Volatility:

As Simple As Standard Deviation?

Introduction

Richard Yasenchak, CFA
Senior Managing Director,
Head of Client Portfolio Management
June 2025

In today's markets, investors must measure risk with care. Whether managing personal savings or institutional portfolios, they often rely on annualized risk estimates to guide capital allocation and long-term planning.

Underestimating risk, even modestly, can lead to unintended downside exposure, capital misallocation, or misinterpretation of a strategy's risk-adjusted return. For long-term investors, risk managers, and fiduciaries, such misjudgments can undermine portfolio objectives.

Volatility is typically viewed as a source of risk, but it can also be a source of return (notably Fernholz, *Journal of Finance*, 1982). Reliable volatility estimates are therefore critical for portfolios seeking to harness it for alpha. In this context, investors must estimate volatility precisely: not just to manage risk, but to enhance performance.

Investors measure portfolio volatility in different ways, often based on the frequency of returns – daily, monthly, or even intraday – as well as the lookback period and the purpose of the estimate. They can observe and report returns precisely, but they must estimate and interpret volatility. That makes it a more nuanced measure, especially when the goal is to forecast future risk rather than simply describe past behavior.

In principle, a true level of portfolio volatility exists: it reflects the inherent variability in a portfolio's return distribution. But investors cannot observe it directly, no matter how frequently they measure returns. Instead, they estimate it using different methods, shaped by the chosen time period, sampling technique, and underlying assumptions — especially when using volatility to support return forecasting, risk budgeting, or portfolio construction decisions.

This paper outlines the limitations of simplistic volatility scaling. We highlight how return structures (particularly autocorrelation, volatility clustering, and extreme outcomes) can materially distort annualized risk. We also illustrate that these effects vary over time, underscoring the value of a dynamic, data-informed approach to risk measurement.

Why Static Scaling Fails: The Role of Serial Correlation

Most investors annualize volatility under the assumption that returns are identically and independently distributed, which implies no autocorrelation and a normal return distribution. Practitioners typically start with monthly return data and apply a simple scaling rule to estimate annual volatility. This shortcut depends on the assumption that returns are independent over time. But that assumption is often dubious: markets frequently violate it, especially during periods of stress or structural change.

That said, it's important to note that more sophisticated models, such as those used in risk systems like Barra, do account for certain autocorrelation effects such as negative autocorrelation. Moreover, volatility estimation does not require returns to follow a normal distribution. We can measure volatility for any distribution; it simply carries different implications in a normal framework.

While return autocorrelations are often close to zero on average, temporary deviations may still bias volatility scaling if not addressed carefully. These deviations reflect a deeper reality: markets often exhibit patterns where past returns influence future ones.

- Negative autocorrelation implies mean-reversion: gains tend to follow losses, and vice versa. This dampens realized risk.
- Positive autocorrelation suggests momentum: gains follow gains, or losses follow losses. This can magnify annualized volatility.

These structures matter because volatility is not just dispersion, but also sequence. **Static rules that ignore this can underestimate or overestimate risk depending on the regime.**

Two hypothetical examples illustrate this point:

1. Investment A alternates monthly between +25% and -20% returns. Its average monthly return is 2.5% and monthly standard deviation is 23%, but its value resets each year. The annualized return is 0%, and the true annual standard deviation is also 0%, far below the 80% estimate from applying the common √12 rule to monthly returns. It highlights how perfect negative autocorrelation can result in zero annual volatility despite high monthly volatility.
2. Investment B gains +20% in the first month of odd years and +1% thereafter; in even years, it loses -20% in the first month and -1% thereafter. Its average monthly return is 0% and monthly standard deviation is 6%. The compound return is -2.1% and the √12 rule estimates annual volatility at 20.7%. However, its actual annual standard deviation is 31.2% due to compounding.[1] It shows how uneven compounding (i.e., volatility timing and sequencing) causes actual annual volatility to be higher than the naïve √12 estimate.

These stylized cases show how the sequence of returns, not just their dispersion, drives realized volatility. Lo and MacKinlay (1988) showed that autocorrelation alone can materially affect volatility estimates.

[1] The annual returns are +33.9% and –28.4%; the arithmetic average of the two is 2.75%; the variance is 0.097, so the standard deviation is $\sqrt{0.097} \approx 31\%$.

