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Tactical Allocation Through the Lens of Correlational Time-Variance, Determinants, and Regimes

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ABSTRACT

We investigate correlations among six primary asset classes from January 1982 to December 2022. Our analysis extends existing literature, on the well-researched stock-bond correlation (SBC), by encompassing 14 supplementary asset class dyads and four correlational regimes. We challenge the archetype of correlational time-invariance that underlies buy-and-hold asset allocation strategies by implementing structural break tests and an innovative Wavelet Coherence (WC) methodology, where our findings reveal temporal instability. Through a multi-method statistical approach, we present robust and persuasive evidence of macroeconomic factors as determinants of temporal change. Leveraging time-varying Granger causality, we unearth elusive yet significant relationships. Our research pivots to practice, illustrating outperformance in portfolios constructed upon the principles of time-varying change, macro drivers, and correlational regimes, thus enabling investors to make more informed decisions, leading to superior risk-adjusted returns amid a dynamically evolving economic landscape.

JEL— C4, C22, C25, G1, G11, G14

Keywords— tactical asset allocation, stock-bond correlation, persistency, portfolio optimization, wavelet coherence, time-varying Granger-causality

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CHAPTER 1: INTRODUCTION

In this paper, we explore correlational relationships, extending the scope of existing literature beyond the extensively researched stock-bond correlation (SBC) by incorporating 14 additional asset class dyads. Utilizing a comprehensive, multi-method econometric analysis and portfolio construction approach, we confront the paradigm of correlational stability that underpins the dogma of buy-and-hold strategic asset allocation.

Our findings reveal that asset class correlations exhibit significant temporal fluctuations, with discontinuities in correlational persistence informed by macroeconomic factors. Moreover, our research examines regimes that combine asset class correlations with market directionality, wherein we find significance in the impact of macroeconomic determinants on these regimes. This facilitates our assessment of the notions of time-varying change and regimes through the lens of portfolio construction.

Our analysis finds that *persistency portfolios*, constructed to test time-invariant, correlational stability, produce an annualized Sharpe ratio of 0.901, underperforming a standard 60/40 benchmark at a Sharpe of 1.078. This outcome implies that "chasing returns" based on the assumption of correlational persistence results in suboptimal performance. Conversely, we construct *regime-switching portfolios*, which incorporate time-variance, macro determinants, and market information. These portfolios yield an annualized Sharpe ratio of 1.128, offering a path to superior risk-adjusted returns for investors.

In contemporary finance, the formative theories of Modern Portfolio Theory (MPT), the Capital Asset Pricing Model (CAPM), Efficient Market Hypothesis

(EMH), and the Random Walk Hypothesis, remain relevant and underpin modern financial advice, where they have developed alongside other asset pricing models to optimize portfolios, manage risk, and inform investment decisions. Predominantly grounded in MPT, CAPM, EMH, and other evolutions, *asset allocation* is the process of constructing portfolios of investments across various asset classes, including stocks, bonds, and cash, within a portfolio to achieve an optimal balance between risk and return (Bodie & Kane, 2020).

Correlation is arguably one of the most important inputs into the portfolio construction process. *Strategic asset allocation* (buy-and-hold) presupposes a substantial market efficiency, implying a high level of correlational stability among asset classes. However, despite the considerable persistence of correlations (Ilmanen, 2003), they exhibit changes over time. *Tactical asset allocation*, on the other hand, permits deviations from conventional allocations to exploit perceived market inefficiencies or trends (Brinson et al., 1991). It relaxes assumptions around correlational stability and embraces correlation change, where it endeavors to optimize risk and reward by adjusting the weightings of distinct assets in a portfolio, aligning with short-term market conditions and opportunities.

Through a rigorous empirical analysis, this research encompasses the central inquiry of whether a more profound comprehension of the time-varying change among asset classes, the macroeconomic determinants of those changes, and regimes based on correlations and market information, contributes to better portfolio construction through tactical allocation ultimately resulting in improved risk-adjusted returns. In this pursuit, we offer five contributions to the literature.

First, we confirm the research on the stock-bond correlation (SBC) while noting a dearth of research on other asset class correlations, which hold equal importance in the realm of portfolio construction. In addition to large-cap stocks and US Treasuries (i.e., SBC), we investigate four additional asset classes: small-cap stocks, international stocks, real estate investment trusts (REITs), and gold. By corroborating the extant literature on the SBC and expanding it to encompass the resultant 14 additional asset class correlations, we offer significant findings that some of the same drivers of SBC - inflation, inflation expectations, leading indicators, and sentiment - inform behavior and induce change in other asset class correlational pairings.

Second, we challenge the assumptions of strategic asset allocation, which posits the persistence and temporal immutability of correlations. Across our 15 dyads, we use correlational analysis with fitted linear regression to visualize and assess their relationships. We add structural break tests where we uncover notable disturbances in temporal stability across 11 of the 15 correlations examined. Our study then employs the innovative *Wavelet Coherence* (WC) to incorporate additional frequencies (i.e., rolling periods) and phase oscillations. Thus, we present substantial evidence that correlations are, indeed, subject to temporal fluctuations, revealing the inherent dynamism and evolving patterns among asset class relationships.

Our findings indicate that stock/stock relationships exhibit higher correlation and stability. Treasuries relationships have intermittent stability, varying correlation, and change over time. REITs exhibit distinct and different behaviors that depend on which asset class they are paired with. Gold maintains its reputation as a volatile, non-correlated, and non-additive asset. These results expose the fallacy of assuming time-invariance and proffer a robust, statistically supported argument for embracing the dynamic nature of change to enhance portfolio construction.

In light of correlations' instability, we inquire into the factors driving their fluctuations. Our third contribution to the literature involves exploring four macroeconomic determinants of SBC: inflation, inflation expectations, leading indicators, and sentiment, where we add to the literature by including our 14 additional asset pairings. We apply a distributed lag model (DL) in conjunction with vector autoregression (VAR) and Granger causality, where we present significant results on the influence of macroeconomic variables as determinants and how they drive change. When causation breaks down due to temporal parameter instability, we address it through the novel time-varying Granger causality method (TVGC). TVGC's forward expanding, rolling, and recursive evolving windows uncover 41 inferences of causality and bidirectional causality between our macro variables and asset correlations that eluded us in a traditional Granger method.

Our fourth contribution broadens our examination of macroeconomic indicators by delving into the assessment of correlational regimes, which incorporate asset classes dynamics with market behaviors. A logit/probit model establishes that macroeconomic variables serve as pivotal determinants in 12 of the 16 combinations with the aforementioned regimes, revealing the compelling nature of macroeconomic determinants in driving time-varying correlational regimes.

Finally, we investigate whether insights gleaned from our study of time-varying correlations, drivers of change, and regimes can enhance tactical asset allocation. Our fifth contribution affirms the applicability of these insights by way of a practical framework. We develop naïve, buy-and-hold benchmarks in addition to optimized portfolios using a Generalized Reduced Gradient (GRG) nonlinear optimizer, allowing us to test persistence and regime-based tactical asset allocation. Through hypothetical portfolio construction, we demonstrate that chasing returns is foolish. Whereas, investors equipped with a comprehensive empirical understanding of correlational time-variance, macroeconomic determinants, and regimes, can achieve superior risk-adjusted returns, where a dollar invested in our regime-switching portfolio in January of 1982 would have grown to $47.87 by December 2022, compared to a buy-and-hold, 60/40 benchmark at $30.61, while offering the same annualized standard deviation of 8.3%.

CHAPTER 2: REVIEW OF THE LITERATURE

2.1. Modern Portfolio Theory

> *I think the most important thing that happened between 1959 and the present is the notion of doing your analysis on asset classes in the first instance. This has become part of the infrastructure that we now rely on. In 1959, I had a theory. I had a rationale, and so on. Now, we have an industry. — Harry Markowitz, (Markowitz, Savage, and Kaplan 2010)*

Modern Portfolio Theory (MPT), also known as mean-variance analysis, constitutes a rigorous mathematical framework for constructing a portfolio of assets that optimizes the expected return subject to a specified level of risk. MPT extends and formalizes the concept of investment diversification, which posits that holding various financial assets reduces overall risk compared to owning a single type of asset. By diversifying, investors aim to attenuate portfolio risk while attaining satisfactory returns.

Harry Markowitz pioneered MPT in his 1952 doctoral dissertation, "Portfolio Selection", and subsequently expanded upon in a series of articles published in the Journal of Finance during the early 1950s (Markowitz, 1952, 1959). In recognition of his groundbreaking contributions to MPT, Markowitz was awarded the Nobel Memorial Prize in Economic Sciences in 1990 (Nobel, 1990). The framework is predicated on the normative principles of Daniel Bernoulli's Expected Utility Theory (Tversky, 1975), which presumes that investors exhibit rational, risk-averse behavior in pursuit of maximizing expected returns while minimizing risk. Moreover, MPT assumes that investors can accurately gauge risk and return and freely transact any market asset at a known price.

As delineated by Markowitz (1952), portfolio construction entails a two-stage process. Initially, investors must identify potential assets for inclusion, taking into account factors such as expected returns, risk levels, the covariance of returns between securities, and their individual preferences and projections concerning future performance. Subsequently, investors can commence building their portfolio by estimating each asset's expected return based on historical data and informed speculation about future performance. Variance, a measure of the anticipated fluctuations in an asset's return, is then computed for each asset, with higher variances signifying greater risk. Having derived each asset's expected return and variance, investors can proceed to assemble their portfolio, striving to strike an optimal balance between risk and return.

In his seminal work, Markowitz (1959) introduced mean-variance optimization as a methodology for investors to determine the optimal portfolio from a set of return distributions over a single period (Elton & Gruber, 1997). Markowitz subsequently termed the array of efficient mean-variance combinations as the Efficient Frontier (Markowitz, 1999), which remains a cornerstone of modern financial practice. The Capital Asset Pricing Model (CAPM) later integrated risk into the portfolio selection process (Perold, 2004), further refining MPT. The theory has continued to evolve and exert considerable influence on academic research and practical applications, with recent advancements encompassing sophisticated mathematical models for portfolio optimization, such as Monte Carlo simulation (Fabozzi et al., 2002) and machine learning techniques (Ünlü & Xanthopoulos, 2021).

2.1.1. The Efficient Frontier

In addition to MPT, Harry Markowitz's (1952) seminal article also introduced the efficient frontier concept. MPT posits that a combination of assets is efficient if it results in the highest possible return for a given level of risk. All possible combinations of securities can be graphed in terms of risk and expected return resulting in a collection of portfolios. This region is the opportunity set without the ability to hold a risk-free asset, where the efficient frontier is the upper boundary of this region, represented by a hyperbolic curve (Merton, 1972).

Markowitz's original article (Markowitz, 1952) assumed that all assets are risky. Tobin (1958) introduced the concept of borrowing and lending at a default-free, risk-free rate often approximated by a T-bill. This simplified the efficient frontier and introduced risk-preference (Perold, 2004), laying the groundwork for the CAPM as a better method to derive the efficient frontier.

The efficient frontier is a graphical representation for investors to select portfolios that offer the best combination of return and risk. Financial analysts have also used it to identify the optimal mix of assets for a given investment goal. In theory, portfolios above the frontier cannot be achieved. More efficient portfolios dominate portfolios below the frontier. The resultant asset allocation is the implementation of an investment strategy that balances risk-reward by adjusting each asset's percentage in an investment portfolio based on risk preference, goals, and time frame. Originally MPT's efficient frontier was derived at the individual security level. However, various asset allocations may be plotted according to return and risk to derive an asset-level efficient frontier, where the focus is on the portfolio.

2.1.2. The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is an extension of MPT, serving as a theoretical instrument to determine the required rate of return for an asset in a well-diversified portfolio, considering the asset's non-diversifiable risk (Treynor, 1962; Sharpe, 1964; Lintner, 1965, 1975; Mossin, 1966). CAPM functions as a positive theory, diverging from MPT's normative nature.

The Sharpe-Lintner-Mossin theorem posits that investors will only hold assets with expected returns equivalent to the CAPM risk premium under equilibrium conditions (Sharpe, 1964; Lintner, 1965, 1975; Mossin, 1966). The model states that the expected return of a security or portfolio is the sum of the risk-free rate and a risk premium determined by *beta*, a measure of systematic risk (Sharpe, 1964). During this period, Sharpe introduced the Sharpe ratio in 1965, a metric of risk-adjusted return including the risk-free return rate or a comparable benchmark Sharpe (1966). Alpha, the measure of excess return, was first introduced by Jensen (1968).

The seminal contributions of the CAPM include: (1) delineating the relationship between systematic risk and expected return for a portfolio; (2) incorporating the time value of money by adding the risk-free rate; (3) introducing beta as a measure of risk; and (4) differentiating between systematic risk (market risk), which is common to all securities, and unsystematic risk, which is idiosyncratic and diversifiable.

While the CAPM remains relevant, its imperfections are often highlighted by critics who point to its simplifying assumptions and occasional inaccuracies in predicting security returns. Perold (2004) provides a summary of CAPM's assumptions: (1) investors are mean-variance optimizers who are risk averse and evaluate investments based on expected return and standard deviation; (2) markets are efficient, securities are infinitely divisible, carry no transaction costs, permit short selling, assume no taxes, exhibit no information asymmetry, and are freely accessible to investors, with all investors being able to borrow at the risk-free rate; (3) investment opportunities are ubiquitous, granting access to all investors; and (4) assumptions of expected returns, standard deviations, and correlations are consistent across investors.

2.1.3. The Efficient Market Hypothesis & Random Walk

The notion that professional investors could not outperform the market was first established by Cowles (1933) and Cowles & Jones (1937). The Efficient Market Hypothesis (EMH) is a financial economics theory positing that asset prices reflect all available information (Malkiel, 1999), thus rendering it impossible to "beat the market." EMH originates in the work of Bachelier, Mandelbrot, and Samuelson, who are credited with formulating the random walk hypothesis (Bachelier, 1900; Mandelbrot, 1967; Samuelson, 1973). The random walk hypothesis offers that financial markets are efficient, with prices fluctuating randomly. This theory is grounded in the idea that market participants consistently seek new information, which is promptly incorporated into prices.

Eugene Fama developed EMH during the 1960s (Fama, 1970), presenting three efficiency tests: weak form, semi-strong form, and strong form. According to Fama (1970), the weak form test examines past prices to determine their ability to predict future prices. The semi-strong form test evaluates both past prices and public information in predicting future prices. In contrast, the strong form test scrutinizes all information, both public and private, for its predictive capacity.

Unwavering advocates of EMH have fueled the growth of an indexing industry, with figures such as Jack Bogle, founder of Vanguard, staunchly defending EMH (Bogle, 1999) until his passing in 2019. Likewise, Malkiel (2003) addresses critiques of EMH, including sentiment, seasonality, momentum, fundamental valuation, equity risk premium, bubbles, and crashes. The 1950s and 1960s witnessed numerous studies highlighting a lack of predictability (Ball & Brown, 1968; Fama et al., 1969), with Yen & Lee (2008) noting that empirical findings during the late 1970s and 1980s were mixed, leading to an increase of return predictors from the 1980s to the mid-2000s (Campbell & Shiller, 1988; Jegadeesh & Titman, 1993; Ang & Bekaert, 2007). Since then, return predictability has grown more elusive (Timmermann & Granger, 2004) and not always performed effectively out-of-sample (Welch & Goyal, 2008).

Market inefficiency and predictability have been undermined by advancements in trading technology, as Chordia et al. (2014) discover that price dislocations have diminished in recent years. Factors contributing to the diverse views on efficiency also encompass access to research (McLean & Pontiff, 2016) and learning (Martineau, 2021). Consequently, support for EMH has been revitalized, with Yen & Lee (2008) asserting that "the EMH is here to stay and will continue to play an important role in modern finance for years to come."

2.2. The Significance of Tactical Asset Allocation

> *Antonio: Believe me, no: I thank my fortune for it, My ventures are not in one bottom trusted, Nor to one place; nor is my whole estate Upon the fortune of this present year: Therefore my merchandise makes me not sad.*
> *- Merchant of Venice, William Shakespeare*

In the early days, the seminal work of Markowitz (1952), MPT, CAPM, and other pricing models were primarily concerned with security selection (Treynor, 1961, 1962; Sharpe, 1964; Lintner, 1965, 1975; Mossin, 1966). However, as these theories evolved and synthesized concepts such as the EMH and the efficient frontier (Canner et al., 1994; Tütüncü & Koenig, 2004), they have found broader applicability at the asset level, leading to the increased study of asset allocation and its relevance to practitioners.

Asset allocation constitutes an investment strategy that seeks to optimize risk and reward by adjusting the weightings of different assets within an investment portfolio. Drawing upon the notion that returns combine linearly, while risks combine non-linearly (Sharpe, 1964, 1966), asset allocation decisions are composed at the asset class level. This allows for the combination of assets with divergent risk, return, and correlation characteristics to create various portfolios tailored to distinct investment objectives. Similar to securities, these asset allocations lie along an efficient frontier. Asset allocation decisions presuppose a modicum of efficiency, informed by EMH. Otherwise, investment selection would disregard this level in favor of sector and security selection, or other inefficiency-exploiting methods such as fundamental analysis, technical analysis, quantitative analysis, and behavioral strategies. Often, these methods are employed only after establishing a foundation through a more conventional asset allocation framework.

Various asset allocation strategies, grounded in investment goals, risk tolerance, timeframes, and diversification, include strategic, dynamic, tactical, and core-satellite allocations. Strategic asset allocation represents a normative approach that combines assets through a mean-variance perspective based on expected rates (Campbell et al., 2002). This approach emphasizes the investor's time horizon and risk tolerance, as these factors influence portfolio selection through goal-orientation while minimizing concern for short-term risk (Brennan et al., 1997). Typically, strategic asset allocation assumes a time horizon exceeding ten years. Moreover, it is a passive strategy, adhering more closely to a random walk and EMH framework, albeit with provisions for time-based or drift-based rebalancing.

When investors deviate from a buy-and-hold policy, strategic asset allocation transitions into an "active" or tactical form, wherein temporary deviations from the investment policy aim to capitalize on capital market disequilibria concerning the investment fundamentals underlying the policy mix (Brinson et al., 1991). Strategic asset allocation contrasts with tactical asset allocation, which Brennan et al. (1997) define as "a single period or myopic strategy which assumes that the decision maker has a (mean-variance) criterion defined over the one period rate of return on the portfolio." Tactical asset allocation adopts a less normative stance and embraces active management through a pseudo-market-timing component driven by current economic conditions and concerns about short-term risks. Whereas strategic asset allocation constitutes movement along the efficient frontier, tactical asset allocation represents movement of the efficient frontier (Statman, 2000). The flexibility of tactical asset allocation has spurred the development of quantitative approaches (Faber, 2007) and, more recently, machine learning methods (Chakravorty et al., 2018).

Dynamic asset allocation addresses portfolio selection in uncertain multi-period settings (Duffie, 2010) and operates under the assumptions of no-arbitrage, single-agent optimization, and equilibrium. This approach entails purchasing appreciating assets during favorable economic environments and selling depreciating assets during weakening conditions (Sørensen, 1999). Consequently, dynamic asset allocation becomes a timing-based strategy driven by the business cycle (Munk & Sørensen, 2010), often referred to as cyclical asset allocation in the literature (Brocato & Steed, 1998) and among practitioners. Long-horizon predictability of asset returns, using steady-state financial ratios, for instance, enhances dynamic asset allocation strategies (Cardinale et al., 2014). These strategies further benefit from disciplined portfolio management, such as risk-based rebalancing strategies (Kohler & Wittig, 2014).

Core-satellite asset allocation is a strategy that divides an investment portfolio into two parts: the core, a portfolio of relatively safe investments, and the satellite, a portfolio of more volatile investments. The core portfolio is designed to provide stability and capital preservation, while the satellite portfolio aims to generate growth. The two portfolios are combined to create an overall portfolio with a higher return than the core portfolio alone. Amenc et al. (2004) also find that this approach offers effective risk management by minimizing tracking error with respect to a benchmark.

In their groundbreaking study, Brinson et al. (1986) studied the effects of security selection, market timing, and investment policy (benchmark buy-and-hold) on 91 pension plans from 1974 to 1983. They discovered that investment policy accounted for 93.6% of the variance in total plan return. A subsequent 1991 study, which investigated the period from 1977 to 1987, confirmed the original finding, attributing 91.5% of the variance to investment policy while updating to account for the changing risk characteristics of a portfolio based on asset class positioning (Brinson et al., 1991). Hensel et al. (1991) contends that the decision to depart from benchmark policies in favor of timing or security selection has the most significant impact on returns and return variability. Building on the Brinson studies, Ibbotson & Kaplan (2000) compared a five asset class allocation of indexes to mutual fund counterparts and concluded that asset allocation (1) explained 40% of return variance across funds, (2) exhibited a 90% correlation between fund and index returns, and (3) accounted for close to 100% of fund returns. Statman (2001) also advocates for the importance of asset allocation but adds that tactical allocation by financial professionals can add value.

2.2.1. Modern Portfolio Theory & Asset Pricing Models

> *. . . to withdraw is not to run away, and to stay is no wise action when there's more reason to fear than to hope; 'tis the part of a wise man to keep himself today for tomorrow, and not venture all his eggs in one basket.*
> *- Don Quixote by Miguel de Cervantes (1615)*

Foundational theories like MPT and the CAPM have evolved significantly since their inception. Financial economists in the early 1970s devised methods for guarding against stock market losses, one of which was portfolio insurance. Leland et al. (1976) pioneered this technique, which employs financial derivatives to shield an investor's portfolio from stock market declines. Despite gaining popularity in the 1980s, portfolio insurance faced criticism for potentially exacerbating market declines, as seen during the 1987 stock market crash (MacKenzie, 2004). However, institutions and pension plans continue to employ portfolio insurance today (Dong & Zheng, 2019).

Postmodern Portfolio Theory (PPT) emerged in 1991 as a comprehensive framework for analyzing and constructing portfolios (Rom & Ferguson, 1994). Contrary to traditional portfolio theory, PPT accommodates a broader range of investor behaviors, rendering it more flexible and realistic for practitioners. PPT advocates argue that investors have individualized target returns, risk is defined by the possibility of falling below the target return rather than standard deviation, risk should be measured by downside deviation or the square of semivariance, and risk-adjusted return should be measured by Sortino ratios instead of Sharpe (Kaplan, 2015).

Value at risk (VaR), a statistical technique for quantifying financial risk within a firm or investment portfolio, was developed by JPMorgan and Banker's Trust in the 1990s (Holton, 2002). VaR estimates the maximum loss that could be incurred over a given period, typically based on the investment's holding period (Jorion, 2000). Although VaR is a crucial tool for managing financial risk, it is limited in that it does not account for all risks and is backward-looking, necessitating its use alongside other risk management tools.

In the realm of risk-based portfolio construction, Clarke et al. (2006) propose the most efficient model as the minimum-variance portfolio, which lies at the left-most tip of the mean-variance efficient frontier and is unique in that security weights are independent of individual expected returns. Low beta (Frazzini & Pedersen, 2014) and risk-parity (Asness et al., 2012) portfolios gained popularity but waned due to long-term "Risk-On" and trending markets. Studies such as Lee (2011) discredited these models, arguing that their empirical efficacy is counterbalanced by execution challenges and the absence of a theory to predict performance relative to the markets. Consequently, these models are relegated to a subset of the MPT paradigm.

Asset pricing models evolved along with MPT, with studies showing that CAPM cannot explain market anomalies like size and value effects. Jegadeesh & Titman (1993) investigated the profitability of momentum investing strategies and challenged the EMH by demonstrating that these strategies can generate significant abnormal returns.

Deviations from CAPM and EMH prompted a shift toward factor models in order to explain EMH anomalies. Fama & French (1992) proposed three factors - market excess return, the outperformance of small versus big companies (SMB), and the outperformance of high book-to-market versus low book-to-market companies (HML) - which better explained stock returns than CAPM. Carhart (1997) expanded on the Fama-French Three-Factor Model (FFM3) by introducing a momentum factor (MOM). Fama & French (2015) later extended their original FFM3 to include two additional factors: profitability (RMW) and investment (CMA). The updated Fama-

French Five-Factor Model (FFM5) was once again updated with a MOM factor by a Ph.D. student of Eugene Fama, Cliff Asness of AQR Capital (Asness, 2014). The evolution in asset pricing models is representative of the continuous refinement of financial theories to better account for market complexities and investor behavior, highlighting the dynamic nature of the field.

2.2.2. Evolution of Asset Allocation Theory & Practice

> *But divide your investments among many places, for you do not know what risks might lie ahead. - Book of Ecclesiastes (935 B.C.)*

MPT, CAPM, EMH, efficient frontier, and asset allocation have endured and continue to underpin financial advice, despite ongoing theoretical and practical developments. In asset allocation research, the focus has predominantly been on whether security selection, timing, sentiment, and momentum contribute to or detract from benchmark policy performance. Bekkers et al. (2009) utilized mean-variance analysis across ten asset classes, finding that real estate, commodities, and high-yield fixed income significantly improved the efficient frontier over a naïve benchmark portfolio. Moreover, Blitz & Van Vliet (2008) demonstrated out-of-sample excess performance net of transaction costs by applying value and momentum strategies to twelve asset classes.

While the literature has placed less emphasis on expanding asset classes in asset allocation studies, focusing instead on factor and strategy-based research, practitioners have significantly broadened their scope. The 1980s witnessed an increase in allocations to small-cap, mid-cap, and international assets in traditional stock/bond portfolios. In 1992, Morningstar introduced the Style Box to aid investors and professionals in determining style and capitalization (Morningstar, 2022). The 1990s and 2000s saw further expansion into emerging markets, real estate, and commodities.

More recently, there has been remarkable growth in alternative investments (Alts), which encompass alternatives to traditional equity and fixed-income securities. Alts may include derivatives, options strategies, commodities, and managed futures (Hoevenaars et al., 2008; Hurst et al., 2013). Furthermore, the Alts category includes non-traded, non-market fixed income, private equity (Korteweg et al., 2022), private debt, and private real estate (Demaria et al., 2021). Hedge fund strategies have also evolved as another Alts subcategory, further subdivided into strategies such as relative-value arbitrage (Gatev et al., 2006), long-short (Fung & Hsieh, 2011), equity hedge (Asness et al., 2001), market neutral, global macro, and event-driven (Ennis & Sebastian, 2003; Fung & Hsieh, 1999).

Presently, wealth and investment management services use MPT applications through asset allocation models employing strategic, dynamic, tactical, or core-satellite methods, where they express their Capital Market Assumptions (CMAs). These CMAs provide realistic expectations for forward-looking risk and return characteristics, enabling practitioners to reach the efficient frontier ex-ante rather than ex-post. The number of recommended asset classes in practice often surpasses those studied in academic literature. Wells Fargo Investment Institute (WFII, 2022) and BlackRock (BlackRock, 2022) recommend allocating to more than 12. Goldman Sachs Asset Management (GSAM, 2022) adopts a core-satellite approach for high and ultra-high net worth clients, allocating to 20 classes, while Vanguard (Vanguard, 2022) suggests up to 10 asset classes in its strategic models. This demonstrates the dynamic and increasingly complex evolution of asset allocation.

2.3. Correlational Change, Determinants, & Regimes

Correlation, a statistical technique that quantifies the strength of linear association between two variables, measures how the variables covary at a constant rate (Barnett et al., 1994). The sample correlation coefficient, represented as 'r,' offers a numerical assessment of the association's strength (Pearson, 1895), and its statistical significance is frequently evaluated through hypothesis testing (Fisher, 1921). While correlation is widely employed in statistical analysis to characterize simple relationships, it should not be used to infer causality (Snee, 1977; Shmueli, 2010). Additionally, correlation may be unsuitable for describing curvilinear associations (Loehlin, 2004).

In the context of portfolio construction, correlation is a crucial element and was a key component in Markowitz's MPT. MPT utilizes correlation to assist investors in diversifying their portfolios to reduce risk without compromising returns. Within MPT, correlation measures the extent to which two or more assets move in unison. A high positive correlation between two assets signifies that they tend to move in the same direction, whereas a high negative correlation implies that they tend to move in opposite directions. Low or zero correlation suggests that the assets move independently of one another.

MPT aims to construct a portfolio with a low overall risk level, which can be achieved by selecting assets with low, negative, or zero correlations. By combining such assets, investors can create a more diversified and less risky portfolio. Numerous empirical studies have demonstrated the benefits of diversification using correlation within MPT. Bollerslev et al. (1992) examined the effects of volatility spillover across different markets, discovering that these spillover effects are related to the correlation between markets. The seminal work of Brinson et al. (1986) discovered that asset allocation accounted for the majority of the variance in pension fund returns, with the primary driver of this variation being the level of diversification in the portfolios.

2.3.1. Correlational Change Over Time

The four most dangerous words in investing are: 'This time it's different.'
- Sir John Templeton

The correlations among stocks, bonds, and other asset classes exhibit variability over time, contingent upon prevailing market conditions and economic factors (Chollete et al., 2009). Connolly et al. (2005) assert that stock market uncertainty influences the return correlation between stocks and bonds. Under conditions of heightened uncertainty, stocks and bonds consistently exhibit negative return correlations. In contrast, a positive correlation emerges when uncertainty is low. This underscores the significance of accounting for market uncertainty when examining asset correlations.

Ilmanen (2003)'s observation of the transition from positive to negative stock-bond correlations over time suggests that the persistence of these correlations is subject to macroeconomic factors and evolving market conditions. The correlation among international equity markets has increased over time (Baele et al., 2010) and demonstrates greater persistence during episodes of extreme market volatility (Longin & Solnik, 2001). This finding implies that diversification benefits become constrained during turbulent periods due to the enduring nature of high correlations among international equity markets.

Although correlations can persist for extended durations, such persistence is not guaranteed. Investors ought to remain alert and continually assess the correlations between various asset classes to ensure optimal portfolio management. Engle (2002) introduces the Dynamic Conditional Correlation (DCC) model to capture these time-varying correlations, furnishing a more accurate comprehension of their persistence. Recognizing the potential for stock-bond and other asset correlations to change over time due to numerous economic and market factors is crucial. Investors and portfolio managers should monitor these correlations and modify their investment strategies to optimize diversification benefits and manage risk. A more profound understanding of the macroeconomic drivers, coupled with an awareness of the prevailing correlational regime, would contribute to more informed portfolio construction.

