

**Volatility Spillover and Asset Allocation: Equity-Currency Spillover Effects
During Macroeconomic Shocks Across the World's Largest Economies**

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Abstract

This study examines the importance of volatility spillovers in global asset allocation through the evaluation of spillover-based portfolio optimization strategies, comparing risk-adjusted performance against traditional correlation-based methodologies. Utilizing daily equity index and currency data from the 25 largest global economies over a twenty-five year period, the application of the Diebold-Yilmaz volatility connectedness framework allows for the quantification of directional and net spillovers across asset classes. Utilizing spillover structures estimated through vector autoregressive (VAR) and forecast error variance decompositions (FEVD) models, the time-varying interdependence driven by macroeconomic and geopolitical certainty can be quantified through four portfolio strategies: Equity portfolios optimized using equity spillovers, equity portfolios optimized using currency spillovers, currency portfolios optimized using equity spillovers, and currency portfolios optimized using currency spillovers. This 2 x 2 design allows for a comparison of within-asset and cross-asset spillover signals, providing insight into whether single asset volatility predicts the fragility of other asset classes, further improving hedged global portfolios.

Introduction and Significance

In modern times, financial markets exist within a highly-integrated global environment. Economic conditions and asset prices are connected across geographic regions, political systems, and of course, asset classes. The expansion of cross-border trade, the growth of multinational corporations, and the increased mobility of capital across borders have boosted the interdependence of world economies. As a consequence, shocks in one market from a macroeconomic announcement, shift in geopolitical sentiment, or economic transformation, are transmitted across borders (Bekaert et al., 2009). This dynamic has elevated the relevance of investigation into spillover effects within asset classes while introducing new challenges for portfolio diversification and risk management. While the world of finance and its stability evolves, the methodologies behind portfolio diversification must evolve in unison.

Traditional approaches to international investment management emphasize diversification benefits. This arises from holding assets whose returns are weakly correlated on a historical basis. Since the adoption of mean-variance optimization, correlation-driven diversification has remained the standard across practitioner and academic applications (Sharpe, 1964). A holistic understanding of the limitations of this approach is required, as correlation structures are not stable over time and tend to converge sharply during extreme market shocks. When diversification benefits are most needed, correlated downside can negate the effectiveness of these strategies. For example, these vulnerabilities were observed during the 2008 Global Financial Crisis, whereas global equity markets

experienced simultaneous declines, geographic diversification lost its strength within portfolios (Beirne et al., 2021). Holding assets internationally contributed to synchronized losses, showing that correlation-based portfolio construction has a particular weakness to systemic global shocks.

To address this, researchers have identified volatility-based methodologies to capture dynamic directional linkages in financial markets. Volatility currently affects asset allocation strategies employed by portfolio managers internationally, and an in-depth understanding and utilization of this phenomenon across asset classes can help identify hedging opportunities and international diversification risks. Volatility spillovers reflect how uncertainty originating in one market spreads to others, influencing price discovery and investor sentiment, crucial pieces of capital allocation decisions. The transmission of risk that arises is not solely linked to price co-movement, but also from structural dependencies. The Diebold-Yilmaz framework quantifies this concept by outlining how volatility in one economy or asset class flows outward to others through forecast error variance decompositions (FEVD) derived from vector autoregressive (VAR) models (Diebold & Yilmaz, 2009, 2012). This approach distinguishes the sources of volatility from recipients to better measure systemic risk across a system. Using this approach, it is possible to understand the impact of volatility spillovers on global asset allocation across asset classes and regions as policymakers and portfolio managers work to mitigate this risk.

There is a growing body of research that demonstrates that volatility transmission intensifies during global uncertainty. Globalization and rapid information flows have increased the speed at which financial shocks can travel, which can be the result of economic policy uncertainty, geopolitical conflict, pandemic disruptions, or tightened monetary policy (Antonakakis et al., 2020). These events reshape the benefits that diversification can bring and can worsen liquidity pressures for globally exposed investors. Portfolio strategies must adapt to incorporate the ever-evolving channels of transmission for global shocks.

Despite a strong and growing body of research highlighting the significance of volatility spillovers, most of the prior research done on this subject is limited in scope. Many studies focus on equity-based connectedness or industry-level spillovers within a single economy. Work by my mentor, Professor Jahangir Sultan of Bentley University, reveals that on a sectoral level in the US, the primary exporters of volatility from the US include sectors like basic materials, financials, industrials, technology, and communications. However, the sector-specific spillovers vary considerably in intensity and direction during varying market conditions, including during financial crises. During the 2008 financial crisis, technology contributed significantly to volatility and subsequent spillovers, which was contrary to the prevailing expectation that the financial sector would dominate in volatility contributions (Sultan & Hasan, 2020). Conventional assumptions about systemic risk may not always hold, however, studies without a cross-asset

perspective may be neglecting important hedging dynamics and exposures that may shape global return streams.

Looking across asset classes, currency markets play a central role in the transmission of international volatility, especially in open economies that are reliant on trade across borders. Exchange rates can influence international flows, imports, and multinational corporation balance sheets, all of which can be seen as significant drivers behind equity markets. Currently, currency volatility can amplify or mitigate equity shocks depending on directional transmission (Coudert et al., 2010). Comprehensive analysis of volatility spillovers across equity and currency markets, with particular emphasis on actionable portfolio optimization frameworks, remains under-represented in previous research works. This is a large oversight, especially for international investors who consistently hold cross-asset exposure and must decide how to hedge based on how movements across asset classes influence each other.

This research helps to address this gap by analyzing volatility across both equities and currencies from the 25 largest global economies, representing the core financial centers of the world with heavy influence on global capital allocation strategies. Using the Diebold-Yilmaz methodology on time-varying data, this study contributes to the literature by evaluating whether spillover-based optimization yields a superior risk-adjusted performance compared to traditional correlation-based approaches to portfolio construction.

A crucial focus of this research is to understand whether incorporating spillover measures meaningfully improves global asset allocation during high-volatility regimes or shocks. This considers the dichotomy investors engage in, where both chasing returns and safeguarding capital from systemic risks are priorities. During periods of elevated uncertainty, negative spillovers from dominant volatility sources such as the US, China, and the Eurozone can contribute to the destabilization of international portfolios, regardless of diversification benefits. An improved understanding of volatility transmission patterns can guide the reallocation of weights toward more resilient regions or spillover-proof asset classes. Volatility connectedness-based models could contribute to reshaping the practices utilized in global portfolio management.

Referring to my methodology, this study expands on VAR framework used in volatility spillover analysis. Nonlinear econometric models and techniques such as cointegration will help capture both short-term dynamics and long-term relationships within data. This highlights criticisms from Hafner et al. (2006) and Billio et al. (2012), who describe the necessity for nonlinear approaches to better understand complex financial interactions such as economic uncertainty spillovers. Further, this study can highlight the evolution of global market interconnectedness. Depending on economic cycles, calm periods of economic uncertainty can reflect lower connectedness while periods containing systematic shocks increase volatility globally. Certain economies may retain influence as net volatility transmitters, reflecting their key role in global finance. Capturing dynamic

patterns through rolling-window VAR estimation can help explore the persistence of global transmitters and receivers of volatility over time, contributing to understanding surrounding the balance of global economic power. Thus, this research's benefits can extend beyond portfolio optimization. Policymakers, regulators, and central banks can draw upon volatility connectedness to measure international vulnerabilities as related to policy decisions, mitigating systemic fragility, and capital flow monitoring while offering a more forward-looking policy lens compared to static indicators.

Beyond these key points, behavioral finance may contribute increased understanding through spillover-relatedness. Since investor behavior is shaped by sentiment, perception of risks, and momentum, volatility spillovers may not simply reflect rational price adjustments, but also fear, capital flight to quality assets, and herd dynamics (Shiller, 2003). By acknowledging behavioral influences in global markets, this study helps to recognize that volatility transmission is not economically deterministic, but is also influenced by collective psychology and institutional decision-making.

In summary, this research presents several unique contributions. With a dual-asset spillover outline, two key asset classes can be examined together to reflect a real-world approach to international investment decision-making process. Further, with a 25-country macro-spillover assessment, a global system structure can be captured rather than regional fragments. Similarly, by testing spillover-optimized portfolios against correlation-optimized portfolios, more

practical evidence can be created to better understand the significance of spillover hedging and subsequent returns. Also, with the integration of economic policy uncertainty understanding, it can be better understood how political and macroeconomic forces shape cross asset volatility propagation while understanding the evolving or persistent nature of volatility transmission.

Since global finance is deeply interconnected and volatility spills across borders and assets in ways that traditional portfolio construction fails to address, portfolio strategies that emphasize an approach to interpreting and integrating directional volatility connectedness offers potential to improve hedged global investment outcomes beyond traditional correlation-based methods. Exploring both equity and currency markets across the 25 leading world economies helps to evaluate the influence of macroeconomic uncertainty through the lens of risk management and investment decision-making.

Literature Review

Modern portfolio theory has been historically dominated by the Markowitz mean-variance optimization framework. By optimizing portfolio weights through an evaluation of expected returns and covariance between assets, investors can construct a theoretically efficient portfolio that reduces risk without sacrificing returns in a complete portfolio (Markowitz, 1952). Despite these strengths, the model's dependence on historical correlation assumes broad stability in cross-

asset relationships that often fail to materialize in interconnected and shock-sensitive global markets. The growth in financial globalization includes the rise of multinational corporations, capital flow barriers, and high-speed information transmissions to yield deep macroeconomic linkages and the non-linear spread of risk across markets. As systemic events develop, correlation-based allocation methods have garnered more criticism to motivate a shift toward volatility-spillover frameworks to better understand and capture the time-varying nature of risks.

