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KEY FINDINGS

- Low-volatility portfolios reduce the exposure to every conceivable structural source of systematic risk.
- Our analysis includes interest rate, implied volatility, liquidity, commodity, sentiment, macroeconomic, and climate risk factors.
- The 2020 COVID-19 pandemic episode illustrates that event risk is harder to control for data-driven methods.

ABSTRACT

This article examines the exposures of low-volatility portfolios to various sources of systematic risk. The analysis includes interest rate, implied volatility, liquidity, commodity, sentiment, macroeconomic, and climate risk factors. The author finds that low-volatility portfolios lower the exposure to all significant drivers of systematic risk. The risk reductions vary from a minimum of 20% to over 90% across the various risk factors. Although low-volatility portfolios are very effective at dampening known structural risk factors, the 2020 COVID-19 pandemic episode illustrates that event risk is harder to control for data-driven methods.

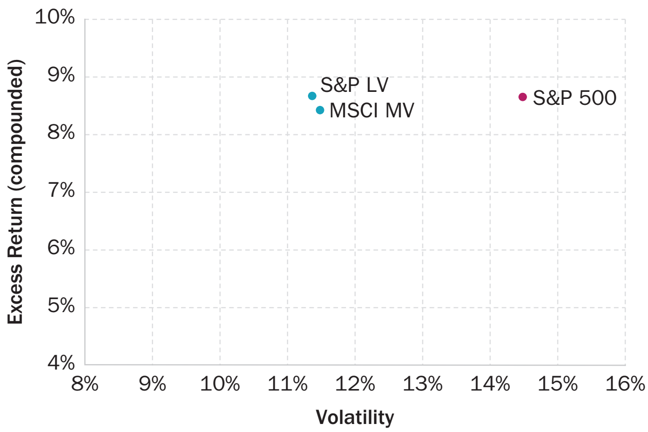
By following a low-volatility approach, investors can lower their exposure to overall systematic equity risk. But does low-volatility investing reduce the exposure to each and every source of systematic risk? To answer this question, we examine how low-volatility portfolios are affected by a wide range of macroeconomic risk factors. Our main finding is that low-volatility portfolios exhibit a lower exposure to every structural risk factor that is a significant driver of overall systematic risk. Event risk, however, is not necessarily mitigated due to the reliance of data-driven methods on past security prices.

In theory, low-risk stocks should have low returns, but empirically, they tend to have market-like or even higher returns. This result was already established by Haugen and Heins (1975) for minimum variance optimized portfolios, and Clarke, de Silva, and Thorley (2006) showed it has continued to hold since. Other studies simply sorted stocks on their past volatility or beta and found a flat or even inverse relation with subsequent returns (e.g., Black 1993; Blitz and van Vliet 2007; and Baker, Bradley, and Wurgler 2011). For an extensive overview of the literature on the low-volatility anomaly, we refer to Blitz, van Vliet, and Baltussen (2020).

Because low-volatility portfolios have less systematic risk, their exposure to the various drivers of systematic risk should, on average, be lower as well; however, because of their concentration in certain segments of the stock market, low-volatility portfolios might be similarly or even more exposed to some specific sources of systematic risk.

EXHIBIT 1

Risk and Return of Low-Volatility Portfolios vs. the Market, January 1991–December 2021



In other words, a lower overall volatility and beta mean does not necessarily imply that low-volatility portfolios protect investors against all possible risk factors. For instance, what if interest rates and inflation rise rapidly, the oil price shows big swings, or industrial production plummets? This article aims to answer this question and finds that low-volatility portfolios offer remarkably robust protection against a wide range of macroeconomic risk factors.

DATA

We use the S&P 500 Index as the reference point and consider two generic low-volatility strategies, namely the MSCI USA Minimum Volatility Index and the S&P 500 Low Volatility Index. The former is based on minimum variance optimization while the latter consists of the 100 stocks in the S&P 500 with the lowest volatility over the past 1 year, inversely weighted by their volatilities. In addition, we consider 10 equally weighted decile portfolios of stocks sorted on their preceding 36-month volatility, based on a universe consisting of the 1,000 largest US stocks at each point in time (van Vliet and de Koning 2022). For all these portfolios, we gather monthly total returns in US dollars in excess of the risk-free return[1] over the sample period from January 1991 to December 2021, which is the longest period for which all the series are available. Exhibit 1 shows that over the full sample, the two low-volatility indexes had virtually the same return as the market but with considerably less volatility, thus confirming the low-volatility anomaly.

For the drivers of systematic risk, we consider interest rate factors, implied volatility factors, liquidity metrics, commodity factors, sentiment measures, traditional macroeconomic indicators, and climate factors. Exhibit 2 provides an overview with brief descriptions and sources. In total, we consider 23 separate risk factors, which should cover the most important dimensions of systematic risk.