2.3.2. Determinants of Correlational Change

The correlation between asset classes is a focus of financial research, especially the stock-bond correlation (SBC). Literature converges on several macroeconomic drivers of SBC and how it changes over time. According to Andersson et al. (2008), correlation is positively related to inflation and economic activity, as measured by GDP, and negatively related to real interest rates. They also find that the correlation is higher during periods of market stress, such as the 2008 financial crisis. Correlation increases in bull markets but not in bear markets (Longin & Solnik, 2001). Jacobsen & Scheiber (2022) reiterate these concepts and posit that financial crises and fluctuations in inflation influence the correlation between stocks and bonds. They further suggest that before 1997, a decline in economic growth was frequently accompanied by an increase in inflation, which led to both government bonds and stocks losing value simultaneously. However, after 1997, there was a negative correlation between government bonds and stocks, particularly during periods of decline in the stock market, owing to the perception that inflation was stable.

Li (2002) notes that inflation expectations can affect the stock-bond correlation because they influence the nominal interest rate, an important driver of bond returns. Additionally, the author suggests that economic growth can play a role in the SBC, as changes in economic growth expectations can lead to changes in stock returns. Ilmanen (2003) examines the impact of macroeconomic factors on the correlation between stocks and bonds. The study finds that: (1) rising inflation leads to a negative SBC while falling inflation results in a positive SBC; (2) strong economic growth expectations create a positive correlation, whereas weak growth expectations yield a negative correlation; (3) increasing interest rates cause a negative SBC, while decreasing interest rates lead to rising bond prices and a positive SBC; (4) the SBC correlation changes over time, necessitating diversification across various asset classes for a well-balanced portfolio in an evolving correlation landscape. Johnson et al. (2013) examines the relationship between stock and bond markets in the United States from 1927 to 2012, suggesting that the SBC correlation is influenced by a range of factors, including macroeconomic conditions, investor sentiment, and government policies. Pericoli (2018) finds that the correlation between stocks and bonds is positively related to economic activity by measuring the growth of Gross Domestic Product (GDP) by consensus estimates and industrial production. He also finds this correlation to be positively related to inflation, indicating that the two markets move together when inflation is high.

Bekaert & Engstrom (2010) examines the relationship between inflation and the stock market, specifically investigating the "Fed Model," which suggests that the stock market's earnings yield should be equal to the long-term government bond yield minus expected inflation. They find that the relationship between the stock market and inflation is complex and not easily explained by the Fed Model. Brixton et al. (2023) posits that the SBC depends not on the level of inflation but on the relative volatility of growth and inflation and the correlation between them.

In contrast, Shiller & Beltratti (1992) use vector autoregression to argue that changes in the correlation between stock prices and bond yields have little to do with changes in inflation rates. The relationship between these two asset classes can be influenced by various factors such as macroeconomic conditions, monetary policies, and market sentiment. During periods of high uncertainty, SBC tends to be positive (Connolly et al., 2005), while during periods of low uncertainty, the correlation is negative. The VIX, or "fear index," a measure of implied volatility in the stock market, also explains SBC correlation. When the VIX is high, reflecting increased investor fear, the stock-bond correlation tends to be positive. This suggests that during times of heightened market sentiment, both stocks and bonds may react similarly to changing market conditions (Bekaert & Hoerova, 2014). Baker & Wurgler (2007) argue that investor sentiment can influence asset prices, especially for stocks that are harder to value or more speculative. When sentiment is positive, investors are more likely to take on riskier assets like stocks, which could result in a negative correlation with bonds. On the other hand, when sentiment is negative, investors may opt for safer assets like bonds, potentially leading to a positive SBC. Inflation expectations are supported as a strong determinant of SBC, where sentiment plays an indirect role, as it can affect inflation expectations and investors' perception of bonds as a hedge against stocks (Campbell et al., 2009).

Other studies look at additional determinants of asset class correlations where Bekaert et al. (2013) investigate the impact of monetary policy on risk, uncertainty, and asset prices, including stock-bond correlations. They find that unconventional monetary policy measures, such as quantitative easing, can affect asset prices and the relationships between different asset classes. Longin & Solnik (2001) analyzed the evolution of international stock market correlations between 1980 and 1999 and found that correlations have increased significantly over time, indicating increased global market integration. Correlation is not related to market volatility per se but to the market trend. Another factor that has led to changes in correlations is the rise of index-based investing, which has led to increased correlations between assets, as many index-based portfolios include similar assets (Bollen & Busse, 2005; Wurgler, 2010).

In recent years, there have been changes in the financial landscape that have led to changes in correlations between assets. For example, increased global interconnectedness has led to an increased correlation between financial markets around the world (Ang & Bekaert, 1999). This increased correlation means that events in one market can have a significant impact on other markets. Forbes & Rigobon (2002) offer that interdependence among stock markets, rather than contagion, is attributed to economic fundamentals, investor sentiment, and monetary policy. On the other hand, contagion refers to the idea that shocks in one market can cause other markets to crash, independent of common factors. This has led to higher levels of risk for portfolios that are not diversified globally.

2.3.3. Correlational Regimes

Correlational regimes pertain to distinct time intervals during which the correlations between various financial assets display particular characteristics or patterns. As these regimes are governed by the same macroeconomic drivers that underpin the underlying correlations, they exhibit analogous patterns of persistence. A better understanding of correlational regimes is crucial for portfolio management, as it enables investors to optimize their risk diversification strategies. Several studies have explored the existence and nature of correlational regimes.

Ang & Bekaert (2002) examine international allocations and identify the presence of regime shifts characterized by alterations in correlations among diverse asset classes. Through a regime-switching model to capture shifts, they discover that optimal portfolio allocations are contingent upon the prevailing regime. Chollete et al. (2009) employ a multivariate regime-switching copula approach to model the international financial returns of stocks, bonds, and other asset classes. Their findings reveal that correlations among these assets evolve over time depending on market conditions and economic factors, substantiating the existence of correlational regimes.

Correlational regimes play a pivotal role in portfolio management and diversification. By understanding and adapting to these regimes, investors can better manage their portfolios and navigate various market conditions. Jacobsen & Scheiber (2022) propose the existence of four correlational regimes: (1) Everyone-Wins: positive stock-bond correlation (SBC) with rising markets; (2) Risk-On: negative or low SBC with rising markets; (3) Flight-to-Safety: negative SBC with declining markets; and (4) Nowhere-to-Hide: positive SBC with declining markets.

Everyone-Wins regimes are typified by periods when markets are favorable, and correlations are positive, leading to positive returns across asset classes. Utilizing a regime-switching model to capture shifts in market conditions and asset correlations, Guidolin & Timmermann (2005) investigate optimal portfolio choices under different market regimes, including periods of positive returns and positive correlations, assisting investors in optimizing their portfolios in response to propitious market environments. During periods of positive returns, correlations change, and when these correlations are high, investors benefit from holding a diverse range of assets (Ang & Bekaert, 2002). Conversely, through wavelet analysis, Rua & Nunes (2009) examine the international comovement of stock market returns and find that correlations tend to be higher during periods of market expansion, limiting diversification benefits during rising markets with positive relationships. Correlation risk is priced in the market, so investors demand a premium for holding assets with high systematic risk during periods of increased correlation, presenting diversification challenges during periods of rising markets with positive correlations (Driessen et al., 2009).

Risk-On regimes are characterized by periods when investors exhibit a heightened appetite for riskier assets, such as stocks, owing to favorable market conditions, economic growth, or increased optimism. Accommodative monetary policies can precipitate Risk-On regimes, where investors have a higher appetite for riskier assets due to increased optimism and low interest rates (Bekaert et al., 2013). Carry trade strategies are associated with Risk-On, as they are exposed to global risk factors. These exposures change over time, suggesting that investors need to monitor Risk-On and risk-off regimes for successful carry trade strategies (Christiansen et al., 2011). Neely et al. (2014) examine the predictive ability of technical indicators for the equity risk premium, which can signal the presence of Risk-On or risk-off regimes. They find that certain technical indicators can help predict equity risk premiums, providing valuable information for investors during Risk-On periods. The stock-bond return relation is more positive during low uncertainty periods, which are typically associated with Risk-On regimes, and more negative during high uncertainty periods, which correspond to risk-off regimes (Connolly et al., 2005).

Flight-to-Safety regimes are characterized by investors' tendencies to reallocate their investments from riskier assets to safer or higher-quality assets during periods of market stress or uncertainty. In such periods, SBC exhibits distinct patterns, with bonds serving as a safe-haven asset when equity markets experience significant downturns (Baur & Lucey, 2009). Geyer et al. (2004) find a similar effect when examining yield spreads in European Monetary Union (EMU) government bonds, where they discover evidence of Flight-to-Safety behavior during market stress, with investors seeking refuge in higher-quality government bonds. In examining the influence of political incumbency on financial market uncertainty in Australia, Smales (2015) suggests that political uncertainty leads to an increase in Flight-to-Safety episodes as investors seek safety in higher-quality assets.

Nowhere-to-Hide regimes are periods when markets experience negative returns, and asset correlations are positive, limiting diversification opportunities for investors. Seo (2023) investigates long-run inflation risk in correlated markets, which render nominal bonds non-hedge assets, force regime shifts, and change the stock-bond return correlation. This leads to a decline in diversification potential across asset classes, resulting in sharply higher levels of investment risk (Cotter et al., 2018). Forbes & Rigobon (2002) analyze stock market comovements and variance, where they disentangle contagion from interdependence. They find that correlations between markets increase during periods of high volatility and negative returns, limiting diversification opportunities and creating Nowhere-to-Hide situations for investors. Hartmann et al. (2004) confirms this by demonstrating that asset class correlations increase significantly during periods of financial stress, thus limiting opportunities for diversification.

Understanding correlational regimes is essential for effective portfolio management and risk diversification. Investors must adapt to these regimes and continuously monitor market conditions, asset correlations, and economic factors to optimize their investment strategies and navigate various market environments.

2.4. Impact of Changing Correlations on Portfolio Construction

Tactical asset allocation is a fundamental aspect of investment management, with the objective of maximizing expected returns while minimizing associated risk. However, the changing correlations among asset classes can pose challenges to the traditional methods of portfolio construction, making diversification and asset allocation more complex. Accounting for changes in the correlation structure among assets can significantly improve portfolio performance and risk management (Guidolin & Timmermann, 2007). It is important to have a better understanding of the role of macroeconomic factors and market conditions in driving correlation changes and their influence on asset allocation decisions.

Changes in correlations can impact the effectiveness of asset diversification. As assets that were once uncorrelated or negatively correlated become positively correlated, the level of diversification in a portfolio may decrease, leading to higher levels of risk (Brixton et al., 2023). To mitigate this risk, portfolio managers may need to adjust their asset allocation strategies by reducing exposure to assets that are becoming more positively correlated and investing in assets that are becoming more negatively correlated. For example, a portfolio manager may reduce exposure to US and European stocks if they are becoming more positively correlated and increase exposure to emerging market stocks, which are becoming more negatively correlated (DeMiguel et al., 2009). Dopfel (2003) finds that a lower SBC may require investors to allocate a higher percentage of their portfolio to equities to achieve a desired level of risk and return. This highlights the importance of considering the changing correlation between assets when making asset allocation decisions.

The impact of macroeconomic factors and market conditions on correlation should be considered when constructing a diversified portfolio. Brixton et al. (2023) suggests that traditional asset classes, such as stocks and bonds, may be more susceptible to these factors, whereas alternative asset classes, such as commodities, real estate, private equity, and hedge funds, may provide additional sources of return and diversification. The bidirectional causality between stocks and bonds suggests that diversification across these two asset classes may not provide complete risk reduction (Baz et al., 2019). Therefore, incorporating alternative asset classes may be necessary to achieve a truly diversified portfolio. Ilmanen et al. (2014) find that commodities tend to perform well during periods of inflation, while real estate tends to perform well during periods of economic growth. They also find that equities tend to perform well during periods of economic growth and low inflation, while bonds tend to perform well during periods of economic slowdown and high inflation. Konno & Yamazaki (1991) add that changes in correlation have important implications for portfolio construction, where investors may need to revise strategies to ensure adequate diversification. This may involve investing in a wider range of assets, including global assets, to reduce portfolio risk.

As global interconnectedness continues to increase and new investment strategies emerge, correlations between assets will continue to evolve (Ang & Bekaert, 1999). Investors must be prepared to adapt their portfolio construction strategies in response to these changes to ensure that their portfolios remain optimal. Embracing alternative asset classes and considering the impact of macroeconomic factors and market conditions on asset correlations will be crucial for maintaining a well-diversified and robust portfolio (Forbes & Rigobon, 2002).

CHAPTER 3: DATA & METHODS

3.1. Data Collection

We use month-end index and price data for six primary asset classes, encompassing the period between January 1982 and December 2022, resulting in a total of 492 observations. The S&P 500 index (*SP*) represents US large-cap equities, while the Russell 2000 index (*R2*) serves as a proxy for US small-cap equities. The MSCI EAFE (*EF*)index is employed to approximate international equities. In accordance with existing literature, the ICE BofA US Treasury index (*UST*) is utilized for bonds. These four indices are sourced from FactSet (2023). The month-end spot price for gold (G) comes from MacroTrends (2023). For real estate, the FTSE Nareit US Total Return Index (*RE*) is adopted (Nareit, 2023). As for the risk-free rate, the three-month T-bill rate is employed, which is obtained from the St. Louis FRED economic database (FRED, 2023b). A comprehensive overview of asset class and portfolio summary statistics is presented in Table 3.1.

For a fundamental measure of expected positive economic activity, we use the CEIC's Leading Indicators for the United States (*CEIC*) (CEIC, 2023). Our psychological variable for growth expectations is Sentiment (*Sent*) which comes from the University of Michigan's Index of Consumer Sentiment (UofM, 2023). As a measure of inflation, we sourced one of the Federal Reserve's preferred measures - the 12-month Trimmed Mean PCE Inflation (π) also from CEIC (CEIC, 2023). Our other psychological variable, two-year Inflation Expectations (π^e), come from St. Louis FRED (FRED, 2023a).

Table 3.1: Summary Statistics: Macros, Assets, & Portfolios

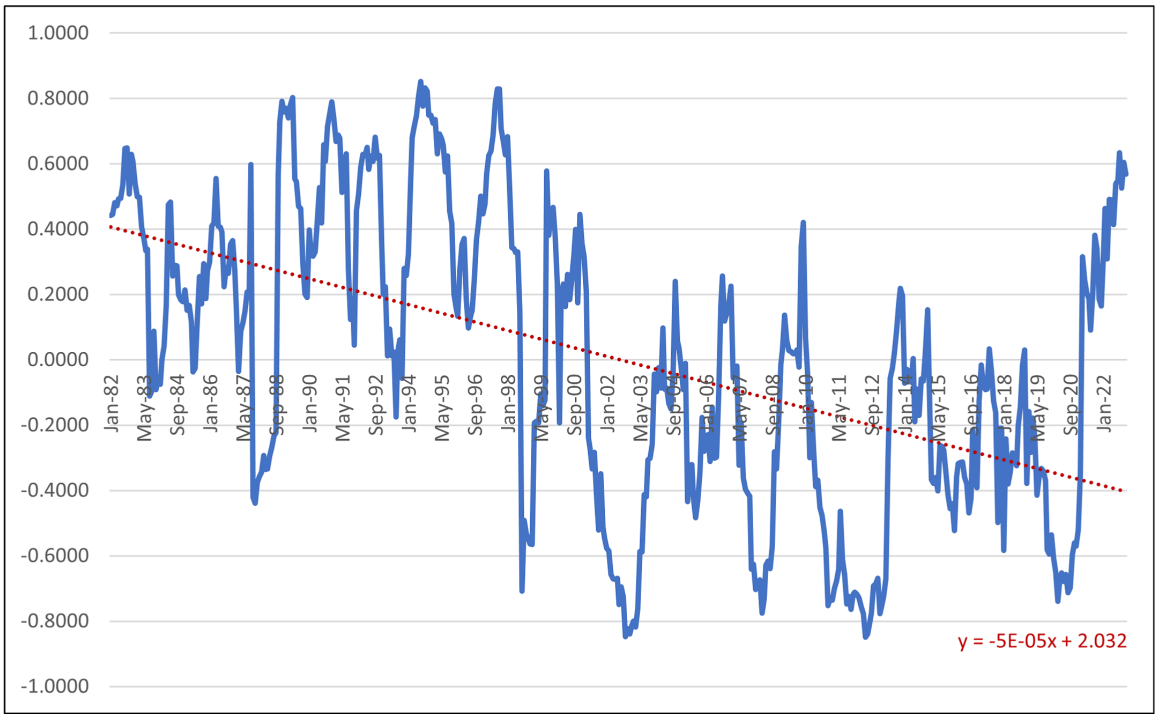
	Num. (mos.)	Min	1st Quartile	Median	AR Mean	Geom Mean	CR ($)	3rd Quartile	Max	SE Mean	Var	Stdev	Skew	Kurt
Macroeconomic Variables														
π (*Inf_12M*)	492	0.800	1.820	2.285	2.549	2.430		3.200	6.830	0.044	0.952	0.976	1.143	1.447
π^e (*ExpInf_2Y*)	492	0.424	1.825	2.644	2.802	2.620		3.525	6.473	0.055	1.472	1.213	0.732	0.026
Sentiment (*Sent*)	492	50.000	78.050	90.450	86.895	85.936		95.425	112.000	0.563	155.958	12.488	-0.587	-0.239
Leading Indicators (*CEIC*)	492	20.281	96.424	101.549	99.857	99.244		106.149	117.919	0.440	95.329	9.764	-2.245	10.927
Asset Classes														
S&P500 (*SP*)	492	-0.215	-0.015	0.014	0.010	0.009	85.205	0.037	0.135	0.002	0.002	0.044	-0.616	1.951
US Treasuries (*UST*)	492	-0.042	-0.003	0.004	0.005	0.005	11.837	0.013	0.087	0.001	0.000	0.015	0.614	2.594
MSCI EAFE (*EF*)	492	-0.184	-0.014	0.013	0.007	0.006	21.460	0.034	0.150	0.002	0.002	0.042	-0.730	2.008
Russell2000 (*R2*)	492	-0.306	-0.027	0.017	0.009	0.008	44.708	0.043	0.184	0.003	0.003	0.056	-0.714	2.705
REITs (*RE*)	492	-0.302	-0.014	0.011	0.009	0.008	41.193	0.035	0.280	0.002	0.002	0.048	-0.885	7.340
Gold (*G*)	492	-0.178	-0.019	0.000	0.004	0.003	3.751	0.026	0.196	0.002	0.002	0.043	0.259	2.259
Benchmark Portfolios														
0/100 (*B0100*)	492	-0.042	-0.003	0.004	0.005	0.005	11.837	0.013	0.087	0.001	0.000	0.015	0.614	2.594
20/80 (*B0280*)	492	-0.047	-0.002	0.006	0.006	0.006	16.928	0.013	0.088	0.001	0.000	0.014	0.366	3.477
40/60 (*B4060*)	492	-0.064	-0.002	0.007	0.007	0.007	23.215	0.016	0.090	0.001	0.000	0.018	-0.254	2.128
60/40 (*B6040*)	492	-0.102	-0.004	0.010	0.007	0.007	30.614	0.021	0.092	0.001	0.001	0.024	-0.639	2.176
80/20 (*B8020*)	492	-0.150	-0.007	0.013	0.008	0.008	38.874	0.026	0.101	0.001	0.001	0.031	-0.806	2.620
100/0 (*B1000*)	492	-0.198	-0.011	0.014	0.009	0.008	47.554	0.031	0.131	0.002	0.002	0.038	-0.882	2.966
Optimized & Persistency Portfolios														
Unconstrained (*OptU*)	492	-0.132	0.001	0.011	0.012	0.012	362.696	0.022	0.098	0.001	0.001	0.024	-0.567	5.565
Pers Unconstrained (*POptU*)	492	-0.188	-0.005	0.007	0.007	0.007	28.096	0.021	0.098	0.001	0.001	0.027	-0.932	7.456
Semi-constrained (*OptC*)	492	-0.112	0.002	0.011	0.012	0.012	303.134	0.022	0.098	0.001	0.000	0.021	-0.551	5.019
Pers Semi-constrained (*POptC*)	492	-0.178	-0.005	0.007	0.007	0.007	29.885	0.021	0.098	0.001	0.001	0.025	-0.958	7.423
Benchmark Constrained (*OptB*)	492	-0.198	0.000	0.009	0.008	0.008	52.506	0.019	0.087	0.001	0.001	0.023	-1.894	15.348
Pers Bench Constrained (*POptB*)	492	-0.198	-0.003	0.007	0.007	0.007	23.900	0.018	0.087	0.001	0.001	0.023	-1.626	13.433
Regime & Regime Switching Portfolios														
Everyone-Wins (*EW*)	492	-0.102	-0.003	0.008	0.007	0.007	25.586	0.018	0.090	0.001	0.000	0.020	-0.600	3.090
Risk-On (*RO*)	492	-0.099	-0.002	0.008	0.007	0.007	33.362	0.019	0.099	0.001	0.000	0.020	-0.253	3.070
Flight-to-Safety (*FTS*)	492	-0.102	-0.004	0.010	0.007	0.007	28.746	0.021	0.090	0.001	0.001	0.023	-0.716	2.362
Nowhere-to-Hide (*NTH*)	492	-0.056	-0.002	0.007	0.007	0.007	28.179	0.016	0.090	0.001	0.000	0.017	-0.041	1.962
Regime-Switching (*RS*)	492	-0.102	-0.004	0.012	0.008	0.008	47.871	0.022	0.099	0.001	0.001	0.024	-0.559	2.279
Optimized Reg-Switch (*RSO*)	492	-0.112	-0.003	0.009	0.007	0.007	30.530	0.019	0.088	0.001	0.000	0.020	-0.710	3.725

Summary statistics from January 1982 to December 2022. Macros: π (*Inf_ 12M*), π^e (*ExpInf_ 2Y*), Leading Indicators (*CEIC*), Sentiment (*Sent*). Asset classes: S&P 500 (*SP*), US Treasuries (*UST*), MSCI EAFE (*EF*), Russell 2000 (*R2*), REITs (*RE*), and Gold (*G*). Benchmark portfolios: 0/100 (*B0100*), 20/80 (*B2080*), 40/60 (*B4060*), 60/40 (*B6040*), 80/20 (*B8020*), 100/0 (*B1000*). Optimized and persistency portfolios: Optimized Unconstrained (*OptU*), Persistency Unconstrained (*POptU*), Optimized Semi-constrained (*OptC*), Persistency Semi-constrained (*POptC*), Optimized Benchmark Constrained (*OptB*), Persistency Benchmark Constrained (*POptB*). Regime and regime-switching: Everyone-Wins (*EW*), Risk-On (*RO*), Flight-to-Safety (*FTS*), Nowhere-to-Hide (*NTH*), Regime-switching (*RS*) , Optimized Regime-switching (*RSO*).

3.2. Correlational Analysis

To perform a comprehensive correlation analysis, we calculate all 15 asset class correlational combinations, yielding rolling 12-month correlation matrices. We fit linear regression lines to the data to aid in the visualization of the changing nature of correlations over time. Figure 3.1 illustrates the rolling 1-year stock-bond correlation (SBC) utilizing the returns of the S&P 500 and US Treasuries.

Figure 3.1: Correlation of the S&P 500 to US Treasuries



This chart portrays the rolling one-year correlation of S&P 500 index to the ICE BofA US Treasury index from January 1982 to December 2022. A linear regression line has been fitted and indicates that the correlation (ρ) has changed from positive ($\rho = 0.4$) to negative ($\rho = -0.4$).

Stationarity is a property of a time series where its statistical characteristics, such as mean, variance, and autocorrelation, remain constant over time. Non-stationarity implies that properties change over time, leading to issues in time series analysis and forecasting, such as spurious regressions, unreliable parameter estimates, inaccurate forecasts, and invalid hypothesis testing (Greene, 2003). To address these issues, it is essential to test for stationarity and transform non-stationary time series into stationary ones. We use the Augmented Dickey-Fuller (ADF) to test for the presence of a unit root in a time series (Dickey & Fuller, 1979; Said & Dickey, 1984).

The ADF test equation is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{3.1}$$

The null hypothesis (H_0) of the ADF test assumes the presence of a unit root (i.e., $\gamma = 0$), while the alternative hypothesis (H_1) asserts the absence of a unit root (i.e., $\gamma < 0$). The test statistic is computed and compared with the critical values to determine whether the null hypothesis can be rejected.

The Schwarz Bayesian Information Criterion (SBIC) is a model selection criterion used in statistical analysis to compare and select the best-fitting model from a set of candidate models (Schwarz, 1978). It balances model complexity and goodness of fit by incorporating both the likelihood of the data given the model and a penalty term proportional to the number of parameters in the model. SBIC favors simpler models with fewer parameters, as it helps to avoid overfitting and choose the most parsimonious model that still adequately explains the data. We use SBIC in our study to determine the optimal lag.

The persistent nature of the stock-bond correlation (SBC) has been well-established in existing literature (Connolly et al., 2005; Ang & Bekaert, 2002), leading to assumptions of stability that inform buy-and-hold strategic allocations. However, it does not fully account for the complexities of asset correlations, which are subject to change over time (Cappiello et al., 2006). Our study uses an autoregressive model (AR) to assess the strength of the inherent time-series moving average of the 15 asset correlations.

An autoregressive (AR) model is a type of linear model employed in econometrics and finance to characterize the behavior of time series data. This model posits that the current value of a variable is linearly dependent on its previous values, with the addition of an error term. AR models are frequently utilized to analyze and forecast time series data, such as stock prices, GDP, or inflation rates (Box et al., 2015).

An Autoregressive (AR) model of order p can be denoted by the subsequent equation:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{3.2}$$

In this representation, y_t is the value of the variable at time t, c is a constant term, ϕ_i are the autoregressive coefficients, and ϵ_t is an error term at time t.

AR models are valuable in investigating short-run and long-run relationships between variables and have demonstrated the persistence of correlational relationships (Malliaropulos, 1998).

Bansal & Yaron (2004) and Baele et al. (2010) use the Newey-West estimator in their analyses of SBC. The Newey-West estimator is a technique for adjusting the standard errors of Ordinary Least Squares (OLS) estimators to account for autocorrelation and heteroskedasticity (Newey & West, 1987).

The Newey-West HAC estimator of the covariance matrix is given by:

$$V_{\text{NW}} = (X'X)^{-1} X' \Omega X (X'X)^{-1} \tag{3.3}$$

where Ω is a consistent estimator of the long-run covariance matrix of the error terms. The Newey-West estimator of Ω is given by:

$$\Omega_{\text{NW}} = \sum_{l=0}^{L} [\omega(l) * (\epsilon\epsilon')_l] \tag{3.4}$$

where $\omega(l)$ is a weighting function that depends on the lag l and $(\epsilon\epsilon')_l$ denotes the autocovariance matrix of the errors at lag l. The summation is taken from $l = 0$ to L, where L is the maximum lag chosen by the user.

The weighting function $\omega(l)$ is commonly chosen to be:

$$\omega(l) = 1 - \frac{(l+1)}{(L+1)} \tag{3.5}$$

This weighting function helps to ensure that the contribution of autocovariances decreases as the lag increases.

Our AR model will show a high R^2 due to correlations being derived from moving averages. Because we aim to demonstrate that correlations are not stable over time, and are, in fact, time-varying, we test for structural breaks to demonstrate the time-varying nature of correlations. A structural break test helps in identifying potential breakpoints in a given dataset, which are points in time when the underlying structure or relationship between variables changes significantly. Structural break models can integrate structural change through any of the model parameters. Bai & Perron (1998) provide the standard framework for testing for multiple breaks in which some, but not all, of the model parameters, are allowed to break at m possible breakpoints as depicted by:

$$y_t = x_t'\beta + z_t'\delta_j + \epsilon_t \tag{3.6}$$

$$t = T_{j-1} + 1, \ldots, T, \tag{3.7}$$

where

- $j = 1, \ldots, m+1$
- y_t is the dependent variable a linear combination of regressors with time-invariant coefficients, x_t', and Z_t denotes the matrix of regressors with time-variant coefficients.

The Bai & Perron (1998) method is a comprehensive approach for testing and estimating structural breaks in time series data, providing valuable insights into the dynamics and stability of economic and financial relationships.

We use correlational analysis to visualize the correlational relationships over time. We apply ADF to test for stationarity in our time-series variables. SBIC offers optimal lags where an AR model confirms the, by design, persistency of correlational moving averages. NW estimator corrects for autocorrelation and heteroskedasticity. Additionally, the Newey-West estimation technique is employed to address potential autocorrelation and heteroskedasticity, providing a robust analysis of the persistent nature of the correlations under investigation.

3.3. Wavelet Coherence

Correlational analysis and AR models offer insights into correlational relationships and persistency, but they do not fully explain the changing nature of correlations over time. Through applying a wavelet analysis, Rua & Nunes (2009) examine the time-frequency dynamics of stock market comovements for a group of developed countries and finds that comovements tend to increase in rising markets. *Wavelet Coherence* (WC) serves as a statistical approach for scrutinizing the time-frequency relationship between two sets of time-series data. In contrast, correlation is a time-domain measure that quantifies the linear relationship between two variables without considering their frequency content or phase relationship.

Th WC technique gauges the extent of similarity and coherence between the series in both time and frequency domains, which enables researchers to distinguish localized regions of elevated comovements, phase relationships, and potential causal connections between the series. WC is predicated on wavelet analysis, a mathematical instrument for disassembling a time-series signal into an array of wavelet functions, each denoting a specific time and frequency (Grinsted et al., 2004).

