PORTFOLIO
MANAGEMENT
RESEARCH

the journal of PORTFOLIO management

MULTI-ASSET STRATEGIES

volume 47 number 4

jpm.pm-research.com

MARCH
2021

Managing Portfolio Volatility

Michael Stamos and Thomas Zimmerer

Allianz Global Investors is a leading active asset manager with over 690 investment professionals in 23 offices worldwide and managing EUR 598 billion in assets for individuals, families and institutions.

Investing is a journey, and we seek to create value with our clients every step of the way. We invest for the long term, employing our global investment and risk capabilities and sustainable investing expertise to create innovative solutions that anticipate future needs. We believe in solving not selling – our goal is to elevate the investment experience for clients, wherever they are based and whatever their investment objectives.

Active is: Allianz Global Investors

Data as at 31 March 2021

Michael Stamos

Dr. Michael Stamos, CFA, is leading the AllianzGI Multi Asset team's development of systematic investment strategies focusing on risk management, asset allocation, risk premia investing, portfolio construction. Michael specialized in the management of Dynamic Allocation, Managed Futures, Risk Premia, and Risk Parity Funds. Michael has 17 years of R&D experience and 13 years of portfolio management experience. Michael received a PhD (summa cum laude) in Finance and holds the Chartered Financial Analyst designation. Prior to joining the firm in 2007, Michael was a Research Assistant at Frankfurt University focusing on optimizing asset allocation and retirement solutions. He has published his work in top-tier journals such Review of Financial Studies, Journal of Banking and Finance, Journal of Portfolio Management, Journal of Risk and Insurance, Journal of Economic Dynamics and Control, Insurance Mathematics and Economics, and Journal of Pension Finance and Economics, and presented his work at many conferences.

Thomas Zimmerer

Thomas Zimmerer was Global Head Multi Asset Investments and Global Head of Product Specialists Multi Asset with Allianz Global Investors, which he joined in 2014. Thomas sadly passed away far too early in December 2020, this article was the last one he could contribute to. As Global Head Multi Asset Investments, he focussed on the firm's dynamic multi-asset strategies. Thomas had investment industry experience since 1997. Before joining Allianz Global Investors, he was a professor of finance and investments at the University of Applied Science in Ansbach, Germany, and served as senior consultant for Alpha Portfolio Advisors, a Germany-based consulting firm, advising institutional investors. Prior to this, Thomas was a portfolio manager with Allianz Asset Management on active bond strategies and active protection strategies.

Thomas had an M.B.A. in economics and finance and a Ph.D. in econometrics from the Uni-versity of Regensburg, Germany.

Managing Portfolio Volatility

Michael Stamos and Thomas Zimmerer

Michael Stamos
is the director of Research-Multi Asset at Allianz Global Investors in Frankfurt, Germany.
Michael.stamos@allianzgi.com

Thomas Zimmerer
was global head of Multi Asset Investments at Allianz Global Investors in New York, NY.

KEY FINDINGS

- We find that active volatility management is beneficial for many major asset classes and for mixed asset portfolios, leading to more consistent wealth accumulation over time.
- In cross-validations, we find that fast-moving volatility forecasts seem beneficial because they have better forecasting accuracy and produce economic gains in terms of risk accuracy and performance.
- We also find significant reduction of tail risks for most assets, except for bonds, where the reduction is minor.

ABSTRACT

The authors revisit asset allocation strategies that aim at actively managing the volatility of multi-asset-class portfolios in response to time-varying volatility forecasts. They use the historical data of 29 major market indexes covering global equities, bonds, currencies, and commodities and apply a common set of exponentially weighted volatility estimates to them. The authors find that active volatility management is beneficial for most of these asset classes and for mixed asset portfolios, leading to more consistent wealth accumulation over time. In cross-validations, they find that fast-moving volatility forecasts seem beneficial because they have better forecasting accuracy and produce economic gains in terms of risk accuracy and performance. The authors also find significant reduction of tail risks for most assets, except for bonds, where the reduction is minor.

TOPICS

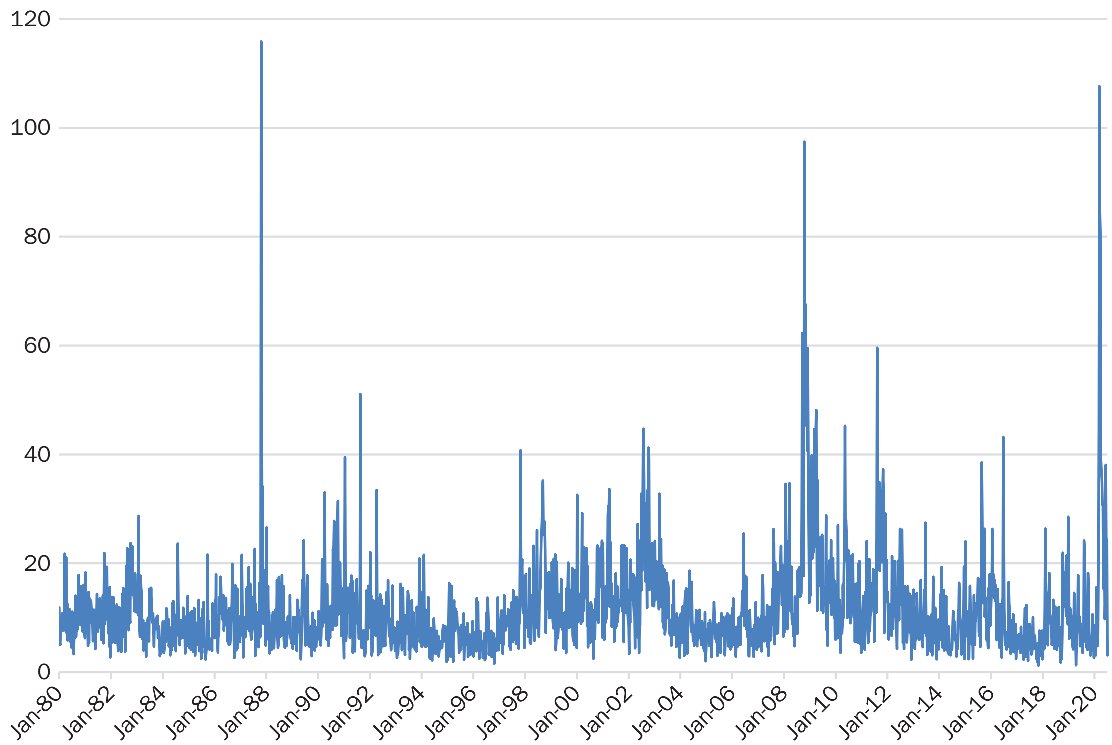
*Portfolio construction, volatility measures, risk management, tail risks, performance measurement**

