How Hedge Funds Navigate Uncertainty: Performance and Risk Through the Lens of the Fung–Hsieh Model and Beta Replication

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Abstract

This thesis examines hedge fund performance and risk through the extended Fung–Hsieh eight-factor model and a beta replication framework. Using monthly data from eleven Credit Suisse Hedge Fund Indexes from 2004 to 2024, it analyzes how hedge fund strategies adapt to uncertainty across periods such as the Global Financial Crisis and the COVID-19 pandemic.

Results show that credit spread and interest rate risks dominate most strategies, with higher model explanatory power (R^2) during market downturns, reflecting stronger systematic influences in stressed environments. The analysis also reveals increasing institutionalization within the hedge fund industry, with performance increasingly driven by broad market factors rather than idiosyncratic manager skill.

By combining factor modeling with replication analysis, the study provides a clearer view of how hedge funds generate and sustain returns across changing market conditions.

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Key words: hedge fund, linear regression, Beta Replication, Fung–Hsieh Model, Global Macro, Managed Futures, Event Driven, Equity Market Neutral, global financial crisis, Covid-19

Sumário

Esta dissertação analisa o desempenho e o risco de hedge funds através do modelo alargado de oito fatores de Fung–Hsieh e de uma análise de replicação de betas. Com base em dados mensais de onze índices do Credit Suisse, no período de 2004 a 2024, o estudo investiga de que forma as diferentes estratégias de hedge funds se ajustam a contextos de incerteza, incluindo a crise financeira (GFC) e a pandemia de COVID-19.

Os resultados evidenciam que os riscos associados ao credit spread e às taxas de juro são predominantes na maioria das estratégias, verificando-se um maior poder explicativo do modelo (R^2) durante períodos de contração dos mercados, o que reflete uma influência sistemática mais forte em ambientes de stress. A análise revela igualmente um grau crescente de institucionalização na indústria de hedge funds, com o desempenho a ser cada vez mais explicado por fatores amplos de mercado, em detrimento da capacidade idiossincrática dos gestores.

Ao combinar modelização por fatores com uma análise de replicação, o estudo oferece uma visão mais clara sobre a forma como os hedge funds geram e sustentam rentabilidades em condições de mercado em constante mudança.

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Table of Abbreviations

ARP - Alternative Risk Premia

BRICS - Brazil, Russia, India, China, and South Africa (5 major Emerging Markets)

CAPM - Capital Asset Pricing Model

CFA - Chartered Financial Analyst

CTA - Commodity Trading Advisors

EM - Emerging Markets

ED - Event-Driven

FX - Foreign Exchange

GDP - Gross Domestic Product

GFC - Global Financial Crisis

HFR - Hedge Fund Research

HFRFOF - Hedge Fund Research Fund of Funds

QE - Quantitative Easing

SEC - Securities and Exchange Commission

SMB - Small Minus Big

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1.Introduction

> "I believe in radical truth and radical transparency. I think the biggest problem with the financial industry is that it has enormous power but very little transparency or quality control." — Ray Dalio (2017)

Hedge funds occupy a central yet opaque position within global financial markets. As Ray Dalio notes, the industry exerts significant influence, but its return-generation and risk-management processes often remain concealed. This combination of impact and limited transparency makes hedge funds both analytically compelling and, at times, controversial.

Despite their scale and market presence, much is still unclear about the underlying drivers of hedge fund performance. Existing debates in finance, such as those on market efficiency, active management, and factor exposures, highlight the need to distinguish true manager skill from returns attributable to systematic risks. Understanding these dynamics is essential not only for investors and regulators but also for assessing the broader role hedge funds play in market stability and price formation. Research that sheds light on these mechanisms therefore contributes meaningfully to both academic literature and industry practice.

This thesis channels that curiosity into a structured analysis by using the extended Fung–Hsieh eight-factor model. It examines how hedge fund strategy indexes behave across different market environments, from stable periods to crises such as the Global Financial Crisis and COVID-19. By comparing performance and factor exposures over time, the study seeks to determine whether hedge fund returns reflect manager skill or primarily common risk factors.

Despite their influence, hedge funds remain difficult to evaluate due to limited disclosure and complex structures. The challenge lies in distinguishing true alpha from returns explained by systematic risks, especially during stress periods when diverse strategies often reveal shared vulnerabilities.

Since Professors William Fung and David Hsieh (Fung and Hsieh, 1999) first introduced their factor model in the late 1990s, relatively few studies have re-examined considering the profound market changes that followed. This gap underscores the need for updated analysis using more recent data and broader strategy coverage, which this thesis aims to address.

The study investigates how much of hedge fund performance can be explained by systematic risk factors versus unique alpha generation. Using the extended Fung–Hsieh model, it analyzes eleven Credit Suisse Hedge Fund Indexes across three market phases, 2004–2011, 2012–2019, and 2020–2024, to assess how factor exposures and explanatory power evolve through different financial cycles, particularly during crises.

The research is guided by three questions:

- To what extent can hedge fund returns be explained by systematic factors?
- How do factor exposures vary across market conditions and crises?
- Which strategies show greater resilience or sensitivity during stress periods?

Beyond standard regression analysis, the thesis employs a beta-replication approach to translate factor loadings into normalized exposure proportions. This provides a clearer view of each strategy's composition by expressing factor sensitivities as long or short percentage exposures.