Autocorrelation in Real Markets: A Dynamic Pattern

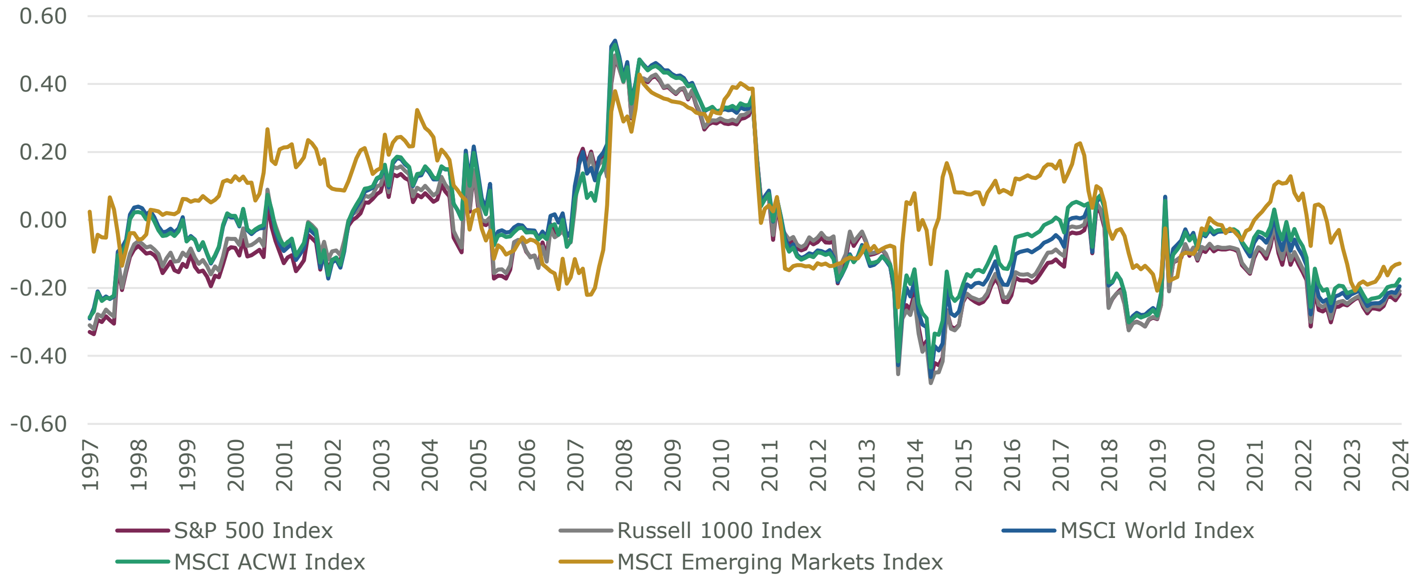
We analyzed monthly returns from 1995 to 2024 across major equity benchmarks. Full-period autocorrelation appears low, but this average will mask important time variation.

Benchmark	Annual Standard Deviation	Annualized Monthly Standard Deviation	Autocorrelation (1-Month Lag)
S&P 500 Index	18.34%	15.20%	0.00
Russell 1000 Index	18.43%	15.42%	0.01
MSCI World Index	17.82%	15.18%	0.04
MSCI ACWI Index	18.05%	15.35%	0.05
MSCI EM Index	29.21%	21.61%	0.11

Even with near-zero average autocorrelation, realized annual volatility often exceeds scaled monthly estimates, especially in emerging markets. Rolling autocorrelation reveals the broader pattern:

Figure 1:

ROLLING 36-MONTH AUTOCORRELATION (1-MONTH LAG) FOR VARIOUS INDEXES, 1995-2024



During 2001–2002 and 2008–2009, positive autocorrelation amplified volatility as market trends persisted. In contrast, negative autocorrelation in the late 1990s and mid-2000s dampened volatility through mean reversion. These shifts underscore the importance of treating return behavior as dynamic.