The WC method transforms two time series, $X(t)$ and $Y(t)$, into wavelets to ascertain the degree of similarity in their time-frequency representations. The formula for calculating wavelet coherence between time series $X(t)$ and $Y(t)$ at scale s and time shift τ is as follows:

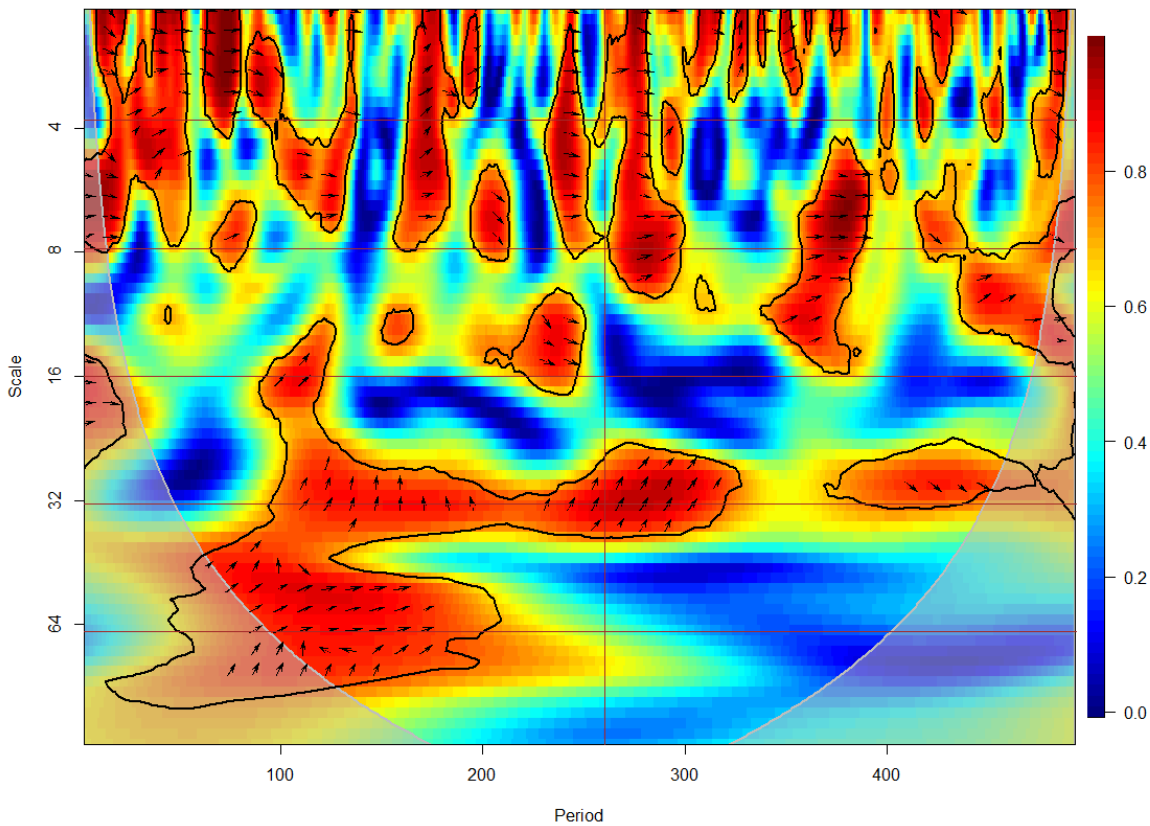
$$C_{W_{xy}}(s,\tau) = \frac{|S(W_{xy}(s,\tau))|^2}{S(W_{xx}(s,\tau)) \cdot S(W_{yy}(s,\tau))} \tag{3.8}$$

In this formula:

- $C_{W_{xy}}(s,\tau)$: Wavelet coherence between time series $X(t)$ and $Y(t)$ at scale s and time shift τ
- $W_{xy}(s,\tau)$: Cross-wavelet transform of $X(t)$ and $Y(t)$ at scale s and time shift τ
- $W_{xx}(s,\tau)$ and $W_{yy}(s,\tau)$: Individual wavelet transforms of $X(t)$ and $Y(t)$ at scale s and time shift τ
- $S()$: Smoothing operator utilized for reducing noise and enhancing coherence values in the numerator and denominator

Our analysis utilizes the innovative wavelet coherence technique to investigate the evolving relationships between the 15 asset class correlations. Figure 3.2 displays a representative output for the Russell 2000 and REITs (*R2RE*).

Figure 3.2: Wavelet Coherence: Russell 2000 & REITs



This figure shows the wavelet coherence (95% significance level) for the correlation of the Russell 2000 and REITs (*R2RE*) from January 1982 to December 2022, denoted by the time Period 0 to 500 months on the x-axis. The right axis indicates coherence from 0.0 to 1.0, where red (≈ 1) represents periods of high comovement, and blue (≈ 0) represents low comovement. The left axis indicates the Scale for the frequency of the wavelet in months. Right arrows depict in-phase oscillation, and left arrows depict anti-phase oscillation.

One can describe the time-frequency relationship between two time series using wavelet coherence (Abdullah, 2016). The horizontal axis represents time, while the vertical axis illustrates frequency. The wavelet coherence identifies regions within the time-frequency space where the two time series exhibit covariance.

Significant interrelations between the time series are indicated by warmer colors (red), whereas colder colors (blue) denote a lower degree of dependence. In addition, blue regions extending beyond significant areas signify the absence of dependence within the series at specific times and frequencies.

The wavelet coherence plots also incorporate arrows to represent the lead/lag phase relations between the time series under examination. A zero phase difference implies that the two time series move in tandem on a specific scale. Arrows pointing to the right or left signify that the time series are in phase or anti-phase, respectively.

In-phase time series move in the same direction, whereas anti-phase time series move in opposite directions. Arrows oriented to the right-down or left-up indicate that the first variable leads, while those pointing to the right-up or left-down demonstrate that the second variable assumes the leading position.

3.4. Macroeconomic Determinants

The literature investigates factors causing fluctuations in the temporal stability of correlations among asset classes, centering on macroeconomic variables such as inflation and measures of economic activity. Shiller & Beltratti (1992) and Baz et al. (2019) utilize a range of econometric methods, including vector autoregression (VAR), Granger causality, and impulse response functions, to examine the causal relationship between stock and bond returns, where they test the sensitivity of independent variables to different lag lengths. Other researchers employ a range of methodologies, including ADF and Johansen cointegration tests, VAR models, distributed lag models (DL), Granger causality tests, variance decomposition, rolling window correlation, dynamic conditional correlation (DCC) models, and ordinary least squares (OLS) regression to scrutinize relationships between variables like inflation, GDP, real interest rates, stock and bond returns, and their stationarity and comovements over time (Bekaert & Engstrom, 2010; Pericoli, 2018; Brixton et al., 2023; Andersson et al., 2008; Engle, 2002; Li, 2002; Campbell et al., 2009).

A distributed lag model (DL) is used in econometrics to model the relationship between variables over time, where the effect of a change in an independent variable on the dependent variable is distributed over multiple time periods. In essence, it captures the delayed effects of explanatory variables on the dependent variable (Sims, 1980).

$$Y_t = \alpha + \sum_{i=0}^{p} \beta_i X_{t-i} + \epsilon_t \tag{3.9}$$

In this equation, Y_t is the dependent variable at time t, X_t is the independent variable at time t, α is a constant term, β_i are the coefficients of the lagged independent variables, p is the maximum lag, and ϵ_t is the error term at time t.

Vector autoregression (VAR) is a multivariate time series model that captures linear interdependencies among multiple time series variables, modeling each variable as a linear combination of its lagged values and the lagged values of other variables. VAR models are commonly employed for forecasting, impulse response analysis, and variance decomposition (Sims, 1980).

A VAR model with p lags for a set of k time series variables can be written as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t \tag{3.10}$$

where:

- Y_t is a $k \times 1$ vector representing the values of the k time series variables at time t.
- $A_1, A_2, \ldots, A_p$ are $k \times k$ coefficient matrices representing the linear relationships between the variables at different lags.
- $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ are the lagged values of the time series variables.

- u_t is a $k \times 1$ vector of error terms that are assumed to be white noise, meaning they are uncorrelated over time and have a constant variance-covariance matrix.

- p is the number of lags included in the model.

Granger causality is a statistical hypothesis test used to determine whether one time series variable can predict another variable more accurately than using the past values of the predicted variable alone. It is important to note that Granger causality does not imply true causality but rather helps to identify temporal relationships between variables. Clive Granger introduced the concept in his seminal paper, "Investigating causal relations by econometric models and cross-spectral methods" (Granger, 1969).

To test if X Granger-causes Y, we can estimate the following two linear regression models:

Restricted Model:

$$Y_t = \alpha_0 + \sum_{i=1}^{p}(\alpha_i * Y_{t-i}) + \varepsilon_t \tag{3.11}$$

Unrestricted Model:

$$Y_t = \beta_0 + \sum_{i=1}^{p}(\beta_i * Y_{t-i}) + \sum_{i=1}^{p}(\gamma_i * X_{t-i}) + u_t \tag{3.12}$$

Here:

- Y_t and X_t are the values of time series Y and X at time t, respectively.

- α_0 and β_0 are the constant terms in the models.

- α_i and β_i are the coefficients of the lagged values of Y in the Restricted and Unrestricted Models, respectively.

- γ_i are the coefficients of the lagged values of X in the Unrestricted Model.
- ε_t and u_t are the error terms in the Restricted and Unrestricted Models.
- p is the number of lags included in the models.

The null hypothesis for the Granger causality test is:

$$H_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0 \tag{3.13}$$

This hypothesis states that the coefficients of the lagged values of X in the Unrestricted Model are jointly equal to zero, implying that X does not help predict Y beyond the information contained in its own past values.

DL studies the delayed effects of independent variables on a dependent variable by incorporating lagged values of the independent variables in the analysis, while the Newey-West estimator addresses autocorrelation and heteroskedasticity in OLS estimators. Vector autoregression models the interdependencies between multiple time series, and Granger causality tests whether one time series can predict another. Through a multi-method approach, we apply each of these techniques to study the effect of macroeconomic variables on asset correlations.

We employ DL models for each macro/correlation relationship to study their time series relationships. To address known persistency and autocorrelation, in addition to addressing heteroskedasticity in OLS estimators, we again use a Newey-West estimator, where the lag length correction is determined by $n^{1/4}$ (Newey & West, 1987) suggesting a correction of five lags. We then apply a VAR model to test the interdependencies between the variables. As a final measure, our study adds Granger to asses the predictive relationship between the macroeconomic variables and the asset correlations in addition to the potential for a bicausal relationship. By employing a variety of econometric techniques, we investigate the impact of macroeconomic variables on asset correlations.

3.5. Time-Varying Granger Causality

Correlations exhibit periods of persistence and stability but also exhibit structural breaks attributed to macroeconomic variables giving rise to a time-invariant nature. When breaks occur, parameter instability ensues, which can make the interdependencies among time series variables difficult to asses through VAR and standard Granger causality models. As with other aspects of structural stability, Granger causality may be supported over one time frame but may be fragile when alternative periods are considered. To address this and to add an additional level of rigor to our analysis of determinants, we utilize a Time-Varying Granger Causality (TVGC) method.

TVGC is a method employed to assess the dynamic causal relationships among multiple time series data. This method builds upon the traditional Granger causality method by allowing for the possibility that the causal relationship between time series may change over time (Thoma, 1994; Swanson, 1998; Psaradakis et al., 2005).

To allow for time variation in Granger causal orderings to evolve, recursive estimation methods are required. Three algorithms generate a sequence of test statistics: the forward expanding (FE) window, the rolling (RO) window, and the recursive evolving (RE) window (Figure 3.3) (Thoma, 1994; Swanson, 1998; Phillips et al., 2015; Baum et al., 2022).

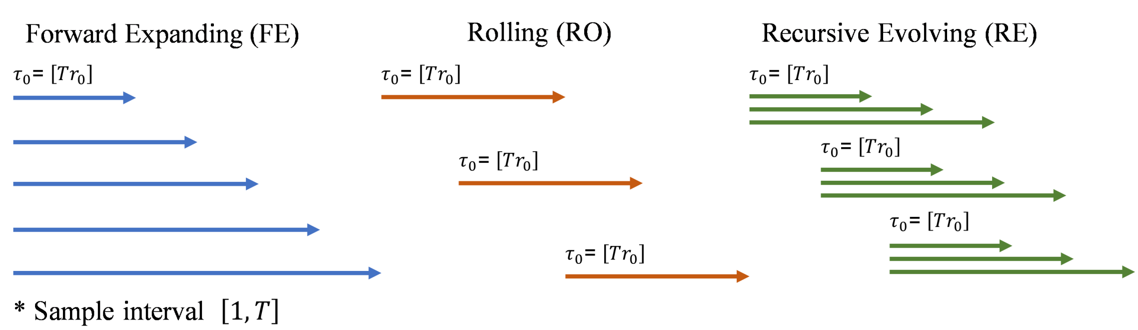
1. In the FE algorithm, the Wald test statistic is first computed for a minimum window length, $\tau_0 = [\mathrm{Tr}_0 0] > 0$, and the sample size then expands sequentially by one observation until the final test statistic is computed using the entire sample. The starting point of every subsample is the first data point. At the

conclusion of the FE algorithm, a sequence of Wald test statistics, Tr1, r with $r_1 = 0$ and $r \in [r_0, 1]$, is obtained.

2. In the RO algorithm, a window [Tw] is rolled through the sample, advancing one observation at a time and computing a Wald test statistic for each window. The output from the RO algorithm is a sequence of test statistics $\mathrm{Tr}_{1,r}$ with $r_1 = r - w$ and $r \in [r_0, 1]$, where each test statistic is computed from a sample of the same size, [Tw], with $0 < w < 1$.

3. The RE algorithm computes a test statistic for every possible subsample of size r_0 or larger, with the observation of interest providing the common endpoint of all subsamples. The procedure is repeated for each point in the sample, subject only to the minimum window size. Therefore, every observation in the sample beyond the first is associated with a set of Wald test statistics. Phillips, Shi, and Yu (2015b) propose that inference be based on a sequence of supremum norms of these statistics. The RE algorithm produces a sequence of test statistics $\mathrm{Tr}_{1,r}$ with $r_1 \in [0, r - r_0]$ and $r \in [r_0, 1]$, which are the sup norms of the Wald statistics at each observation.

Figure 3.3: Time-Varying Granger Causality Windows



Time-Varying Granger Causality: Forward Expanding (FE), Rolling (RO), and Recursive Evolving (RE) windows. Adapted from Baum et al. (2022).

TVGC is used in our study to analyze the causal relationships between variables in a dynamic system. Unlike traditional Granger causality, which assumes constant causal relationships over time, time-varying Granger causality allows for changes in these relationships. This makes it particularly useful for studying complex systems, where causal interactions may evolve over time due to factors like changing external conditions or structural adaptations.

3.6. Testing Correlational Regimes

Understanding the evolution of correlations over time is crucial for informed portfolio decision-making. Investors must identify the correlational regime in which they operate to comprehend better the interplay between the autoregressive component of asset correlations and the distributed lag component of lagged macro variable determinants. Drawing from Jacobsen & Scheiber (2022), four correlational regimes are defined as follows:

1. Everyone-Wins (EW): positive SBC with rising markets;
2. Risk-On (RO): negative/low SBC with rising markets;
3. Flight-to-Safety (FTS): negative SBC with declining markets;
4. Nowhere-to-Hide (NTH): positive SBC with declining markets.

These regimes are determined based on the signs of the 12-month rolling averages of the S&P 500 returns (indicating positive or negative markets) and the S&P 500 to US Treasuries correlation ($SPUST$, signifying positive/negative SBC). Each regime is binary coded as 1 (presence) or 0 (absence).

We use logistic regression to model the relationship between a binary dependent variable and one or more independent variables. This method estimates the event occurrence probability based on independent variables using the logistic function (Cox, 1958), as expressed in the generalized equation:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}} \tag{3.14}$$

where, $P(Y = 1 \mid X)$ is the probability of the dependent variable Y being 1 (i.e., the event occurring) given the independent variables $X_1, X_2, \ldots, X_n$. The parameters $\alpha, \beta_1, \beta_2, \ldots, \beta_n$ represent the regression coefficients, and e is the base of the natural logarithm.

For consistency, the same macroeconomic variables are tested on the presence of positive regimes. As binary outcomes, a lagged logistic (logit) regression is performed, with SBIC to determine optimal lags. The lagged logit equation is thus:

$$P(Y_t = 1 \mid X_t) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_p X_{t-p})}} \tag{3.15}$$

In this equation, $P(Y_t = 1 \mid X_t)$ is the probability of the dependent variable Y_t being 1 (i.e., the event occurring) at time t given the lagged independent variables $X_{t-1}, X_{t-2}, \ldots, X_{t-p}$. The parameters $\alpha, \beta_1, \beta_2, \ldots, \beta_p$ represent the regression coefficients, p is the maximum lag, and e is the base of the natural logarithm.

A probit regression (probit) is also conducted for robustness, as it is a statistical method used to model binary or dichotomous outcome variables (Greene, 2003). The probit model, a generalized linear model (GLM), estimates the probability of an event occurring based on one or more independent variables. This model employs the cumulative distribution function (CDF) of the standard normal distribution, known as the probit function, as the link function to map the linear combination of the independent variables to the probability of the outcome variable.

3.7. Optimized, Persistency, & Regime Portfolios

3.7.1. Asset Classes & Benchmark Portfolios

To extend the literature beyond a naïve, two-asset stock-bond portfolio, we construct asset allocation models composed of six asset classes. By reviewing the current and long-term capital market assumptions and strategic asset allocations of asset managers, broker/dealers, and research providers such as Vanguard (2022), BlackRock (2022), Wells Fargo Investment Institute (WFII, 2022), Goldman Sachs Asset Management (GSAM, 2022), and Morningstar (Kaplan, 2015), we develop six asset allocation models of varying risk levels. These prudent allocations cater to an investor's risk tolerance and serve as benchmark buy-and-hold portfolios. These *benchmark portfolios* are outlined in Figure 3.2.

Table 3.2: Benchmark Portfolios Asset Weightings

Risk Model	0/100	20/80	40/60	60/40	80/20	100/0
Variable	(*B0100*)	(*B2080*)	(*B4060*)	(*B6040*)	(*B8020*)	(*B1000*)
S&P500 (*SP*)	0.0%	8.0%	16.0%	24.0%	32.0%	40.0%
MSCI EAFE (*EF*)	0.0%	4.0%	8.0%	12.0%	16.0%	20.0%
Russell 2000 (*R2*)	0.0%	4.0%	8.0%	12.0%	16.0%	20.0%
REITs (*RE*)	0.0%	2.0%	4.0%	6.0%	8.0%	10.0%
Gold (*G*)	0.0%	2.0%	4.0%	6.0%	8.0%	10.0%
US Treasuries (*UST*)	100.0%	80.0%	60.0%	40.0%	20.0%	0.0%
Total	*100.0%*	*100.0%*	*100.0%*	*100.0%*	*100.0%*	*100.0%*

This table outlines the asset class weightings used to compose benchmark portfolios with scaled risk objectives from 0/100 (low risk, 100% US Treasuries) to 100/0 (all risk assets, no treasuries). Variable names are depicted in parentheses.

The expected return ($E(R_p)$) the benchmark portfolios is given by:

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \tag{3.16}$$

where:

- $E(R_p)$ is the expected return of the portfolio.
- w_i is the weight of asset i in the portfolio.
- $E(R_i)$ is the expected return of asset i.
- n is the number of assets in the portfolio.

The cumulative return (CR) is given by:

$$CR = (1 + r_1)(1 + r_2) \cdots (1 + r_n) - 1 \tag{3.17}$$

where:

- CR is the total return of an investment over a given period, accounting for all gains and losses;
- $r_1, r_2, \ldots, r_n$ are the returns for each monthly period.

And the portfolio standard deviation σ_p for a six-asset portfolio is given by (Markowitz, 1952):

$$\sigma_p = \sqrt{\sum_{i=1}^{6} \sum_{j=1}^{6} w_i w_j \sigma_i \sigma_j \rho_{ij}} \tag{3.18}$$

, where:

- σ_p is the portfolio standard deviation;
- i and j are the indices for the six assets in the portfolio;
- w_i and w_j are the weights of assets i and j in the portfolio;

- σ_i and σ_j are the standard deviations of assets i and j ;
- ρ_{ij} is the correlation coefficient between the returns of assets i and j.

This allows for the computation of Sharpe ratios SR (Sharpe, 1966), which is a measure of the risk-adjusted return of an investment and is given by:

$$SR = \frac{E(R_p) - R_f}{\sigma_p} \tag{3.19}$$

where:

- $E(R_p)$ is the expected return of the portfolio.
- R_f is the risk-free rate of return.
- σ_p is the standard deviation, which represents the portfolio's risk.

Additional portfolio metrics include the Information Ratio, Sortino Ratio, and Maximum Drawdown.

The Information Ratio (IR) (Treynor & Black, 1973) is a measure of the risk-adjusted excess return of a portfolio relative to a benchmark and is given by:

$$IR = \frac{E(R_p - R_b)}{\sigma_{p-b}} \tag{3.20}$$

where:

- $E(R_p - R_b)$ is the expected excess return of the portfolio over the benchmark.
- R_p is the return of the portfolio.
- R_b is the return of the benchmark.

- σ_{p-b} is the standard deviation of the excess return of the portfolio over the benchmark, which represents the portfolio's active risk.

The Sortino ratio (Sortino & Van Der Meer, 1991) is a measure of the risk-adjusted return of an investment, which considers only the downside risk, and is given by:

$$\text{Sortino Ratio} = \frac{E(R_p) - R_f}{\sigma_d} \tag{3.21}$$

where:

- $E(R_p)$ is the expected return of the portfolio.
- R_f is the risk-free rate of return.
- σ_d is the downside deviation or downside risk, which represents the volatility of the portfolio's negative returns.

The *maximum drawdown* (MDD) is defined as:

$$MDD = \max_t \left(\max_{0 \leq s \leq t} P_s - P_t \right) \tag{3.22}$$

where P_t represents the asset price at time t.

These benchmark portfolios construct their own efficient frontier for a given time period. By analyzing these portfolios and their associated metrics, investors can make more informed decisions regarding asset allocation and risk management. Furthermore, understanding the time-varying change of correlation and its effects on different regimes allows for better portfolio optimization and potential regime-switching strategies, which can lead to improved risk-adjusted returns. In addition to the performance metrics for the individual asset classes themselves, we use these portfolios as "benchmarks" in testing optimized, persistency, regime, and regime-switching portfolios.

3.7.2. Portfolio Optimization

The benchmark portfolios serve as reference points for further investigation into correlational persistency and correlational regimes. To examine persistency, we utilize the average 12-month rolling returns, 12-month standard deviations, and 12-month correlations for each asset class to maximize the Sharpe ratio. 12-month periods are used as they offer enough information to incorporate trends and relationships. However, they are not so long as to allow markets to become too efficient. Although we want to use historical data to inform portfolio construction, we need to operate nimbly and within shorter windows in order to have portfolio outperformance.

The Solver optimization add-in was developed by Frontline Systems Inc (Solver, 2023). Solver provides several optimization methods for addressing different problem types. Three primary categories of optimization are available:

Linear programming (LP) or "LP Simplex" is used for linear optimization problems where both the objective function and constraints are linear. As the risk vs. reward function of portfolio construction is nonlinear (Perold, 2004), this method is not appropriate for this study.

Nonlinear programming (NLP) addresses optimization where the objective function, constraints, or both are nonlinear. Solver offers multiple algorithms, such as the Generalized Reduced Gradient (GRG) nonlinear method. GRG nonlinear is useful for intricate portfolio optimization problems, where the relationship between the risk and return of the assets in the portfolio is not linear (Lasdon et al., 1978).

The *genetic algorithm* (GA) is an evolutionary algorithm used for complex optimization problems that may not be suitable for traditional gradient-based methods. Inspired by the process of natural selection, this algorithm can be applied to both linear and nonlinear problems, including those with discontinuities and non-differentiable functions (Golberg, 1989).

Both the GRG and GA methods were tested in our study. As the risk/return function is curvilinear, the GRG method consistently yields globally optimal solutions, whereas the GA method is slower and produces suboptimal solutions. Consequently, the GRG method is chosen for portfolio optimization. The Solver/GRG method is widely supported in the literature for broad asset allocation portfolio optimization (Mun, 2010; Kulali, 2016).

The GRG nonlinear method works iteratively, adjusting the weights of the assets in the portfolio to minimize or maximize the target vector, which is often a measure of risk (e.g., portfolio variance) or a combination of risk and return (e.g., the Sharpe ratio). The generalized nonlinear optimization problem can be formulated as follows:

Problem Formulation:

The nonlinear optimization problem can be formulated as follows:

$$\begin{aligned} \text{Maximize:} \quad & f(x) \quad \text{subject to} \\ & h(x) = 0 \quad \text{(equality constraints)} \\ & g(x) \leq 0 \quad \text{(inequality constraints)} \end{aligned}$$

where $f(x)$ is the objective function, $h(x)$ represents equality constraints, and $g(x)$ represents inequality constraints.

GRG Algorithm:

1. Decomposition: GRG decomposes the problem into a sequence of linearized subproblems, which are solved iteratively. At each iteration, the algorithm linearizes the constraints using a Taylor series expansion.

2. Reduced gradient: Reduced gradient is calculated as the gradient of the objective function with respect to the nonbasic (independent) variables, while the basic (dependent) variables are expressed in terms of the nonbasic variables.

3. Line search: The algorithm performs a line search along the reduced gradient direction to find an optimal step size that improves the objective function.

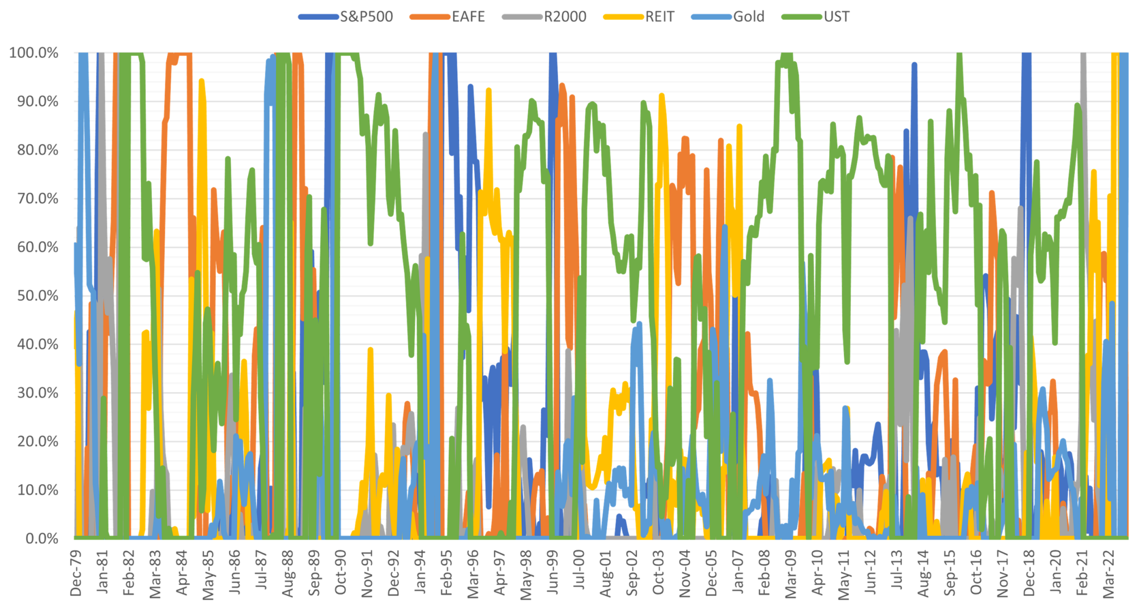
4. Update: The variables are updated based on the optimal step size, and the algorithm checks for convergence.

5. Convergence: If the algorithm converges, the solution is considered optimal. Otherwise, the algorithm continues with the next iteration.

Our target vector is the maximization of the Sharpe ratio. Solver optimizes the weights of the asset classes to maximize the Sharpe using the GRG method for one period at a time. To address this limitation, we code a Visual Basic macro to loop the Solver over multiple periods. The output results in a combination of optimal returns, standard deviations, and asset weights over all 492 monthly rolling periods.

Three optimal models are developed for all periods. The Optimized Unconstrained model ($OptU$) allows for a range from 0% to 100% for all asset classes (S&P 500, Russell 2000, EAFE, REITs, Gold, US Treasuries). The Optimized Semi-constrained model ($OptC$) allows a range of 0% to 100% for S&P 500 and US Treasuries but restricts all other assets to an upper bound of 50%. The Optimized Benchmark-constrained model ($OptB$) constrains the output weightings to fall along the efficient frontier of the benchmark portfolios, where the 100% risk portfolio is represented by 40% S&P 500, 20% EAFE, 20% Russell 2000, 20% REITs, 20% Gold, and the low risk portfolio is 100% US Treasuries. All models do not employ leverage of any kind, nor do they allow shorting of assets. Figure 3.4 depicts the optimal asset weights of *OptU* as they change over time.

Figure 3.4: Optimal Unconstrained Portfolio Asset Weights



This chart illustrates the asset weights for the optimal unconstrained model as they change from January 1982 through December 2002. Asset weights for the S&P 500, EAFE, R2000, Gold, and US Treasuries are determined by the GRG nonlinear optimization method applied through a Visual Basic loop over 492 monthly periods.

As expected, the optimal portfolios exhibit significant outperformance in terms of cumulative returns and risk-adjusted returns. This is discussed further in the *Results* section and serves as an argument for examining correlational temporal change and its potential to improve portfolio construction.

The outperformance of the optimal portfolios is noteworthy, albeit unattainable, as it would require an investor to have foresight or, at minimum, perfect concurrent information and the ability to act on it immediately. However, given the sizable outperformance, an investor need not achieve such results precisely; instead, they must achieve results close enough to outperform relative benchmarks and asset classes still.

3.7.3. Persistency Portfolios

The literature suggests that the momentum effect is driven by the underreaction of investors to information (Lin, 2020), in addition to investors' behavioral biases, such as overconfidence and herding, and the slow diffusion of information in financial markets (Chen et al., 2018). With the understanding that asset correlations are constructed from moving averages and are, consequently, persistent, we construct portfolios based on the premise that if the momentum of correlational persistency holds, a "fast following" portfolio should still yield above-average performance. We refer to these as *persistency portfolios*.

The persistency portfolios are simply constructed by purchasing the most recent asset class weightings of the optimal portfolio. Each month the persistency portfolio effectively holds the optimal portfolio with a one-month lag. The persistent portfolios are constructed for each of the optimal portfolios and are denoted $POptU$, $POptC$, and $POptB$, representing unconstrained, semi-constrained, and benchmark constrained, respectively. They are represented by:

Unconstrained Persistency Portfolio Model:

$$\begin{aligned} POptU = & w_{t-1}SP_{OptU} + w_{t-1}UST_{OptU} + w_{t-1}EF_{OptU} + \\ & w_{t-1}R2_{OptU} + w_{t-1}RE_{OptU} + w_{t-1}G_{OptU} \end{aligned} \tag{3.23}$$

Semi-constrained Persistency Portfolio Model:

$$\begin{aligned} POptC = & w_{t-1}SP_{OptC} + w_{t-1}UST_{OptC} + w_{t-1}EF_{Optc} + \\ & w_{t-1}R2_{OptC} + w_{t-1}RE_{OptC} + w_{t-1}G_{OptC} \end{aligned} \tag{3.24}$$

Benchmark Constrained Persistency Portfolio Model:

$$\begin{aligned} POptB = & w_{t-1}SP_{OptB} + w_{t-1}UST_{OptB} + w_{t-1}EF_{OptB} + \\ & w_{t-1}R2_{OptB} + w_{t-1}RE_{OptB} + w_{t-1}G_{OptB} \end{aligned} \tag{3.25}$$

where:

- $w_{t-1}SP_{Opt(U,C,B)}$ is the one-month lagged weight of the S&P 500 for the Opt(U,C,B) portfolios.
- $w_{t-1}UST_{Opt(U,C,B)}$ is the one-month lagged weight of US Treasuries for the Opt(U,C,B) portfolios.
- $w_{t-1}EF_{Opt(U,C,B)}$ is the one-month lagged weight of the MSCI EAFE for the Opt(U,C,B) portfolios.
- $w_{t-1}R2_{Opt(U,C,B)}$ is the one-month lagged weight of the Russell 2000 for the Opt(U,C,B) portfolios.
- $w_{t-1}RE_{Opt(U,C,B)}$ is the one-month lagged weight of REITs for the Opt(U,C,B) portfolios.
- $w_{t-1}G_{Opt(U,C,B)}$ is the one-month lagged weight of Gold for the Opt(U,C,B) portfolios.