A common critique of correlation-based diversification is its failure during crises, known as correlation breakdown. As noted by Geert Bekaert and colleagues of the Columbia University Business School, correlations by nature are not stationary parameters. Correlations fluctuate with market regimes and spike under stress, which undermines diversification benefits when investors need risk protection. This phenomenon is called "correlation breakdown" and was first observed during the 2008 financial crisis (Bekaert et al.). During the 2008 Global Financial Crisis and the Covid-19 pandemic, co-movement among global assets surged structurally, leading to synchronized crashes and contagion across borders in financial assets. Bekaert and colleagues argue that this pattern is less reflective of permanent global financial integration than it is of volatility clustering, the phenomenon where systemic fear causes global investors to simultaneously de-risk, which compresses correlations regardless of fundamentals. Bekaert and colleagues demonstrate that international correlations tend to rise in turbulent times not due to increased economic integration, highlighting the main flaw in

correlation-based optimization in non-stationary correlations during market downturns. This highlights how diversification disappears when most needed, calling into question the validity and dominance of mean-variance optimization techniques. From the assumptions that the model is based on, correlations are treated as symmetric, instantaneous, and ambiguous, meaning they cannot detect or react when international markets transmit risk and instead absorb it (Diebold and Yilmaz, 2012). This limits the capacity of the models in the presence of spillover behavior.

The literature has migrated to more dynamic models to detect and adapt to directional volatility transmission, identifying risk transmitters and risk receivers. The Diebold-Yilmaz volatility connectedness index (2009, 2012) is the most influential advancement of this field, build upon variance decompositions from VAR frameworks to decompose forecast error variance into components attributing from shocks in a variety of markets or assets. This helps to produce a connectedness network where spillovers can be tracked across markets, time, and directions. Diebold and Yilmaz observed that return spillovers trend gradually upward with globalization and that volatility spillovers spread suddenly during crises (2009, 2012). While globalization may help to smooth baselines across markets, volatility spillovers transmit systemic panic and financial instability. This represents the forces that shape downside risk and drawdowns in portfolios left exposed by mean-variance strategies (Beirne et al., 2021). Volatility spillovers provide insights into causality, next exposure, temporal evolution, asymmetry, and

crisis amplification, all of which are not provided by correlations. This highlights that volatility spillover measures more accurately represent real-world financial relationships build for modern financial markets.

Another contribution to the literature on volatility spillovers is from Forbes and Rigobon (2001, 2002), who challenged common interpretations of financial contagion. They argued that correlation during crises does not represent an increase in interdependence, but instead represents a volatility-driven bias in correlation estimates. When volatility rises dramatically, correlation measures the rise in volatility as a byproduct of noise rather than meaningful fundamental transmission (Forbes and Rigobon, 2002). Adjusted correlation measures separate true contagion within structural mechanisms from the interdependence between markets that manifest more visibly during periods of sovereign or climate stress (Billio et al., 2012). This work is key due to influencing classifications of systemic events, furthering discussion around volatility relationships that lead to false markers of financial stability.

Diebold and Yilmaz expanded on this critique by highlighting a methodology on how to measure spillovers in their 2012 paper. This enhancement helped to resolve identification issues in earlier decomposition methods by using generalized FEVDs, which enabled variable-ordering interdependent estimations (Barunik et al., 2016; Diebold & Yilmaz, 2012). This helped categorize transmitters, receivers, and net contributions of volatility to catalyze volatility spillover literature further.

In the effort of expanding the use cases for spillover analytics, portfolio construction was the next interpreted purpose, extending the usefulness of spillover analytics beyond macro-financial interpretation. Ahmed and Sultan (2020) demonstrated that spillover-screened portfolios, especially those that avoid high spillover transmitters, generate superior Sharpe ratios during periods of market uncertainty. Through sectoral analysis in the US equity market, the traditional assumptions that systemic risk leaders do not necessarily hold this relationship across periods of market stress, such as the financial sector in 2008. This is an insight available through only this type of analysis, applicable across asset classes (Ahmed et al., 2020). From Sultan and Hasan's work, technology firms became major volatility exporters in 2008-2009 due to overleverage in innovation-sensitive industries while investor risk-perception began to shift (2020). The time-varying leadership in volatility transmission is something with demonstrated significance toward portfolio construction, but is something that correlation matrices cannot capture.

Even with these advancements, the literature remains narrow in several dimensions because most studies focus on single-asset spillover networks, particularly equities. This is despite the fact that global portfolios operate across asset classes and currency exposures are often integral to cross-border investment. Currency markets are the primary mechanism through which international capital allocation translates into domestic return uncertainty. Exchange rate fluctuations influence import costs, earnings, interest rate parity,

and global liquidity cycles (Coudert et al., 2010). FX markets play a key role in amplifying or dampening equity spillovers depending on hedging behaviors, central bank decisions, and corporate exposures, especially in emerging markets (Leon-Ledesma et al., 2014). Neglecting currency dynamics produces incomplete estimates of global risk transmission.

Another perspective of the research shows that equity and currency shocks are connected and driven by similar global forces, rather than isolated asset-specific dynamics. Charles Engel of the University of Wisconsin-Madison shows that exchange rates respond systematically to international risk conditions, specifically, changes in global risk premiums and required rates of return based on levels of macroeconomic uncertainty (2014). His work shows that currency movements represent swings in global risk sentiment instead of traditional fundamentals such as interest rates or purchasing power (Engel, 2014). This shows that currency markets are risk-sensitive, meaning that they are seen to react immediately after changes in investor uncertainty or volatility. From this it can be concluded that currency markets incorporate information earlier than equity markets as risk conditions shift in the macroeconomic environment.

Peter Dunne, Harald Hau, and Michael Moore from the Central Bank of Ireland, the University of Geneva, and Queen's University Belfast respectively complement this idea. Their work shows that equity market performance influences currency order flow, and thus, broad international liquidity. Maintaining consistency with other literature in this subject, they show that equity downturns

trigger currency depreciation through international portfolio rebalancing and market maker risk constraints with high-frequency data (Dunne et al., 2010). This shows that equity shocks can precede currency adjustments when disturbances are equity-specific only. This could include corporate earnings surprises, leverage changes, or competitive dynamics. Their work also shows that currency markets amplify equity shocks as equity investors reduce risk exposure. When equity investors do so, the currencies of high-beta countries weaken and generate spillovers that further transmit equity volatility (Dunne et al., 2010). When shocks are global in nature, both markets respond jointly instead of one market reflecting a lag behind the other.

Markus Brunnermeier and colleagues of Princeton University (2009) represent currency behavior by framing exchange rate movements through the context of carry trades. Their model show that currency markets experience crash risk when investors face funding-related issues that cause constrained investors to unwind positions in currencies (Brunnermeier et al., 2009). This is not triggered by currency-specific information, but instead by tightening financial conditions internationally that manifest through broad-market stress. Currency markets here adjust rapidly and show sharp drawdowns unrelated to news that creates a connection between poor equity market conditions and currency instability. This shows that currencies either follow equities during equity-related shocks, or precede them when constraints in the FX market restrict global investors.

To discuss this in more depth, it is important to visit the cross-asset literature surrounding spillover analysis. While sectoral spillover analysis has demonstrated implications on equity portfolio construction, a key step is applying spillover analysis across asset classes. This perspective helps recognize that investors rarely hold equity-only portfolios and remain exposed to a variety of assets including currencies, commodities, and bonds. Cross-asset volatility connectedness has emerged as a foundational consideration for hedging effectiveness during periods of market stress.

Early work identified bi-directional volatility transmission patterns in integrated markets. Lucía de las Nieves Morales from the Dublin Institute of Technology first identified bi-directional patterns in integrated markets through the examination of G7 countries. From this investigation, it was found that equity shocks frequently propagate into currency markets and vice-versa, especially during risk-off phases that are driven by shocks or broad macroeconomic panic. When equity markets experience drawdowns, safe-haven currencies appreciate as capital flows rotate defensively to form a systemic volatility channel between the two asset classes (Morales, 2008). This demonstrates that currency exposure is not a passive component of equity returns, but conditions the direction, size, and persistence of global shocks.

Further studies build on these insights in the context of emerging markets. Klaus Grobys of the University of Vaasa (2015) utilizes a Copula-CoVaR approach to show that stock-FX risk spillovers intensify when skewness and kurtosis are

pronounced during crises. The paper highlights non-linear tail-risk dependence, showing that currency hedging is more difficult under market stress due to sudden amplification of co-movement (Grobys, 2015). This has a strong implication on cross-asset portfolio hedging, where static correlations understand joint downside exposure during volatility clustering effects, building further on the critiques of Markowitz-style diversification in portfolios.

Evidence from Latin America further helps to outline this vulnerability. Muhammad Usman and colleagues from the University Islamabad find that persistent and statistically significant volatility spillovers between Latin American equity and exchange rate markets. In this environment, depreciating local currencies amplify equity volatility through international funding channels, showing that currency market uncertainty frequently leads to equity market volatility (Usman et al., 2022). Failing to model FX-originating spillovers produces structurally incomplete risk forecasts for globally diversified investors, suggesting that cross-asset early warning signals are critical for mitigating tail risk during shocks.

Global multi-asset evidence helps to strengthen these points. Sang Hoon Kang et al. (2019) of Pusan National University assesses dynamic spillovers among stock, commodity, bond, and VIX indices to find that equities are the primary stock transmitters while commodities and bonds vary in response depending on regime. The results highlight several main insights. Firstly, diversification benefits deteriorate in high-correlation periods following global

crises, meaning cross-asset connectedness must be incorporated into portfolios dynamically rather than assumed constant (Kang et al., 2019). Further, shock receivers like bonds can become residual hedging tools, but fail during market periods when systemic pressure rises. This highlights that an effective strategy utilizing spillover analysis must be long volatility-absorbing assets and short risk transmitters, creating asymmetric hedging portfolios capable of preserving returns under stress (Kang et al., 2019).