By combining statistical and economic perspectives, the study examines how hedge fund strategies adjust, how their market sensitivities evolve, and what truly drives returns under changing conditions. Its goal is not to solve the mystery of hedge funds but to clarify it, bringing greater transparency to an area of finance that often resists it and helping investors, researchers, and students better understand where genuine skill ends and systematic risk begins.

The study contributes to the literature by updating empirical evidence using recent periods of heightened uncertainty, thereby allowing established performance-attribution models to be reassessed in a modern context. It further extends existing frameworks by examining how hedge fund risk exposures evolve across different market regimes, offering insights into the adaptability, persistence, and true drivers of returns.

The dissertation is structured as follows. In the next section, I present the literature review, outlining the academic foundations related to hedge fund performance, dynamic factor exposures, and the influence of macroeconomic conditions. The following section provides an overview of hedge fund strategies, describing equity-related, event-driven, relative-value, and opportunistic approaches, along with the composite benchmark used in later analysis. Subsequently, the dissertation introduces the extended eight-factor Fung–Hsieh model, explaining its theoretical underpinnings and relevance for capturing hedge fund risk dynamics. The empirical analysis then follows, covering the full sample from 2004 to 2024 and the three subperiods, each including both regression analysis and beta-replication to evaluate how factor sensitivities and return drivers evolve over time. The dissertation concludes by summarizing the key findings, discussing their implications, and outlining directions for future research.

2.Literature Review

Alternative investments have become a central component of modern portfolios, valued for their potential to enhance returns and diversify risk beyond traditional holdings such as stocks and bonds. They include real assets, private equity, venture capital, and hedge funds, the latter standing out for their flexibility, sophistication, and influence on global markets. Growing investor interest in alternative strategies reflects both a desire for return streams with lower correlations to traditional assets (CFA Institute, 2025), yet they typically involve longer investment horizons, reduced liquidity, and less efficient markets than traditional assets. As the CFA Institute notes, these assets frequently require specialized valuation expertise, exhibit structural and contractual features, such as large capital commitments, extended life cycles, and incentive-based fee arrangements, and often display return patterns that differ markedly from public equity and debt markets. Consequently, alternative investments are generally allocated to the long-term segment of institutional portfolios, particularly among sophisticated investors such as pension funds, sovereign wealth funds, and endowments, who are best positioned to accommodate their illiquidity and performance-evaluation complexities. Broader analyses of alternative-asset roles (Cumming, Haß, & Schweizer, 2013) similarly highlight how alternatives contribute to strategic allocation by offering differentiated risk premia, inflation protection, and diversification benefits that traditional asset classes often fail to provide.

Alternative assets differ from traditional investments in several respects, particularly in liquidity, accessibility, and regulation. They are generally less liquid; for example, selling a private equity stake requires direct negotiation, unlike the ease of trading public equities. Hedge funds, too, often impose lock-up periods, redemption notice requirements, and gates to manage liquidity risk. These features alter portfolio construction by introducing liquidity horizons that require careful alignment with investor liabilities. Moreover, many alternatives are restricted to accredited or high-net-worth investors due to their complexity and risk. According to the U.S. Securities and Exchange Commission (SEC, 2023), an accredited investor must have a net worth exceeding $1 million (excluding primary residence) or a yearly income above $200,000 individually ($300,000 jointly). Though around 18.5% of U.S. households met these thresholds in 2022, inflation-adjusted figures suggest the true share is closer to 6.5%, underscoring that alternative investments remain largely confined to affluent investors. This segmentation reflects long-standing concerns about investor protection, but also macroprudential considerations. As Clancy, Dixon, and Kumar (2012) note, hedge funds' use of similar strategies can result in crowded trades, where many funds hold correlated or overlapping exposures. When market conditions deteriorate, the simultaneous unwinding of these positions can intensify market stress and heighten the risk of destabilizing spillovers across the financial system.

Hedge funds, as one of the most prominent categories within alternative assets, occupy a distinctive position in global financial markets. They are privately organized investment vehicles that seek absolute returns rather than performance relative to a benchmark, enabling them to target opportunities missed by long-only or benchmark-constrained investors. As Stulz (2007) notes, hedge funds are characterized by a high degree of flexibility: they can use leverage, derivatives, short selling, and arbitrage strategies unavailable to traditional investment vehicles. This structural openness allows hedge funds to exploit market inefficiencies across both liquid and illiquid assets, making them particularly attractive for investors seeking uncorrelated sources of return. Yet, this flexibility also introduces governance and agency challenges. Most hedge funds operate as limited partnerships, with managers acting as general partners who invest alongside limited partners. While certain contractual features, such as incentive fees, co-investment, and high-water marks, can help align manager and investor interests (Agarwal, Daniel & Naik, 2009), poorly performing funds often increase return volatility in an attempt to recover losses, particularly under high-water-mark compensation, thereby heightening systemic risk (Andrews & Gadgil, 2024).

Rabener (2022) challenges the common narrative that hedge funds and other alternatives reliably deliver uncorrelated returns, arguing that their diversification benefits can be overstated and are far more sensitive to market regimes than many institutional investors assume. His analysis shows that correlations across alternative strategies often rise during periods of stress, complicating their role as unconditional diversifiers. Kerzérho (2025) notes that hedge funds no longer deliver the exceptional alpha characteristic of the industry's early decades, the broader literature indicates that genuine skill is scarce, and that past outperformers rarely sustain their edge over time. For investors, this underscores the importance of looking beyond listed funds and avoiding indiscriminate allocations: some hedge fund strategies offer meaningful diversification, but others introduce financing, liquidity, and tail-risk exposures that traditional metrics such as volatility and correlation fail to fully capture.