By analyzing the performance of these portfolios, we aim to determine whether the observed outperformance of optimal portfolios can be partially replicated through the use of persistency portfolios that rely on fast-following and correlational temporal stability. This approach could provide investors with a more feasible method for capturing above-average performance without the need for perfect foresight or the ability to act on information with immediacy. Alternatively, it could show that chasing returns does not add value. Regardless, the results of this analysis can offer valuable insights for portfolio construction and asset allocation decisions based on the persistence of asset correlations and the momentum effect in financial markets.

3.7.4. Regime Testing

Correlations among asset classes may endure for certain durations; however, our research reveals that they fluctuate over time. Extant literature points to various macroeconomic variables, such as inflation (π) (Ilmanen, 2003), inflation expectations (π^e) (Li, 2002), leading indicators ($CEIC$) (Pericoli, 2018), and sentiment ($Sent$) (Johnson et al., 2013), as factors that contribute to changes in correlations. Correlational regimes, such as Everyone-Wins (EW), Risk-On (RO), Flight-to-Safety (FTS), and Nowhere-to-Hide (NTH), incorporate the effects of persistency disrupted through structural breaks, while reflecting the influence of macroeconomic environments. We use the binary coded regimes from our logit/probit regressions of macro variables and apply relevant benchmark portfolios that best represent the characteristics of each regime.

The EW regime is characterized by positive SBC and positive markets. As all assets should respond positively in this environment, holding the most broadly diversified, risk-adjusted portfolio should yield favorable results. When this regime is present (EW_p), we apply the "all-weather" 60/40 benchmark portfolio ($B6040$), where 60 signifies a 60% allocation to risk assets, and 40 denotes a 40% allocation to US Treasuries. A negative EW regime (EW_n) is allocated a 40/60 benchmark portfolio ($B4060$).

During a RO period, investors tend to invest in higher-risk assets such as stocks due to favorable market conditions or increased optimism. RO positive (RO_p) receives an allocation of the 80/20 benchmark ($B8020$), with a 20/80 ($B2080$) allocation when RO is negative (RO_n).

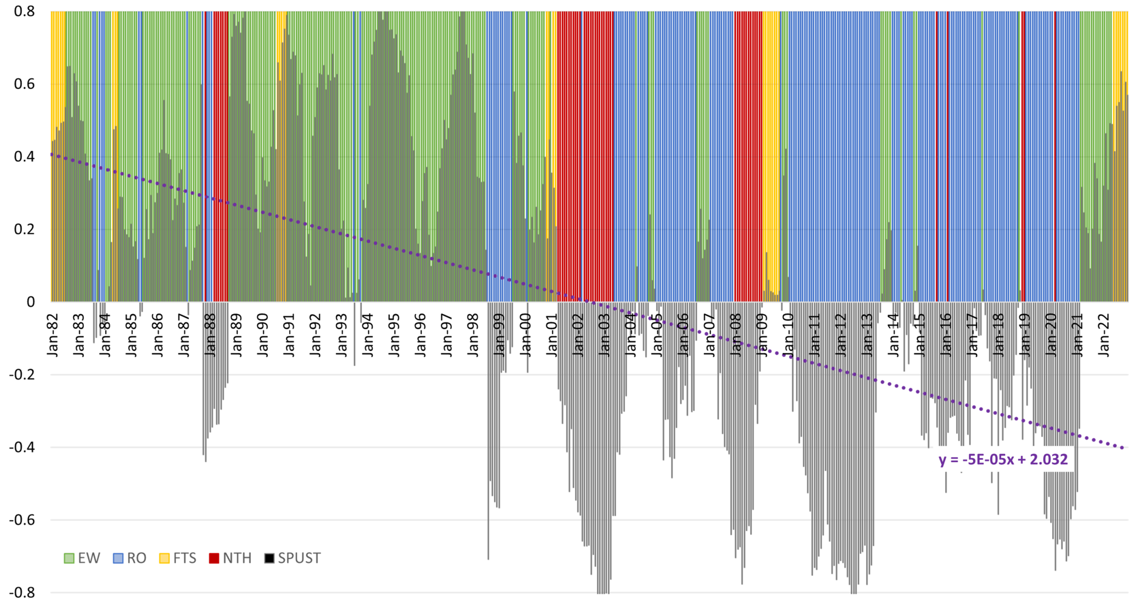
In periods of market stress or uncertainty, investors often engage in a “flight to safety” by reallocating their investments from riskier assets to more secure or higher-quality assets. This behavior results in a surge in demand for low-risk assets, such as government bonds, while causing a decrease in the value of riskier assets like equities (Campbell & Taksler, 2003). These environments are transitory and typically short-lived. An *FTS* positive environment (FTS_p) receives an allocation of the 40/60 benchmark portfolio (*B4060*), with a 60/40 allocation (*B6040*) when *FTS* is negative (FTS_n).

Lastly, in a *NTH* correlation regime, markets experience negative returns, and asset correlations exhibit positive trends, thus limiting diversification opportunities. Such regimes are generally observed following a transition from an *FTS* regime (Jacobsen & Scheiber, 2022). We allocate the most risk-off benchmark portfolio, 0/100 (*B0100*), to a positive *NTH* regime (NTH_p), and a 40/60 allocation (*B4060*) when the regime is not present (NTH_n).

An understanding of the optimal benchmark portfolio for each regime enables the recombination of all four regimes into their chronological sequence from January 1982 to December 2022. Figure 3.5 illustrates the presence of regimes over time, reinforcing the literature which suggests that the stock-bond correlation (SBC) has evolved, with SBC being positive before 1997 (as shown by the *EW* regime) and transitioning to negative after 1997 (as shown by the *RO* regime) (Brixton et al., 2023). This observation also supports the argument of Jacobsen & Scheiber (2022) that *FTS* is a brief, transitory regime.

The resultant *regime-switching* portfolio (*RS*) applies the benchmark portfolio tested in our binary regime models. Thus when the *EW* regime is becomes present, a 60/40 (*B6040*) allocation is used. For *RO* we use 80/20 (*B8020*), for *FTS*, 40/60 (*B4060*), and we apply 0/100 (*B0100*) to *NTH*. The asset allocation is “switched”

Figure 3.5: Correlational Regimes from January 1982 to December 2022



This figure illustrates the presence of the Everyone-Wins (EW, green), Risk-On (RO, blue), Flight-to-Safety (FTS, yellow), and Nowhere-to-Hide (NTH, red) regimes from January 1982 to December 2022. The y-axis denotes correlation. Gray bars illustrate the stock-bond correlation ($SPUST$), with a fitted linear regression line in purple.

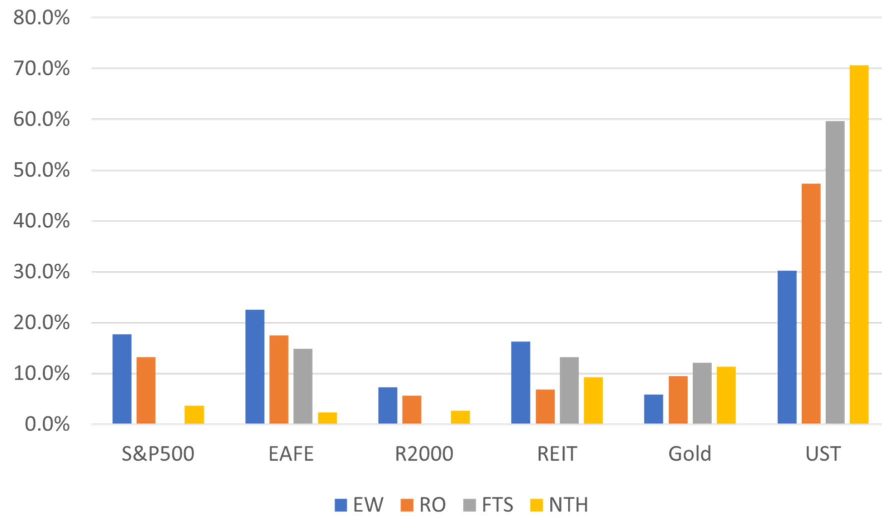
to its respective regime/allocation relationship one month after the regime becomes present. This facilitates a real-time applicability of this portfolio.

In a final portfolio examination, our study forgoes applying the asset allocations of optimal benchmark portfolios to the regimes and instead revisits the unconstrained optimal portfolios ($OptU$). Here, we calculate the average asset allocation for each regime throughout the entire period from January 1982 to December 2022. Asset weights for each regime are displayed in Table 3.6.

The "optimal asset weights" and applied one month after the regime becomes present, similar to the regime-switching model, only not with benchmark portfolio allocations. We refer to this model as an *optimized regime-switching* portfolio (RSO).

We study asset class correlations in different correlational regimes, such as Everyone-Wins (EW), Risk-On (RO), Flight-to-Safety (FTS), and Nowhere-to-

Figure 3.6: Asset Class Weights for Optimized Regime Portfolio



This figure shows the average asset class weightings per regime from January 1982 to December 2022 based on the output of the GRG-optimized portfolios.

Hide (NTH), which are influenced by macroeconomic factors. Our analysis uses binary-coded regimes individually and applies benchmark portfolios representative of each regime's characteristics. The regime-switching (RS) portfolio reaggregates the regimes into their temporal sequence and applies the respective benchmark portfolios from the binary regime study. The optimized regime-switching (RSO) portfolio uses the average asset allocation for each regime throughout the entire period.

CHAPTER 4: RESULTS

In accordance with the structure and framework of the *Review of the Literature* and *Data & Methods* sections, we present significant results that not only corroborate the existing literature but also extend it with intriguing findings.

4.1. Correlational Analysis

Figures A.1, A.2, A.3, A.4, and A.5 display the rolling one-year correlations for all 15-asset class combinations. Although correlations within such short intervals can be noisy, the inclusion of linear regression lines provides a clearer representation of the stability or fluctuations in these relationships over time. The correlation change between the S&P 500 and US Treasuries (*SPUST*) is in line with the literature, which documents a shift from positive to negative correlations in the late 1990s (Baele et al., 2010; Brixton et al., 2023; Jacobsen & Scheiber, 2022). Rolling average correlations range between $-0.40 \leq \rho \leq 0.40$, with sharp positive turns during periods of market stress, such as in 2008 and the more recent bear market for both stocks and bonds in 2022. Similar patterns are observed between other US Treasuries and stock assets like the MSCI EAFE and the Russell 2000 (*USTR2*), which have also experienced a shift from positive to negative correlations, albeit with weaker relationships (*USTEF*, $-0.44 \leq \rho \leq 0.18$ and *USTEF*, $-0.45 \leq \rho \leq 0.22$).

Treasuries and REITs exhibit a weak positive correlation over time that has moderately declined, ranging from *USTRE* $\rho = 0.02$ to $\rho = 0.21$. A marginally increasing, yet weaker, relationship is observed between Treasuries and Gold, where *USTG*, $0.02 \leq \rho \leq 0.17$.

Strong relationships are found between stock assets. The correlation between the S&P 500 and the Russell 2000 has remained relatively stable at *SPR2*, $\rho \approx 0.8$, while the correlation between the S&P 500 and the MSCI EAFE has fallen between $0.58 \leq \rho \leq 0.88$ (*SPEF*), increasing towards higher correlation over time.

Barring a few annual exceptions, REITs demonstrate a moderate and positive relationship with stock assets. The *SPRE* correlation has increased from an average of $\rho = 0.56$ to $\rho = 0.61$. For *R2RE*, the correlation lies in the average range of $0.61 \leq \rho \leq 0.59$, and the REIT/EAFE correlation (*EFRE*) has increased from $\rho = 0.35$ to $\rho = 0.57$.

Gold, although characterized by low correlation and high volatility, exhibits an unsteady relationship with the S&P 500 (*SPG*). Correlational peaks reach as high as 0.72 and as low as -0.78, with an average ranging between $-0.07 \leq \rho \leq 0.01$. Similarly, *EFG* falls between $-0.01 \leq \rho \leq 0.08$, and *R2G* ranges from $-0.18 \leq \rho \leq 0.02$, with both displaying spikes in negative and positive correlation. These results suggest that gold maintains its role as a low-correlation asset in the context of a diversified portfolio.

The analysis of asset class correlations substantiates existing literature while also providing new insights into the dynamic relationships among various asset classes. The study confirms the transition of stock-bond correlations from positive to negative in the late 1990s, as well as the presence of strong relationships between stock/stock relationships. Furthermore, the results reveal the relatively weak but fluctuating correlations between Treasuries, REITs, and gold, highlighting the potential benefits of including these assets in a diversified portfolio.

4.2. Correlational Change & Structural Break Outcomes

The implementation of an AR is conducted and delineated in Table 4.1. This approach begins with the determination of the optimal lag to test through SBIC. The

Newey-West estimator is chosen due to its capacity to rectify heteroskedasticity issues while incorporating $n^{1/4} = 5$ lags. All models are significant at 99%. The observation of significant outcomes serves as an indication that historical values act as influential factors in determining present values, thus substantiating the autoregressive and enduring time-series characteristics of the correlations. However, this is by design, as rolling correlations are determined through moving averages.

Table 4.1: AR Model & Structural Breaks

		AR Model		Breaks
Corr	SBIC	F	R^2	(5% CV)
SPUST	1	5083.99***	0.898	5
SPEF	1	930.38***	0.831	1
SPR2	2	327.10***	0.718	5
SPRE	2	606.09***	0.706	5
SPG	1	2221.88***	0.794	2
USTEF	1	4040.06***	0.870	0
USTR2	1	3298.99***	0.866	0
USTRE	1	1700.55***	0.820	5
USTG	1	1546.11***	0.770	2
EFR2	1	1060.53***	0.803	1
EFRE	1	1022.62***	0.785	1
EFG	1	1416.56***	0.746	2
R2RE	1	936.76***	0.813	0
R2G	1	2343.80***	0.823	1
REG	1	1978.60***	0.781	0

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table summarizes results for an AR model, while incorporating lags (max lag = 5) through Newey-West estimator. Optimal lags are determined through SBIC. This yields high R^2 values and F-statistics at 99%. Structural breaks (Breaks) are indicated using Bai & Perron 95% Critical Values (CV). Asset class correlation pairings are defined as: *SPUST* = S&P 500/US Treasuries *SPEF*, = S&P 500/MSCI EAFE, *SPR2* = S&P 500/Rusell 2000, *SPRE* = S&P 500/REITs, *SPG* = S&P 500/Gold, *USTEF* = US Treasuries/MSCI EAFE, *USTRE* = US Treasuries/REITs, *USTR2* = US Treasuries/Russell 2000.

Our primary focus is not on affirming the persistency of correlations but rather on discerning if and when the time-series stability of these correlations falters. To this end, we employ the methodology of Bai & Perron (1998) to identify structural breaks at 95% critical values where. We observe significant breaks for 11 asset class correlations. Specifically, *SPEF*, *EFR2*, *EFRE*, and *R2G* demonstrate single breaks between January 1982 and December 2022, while two or more breaks are found for *SPUST*, *SPR2*, *SPRE*, *SPG*, *USTRE*, *USTG*, and *EFG*. Conversely, no breaks are identified for *USTEF*, *USTR2*, *R2RE*, and *REG*. It is worth mentioning that correlations involving gold exhibit comparatively lower F-values and R^2 values. It is also noteworthy that all correlations involving the S&P 500 exhibit at least one break, where *SPUST*, representing the extensively studied stock-bond correlation (SBC), displays the highest number of breaks at five.

Our results corroborate the extant literature on SBC by showing the enduring nature of this correlation while adding that this persistence cannot be assumed. Moreover, our study reveals the changing (non-changing) nature of 14 other asset pairings. Each model generates high R^2 values, suggesting that historical values can elucidate a significant portion of the variance. However, this outcome is inherently derived from the 12-month moving averages from which the correlations are calculated. Although these findings largely serve to substantiate prevailing knowledge, the purpose of our AR model is not to confirm the persistency of correlations but rather to provide a foundation for comparing instances where they break down. To this end, we apply Bai & Perron (1998) structural breaks at 95% critical values, where we discover significant and multiple breaks in 11 of the 15 asset correlations. This evidence indicates that the stability of asset class correlations over time cannot be taken for granted, thereby challenging the fundamental premise of buy-and-hold strategic asset allocation, which relies on time-invariant correlations.

4.3. Findings from Wavelet Coherence

We present the results of our wavelet coherence (WC) analysis, which scrutinizes the evolving nature of comovements across 15 asset class combinations, are presented in Appendix Figures A.6, A.7, A.8, A.9, and A.10. The WC values range from 0 to 1; values approaching 1 signify strong coherence (high comovement), whereas those near 0 denote weak coherence (low comovement) between two time series at specific instances and frequencies. Rightward arrows display in-phase coherence. In other words, the two asset class wavelet are synchronized. Leftward arrows exhibit anti-phase coherence, meaning there is an asynchronous lead/lag relationship. Downward arrows represent trending negative comovements, and upward arrows imply positive comovements. The arrow's quadrant indicates which time series precedes or follows the other.

In the context of asset coherence, the horizontal axis signifies time by the number of periods; for example, "400" denotes 400 months after January 1982. The scale represents the time rolling period for consideration, with "16" corresponding to a 16-month coherence.

Interpreting the WC results for the $SPUST$ coherence (Figure 4.1), the top-left quadrant demonstrates strong comovements between treasuries and stocks for rolling periods ranging from 1 to 8 months. This relationship between 1 and 8 months persists relatively consistently. Rolling average correlations previously reported fall between $-0.40 \leq \rho \leq 0.40$. Consequently, the WC output is anticipated to exhibit a fair amount of blue to yellow, which is indeed observed. Phase shifts transpire during the 300 to 400 periods, indicating high coherence periods amid market stress, such as in 2008, 2020, and 2022. Leftward arrows represent anti-phase and signify asynchronous relationships between treasuries and stocks, suggesting that one asset leads or lags the other. Conversely, subsequent periods display rightward arrows, indicating in-phase relationships where the oscillations of stocks and bonds synchronize.

SPR2 (Figure 4.2) reveals a high coherence relationship, as anticipated between the S&P 500 and the Russell 2000. Correlations between these two indices average ≈ 0.80, with peaks nearing 1. The abundant red in the WC output for *SPR2* confirms a strong comovement relationship characterized by temporal stability and consistency across short and long frequencies. Moreover, the rightward arrows demonstrate an in-phase signal pattern, signifying the synchronous oscillation of the two assets.

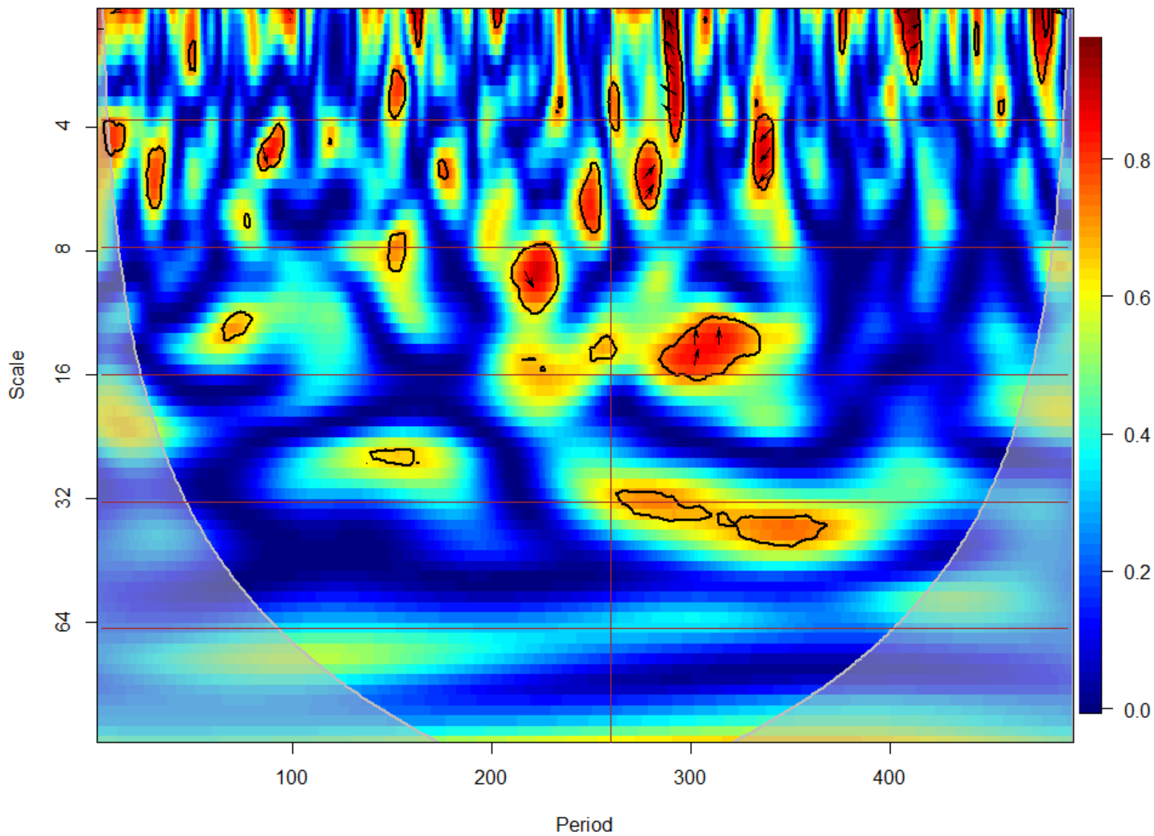


Figure 4.1: Wavelet Coherence: S&P 500 & US Treasuries

This figure shows the wavelet coherence (95% significance level) for the comovement of the S&P 500 to US Treasuries (*SPUST*) from January 1982 to December 2022, denoted by the time Period 0 to 500 months on the x-axis. The right axis indicates coherence from 0.0 to 1.0, where red (≈ 1) represents periods of high comovement, and blue (≈ 0) represents low comovement. The left axis indicates the Scale for the frequency of the wavelet in months. Right arrows depict in-phase oscillation, and left arrows depict anti-phase oscillation.

Examining the remaining WC method outputs (Figures A.6, A.7, A.8, A.9, and A.10), strong coherent and comovement relationships are supported among the balance of equity assets, such as *SPEF* and *EFR2*. Other treasury/stock relationships (e.g., *USTEF* and *USTR2*) exhibit patterns similar to the *SPUST* output, with moderate relatinships at low frequencies, weaker comovement as frequencies increase, but relative stability throughout the 492 rolling time periods, albeit with instances of high coherence during periods of market stress.

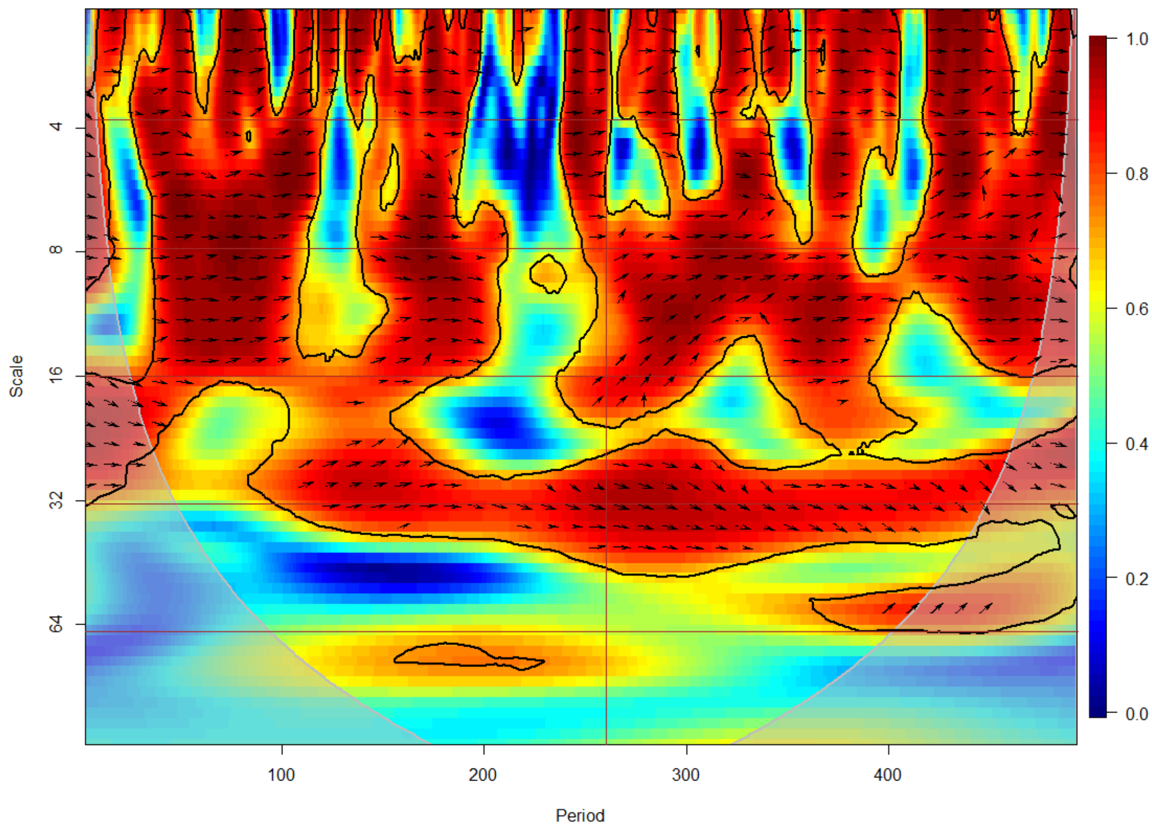


Figure 4.2: Wavelet Coherence: S&P 500 & Russell 2000

This figure shows the wavelet coherence (95% significance level) for the comovement of the S&P 500 & Russell 2000 (*SPR2*) from January 1982 to December 2022, denoted by the time Period 0 to 500 months on the x-axis. The right axis indicates coherence from 0.0 to 1.0, where red (≈ 1) represents periods of high comovement, and blue (≈ 0) represents low comovement. The left axis indicates the Scale for the frequency of the wavelet in months. Right arrows depict in-phase oscillation, and left arrows depict anti-phase oscillation.

The REIT/equity relationships, including *SPRE*, *EFRE*, and *R2RE*, display patterns that lie between stock/stock relationships and stock/treasury relationships. This observation is intuitive, as REITs possess the stable component of the underlying land or property expected to grow, generally offer yields or distributions, and simultaneously exhibit sensitivity to fluctuations in inflation and interest rates.

Relationships between gold and equities (*SPG*, *EFG*, and *R2G*) are characterized by noise, low coherence, and isolated instances of high comovement, where phases and oscillations frequently reverse. Stronger relationships are observed between gold and REITs (REG) and gold and Treasuries ($USTG$), particularly at higher frequencies. However, gold's relationship with all assets is sporadic, thus supporting its classification as a non-correlated asset.

Our wavelet coherence analysis uncovers strong, dynamic relationships between treasuries and stocks for 1 through 8-month rolling periods, displaying high coherence during market stress. The S&P 500 and Russell 2000 exhibit strong coherence, with assets oscillating synchronously. Equity assets display strong coherent relationships, while treasury/stock relationships are moderate at low frequencies and weaker at higher frequencies. REIT/equity relationships fall between stock/stock and stock/treasury relationships, reflecting the unique characteristics of REITs. Gold's relationships with other assets are generally noisy and sporadic, supporting its role as a non-correlated asset.

4.4. Results of Macroeconomic Determinants

In order to expand the existing literature beyond the conventional stock-bond correlation (SBC) discourse, we investigate four macro variables: 12-month Trimmed Mean PCE Inflation (π), inflation expectations (π^e), leading indicators ($CEIC$), and sentiment ($Sent$). These variables are tested against all 15 asset class correlations. Schwarz Bayesian Information Criterion (SBIC) tests up to 12 lags to determine the optimal lag for our macro variables. Three regression models are utilized to examine the impact of macro variables on correlations: a distributed lag model (DL) with Newey-West estimator (NW), vector autoregression (VAR), and Granger causality (Granger). The analysis uncovers intriguing and persuasive evidence that macro variables influence the relationships between asset classes. The results are discussed below.

4.4.1. Inflation

Our research supports the influence of inflation on SBC (Baele et al., 2010; Connolly et al., 2005). Inflation (π) is tested on SBC ($SPUST$) using a DL model with NW estimator, regressing the second lag as determined by SBIC. The model is statistically significant at 99% and with an R^2 of 0.258. Our VAR model results in a significant one-way effect of π on $SPUST$ at 99%, with Granger causality significant at 99%.

Table 4.2: Macro Determinants of Correlations: Inflation

π		DL Model		VAR Model		Granger	
				π-->Corr	Corr-->π	π-->Corr	Corr-->π
Corr	SBIC	F	R^2	P > z	P > z	X^2	X^2
SPUST	2	22.66***	0.258	0.001***	0.836	11.925***	0.043
SPEF	3	14.51***	0.065	0.163	0.905	1.950	0.014
SPR2	2	1.88	0.009	0.188	0.002***	1.736	9.435***
SPRE	2	6.79***	0.043	0.241	0.144	1.377	2.136
SPG	3	0.61	0.007	0.941	0.519	0.005	0.416
USTEF	2	39.24***	0.196	0.000***	0.920	13.633***	0.920
USTR2	2	60.41***	0.290	0.000***	0.978	19.463***	0.001
USTRE	2	10.81***	0.065	0.107	0.388	2.592	0.745
USTG	3	0.56	0.007	0.713	0.153	0.135	2.044
EFR2	3	5.18**	0.037	0.142	0.550	2.154	0.358
EFRE	3	0.35	0.003	0.543	0.332	0.370	0.940
EFG	3	0.11	0.001	0.918	0.472	0.011	0.517
R2RE	2	4.15**	0.026	0.063*	0.004***	3.451*	8.264***
R2G	3	6.10**	0.055	0.305	0.206	1.053	1.602
REG	3	9.27	0.083	0.012**	0.752	6.253**	0.099

*** p < 0.01, ** p < 0.05, * p < 0.1

This table summarizes the multi-method approach to investigate 12-month Trimmed Mean PCE Inflation (π) as a determinant of asset class correlations. Variables for each correlational relationship (Corr) are shown on the left. SBIC determines optimal lags. F-statistics and R^2 values are reported for the DL model with NW estimator. A VAR model for the interdependencies of correlations and π is summarized to demonstrate lags offering significant equations ($P > z$). χ^2 results are reported from our Granger model.