Because the aim of our analysis is to examine risk factors that affect the stock market as a whole, we do not include cross-sectional factors, that is, factors that take a long position in one group of stocks and a short position in another group of stocks, such as the Fama and French (1993, 2015) asset pricing factors. If half of the total stock market capitalization is considered to be value and the other half growth, then the market will be mechanically neutral to such a value-minus-growth factor. Estimated exposures may be different from zero for cross-sectional factors that are defined differently, but this then essentially reflects the choice of factor definition. For this reason, we only consider exogeneous or market aggregate signals.

RESULTS

We assess the importance of each individual risk factor by conducting univariate regressions of monthly excess stock returns of the market and two low-volatility indexes on a given risk factor, using the contemporaneous observations.[2] The main

[1] The risk-free return is from the Kenneth French data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] We do not conduct multivariate regressions because (1) some factors with very high explanatory power, such as VIX, are likely to dominate; (2) some risk factors may be highly correlated, leading to multicollinearity issues; and (3) some factors are only available with a quarterly frequency.

EXHIBIT 2
Overview of Risk Factors Considered in This Study

	Description	Source
Interest rate		
10Y yield	Change in 10-year US Treasury bond yield	FRED
3M rate (level)	Yield level on Treasury bills	Kenneth French
Slope YC (level)	Yield difference between 10-year US Treasury bonds and Treasury bills	FRED, Kenneth French
TED	Change in TED spread	FRED
BE-INF*	Change in 10-year breakeven inflation rate	FRED
DEF	Change in yield difference between BAA and AAA corporate bonds	FRED
Volatility		
VIX	Change in VIX Index (S&P 500 implied volatility)	Datastream
MOVE	Change in MOVE Index (Treasury bond implied volatility)	Bloomberg
Liquidity		
PS liq	Pastor–Stambaugh liquidity (innovation) factor	Robert Stambaugh homepage
ICR**	He–Kelly–Manela intermediary capital risk factor	Bryan Kelly homepage
Commodity		
Oil	% change in WTI oil price	Datastream
Gold	% change in gold price	Datastream
Sentiment		
ISM	Change in US purchasing managers sentiment index	Datastream
ConsSent	Change in Michigan consumer sentiment index	Datastream
InvSent***	Baker and Wurgler (2006) sentiment index	Jeffrey Wurgler homepage
EPU	Change in log US Economic Policy Uncertainty Index	EPU homepage
GPR	Change in Caldara–Iacoviello geopolitical risk factor	Matteo Iacoviello homepage
Macro		
GDP	% change in US real GDP per capita	Datastream
Unemployment	% change in the US unemployment rate	Datastream
Industrial prod	% change in US industrial production	Datastream
CPI	% change in US consumer price index (inflation)	Datastream
Earnings		
Earnings	% change in aggregate stock earnings	Robert Shiller homepage
Climate		
CO_2 emissions	% change in US CO_2 emissions from energy consumption, seas. adj.	US Energy Information Administration

NOTES: *Data from January 2003. **Data until November 2018. ***Data until December 2018.

TED = Treasury EuroDollar rate; VIX = Volatility IndeX; ISM = Institute for Supply Management; GDP = gross domestic product; FRED = Federal Reserve Database; WTI = West Texas Intermediate.

results for the interest rate, implied volatility, liquidity, commodity, and sentiment factors are presented in Exhibit 3.

The first row of the exhibit shows that the S&P 500 reference portfolio has a significantly positive loading on the 10-year bond yield, meaning that falling yields tend to coincide with low stock returns. The economic rationale behind this relationship is that Treasury bonds typically act as a safe haven during times of extreme stress, so bond prices go up and hence yields go down while the stock market crashes. The exposures of the two low-volatility portfolios to bond yield changes are much smaller and in fact both statistically indistinguishable from zero. In other words, the low-volatility portfolios are much less sensitive or even immune to yield changes.

EXHIBIT 3

Estimated Exposures toward Various Fixed-Income, Commodity, and Sentiment Risk Factors, January 1991–December 2021