Recent COVID-19–related market turmoil has dramatically shown that the assumption of constant stock market volatility is far from reality. During these volatile times—the Chicago Board Options Exchange Volatility Index, the so-called fear index, hit an all-time closing high of 82.69 on March 16 which is approximately 4 times higher than its average level. Not accounting for those swings in market volatility and involved tail risks can have potentially catastrophic outcomes and can be so distressing that panic reactions are possible. Not only option implied volatility measures but also market returns-based volatility measures have exhibited sharp moves. For example, Exhibit 1 shows the realized volatility of the MSCI World

*All articles are now categorized by topics and subtopics. View at PM-Research.com.

EXHIBIT 1

Realized Volatility of MSCI World Index (1980–June 2020)



NOTE: The exhibit shows the realized volatility of the MSCI World Index during the 2,114 weeks between January 1, 1980 and June 30, 2020, calculated based on the daily returns of MSCI World on a week-by-week basis.

Index[1] during each of the 2,114 weeks between January 1, 1980 and June 30, 2020. The chart is dominated by three towering volatility spikes—the 1987 crash, the 2008 Global Financial Crisis, and the COVID-19 pandemic crisis of 2020—at which annualized volatility rose to levels around 100%, more than six times higher than the average volatility of 15%.[2] Such events are felt as if, during that week, the allocation to equities were six times higher than the actual level. Three events in a little more than 40 years sets the probability of such events at around one event in every 10 to 15 years. Less cataclysmic, but still major, events happen when volatility doubles to above 30%. This happens approximately every 65 weeks, or, roughly speaking, between one and two times per year.[3]

Although the aforementioned empirical facts are well known, many portfolio construction processes assume that volatility is constant, either explicitly or implicitly. Although this assumption is sensible on average, there is actually a huge deviation from this average over time. Hence, we revisit the advantages and disadvantages of managing portfolio volatility. This article will ask the following questions: What is the right volatility predictor for most asset classes? Is managing portfolio volatility possible? Is managing volatility economically beneficial in terms of risk-adjusted returns? How applicable is volatility management across asset classes?

[1] We measure volatility using one of the most widely diversified stock market indexes, the MSCI World Index, which covers 23 developed countries, representing roughly 85% of the free float-adjusted market capitalization in each country.

[2] The volatility of the MSCI World Index using daily returns from 1980 to June 2020 is 14.6%.

[3] The authors prefer ranges instead of decimal point estimates to be less prone to pseudo-accuracy.

It should be noted, of course, that the benefits of volatility-managed strategies are documented in seminal papers, some dating to nearly two decades ago, such as those by Fleming, Kirby, and Ostdiek (2001, 2003), and in more recent research, such as that by Dreyer and Hubrich (2019) and Bollerslev et al. (2018). This research confirmed the positive economic value of volatility targeting for a range of asset classes, whereas Harvey et al. (2018) found that the impact on the Sharpe ratio of bonds, currencies, and commodities is negligible.

Furthermore, a wide range of volatility prediction models has been tested in the academic literature, with most studies applying rather simplistic models. Andersen and Bollerslev (1998) likewise found that standard volatility models provide accurate forecasts. In the literature, different volatility models of various complexities have been applied on different sets of assets or risk factors, and different analyses of assessing economic gains have been applied. For example, see Fleming et al. (2001, 2003), Moskowitz, Ooi, and Pedersen (2012), Asness, Moskowitz, and Pedersen (2013), Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), Moreira and Muir (2017). We seek to contribute to the existing literature generalizing and cross-validating previous work by making a consistent assessment of the benefits of volatility-managed strategies using a common set of volatility predictors for a broad set of asset classes and by conducting a common assessment of forecasting accuracy, risk-adjusted performance, and tail risks.