Further, perspectives from BRICS economies help to illustrate the complexity of global dependency structures surrounding risk sharing across borders. Tsepiso Nyopa from Rhodes University highlights that volatility spillovers between BRICS equity and currency markets are time-varying and crisis-amplifying, driven primarily by commodity exposure and trade dependency (2022). Further, this paper argues that ignoring FX risks underestimates broader systemic fragility since exchange rate depreciations coincide with equity market collapses that create a feedback loop and accelerate capital flight (Nyopa, 2022).

Finally, policy-driven uncertainty is a crucial force in volatility propagation. Unpredictable economic policies related to trade, conflict, and inflation can influence portfolio flows and worldwide investor conviction. Antonakakis et al. (2020) and Chatziantoniou et al (2020). use EPU indices to show that uncertainty shocks large economies can rapidly cascade through FX markets before eventually manifesting in equity market moves. Numerous studies highlight that macroeconomic shocks, monetary policy changes, and geopolitical events act as

catalysts of volatility spillovers on multiple occasions (Smales, 2021; Malik & Hammoudeh, 2007). A few of these studies integrate these drivers within VAR frameworks that are used to measure spillovers. This suggests that volatility spillover models must require macro-policy variables to detect early warning signals of contagion, reinforcing the weakness of correlation-only allocation rules further.

Behavioral finance further deepens understanding of spillovers. Shiller (2003) emphasizes that asset price reactions to uncertainty do not reflect solely rational adjustments. Fear contagion, herd behavior, and reflexivity represent non-linear shock propagation. Panic-induced de-leveraging and capital flight to quality assets often triggers spillovers to reserve currencies, representing behavioral channels that connect currency and equity shock propagation. Haghighi et al. (2024) argue that retail investor sentiment is seen as a lagging indicator of volatility, while others often argue that panic-driven behaviors can serve as warning signals for market downturns. This highlights that volatility is often transmitted via psychological mechanisms that traditional covariance analysis often treats as statistical noise.

As spillover understanding has advanced, the methodology behind spillover analysis has also advanced. Standard linear VAR techniques have often failed to capture a variety of considerations, including regime-switching, tail dependencies, volatility clustering, and liquidity spirals. Hafner and Herwartz (2006) and Billio et al. (2012) advocate for nonlinear approaches to spillover

analysis, including threshold VAR, Markov-switching dynamics, and GARCH connectedness models to reflect more realistic shock transmission dynamics. Weiju Xu et al. (2019) proposes separating short-term accelerations from long-run volatility manifestation dynamics, which influence horizons in portfolio allocation. While most studies focus on short-term spillovers, which miss the cumulative effects over time that may guide strategic asset allocation in most portfolios, cointegration and vector error correlation models (VECM) offer a solution but are underutilized (Pesaran et al., 2000; Hafner & Herwartz, 2006). A longer time horizon of study would allow for better insights into how shocks propagate through different economic regimes.

The call for dataset horizons that span multiple shock-based and calm regimes help enable an evaluation of whether spillover intensification helps create lasting structural shifts or temporary panic. Additional work has highlighted data frequency considerations. Andersen et al. (2003) and Barunik et al. (2016) demonstrate that the use of high-frequency intraday data substantially improves volatility estimation accuracy by minimizing aggregation distortion. Computation constraints and data access barriers limit the widespread adoption of intraday spillover models, but the significance behind daily or intraday data remains (Golosnoy, 2016). While daily data represents a widely-accepted solution, directional spillover effects may be underestimated during fast-moving periods of stress.

Beyond market prices, global investment flows can contribute to volatility transmission. UNCTAD and OECD evidence outlines that foreign direct investment (FDI) dynamics, which are sensitive to geopolitical tension and industrial policy, restructure the network of international volatility vulnerabilities. As an example, declining capital inflows into China in recent years due to decoupling initiatives and increasing investments in US markets heightens American spillover contribution to global markets. Further, in 2024, global FDI flows reached \$1.4 trillion, which is an 11% increase from the year before. Excluding significant financial flows from European economies, the global FDI flows decreased by 8%, highlighting challenges in the international landscape outside of the Europe region (UNCTAD). The United States maintained its position as the leading FDI recipient, attracting substantial investments because of its stable economic environment and legal frameworks. Brazil and Mexico also had large global FDI inflows, specifically due to their large markets and ongoing reform (OECD). Developing countries experienced a 2% decrease in FDI, adding to last year's similar decline. Central and West Asia as well as South America were specifically affected, with reductions in project finance (OECD). This trend contributes to concerns for infrastructure development and sustainable development goals. Cross-border M&A activity in advanced economies saw a slight increase by 16%, indicating resilience in certain sectors, despite greenfield investments declining significantly and reaching their lowest in two years (OECD). This landscape reflects complexity in economic, political, and policy factors. Some economies continue to flourish

and attract investments, while some economies fail to attract investment. Shifting topologies in global markets require models and approaches to portfolio construction that better reflect real-time global capital mapping. Similarly, this highlights the importance of understanding the effects of global economic uncertainty and the impact of investment flows internationally. Through this understanding, further advancements can be made toward holistic and stable portfolio management during times of volatility.

The role of derivatives in spillover transmission is another component of literature on this topic. Financial innovation post-2008 has helped create more developed channels for leverage and synthetic exposure to assets. As explored by Baltzer et al. (2019), speculative derivative positioning often precedes and accelerates spot price volatility shocks. Because cross-asset derivatives including currency futures, index options, and swaps that hold non-linear payoffs, they can produce volatility acceleration and may serve as leading crisis indicators if incorporated into spillover portfolio construction. Further, other instruments such as derivatives and structured financial products, with leverage and liquidity effects, can amplify volatility spillovers (Acharya et al., 2010). This creates broad implications for future study across asset classes with emphasis on non-linear return structures to match the dynamic nature of spillover effects. This neglect is problematic given the increased volume of exchange-traded derivatives after the 2008 financial crisis. Including derivatives in spillover models can alter our understanding of systemic risk and lead to improved hedging strategies.

Further, AI and machine learning methodologies have developed as tools for spillover forecasting. Studies from Gu et al. (2025) demonstrate that deep learning architectures have captured non-stationary dynamics, volatility clustering, and tail events that traditional econometric methods struggle to predict. Neural network models can track sequential volatility dependencies with heightened responsiveness to crisis-driven shock structures, while random forest models can reveal nonlinear predictor relationships across market variables. Beyond macro-financial channels for volatility transmission, investor attention has emerged as a measurable behavioral factor that influences the price dynamics of a variety of assets. Da, Engelberg, and Gao (2011) propose the search volume index (SVI) from Google Trends as a high-frequency proxy for investor attention. When investors allocate attention during shocks, volatility can amplify as price adjustments become more sentiment-driven rather than fundamental-based. Where classical models assume stable structure, AI approaches dynamic features such as search behavior or sentiment in a more adaptive way (Da et al., 2011). While AI/ML methods present black-box characteristics and associated challenges, hybrid frameworks that combine machine learning with econometric reasoning can represent next steps for spillover measurement.

While the literature surrounding volatility spillovers advances, there are several key gaps that remain. There remains a limited application of cross-asset analysis, as most studies prioritize equity spillovers and negate currency effects while treating them as background noise. Considering cross-asset spillovers from

asset classes such as currencies may help to better outline the drivers of international risk. Further, few papers rigorously test if spillover-optimized portfolios outperform correlation-based portfolios in a real-world setting across multiple regimes, reflecting insufficient performance validation behind the methodology. With shorter sample periods, missing macroeconomic context from policy uncertainty and geopolitical tensions, previous literature can be expanded by studies demonstrating the broadening of investigation into volatility spillovers in a portfolio construction setting.

This study responds to these shortcomings by modeling spillover connectedness between equity indices and currency markets while aiming to compare four unique spillover strategies in a 2x2 structure, incorporate policy-driven volatility dynamics, and establish volatility dynamic durability across regimes. The cross-country and cross-asset perspectives demonstrate a unique contribution alongside the empirical test behind performance of spillover coefficient-based portfolios, representing both a theoretical and applied contribution. As the literature concludes that global portfolio management must evolve, volatility spillover analysis offers a more robust and causal approach to understanding crisis transmission channels. Direct connectedness measures provide investors with intelligence to avoid systemic risk transmitters, capitalize on volatility-absorbing assets, and hedge against broad instability. Because of global contagion and shocks, traditional portfolio optimization appears outdated,

justifying an inquiry into whether portfolios structured using volatility spillover deliver meaningfully enhanced performance.

Methodology

This study employs an empirical framework in multiple phases to evaluate whether volatility-connectedness measures help to improve approaches to global portfolio allocation compared to traditional correlation-based allocation. This paper aims to provide a comprehensive assessment of how risk transmits across asset classes and whether the operationalization of spillover coefficients contributes strongly to global investment management approaches.

Daily data points were collected from both equity and currency markets for this study. From equities, the price data of equity indices from the 25 largest global economies during the period of 01/04/2000 to 12/31/2024 was collected. These economies represent the largest financial centers globally and the broadest investable markets. Further, currency market data from bilateral exchanges between the US and foreign nations were collected using the same periodicity. All data was collected utilizing a Bloomberg terminal and represents the basis of unified analysis of cross-asset volatility transmission. All markets, denominated in USD or with USD as the base currency, contribute to portfolio weightings. Asian markets are lagged by one day to account for regional time differences. For the

purpose of this study, the perspective of portfolios will be based on spillover from single nations to all other nations in sample sub portfolios discussed later.