	Coefficients			*t*-Statistics		
	S&P 500	MSCI MV	S&P LV	S&P 500	MSCI MV	S&P LV
Interest rate						
10Y yield	3.46	1.44	0.50	3.47	1.80	0.63
3M rate (level)	–0.07	–0.06	–0.05	–0.71	–0.72	–0.62
Slope YC (level)	–0.11	–0.08	–0.07	–0.92	–0.87	–0.74
TED	–3.32	–1.78	–1.80	–3.39	–2.27	–2.32
BE-INF	9.63	5.07	4.90	5.21	3.29	3.30
DEF	–15.09	–10.15	–9.07	–8.21	–6.79	–6.06
Volatility						
VIX	–0.65	–0.48	–0.43	–19.92	–17.82	–14.61
MOVE	–0.09	–0.06	–0.06	–6.13	–5.36	–4.94
Liquidity						
PS liq	0.16	0.12	0.11	4.37	4.15	3.96
ICR	0.45	0.31	0.26	19.14	15.28	11.67
Commodity						
Oil	0.10	0.06	0.03	5.01	3.68	2.14
Gold	–0.01	0.02	0.01	–0.17	0.59	0.37
Sentiment						
ISM	0.60	0.37	0.23	5.43	4.14	2.64
ConsSent	0.30	0.21	0.19	5.97	5.30	4.60
InvSent	–0.91	–0.54	–0.06	–2.54	–1.89	–0.20
EPU	–0.06	–0.03	–0.03	–4.82	–3.23	–2.89
GPR	–0.12	–0.08	–0.02	–1.84	–1.52	–0.49

NOTES: Insignificant risk factors are reported in gray.

MV = minimum volatility; LV = low volatility.

At first glance, this result may seem to be at odds with Baker and Wurgler (2012) and Blitz (2020), who found that low-volatility stocks exhibit an increased interest rate sensitivity and can therefore be regarded as bond-like stocks. Their conclusions, however, hold when low-volatility portfolios are examined *relative* to the market, that is, when the market is regarded as the neutral reference point, so ignoring that the market has a certain rate sensitivity itself. In contrast, we find that low-volatility stocks are in fact less rate sensitive than the market in an *absolute* sense.

The next two rows in Exhibit 3 show that both the market and the low-volatility portfolios have insignificant exposures to the risk-free rate level and the slope of the yield curve level. In other words, these two indicators do not appear to be relevant drivers of systematic equity risk. The market, however, does have highly significant exposures to changes in the TED spread (difference between 3-month LIBOR and 3-month T-bill rate), changes in the break-even inflation rate (derived from inflation-linked bond prices), and changes in the default spread (difference between yield on BAA- and AAA-rated bonds). For the low-volatility portfolios, these exposures are approximately one-third to one-half lower, implying that they are considerably less exposed to these sources of systematic risk.

Turning to the implied volatility factors, we find that the market has very strong negative betas toward changes in the VIX Index (implied volatility of S&P 500 Index options) and the MOVE Index (implied volatility of Treasury bonds); that is, rising implied volatilities tend to coincide with negative market returns. Again, these exposures are much smaller for the low-volatility portfolios. Similarly, the low-volatility portfolios dampen the significant exposures of the market toward liquidity risk. The metrics considered here are the widely used Pastor and Stambaugh (2003) liquidity factor and the intermediary capital risk factor of He, Kelly, and Manela (2017), which reflects the equity capital ratios of financial intermediaries.

Next, we consider the commodity factors. Most notably, the market has a highly significant beta toward changes in the oil price while the low-volatility portfolios have an oil beta that is only about half as large. Given the finding of Blitz (2022) that fossil fuel stocks have particularly large oil betas, this result indicates that low-volatility strategies tend to stay away from such stocks. This reduced fossil fuel exposure suggests that low-volatility investing implicitly mitigates climate risk. All the betas toward changes in the gold price are insignificant, implying that it is not a relevant systematic risk factor.

The results for the sentiment measures are in line with the previous findings. Regardless of whether we look at the ISM purchasing managers index, consumer sentiment, investor sentiment according to the definition of Baker and Wurgler (2006), or the economic policy uncertainty index of Baker, Bloom, and Davis (2016), we find that the market has highly significant betas while the low-volatility portfolios have consistently smaller betas. Thus, low-volatility portfolios are consistently less exposed to changes in sentiment. The geopolitical risk factor of Caldara and Iacoviello (2022) shows up as insignificant in our analysis.

Next, we examine the exposures toward traditional macroeconomic indicators, such as GDP. The nature of these data requires us to switch from a monthly to a quarterly data frequency. Another methodological change is that we regress quarterly stock returns not only on the macroeconomic indicators over the same quarter but also over the subsequent two quarters because stock prices tend to react much faster to changes in macroeconomic conditions than the real economy. The results of this analysis are reported in Exhibit 4.