A BRIEF LOOK AT HISTORICAL VOLATILITY PATTERNS OF EQUITY MARKETS

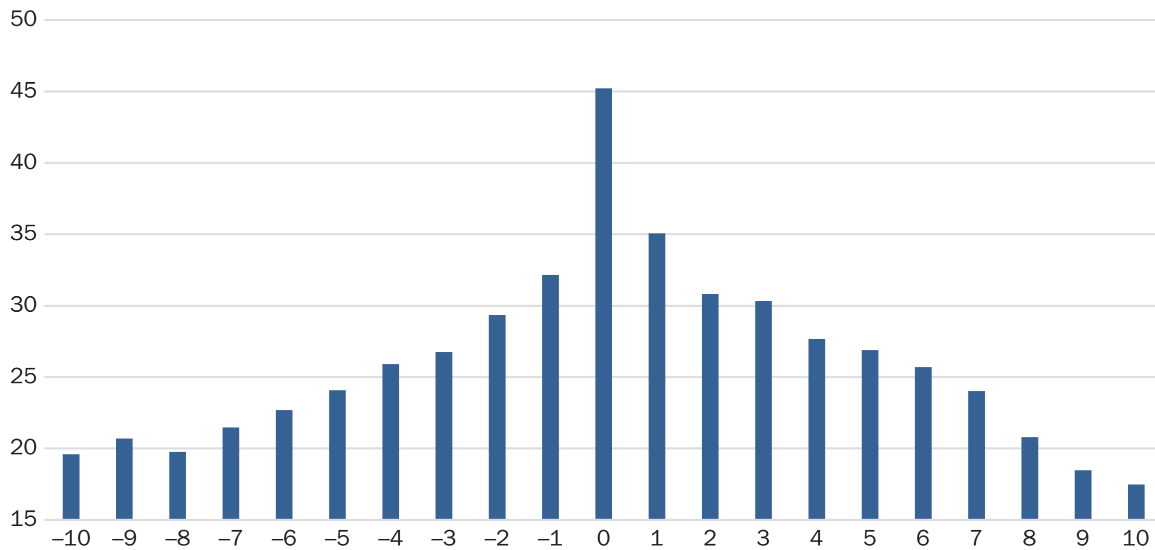
Empirical studies have established that equity market volatility is serially correlated and, hence, more predictable than a random walk process. For instance, volatility clustering describes the pattern in which above-average volatility levels tend to persist for some time. Exhibit 2 visualizes this volatility-clustering pattern by looking at average volatility levels before and after weeks with peak volatility, defined as a week's volatility being higher than 30%.

Exhibit 2 shows that average volatility rises gradually in the 10 weeks before it reaches peak levels. Furthermore, after peak volatility weeks, it takes about 10 weeks for volatility to return to more normal levels. This gradual hump shape explains why it may make sense to react to changing volatility levels in markets when managing portfolio volatility. The more common statistical way of showing this predictability is to look at the serial-correlation function of weekly volatility levels, which is depicted in Exhibit 3. High serial correlation indicates that high volatility tends to be followed by high volatility—high or above-average market fluctuation tends to last for some weeks. In financial time series, correlation numbers are seldom so high and so significant.

It is natural to ask whether the degree of predictability prevailed over time or whether it was high in the beginning and then faded. For instance, the cost of information gathering and that of trading have shrunk with better information technology and with markets and information becoming more liquid. From a statistical point, the short answer is: Yes, volatility is still, to some degree, predictable. A look at the autocorrelation functions for each of the past four decades (Exhibit 4) shows a similar degree of persistency during all decades, with the decade 2010–2020 ranging in the middle for most lags. In addition, the shape of the autocorrelation function with its exponential decay is very similar for all decades. This indicates that a similar type of volatility predictor could be used for all decades without losing too much information. This result overall is rather surprising at first glance because it seems to contradict the notion that markets become more efficient. Yet a violation of market efficiency is not needed because it does not imply that abnormal returns can be generated.

EXHIBIT 2

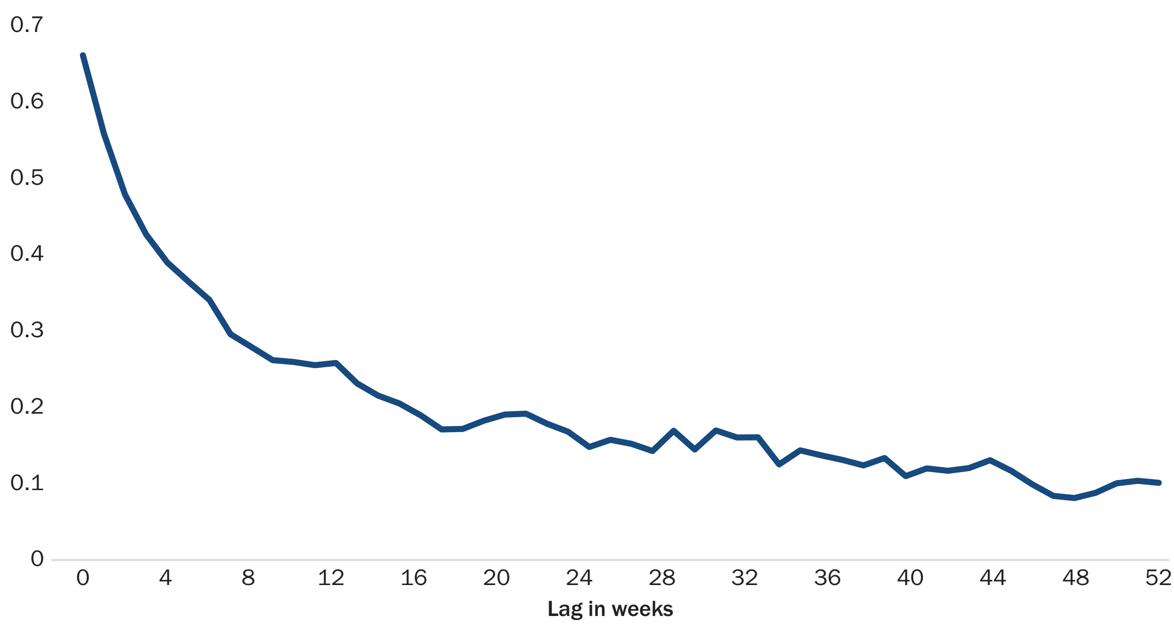
Average Volatility in Weeks Surrounding Weeks with Volatility of 30% or More



