using the 500 largest stocks primary listed on US exchanges can be found in Appendix.

Figure 4 Historical Sector Allocation Developed Europe Low Downside Volatility



REGRESSION ANALYSIS

To evaluate the explanatory power of the volatility and the competing downside volatility factor we perform a regression analysis similar to the three-factor model introduced by Fama and French (1993) that tests the asset pricing model defined as,

$$E\left(R_i - R^{Mkt}\right) = \alpha + \beta_i^{LMH} \cdot (R^{LMH}) + \beta_i^{SMB} \cdot (R^{SMB}) + \beta_i^{D/V} \cdot \left(R^{D/V}\right) + \varepsilon_i, \tag{3}$$

where α is a constant, β_i^X is the factor exposure of stock i to the risk premium R^X associated with factor X and ε_i is the error term. By testing this asset pricing model, we can assess how the excess return of a stock can be explained by different risk drivers. For our analysis regarding the distinction between downside volatility and volatility, we especially want to evaluate the sign and magnitude of $\beta_i^{D/V}$, which represents β_i^{DVol} or β_i^{Vol} respectively. We therefore run two regression analyses using both downside volatility and volatility. If our estimated factor exposure of the downside volatility and the volatility factor is larger than zero with a positive risk premium R^{Vol} or R^{DVol} respectively, then a lower (downside) volatility of stock i is associated with a higher expected excess return $E(R_i - R^{Mkt})$. Here, Mkt denotes the market return, LMH is the excess return of portfolios that have a low Price-to-Book ratio over portfolios that have a high Price-to-Book ratio, SMB is the excess return of portfolios that consist of small market capitalization stocks over portfolios that have a high market capitalization and Vol is the excess return of portfolios that contain stocks with a low volatility over portfolios formed using high volatility stocks.

Formulae 4-6 Factor construction. LMH is Low-Minus-High Price-to-Book ratio, SMB is Small-Minus-Big market capitalization, Vol is volatility and DVol is downside volatility.

$$LMH = \left(\tfrac{1}{9}\right) \cdot \left((1+2+3+4+5+6+7+8+9) - (19+20+21+22+23+24+25+26+27)\right)$$

$$SMB = \left(\tfrac{1}{9}\right) \cdot \left((1+2+3+10+11+12+19+20+21) - (7+8+9+16+17+18+25+26+27)\right)$$

$$(D)Vol = \left(\tfrac{1}{9}\right) \cdot \left((1+4+7+10+13+16+19+22+25) - (3+6+9+12+15+18+21+24+27)\right)$$

Table 3 Factor construction. P is the number of the constructed portfolio and PB is the Price-to-Book ratio.

Value	Size	(Downside) Volatility	P
Low PB	Small	Low	1
		Medium	2
		High	3
	Medium	Low	4
		Medium	5
		High	6
	Large	Low	7
		Medium	8
		High	9
Neutral PB	Small	Low	10
		Medium	11
		High	12
	Medium	Low	13
		Medium	14
		High	15
	Large	Low	16
		Medium	17
		High	18
High PB	Small	Low	19
		Medium	20
		High	21
	Medium	Low	22
		Medium	23
		High	24
	Large	Low	25
		Medium	26
		High	27

The factor associated with downside volatility, $DVol$, is built analogously to Vol with the distinction that the downside volatility as defined in Formula 1 is applied.

To receive the factors under consideration we follow the construction logic illustrated in Table 3 and Formulae 4-6. We form 2 times 27 portfolios sorted for value, size and volatility or downside volatility respectively. Our analyzed timeframe covers daily data from February 2002 until September 2017. In a first step, we regress each time series of daily excess returns for the stocks that have all the required data available according to Formula 3. For those stocks we each compute the factor exposures using the time series for LMH, SMB and $Vol/DVol$. We then use the computed factor exposures to run a cross-sectional regression of the daily excess returns for all assets on their respective factor exposures to estimate the overall risk premia associated with the considered factors.

Table 4 contains the results of the cross-sectional regression. The first column of risk premia illustrates the results for the cross-sectional regression where common volatility is included as an explanatory variable. We find that there indeed is a risk premium associated with having low volatility, i.e. stocks that exhibit a low volatility have higher expected excess returns. The same phenomenon can be observed if we include downside volatility. That means that there is a risk premium associated with having a lower downside volatility. This risk premium is not significantly lower than the one associated with the plain volatility factor, which shows that the low risk anomaly is being picked up by adding the downside volatility factor.

Table 4 Risk premia per factor for the monthly cross-sectional regression. Test statistics in parentheses. FF3 is the Fama and French (1993) three-factor model. V and DV are the regressions that include volatility and downside volatility respectively.

Factor	FF3V	FF3DV
Value	0.38% (24.05)	0.37% (22.76)
Size	1.16% (79.68)	1.16% (79.81)
Volatility	0.24% (14.23)	
Downside Volatility		0.20% (11.83)

CONCLUSION

Leverage constraints can inherently cause a supply and demand shock that compromises the risk-return relationship. As they are not allowed to use leverage to increase their exposure to low risk stocks, as suggested by the CAPM, investors bid up high risk stocks while underweighting low risk stocks to achieve their target risk profile. Some institutional investors, however, can use leverage and thus exploit this asymmetry on a big scale. Yet, constrained investors can benefit from this asymmetry too by including a low idiosyncratic risk factor into their factor portfolio.