EXHIBIT 4

Estimated Exposures toward Various Macroeconomic Risk Factors, January 1991–December 2021

	Coefficients			*t*-Statistics		
	S&P 500	MSCI MV	S&P LV	S&P 500	MSCI MV	S&P LV
GDP						
Quarter same	0.72	0.61	0.85	1.50	1.58	2.29
Quarter + 1	2.45	1.75	1.45	5.06	4.49	3.91
Quarter + 2	0.14	0.07	–0.13	0.29	0.17	–0.35
Unemployment						
Quarter same	–0.13	–0.34	–0.78	–0.19	–0.63	–1.54
Quarter + 1	–3.45	–2.76	–2.64	–5.01	–5.10	–5.17
Quarter + 2	–0.40	–0.48	–0.35	–0.59	–0.89	–0.69
Industrial Prod						
Quarter same	0.10	0.19	0.32	0.30	0.70	1.22
Quarter + 1	2.14	1.54	1.23	6.39	5.69	4.64
Quarter + 2	0.15	0.00	–0.18	0.44	0.01	–0.68
CPI						
Quarter same	0.09	0.76	1.06	0.06	0.66	0.97
Quarter + 1	4.09	2.22	1.68	2.77	1.88	1.49
Quarter + 2	–0.94	–0.81	–0.60	–0.69	–0.75	–0.59

(continued)

EXHIBIT 4 *(continued)*

Estimated Exposures toward Various Macroeconomic Risk Factors, January 1991–December 2021

	Coefficients			*t*-Statistics		
	S&P 500	MSCI MV	S&P LV	S&P 500	MSCI MV	S&P LV
Earnings						
Quarter same	0.03	0.03	0.04	1.46	1.54	2.09
Quarter + 1	0.06	0.04	0.02	2.30	2.14	1.22
Quarter + 2	0.03	0.02	0.01	1.41	1.02	0.79
CO_2 Emissions						
Quarter same	–0.12	–0.02	0.15	–0.54	–0.13	0.82
Quarter + 1	1.22	0.95	0.79	5.51	5.39	4.54
Quarter + 2	0.38	0.26	0.11	1.68	1.42	0.61

NOTE: Same quarter and two quarters ahead exposures are shown in gray because they are generally insignificant.

We observe that the stock market has highly significant exposures toward all the macroeconomic indicators (GDP, unemployment, industrial production, and US Consumer Price Index [CPI]) over the subsequent quarter. The loadings on the same quarter and the second next quarter are generally insignificant, indicating that the market is roughly one quarter ahead of the real economy. In line with the results for the other risk factors, the low-volatility portfolios have consistently weaker exposures to all these macroeconomic risk factors. The reduction in the exposures varies between roughly 20% (for unemployment) and 50% (for CPI). The exhibit also shows that low-volatility portfolios are less sensitive than the market to changes in aggregate corporate earnings.

The final part of the exhibit shows that low-volatility stocks are less exposed to changes in aggregate CO_2 emissions. For this analysis, we use CO_2 emissions data provided by the US Energy Information Administration, inspired by Choi, Jo, and Park (2017), who used these data to estimate CO_2 betas and found that stocks with low CO_2 betas significantly outperform those with high CO_2 betas. As the raw data exhibit strong seasonality, we adjust current quarter CO_2 changes by subtracting the average CO_2 change in the same quarter over the preceding 10 years. Similar to the macroeconomic and aggregate earnings measures, we find that the stock market has a highly significant exposure toward changes in CO_2 emissions one quarter ahead while for the low-volatility portfolios, this exposure is smaller. This is another indication that low-volatility portfolios are less exposed to climate risk.

As a robustness test, we examine the same exposures for the 10 volatility-sorted decile portfolios. For the interest rate, volatility, liquidity, commodity, and sentiment risk factors, we report the betas based on contemporaneous monthly observations in Exhibit 5 while for the macroeconomic indicators, corporate earnings, and CO_2, we consider the betas toward the next quarter observations in Exhibit 6. The risk factors that were previously found to be insignificant are omitted from this analysis. For almost every risk factor, we observe that the low-volatility portfolio has the smallest exposure and the high-volatility portfolio the largest exposure, with a pattern in between that is almost perfectly monotonic. Thus, the previous results for the two low-volatility indexes turn out to be exceptionally robust.

In sum, low-volatility portfolios exhibit a dampened exposure toward every risk factor that is a significant driver of systematic market risk. This conclusion holds for a wide range of risk metrics stemming from different sources, and the observed patterns are highly robust across portfolios sorted on past volatility.

EXHIBIT 5

Estimated Betas toward Interest Rate, Implied Volatility, Liquidity, and Commodity Factors, January 1991–December 2021