NOTES: This exhibit shows average volatility on a week-by-week basis around weeks with volatility higher than 30%. The volatility peak is per definition located at week 0 on the *x*-axis. The calculation is based on the week-by-week volatility of MSCI World from January 1, 1980 to June 30, 2020. Negative numbers represent weeks before those weeks in which volatility was >30%, with positive numbers in the subsequent weeks.

EXHIBIT 3

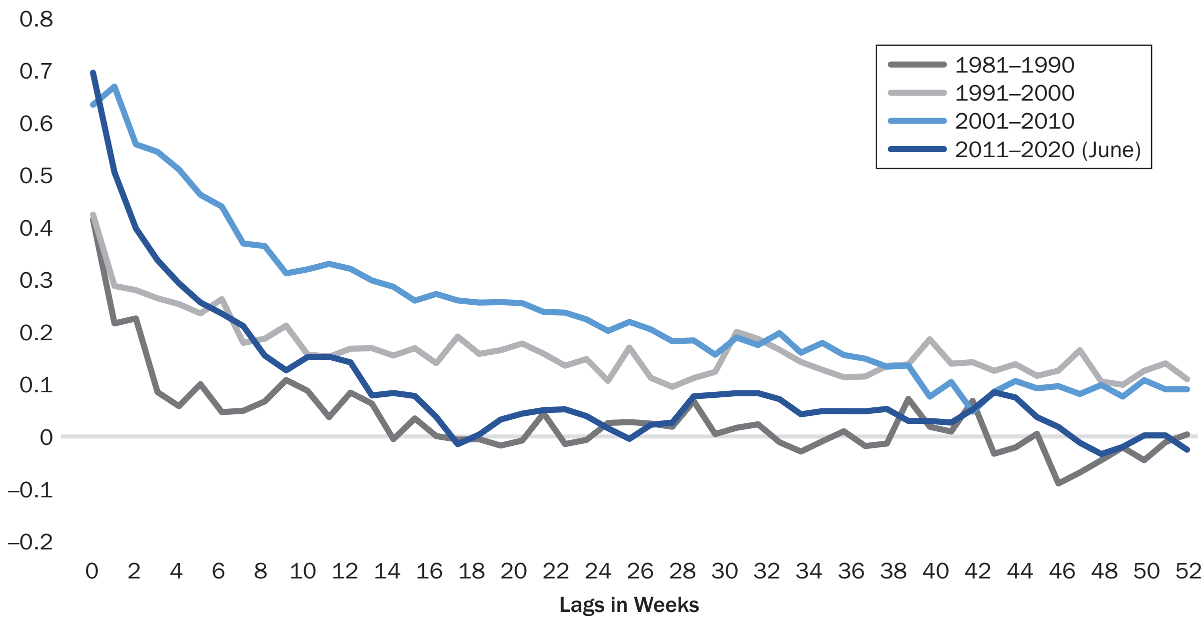
Serial Correlation of Week-by-Week Volatility



NOTES: This exhibit shows the serial correlation of weekly volatility between a lag of 1 week to 52 weeks. The calculation is based on the week-by-week volatility of MSCI World from January 1, 1980 to June 30, 2020.

EXHIBIT 4

Serial Correlation of Weekly Volatility on a Decade-by-Decade Basis



NOTES: This exhibit shows the serial-correlation function of week-by-week volatility for each decade from January 1, 1980 to June 30, 2020. Calculation is based on week-by-week volatility of MSCI World over the period.

After all, it is only the size of the market move that can be somewhat predicted, not the actual direction of the move.

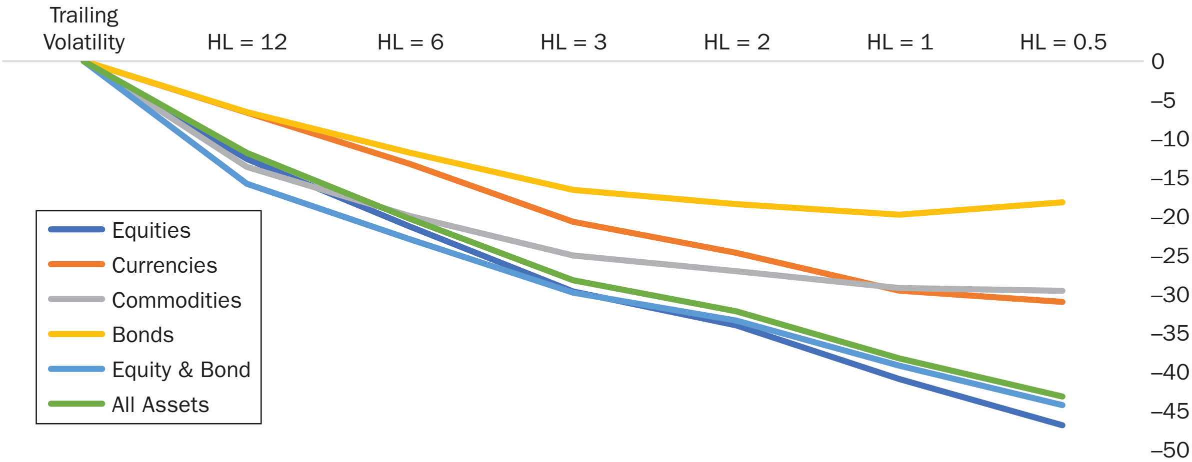
FORECASTING VOLATILITY: A CROSS-ASSET PERSPECTIVE