Wilson (2023) proposes a new measure of hedge-fund manager skill(Edge) designed to predict out-of-sample (OOS) performance by distinguishing genuine alpha from returns generated through hidden exposures to downside risks. He argues that many hedge funds produce attractive in-sample Sharpe ratios by implicitly selling volatility or loading on latent crash-risk factors, which leads to poor OOS outcomes during market turbulence. By incorporating both alpha and benchmark beta, the Edge measure identifies managers whose returns are not driven by these hidden risks. Using a Short VIX benchmark, Wilson finds that only about 3% of hedge funds deliver persistent OOS alpha, with nearly half belonging to global macro strategies, consistent with evidence that macro-oriented and trend-following funds benefit during stress periods.

Other Practitioner studies such as Amundi (2023) and Morningstar (2023) further show that hedge funds and fund of funds continue to occupy an intermediate position among alternatives, lower expected returns than private equity but superior risk-adjusted diversification benefits.

A defining feature of hedge funds is their strategic diversity. Rather than following a single investment philosophy, hedge funds deploy strategies ranging from relative value and market-neutral approaches to directional macro, event-driven, and trend-following tactics. This diversity allows hedge funds to intermediate different forms of risk, credit, volatility, liquidity, and macroeconomic exposures, across shifting market environments. It also complicates performance attribution, as strategy heterogeneity results in return distributions that vary in skewness, kurtosis, and tail dependence. As Avci and Benmahi (2022) note, hedge funds contribute meaningfully to market liquidity and economic resilience, but they also face significant challenges related to performance dispersion, governance, and regulatory complexity. Further research deepening this understanding, such as Hitaj and Noori (2023), shows that hedge-fund style returns are strongly conditioned by macroeconomic regimes, with different strategies outperforming or lagging depending on levels of volatility, growth, and market uncertainty. Complementary evidence from Metzger and Shenai (2019) demonstrates that hedge-fund strategies exhibit markedly different performance profiles during crisis and post-crisis periods, with the financial crisis of 2007–2009 producing uniformly insignificant alphas, while the subsequent liquidity-rich environment allowed certain strategies, particularly Convertible Arbitrage, Fixed Income Arbitrage, Multi-Strategy, and Global Macro, to outperform the S&P 500 on a risk-adjusted basis. Their analysis shows that correlations with the market also shifted meaningfully across the two periods, with some strategies becoming more aligned with the S&P 500 after the crisis and others becoming less so, indicating that strategy performance and diversification benefits evolve with market conditions. Overall, their findings highlight that hedge-fund performance is highly sensitive to whether markets are rising or falling, with Short Selling and Managed Futures performing best in downturns, while other arbitrage-based strategies excel in rising markets, reinforcing the importance of aligning strategy selection with the prevailing investment environment.

Opacity further complicates performance evaluation. Hedge funds operate with limited disclosure requirements under private placement exemptions from the Investment Company Act of 1940, allowing innovation but restricting data availability (SEC, 2023). This makes it difficult to disentangle true alpha from systematic factor exposures or to identify the extent to which performance reflects skill, leverage, or favorable market environments. Databases suffer from well-known biases, including selection bias, survivorship bias, and backfill bias. Brown, Goetzmann, and Ibbotson (1999) estimate survivorship bias at approximately 3%, while Chen, Ibbotson and Zhu(2011) document estimates exceeding 5%. Backfill bias can inflate early returns by more than 1%. These distortions make rigorous empirical evaluation challenging and underscore the need for careful data curation. Strömqvist (2009) notes that hedge funds' lack of transparency is often cited as a risk but argues that their opacity is not exceptional when compared with other large, lightly regulated investors such as sovereign wealth funds. She finds little evidence that hedge funds were the primary drivers of the financial crisis, emphasizing instead that they were broadly negatively affected by the downturn and by short-selling restrictions that impaired traditional arbitrage strategies.

To mitigate data issues, this study uses Credit Suisse Hedge Fund Indexes, which are rules-based, investable benchmarks designed to reduce voluntary reporting biases. They replace rather than delete defunct funds, avoid pre-inclusion performance backfilling, and apply transparent liquidity and size criteria, providing a cleaner dataset for empirical analysis.

Early attempts to model hedge-fund performance relied on linear frameworks such as CAPM or the Fama–French three-factor model. However, hedge-fund returns often display nonlinear, asymmetric patterns resembling option payoffs due to embedded leverage, dynamic trading, and exposure to tail risks. Fung and Hsieh (1999, 2001, 2004) addressed this gap by proposing specialized multi-factor models that incorporate traditional equity and bond exposures alongside trend-following factors designed to capture the convexity of managed futures strategies. These models represent a major shift in hedge-fund performance attribution by explicitly accounting for nonlinear factor loadings. Chen, Ibbotson and Zhu (2011) further advanced this line of inquiry by decomposing hedge-fund returns into alpha, beta, and cost components, showing that systematic exposures account for much of the industry's aggregate performance. Their findings helped reframe the longstanding debate on whether hedge funds deliver persistent alpha or primarily capture compensated risks available through liquid markets.