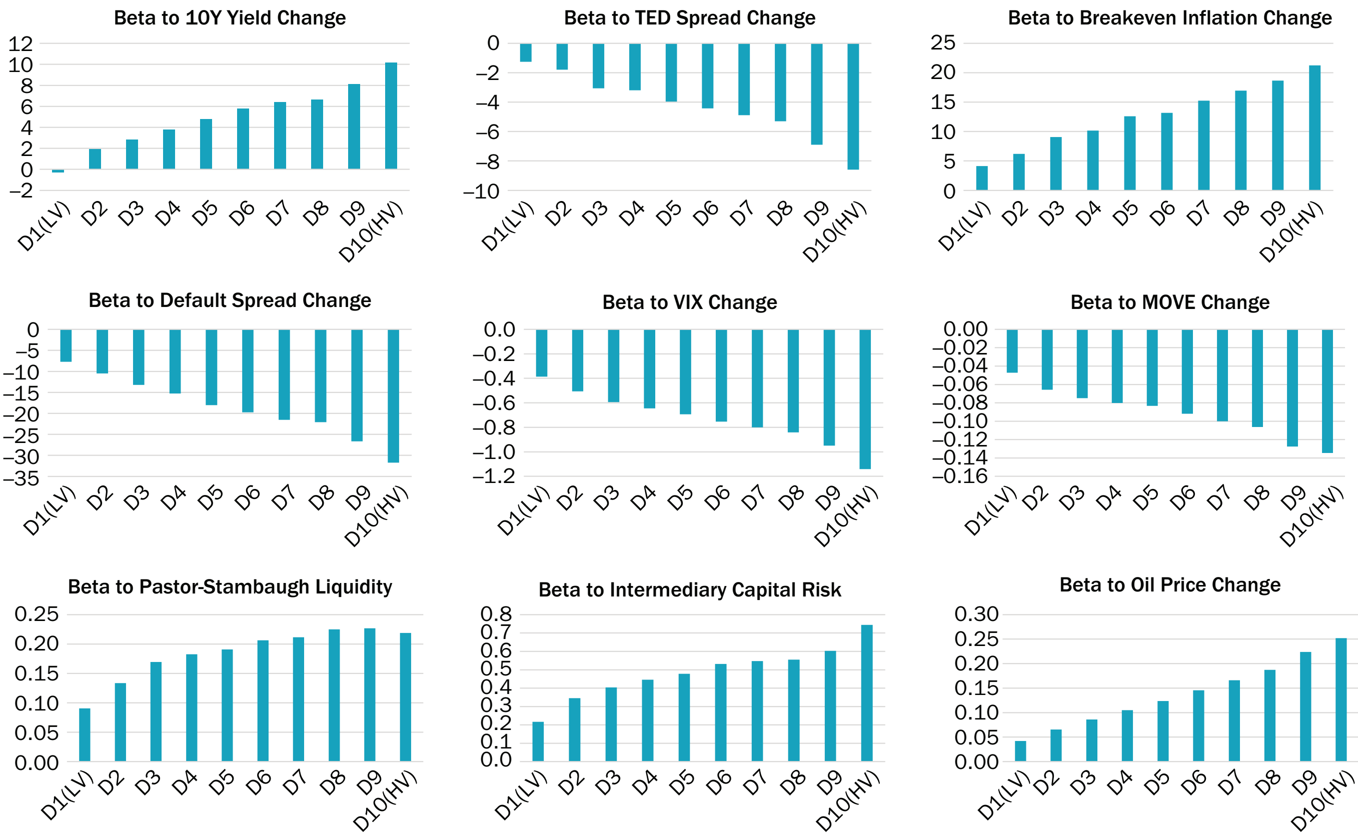


EXHIBIT 6

Estimated Betas toward Macroeconomic, Corporate Earnings, and Climate Risk Factors, January 1991–December 2021