A 25-year sample was chosen to capture multiple business cycles, a variety of market shocks and crashes, and a variety of geopolitical and monetary shifts. Daily frequency ensures adequate sensitivity to short-horizon volatility bursts that spillover across markets, in alignment with prior Diebold-Yilmaz applications from previous literature.

For each data series, several transformations were applied to ensure accuracy and applicability. Returns data was converted to log-price returns using the following formula to ensure continuously compounded returns. This stabilizes variance, normalizes high-frequency data, and ensures that returns meet requirements for VAR stability and invertibility.

$$r_t = \ln \left(\frac{P_t}{P_{t-1}} \right)$$

Because the dataset spans 25 globally diverse markets with diverse trading calendars, synchronization of trading dates was necessary to eliminate non-overlapping observations. All markets were merged into a single panel by retaining dates in which every market recorded trades, removing structural breaks from regional holidays or partial-day closures. This prevents cross-market lag relationships that could distort connectedness measures. Another key part of this study's design is the division of the 01/04/2000-12/31/2024 sample into structurally meaningful subperiods. These subperiods correspond directly to

major global market regimes and are key for evaluating if spillover-based portfolios behave consistently during a variety of market periods. Five non-overlapping windows are constructed, the first being 01/04/2000-12/19/2006, representing the pre-global financial crisis environment that marks accelerating globalization, relative stability in monetary policy, and low systemic risk. The second period, spanning from 01/01/2007-04/30/2009, captures the onset and peak of the 2008 financial crisis with extreme volatility and cross-market contagion. The third period spans from 05/01/2009-12/31/2019, reflecting the postcrisis expansion period. During this period, quantitative easing, suppressing volatility and rising international capital flows were observed. The fourth period, from 01/01/2020-05/05/2023, encompasses the initial Covid-19 shock and reopening dynamics, in which markets experienced rapid volatility spikes and international policy intervention. The final period from 05/06/2023-12/31/2024 represents the post-pandemic normalization marked by inflation pressures, tightening monetary policy, and geopolitical diversification efforts. These windows will allow spillovers and performance to be evaluated in environments with fundamentally different volatility dynamics, uncertainty, and transmission. These periods allow the analysis to capture the benefits of spillover-optimized allocation across concentrated and stable periods, to better test the value of this methodology of portfolio construction.

A crucial step in preparing the data is the construction of the return panel without missing observations. While international financial data contains gaps

because of trading calendar events or data vendor inconsistencies, VAR and FEVD procedures require a complete rectangular dataset with no missing entries. To fulfill these requirements, systematic and reproducible missing-data handling procedure consistent with practices in the volatility connectedness literature was implemented. As raw prices were originally converted into daily percentage returns, the propagation of NaN values continued whenever source prices were not available. Rather than interpolating or forward-filling to artificially smooth volatility dynamics, all missing values were preserved through an additional step when converting returns. A synchronous return panel was constructed with a two-stage trimming process that identifies the earliest date at which all assets begin reporting valid returns and the latest date at which all assets remain available, identifying the maximal intersection window across markets. With this aligned window, every row that contains a missing value is dropped to ensure that the final dataset is free of gaps and is compatible with VAR estimation. This approach preserves the integrity of the autocovariance structure and avoids lag effects from asynchronous trading. This method aligns with spillover methodology guidelines that recommend retaining only the intersection of valid observations across a series rather than interpolating missing values in order to yield a stable and stationary panel for connectedness estimation. Before estimation is completed, extreme outliers are winsorized at the tails to stabilize the covariance matrix.

Volatility spillovers are estimated using the Diebold-Yilmaz (2012) connectedness framework, which combines a VAR model with generalized FEVD

calculations. For each asset class, high-dimensional VAR systems are estimated using lag orders. VAR(k) systems were estimated of the form:

$$r_t = \Phi_1 r_{t-1} + \dots + \Phi_k r_{t-k} + \varepsilon_t$$

where r_t is the vector of daily returns across markets, k represents the chosen lag length, and ε_t is an innovation vector with covariance Σ . Fallback mechanisms are applied when estimations encounter singularities. The VAR is then expressed in its infinite moving-average representation:

$$r_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

Here ε_i represents the shock vector for the covariance matrix, and A_i represents the matrix describing how past shocks affect today's returns, which characterizes the dynamic propagation of shocks over time. To avoid ordering dependence in the variance decomposition, the analysis uses the generalized FEVD of Pesaran and Shin (1998) to attribute forecast error variance shocks in each market without orthogonalization. The proportion of the H -step-ahead forecast error variance of the market i attributable to shocks in the market j is given by:

$$\theta_{ij}(H) = \frac{\sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sigma_{ij} \sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}$$

The resulting FEVD matrix represents the proportion of each market's forecast error variance attributable to shocks in each other market. The output's spillover matrix is in the form:

$$\Theta = [\theta_{ij}]$$

Where Θ_{ij} represents the proportion of market i 's forecast error variance explained by shocks in market j . This yields system-wide and directional connectedness measures, including total spillovers, directional spillovers outward from each country, and directional spillovers inward that are absorbed by each country. Finally, using these metrics, the net spillover for each market is calculated as the difference between the two. These metrics represent the beginning of the portfolio construction phase, enabling within-asset and cross-asset comparisons of volatility transmission.

To evaluate the asset allocation implications of these spillover structures, the FEVD-connectedness measures are implemented into a portfolio optimization framework. Traditional benchmark portfolios are constructed using a Markowitz mean-variance optimization framework with historical covariance matrices and long-only constraints. In contrast, spillover-based portfolios weigh assets according to connectedness characteristics in a similar long-only fashion. Depending on the high or low spillover orientation of the portfolio, markets that act as persistent volatility transmitters receive lower weights, while markets that act as stabilizers or absorbers receive higher weights. This operationalizes the idea

that risk-efficient portfolios should de-emphasize assets that contribute to systemic risk with a high-risk perspective. This study implements a novel 2x2 portfolio design that compares four configurations: Equity portfolios optimized using equity spillovers, equity portfolios optimized using currency spillovers, currency portfolios optimized using equity spillovers, and currency portfolios optimized using currency spillovers. To operationalize spillover coefficients into portfolio weightings, for spillover matrix S :

$$w_i \propto \frac{1}{1 + Spillover_i}$$

Where $Spillover_i$ represents either spillover to others, from others, or net spillovers. This design expands the literature by evaluating not only whether single-asset spillovers improve portfolio performance, but also whether cross-asset spillovers provide predictive information for more effective approaches to risk management. It contributes by testing hypotheses regarding whether foreign exchange markets, which are more sensitive to macroeconomic shocks, contain leading information about equity market fragility. Further, it helps outline whether equity market spillovers translate into currency volatility through capital flows and safe-haven dynamics.

Correlation-based and spillover-based portfolios are evaluated through backtesting. A rolling-window framework recomputes the VAR, FEVD, and covariance matrices at each window, updates portfolio weights, and evaluates returns. Portfolio weights for high and low spillover portfolios are determined by

nations that fall above or below the median net spillover across the sample during a specific period of analysis. Either 25 or 24 panels are drawn from spillover matrices at each period, with the median governing high and low spillover nations and splitting them into two portfolios. These portfolios are created from the perspective of one nation versus all others in a case-study format, leading to 25 or 24 portfolios that isolate spillover effects between one nation and all others. The nations are used to create minimum-variance-optimized portfolios, of which performance is assessed using annualized returns, volatility, maximum drawdowns, and Sharpe ratios as the primary statistic for risk-adjusted performance. These are compared against portfolio performance to evaluate whether spillover optimized strategies exhibit enhanced resilience when traditional diversification weakens. This combination of spillover structures, cross-asset testing, dynamic portfolio optimization, and uncertainty regime classification contributes to a methodology capable of assessing how volatility transmits and effects asset allocation outcomes.

Findings

Across the full sample, the spillover analysis helps to identify the evolving nature of the international interconnectedness across both equity and currency markets. The correlations between national equity and currency returns and the VIX help provide the first look at systemic risk sensitivity across the largest global

markets included in this study. From the full period, nearly every major national equity index shows strong negative correlations with the VIX, reflecting broad global sensitivity to risk. The US shows the strongest negative correlation to the VIX, which is between -70% to -80% percent across individual periods and the whole period. This reflects its position as the market most tightly influenced to global volatility shocks, represented as an inverse correlation of high magnitude. Most European and Asian markets fall within the -30% to -55% range of correlation. Specific emerging markets including Turkey, Brazil, and Mexico demonstrate deeper negative correlations during crisis periods such as the 2008 crash and Covid-19 crisis. This confirms that global shocks erode diversification across regions as risk spreads. After Covid, correlations remained elevated compared to pre-2019 levels, suggesting a structural shift in the dynamics between risk and market performance. As discussed, since traditional correlation-based strategies weaken during period when investors require downside protection and hedging the most, identifying directional risk transmission can further motivate the role of spillover measures used later in the analysis of the results.

The summary statistics for equity and currency returns show risk dynamics within the correlations between national assets and the VIX. Average daily equity returns vary across markets. Developed markets such as the US, the UK, and Australia show consistent, positive average returns. However, emerging markets such as Brazil and India display higher average returns but larger standard

deviations. Currency markets show similar patterns. While average FX returns are small, the standard deviations in returns are significant, with emerging-market currencies showing the highest variability. These statistics illustrate why spillover-based measures may outperform traditional allocation methods, with asset classes that have higher baseline volatility also potentially exhibiting more erratic participation in risk transmission. This makes traditional diversification unreliable, especially during periods of elevated market stress.