This section expands the analysis to a broad and global asset class universe that covers major financial markets. Specifically, it consists of eight equity markets, six currencies, six commodities, and nine bond markets (for a list of indexes used, see the Appendix). In the following analysis, we mostly use actual traded instruments such as futures contracts to make this study as realistic and tradeable as possible. One exception is currencies, in which we use daily carry-adjusted performance indexes. What all the indexes have in common is that they represent excess returns above the riskless interest rate. In a next step, we construct for all these markets six equal-weighted portfolios—equities, currencies, commodities, bonds, equities and bonds, and all assets—and compute their daily return streams starting on January 1, 1990 to have as many indexes as possible available. To formalize the predictive accuracy of the volatility prediction, we define the forecast error as the average of the squared differences of estimated volatility in a week minus the realized volatility in the subsequent week. Please note again that we avoid overlapping observations by measuring a week's volatility using its five single-day returns. In Exhibit 5, it becomes apparent that exponentially weighted moving average (EWMA) volatility estimates have improved volatility forecasting accuracy compared to a simple trailing volatility estimate, which uses all past data.[4] The reduction in the forecast error is between

[4] Among the multitude of ways to model volatility, we chose a parsimonious way, fully aware that there are basically limitless possibilities. We do so because we want to show that even with the most direct and transparent volatility model, there are benefits. If there would be benefits only when using

EXHIBIT 5

Reduction of Forecast Error (%) of EWMA Estimates vs. Trailing Volatility Estimates



NOTES: The exhibit shows a reduction in the mean-squared forecast error of EWMA estimates with various half-lives (HL) relative to the trailing volatility estimate. The trailing volatility estimate uses all the trailing daily returns in an equal-weighted manner. The EWMA estimates are exponentially weighted with half-lives defined in number of months. The calculation is based on data of 29 capital market indexes and evaluated for the period January 1, 1990 to June 30, 2020.

15% for an EWMA estimate with a 12-month half-life and up to 40% for a 0.5-month half-life. The substantial reduction of the forecast error is also consistent across all six equal-weighted, single-asset portfolios.

MANAGING PORTFOLIO VOLATILITY AND HITTING A VOLATILITY TARGET

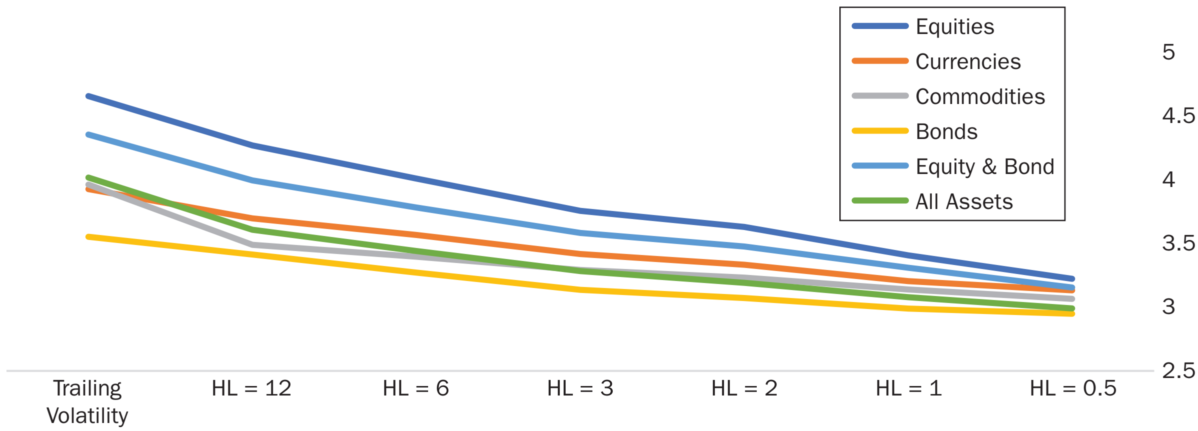
The preceding analysis implies that volatility levels are somewhat predictable and that large daily market moves tend to be followed by large moves again for some short time frame. If the investor has a strong preference for stable volatility over time, the required policy would be to reduce the exposure to equities once a large move has happened, in anticipation of future elevated volatility. Although most investors implicitly target a volatility level, there are very different approaches to this risk-budgeting exercise. The most prominent way is investors forming a belief about long-term or average asset class volatility and sizing their investment according to this belief. These estimates are usually derived from many years of trailing history, equally weighted. Such trailing volatility estimates hardly move over time so that allocations are rather stable in nature and very close to a fixed strategic asset allocation. A second approach is more dynamic, by giving more weight to recent market volatility. This is usually done by applying EWMA volatility estimates, which, by definition, use exponentially weighted volatility estimates.[5] The benefit may be that strategies using EWMA estimates are better at hitting a certain volatility target because they have better volatility forecasting accuracy. We run managed volatility portfolios (MVPs)

the most complicated model, we would doubt the validity and would have concerns about hindsight bias in model selection. In addition, the focus of this study is more to show that volatility persistency is a feature in most major asset classes.