A parallel research stream examines hedge-fund replication, demonstrating that a substantial portion of hedge-fund returns can be approximated using liquid futures or options. Hasanhodzic and Lo (2007) show that dynamic linear replication strategies can capture core risk exposures, while Agarwal and Naik (2004) highlight the importance of nonlinear option-based payoffs in explaining hedge-fund returns. These findings imply that some aspects of hedge-fund performance can be systematically reproduced at lower cost. Additional work such as Hocquard, Papageorgiou, and Rémillard (2008) shows that the statistical properties of major hedge-fund indices, including volatility, dependence structures, and higher-moment characteristics, can be closely replicated using systematic, tradable exposures, reinforcing the broader "expensive beta" debate. Asness, Krail, and Liew (2001) were among the earliest proponents of this perspective, arguing that many hedge-fund strategies simply repackage well-known risk premia under high-fee structures.

The emergence of systematic Alternative Risk Premia (ARP) strategies has further blurred the line between hedge funds and replicable factor exposures. ARP strategies package systematic styles, value, carry, momentum, volatility, into transparent, rules-based products, challenging the notion that hedge-fund alpha represents manager skill rather than exposure to common risk premia. Roncalli's (2017) findings reinforce this critique, arguing that much of what is typically labeled alpha is better understood as alternative beta. These insights coincide with broad industry changes, including increased competition, fee pressure, and institutionalization. Sullivan (2021) shows that hedge-fund alpha declined markedly from the pre-crisis to post-crisis periods, consistent with the hypothesis that easily replicable factors absorb much of the return variation previously attributed to manager skill.

Recent research highlights the rising institutionalization of the hedge-fund industry. Getmansky, Lo, and Mei (2015) and Barth et al. (2020) document how the sector has shifted toward larger, more liquid, and more transparent strategies in response to institutional investor demands and post-crisis regulatory reforms. The GFC also underscored the need for regulators to obtain greater transparency from hedge funds in order to assess systemic risks—particularly in strategies such as correlation trades, and to monitor crowded positions that could amplify market stress. This structural shift has been accompanied by greater commonality of exposures, as Ang, Gorovyy, and van Inwegen (2011) show that changes in hedge-fund leverage are driven primarily by economy-wide factors rather than idiosyncratic fund characteristics. Heightened interconnectedness increases the risk of crowded trades, with Levich and Pojarliev (2010) demonstrating that currency funds exhibit strong co-movement due to shared exposures to carry and trend-following signals. Patton and Ramadorai (2013) highlight that hedge-fund risk exposures are highly dynamic, adjusting in response to volatility, liquidity conditions, and performance cycles. Crowding has emerged as a central determinant of systemic vulnerability. The liquidity spiral framework of Brunnermeier and Pedersen (2009) illustrates how funding constraints and diminishing market liquidity interact to amplify losses during stressed environments. Complementary evidence from Dragomirescu-Gaina et al. (2021) emphasizes the trade-off between decision speed and accuracy under heightened uncertainty, further complicating risk management.

Machine-learning techniques have recently emerged as powerful tools for modeling and understanding hedge-fund returns. Traditional linear factor models, while effective at capturing broad market exposures, are limited in their ability to represent nonlinear and interaction effects that characterize many hedge-fund strategies. Gu, Kelly, and Xiu (2020) demonstrate that machine-learning–based factor models can uncover return-predictive structures that conventional linear methods miss, substantially improving explanatory power across asset classes. Their findings show that flexible algorithms such as neural networks and tree-based methods capture complex patterns in asset returns, opening new possibilities for hedge-fund replication, risk decomposition, and factor construction. Although these techniques do not solve fundamental identification challenges, they offer a powerful complement to the econometric models that have historically dominated hedge-fund analysis.

The macroeconomic regime remains central to hedge-fund performance. Drechsel and Tenreyro (2017) highlight the role of commodity shocks in emerging markets, demonstrating how exogenous supply disturbances reverberate across asset classes. Hurst, Ooi, and Pedersen (2013) show that time-series momentum performs strongly during crises when traditional assets falter, underscoring the value of strategies that profit from extended dislocations. The post-2020 environment represents a clear break from the low-volatility, liquidity-driven regime of the 2010s: inflation shocks, rapid monetary tightening, and rising cross-asset dispersion have revived the opportunity set for macro and trend-following managers. Practitioner analyses such as those by CFM (2022) and Mercer (2022) support this shift, documenting that systematic macro and trend-following strategies historically perform best during inflationary stress. Additional evidence from Ben Khelife and Hmaied (2022) and Benkraiem et al. (2021) shows that the COVID-19 crisis materially reshaped hedge-fund dynamics, with the former documenting significant pandemic-driven disruptions to performance and altered equity and bond market transmission mechanisms in North American hedge funds, and the latter revealing substantial declines in Event Driven, Relative Value, and Distressed Debt strategies alongside shifting causal linkages between cryptocurrency and traditional hedge-fund styles.

Taken together, the literature portrays hedge funds as complex, adaptive, and integral components of modern financial markets. Their combination of flexibility and systematic exposures allows them to operate across diverse macroeconomic regimes and market structures. Yet their opacity, evolving structure, and sensitivity to liquidity and funding conditions make rigorous performance attribution challenging. These considerations motivate the present study's use of an extended Fung–Hsieh eight-factor model to analyze eleven Credit Suisse Hedge Fund Indexes over 2004–2024, examining how exposures evolve across crisis and non-crisis environments, how strategy co-movements shift through time, and how the balance between alpha and beta has changed in response to industry maturation and broader macroeconomic forces.

3.Hedge Fund Strategies

Hedge funds encompass a wide range of investment approaches, each designed to exploit different sources of return and manage risk in distinct ways. Understanding these differences is essential to interpret performance results and the factor sensitivities that emerge from the empirical analysis.
As outlined by the CFA Institute (2025), hedge fund strategies can generally be grouped into four main categories: Equity-Related, Event-Driven, Relative-Value, and Macro or Opportunistic strategies. This classification provides a useful framework for examining the eleven Credit Suisse Hedge Fund Indexes analyzed in this study. Each index represents a distinct investment style, capturing how hedge funds seek to generate returns through either directional bets, relative pricing, or event-specific opportunities.