Table 1*Correlation Between National Aggregate Stock Returns and VIX Returns*

	USA	China	Germany	Japan	India	UK	France	Italy	Canada	Brazil	Russia	South Korea	Australia
Full-Sample	-72.63%	-16.30%	-41.96%	-4.22%	-17.11%	-39.52%	-41.75%	-40.52%	-50.39%	-41.97%	-2.42%	-13.00%	-18.16%
Pre-Financial Crisis	-74.15%	-7.13%	-42.71%	-6.50%	-6.34%	-33.68%	-37.32%	-34.63%	-46.08%	-38.39%	-18.16%	-8.89%	-4.42%
Financial Crisis	-76.19%	-15.87%	-41.89%	1.61%	-24.99%	-41.75%	-41.38%	-36.26%	-54.19%	-60.66%	-30.93%	-18.33%	-17.98%
Post-Financial Crisis, Pre-Covid Crisis	-79.51%	-22.85%	-45.67%	-1.99%	-20.47%	-46.27%	-47.68%	-44.88%	-54.41%	-40.79%	-34.91%	-16.71%	-22.47%
Covid Crisis	-71.57%	-21.17%	-42.10%	-4.09%	-21.49%	-37.60%	-41.84%	-43.84%	-56.04%	-40.83%	2.46%	-8.45%	-23.08%
Post-Covid Crisis	-75.64%	-11.38%	-29.20%	-25.41%	-18.18%	-29.24%	-25.32%	-23.96%	-47.31%	-33.43%	-	-18.65%	-23.52%

	Spain	Mexico	Indonesia	Turkey	Netherlands	Saudi Arabia	Switzerland	Poland	Taiwan	Belgium	Sweden	Ireland
Full-Sample	-38.68%	-47.21%	-10.75%	-20.68%	-41.58%	-14.23%	-33.95%	-28.60%	-11.34%	-37.11%	-36.91%	-34.55%
Pre-Financial Crisis	-35.11%	-49.70%	-3.12%	-13.36%	-37.04%	-	-28.58%	-16.69%	-8.67%	-28.93%	-30.29%	-18.40%
Financial Crisis	-39.64%	-63.40%	-14.94%	-36.44%	-41.62%	-	-34.47%	-30.24%	-10.83%	-37.73%	-37.47%	-36.99%
Post-Financial Crisis, Pre-Covid Crisis	-42.18%	-46.57%	-13.44%	-26.94%	-47.02%	-13.21%	-40.20%	-33.52%	-15.38%	-42.31%	-42.81%	-41.24%
Covid Crisis	-40.13%	-43.59%	-15.52%	-18.12%	-43.78%	-16.03%	-34.68%	-34.47%	-7.84%	-41.91%	-41.53%	-39.55%
Post-Covid Crisis	-18.38%	-33.59%	-12.36%	-12.03%	-31.03%	-13.82%	-22.51%	-20.73%	-18.11%	-25.88%	-25.13%	-21.78%

Table 2*Correlation Between National Aggregate Currency Returns and VIX Returns*

	China	Germany	Japan	India	UK	France	Italy	Canada	Brazil	Russia	South Korea	Australia
	Yuan	Euro	Yen	Rupee	Pound	Euro	Euro	CAD Dollar	Real	Ruble	Won	AUD Dollar
Full-Sample	1.98%	0.58%	0.00%	0.04%	1.73%	0.58%	0.58%	0.37%	-1.50%	-0.04%	-1.03%	0.95%
Pre-Financial Crisis	4.63%	2.95%	6.29%	3.47%	2.70%	2.95%	2.95%	0.42%	-2.58%	4.09%	-0.47%	1.96%
Financial Crisis	0.27%	-1.20%	0.60%	1.30%	0.51%	-1.20%	-1.20%	-2.30%	-2.80%	1.79%	-2.98%	0.81%
Post-Financial Crisis, Pre-Covid Crisis	3.25%	-1.09%	-3.46%	-2.57%	0.80%	-1.09%	-1.09%	-0.47%	-2.02%	-2.70%	-1.61%	-1.32%
Covid Crisis	5.42%	2.69%	-4.27%	7.22%	2.90%	2.69%	2.69%	4.91%	1.78%	2.19%	5.46%	6.26%
Post-Covid Crisis	-6.59%	4.07%	8.78%	-2.29%	5.31%	4.07%	4.07%	4.84%	0.36%	3.80%	-3.36%	4.01%

	Spain	Mexico	Indonesia	Turkey	Netherlands	Saudi Arabia	Switzerland	Poland	Taiwan	Belgium	Sweden	Ireland
	Euro	Peso	Rupiah	Lira	Euro	Riyal	Franc	Zloty	TWD Dollar	Euro	Krona	Euro
Full-Sample	0.58%	1.28%	1.00%	-0.72%	0.58%	0.18%	-1.14%	0.50%	1.14%	0.58%	1.66%	0.58%
Pre-Financial Crisis	2.95%	0.23%	1.66%	-1.19%	2.95%	-1.31%	1.83%	6.84%	5.98%	2.95%	4.31%	2.95%
Financial Crisis	-1.20%	-2.83%	-0.22%	-9.20%	-1.20%	-0.31%	2.44%	-1.36%	1.49%	-1.20%	-1.97%	-1.20%
Post-Financial Crisis, Pre-Covid Crisis	-1.09%	1.60%	-1.30%	0.52%	-1.09%	0.75%	-3.15%	-2.17%	-0.51%	-1.09%	0.51%	-1.09%
Covid Crisis	2.69%	4.86%	9.38%	1.81%	2.69%	3.14%	-2.19%	1.70%	0.26%	2.69%	3.89%	2.69%
Post-Covid Crisis	4.07%	-0.82%	-1.60%	1.34%	4.07%	-13.18%	-0.06%	5.56%	1.31%	4.07%	4.37%	4.07%

Covariance matrices further reinforce these findings by highlighting the cross-sectional dependence that underlies global market co-movement dynamics. The equity covariance matrix shows clear regional clustering dynamics, with European markets exhibiting tightly linked covariances with one another. This highlights a clear dynamic foundational to shocks: countries that exhibit integrated economic policy, capital flows, and proximity may represent a strategic opportunity for asset allocators and nuanced understanding regarding spillover risk. Asian markets exhibit risk connectedness through Japan, China, and South Korea. Interestingly, Latin American markets such as Brazil and Mexico show stronger covariances with the US than with each other, despite regional similarities. This potentially reflects dependence on US growth cycles and commodity-driven capital flows between these nations and the US. Russia has a high variance and disproportionately large covariance as shown in the chart, skewing the matrix and highlighting its potential role as an international volatility amplifier rather than an absorber. Currency covariances further reinforce the notion of regional clustering, with European markets showing strong relationships and emerging markets showing wider variance patterns. These patterns highlight important context behind clustering: while these data points are crucial toward understanding global dynamics, these metrics fail to capture directional transmission effects, further motivating the following analysis.

Table 3

[illegible]

Currency Return Covariance Matrix – Whole Period



The spillover tables reveal the directional nature of volatility transmission between markets across periods of investigation for this study. In the pre-financial crisis period (period 1), overall spillover across equities and currencies is modest, although certain markets like the US and China are seen to show above-average outbound spillover effects. Smaller markets such as Ireland and Belgium function as absorbers of volatility rather than transmitters. During the 2007-2009 financial crisis, spillover levels rise across all markets, as shown in the periodic heatmaps

through widespread red and yellow clusters. This shows the synchronicity of global shock transmission. The US transmits more than 20-25% of its volatility to other markets as a volatility exporter, showing how even isolated markets become more connected through systemic risk from the US.

Currency spillovers show a similar shift as the unwinding of trades and global investment causes the Japanese yen and Swiss franc to emerge as major volatility transmitters due to safe-haven demand. In the period that follows the 2008 financial crisis, spillovers decline substantially. This aligns with the decade of historically low volatility and monetary stimulus initiatives to aid in global market recovery after the crisis. Connectivity remains after the crash but is more contained, with outbound spillovers falling to 3-8% for many markets. The Covid-19 crisis reverses this pattern, as shown in the spillover matrices for 2020-2023. These matrices show elevated connectedness at levels rivaling the financial crisis, with the US serving as the primary transmitter of volatility again with volatility transmitted at above 19-21%. This stands in contrast to markets like China, Japan, and South Korea, who represent significantly elevated bidirectional spillovers. The post-Covid period demonstrates partial normalization across assets and markets, though spillovers remain above pre-2019 levels. This indicated that global markets may have transitioned to a higher-connectivity environment.

Table 5 & 6*Equity Spillover Results*

	1/4/2000 - 12/29/2006			1/1/2007 - 4/30/2009			5/1/2009 - 12/31/2019			1/1/2020 - 05/05/2023			5/6/2023 - 12/31/2024			01/04/2000 - 12/31/2024		
	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)
USA	74.53	99.90	25.37	86.95	105.80	18.85	79.97	81.81	1.84	87.01	83.81	-3.20	73.59	86.69	13.09	84.23	86.23	2.01
China	61.02	33.75	-27.27	84.44	47.81	-36.63	81.21	69.00	-12.20	78.73	40.68	-38.05	81.58	56.73	-24.85	79.57	54.64	-24.93
Germany	86.30	134.42	48.12	92.17	117.10	24.93	89.65	129.18	39.53	91.86	137.00	45.14	90.61	114.94	24.33	90.88	134.33	43.44
Japan	64.83	31.92	-32.90	82.31	22.72	-59.59	71.27	24.89	-46.38	80.06	28.06	-51.99	81.17	57.06	-24.11	72.37	29.44	-42.93
India	54.96	28.15	-26.81	65.85	57.40	-28.46	75.91	47.90	-28.01	87.65	67.36	-20.30	82.07	42.42	-39.65	82.93	63.01	-19.92
UK	84.77	106.65	21.88	91.96	117.53	25.58	89.25	126.02	36.78	91.55	121.87	30.32	89.52	127.67	38.15	90.60	128.65	37.95
France	97.36	135.07	47.71	92.42	123.15	30.74	90.24	138.03	47.79	91.89	139.56	47.67	89.74	105.31	16.06	91.21	138.69	47.46
Italy	85.72	116.50	30.78	92.07	116.93	24.86	88.00	108.52	20.52	91.29	134.95	43.66	89.81	100.14	10.34	89.71	116.73	27.03
Canada	72.29	80.92	8.64	87.55	89.35	1.80	84.42	101.68	17.26	88.95	117.38	27.43	81.34	119.65	38.31	87.96	112.45	24.49
Brazil	68.44	67.45	-0.98	89.11	100.21	11.10	75.59	54.13	-21.47	86.21	77.70	-8.51	78.08	96.97	18.88	82.52	67.43	-15.09
Russia	57.39	33.10	-24.09	88.10	74.93	-13.17	79.61	66.75	-12.86	63.29	29.04	-34.25	0.00	0.00	0.00	58.63	33.84	-24.79
South Korea	68.91	46.55	-22.37	84.80	61.62	-23.17	82.05	68.26	-13.78	84.55	52.47	-32.08	81.84	63.58	-18.26	82.80	61.02	-21.78
Australia	75.67	38.64	-37.03	91.52	86.32	-5.20	81.88	68.46	-13.43	88.96	79.21	-9.75	88.83	93.85	5.02	86.05	78.24	-7.81