[5] Other ways are to be more tactical by using much more complex qualitative or quantitative approaches to predict risk events, or using options to manage tail risks.

EXHIBIT 6

Average Difference (%) between Realized Volatility and Target Volatility



NOTES: The exhibit shows how well volatility targeting strategies hit the volatility target of 10%. This is calculated for volatility targeting strategies that use trailing volatility and EWMA-type volatility forecasts with half-lives (HL) expressed in months. Calculation is based on data of 29 capital market indexes and evaluated for the period January 1, 1990 to June 30, 2020.

targeting a volatility of 10% and use the following portfolio-sizing mechanism at each point in time:

$$\text{Target exposure} = \frac{\text{Target volatility}}{\text{Forecasted volatility}}$$

Based on the this portfolio policy, we compute the daily returns of each MVP, and then we compute the time series of the MVPs' realized volatility on a week-by-week basis. Exhibit 6 shows that the realized volatility of MVPs fluctuates by a substantial degree around the volatility target of 10%. For all portfolios checked, the widest fluctuation happens when applying the slow-moving trailing volatility estimate. On average the absolute deviation is approximately four percentage points around the 10% target. Using EWMA-type estimates reduces the fluctuation to slightly above 3% when using the fastest estimate with a half-life of 0.5 months. This result, after all, is in line with our previous finding that faster-moving EWMA-type estimates have better forecasting accuracy for all portfolios tested.

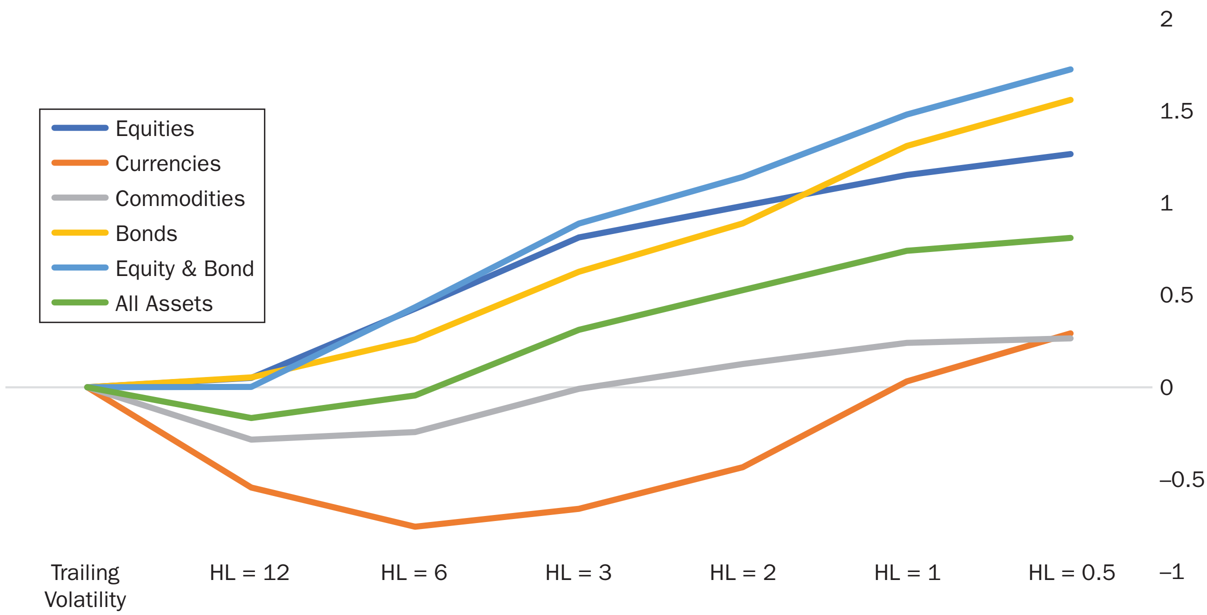
ECONOMIC GAINS MEASURED BY RISK-ADJUSTED RETURNS

Next, we assess the impact on performance by measuring risk-adjusted returns for the MVP determined earlier. Although hitting a volatility target may be one of an investor's preferences, it is also necessary to understand whether this comes at a performance cost or performance advantage.

To make all tested MVP returns comparable on a risk-adjusted basis, we scale all strategy returns to reach a volatility of exactly 10% per year. The simple trailing volatility strategy especially can be quite far off the 10% target; hence, a scaling of returns is necessary. We measure the return improvement as alpha relative to the volatility target–based strategy. The better volatility target accuracy tends not to cost return but instead to slightly increase return. The strongest and most consistent improvements are visible for equities and bonds, although results are mixed for commodities and currencies (Exhibit 7).

EXHIBIT 7

Annualized Outperformance (%) of EWMA Volatility Estimate Portfolios vs. Those Using Trailing Volatility Estimates



NOTES: The exhibit shows the outperformance of EWMA-based volatility targeting versus full trailing volatility–based targeting. All strategies' return streams are scaled to have a volatility of exactly 10% to make risk-adjusted performance comparable. The calculation is based on data of 29 capital market indexes and evaluated for the period January 1, 1990 to June 30, 2020.