A. Equity-Related Strategies

Equity-related hedge funds take long and short positions in publicly traded stocks, aiming to profit from relative mispricing, factor exposures, or regional growth opportunities. While some strategies, such as Equity Market Neutral, attempt to eliminate most market risk, others maintain directional exposure to equity markets, particularly in emerging economies where shorting is limited.

A particularly prominent equity strategy in the hedge fund universe is Long/Short Equity, which combines fundamental stock selection with dynamic hedging to manage market exposure. These funds typically represent one of the largest categories in terms of assets under management and play a central role in studies of hedge fund performance. Unfortunately, reliable and consistent data for a dedicated Credit Suisse Long/Short Equity Hedge Fund Index were not available for the full sample period of this study. As a result, this strategy could not be included in the analysis. Nevertheless, its influence is indirectly captured through the Credit Suisse Hedge Fund USD composite index, which aggregates performance across all underlying strategies and contains a significant share of equity-oriented funds.

The performance of equity-related strategies is largely driven by stock selection, market direction, and style factors such as size and value. From a systematic perspective, these funds tend to load on market and size factors, with some also showing exposure to momentum or volatility components.

The relevant indexes analyzed are:

- Credit Suisse Equity Market Neutral Hedge Fund USD, which focuses on a market-neutral long/short equity approach that relies on relative performance between equities to generate alpha while maintaining low correlation with the broader market.

- Credit Suisse Emerging Markets Hedge Fund USD, which captures funds primarily investing in developing market equities and bonds. Although often classified as Equity-Related due to their long-biased exposure to regional equity markets, EM hedge funds can also be viewed as Opportunistic or Macro strategies. This is because many managers take top-down positions across asset classes, including sovereign debt and currencies, seeking to profit from macroeconomic and policy trends that affect emerging economies. Their returns are therefore shaped by both equity market direction and macroeconomic conditions such as interest rates, capital flows, and commodity prices.

B. Event-Driven Strategies

Event-driven funds seek to profit from opportunities created by corporate events, such as mergers, acquisitions, restructurings, or bankruptcies. Their returns depend more on the outcomes of these specific events than on general market movements.
According to the CFA Institute (2025), this category includes Merger Arbitrage, Distressed Debt, Special Situations, and Event Multi-Strategy funds. These strategies are often sensitive to credit spreads, liquidity, and market volatility, as deal execution risk increases during periods of stress.

The indexes analyzed include:

- Credit Suisse Event Driven Hedge Fund USD, which provides a broad representation of event-driven styles.

- Credit Suisse Event Driven Distressed Debt Hedge Fund USD, focused on securities of financially troubled companies, sensitive to credit and recovery risk.

- Credit Suisse Event Driven Risk Arbitrage Hedge Fund USD, which seeks to capture merger and acquisition spreads, typically with low market beta but high event-specific risk.

- Credit Suisse Event Driven Multi Strategy Hedge Fund USD, which blends multiple event-driven approaches to diversify risk across corporate actions.

Event-driven strategies generally perform well in stable or expanding markets but can experience drawdowns during crises, when deal activity slows and credit conditions tighten.

C. Relative-Value Strategies

Relative-value hedge funds aim to exploit pricing inefficiencies between related securities while maintaining limited directional exposure. They rely on convergence trades and arbitrage opportunities across fixed income, convertibles, and derivatives markets.
As described by the CFA Institute (2025), this category encompasses Fixed-Income Arbitrage, Convertible Arbitrage, and Volatility Arbitrage strategies. Returns are primarily driven by spread convergence, yield-curve shifts, and volatility pricing, with key systematic exposures to bond and credit-spread factors.

The relevant indexes are:

- Credit Suisse Convertible Arbitrage Hedge Fund USD, which typically takes long positions in convertible bonds and short positions in the underlying equities, earning returns from volatility and credit-spread mispricings.

- Credit Suisse Multi Strategy Hedge Fund USD, which combines relative-value, arbitrage, and opportunistic trades across asset classes to achieve diversified, steady risk-adjusted returns.

Relative-value strategies tend to deliver consistent, moderate returns but can be vulnerable to liquidity shocks and funding stress, as seen during the 2008 crisis when arbitrage spreads widened sharply.

D. Opportunistic Strategies

Opportunistic strategies take directional positions across global markets, using either discretionary macroeconomic analysis or systematic trend-following models. Their performance depends on capturing broad movements in interest rates, currencies, commodities, and equity indexes.

According to the CFA Institute (2025), these strategies are typically exposed to trend-following and global market factors rather than firm-specific risks. They can act as diversifiers in portfolios because their performance often improves during market downturns.

The two indexes analyzed are:

- Credit Suisse Global Macro Hedge Fund USD, representing managers who take cross-asset and cross-country positions based on macroeconomic views or policy expectations.

- Credit Suisse Managed Futures Hedge Fund USD, composed of systematic, momentum-driven strategies (often referred to as CTAs) that trade futures and forwards across asset classes. These funds tend to benefit from extended price trends and have historically shown defensive characteristics during crises.