We introduce a new approach of risk factor investing in the index context. While standard deviation, as used in classic low volatility strategies, punishes positive and negative deviations from mean returns equally, downside volatility only considers negative returns when calculating an asset's risk. By constructing low risk factor strategies that build on the principle of downside volatility, investors can exploit the asymmetry in the risk-return relationship, while considering their actual risk: Deviations to the downside. Using historical simulations for the European stock market, we show that a low downside volatility strategy successfully manages to pick up the outperformance associated with the low risk anomaly. We can further observe that the factor index created on low downside volatility is realizing higher annual mean returns, lower standard deviations, lower downside deviations and higher Sharpe and Sortino ratios than the low volatility strategy. The strategy further adjusts its exposure to industries that face a longer crisis period. This can be observed in the turmoil period following the default of Lehman Brothers in 2008 and 2009, when the factor strategy's exposure to the finance sector is dramatically reduced. Using cross-sectional regression analysis, we complement these findings. We run the regression on market excess returns, value and size factors as well as our downside volatility factor. We show that there is a positive relationship between low downside volatility and higher expected market excess returns.

We conclude that by adding low downside volatility to a factor investing portfolio, an investor can harvest the low risk anomaly while avoiding the downside of low volatility.

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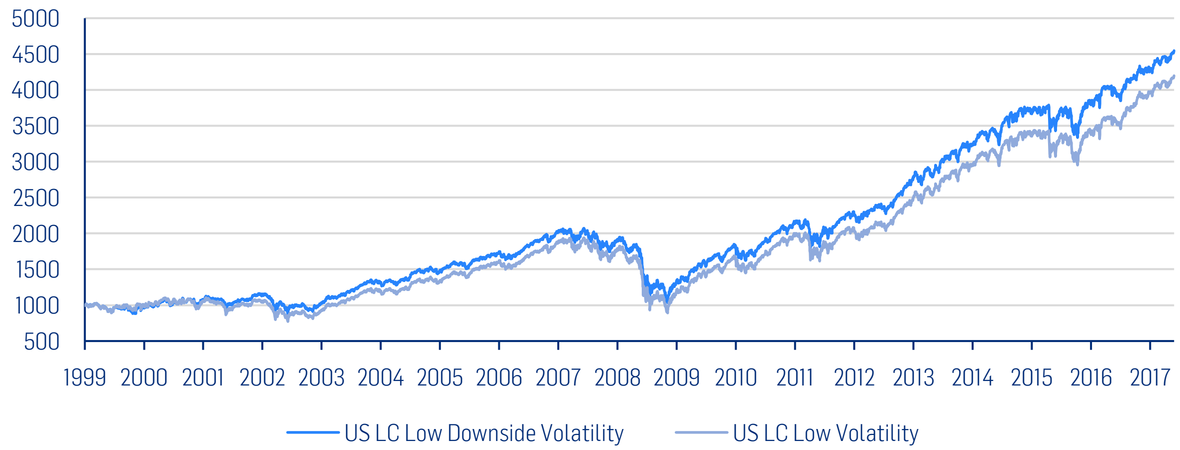
APPENDIX: HISTORICAL SIMULATION US LARGE CAP

Figure 5 Backtest Low Downside Volatility and Low Volatility US LC

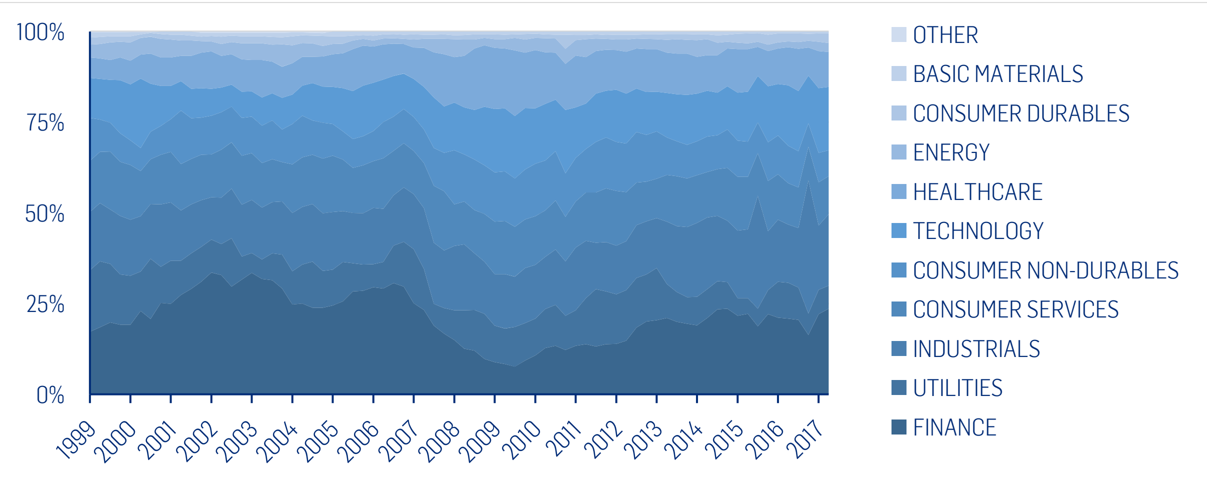


We run historical simulations applying the two competing strategies on the 500 largest stocks primary listed on US exchanges. Figure 5 shows the corresponding performance, Table 5 summarizes the performance measures and Figure 6 shows the historic sector allocation of the low downside volatility strategy. We can observe that the low downside volatility strategy is able to pick up the low risk anomaly while generating lower standard and downside deviations than the low volatility strategy. The results are in line with the findings for the Developed European stock market.

Table 5 Performance Measures US LC Low Downside Volatility (DVol) and Low Volatility (Vol). Measures are per annum.

Measure	Low DVol	Low Vol
Mean Return	8.27%	7.82%
Standard Deviation	16.27%	17.88%
Downside Deviation	11.46%	12.63%
Max Drawdown	-50.04%	-54.04%
Sharpe Ratio	0.51	0.44
Sortino Ratio	0.72	0.62

Figure 6 Historic Sector Allocation US LC Low Downside Volatility



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