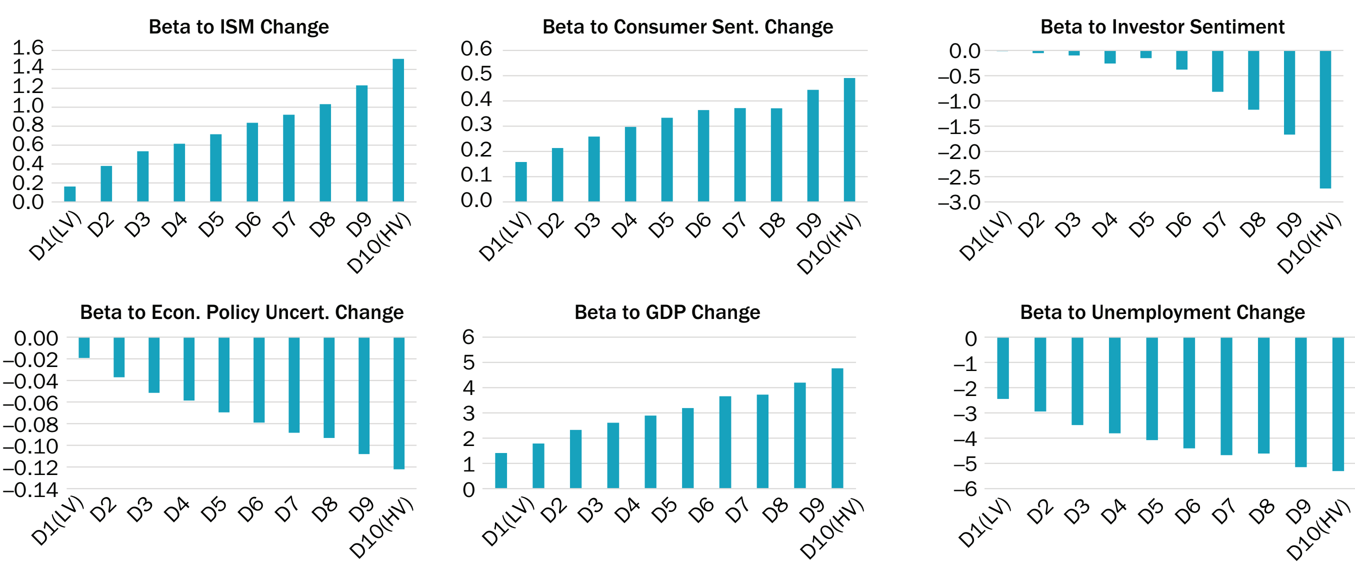


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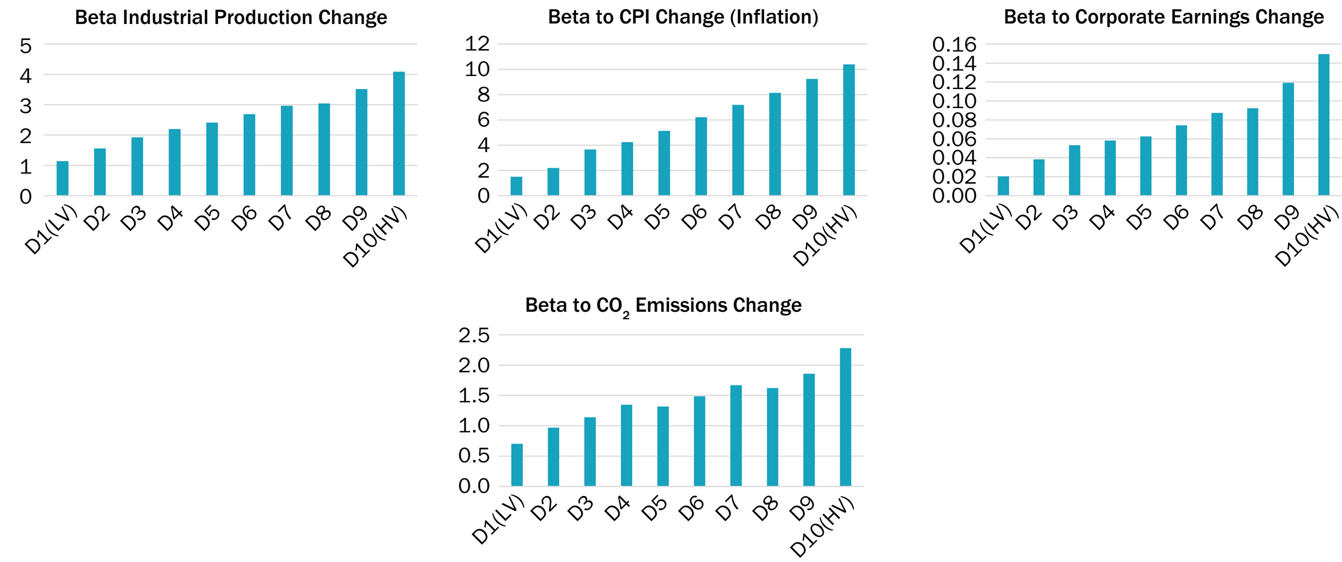
EXHIBIT 6 *(continued)*

Estimated Betas toward Macroeconomic, Corporate Earnings, and Climate Risk Factors, January 1991–December 2021



THE EXCEPTION THAT PROVES THE RULE

No investment strategy is entirely foolproof, and even low-volatility portfolios can sometimes be caught off guard. A concrete example is the COVID-19 pandemic of 2020. Exhibit 7 shows that instead of providing downside protection, the low-volatility portfolios experienced similar losses as the market portfolio during this exceptional event. Moreover, they lagged the market in the subsequent recovery. Although the observations over such a relatively short and highly unusual period should perhaps not be generalized, one might be tempted to conclude that the pandemic beta of low-volatility portfolios was about 1, or perhaps even higher.

What makes the COVID-19 pandemic so different from the wide variety of macroeconomic risks that low-volatility portfolios can generally cope with very well? The problem appears to be that COVID-19 caught investors completely off guard. Online stocks that used to be rather speculative, such as Zoom and Netflix, suddenly became defensive holdings when the world went into lockdown, while traditionally safe offline stocks, such as commercial real estate, suddenly became high risk. Past stock prices do not properly reflect a certain risk factor if investors previously dismissed it as irrelevant or were simply unaware of it. Bond markets, commodity markets, sentiment, and macroeconomic indicators structurally affect stock price movements, allowing low-volatility portfolios to adapt continuously to this information. But when a novel risk factor rapidly becomes the dominant theme, data-driven methods understandably need some time to adjust.