E. Composite Benchmark

The Credit Suisse Hedge Fund USD Index serves as a composite benchmark encompassing all underlying strategies. It does not represent a specific investment style but rather aggregates the performance of multiple hedge fund categories.
Functionally, it operates as a Fund of Funds–style index, serving as a proxy for the overall hedge fund asset class. This makes it a useful benchmark for assessing the relative performance of individual strategy groups and comparing the results of this study with earlier research, particularly the original Fung and Hsieh (2001, 2004) analyses, which modeled the

behavior of the hedge fund industry as a single composite portfolio.
In this thesis, the composite index provides a reference point for evaluating whether the aggregate exposures of the Credit Suisse universe align with those identified by Fung and Hsieh two decades earlier.

The eleven indexes analyzed in this study collectively represent the key strategy groups recognized in both academic literature and industry practice. Each strategy reflects a distinct investment philosophy and exposure pattern, implying different sensitivities to systematic risk factors.
By mapping these strategies into the extended Fung–Hsieh eight-factor model, the empirical analysis that follows examines how their factor exposures vary across market environments and how these relationships evolve during periods of financial stress such as the GFC and the COVID-19 shock.

4.Extended 8-Factor Fung Hsieh Model

Due to the very specific nature of hedge funds, including their use of leverage, short-selling, derivatives, among other instruments, traditional asset pricing models, like CAPM or Fama-French factors, can't explain hedge fund returns reasonably well. In the late 90s, Professors William Fung and David A. Hsieh , wrote a paper on hedge fund returns and found that Hedge Funds couldn't be explained by linear models as they often behaved like options.

In 2001, they first developed their 7-factor model which included trend-following factors by using options.

They combined lookback options, which provide the holder with the ability to choose its best price during the option's life. Because they wanted to study how the trend of different instruments affected Hedge Fund returns, they used a lookback straddle, which is effectively holding both a lookback call and a lookback put, thus profiting off large swings in any direction. They used 3 factors to study this behavior:

- Bond Trend-Following Factor: This factor is constructed with the payoff from lookback straddles on U.S. Treasury Bond Futures. By tracking the convex return nature of Fixed income Markets, this model captures Hedge Fund Returns when yields fall sharply and bond prices rise, thus providing a profit to a long trend-following position. Conversely, if yields rise considerably, the Hedge fund establishes a short position and profits as well.

- Currency Trend-Following Factor: This factor is constructed from the payoff of lookback straddles on FX futures. Similar to the bond trend-following factor, its payoff increases when currency prices exhibit strong directional movements, either upward or downward. This captures the convex return profile of trend-following strategies in currency markets. Currency trend-following is particularly relevant for Commodity Trading Advisors (CTAs) and hedge funds employing time-series momentum strategies in FX markets, as discussed by Hurst, Ooi, and Pedersen (2013).

- Commodity Trend-Following Factor: This factor is built on the payoff of lookback straddles on commodity futures, such as energy, metals or agriculture futures. Commodity markets are especially affected by large swings in prices, due to geopolitical problems, natural phenomenon or other supply shocks, which is captured by this factor by its payoff in circumstances where a long position is benefited by a commodity price surge, or by a short position when a commodity's price falls significantly.

As Fung and Hsieh (2004, p. 14) note, "Trend-following strategies thrive when conventional asset markets are distressed, which provides a valuable diversifying source of return to portfolios of conventional assets.". These factors replicate the convex payoff structure of systematic momentum strategies and make it possible to study the performance, risk exposures, and diversification benefits of trend-following hedge funds in far greater depth than traditional linear factor models allow.

The remaining four factors of the original model are divided into two equity-driven factors and two interest rate driven factors:

- Equity Market Return Factor: Using the S&P 500's return as a proxy, we consider the American stock market exposure, which is still a significant driving force in hedge fund returns. Even funds that claim to be market neutral often display some sensitivity to equity movements, whether through long/short positions, derivatives, or tactical allocation decisions. Since equity beta can be a major driver of hedge fund performance, this factor is crucial in distinguishing returns generated from systematic stock market risk from those attributable to true manager skill. By including the S&P 500 return directly, the Fung and Hsieh model ensures that any equity-driven component of hedge fund returns is appropriately recognized.

- Size Factor: This size factor allows us to compare the return difference between small cap stocks and large cap stocks. As initially discussed by Rolf Banz (1981), when looking at US broad market stock data, there appeared to be a size effect in which small caps outperformed large cap stocks. Fama and French later incorporated this notion into their three-factor model which they called SMB (Small Minus Big). The size factor becomes important when studying hedge fund returns because many funds seek opportunities in smaller-cap stocks, which are often less liquid than large-cap equities. This lack of liquidity, along with reduced analyst coverage and greater potential for mispricing, can create attractive profit opportunities for hedge fund managers. By including the Size factor, the Fung and Hsieh model accounts for systematic exposure to small-cap risk that might otherwise be mistaken for the manager's alpha which we'll cover later. Fung and Hsieh used at the time the Wilshire Small Cap 1750 and the Wilshire Large Cap 750 indexes.

- Bond Market Factor: This factor measures the changes in the yield of the 10-year U.S. Treasury and it's included to measure the hedge fund return's sensitivity to shifts in the 10-year risk-free rate, which is a global benchmark for the longer maturities. While all hedge funds are exposed to interest rate risk, some strategies are often more affected than others. For example, Global Macro Funds which make investments based on macroeconomic trends, whether it is on commodities, equities or bonds, and these trends are directly affected by swings in interest rates. Some hedge funds that use this strategy bet directly on government bond futures. Another strategy that is often impacted by changes in the 10-year yield is fixed income arbitrage. These funds are dedicated to finding inefficiencies in bond pricings and are typically over leveraged because these discrepancies are quite small in nature, thus using leverage to generate meaningful returns. This excess in leverage can magnify losses or gains, depending on whether the interest rate moves as the fund foresaw or against it.