We follow the method above for π's effects on the remaining 14 correlational relationships, where we summarize the results in Table 4.2. Items of interest among these tests follow. The DL models demonstrate significant effects of π on 9 of 15 correlational relationships.

Interestingly, we find that S&P 500/Russell 2000 ($SPR2$) correlation has a one-way effect on π in our VAR model and Granger-causality at 99%, but there are no significant effects of π on $SPR2$ in any model.

π also shows no significant effects on *REG* through a DL model, but we do find one-way effects through VAR at 95% and where π Granger-causes *REG* (95% significance). Thus we cannot speak to π as a determinant of REIT/Gold correlations, but we can conclude that there is a one-directional interdependency.

Our DL models show the significance at 99% of the effects of π on the treasury correlations of *USTEF*, *USTR2*, and with notably high R^2 values at 0.196 and 0.296, respectively. π affects these two correlations at 99% one-way in our VAR models, and we find one-way Granger-causality of π on *USTEF* at and of π on *USTR2* both at 99%.

It is notable that the relationship of π with REIT correlations demonstrates intermittent significance throughout our models. Nonetheless, we can conclude that π as a macroeconomic determinant has the strongest effect on correlations with US Treasuries.

4.4.2. Inflation Expectations

The impact of π as a determinant of correlations is pervasive, affecting several correlations and operating significantly in two or three lags. Existing literature posits that inflation expectations (π^e) also play a crucial role in driving correlations and changes in correlations (Li, 2002; Campbell et al., 2009). Continuing our multi-method approach, we study examines the impact of π^e on 15 asset correlations (Table 4.3).

π^e on the SBC relationship (*SPUST*) is investigated, revealing immediate and substantial consequences. Our DL with NW estimator finds significance with at 99%, and an R^2 of 0.353. VAR models are bidirectional at 95% for *SPUST* and π^e, where we also find a significant two-way Granger-causality relationship at 99%.

Unlike π, where we find significance in 9 of 15 asset correlations in our DL models, π^e yields 8 of 15, and in a few differing π^e/correlation relationships. However,

Table 4.3: Macro Determinants of Correlations: Inflation Expectations

π^e		DL Model		VAR Model		Granger	
				π^e-->Corr	Corr-->π^e	π^e-->Corr	Corr-->π^e
Corr	SBIC	F	R^2	P > z	P > z	X^2	X^2
SPUST	1	60.94***	0.353	0.026**	0.044**	4.942**	4.059**
SPEF	1	28.25***	0.132	0.134	0.060*	2.242	3.526*
SPR2	1	1.24	0.009	0.840	0.475	0.041	0.511
SPRE	1	0.00	0.000	0.671	0.657	0.181	0.198
SPG	1	0.81	0.008	0.769	0.946	0.086	0.046
USTEF	1	50.11***	0.264	0.023**	0.202	5.156**	1.629
USTR2	1	71.86***	0.361	0.008***	0.014**	7.124***	5.999**
USTRE	1	8.51***	0.064	0.435	0.205	0.610	1.607
USTG	1	0.80	0.007	0.826	0.461	0.048	0.544
EFR2	1	12.24***	0.092	0.182	0.069*	1.781	3.301*
EFRE	1	0.79	0.007	0.474	0.528	0.512	0.398
EFG	1	0.00	0.000	0.983	0.509	0.000	0.437
R2RE	1	0.05	0.000	0.920	0.588	0.010	0.293
R2G	1	6.11**	0.039	0.423	0.566	0.641	0.329
REG	1	8.86***	0.066	0.164	0.505	1.939	0.446

*** p < 0.01, ** p < 0.05, * p < 0.1

This table summarizes the multi-method approach to investigate 2-year inflation expectations (π^e) as a determinant of asset class correlations. Variables for each correlational relationship (Corr) are shown on the left. SBIC determines optimal lags. F-statistics and R^2 values are reported for the DL model with NW estimator. A VAR model for the interdependencies of correlations and π^e is summarized to demonstrate lags offering significant equations ($P > z$). χ^2 results are reported from our Granger model.

where they are similar is that π^e affects all treasury correlations in addition to SBC (*SPUST*) as mentioned above. Further, regarding treasuries, DL models are significant for *USTEF*, *USTR2*, and *USTRE*, at 99%, where we find high R^2 values for *USTEF* ($R^2 = 0.264$) and *USTR2* ($R^2 = 0.361$). A VAR model shows a one-way relationship at 95% between π^e and *USTEF* and where we find π^e Granger-causes *USTEF* at 95%. The π^e relationship with *USTR2* is bidirectional and bicausal where π^e Granger-causes *USTR2*, and Granger-causes *USTR2* Granger-causes π^e, both at 95%.

π^e has a notable effect on the EAFE relationship with domestic stocks. Our DL model for *SPEF* and *EFR2* is significant at 99% with $R^2 = 0.132$ and 0.009, respectively. Further, it is a significant determinant of two gold correlations, *R2G* (significant at 95%, $R^2 = 0.039$) and *REG* (significant at 99%, $R^2 = 0.066$).

Our investigation into the effect of 2-year expected inflation (π^e) on the SBC (*SPUST*) revealed a bicausal relationship with Granger causality in both directions. We also find π^e significantly impacts all treasury correlations and notably influences the EAFE relationship with domestic stocks. Additionally, π^e serves as a crucial determinant for two gold correlations, suggesting the importance of considering π^e in macroeconomic analysis and asset allocation decisions.

4.4.3. Leading Indicators

Turning to our economic variables (Table 4.4), we report the results of leading indicators (*CEIC*) as a determinant for correlations. We do not find a significant impact on the stock-bond correlation (*SPUST*) in any of our models when tested for two lags, as suggested by SBIC. We also find no relationship between treasury correlations and the MSCI EAFE (*USTEF*) and the Russell 2000 (*USTR2*). A DL model shows a moderate relationship between *CEIC* and *USTRE* at 95% and with $R^2 = 0.034$.

We observe the impacts of *CEIC* is most pronounced with stock/stock and stock/REIT correlations. *SPEF*, *SPR2*, and *EFR2* are significant under at DL model at 95%, albeit with low R^2 values at 0.020, 0.074, and 0.062, respectively.

DL is significant at 99% the for stock/REIT correlations, *SPRE*, *EFRE*, *R2RE*, but again demonstrating low R^2 values at 0.039, 0.062, and 0.099, respectively. VAR models yield mixed results for these three, where we do not find a significant result for *SPRE*. At 99% *CEIC* has a one-way effect on *EFRE*. *CEIC* and *R2RE*, however, are bidirectional at 95% through our VAR model and Granger shows bicausality at 95%.

Thus, leading indicators (*CEIC*) do not affect relationships with treasuries. The influence of *CEIC* is more pronounced in stock/stock and all REIT correlations (including treasuries). The strongest relationship was found between *CEIC* and the

Table 4.4: Macro Determinants of Correlations: Leading Indicators

CEIC		DL Model		VAR Model		Granger	
				CEIC-->Corr	Corr-->CEIC	CEIC-->Corr	Corr-->CEIC
Corr	SBIC	F	R^2	P > z	P > z	X^2	X^2
SPUST	2	0.01	0.835	0.895	0.835	0.018	0.043
SPEF	2	4.28**	0.020	0.902	0.066*	0.015	3.3899*
SPR2	2	14.58**	0.074	0.025**	0.919	5.021**	0.010
SPRE	2	7.20***	0.039	0.059*	0.120	3.572*	2.414
SPG	2	0.06	0.000	0.014**	0.152	6.046**	2.047
USTEF	2	0.11	0.001	0.508	0.528	0.437	0.397
USTR2	2	0.49	0.005	0.385	0.756	0.756	0.096
USTRE	2	4.99**	0.034	0.308	0.915	1.040	0.011
USTG	2	0.80	0.006	0.221	0.195	1.497	1.679
EFR2	2	15.86***	0.062	0.149	0.069*	2.078	3.317*
EFRE	2	15.10***	0.064	0.041**	0.911	4.187**	0.012
EFG	2	0.17	0.000	0.045**	0.163	4.016**	1.948
R2RE	2	24.39***	0.099	0.001***	0.016**	10.806***	5.823**
R2G	2	0.60	0.003	0.061*	0.223	3.502*	0.223
REG	2	1.25	0.007	0.099*	0.026**	2.716*	4.94**

*** p < 0.01, ** p < 0.05, * p < 0.1

This table summarizes the multi-method approach to investigate leading indicators (*CEIC*) as a determinant of asset class correlations. Variables for each correlational relationship (Corr) are shown on the left. SBIC determines optimal lags. F-statistics and R^2 values are reported for the DL model with NW estimator. A VAR model for the interdependencies of correlations and *CEIC* is summarized to demonstrate lags offering significant equations ($P > z$). χ^2 results are reported from our Granger model.

Russell 2000/REITs correlation (*R2RE*), which exhibited a bidirectional and bicausal relationship, suggesting that *CEIC* plays a crucial role in understanding stock and REIT correlations.

4.4.4. Sentiment

Sentiment (*Sent*) from the University of Michigan's Index of Consumer *Sent* is used as a psychological measure for growth expectations (Johnson et al., 2013). Results of our study of *Sent* as a determinant of correlations are found in Table 4.5).

Other than the US Treasury/REIT (*USTRE*) correlation where a DL model is significant at 95% where $R^2 = 0.037$, *Sent* does not have any significant effects on US Treasury correlations. However, *Sent* does have a significant and similar effect

Table 4.5: Macro Determinants of Correlations: Sentiment

Sent		DL Model		VAR Model		Granger	
				Sent-->Corr	Corr-->Sent	Sent-->Corr	Corr-->Sent
Corr	SBIC	F	R^2	P > z	P > z	X^2	X^2
SPUST	1	1.03	0.012	0.481	0.160	0.498	1.972
SPEF	1	6.15	0.034	0.372	0.475	0.796	0.509
SPR2	1	15.45***	0.174	0.018**	0.192	5.606**	1.704
SPRE	1	64.34***	0.308	0.001***	0.135	10.989***	2.235
SPG	1	0.49	0.003	0.275	0.750	1.189	0.101
USTEF	1	1.21	0.013	0.527	0.244	0.400	1.360
USTR2	1	1.43	0.018	0.844	0.237	0.021	1.397
USTRE	1	4.10**	0.037	0.783	0.151	0.076	2.063
USTG	1	0.16	0.000	0.892	0.896	0.019	0.017
EFR2	1	20.94***	0.100	0.096*	0.279	2.769*	1.172
EFRE	1	54.04***	0.280	0.000***	0.354	14.337***	0.858
EFG	1	1.34	0.011	0.132	0.876	2.271	0.024
R2RE	1	25.39***	0.204	0.005***	0.856	7.883***	0.033
R2G	1	0.60	0.761	0.388	0.681	0.746	0.017
REG	1	0.01	0.080	0.309	0.814	1.035	0.055

*** p < 0.01, ** p < 0.05, * p < 0.1

This table summarizes the multi-method approach to investigate sentiment (*Sent*) as a determinant of asset class correlations. Variables for each correlational relationship (Corr) are shown on the left. SBIC determines optimal lags. F-statistics and R^2 values are reported for the DL model with NW estimator. A VAR model for the interdependencies of correlations and *Sent* is summarized to demonstrate lags offering significant equations ($P > z$). χ^2 results are reported from our Granger model.

on two stock/stock correlations *SPR2* and *EFR2*, as well as three REIT correlations (*SPRE*, *EFRE*, and *R2RE*).

Sent's effects are significant at 99% for the Russell 2000 correlations *SPR2* and *SPRE* for both DL models, where it demonstrates a one-way relationship at 95% determined through VAR and a one-way Granger-causality at 95% for *SPR2* and 99% for *SPRE*. R^2's explain a high level of variance at $R^2 = 0.174$ for *SPR2* and $R^2 = 0.308$.

We find *Sent* on the relationships *EFR2* and *EFRE* is significant, where DL is significant at 99% for both. R^2s are high at $R^2 = 0.100$ for *EFR2* and $R^2 = 0.280$ *EFR2*. VAR and Granger-causality are significant of *Sent* on both, albeit at 99% for *EFR2* and 90% for *EFRE*.

A DL model demonstrates significance at 99% and with $R^2 = 0.204$ for *Sent* on *R2RE*. It also demonstrates unidirectional effects through VAR at 99%, and Sent Granger-causes *R2RE*, also at 99%.

We find parallels between leading indicators and sentiment where both do not affect treasury relationships and are determinants of stock and REIT correlations. Sentiment acts early but on fewer correlations. When it is a determinant of correlations, its effects are stronger, as described by R^2 values determining more of the variance.

4.5. Results of Time-Varying Granger Causality

A causal or bicausal association between macroeconomic variables and asset correlations might be anticipated. Although some of our Granger findings reveal significant relationships, causal connections can break down due to structural breaks and variations in underlying relationships between variables over time. To enhance the rigor of our analysis, we employ a time-varying Granger causality (TVGC) method that accounts for time-series parameter instability by permitting the coefficients' structures and patterns to evolve.

4.5.1. Inflation

TVGC analysis conducted in our study unveils a significant relationship between π, and asset correlations, suggesting a dynamic and interdependent association as demonstrated in Table 4.6. We find REIT correlations exhibit a dynamic relationship with π. In particular, π Granger-causes *SPRE*, and *SPRE* Granger-causes π for rolling (RO) and recursive evolving (RE) windows, thus demonstrating a bicausal relationship at 95%. Furthermore, a bicausal relationship is observed where π Granger-causes *USTRE*, and *USTRE* Granger-causes π for RE at 95%.

Additionally, a bicausal relationship is present in which π Granger-causes *R2RE* and EFRE Granger-causes π for RO and RE windows at 95%, accompanied by a one-

Table 4.6: Time-Varying Granger Causality: Inflation

	GC?	MW (FE)	MW (RO)	MW (RE)	*GC?*	MW (FE)	MW (RO)	MW (RE)
Test		10.079	9.130	10.079		4.206	7.492	11.552
95%	π --> SPUST	12.852	11.453	13.119	SPUST --> π	11.558	11.673	11.694
99%		18.784	18.748	18.784		19.028	17.780	19.028
Test		2.330	7.690	8.336		3.553	10.239	12.309
95%	π --> SPEF	8.138	7.871	8.138**	SPEF --> π	8.273	7.78**	8.524**
99%		12.964	13.032	13.032		11.792	14.159	14.382
Test		2.921	7.171	9.495		0.844	8.588	10.913
95%	π --> SPR2	8.387	9.559	9.792	SPR2 --> π	7.866	8.228**	8.424**
99%		13.594	16.965	17.368		12.637	12.107	13.372
Test		9.092	13.459	18.610		3.284	15.985	17.115
95%	π --> SPRE	11.918	12.433**	12.834**	SPRE --> π	11.375	12.345**	12.345**
99%		18.077	16.120	18.077***		18.193	19.040	19.053
Test		8.798	12.698	13.890		7.656	11.835	12.288
95%	π --> SPG	10.713	10.275**	11.402**	SPG --> π	7.732	7.777**	8.593**
99%		17.489	17.068	17.489		9.976	12.191	12.191***
Test		1.383	5.718	6.295		2.107	7.053	11.489
95%	π --> USTEF	7.941	8.536	8.708	USTEF --> π	10.328	10.652	10.652**
99%		10.153	10.809	10.809		20.266	20.956	21.281
Test		5.060	5.003	5.060		3.636	6.705	6.960
95%	π --> USTR2	10.110	10.538	11.569	USTR2 --> π	7.623	7.919	8.593
99%		12.844	14.969	15.244		12.790	12.065	12.790
Test		5.225	8.367	11.158		3.450	11.938	18.178
95%	π --> USTRE	9.268	9.486	9.687**	USTRE --> π	11.690	10.16**	11.69**
99%		16.038	15.856	16.038		15.623	14.927	15.623***
Test		5.181	5.063	5.733		5.059	9.488	9.776
95%	π --> USTG	9.555	9.444	10.176	USTG --> π	9.114	10.266	10.450
99%		13.635	14.072	15.037		12.040	12.755	12.893
Test		1.491	6.539	6.539		4.840	15.287	15.287
95%	π --> EFR2	10.153	10.830	10.952	EFR2 --> π	8.590	9.091**	9.399**
99%		15.140	13.779	15.191		15.635	19.918	19.918
Test		5.892	26.095	27.162		1.647	10.677	10.854
95%	π --> EFRE	10.914	11.022**	11.099**	EFRE --> π	10.192	10.035**	10.841**
99%		14.503	14.34***	14.532***		13.316	13.823	14.309
Test		2.291	15.517	15.568		8.921	10.536	10.730
95%	π --> EFG	8.106	8.649**	8.703**	EFG --> π	7.904**	8.067**	8.815**
99%		12.367	16.790	16.877		11.124	10.952	11.124
Test		12.091	21.813	21.813		6.381	15.298	17.058
95%	π --> R2RE	8.466**	8.342**	8.525**	R2RE --> π	10.154	12.532**	12.792**
99%		12.821	14.446***	15.326***		16.088	18.809	20.666
Test		6.868	13.751	14.419		5.543	8.044	8.333
95%	π --> R2G	11.839	11.346**	12.602**	R2G --> π	8.039	8.894	9.570
99%		16.593	16.299	17.565		14.330	13.655	15.143
Test		8.082	9.271	10.510		3.883	8.832	9.689
95%	π --> REG	8.914	9.346	9.78**	REG --> π	7.824	8.419**	8.825**
99%		12.873	11.893	12.938		13.417	13.039	13.417

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table summarized the results of time-variant Granger causality (TVGC) for the relationship between inflation (π) and asset class correlations. Columns illustrate Max-Wald statistics for Forward-Expanding (FE), Rolling (RO), and Recursive Evolving (RE) windows. Rows demonstrate results for the 95$^{\text{th}}$ and 99$^{\text{th}}$ percentile test statistics. The Granger-cause relationship (*GC?*) being tested is found in the left-hand column. Thus, the first four rows read left to right, test if π Granger causes *SPUST*, and if *SPUST* Granger causes π.

way relationship where π Granger-causes *EFRE* Granger-causes for RO and recursive evolving (RE) at 99% significance. Bicausality exists between *R2RE* and π for RO and RE windows at the 95%, with a one-way relationship where π Granger-causes *R2RE* for forward expanding (FE) at 95% significance, and for RO and RE at the 99% significance.

Notable one-way relationships are observed among the stock/stock correlations and π, wherein *SPEF*, *SPR2*, and *EFR2* Granger-cause π for RO and RE at the 99% significance. Gold exhibits a bicausal relationship with π in its correlations with the S&P 500 (*SPG*) and EAFE (*EFG*) for RO and RE at the 99% significance. An intriguing discovery is the absence of a causal relationship in the stock-bond correlation (*SPUST*), yielding no significance when tested against π. This pattern re-emerges with the Russell 2000/Treasury relationship (*USTR2*).

4.5.2. Inflation Expectations

TVGC results reveal that the correlations between π^e, and asset dyads are less dynamic compared to those among π. A summary of the findings is provided in Table 4.7. Despite the less dynamic nature, it is observed that *USTEF* Granger-causes π^e and π^e Granger-causes *USTEF* for both rolling (RO) and recursive evolving (RE) windows at 99% significance. The effects of π^e are primarily unidirectional, with several noteworthy findings.

Significant unidirectional relationships include SPUST Granger-causing π^e for forward expanding (FE), RO, and RE windows at 95%, and RO and RE at 99%. Additionally, USTEF Granger-causes π^e for RO and RE windows at 99%. Other relationships include *SPRE*, *SPRG*, *USTR2*, *USTRE*, *EFR2*, *EFG*, and *R2G* Granger-causing π^e at various significance levels and window types.

We emphasize that the association with treasury correlations exhibits a more pronounced presence than with π. Interestingly, numerous asset correlations maintain

Table 4.7: Time-Varying Granger Causality: Inflation Expectations

	GC?	MW (FE)	MW (RO)	MW (RE)	*GC?*	MW (FE)	MW (RO)	MW (RE)
Test	π^e --> SPUST	2.209	7.734	9.051	SPUST --> π^e	7.897	25.207	29.216
95%		9.301	9.226	10.126		7.135**	7.056**	7.427**
99%		12.504	11.527	12.504		9.995	13.003***	13.144***
Test	π^e --> SPEF	1.870	10.144	10.529	SPEF --> π^e	2.760	9.510	9.876
95%		9.539	9.735**	9.841**		8.740	9.564	10.145
99%		13.966	14.640	14.640		17.792	16.896	18.252
Test	π^e --> SPR2	1.668	4.684	5.514	SPR2 --> π^e	2.925	7.480	7.482
95%		8.941	8.658	9.515		12.874	12.874	13.740
99%		18.778	16.668	19.297		22.637	22.708	25.978
Test	π^e --> SPRE	5.060	5.225	8.860	SPRE --> π^e	7.542	10.282	11.109
95%		9.993	9.876	10.378		7.985	8.268**	8.603**
99%		13.372	13.181	13.372		11.998	11.952	11.998
Test	π^e --> SPG	1.621	4.835	5.751	SPG --> π^e	4.005	13.288	14.342
95%		10.179	10.033	10.734		9.528	9.439**	9.862**
99%		14.438	13.597	14.438		12.581	14.328	14.328***
Test	π^e --> USTEF	7.604	13.575	13.999	USTEF --> π^e	3.130	14.707	15.902
95%		10.092	9.716**	10.245**		7.050	6.709**	7.309**
99%		13.371	13.497***	13.497***		9.372	9.542***	9.542***
Test	π^e --> USTR2	2.098	7.297	8.856	USTR2 --> π^e	7.876	8.765	9.746
95%		9.674	8.930	9.674		7.676**	7.487**	8.07**
99%		13.426	13.426	13.426		11.606	10.648	11.606
Test	π^e --> USTRE	1.474	8.757	8.757	USTRE --> π^e	6.172	8.908	10.072
95%		10.030	9.690	10.030		9.200	8.531**	9.2**
99%		14.197	14.109	14.334		12.025	16.528	16.528
Test	π^e --> USTG	3.926	5.709	7.131	USTG --> π^e	3.233	6.817	6.916
95%		9.869	8.961	9.918		7.505	9.222	9.243
99%		12.394	11.891	12.394		17.699	17.699	17.699
Test	π^e --> EFR2	2.963	6.816	7.378	EFR2 --> π^e	3.802	10.193	10.336
95%		10.457	10.799	10.799		8.225	9.185**	9.185**
99%		16.369	16.154	16.369		13.585	13.632	14.640
Test	π^e --> EFRE	4.220	6.605	7.814	EFRE --> π^e	6.651	9.927	13.351
95%		12.434	12.599	12.964		10.333	9.791**	10.333**
99%		19.381	19.381	19.381		14.142	14.239	15.214
Test	π^e --> EFG	4.586	6.658	8.770	EFG --> π^e	5.099	9.898	9.898
95%		9.160	8.902	9.359		9.135	9.231**	9.827**
99%		15.262	14.291	15.262		13.757	17.530	17.599
Test	π^e --> R2RE	3.684	9.662	9.989	R2RE --> π^e	4.108	7.095	8.099
95%		7.673	8.113**	8.462**		7.009	8.874	9.246
99%		13.774	13.774	14.470		15.107	15.270	15.642
Test	π^e --> R2G	1.954	9.512	9.512	R2G --> π^e	4.935	22.046	23.232
95%		9.618	10.006	11.248		6.768	7.556**	7.58**
99%		13.664	15.363	15.454		11.555	12.303***	14.812***
Test	π^e --> REG	6.456	11.621	12.965	REG --> π^e	5.315	11.649	12.659
95%		9.944	10.13**	10.794**		8.653	8.519**	8.896**
99%		13.075	14.804	16.595		12.780	14.598	15.029

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table summarized the results of time-variant Granger causality (TVGC) for the relationship between inflation expectations (π^e) and asset class correlations. Columns illustrate Max-Wald statistics for Forward-Expanding (FE), Rolling (RO), and Recursive Evolving (RE) windows. Rows demonstrate results for the 95$^{\text{th}}$ and 99$^{\text{th}}$ percentile test statistics. The Granger-cause relationship (*GC?*) being tested is found in the left-hand column. Thus, the first four rows read left to right, test if π^e Granger causes $SPUST$, and if $SPUST$ Granger causes π^e.

a causal relationship wherein they Granger-cause π^e, yet π^e does not reciprocate by Granger-causing these correlations.

4.5.3. Leading Indicators

A salient finding of our analysis of leading indicators (*CEIC*) and correlations is the absence of bidirectional causation, as detailed in Table 4.8.

Similar to the case with π^e, correlations Granger-cause *CEIC* more frequently than *CEIC* Granger-causes correlations. Notable findings in this regard include *SPUST*, *SPR2*, and *EFR2* Granger-causing *CEIC* for rolling (RO) and recursive evolving (RE) windows at a 95% significance. Furthermore, *SPRE*, *EFRE*, and *R2RE* Granger-cause *CEIC* for forward expanding (FE), RO, and RE windows at a 99%, as do *REG* and *USTRE*, with the exception of the FE window.

The TVGC analysis reveals significance in the one-way effects of *CEIC* Granger-causing *SPEF*, *USTEF*, and *USTR2* for RO and RE windows at a 95% significance. A key takeaway from these results is that correlations more frequently Granger-cause leading indicators than leading indicators Granger-cause correlations.

4.5.4. Sentiment

The relationship between sentiment (*Sent*) and asset class correlations exhibits a unique and dynamic nature, as shown in Table 4.9. Our TVGC analysis uncovers bidirectional Granger-causality in several relationships. Specifically, *Sent* and *SPEF* demonstrate a bidirectional Granger-causal relationship for RO and RE windows at 95%. Similarly, *Sent* and *SPRE*, as well as *Sent* and *EFRE*, exhibit bidirectional Granger-causality for RO and RE windows at a 95% significance.

In addition, *Sent* unilaterally Granger-causes *SPR2* for all window types, and at a 99% significance. Certain correlations that one-way Granger-cause *Sent* include *SPUST* for RO and RE windows at a 95%, *SPG* for RO and RE windows at a 99%,

Table 4.8: Time-Varying Granger Causality: Leading Indicators

	GC?	MW (FE)	MW (RO)	MW (RE)	GC?	MW (FE)	MW (RO)	MW (RE)
Test	CEIC --> SPUST	6.788	9.828	10.011	SPUST --> CEIC	6.164	11.155	11.155
95%		11.620	10.881	11.620		9.222	9.233**	9.58**
99%		18.560	20.644	20.683		12.174	12.129	12.174
Test	CEIC --> SPEF	7.130	10.896	11.624	SPEF --> CEIC	1.794	8.112	8.112
95%		8.786	8.953**	9.5**		8.014	9.178	9.223
99%		11.485	13.253	13.683		12.579	13.542	13.542
Test	CEIC --> SPR2	8.446	7.183	8.446	SPR2 --> CEIC	4.838	13.203	13.203
95%		9.135	11.261	11.502		8.132	8.951**	8.993**
99%		16.620	18.387	18.387		11.820	15.074	15.074
Test	CEIC --> SPRE	3.980	5.881	6.923	SPRE --> CEIC	20.594	21.671	24.990
95%		12.349	13.841	14.725		6.99**	8.073**	8.316**
99%		17.015	16.775	17.429		9.378***	9.6***	10.979***
Test	CEIC --> SPG	1.992	4.172	4.973	SPG --> CEIC	2.078	5.583	6.770
95%		9.848	9.845	11.201		7.223	8.564	8.564
99%		14.110	14.434	14.998		10.752	13.498	13.498
Test	CEIC --> USTEF	5.036	9.430	9.680	USTEF --> CEIC	3.741	5.701	6.126
95%		9.561	9.347**	9.706		9.956	9.834	10.340
99%		13.144	13.812	14.157		14.526	18.454	18.454
Test	CEIC --> USTR2	2.813	9.880	9.882	USTR2 --> CEIC	3.497	8.709	9.026
95%		7.201	8.241**	8.4**		10.809	10.973	11.446
99%		11.437	11.254	11.609		16.875	15.531	16.875
Test	CEIC --> USTRE	3.818	5.810	8.541	USTRE --> CEIC	8.877	22.362	29.385
95%		9.914	9.283	9.914		8.678**	9.863**	10.136**
99%		16.080	16.080	16.080		13.505	13.312***	13.794***
Test	CEIC --> USTG	2.255	7.792	8.678	USTG --> CEIC	4.097	8.830	8.986
95%		12.016	11.944	12.342		7.981	9.055	9.230
99%		15.251	16.113	16.451		16.452	14.884	16.556
Test	CEIC --> EFR2	8.558	9.011	9.177	EFR2 --> CEIC	5.187	15.405	15.405
95%		11.408	11.245	11.651		11.457	11.564**	12.186**
99%		16.692	16.222	16.692		14.490	18.326	18.326
Test	CEIC --> EFRE	3.653	8.345	9.289	EFRE --> CEIC	15.702	27.956	33.279
95%		8.828	9.036	9.399		8.076**	8.462**	8.547**
99%		11.650	11.197	11.650		14.367***	13.095***	14.367***
Test	CEIC --> EFG	4.295	7.702	7.702	EFG --> CEIC	2.433	10.400	10.618
95%		9.869	11.131	11.237		9.518	11.536	11.718
99%		19.499	18.949	19.499		13.616	15.337	15.337
Test	CEIC --> R2RE	4.680	5.926	5.926	R2RE --> CEIC	28.402	40.648	48.181
95%		12.343	11.948	12.343		8.181**	8.327**	9.113**
99%		18.311	18.427	18.427		12.025***	11.457***	12.025***
Test	CEIC --> R2G	3.206	5.588	7.423	R2G --> CEIC	2.857	9.471	9.490
95%		8.386	8.952	10.058		9.300	9.891	9.939
99%		12.141	14.078	14.120		12.293	12.364	13.920
Test	CEIC --> REG	2.827	8.277	10.678	REG --> CEIC	3.138	16.143	17.979
95%		9.601	11.360	12.018		8.725	8.71**	8.836**
99%		14.077	18.474	18.747		16.814	15.199***	16.814***

*** p < 0.01, ** p < 0.05, * p < 0.1

This table summarized the results of time-variant Granger causality (TVGC) for the relationship between leading indicators (*CEIC*) and asset class correlations. Columns illustrate Max-Wald statistics for Forward-Expanding (FE), Rolling (RO), and Recursive Evolving (RE) windows. Rows demonstrate results for the 95$^{\text{th}}$ and 99$^{\text{th}}$ percentile test statistics. The Granger-cause relationship (*GC?*) being tested is found in the left-hand column. Thus, the first four rows read left to right, test if *CEIC* Granger causes *SPUST*, and if *SPUST* Granger causes *CEIC*.