	1/4/2000 - 12/29/2006			1/1/2007 - 4/30/2009			5/1/2009 - 12/31/2019			1/1/2020 - 05/05/2023			5/6/2023 - 12/31/2024			01/04/2000 - 12/31/2024		
	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)
Spain	85.49	116.13	30.64	91.74	114.12	22.38	88.60	116.24	27.64	90.94	121.54	30.60	88.20	100.61	12.41	89.89	117.68	27.79
Mexico	75.13	90.67	15.53	87.39	109.70	22.31	80.43	74.67	-5.75	87.59	86.82	-0.78	80.21	104.30	24.09	84.40	79.68	-4.73
Indonesia	39.01	15.08	-23.94	85.27	50.36	-34.92	69.91	34.25	-35.66	83.97	35.19	-48.78	82.42	46.35	-36.07	77.15	33.16	-43.99
Turkey	51.09	24.49	-26.60	89.10	87.60	-1.50	68.48	35.68	-32.80	72.47	30.29	-42.13	73.40	41.48	-31.92	70.57	32.93	-37.64
Netherlands	86.70	122.63	35.93	91.62	118.49	26.87	89.61	127.81	38.20	90.32	112.80	22.49	86.05	96.14	10.09	89.92	120.46	30.54
Saudi Arabia	0.00	0.00	0.00	0.00	0.00	0.00	48.03	19.13	-28.91	78.30	64.31	-13.99	77.45	81.53	-15.92	62.75	20.64	-42.11
Switzerland	83.30	84.44	1.13	90.72	109.23	18.52	87.84	105.43	17.59	89.72	102.07	12.34	88.77	82.94	-5.82	88.71	104.76	16.05
Poland	67.28	46.78	-20.50	89.91	89.93	0.02	83.42	76.69	-6.73	88.70	102.60	13.90	86.17	85.64	-0.53	86.57	86.59	0.02
Taiwan	56.97	26.92	-30.06	82.47	42.44	-40.03	80.38	59.14	-21.23	83.24	35.90	-47.34	81.68	64.29	-17.40	81.09	51.29	-29.79
Belgium	82.78	88.28	5.50	90.70	97.10	6.40	86.86	94.06	7.20	91.01	115.78	24.76	83.95	73.49	-10.45	89.17	105.24	16.06
Sweden	82.74	96.31	13.56	91.33	103.93	12.60	88.56	113.17	24.61	91.22	123.57	32.35	89.56	100.28	10.73	90.07	120.52	30.46
Ireland	75.92	54.29	-21.64	88.64	84.17	-4.48	86.63	92.88	6.25	89.82	107.32	17.50	84.56	88.05	3.49	88.68	101.37	12.69

Table 7 & 8

Currency Spillover Results

	1/4/2000 - 12/29/2006			1/1/2007 - 4/30/2009			5/1/2009 - 12/31/2019			1/1/2020 - 05/05/2023			5/6/2023 - 12/31/2024			01/04/2000 - 12/31/2024		
	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)
China	87.59	7.14	-80.45	59.72	16.14	-43.58	44.21	15.99	-28.22	69.62	51.98	-17.64	81.46	102.48	21.02	40.05	16.46	-20.55
Germany	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Japan	63.07	61.81	-1.26	72.66	76.08	3.42	16.55	6.29	-12.26	45.60	21.04	-24.55	82.67	89.57	6.91	31.36	16.34	-15.03
India	40.63	19.98	-20.65	59.46	35.60	-23.86	61.83	46.83	-15.00	71.34	65.94	-5.40	83.39	64.54	-18.86	59.51	45.13	-14.39
UK	75.22	97.28	22.06	78.31	64.68	-13.63	69.03	61.16	-7.87	78.20	87.48	9.27	88.19	84.83	-3.36	72.60	73.74	1.14
France	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Italy	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Canada	51.57	33.71	-17.86	74.14	68.88	-5.26	76.75	89.13	12.38	78.52	92.94	14.42	86.39	71.92	-14.46	76.37	91.78	15.42
Brazil	34.89	30.34	-4.55	76.33	95.58	19.25	67.38	55.97	-11.41	62.36	42.93	-19.43	83.27	74.55	-8.72	66.85	59.38	-7.47
Russia	63.09	55.57	-7.52	81.57	86.38	4.82	64.93	51.98	-12.94	46.13	24.67	-21.46	76.38	65.51	-10.86	53.56	33.71	-19.85
South Korea	56.61	35.08	-21.52	72.19	79.06	6.87	74.19	81.14	6.96	79.62	107.79	28.17	81.02	96.33	15.31	53.56	33.71	-19.85
Australia	71.37	82.86	11.49	81.08	108.45	27.36	79.64	107.94	28.30	81.38	116.59	35.22	88.29	106.97	18.68	77.89	104.02	26.14

	1/4/2000 - 12/29/2006			1/1/2007 - 4/30/2009			5/1/2009 - 12/31/2019			1/1/2020 - 05/05/2023			5/6/2023 - 12/31/2024			01/04/2000 - 12/31/2024		
	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)	From Others (C)	To Others (C)	Net Spillover (C)
Spain	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Mexico	33.01	31.24	-1.76	77.47	89.00	11.53	75.34	84.59	9.25	74.82	79.13	4.31	82.02	64.83	-17.38	73.80	84.43	10.63
Indonesia	29.93	17.23	-12.70	56.40	35.76	-20.64	58.75	41.41	-17.34	71.59	67.07	-4.52	85.75	80.46	-5.29	58.88	44.23	-14.65
Turkey	40.28	29.62	-10.66	75.69	92.06	16.38	72.35	70.63	-1.72	29.42	12.26	-17.16	77.23	45.28	-31.95	67.43	61.91	-5.52
Netherlands	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Saudi Arabia	0.00	0.00	0.00	0.00	0.00	0.00	4.05	1.48	-2.57	79.76	94.25	14.48	0.00	0.00	0.00	3.84	2.42	-1.42
Switzerland	77.99	107.20	29.20	77.08	72.64	-4.44	65.81	55.82	-9.99	72.88	65.73	-7.16	87.62	94.54	6.92	64.03	50.49	-13.55
Poland	65.95	68.99	3.04	82.34	101.89	19.56	80.31	110.19	29.88	79.31	95.04	15.73	86.65	91.59	4.95	79.53	108.83	29.30
Taiwan	57.13	38.32	-18.81	62.03	53.38	-28.65	66.93	58.91	-8.03	56.03	26.38	-29.65	76.00	87.98	11.98	61.70	50.07	-11.63
Belgium	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56
Sweden	77.59	109.18	31.59	81.75	93.25	11.49	78.84	99.14	20.30	81.71	109.09	27.38	86.55	99.93	13.38	78.92	104.60	25.68
Ireland	78.75	112.49	33.75	83.56	102.95	19.39	77.68	97.98	20.29	79.76	94.25	14.48	87.53	109.26	21.74	77.70	98.26	20.56

These spillover dynamics feed directly into the results of the study, where connectedness measures are operationalized to construct spillover-screened portfolios. Across almost all periods, applying spillover filters to portfolio construction improves overall portfolio behavior against unscreened, min-variance optimized benchmarks. In equities, portfolios optimized on equity spillovers show the largest improvements during non-crisis periods (2000–2006 and 2009–2019). High-spillover exclusion raises Sharpe ratios by reducing exposure to volatility

transmitters internationally, which are typically the markets that experience the deepest drawdowns during systemic shocks. During crisis periods, while all portfolios lose value, spillover-filtered portfolios still experience smaller losses and better risk-adjusted returns through their Sharpe ratios. Notably, equity portfolios constructed using currency spillovers frequently outperform those constructed using equity spillovers, a key contribution of the study and understanding surrounding cross-asset spillover dynamics. This suggests that currency markets embed forward-looking macroeconomic information of relevance to equity markets. This information may come in the form of liquidity and global risk sentiment, that equity markets absorb with a lag. Several crisis and recovery windows display better Sharpe ratios for portfolios using currency-spillover screening, indicating cross-asset predictive power of relevance to the literature on spillover dynamics.

Currency portfolios optimized on equity spillovers present a different pattern. While low-spillover currency portfolios provide the best risk-adjusted performance, high-spillover currencies, such as the Japanese yen or the Swiss franc, become beneficial during crises as they begin to act as safe-haven assets. This asymmetry shows that connectedness must be understood and analyzed within the economic role of the market internationally, rather than a signal that represents risk profiles across asset classes. Currency portfolios optimized on currency spillovers show intuitive results. High-spillover FX markets consistently underperform due to elevated volatility risk and strong sensitivity to calm global

conditions. Low-spillover currencies perform the best across almost all periods against high spillover counterparts, forming the most stable portfolio configuration of the four combinations of asset allocation that are explored in this study.