Beyond Autocorrelation: Other Distortions in Annualized Risk

Autocorrelation is only one way that return patterns can distort volatility estimates. Other structural features (especially volatility clustering, extreme outcomes, and compounding) further weaken the reliability of static volatility scaling. Volatility clustering refers to the persistence of elevated or subdued volatility over time, a well-established phenomenon in empirical finance. Even when monthly standard deviations appear stable, long sequences of elevated volatility can drive annual risk far above naive expectations. Compounding also plays a role: monthly returns accumulate multiplicatively, so the distribution of annual returns is not a linear extension of monthly behavior. Meanwhile, calendar-driven anomalies, such as tax-loss selling or seasonal flows, can create return sequences that defy simple statistical modeling.

Perhaps most significantly, **financial returns rarely follow a normal distribution**. They often exhibit fat tails and skewness, meaning that extreme events are more common and returns more imbalanced than traditional models assume. Foundational research in both statistics and finance highlighted these departures decades ago (most notably by Mandelbrot, 1963, on heavy tails and Fama, 1965, on market efficiency under non-normal returns), and more recent studies continue to observe these characteristics in modern markets (e.g., Cont, 2001; *Journal of Finance*, 2024; NAJEF, 2022).

For example, recent analysis of U.S. equity markets shows growing fluctuations in both skewness and kurtosis points to an increased frequency and severity of extreme return events. Skewness reflects asymmetry in returns, indicating whether outliers are more likely to be positive or negative. Most equity markets exhibit negative skews, meaning that risk models that assume symmetry may underestimate the likelihood of sharp losses. Kurtosis captures the likelihood of extreme moves in either direction. Both dimensions help explain why financial markets often defy the assumptions of conventional models. (See the following figures 2 and 3.)