Table 4.9: Time-Varying Granger Causality: Sentiment

	GC?	MW (FE)	MW (RO)	MW (RE)	*GC?*	MW (FE)	MW (RO)	MW (RE)
Test	Sent --> SPUST	3.848	6.240	7.391	SPUST --> Sent	5.698	13.479	13.531
95%		9.297	9.277	9.503		10.584	13.256**	13.259**
99%		13.473	14.021	14.021		15.428	16.561	17.103
Test	Sent --> SPEF	2.959	9.332	10.041	SPEF --> Sent	5.842	17.997	17.997
95%		8.339	8.599**	8.803**		8.446	8.876**	9.78**
99%		12.534	12.059	12.534		12.467	14.162***	14.162***
Test	Sent --> SPR2	9.665	25.703	25.703	SPR2 --> Sent	7.548	8.177	8.620
95%		7.558**	7.558**	7.868**		9.522	9.901	9.991
99%		8.79***	13.519***	15.183***		14.563	14.267	14.563
Test	Sent --> SPRE	6.385	11.685	11.745	SPRE --> Sent	6.288	10.520	10.520
95%		10.092	11.181**	11.43**		10.347	10.107**	10.347**
99%		14.282	14.012	14.282		22.593	21.077	22.593
Test	Sent --> SPG	1.969	3.239	3.594	SPG --> Sent	6.734	17.687	20.299
95%		9.420	9.640	10.576		8.899	10.062**	10.578**
99%		13.220	14.982	14.982		14.469	14.469***	14.469***
Test	Sent --> USTEF	1.739	4.310	4.401	USTEF --> Sent	3.100	19.896	19.896
95%		8.156	8.578	9.320		7.574	8.072**	8.258**
99%		13.217	13.217	14.403		10.474	12.258***	12.49***
Test	Sent --> USTR2	1.915	8.874	9.307	USTR2 --> Sent	4.434	9.525	9.525
95%		8.655	8.568**	9.381		9.255	9.646	10.164
99%		11.202	13.484	14.282		13.329	13.138	13.329
Test	Sent --> USTRE	2.164	6.077	8.250	USTRE --> Sent	12.073	18.864	19.600
95%		7.384	7.932	8.186**		10.128**	10.773**	10.925**
99%		13.736	13.796	13.796		17.313	16.365***	17.313***
Test	Sent --> USTG	5.031	9.186	9.268	USTG --> Sent	2.964	7.263	7.288
95%		8.583	9.049**	9.798		8.257	9.027	9.540
99%		17.469	17.469	17.469		17.218	17.296	17.296
Test	Sent --> EFR2	4.808	5.888	8.065	EFR2 --> Sent	4.642	6.255	7.342
95%		9.424	9.759	9.759		7.622	8.618	8.787
99%		15.353	15.353	15.411		12.090	13.096	14.637
Test	Sent --> EFRE	7.677	15.496	15.565	EFRE --> Sent	8.392	14.131	14.265
95%		9.919	9.639**	10.249**		8.036**	9.041**	9.18**
99%		17.092	16.563	17.092		12.552	12.377***	12.819***
Test	Sent --> EFG	6.001	7.659	8.834	EFG --> Sent	8.137	13.557	14.660
95%		7.574	7.664	8.406**		8.794	8.69**	8.942**
99%		10.808	10.594	10.808		12.089	11.442***	12.613***
Test	Sent --> R2RE	6.481	7.814	7.814	R2RE --> Sent	12.025	13.275	14.523
95%		12.335	12.054	12.566		11.37**	11.37**	11.534**
99%		17.640	17.316	17.640		19.105	19.105	19.105
Test	Sent --> R2G	3.028	4.790	5.012	R2G --> Sent	9.121	21.781	25.332
95%		10.486	12.006	13.582		8.746**	9.999**	10.86**
99%		15.955	15.824	16.040		14.558	14.778***	16.788***
Test	Sent --> REG	5.297	4.240	6.874	REG --> Sent	5.057	7.491	8.020
95%		10.420	10.638	11.462		8.064	9.769	10.009
99%		16.288	15.443	16.314		11.993	13.804	14.772

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table summarized the results of time-variant Granger causality (TVGC) for the relationship between sentiment (*Sent*) and asset class correlations. Columns illustrate Max-Wald statistics for Forward-Expanding (FE), Rolling (RO), and Recursive Evolving (RE) windows. Rows demonstrate results for the 95^{th} and 99^{th} percentile test statistics. The Granger-cause relationship (*GC?*) being tested is found in the left-hand column. Thus, the first four rows read left to right, test if *Sent* Granger causes *SPUST*, and if *SPUST* Granger causes *Sent*.

and both *R2RE* and *R2G* for FE windows at a 95% significance and RO and RE windows at a 99%.

Our study examines the causal and bicausal relationships between macro variables and asset correlations. We utilized a time-varying Granger causality method to account for parameter instability in time-series data, where we reveal 41 additional significant relationships that eluded us in our macro variable study using standard Granger. Our findings demonstrate significant relationships between π and asset correlations. Furthermore, we observed various unidirectional and bidirectional relationships involving REIT correlations and π, as well as stock/stock correlations and gold. However, we found no causal relationship in the stock-bond correlation ($SPUST$) when tested against π. In the case of π^e, the associations were less dynamic but still significant in some cases. Notably, we found that asset correlations more often Granger-cause leading indicators than the reverse. Our analysis also reveals that sentiment exhibits unique and dynamic relationships with asset class correlations, highlighting the interdependencies of psychological variables with correlations.

4.6. Analysis of Macro Variables & Regimes

The persistence of correlations, combined with market movements, facilitates the establishment of correlational regimes. We examine the binary outcome variables Everyone-Wins (*EWp*), Risk-On (*ROp*), Flight-to-Safety (*FTSp*), and Nowhere-to-Hide (*NTHp*) using logistic regression (logit). Summary results are presented in Table 4.10.

When analyzing the relationship between the binary outcome variable *EWp* and inflation (π), the model is statistically significant at 99% with a Pseudo R^2 of 0.0816, indicating that it accounts for 8.16% of the variance. These results demonstrate that a one-unit increase in the π variable is associated with approximately 2.15 times higher odds of the *EWp* regime occurring, as evidenced by the statistically significant odds ratio of 2.148 (95% CI: [1.721, 2.681]). We find similar results for the *ROp* regime

Table 4.10: Macro Determinants of Correlational Regimes

		Logit			Probit		
Macro	Regime	LR X^2	P>X^2	Ps R^2	LR X^2	P>X^2	Ps R^2
Inflation (π)	EW	54.77***	0.000	0.082	53.07***	0.000	0.079
	RO	151.85***	0.000	0.232	146.92***	0.000	0.224
	FTS	32.07***	0.000	0.142	30.97***	0.000	0.137
	NTH	0.01	ns	0.000	0.02	ns	0.000
Inflation Expectations (π^e)	EW	124.23***	0.000	0.181	116.78***	0.000	0.174
	RO	157.96***	0.000	0.241	149.91***	0.000	0.228
	FTS	12.89***	0.000	0.053	11.56***	0.001	0.048
	NTH	3.71*	0.054	0.011	3.97**	0.046	0.012
Leading Indicators (CEIC)	EW	7.98**	0.046	0.012	8.13**	0.044	0.012
	RO	13.44***	0.001	0.021	10.91***	0.004	0.017
	FTS	35.39***	0.000	0.153	35.63***	0.000	0.154
	NTH	7.95**	0.019	0.024	7.95**	0.019	0.024
Sentiment (Sent)	EW	18.59***	0.000	0.028	18.71***	0.000	0.028
	RO	0.64	ns	0.001	0.64	ns	0.001
	FTS	43.97***	0.000	0.195	40.36***	0.000	0.179
	NTH	4.09	ns	0.013	4.15	ns	0.013

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This summarizes the results of lagged logit/probit regressions to determine the effects of the macroeconomic variables of inflation (π), inflation expectations (π^e), leading indicators ($CEIC$), and sentiment ($Sent$) on the Regimes (Y-variables), Everyone-Wins (EW), Risk-On (RO), Flight-to-Safety (FTS), and Nowhere-to-Hide (NTH) regimes. Optimal lags are determined by SBIC. For both the logit and probit models, the results of the likelihood ratio chi-square test (LR χ^2), p-value associated with the chi-square test ($P > \chi^2$), and the Pseudo R^2 are reported. "ns" = insignificant results for $\alpha = 0.10$.

at 99%, wherein a higher variance is explained by a Pseudo R^2 of 0.232. The $FTSp$ regime is significant at 99% with a Pseudo R^2 of 0.137. However, we do not find significant results for the effects of inflation on $NTHp$.

The effects of inflation expectations (π^e) on regimes yield similar results to inflation, where EWp, ROp, and $FTSp$ are significant at 99%. Pseudo R^2 is higher for EWp (Pseudo R^2 = 0.181) and ROp (Pseudo R^2 = 0.241), but lower for $FTSp$ with a Pseudo $R^2 = 0.053$. However, we also discover that π^e is a determinant of the $NTHp$ regime at 90%, albeit with a low Pseudo R^2 of 0.011.

Leading indicators (*CEIC*) are significant for all regimes at 95%, but account for small variances in *EWp*, *ROp*, and *NTHp*, where Pseudo R^2s are below 0.030. In the case of *FTSp*, *CEIC* exhibits a higher Pseudo R^2 of 0.153.

Sentiment does have a significant effect on the *ROp* and *NTHp* regimes. We find *Sent* is a determinant of *EWp* at 99% but with low explanatory power (Pseudo $R^2 = 0.028$). However, it does exert considerable effects on *FTSp* at 99% with a Pseudo R^2 of 0.195. Reinforcing the notion that psychological variables act earlier than fundamental variables.

To ensure robustness, we examine all four macro variables on the four regimes using a Probit model. The results are nearly identical, with only minor variations in significance levels and explanations of variance. Therefore, the probit models confirm the findings of the logit models discussed above.

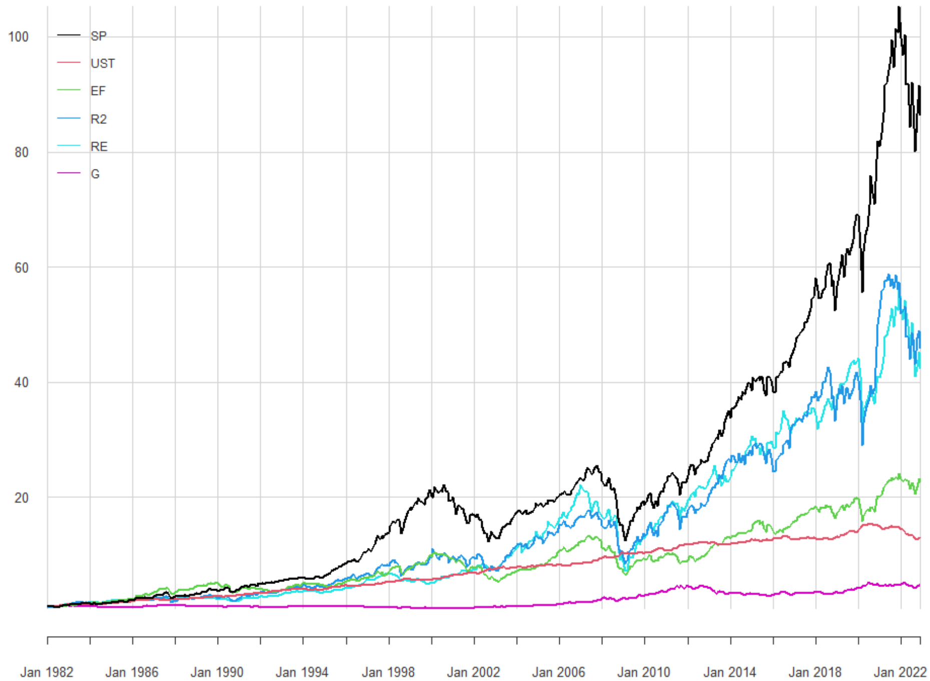
4.7. Portfolio Construction & Testing

4.7.1. Asset Classes

We offer a better understanding of correlational relationships between asset classes, how they are time-varying when they exhibit breaks, and their changing nature over time. This enables the testing of macro variables to investigate the determinants and causes of change. We then apply these macro variables to correlational regimes that incorporate the correlational environment and the market environment. This underpins our transition into a portfolio construction and testing framework, where we seek to determine if our understanding of the nature of correlations can improve tactical asset allocation and overall performance. Figure 4.3 illustrates the cumulative performance of the six asset classes for the full time period of January 1982 to December 2022.

A heat map of performance and risk metrics for all asset classes and model portfolios is located in Table 4.11. Cumulative returns discussed hereafter represent

Figure 4.3: Cumulative Returns: Asset Classes



This figure illustrates the cumulative returns of the S&P 500 (SP), US Treasuries (UST), MSCI EAFE (EF), Russell 2000 ($R2$), REITs (RE), and Gold (G) from January 1982 to December 2022.

the growth of a dollar over the entire time period from January 1982 to December 2022. Thus, in the case of the S&P 500 (SP), $1 invested in January 1982 would have grown to $85.20 by December 2022. Reviewing some of the key findings of the individual asset classes as represented by the indices, S&P 500 (SP), US Treasuries (UST), MSCI EAFE (EF), Russell 2000 ($R2$), FTSE Nareit (RE), and Gold (G), we offer the following observations.

SP exhibits the highest cumulative and annualized returns at $CR = 85.2$ and $R_a = .115$, respectively. UST display the highest Sharpe ratio on an annualized basis ($SR_a = 1.249$), but coupled with a lower cumulative return at $CR = 11.84$. The annualized standard deviation is highest for the $R2$ ($SD_a = .195$), making it the most volatile asset class.

Table 4.11: Performance Heat Map: All Assets & Portfolios

	Return (cum.)	Return (ann.)	SD (mo.)	SD (ann.)	SR Mo. (Rf=0.3%)	SR Ann. (Rf=3.6%)	Sortino (MAR=2.9%)	IR (UST)	IR (60/40)	IR (S&P500)	MDD	VaR (95%)
Asset Classes												
SP	85.205	0.115	0.044	0.153	0.161	0.752	0.826	0.316	0.327		0.510	-0.069
UST	11.837	0.064	0.015	0.051	0.158	1.249	0.951		-0.276	-0.316	0.184	-0.018
EF	21.460	0.079	0.042	0.147	0.101	0.538	0.487	0.091	-0.094	-0.341	0.508	-0.072
R2	44.708	0.098	0.056	0.195	0.115	0.500	0.565	0.162	0.075	-0.160	0.529	-0.082
RE	41.193	0.096	0.048	0.168	0.121	0.570	0.595	0.183	0.063	-0.136	0.679	-0.062
G	3.751	0.039	0.043	0.150	0.026	0.259	0.138	-0.165	-0.304	-0.352	0.476	-0.057
Benchmark Portfolios												
B0100	11.837	0.064	0.015	0.051	0.158	1.249	0.951		-0.276	-0.316	0.184	-0.018
B0280	16.928	0.073	0.014	0.048	0.216	1.506	1.285	0.305	-0.261	-0.314	0.149	-0.015
B4060	23.215	0.081	0.018	0.061	0.211	1.333	1.152	0.290	-0.247	-0.318	0.164	-0.021
B6040	30.614	0.088	0.024	0.082	0.185	1.078	0.950	0.276		-0.327	0.277	-0.033
B8020	38.874	0.094	0.031	0.106	0.164	0.887	0.817	0.261	0.216	-0.339	0.383	-0.047
B1000	47.554	0.099	0.038	0.132	0.149	0.751	0.731	0.246	0.200	-0.319	0.475	-0.058
Optimized & Persistency Portfolios												
OptU	362.696	0.155	0.024	0.081	0.399	1.900	2.426	1.142	0.877	0.291	0.210	-0.023
POptU	28.096	0.086	0.027	0.095	0.156	0.901	0.801	0.233	-0.028	-0.220	0.243	-0.031
OptC	303.134	0.150	0.021	0.073	0.423	2.042	2.626	1.225	0.894	0.261	0.182	-0.019
POptC	29.885	0.087	0.025	0.087	0.173	1.000	0.892	0.275	-0.009	-0.215	0.208	-0.029
OptB	52.506	0.102	0.023	0.078	0.240	1.303	1.199	0.516	0.213	-0.102	0.244	-0.027
POptB	23.900	0.082	0.023	0.080	0.167	1.019	0.822	0.230	-0.096	-0.266	0.244	-0.030
Regime & Regime Switching Portfolios												
EW	25.586	0.083	0.020	0.069	0.197	1.209	1.035	0.279	-0.197	-0.320	0.179	-0.025
RO	33.362	0.090	0.020	0.070	0.221	1.287	1.214	0.367	0.045	-0.214	0.149	-0.028
FTS	28.746	0.086	0.023	0.079	0.184	1.088	0.937	0.264	-0.179	-0.337	0.277	-0.033
NTH	28.179	0.086	0.017	0.058	0.242	1.478	1.394	0.428	-0.045	-0.240	0.164	-0.019
RS	47.871	0.100	0.024	0.082	0.223	1.218	1.181	0.415	0.261	-0.149	0.179	-0.033
RSO	30.530	0.088	0.020	0.070	0.213	1.263	1.114	0.332	-0.002	-0.252	0.186	-0.028

This table summarizes the performance and risk metrics for the six asset classes, benchmark portfolios, optimal and persistency portfolios, and regime and regime-switching portfolios from January 1982 to December 2022. Cumulative and annualized returns are listed first. Abbreviations: SD = standard deviation (monthly & annualized), SR = Sharpe Ratio, Sortino = Sortino Ratio, IR = Information Ratio (UST, 60/40, S&P 500 benchmarks), MDD = Maximum Drawdown, VaR = Value-at-Risk. Green represents a more favorable outcome for the metric, and red represents a less favorable outcome.

International stocks, as represented by EF, have a cumulative return of $CR = 21.46$ and an annualized return of $R_a = 0.079$, with a $SR_a = 0.538$, placing them in the middle of the six asset classes in terms of total returns and risk-adjusted returns. RE is the third highest performing asset class in terms of cumulative returns ($CR = 11.84$) and annualized returns of $R_a = 0.960$, but we point out that it demonstrates the largest maximum drawdown ($MDD = .679$) of all assets.

We draw attention to the fact that Gold offers little performance value over the full period. It demonstrates the lowest $CR = 21.46$, lowest $R_a = 0.079$, and with a high $SD_a = .150$, resulting in the worst Sharpe among the six assets ($SR_a = 0.259$)

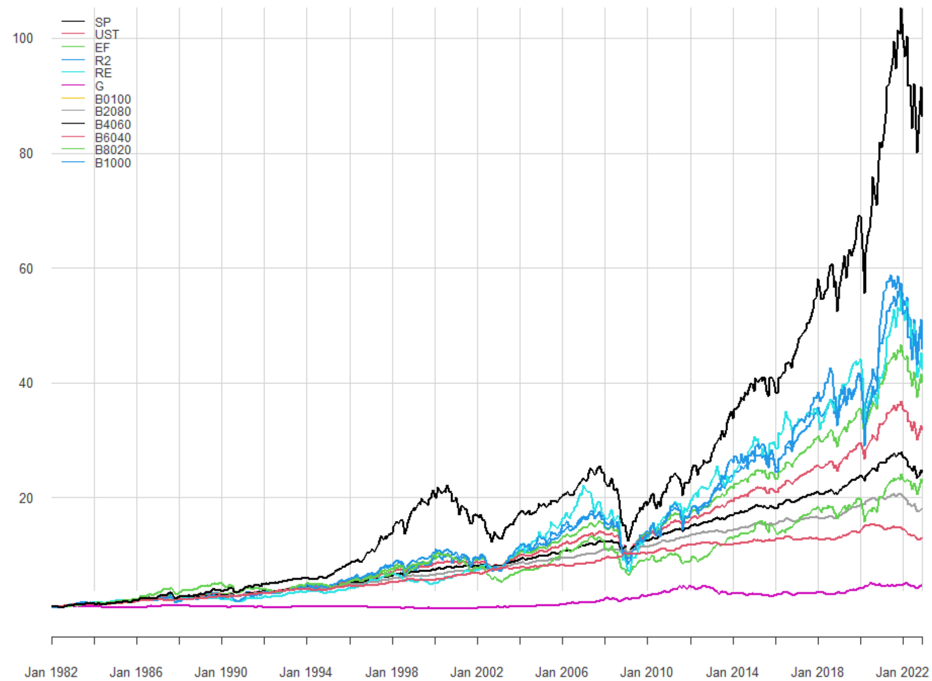
We summarize the six assets by offering that the S&P 500 provides the highest returns, whereas Treasuries offer the best risk-adjusted performance. International stocks and REITs exhibit moderate returns and risk-adjusted performance compared to other asset classes, with relatively high volatility. Gold underperforms in terms of risk-adjusted returns, and the Russell 2000 demonstrates the highest volatility among all asset classes.

4.7.2. Benchmark Portfolios

The benchmark portfolios are comprised of six primary asset classes, ranging from low-risk to high-risk portfolios. The lowest risk portfolio, denoted as *B0100*, consists of 100% US Treasuries, while the highest risk portfolio, *B1000*, is constructed entirely of risk assets with a 0% allocation to treasuries. Four intermediate portfolios (*B2080*, *B4060*, *B6040*, and *B8020*) are established between these two extremes, offering varying levels of risk that lie along an efficient frontier. Figure 4.4 shows the cumulative returns for the benchmark portfolios since January 1982.

Benchmark portfolios exhibit a trade-off between risk and return. High-risk portfolios, such as *B1000* (0% treasuries), yield higher annualized returns ($R_a = .099\%$) but lower annualized Sharpe ratios ($SR_a = 0.751$) and larger maximum drawdowns ($MDD = 0.476$). Conversely, low-risk portfolios like *B0100* (100% treasuries) generate lower annualized returns ($R_a = .064$) but higher annualized Sharpe ratios ($SR_a = 1.249$) and smaller maximum drawdowns ($MDD = 0.184$). Among all benchmark portfolios, *B2080*, a lower-risk option, has the highest annualized Sharpe ratio ($SR_a = 1.506$). Volatility, as measured by the annualized standard deviation, is lowest for *B0100* ($SD_a = .059$) and highest for *B1000* ($SD_a = 0.132$).

Figure 4.4: Cumulative Returns: Benchmark Portfolios



This figure illustrates the cumulative returns (growth of a \$1) for the benchmark portfolios and includes the six underlying asset classes from January 1982 to December 2022. *B0100* is the lowest risk portfolio representing 0/100, or 100% US Treasuries. *B1000* represents a 100/0 combination of all risk assets, no treasuries. 20/80 = *B2080*, 40/60 = *B4060*, 60/40 = *B6040*, 80/20 = *B8020*.

While individual asset classes have distinct return and risk characteristics, diversified benchmark portfolios provide a spectrum of options for investors to balance risk and return based on their preferences. Lower-risk portfolios have better risk-adjusted performance but lower returns, while higher-risk portfolios offer higher returns but also increased downside risk and volatility.

4.7.3. Optimal & Persistency Portfolios

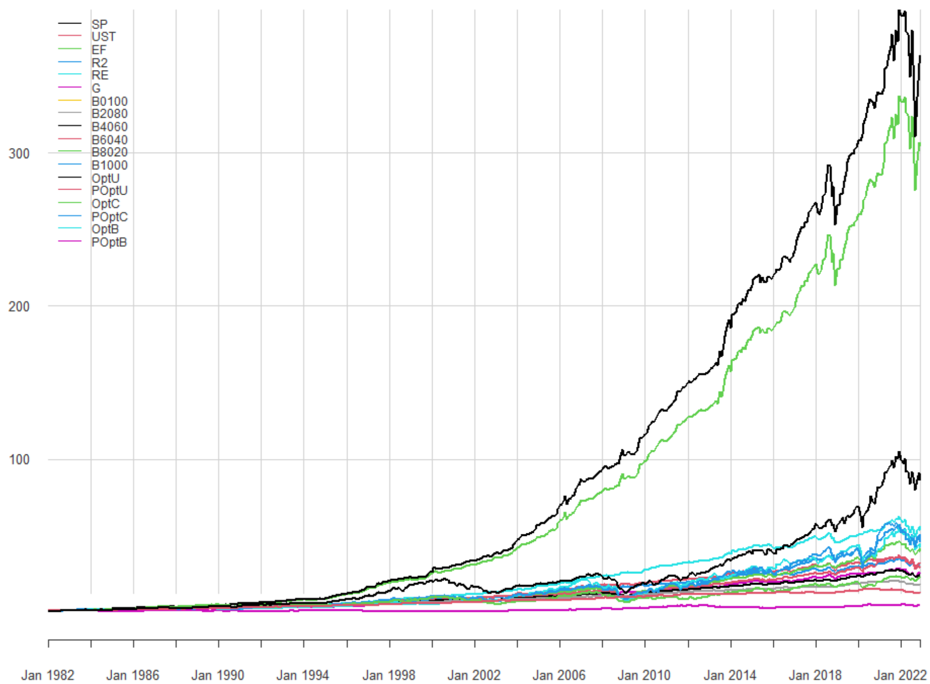
Optimal portfolios are built using the GRG nonlinear method and encompass three types: *OptU* (unconstrained), *OptC* (semi-constrained), and *OptB* (benchmark-constrained). Our analysis reveals that the *OptU* portfolio, which permits any asset class to be held at any weight ranging from 0% to 100%, attains the highest performance among all portfolios and asset classes. The returns, $CR = 362.70$ and $R_a = 0.155$, significantly surpass those of the all-equity benchmark (*B1000*) and the S&P 500 (*SP*). Moreover, the Sharpe ratio, $SR_a = 1.900$, indicates exceptional risk-adjusted returns.

The semi-constrained portfolio (*OptC*) allows the S&P 500 and US Treasuries to range from 0% to 100% while constraining the other four asset classes to a range of 0% to 50%. This portfolio also demonstrates respectable performance with $CR = 303.134$, $R_a = 0.150$, and $SR_a = 2.042$. Our benchmark-constrained portfolio (*OptB*) constrains the asset classes to the same ratios as the benchmark portfolios but allows GRG to optimize freely across the spectrum of the efficient frontier. Although this portfolio underperforms the other optimized models, it still delivers results that exceed all benchmark portfolios, with returns of $CR = 52.506$ and $R_a = 0.102$, and a Sharpe ratio of $SR_a = 1.303$.

The optimal portfolios are designed with the benefit of hindsight, wherein an investor would require perfect information and the ability to act upon it concurrently to achieve the desired results. The purpose of the optimal portfolios is to test correlational stability and time-invariance. To this end, we construct *persistency portfolios* by purchasing the asset allocations of the optimal portfolios with a one-month lag. Three portfolios are constructed to follow each optimal portfolio: *POptU* (unconstrained) follows *OptU*, *POptC* (constrained) follows *OptC*, and *POptB* (benchmark constrained) follows *OptB*. If temporal stability is present, even though we may not achieve the performance of the optimal portfolios, a "fast-following" persistency portfolio could still produce meaningful results given the disparity in performance between benchmark and optimal portfolios.

POptU results in $CR = 28.096$, $R_a = 0.86$, and $SR_a = 0.901$, placing it notably below its optimal counterpart. Additionally, it falls between the *B4060* and *B6040* in terms of returns, but with a $SR_a = 0.901$, which is lower than both due to a higher standard deviation. The performance of the *PoptC* and *POptB* portfolios is even less remarkable, as shown in Table 4.4. Consequently, the persistence portfolios fail to capture the meaningful performance of their optimal counterparts. Some of this underperformance can be attributed to model design and the inability to react in a timely fashion due to monthly data. Nonetheless, the primary takeaway is that chasing returns based on the assumption of time-invariance does not prove to be a value-adding strategy. Figure 4.5 illustrates the cumulative returns of the optimal and persistency portfolios.

Figure 4.5: Cumulative Returns: Optimal & Persistency Portfolios



This figure builds on Figures 4.3 and 4.4 by adding the cumulative returns of the optimal and persistency portfolios from January 1982 to December 2022. *OptU* = Optimized Unconstrained, *POptU* = Persistency Unconstrained, *OptC* = Optimized Semi-constrained, *POptC* = Persistency Semi-constrained, *OptB* = Optimized Benchmark Constrained, *POptB* = Persistency Benchmark Constrained.

4.7.4. Regime & Regime-switching Portfolios

Regime Portfolios

The correlation-based regime portfolios are classified into four distinct categories: *Everyone-Wins* (*EW*), *Risk-On* (*RO*), *Flight-to-Safety* (*FTS*), and *Nowhere-to-Hide* (*NTH*). The *EW* portfolio employs the asset allocation strategy of the *B6040* benchmark, while the *RO* strategy incorporates the *B8020* benchmark, the *FTS* strategy utilizes the *B4060* benchmark, and the *NTH* strategy adopts the *B0100* benchmark.

Juxtaposing the performance of the *EW*, *RO*, *FTS*, and *NTH* portfolios with their benchmark counterparts, the *EW* portfolio yields an annualized Sharpe ratio of $SR_a = 1.209$, an annualized return of $R_a = 0.083$, and a cumulative return of $CR = 25.58$, situating it between the 40/60 (*B4060*) and 60/40 (*B6040*) portfolios as delineated in Table 4.11. Conversely, the *RO* portfolio generates $R_a = 0.090$, $CR = 33.36$, placing it between a 60/40 (*B6040*) and 80/20 (*B8020*) in terms of returns; nevertheless, with $SR_a = 1.287$, it is closer to a 40/60 (*B4060*), thereby exhibiting a favorable risk-adjusted performance in comparison to the benchmarks.