The portfolio statistics across the entire study confirm the value of connectedness-based portfolio construction. Specific nations that got included in high or low spillovers can be seen in Appendix A. Sharpe ratios across the full 2000-2024 sample improve from 0.24 in unscreened equity portfolios to 0.28-0.31 in low spillover screening portfolios. Currency portfolios show even larger improvements, especially when optimized using currency spillovers. Crisis-period results during the 2008 crisis and Covid-19 pandemic show that drawdowns are reduced relative to unscreened benchmarks, demonstrating that spillover-filtered portfolios provide meaningful downside risk protection compared to correlation-based portfolios. Cross-asset results, as seen in equity portfolios optimized with currency spillovers, show a new dimension of understanding regarding international risk sharing dynamics. Information from one market's risk can enhance the portfolio construction in another. This suggests that connectedness captures dynamics that are not observable through single-asset correlations in equities or currencies. These results demonstrate that spillover information dynamically applied across periods yields more resilient global portfolios and outperforms traditional correlation-based portfolios under certain conditions in terms of stability and risk-adjusted returns.

Further analysis involves the correlation structure across the 8 portfolio strategies run for this study. This includes equity portfolios optimized on equity spillovers (EEL and EEH), equity portfolios optimized on currency spillovers (ECL and ECH), currency portfolios optimized on equity spillovers (CEL and CEH), and currency portfolios optimized on currency spillovers (CCL and CCH). The correlations between these strategies across time horizons show differences including a clear clustering effect between portfolios. Equity-based strategies tend to correlate strongly with one another, suggesting equity return dynamics regardless of the spillover optimization technique used. Also, the correlation between equity strategies and currency strategies is substantially lower than same-asset correlations. This indicates that the two sets of strategies respond in different ways to global risk, reinforcing that spillover dynamics in one asset class do not fundamentally present themselves in the other. Looking at the periods of global crisis, the strategies become further separated. During the 2008 crisis and the Covid crisis, high spillover equity strategies (EEH and ECH) and low spillover currency strategies (CEL and CCL) share strongly negative correlations. This shows that spillover portfolio optimization doesn't reduce volatility but instead alters the direction of shocks at the asset and portfolio level. High spillover portfolios are seen to tilt toward systemic risk while low spillover portfolios hold a defensive position that behave slightly countercyclically. Cross-asset strategies clearly sit between clusters of pure equity and currency portfolios that are highly correlated among themselves but not with each other.

Table 9

Summary Statistics for Equity Returns

	USA	China	Germany	Japan	India	UK	France	Italy	Canada	Brazil	Russia	South Korea	Australia
Average Return	0.0290%	0.0207%	0.0164%	0.0092%	0.0369%	0.0134%	0.0174%	0.0125%	0.0277%	0.0230%	-0.2091%	0.0224%	0.0314%
Standard Deviation	1.2288%	1.7502%	1.5579%	1.3385%	1.6372%	1.3370%	1.5200%	1.6376%	1.3731%	2.1845%	17.0898%	1.9485%	1.4669%

	Spain	Mexico	Indonesia	Turkey	Netherlands	Saudi Arabia	Switzerland	Poland	Taiwan	Belgium	Sweden	Ireland
Average Return	0.0165%	0.0247%	0.0316%	0.0047%	0.0223%	0.0336%	0.0262%	0.0121%	0.0280%	0.0106%	0.0201%	0.0033%
Standard Deviation	1.6324%	1.6310%	1.8711%	2.6844%	1.4952%	1.2264%	1.1540%	1.9325%	1.5403%	1.4689%	1.7964%	1.7271%

Table 10

Summary Statistics for Currency Returns

	China	Germany	Japan	India	UK	France	Italy	Canada	Brazil	Russia	South Korea	Australia
	Yuan	Euro	Yen	Rupee	Pound	Euro	Euro	CAD Dollar	Real	Ruble	Won	AUD Dollar
Average Return	0.0023%	0.0002%	-0.0068%	-0.0149%	-0.0041%	0.0002%	0.0002%	0.0001%	-0.0219%	-0.0245%	-0.0042%	-0.0010%
Standard Deviation	0.1951%	0.5829%	0.6170%	0.4145%	0.5755%	0.5829%	0.5829%	0.5346%	1.0498%	1.0849%	0.6547%	0.7688%

	Spain	Mexico	Indonesia	Turkey	Netherlands	Saudi Arabia	Switzerland	Poland	Taiwan	Belgium	Sweden	Ireland
	Euro	Peso	Rupiah	Lira	Euro	Riyal	Franc	Zloty	TWD Dollar	Euro	Krona	Euro
Average Return	0.0002%	-0.0118%	-0.0137%	-0.0650%	0.0002%	-0.0002%	0.0085%	0.0001%	-0.0002%	0.0002%	-0.0044%	0.0002%
Standard Deviation	0.5829%	0.7327%	0.6482%	1.1463%	0.5829%	0.0611%	0.6687%	0.8315%	0.2903%	0.5829%	0.7316%	0.5829%

Table 11

Portfolio Summary and Backtesting Results

Equity Portfolios Optimized on Equity Spillover Effects													
1/4/2000 - 12/29/2006				1/1/2007 - 4/30/2009				5/1/2009 - 12/31/2019				1/1/2020 - 05/05/2023	
	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening
Annual Return	2.35%	3.90%	6.63%	-12.86%	-14.40%	-14.66%	9.17%	8.51%	9.52%	7.34%	6.73%	7.16%	10.69%
Annual Std.	9.48%	11.63%	13.64%	15.93%	19.34%	24.59%	9.43%	11.47%	13.22%	14.28%	16.18%	17.84%	9.63%
Sharpe Ratio	-0.01	0.13	0.31	-0.96	-0.87	-0.70	0.71	0.53	0.54	0.34	0.26	0.28	0.86

Equity Portfolios Optimized on Currency Spillover Effects													
1/4/2000 - 12/29/2006				1/1/2007 - 4/30/2009				5/1/2009 - 12/31/2019				1/1/2020 - 05/05/2023	
	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening
Annual Return	2.35%	4.15%	8.96%	-12.86%	-10.86%	-15.02%	9.17%	7.05%	9.61%	7.34%	7.07%	6.69%	10.69%
Annual Std.	9.48%	9.88%	14.76%	15.93%	17.01%	28.24%	9.43%	10.42%	14.37%	14.28%	15.10%	18.35%	9.63%
Sharpe Ratio	-0.01	0.17	0.44	-0.96	-0.78	-0.62	0.71	0.44	0.50	0.34	0.31	0.23	0.86

Currency Portfolios Optimized on Equity Spillover Effects													
1/4/2000 - 12/29/2006				1/1/2007 - 4/30/2009				5/1/2009 - 12/31/2019				1/1/2020 - 05/05/2023	
	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening
Annual Return	0.82%	0.37%	1.35%	-1.08%	2.02%	0.64%	4.40%	-0.82%	-0.77%	8.24%	-1.56%	-0.77%	5.10%
Annual Std.	3.23%	4.34%	5.83%	5.41%	5.04%	7.00%	11.77%	4.60%	6.61%	18.58%	3.58%	4.87%	12.11%
Sharpe Ratio	-0.50	-0.48	-0.19	-0.65	-0.08	-0.26	0.17	-0.71	-0.49	0.31	-1.12	-0.68	0.22

Currency Portfolios Optimized on Currency Spillover Effects													
1/4/2000 - 12/29/2006				1/1/2007 - 4/30/2009				5/1/2009 - 12/31/2019				1/1/2020 - 05/05/2023	
	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening	Low Spillover	High Spillover	No Screening
Annual Return	0.82%	0.32%	1.65%	-1.08%	2.22%	0.40%	4.40%	-0.79%	-0.37%	8.24%	-1.34%	-0.56%	5.10%
Annual Std.	3.23%	4.08%	6.93%	5.41%	4.83%	9.02%	11.77%	4.47%	7.94%	18.58%	3.38%	5.90%	12.11%
Sharpe Ratio	-0.50	-0.52	-0.12	-0.65	-0.05	-0.23	0.17	-0.73	-0.36	0.31	-1.12	-0.51	0.22

Table 12

Equity Portfolio Backtesting Statistics

Equity Portfolios Optimized on Equity Spillover Effects											
	1/4/2000 - 12/29/2006		1/1/2007 - 4/30/2009		5/1/2009 - 12/31/2019		1/1/2020 - 05/05/2023		5/6/2023 - 12/31/2024		01/04/2000 - 12/31/2024
	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	
Average Return	25.60%	50.52%	-31.07%	-33.69%	135.40%	154.49%	19.90%	20.36%	12.95%	11.88%	168.77%
Median Return	27.93%	52.35%	-27.47%	-35.33%	130.52%	160.95%	23.11%	20.95%	10.29%	10.27%	162.21%
Maximum Return	61.77%	104.95%	-20.90%	-17.89%	247.24%	250.36%	28.17%	27.64%	31.72%	28.22%	306.18%
Minimum Return	4.86%	5.86%	-57.12%	-40.27%	75.13%	82.69%	-2.92%	14.18%	0.72%	-3.56%	59.59%
Return Range	56.91%	99.09%	36.22%	22.38%	172.11%	167.67%	31.09%	13.46%	31.00%	31.78%	246.59%