However, EWMA estimates with a 0.5-month half-life have a fairly robust, positive alpha across all tested portfolios. Alphas range up to levels of above 1% for equities and bonds to slightly below 0.5% for currencies and commodities portfolios.

A LOOK AT TAIL RISKS

One aim of volatility-targeting strategies is to dampen the downside risks to avoid catastrophic returns. We deem catastrophic returns those that have the potential to destroy, in a relatively short period of time, the performance of multiple years. This could be especially devastating if investors are close to retirement; for example, Hocquard, Ng, and Papageorgiou (2013) showed that volatility targeting normalizes the negatively skewed return distribution of an equity portfolio, thereby lowering tail risks. We expand that knowledge of target volatility's risk management function to a cross-asset context. Exhibit 8 shows that tail risks in all asset classes, except bonds, can be substantially reduced through using EWMA estimates, not only for equities but also for other asset classes. For instance, in the case of equities, the reduction is from an almost 24% loss to, in the best case, a 17% loss. Furthermore, in the case of currencies and commodities, there are substantial reductions in tail risks. In the case of bonds, there is a small benefit only if very fast half-lives are used. It also becomes clear that the best tail risk mitigation was achievable with short half-lives of 0.5 and 1 month.

CONCLUSIONS

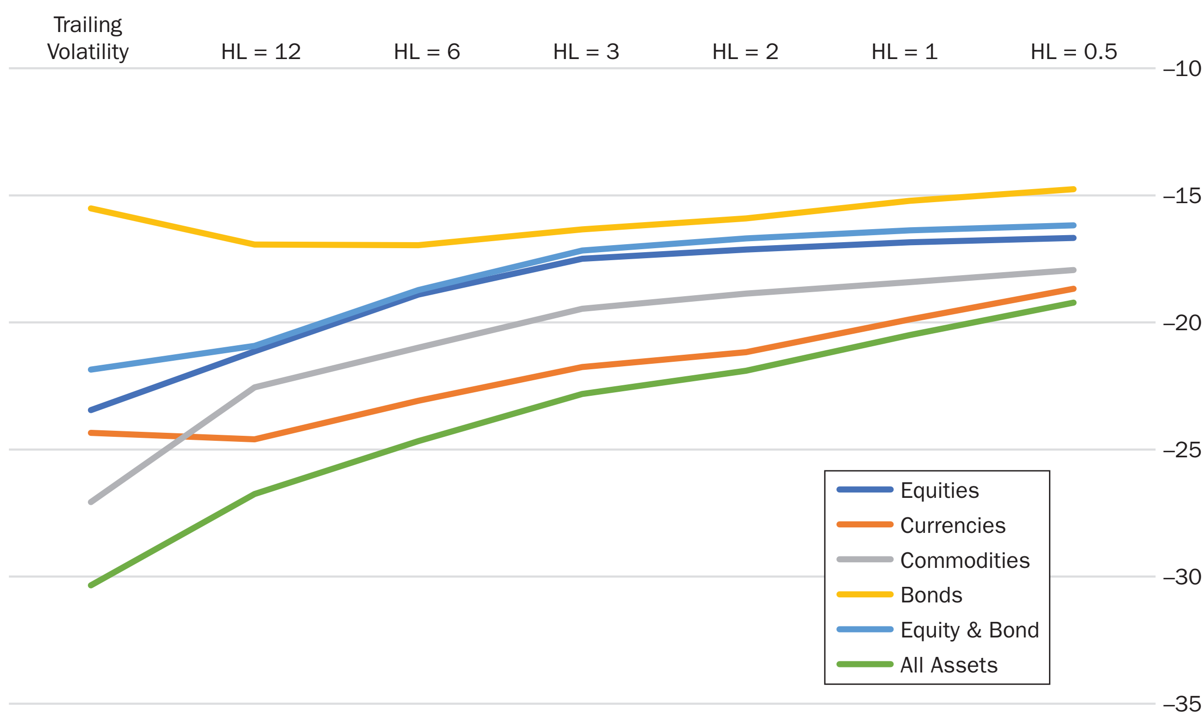
In light of the pandemic-induced volatility spike in equity markets during March 2020, the purpose of this study is to revisit the benefits of active volatility management in equity markets and in other asset classes such as bonds, currencies, and commodities, altogether covering 29 prominent indexes.

Our research finds that predictability in equity market volatility has been evident for decades, even as markets and information access became increasingly efficient. That volatility predictability can be exploited by using dynamic allocation strategies, which has historically led to smaller fluctuation in portfolio volatility, lower tail risks, and higher Sharpe ratios. These results were largely cross-validated in other asset classes, such as bonds, currencies, and commodities.

Our research also found that volatility predictor speeds are important and that exponential estimates with short half-lives of 0.5 or 1 month delivered the best forecasting accuracy consistently across all asset classes. Managed volatility portfolios using estimates with short half-lives consistently led to the most substantial reduction in volatility fluctuation. The data reveal that risk-adjusted performance improvements were strong for equities and bonds and were mixed to negative for currencies and commodities. Finally, tail risks were reduced for equities, currencies, and commodities to a substantial degree, with smaller tail risk reduction for bond portfolios.