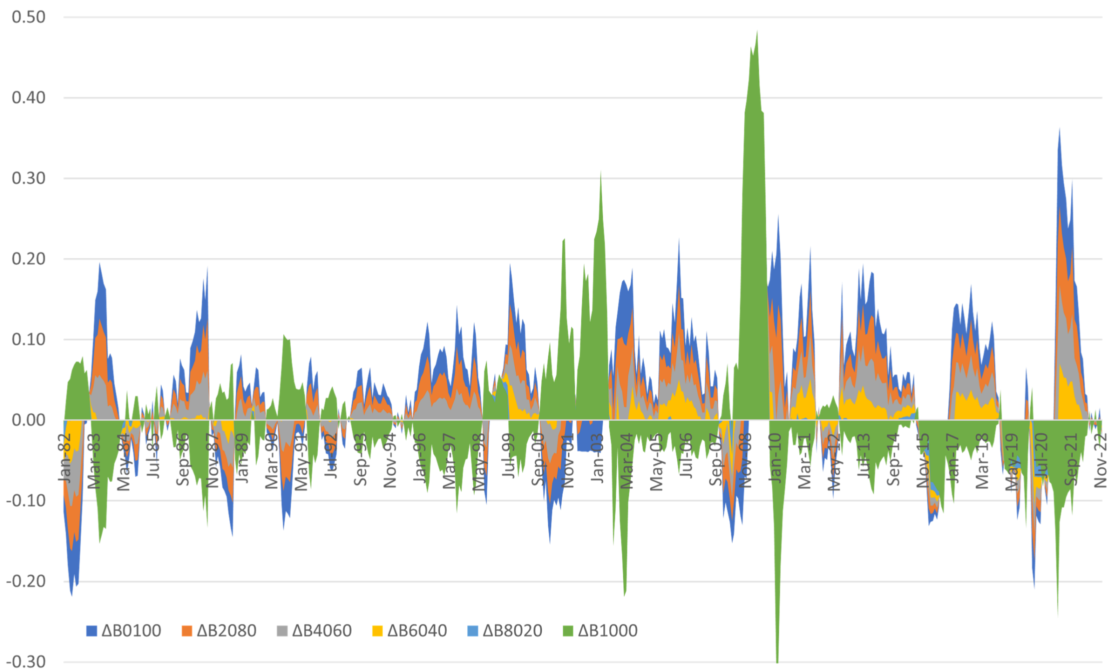
We find that the *FTS* portfolio demonstrates the lowest Sharpe ratio among the regime-based models at $SR_a = 1.088$, and its returns are relatively modest, falling below the *B6040* benchmark. While the *NTH* portfolio affords respectable returns at $R_a = 0.086$, $CR = 28.17$, positioning it between the *B4060* and *B6040* benchmarks, it exhibits the second-highest Sharpe ratio ($SR_a = 1.478$) among all regime and benchmark portfolios, attributable to a low standard deviation $SD_a = 0.058$.

Three of the regime portfolios offer substantial risk-adjusted returns. Both *EW* and *NTH* portfolios exhibit moderate risk profiles while surpassing the returns of benchmarks with similar risk. The *RO* portfolio, on the other hand, provides higher returns, albeit coupled with the risk levels of more moderate benchmarks.

Regime-Switching Portfolios

The *regime-switching* portfolio (*RS*) is constructed by reassembling the four correlation-based regime portfolios into their inherent chronological sequence. The portfolio subsequently applies ("switches") the respective benchmark portfolio allocations one month after the regime becomes present, thus offering real-time applicability. In contrast, the *optimized regime-switching* portfolio (*RSO*) also employs the natural temporal occurrence of regimes. However, substitutes the average optimized allocation from January 1982 to December 2022 for each respective regime, as determined by GRG nonlinear optimization. As with *RS*, *RSO* switches its allocation one month after the regime becomes present and is, therefore, an executable, real-world strategy.

Figure 4.6: Regime-Switching Outperformance



This figure plots the difference between the rolling one-year returns of the regime-switching (*RS*) portfolio and the benchmark portfolios (e.g., Δ*B6040* represents the difference between *RS* and the *B6040* portfolio). The preponderance of positive values from January 1982 to December 2022 demonstrates the outperformance of *RS*.

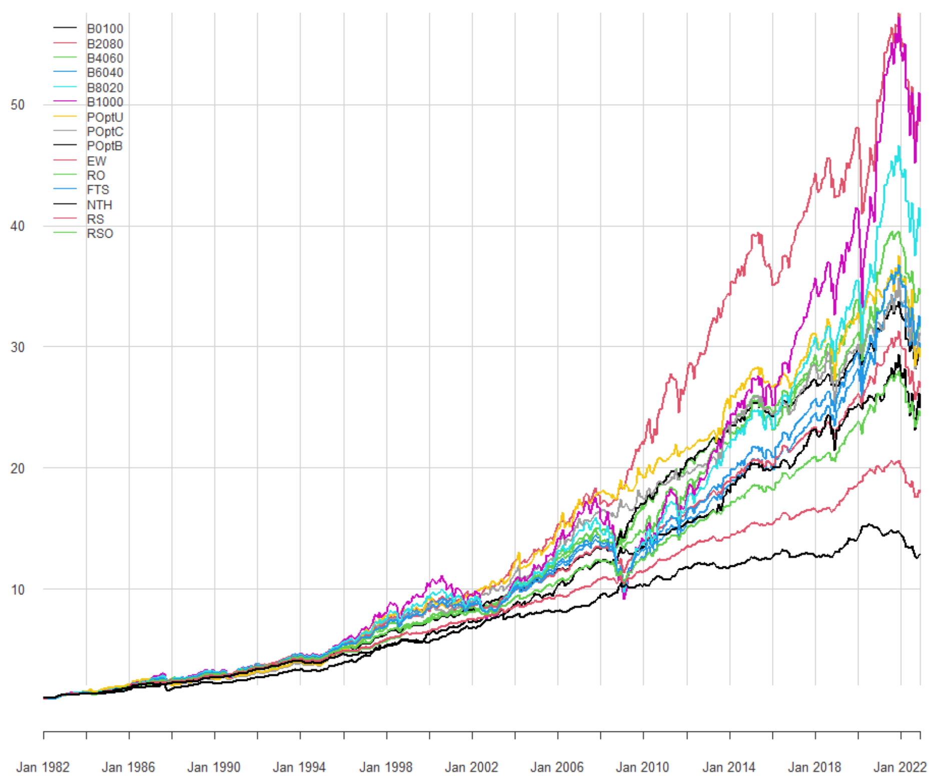
In reference to Table 4.11, the *RS* portfolio exhibits substantial risk-adjusted performance. With an annualized return of $R_a = 0.100$ and a cumulative return of $CR = 47.87$, the returns surpass even the most aggressive benchmark, *B1000*, which allocates 0% to US Treasuries. Remarkably, the portfolio achieves this feat with a standard deviation identical to the *B6040* at $SD_a = 0.082$, yielding a Sharpe ratio of $SR_a = 1.218$. Figure 4.6 illustrates the outperformance of the *RS* portfolio in comparison to the buy-and-hold benchmarks.

The *RSO* portfolio, while offering a respectable return profile, underperforms the *RS* portfolio on a total return basis. With an annualized return of $R_a = 0.088$ and a cumulative return of $CR = 30.53$, the returns closely resemble those of a *B6040* benchmark. However, the portfolio achieves a standard deviation of $SD_a = 0.070$ and a Sharpe ratio of $SR_a = 1.263$, outperforming the *B6040* on a risk-adjusted basis, thereby securing its position as a superior alternative to an all-weather benchmark.

Synthesizing the findings of our investigation, we offer Figure 4.7, which delineates the cumulative returns for our portfolios constructed to examine persistency, binary regimes, and regime-switching, as compared to buy-and-hold reference portfolios. Furthermore, we encapsulate our performance metrics for the aforementioned portfolios in Table 4.12 and in Figure 4.8, which plots the test portfolios against the efficient frontier of the benchmark portfolios for our study's full-time period.

We conclude that both the *RS* and *RSO* portfolios demonstrate enhanced risk-adjusted performance compared to the benchmark portfolios. We thus conclude that regime-switching models premised on an understanding of time-varying changes, macroeconomic drivers, and their resulting correlational regimes can improve tactical allocation models, leading to superior risk-adjusted returns for investors.

Figure 4.7: Cumulative Returns: Portfolio Testing & Benchmarks



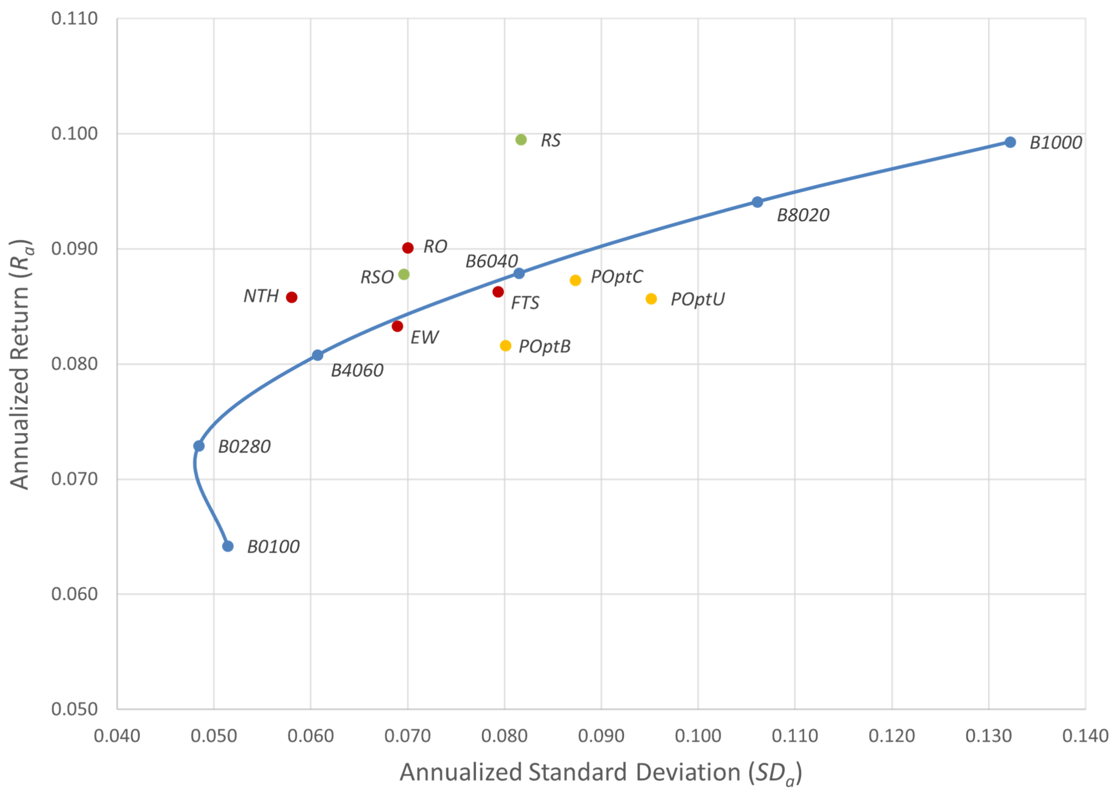
This figure illustrates the cumulative returns of all tested portfolios (persistency, regime, & regime-switching) as compared to benchmarks from January 1982 to December 2022.

Table 4.12: Performance Heat Map: Portfolio Testing & Benchmarks

	Return (cum.)	Return (ann.)	SD (mo.)	SD (ann.)	SR Mo. (Rf=0.3%)	SR Ann. (Rf=3.6%)	Sortino (MAR=2.9%)	IR (UST)	IR (60/40)	IR (S&P500)	MDD	VaR (95%)
Benchmark Portfolios												
B0100	11.837	0.064	0.015	0.051	0.158	1.249	0.951		-0.276	-0.316	0.184	-0.018
B0280	16.928	0.073	0.014	0.048	0.216	1.506	1.285	0.305	-0.261	-0.314	0.149	-0.015
B4060	23.215	0.081	0.018	0.061	0.211	1.333	1.152	0.290	-0.247	-0.318	0.164	-0.021
B6040	30.614	0.088	0.024	0.082	0.185	1.078	0.950	0.276		-0.327	0.277	-0.033
B8020	38.874	0.094	0.031	0.106	0.164	0.887	0.817	0.261	0.216	-0.339	0.383	-0.047
B1000	47.554	0.099	0.038	0.132	0.149	0.751	0.731	0.246	0.200	-0.319	0.475	-0.058
Persistency Portfolios												
POptU	28.096	0.086	0.027	0.095	0.156	0.901	0.801	0.233	-0.028	-0.220	0.243	-0.031
POptC	29.885	0.087	0.025	0.087	0.173	1.000	0.892	0.275	-0.009	-0.215	0.208	-0.029
POptB	23.900	0.082	0.023	0.080	0.167	1.019	0.822	0.230	-0.096	-0.266	0.244	-0.030
Regime & Regime Switching Portfolios												
EW	25.586	0.083	0.020	0.069	0.197	1.209	1.035	0.279	-0.197	-0.320	0.179	-0.025
RO	33.362	0.090	0.020	0.070	0.221	1.287	1.214	0.367	0.045	-0.214	0.149	-0.028
FTS	28.746	0.086	0.023	0.079	0.184	1.088	0.937	0.264	-0.179	-0.337	0.277	-0.033
NTH	28.179	0.086	0.017	0.058	0.242	1.478	1.394	0.428	-0.045	-0.240	0.164	-0.019
RS	47.871	0.100	0.024	0.082	0.223	1.218	1.181	0.415	0.261	-0.149	0.179	-0.033
RSO	30.530	0.088	0.020	0.070	0.213	1.263	1.114	0.332	-0.002	-0.252	0.186	-0.028

This table summarizes the performance and risk metrics for our tested portfolios - persistency, regime, and regime-switching - as compared to benchmark portfolios from January 1982 to December 2022. Cumulative and annualized returns are listed first. Abbreviations: SD = standard deviation (monthly & annualized), SR = Sharpe Ratio, Sortino = Sortino Ratio, IR = Information Ratio (UST, 60/40, S&P 500 benchmarks), MDD = Maximum Drawdown, VaR = Value-at-Risk. Green represents a more favorable outcome for the metric, and red represents a less favorable outcome.

Figure 4.8: Efficient Frontier: Portfolios vs. Benchmarks



This figure depicts the efficient frontier for the benchmark portfolios over the full period from January 1982 to December 2022. Persistency, regime, and regime-switching portfolios are plotted. *RS*, *RO*, *RSO*, and *NTH* portfolios fall above the efficient frontier. This illustrates that knowledge of regimes, time-varying correlations, and macro determinants of change can lead to better risk-adjusted returns through tactical asset allocation.

CHAPTER 5: DISCUSSION

In this study, we undertake a comprehensive examination of 492 month-end index and price data observations spanning from January 1982 to December 2022, encompassing six principal asset classes. US large-cap equities represented by the S&P 500 (SP), US small-cap equities represented by the Russell 2000 ($R2$), international equities where we use the MSCI EAFE (EF), bonds represented by the ICE BofA US Treasury index (UST), spot gold (G), and real estate represented by the Nareit Total Return index (RE). Our research seeks to ascertain whether a better understanding of time-varying correlational shifts, determinants, and regimes can contribute to superior portfolio construction through tactical asset allocation.

Our investigation of rolling one-year correlations for 15 asset class combinations establishes that correlations are indeed subject to temporal variation. Correlational analysis of asset dyads via rolling one-year periods and fitted linear regressions substantiates existing literature, revealing a transition from positive to negative correlation between the S&P 500 and US Treasuries in the late 1990s. Extending this analysis to encompass 14 other asset class dyads, we discern robust and moderately stable correlational relationships among stock correlations. Treasury correlations with stocks and REITs display volatility and have decreased over time with significant structural breaks, while correlations between REITs and stocks are moderate but also exhibit intermittent breaks, albeit with more asset class contingencies. Gold maintains its status as a non-correlated asset.

Correlations are predicated on moving averages, signifying that much of the variance in determining their current values is attributable to persistency. Our AR model corroborates this notion. However, it is important not to assume time-invariance of correlations, as structural breaks may transpire. Following Bai & Perron (1998), we implement structural break tests, which yield significant findings indicating breaks in 11 of the 15 correlational pairings under investigation. Notably, five breaks occur in the extensively examined stock-bond correlation ($SPUST$), while five additional breaks are identified in the S&P 500/Russell 2000 (*SPR2*), S&P 500/REIT ($SPRE$), and treasury/REIT ($USTRE$) correlations. Furthermore, seven other asset class pairings exhibit one or more breaks.

Subsequent visualization through wavelet coherence analysis elucidates dynamic and evolving relationships between the S&P 500 and treasuries, where coherence amplifies during periods of market distress. This association is more potent in shorter frequencies, and lead/lag phase relationships undergo frequent alterations. A high coherence relationship is evident between stock/stock dyads. Other treasury/stock comovements exhibit patterns akin to the SBC ($SPUST$), demonstrating significant shifts in the strength and direction of their relationships owing to frequency and phase dynamics. REITs exhibit greater stability in their interactions with other assets, albeit with lower coherence. Gold reasserts its reputation as a volatile, non-correlated asset, which is confirmed through lower coherence.

Combining correlational analysis, an AR model in conjunction with structural break tests, and visualization through wavelet coherence, we unveil substantial and noteworthy findings that attest to the time-varying nature of correlations. This revelation challenges the prevailing paradigm of efficiency and correlational stability that undergirds portfolio construction via buy-and-hold, strategic asset allocation.

Owing to the time-varying nature of correlations, we endeavor to ascertain the determinants of change. Through a rigorous econometric investigation employing a distributed lag model (DL) with a Newey-West estimator, vector autoregression (VAR), and Granger causality, we undertake a comprehensive analysis of four macro variables — namely, inflation (π), inflation expectations (π^e), leading indicators (*CEIC)*, and sentiment (*Sent*) — to determine their impact on correlational shifts.

Our findings reveal significant evidence that macroe variables exert influence on asset class correlational dyads. Our DL model demonstrates π affects nine correlations, with optimal lags ranging from two to three periods. VAR models confirm six uni-directional relationships only, where Granger-causality is also one-way. The highest R^2 values are observed for π as a determinant of US Treasury correlations. In contrast, the effects of π^e on seven correlations manifest more rapidly, typically within the first lag, and exhibit higher R^2 values in correlations where significance is shared with π. Although π^e exhibit fewer significant effects in VAR and Granger models, a notable bidirectional, bicausal relationship emerges in the treasury correlation to the S&P 500 and Russell 2000 (*SPR2*).

With regard to our measure of expected economic activity, we discern significant influences of *CEIC* as drivers of seven correlations. However, the R^2 values for *CEIC* are the lowest among all examined macroeconomic variables. VAR and Granger models exhibit no significance in several asset correlations that are deemed significant in our DL models. Interestingly, unlike π and π^e variables, *CEIC* has negligible impact on treasury correlations, with significance predominantly found in stock and REIT relationships. In comparison, *Sent* affects six correlations and mirrors the immediacy and impact of inflation expectations, high R^2 values relative to leading indicators. Our VAR and Granger models demonstrate that *Sent*'s influence is one-way, acting solely on correlations without being affected by them.

We add rigor to our analysis by pushing deeper into the causal and bicausal study of our macro variables and correlations. Through the forward expanding, rolling, and recursive evolving windows of time-varying Granger causality, we find significant effects in 41 additional relationships that remained undetected in using a standard Granger methodology. Our analysis highlights substantial relationships between inflation (π) and asset correlations, with various unidirectional and bidirectional associations involving REIT correlations, π, stock/stock correlations, and gold. Interestingly, no causal relationship was found in the stock-bond correlation ($SPUST$) when tested against π. The connections with expected inflation (π^e) were less dynamic, yet significant in certain cases. Our findings also demonstrate that asset correlations tend to Granger-cause leading indicators more frequently than the opposite. Furthermore, we observed unique and dynamic relationships between sentiment and asset class dyads, emphasizing the interdependencies between psychological variables and correlations.

Understanding the evolution of correlations over time is crucial for informed portfolio decision-making. Following Jacobsen & Scheiber (2022), our study defines four binary correlational regimes: (1) Everyone-Wins (EW), (2) Risk-On (RO), (3) Flight-to-Safety (FTS), and (4) Nowhere-to-Hide (NTH), where we use a logit/probit model to examine the relationship between these binary regimes and our macro variables. Our findings indicate that π and π^e significantly shape the EW, RO, and FTS regimes, whereas their influence on the NTH regime is minimal. $CEIC$ also plays a role in accounting for the variation observed in all regimes, with the most pronounced effect found in the FTS regime. $Sent$ exerts a more selective influence, primarily affecting the EW and FTS regimes and acting earlier than other fundamental variables. As with our study of macros on asset correlations, psychological variables operate more swiftly and with a greater degree of explanation in variance compared to fundamental variables. The robustness of these findings, as corroborated by the probit model analysis, emphasizes the importance of considering these macroeconomic factors when evaluating and predicting correlational regimes in financial markets.

Our study addresses another gap in the literature left by a multitude of empirical studies that assert their research bears implications for portfolio construction and investors. Yet, they provide no pragmatic solutions to address these implications. To bridge this gap, we pivot to the practical realm, where we develop benchmark portfolios and representative model portfolios tailored to scrutinize the constructs of time-variance, macroeconomic impacts, and correlational regimes through tactical allocation. We construct six benchmark asset allocation models with varying risk levels as a basis for comparison and represent a pragmatic buy-and-hold strategic asset allocation strategy. The all-weather 60/40 (*B6040*) yields an annualized return of $R_a = 8.8\%$, a cummulative return of $CR = 30.614$ and an annualized Sharpe of $SR_a = 1.078$. Our heat map depicting performance metrics for all asset classes summarizes our results (Tables 4.11 and 4.12).

We devise optimal, albeit arguably unattainable, portfolios by maximizing the Sharpe ratio for each of our 492 periods utilizing a GRG nonlinear optimizer. We create three optimal models, including optimized unconstrained (*OptU*), optimized semi-constrained (*OptC*), and optimized benchmark-constrained (*OptB*), each imposing varying degrees of restrictions on asset allocations. These resulting optimal portfolios exhibit considerable outperformance in terms of both return and risk-adjusted return. The *OptU* portfolio yields an average annualized return of $R_a = 15.5\%$, a $CR = 362.696$, and an annualized Sharpe of $SR_a = 1.900$, compared to the S&P 500 at $R_a = 11.5\%$, a $CR = 85.205$, and $SR_a = 0.752$.

Persistency portfolios (*POptU*, *POptC*, *POptB*) adhere to the optimal portfolio asset weightings, with a one-month lag. They test "persistency" under the premise that if correlations hold, so should performance. While our results reveal that these portfolios offer lower standard deviations (e.g., *POptU*'s $SD_a = 9.5\%$), they underperform in terms of returns and Sharpe ($R_a = 8.6\%$, $CR = 28.096$, $SR_a = 0.901$).

Consequently, the pursuit of returns predicated on the assumption of correlational temporal invariance does not yield additional value.

The persistency portfolios rely exclusively on the time-based stability of correlations. On the other hand, the regime-based portfolios (*EW*, *RO*, *FTS*, and *NTH*) incorporate macroeconomic determinants and market information. The *RO* regime, which uses an 80/20 (*B8020*) upside, 40/60 downside allocation, performs well as indicated by its moniker ($R_a = 9.0\%$, $CR = 33.362$, $SR_a = 1.287$). An *NTH* model offers a conservative profile at, $R_a = 8.6\%$, $CR = 28.179$, and $SR_a = 1.478$. However, recombining all regimes into their natural temporal order allows us to construct regime-switching (*RS*) and optimized regime-switching portfolios (*RSO*) that result in $R_a = 10.0\%$, $CR = 47.871$, $SR_a = 1.218$ for *RS*, and $R_a = 8.8\%$, $CR = 30.530$, $SR_a = 1.263$ for *RSO*.

The regime and regime-switching portfolios demonstrate adaptability to correlational change and market conditions, thereby exploiting opportunities via tactical allocation. This well-informed methodology represents a practical application of our empirical study and, ultimately, the culmination of our research endeavor. Correlations serve as a fundamental component in the process of portfolio construction. By eschewing the prevailing orthodoxy of correlational stability, we can embrace time-varying changes. Through comprehension of determinants driving these changes, we arrive at correlational regimes that also incorporate market information. Informed through knowledge of the correlational temporal change, drivers of change, and regimes, investors can indeed achieve superior risk-adjusted returns.

5.0.1. Implications, Limitations, & Future Directions

We have expanded upon the existing body of literature by illustrating that the notion of time-varying change, macro determinants, and correlation regimes offer value in finding a deeper understanding of asset class correlations, as it leads to better portfolio construction. Moreover, our study discovers that the macroeconomic factors of inflation, inflation expectations, leading indicators, and sentiment, which act as determinants of change for the stock-bond correlation, similarly affect changes in 14 additional asset class pairings. Despite this study's broad approach, it cannot fully explain all of these relationships; and where it achieves breadth, it is limited in depth. We suggest that many of these asset class correlational relationships are worthy of further, more granular study.

There is an extensive body of research spanning multiple decades focusing solely on stock-bond correlations. Despite its multifaceted approach, our study is incapable of providing a comprehensive explanation for all extant relationships. The scope of this investigation could be broadened by delving further into macro determinants that apply to all correlational regimes. Simultaneously, a more profound and meticulous examination of under-researched, under-utilized asset classes, as well as the implementation of additional statistical methodologies, would add rigor to this research.

The preliminary findings about correlational regimes are promising. In studying the macro drivers of regimes, we not only corroborate the established literature but also propose novel avenues for the application and understanding of these regimes, thereby facilitating more optimal portfolio construction. Future research should encompass a more extensive evaluation of additional factors that influence these regimes. Furthermore, a more nuanced comprehension of their functioning within varying rolling windows is recommended for subsequent studies. The present analysis confines the regimes to conventional positive/negative correlations in conjunction with ascending/descending markets. Nonetheless, regimes could potentially extend beyond these parameters to encompass economic factors, monetary and fiscal policies, and political environments.

Our inquiry contributes to practical applications by demonstrating that the comprehension of correlational temporal fluctuations, macro drivers of change, and correlational regimes need not be confined to empirical research and academia. Rather, we provide evidence of their real-world relevance to tactical asset allocation and portfolio construction. However, our study is constrained by the trade-off between internal and external validity. It would align better with the extant literature that uses three, five, and ten-year rolling correlations. However, our ADF testing indicated the presence of a unit root in many three and five-year correlations, exposing our study to non-stationarity and spurious regressions. Concerning portfolio testing, we intentionally select one-year correlations to manifest more pronounced effects that better inform the implementation of tactical allocation shifts, typically executed over shorter temporal horizons.

We are restricted to monthly data and conventional asset classes, encompassing asset classes that exhibit suboptimal performance when assessed on a risk-adjusted basis (e.g., gold). This constraint bears particular significance for the persistency portfolios, which could potentially be augmented by embracing more granular time intervals, such as weekly or daily, and incorporating a broader spectrum of asset classes (e.g., commodities, emerging markets, high-yield debt, international debt, private equity, etc.). Nevertheless, this would necessitate a more rigorous approach to optimization methods. As such, we propose this as an additional avenue for future investigation.

CHAPTER 6: CONCLUSION

We offer a comprehensive examination of 492 month-end indices encompassing six principal asset classes spanning from January 1982 to December 2022, where we make significant strides in understanding the time-varying nature of correlations and their implications for portfolio construction. We extend the discourse beyond the traditional stock-bond correlation to encompass 14 other asset class relationships. Our research demonstrates that correlations are subject to temporal variation, and macroeconomic variables exert influence on asset class correlational dyads. By utilizing a range of advanced methodologies and incorporating macroeconomic variables, the study sheds light on the determinants of correlational shifts and their effects on various market regimes.

We employ time-series econometric methodologies such as autoregressive, distributed lag, and vector autoregression models, in addition to more rigorous structural break tests, wavelet coherence, and time-varying Granger causality. We challenge the prevailing paradigm of efficiency and correlational stability that is the mainstay of portfolio construction via buy-and-hold, strategic asset allocation. In light of the time-varying nature of correlations, we offer a deterministic framework to determine the impact of macroeconomic variables on correlational shifts. Our findings reveal that macro-level determinants, such as inflation, inflation expectations, leading indicators, and sentiment, which impact the alteration in the stock-bond correlation, also wield influence on other asset class dyads. However, the magnitude of these effects varies depending on the particular correlation under examination.

We provide pragmatic solutions by constructing benchmark portfolios and model portfolios tailored to exploit an understanding of correlational time-variance, drivers of change, and regimes through tactical allocation. Resultant regime-switching portfolios demonstrate adaptability to fluctuating market conditions, thereby capitalizing on opportunities spanning various asset classes.

By eschewing the prevailing orthodoxy of correlational stability and embracing time-varying change, macroeconomic determinants, and correlational regimes, investors can attain superior risk-adjusted returns through the implementation of tactical asset allocation strategies. This study contributes to the extant literature on time-varying correlations and drivers of change while offering practical implications for portfolio construction and risk management in the realm of finance.