Figure 2: More downside than upside shocks in U.S. stocks

250-DAY SKEWNESS OF DAILY RETURNS: S&P 500 INDEX OVER THE PAST 30 YEARS

As of March 31, 2025

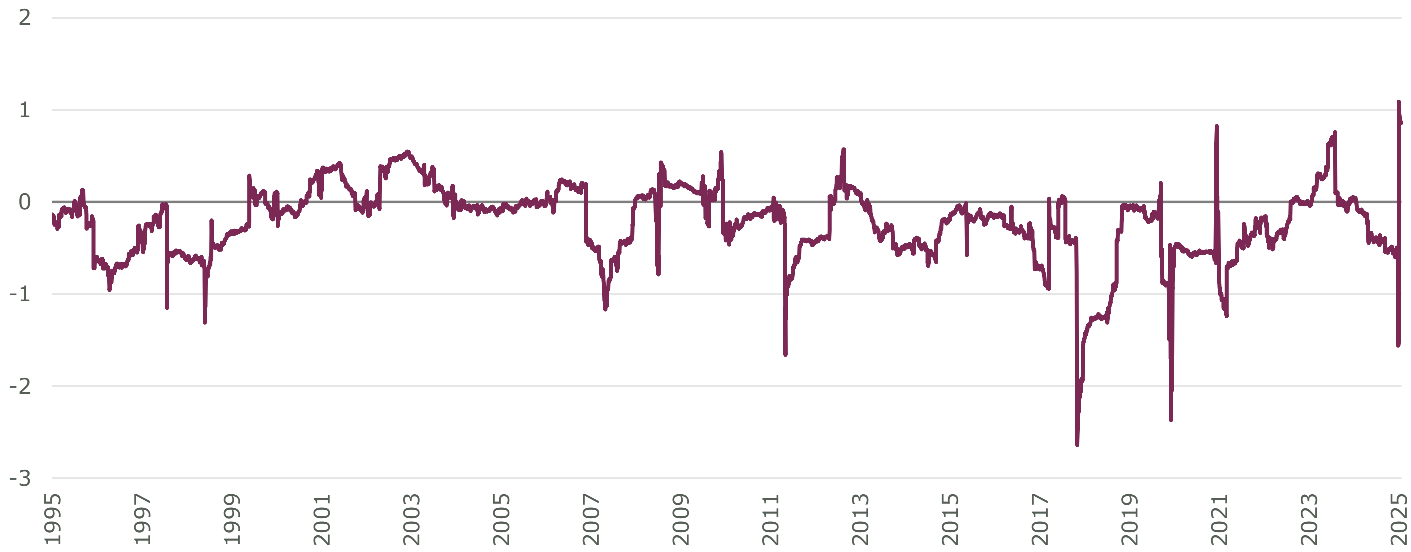
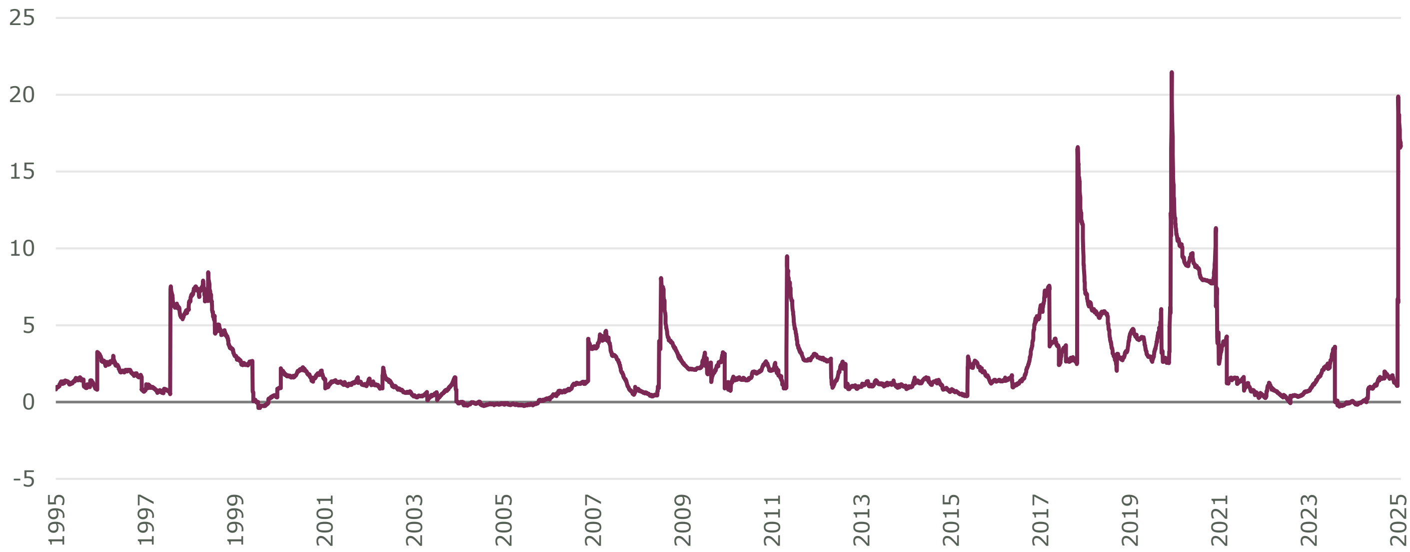


Figure 3: Extreme moves increasing in U.S. stocks

250-DAY KURTOSIS OF DAILY RETURNS: S&P 500 INDEX OVER THE PAST 30 YEARS

As of March 31, 2025



These patterns have significant implications for risk management, as simplified assumptions (even those that appear conservative) can materially underestimate real-world downside risk. This is particularly relevant when modeling forward-looking risk measures such as Value at Risk (VaR), expected shortfall, expected tracking error, and expected volatility, each of which can potentially misrepresent actual risk if based on unrealistic distributional assumptions.

Why This Matters for Investors

The implications of these distortions extend well beyond theoretical modeling: they shape real-world decisions. If investors underestimate volatility, they may unknowingly increase position sizes, misjudge portfolio diversification, or take on leverage levels that appear justified on paper but expose them to larger drawdowns in practice.

Even seemingly small differences in volatility assumptions can materially affect expected Sharpe ratios, making some strategies appear more efficient than they truly are. This, in turn, influences manager selection, strategy approval, and overall confidence in a portfolio’s construction. Governance challenges also emerge when risk constraints are breached, not due to portfolio behavior, but because the underlying risk metrics failed to capture shifting dynamics. For institutions managing capital over decades, inaccurate volatility forecasts can lead to flawed liquidity planning, affecting everything from redemption policies to cash flow expectations during times of stress.

As automated tools and machine learning play a greater role in portfolio oversight, the need for precision may grow. When models are trained on oversimplified or static assumptions, they risk perpetuating poor decisions. In an environment where risk itself is dynamic, **investors must treat volatility estimation as a core input — not a mechanical output.**

How Intech Approaches Volatility Differently

At Intech, we treat volatility as a structural feature of markets, not just noise to be managed. Our process is designed to recognize that volatility, when captured correctly, can serve as a return source and not solely a source of risk.