EXHIBIT 8

Conditional Value-at-Risk (1%) over 120 Days for Target Volatility Strategies with Realized Volatility of 10%



NOTES: The exhibit shows conditional value at risk (calculated at 1%) over 120 days using daily returns for target volatility strategies that use full trailing volatility forecasts and EWMA volatility forecasts. All return streams are scaled to have a volatility of exactly 10% to make tail risks comparable. Calculation is based on data of 29 capital market indexes and evaluated for the period January 1, 1990 to June 30, 2020.

APPENDIX

EXHIBIT A1

Descriptive Data of Asset Classes

Name	Ticker	First Date	Arith. Return p.a. (%)	Volatility p.a. (%)	Skew	Kurtosis
US Equities	SP1 Index	April 23, 1982	8.7	19.3	–1.0	49.5
CAN Equities	PT1 Index	September 9, 1999	6.2	19.3	–0.5	15.7
GE Equities	GX1 Index	November 27, 1990	7.3	22.5	–0.1	6.6
FR Equities	CF1 Index	December 9, 1988	6.0	22.0	–0.1	5.7
UK Equities	Z1 Index	March 1, 1988	4.5	18.0	–0.1	6.5
JP Equities	TP1 Index	May 18, 1990	1.5	22.8	0.1	9.4
AU Equities	XP1 Index	May 4, 2000	4.7	16.7	–0.5	8.7
HK Equities	HI1 Index	April 3, 1992	10.2	27.3	0.5	13.0
Yen	JPYUSDCR Curncy	January 3, 1989	–1.1	10.7	0.4	5.7
AUD	AUDUSDCR Curncy	January 2, 1985	3.0	11.8	–0.3	8.9
EUR	EURUSDCR Curncy	January 3, 1989	0.1	9.8	0.0	1.9
GBP	GBPUSDCR Curncy	January 9, 1987	1.3	9.7	–0.4	6.3
BRL	BRLUSDCR Curncy	January 4, 1999	3.9	17.5	–0.1	9.7
MXN	MXNUSDCR Curncy	January 4, 1999	2.4	11.6	–0.6	10.3
Gold	GC1 Comdty	January 6, 1975	1.9	19.1	0.0	7.3
Oil	CL2 Comdty	April 4, 1983	7.2	34.8	–0.6	17.7
Nat Gas	NG1 Comdty	April 5, 1990	–7.7	49.2	0.5	5.8
Copper	HG1 Comdty	December 8, 1988	6.1	26.0	0.0	4.5
Corn	C1 Comdty	January 6, 1970	–3.5	23.1	0.1	2.6
Soybean Oil	S1 Comdty	January 6, 1970	3.8	23.4	–0.1	3.1
US Long Bonds	US1 Comdty	August 24, 1977	4.3	11.1	0.0	2.6
US Bonds 10Y	TY1 Comdty	May 5, 1982	4.6	6.6	0.1	3.7
US Bonds 2Y	TU1 Comdty	June 27, 1990	1.4	1.6	–0.1	6.1
GE Long Bonds	UB1 Comdty	October 6, 1998	6.1	11.3	–0.2	2.7
GE Bonds 10Y	RX1 Comdty	November 27, 1990	4.4	5.3	–0.2	2.0
GE Bonds 2Y	DU1 Comdty	March 11, 1997	0.8	1.2	–0.3	6.1
CAN Bonds	CN1 Comdty	September 19, 1989	3.8	6.1	–0.2	2.3
UK Bonds	G1 Comdty	November 22, 1982	3.1	7.3	0.0	3.7
JP Bonds	JB1 Comdty	October 22, 1985	2.9	4.6	–0.7	12.9

REFERENCES

Andersen, T., and T. Bollerslev. 1998. "Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts." *International Economic Review* 39 (4): 885–905.

Asness, C., T. Moskowitz, and L. Pedersen. 2013. "Value and Momentum Everywhere." *The Journal of Finance* 68 (3): 929–985.

Bollerslev, T., B. Hood, J. Huss, and L. Pedersen. 2018. "Risk Everywhere: Modeling and Managing Volatility." *The Review of Financial Studies* 31 (7): 2729–2773.

Daniel, K., and T. Moskowitz. 2016. "Momentum Crashes." *Journal of Financial Economics* 122 (2): 221–247.

Dreyer, A., and S. Hubrich. 2019. "Tail Risk Mitigation with Managed Volatility Strategies." *The Journal of Investment Strategies* 8 (1): 29–56.

Fleming, J., C. Kirby, and B. Ostdiek. 2001. "The Economic Value of Volatility Timing." *The Journal of Finance* 56 (1): 329–352.

——. 2003. "The Economic Value of Volatility Timing Using 'Realized' Volatility." *Journal of Financial Economics* 67 (3): 473–509.

Harvey, C., E. Hoyle, R. Korgaonkar, S. Rattray, M. Sargaison, and O. van Hemert. 2018. "The Impact of Volatility Targeting." *The Journal of Portfolio Management* 45 (1): 14–33.

Hocquard, A., S. Ng, and N. Papageorgiou. 2013. "A Constant-Volatility Framework for Managing Tail Risk." *The Journal of Portfolio Management* 39 (2): 28–40.

Moreira, A., and T. Muir. 2017. "Volatility-Managed Portfolios." *The Journal of Finance* 72 (4): 1611–1644.

Moskowitz, T., Y. Ooi, and L. Pedersen. 2012. "Time Series Momentum." *Journal of Financial Economics* 104 (2): 228–250.