To check whether COVID-19 is perhaps not the only challenging event in the sample, Exhibit 8 reports the ex post volatility of the two low-volatility indexes and the market over time. An absence of risk reduction could indicate another disruptive event or perhaps an elevated exposure to a certain overlooked systematic risk factor. However, the graphs show that, with the sole exception of the COVID-19 episode, the low-volatility portfolios delivered a consistent risk reduction compared to the market.[3]

[3] Interestingly, the MSCI Minimum Volatility Index still provided a volatility reduction during the COVID-19 period, despite experiencing a similar drawdown as the market.

EXHIBIT 7

Return during the COVID-19 Pandemic Crash, February 2020–December 2020

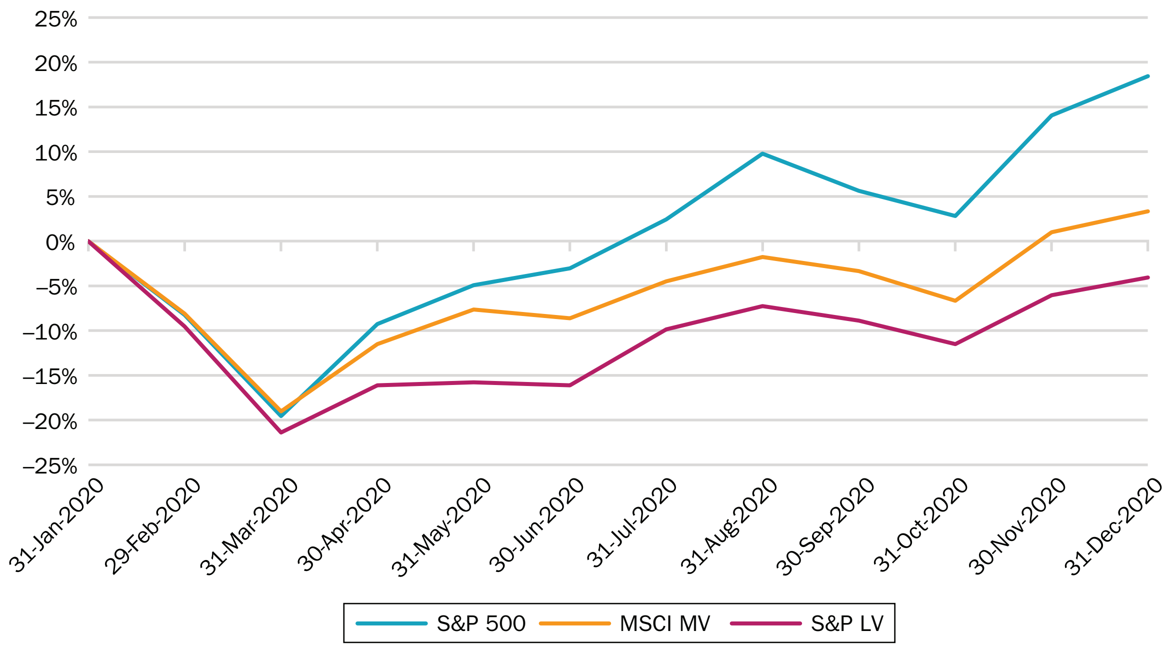
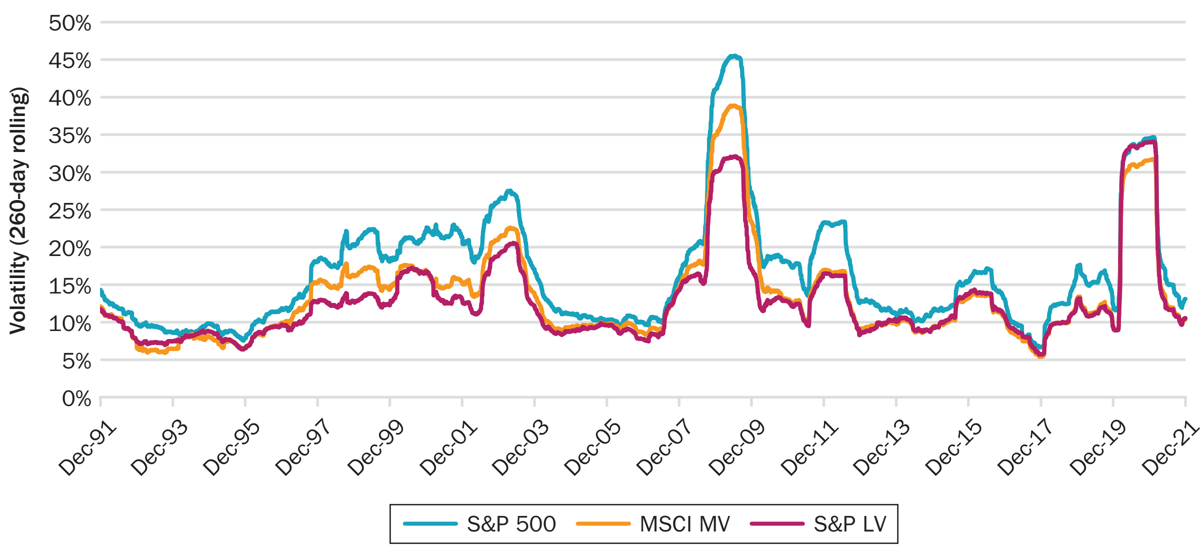