- Credit Spread Factor – This factor measures the credit spread, or more specifically the credit risk premium, by tracking the spread between Moody's Baa Yield and the Federal Reserve's 10-year constant maturity yield. Certain hedge fund strategies are directly affected by the credit spread between the U.S. 10-year treasury and corporate bonds, such as convertible arbitrage or distressed debt. When credit spreads decrease, strategies that are long corporate bonds tend to benefit. However, when spreads widen, long corporate bond funds tend to lose. In downturn situations, where credit spreads tend to spike due to a flight to safety, funds with long credit exposure tend to experience magnified losses, while those who are short on credit spread might profit. By including this factor, the model tries to distinguish hedge fund returns provoked by credit spread tightening from manager's alpha.

Fung and Hsieh later added an eighth factor, the Emerging Market Risk Factor, proxied by the MSCI Emerging Market Index, recognizing the rapid rise of EM hedge funds during the 2000s. As Strömqvist (2006, p. 89) notes, "The number of emerging market hedge funds increased exponentially during the first half of the sample period, peaking with over 200 funds at the end of 1997 and beginning of 1998."

This expansion can be attributed to strong economic growth in EM, particularly the BRICS, along with improved market infrastructure and liquidity. As capital controls eased, hedge funds could allocate more capital, while EM investments offered diversification and lower correlation with U.S. equities. Institutional investors, including pension and sovereign wealth funds, also increased allocations to EM hedge funds.

The commodity supercycle of the 2000s further accelerated emerging market growth. As Drechsel and Tenreyro (2017) highlight, rising commodity prices had significant positive effects on GDP, consumption, and investment across commodity-exporting emerging economies. This trend is reflected in the HFR Emerging Markets Industry Report (2011), which shows rapid growth in EM hedge fund assets under management between 2002 and 2011.

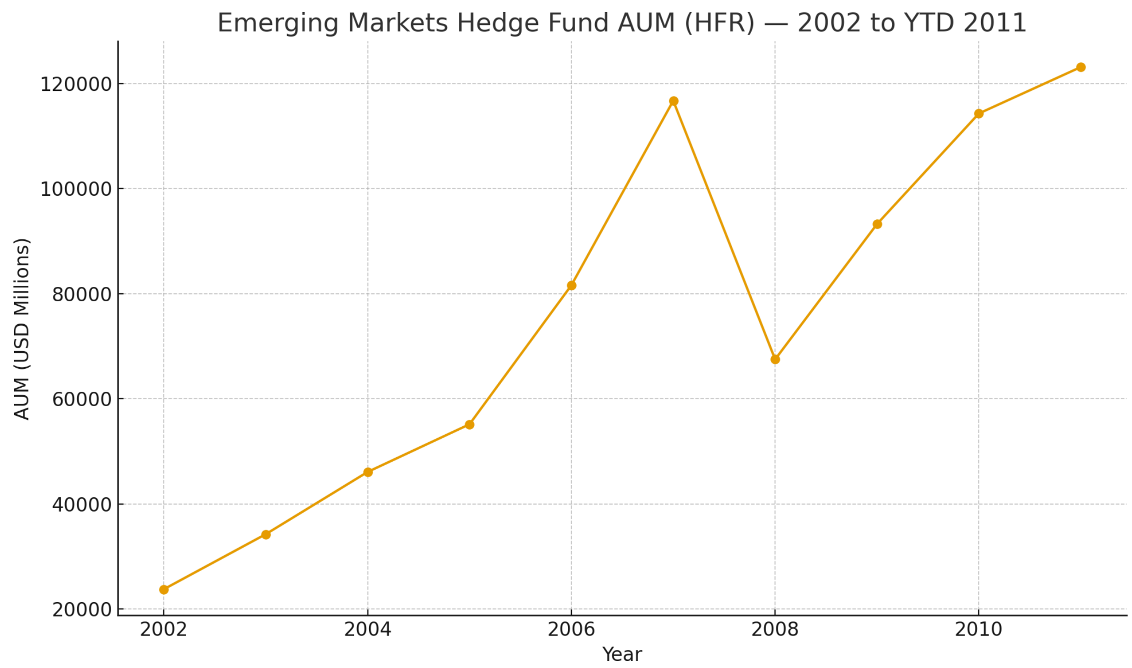

Figure 1 - Growth of Assets / Net Asset Flows — Emerging Markets 2002–YTD Q2 2011", Source: HFR – Emerging Markets Industry Report (Sample Extract, 2011)

For this analysis, the following proxies are used to study each of the eight factors:

- Trend-Following Factors: Data from Professor Hsieh's library (Bond, Currency, Commodity)[1]

- Equity Market Factor: S&P 500 monthly return

- Size Factor: Russell 2000 monthly return minus S&P 500 monthly return

- Bond Market Factor: Monthly change in the 10-year U.S. Treasury yield

[1] Data obtained from Professor Hsieh's Library: http://people.duke.edu/~dah7/DataLibrary/TF-Fac.xls

- Credit Spread Factor: Monthly change in Moody's Baa yield minus the 10-year Treasury yield

- Emerging Market Factor: Credit Suisse Emerging Market Index monthly return

The hedge fund strategy indexes analyzed are the eleven Credit Suisse Hedge Fund Index categories: Convertible Arbitrage, Event Driven Distressed Debt, Event Driven Multi Strategy, Event Driven Risk Arbitrage, Emerging Markets, Equity Market Neutral, Event Driven, Global Macro, Hedge Fund Composite, Multi Strategy, and Managed Futures.