Equity Portfolios Optimized on Currency Spillover Effects											
	1/4/2000 - 12/29/2006		1/1/2007 - 4/30/2009		5/1/2009 - 12/31/2019		1/1/2020 - 05/05/2023		5/6/2023 - 12/31/2024		01/04/2000 - 12/31/2024
	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	
Average Return	29.76%	74.47%	-24.82%	-35.75%	100.34%	150.56%	21.85%	18.16%	11.73%	9.07%	164.11%
Median Return	27.50%	83.25%	-23.67%	-36.77%	92.61%	149.36%	22.39%	18.09%	14.46%	5.40%	161.24%
Maximum Return	96.41%	107.21%	-18.10%	-25.15%	120.68%	190.73%	26.64%	24.53%	17.52%	26.37%	232.94%
Minimum Return	17.90%	20.71%	-44.28%	-40.04%	75.15%	113.66%	11.24%	10.34%	5.29%	-3.55%	122.61%
Return Range	78.51%	86.50%	26.18%	14.88%	45.53%	77.07%	15.41%	14.18%	12.23%	29.92%	110.33%

Table 13

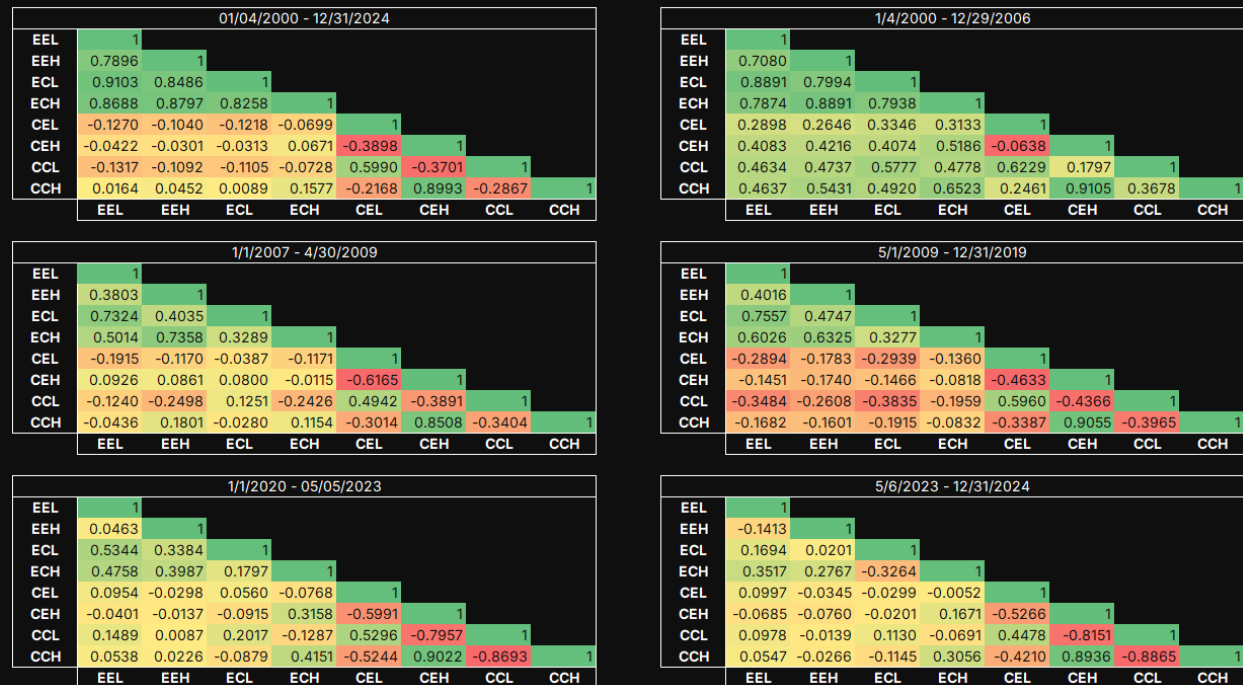
Currency Portfolio Backtesting Statistics

Currency Portfolios Optimized on Equity Spillover Effects											
	1/4/2000 - 12/29/2006		1/1/2007 - 4/30/2009		5/1/2009 - 12/31/2019		1/1/2020 - 05/05/2023		5/6/2023 - 12/31/2024		01/04/2000 - 12/31/2024
	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	
Average Return	1.97%	8.89%	4.50%	1.08%	-9.34%	-8.57%	-5.20%	-2.87%	0.16%	2.83%	-6.99%
Median Return	0.03%	3.26%	3.42%	3.42%	-8.83%	-6.01%	-3.29%	-0.41%	-0.39%	2.10%	-0.10%
Maximum Return	25.64%	23.89%	17.22%	8.92%	0.10%	-0.19%	0.51%	2.56%	9.44%	11.76%	38.07%
Minimum Return	-8.18%	-11.26%	-2.65%	-16.91%	-37.59%	-28.03%	-18.33%	-11.48%	-7.80%	-3.35%	-49.39%
Return Range	33.83%	35.14%	19.87%	25.83%	37.70%	27.84%	18.84%	14.04%	17.24%	15.11%	87.45%

Currency Portfolios Optimized on Currency Spillover Effects											
	1/4/2000 - 12/29/2006		1/1/2007 - 4/30/2009		5/1/2009 - 12/31/2019		1/1/2020 - 05/05/2023		5/6/2023 - 12/31/2024		01/04/2000 - 12/31/2024
	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	Low Spillover	High Spillover	
Average Return	1.72%	10.30%	5.19%	0.45%	-9.01%	-6.95%	-4.54%	-2.41%	-0.74%	2.31%	-7.17%
Median Return	2.32%	8.30%	3.10%	6.81%	-9.35%	-7.86%	-4.87%	-2.14%	-0.63%	1.39%	-15.09%
Maximum Return	12.41%	18.22%	12.85%	16.32%	-3.01%	0.38%	0.00%	0.65%	3.57%	11.89%	17.37%
Minimum Return	-1.80%	-3.62%	-9.76%	-16.73%	-22.32%	-17.18%	-7.28%	-7.66%	-4.02%	-3.50%	-26.55%
Return Range	14.21%	21.84%	22.60%	33.05%	19.31%	17.57%	7.28%	8.31%	7.59%	15.40%	43.92%

Table 14

Strategy Correlation Matrices



While these findings represent the practical advantages of incorporating information on international volatility spillovers into portfolio construction, some implications emerge from the data. The mechanics and the trade-offs of spillover-based portfolios outline that the primary strength of spillover portfolios is its ability to identify and underweight systemic risk transmitters. These markets disproportionately amplify global volatility and exhibit unstable co-movement dynamics during periods of international stress. Unlike correlation-based methods which only measure linear co-movement, spillover dynamics offer a forward-looking dimension to risk management practice. Cross-asset spillovers help to indicate that currency spillovers appear to anticipate shifts in global risk sentiment, allowing equity portfolios to adjust and allocate away from vulnerable markets before drawdowns materialize in equities.

However, spillover-based strategies come with limitations. Connectedness measures are model-dependent, relying on VAR specifications, stationary conditions, or changes in estimation windows. Small changes in data or estimation windows can materially affect spillover coefficients, introducing sensitivity that covariance-based methods do not face. Further, identifying high-spillover markets as “undesirable” is context-dependent. As observed in the currency portfolios, high-spillover currencies can become safe-haven assets during global stress. While high or low volatility spillover does not mean high or low correlation, this raises a key consideration in how spillover magnitude alone may misclassify assets that can serve strong hedging roles despite high spillover attributes. This represents the risk of over-engineering the interpretations of spillover results without considering underlying macroeconomic or geopolitical forces that drive quantitative results. Also, spillover strategies may exclude large clusters of interconnected markets, leading to concentration risk that presents itself in higher allocation toward riskier markets. Finally, portfolio rules based on static spillover thresholds may lag dynamics unless updated frequently, raising several concerns over spillover and transactional costs for portfolio managers in particular.

Taken together, these contrasts and considerations show that spillover-based portfolios are not a replacement for correlation-based methods. Instead, it may act as a framework for capturing systemic risk that complements traditional methods of portfolio construction. The evidence in this study suggests that

combining approaches may help to build a more robust allocation strategy, especially in environments characterized by uncertainty.

Conclusion

This study set out to contribute to broad understanding on volatility spillovers across equity and currency markets. A goal is to identify meaningful improvements in global portfolio allocation relative to traditional correlation-based diversification methods. Using 25 years of data across the 25 largest world economies, the application of the Diebold-Yilmaz framework identifies that many of the largest global economies are interdependent and regime-dependent regarding currency and equity performance. The results show that volatility transmission intensifies during crisis and weakens during expansions, but consistently reflects macro-financial forces across shocks. This contributes to the understanding on why correlation-based methods of portfolio construction lose reliability when systemic protection is most essential.

The spillover findings outline a few key patterns. First, volatility is seen to flow in an imbalanced way, with certain markets such as the US, China, Japan, and major European economies acting as persistent transmitters. Smaller emerging markets act more often as receivers. Secondly, currency markets contain forward-looking information that complements equity market fragility that supports portfolio resilience. Finally, the Covid-19 period and post-pandemic

phase suggest that global connectedness across markets may have structurally risen, reducing the stability of traditional diversification moving forward and in modern markets.

Collectively, these findings show that spillover analytics and their integration into global portfolio management techniques can enhance stability, resilience, and risk-adjusted returns during periods of crisis. Spillover-based optimization does not replace classical frameworks, but extends their concepts by providing directional and causal insights into how shocks propagate. For investors and policymakers, navigating an interconnected global financial system can be improved with awareness on spillover methodologies.

Future research may extend further into higher-frequency data and derivative-driven volatility channels, as well as application into machine-learning connectedness forecasting methods. Overall, the evidence presented in this study strongly suggests that volatility spillovers offer essential enhancements to global measures of risk and portfolio management.

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Portfolio Country Composition

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