EXHIBIT 8

Volatility 260-Day Rolling

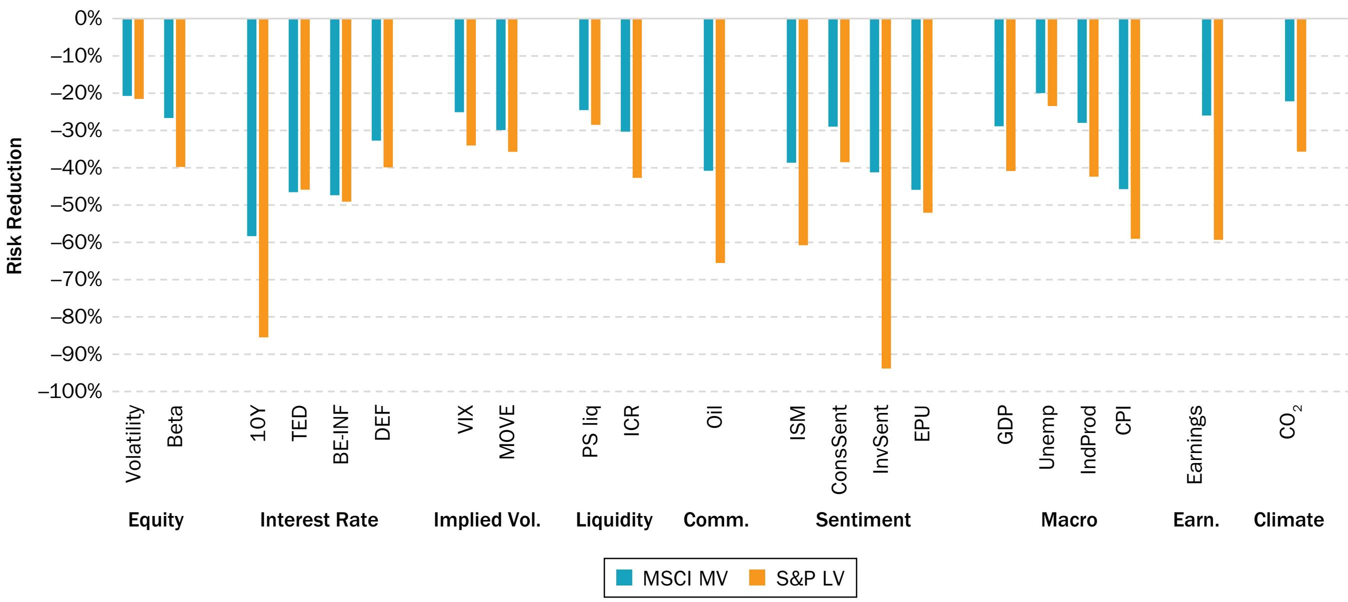


CONCLUSION

We examined the exposure of low-volatility portfolios to a wide range of systematic risk sources, including interest rate, implied volatility, liquidity, commodity, sentiment, macroeconomic, and climate risk factors. Our main result is that low-volatility portfolios do not merely reduce risk in general but also consistently lower the exposure to the various drivers of systematic risk. The summary in Exhibit 9 shows that the reductions in beta exposures range from at least 20% to over 90% across the different risk factors.

EXHIBIT 9

Summary of Risk Reduction Provided by Low-Volatility Portfolios



NOTE: This exhibit shows the reduction of the contemporaneous monthly beta for the interest rate, implied volatility, liquidity, commodity, and sentiment factors, and the reduction of beta toward next quarter data for the macroeconomic, aggregate earnings, and climate factors.

Although low-volatility portfolios offer remarkably consistent and robust risk reductions, we show that they failed to provide downside protection during the COVID-19 pandemic stock market crash of 2020. We argue that data-driven methods can be temporarily challenged by novel events that unfold very rapidly and catch the market by surprise. Altogether, our results imply that every conceivable risk factor that structurally affects security returns is effectively identified and controlled by low-volatility strategies.

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