We avoid generic scaling shortcuts. Instead, we monitor volatility and correlation behavior using daily data and proprietary models. Our portfolios are designed to adjust to changing risk conditions, identifying periods when return persistence (or mean reversion) may signal hidden risks or potential rewards.

Our rebalancing process plays a central role. By reallocating capital as volatility evolves, we maintain broad diversification and systematically capture inefficiencies. Volatility informs decisions across the process: from stock selection to portfolio construction to execution.

Across all our equity strategies (long-only, 130/30 extension, or defensive), we integrate stock-level and volatility-level signals. **This approach potentially allows us to pursue consistency, reduce dependence on directional market views, and support long-term portfolio risk efficiency.**

Conclusion

Measuring risk is more than a technical detail, it’s a foundational step in portfolio management. Relying on outdated shortcuts can produce risk estimates that mislead more than they inform.

Investors should adopt methods that reflect the true complexity of market behavior, including autocorrelation, volatility clustering, and fat tails. By moving beyond static assumptions, they can make better-informed decisions and construct portfolios better equipped for uncertainty.

The goal is not to add complexity, but to improve the accuracy of risk measurement. More accurate risk measurement can better support strategy evaluation, enhance governance, and help maintain investor confidence in a changing market environment.

Lastly, precision in volatility estimation isn’t just about controlling risk; it can also help identify opportunity. For investors seeking to harness volatility as a potential contributor to return, over- or underestimating volatility not only exposes portfolios to downside risk, but also limits the ability to capture alpha. Effective risk measures, therefore, serve both defensive and offensive roles in a portfolio by adapting to evolving data and market structures.

About Intech

Intech is a global quantitative asset manager that applies advanced mathematics and systematic portfolio rebalancing to harness a reliable source of excess returns and a key to risk control — stock price volatility. Intech applies its investment approach across four investment platforms which differ by risk-return objective: relative or absolute. Intech also integrates fundamental-based information to identify stocks with favorable underlying characteristics, complementing its volatility-based models that target stocks with attractive trading profit potential due to their volatility characteristics. These strategies only differ by the client's desired benchmark and risk budget and include enhanced equity, active equity, defensive equity, and absolute return investment solutions within the U.S., global, and non-U.S. regions.

Main Office

Intech Investments, LLC

250 South Australian Avenue

Suite 1700

West Palm Beach, FL 33401

United States of America

+1-561-775-1100

Disclaimer and Other Important Information

The information expressed herein is subject to change without notice based on market or other conditions. The views presented are for general informational purposes only and do not constitute investment advice, an offer to sell, or a solicitation of an offer to buy any security, investment product, or service. Nothing herein should be construed as a recommendation, endorsement, or sponsorship of any company, security, or investment strategy, nor does it purport to address the financial objectives, situation, or specific needs of any individual investor or organization. This information should not be the sole basis for any investment decision. The appropriateness of a particular investment or strategy will depend on individual circumstances and objectives.

All information is provided as of the publication date and may be superseded by subsequent market developments or other events. Past performance is not indicative of future results. Investing involves risk, including the possible loss of principal and fluctuation of value. The value of investments may go down as well as up, and investors may not recover the full amount originally invested.

Certain references herein to proprietary models or quantitative methodologies reflect the firm's current approach and are subject to change. These models have inherent limitations, including assumptions about market behavior, data accuracy, and sensitivity to unforeseen events. No model can guarantee future performance or prevent loss.

Information contained herein may include data or insights derived from third-party sources believed to be reliable, but we do not guarantee its accuracy or completeness. We disclaim any liability for errors or omissions arising from such third-party information.

This material is intended solely for use by institutional investors and is not intended for public distribution. It may not be distributed or used in any jurisdiction where such distribution would be contrary to local laws or regulations. Access to this material by non-qualified investors is strictly prohibited.

Indexes are unmanaged, do not incur management fees, and cannot be invested in directly.

Hypothetical or illustrative examples provided are for informational purposes only, do not reflect actual trading or investment results, and should not be relied upon as indicative of future performance.