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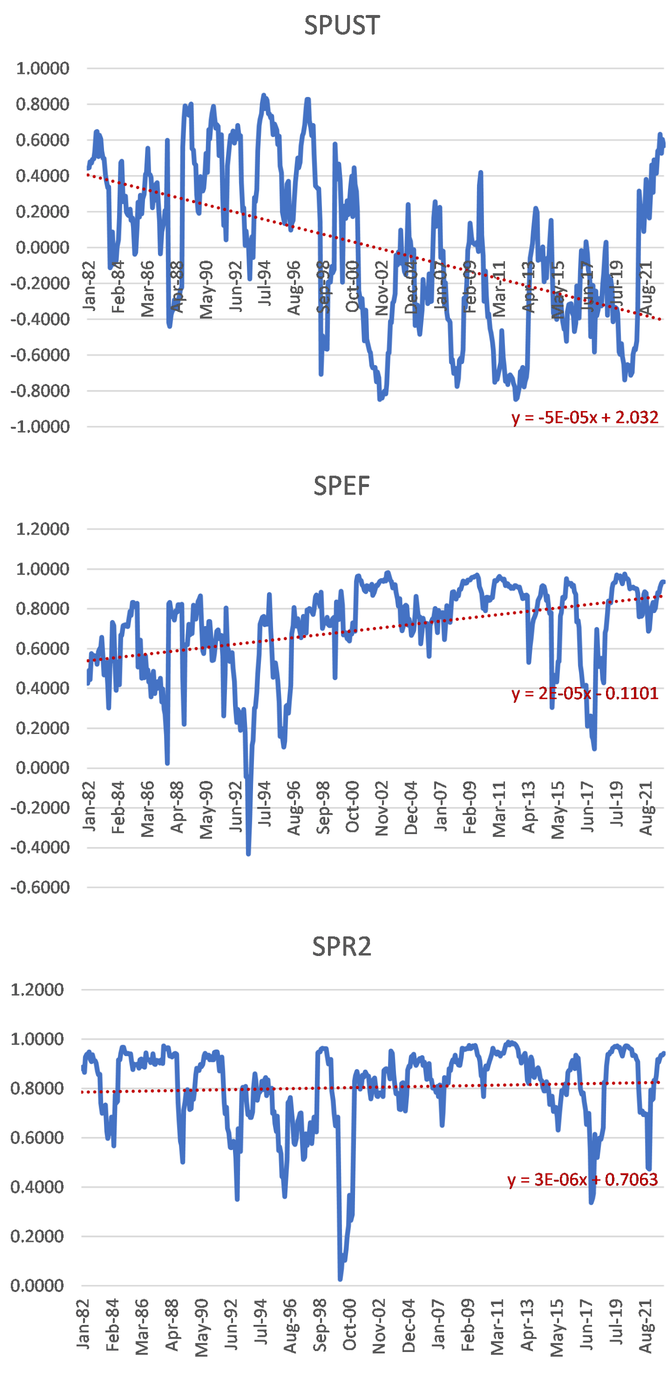
APPENDIX A

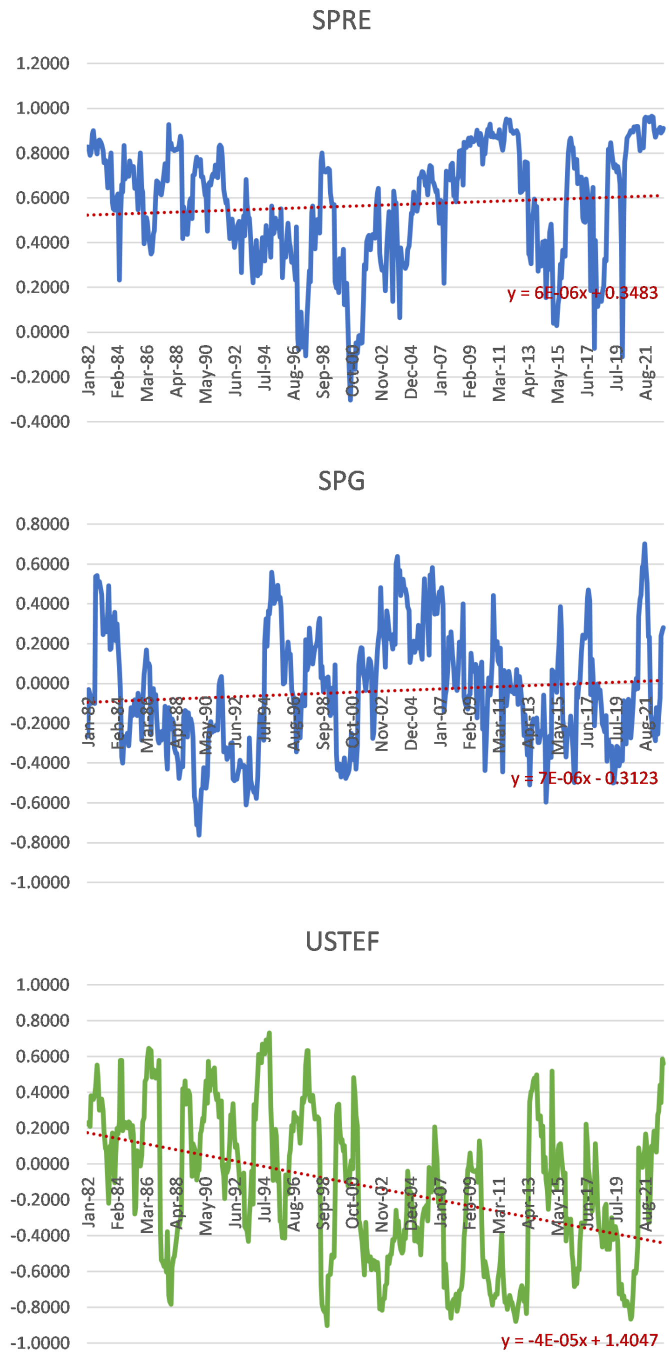
CORRELATIONS & WAVELET COHERENCE

Figure A.1: Asset Class One-Year Correlations (1-3)



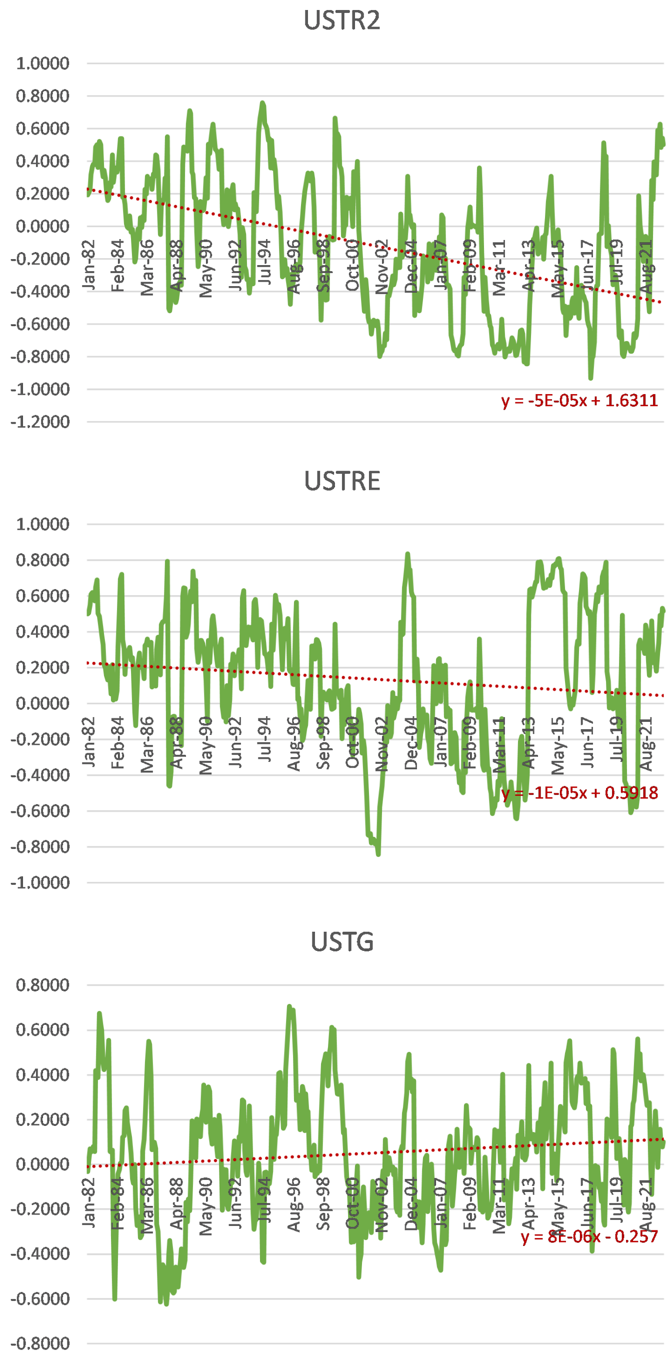
This figure demonstrates 1 through 3 rolling asset class correlation combinations from January 1982 to December 2022. *SPUST* = S&P 500/US Treasuries, *SPEF* = S&P 500/MSCI EAFE, *SPR2* = S&P 500/Russell 2000

Figure A.2: Asset Class One-Year Correlations (4-6)



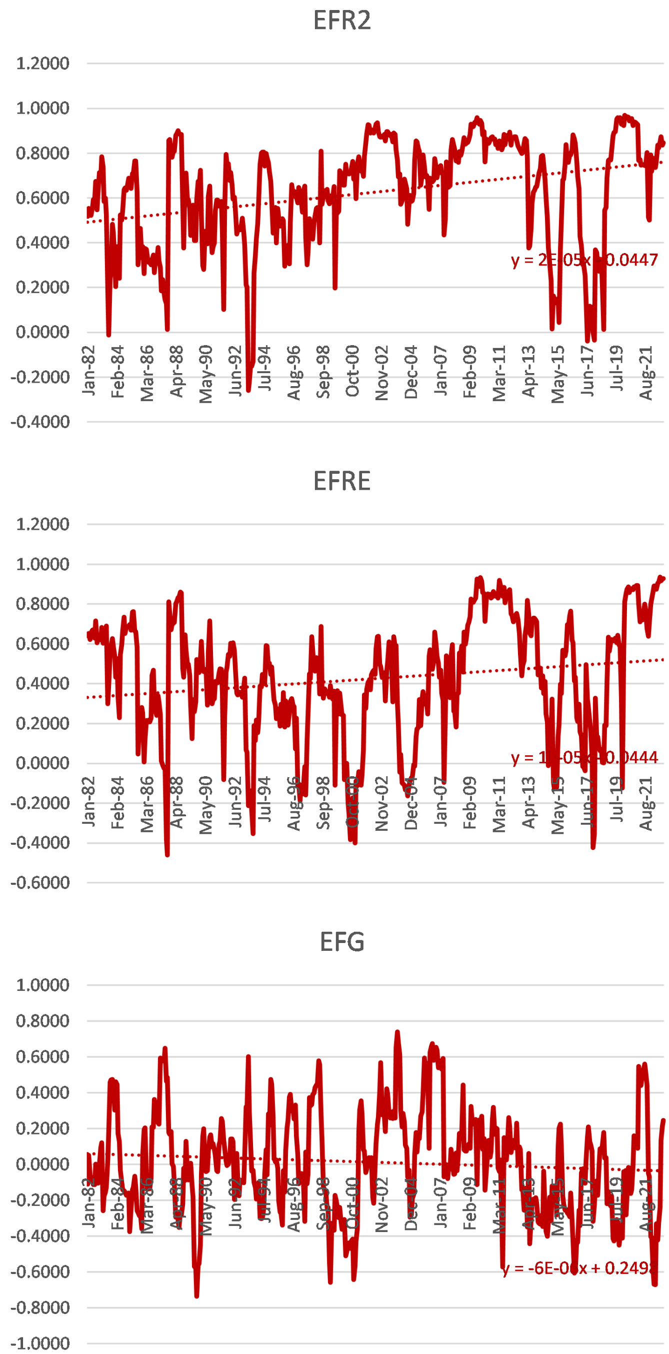
This figure demonstrates 4 through 6 rolling asset class correlation combinations from January 1982 to December 2022. *SPRE* = S&P 500/REITs, *SPG* = S&P 500/Gold, *USTEF* = US Treasuries/MSCI EAFE

Figure A.3: Asset Class One-Year Correlations (7-9)



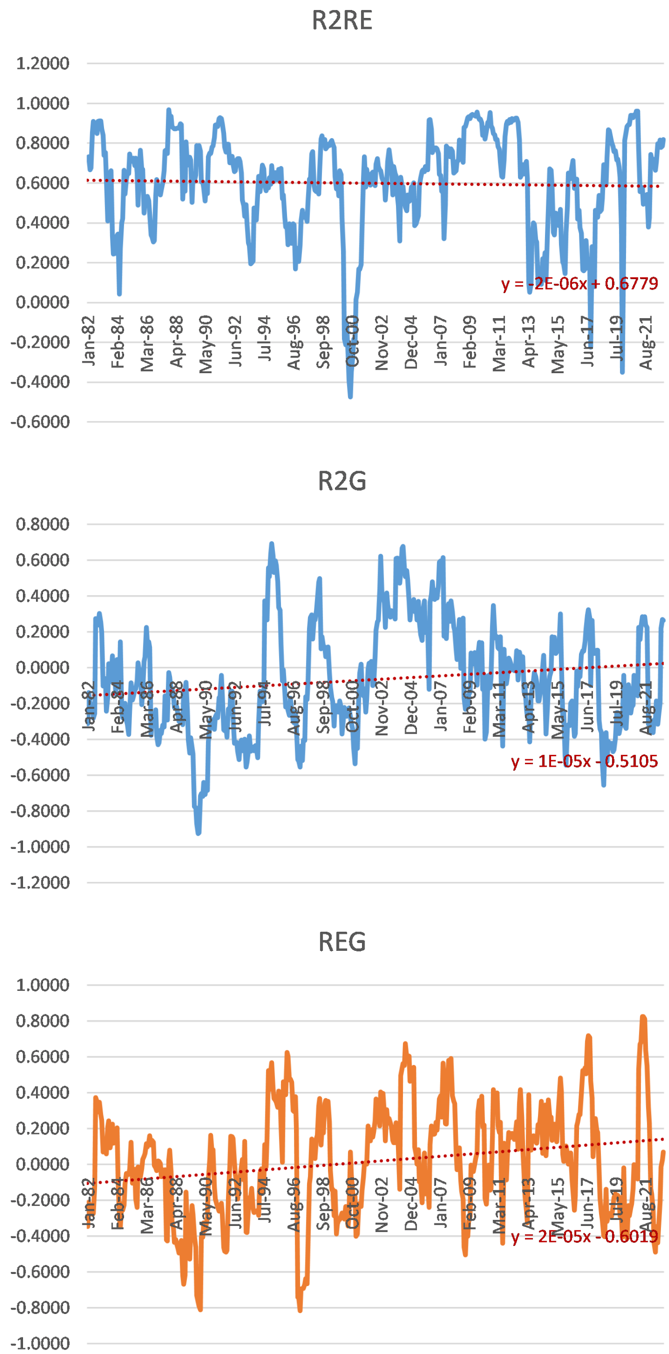
This figure demonstrates 7 through 9 rolling asset class correlation combinations from January 1982 to December 2022. *USTR2* = US Treasuries/Russell 2000, *USTRE* = US Treasuries/REITs, *USTG* = US Treasuries/Gold

Figure A.4: Asset Class One-Year Correlations (10-12)



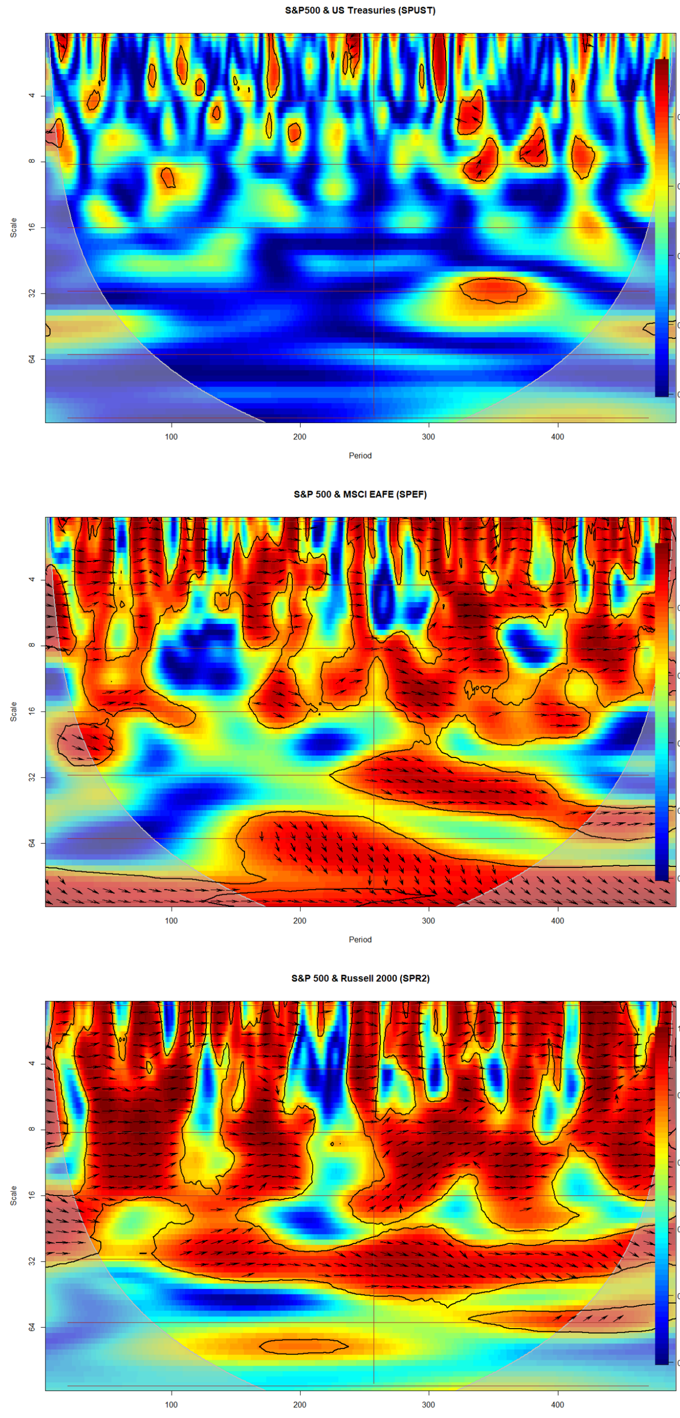
This figure demonstrates 10 through 12 rolling asset class correlation combinations from January 1982 to December 2022. *EFR2* = MSCI EAFE/Russell 2000, *EFRE* = MSCI EAFE/REITs, *USTG* = MSCI EAFE/Gold

Figure A.5: Asset Class One-Year Correlations (13-15)



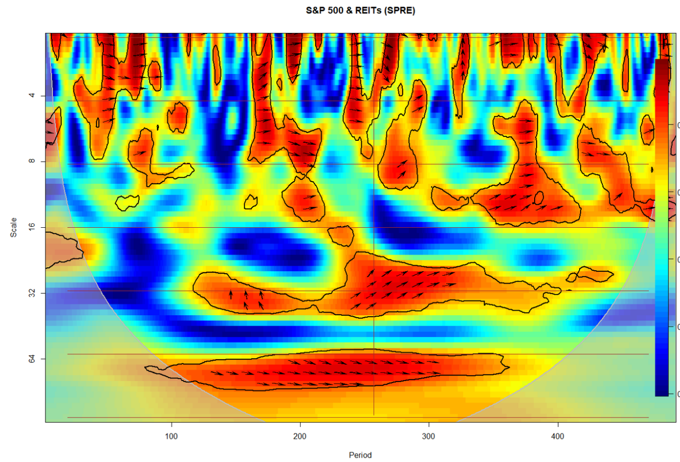
This figure demonstrates 10 through 12 rolling asset class correlation combinations from January 1982 to December 2022. *R2RE* = Russell 2000/REITs, *R2G* = Russell 2000/Gold, *REG* = REITs/Gold

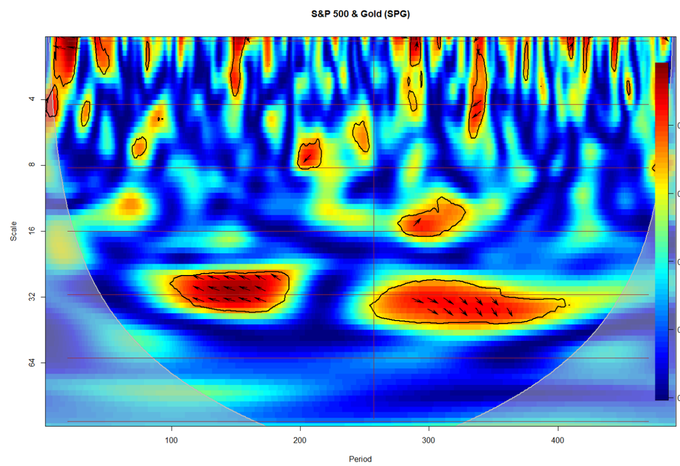
Figure A.6: Wavelet Coherence Asset Class Dyads (1-3)

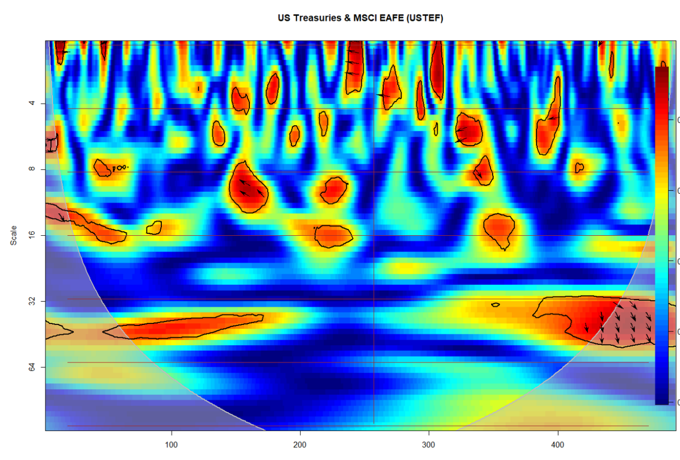


This figure demonstrates wavelet coherence at 95% for asset dyads 1-3 from Jan-82 to Dec-22 (period 0 to 500 months). Right axis shows coherence (0.0 to 1.0), where red represents high comovement, and blue represents low comovement. Left axis shows wavelet frequency in months. Right arrows depict in-phase oscillation; left arrows depict anti-phase oscillation.

Figure A.7: Wavelet Coherence Asset Class Dyads (4-6)

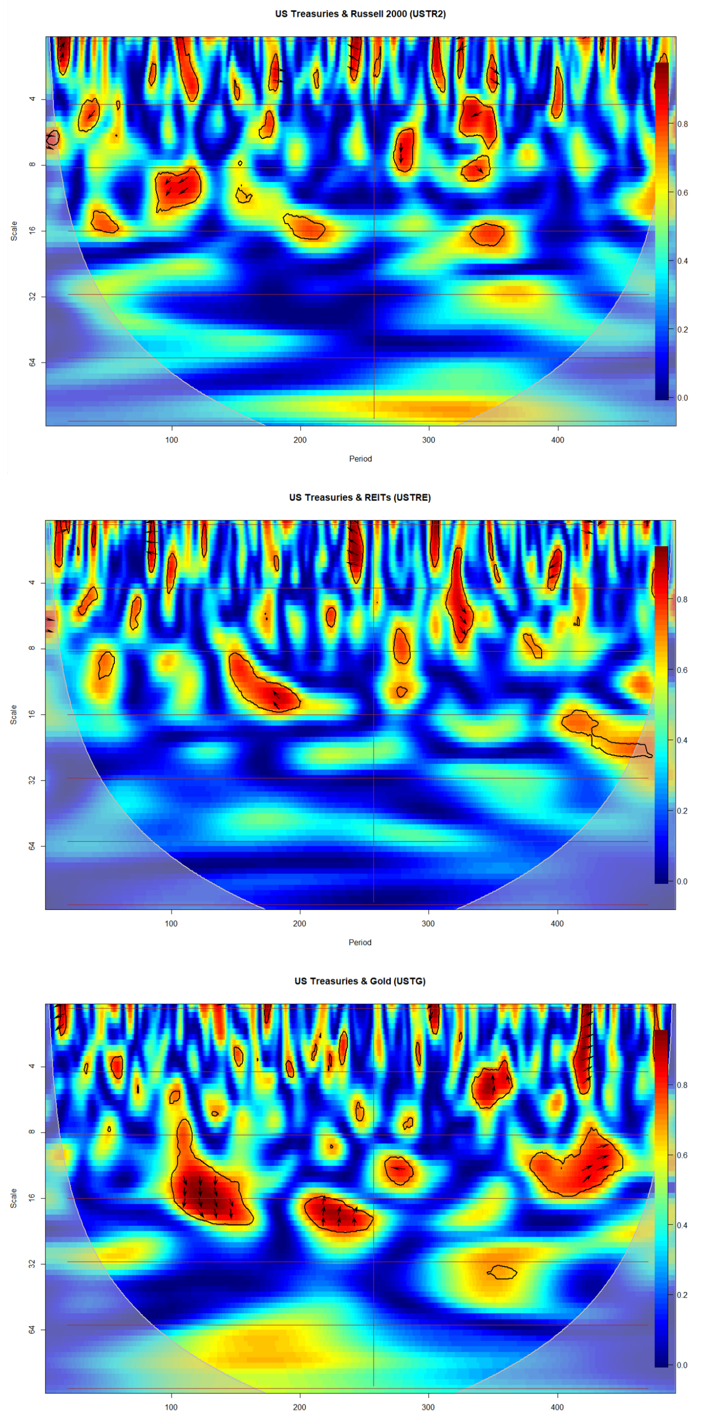






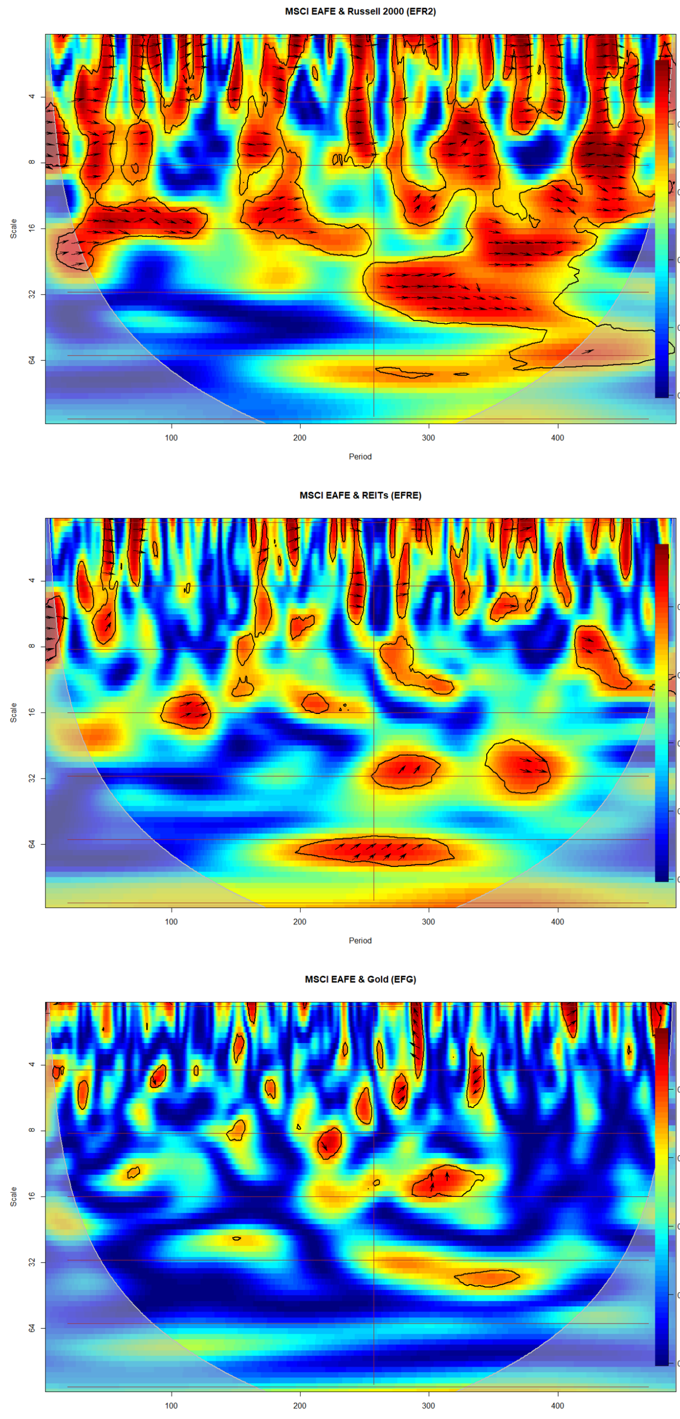
This figure demonstrates wavelet coherence at 95% for asset dyads 4-6 from Jan-82 to Dec-22 (period 0 to 500 months). Right axis shows coherence (0.0 to 1.0), where red represents high comovement, and blue represents low comovement. Left axis shows wavelet frequency in months. Right arrows depict in-phase oscillation; left arrows depict anti-phase oscillation.

Figure A.8: Wavelet Coherence Asset Class Dyads (7-9)



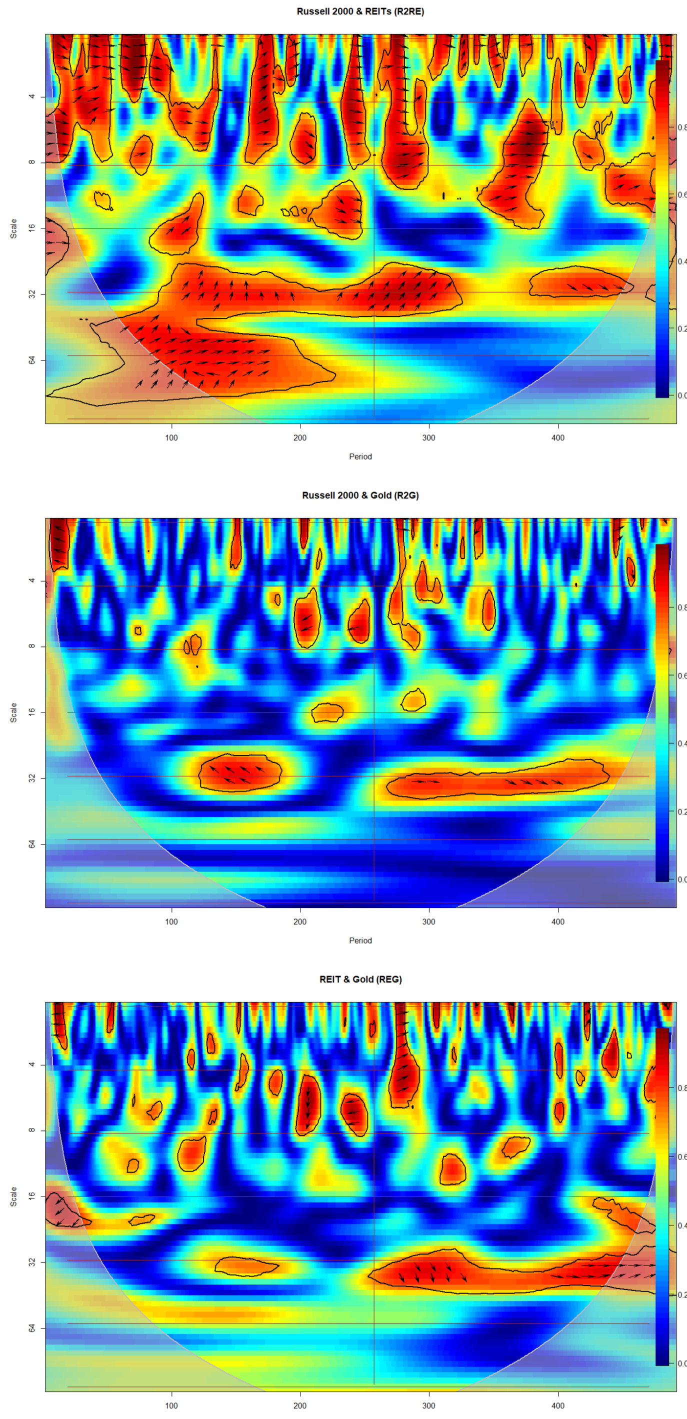
This figure demonstrates wavelet coherence at 95% for asset dyads 7-9 from Jan-82 to Dec-22 (period 0 to 500 months). Right axis shows coherence (0.0 to 1.0), where red represents high comovement, and blue represents low comovement. Left axis shows wavelet frequency in months. Right arrows depict in-phase oscillation; left arrows depict anti-phase oscillation.

Figure A.9: Wavelet Coherence Asset Class Dyads (10-12)



This figure demonstrates wavelet coherence at 95% for asset dyads 10-12 from Jan-82 to Dec-22 (period 0 to 500 months). Right axis shows coherence (0.0 to 1.0), where red represents high comovement, and blue represents low comovement. Left axis shows wavelet frequency in months. Right arrows depict in-phase oscillation; left arrows depict anti-phase oscillation.

Figure A.10: Wavelet Coherence Asset Class Dyads (13-15)



This figure demonstrates wavelet coherence at 95% for asset dyads 13-15 from Jan-82 to Dec-22 (period 0 to 500 months). Right axis shows coherence (0.0 to 1.0), where red represents high comovement, and blue represents low comovement. Left axis shows wavelet frequency in months. Right arrows depict in-phase oscillation; left arrows depict anti-phase oscillation.