The period 2004–2024 offers a particularly rich and underexplored timeframe for studying hedge fund performance through the lens of the Fung and Hsieh model. It encompasses major market events such as the GFC (2007–2009), the era of QE and historically low interest rates, the subsequent policy normalization attempts by central banks, and the COVID-19 pandemic followed by the post-2021 inflationary and high-rate environment. These distinct phases create an ideal setting to analyze how hedge fund factor exposures evolve across changing market regimes.

5. Model Regression and Beta Replication Analysis

5.1. 2004-2024 Analysis

5.1.1. 2004-2024 Regression Analysis

The analysis begins with the full 2004–2024 period, which encompasses multiple market regimes and structural shifts relevant to hedge fund returns, before turning to sub-periods. **Appendix Table 1** reports the eight-factor regression results for the full sample, including estimated coefficients, standard errors, intercepts, and R^2 values for each hedge fund index. This table provides the core evidence on how well the Fung and Hsieh (2004) framework explains hedge fund performance over the past two decades.

The model fit varies considerably across strategies. The highest R^2 values are observed for Convertible Arbitrage, ED Multi-Strategy, Emerging Markets, and ED Distressed Debt. For Distressed Debt, this is intuitive: returns are heavily driven by credit risk and equity market sensitivity, especially in downturns, both of which are captured by credit and equity factors. EM strategies naturally load on the EM factor and are also credit-sensitive. ED Multi-Strategy funds combine distressed, merger arbitrage, and other corporate event-driven trades, so their aggregate performance is closely aligned with the model's equity and credit-related factors, which jointly capture the main sources of risk in event-driven situations.

Convertible Arbitrage is the strategy best explained by the model. Its basic trade, being long in a convertible bond (debt plus an embedded equity option) and short the underlying equity to hedge, makes returns largely driven by systematic exposures to credit spreads, interest rates, and equity, all of which feature in the eight-factor specification. By contrast, Managed Futures displays the lowest R^2, consistent with nonlinear, momentum-driven trading that linear regressions approximate only imperfectly.

Beyond factor loadings, the intercept term is central. In this setting, the intercept is interpreted as the hedge fund manager's monthly alpha: the component of returns not explained by systematic risk factors such as equity, credit, interest rates, or trend-following exposures. A positive and statistically significant intercept indicates that a strategy delivers returns above what would be expected given its factor exposures and thus reflects genuine manager skill, superior security selection, or access to unique opportunities. An insignificant or negative intercept suggests that apparent “alpha” in raw returns is actually explained by systematic risk-taking or that the strategy underperforms after adjusting for factor exposures. In this sense, monthly alpha serves as a benchmark for distinguishing true value-added from disguised beta.

Fung and Hsieh (2004) show how this distinction matters in practice. In their original study, the fund-of-funds index exhibited a significant intercept over the full sample, but this “alpha” was largely an illusion driven by the late-1990s bull market. Once the sample was split into sub-periods, alpha became statistically insignificant and its magnitude declined sharply. This provides a useful reference point for interpreting the intercepts in **Appendix Table 1.**

In our sample of eleven hedge fund strategies, only two, Managed Futures and Equity Market Neutral, exhibit statistically insignificant intercepts. For Managed Futures, this indicates that performance is largely attributable to trend-following payoffs captured by the PTFS factors, rather than persistent manager skill. For Equity Market Neutral, the insignificant intercept implies that, despite having near-zero market beta, these strategies do not consistently generate stock-picking alpha beyond their embedded style and factor exposures.

By contrast, Global Macro and Multi-Strategy stand out as the categories with the highest and most robust alphas over 2004–2024. Their returns cannot be fully explained by exposure to equity, credit, interest-rate, or trend-following factors, highlighting their capacity to generate idiosyncratic, discretionary performance. Global Macro managers, with the flexibility to trade across asset classes and regions, can exploit macroeconomic dislocations, policy shifts, and global imbalances. Multi-Strategy funds benefit from the ability to reallocate capital dynamically across diverse styles, capturing relative-value and event-driven opportunities that are difficult to access within a single-strategy mandate. The persistence of significant alpha in these categories suggests that, over the past two decades, their performance has been driven not merely by exposure to common risk premia, but by genuine manager skill in navigating complex and evolving market environments.

The 2004–2024 period provided repeated opportunities for macro and multi-strategy managers to exploit large market dislocations and policy shifts. Episodes such as the GFC, the Eurozone sovereign debt crisis, the 2013 “taper tantrum”, the COVID-19 shock, and the post-2021 inflation and rate-hiking cycle were all characterized by sharp moves in safe-haven assets, emerging-market currencies and bonds, and long-dated sovereign yields. In such environments, global macro and trend-following strategies typically seek to profit from flight-to-quality flows (for example, into the U.S. dollar and Treasuries), from stress in peripheral sovereign markets, and from persistent trends in rates, currencies, and commodities. Multi-strategy funds, in turn, can allocate opportunistically to capital-structure, distressed-credit, merger, and event-driven trades as volatility and dispersion increase. These crisis and regime-shift periods are therefore consistent with the statistically significant intercepts estimated for Global Macro and Multi-Strategy indexes in the regression analysis, suggesting that at least part of their performance reflects active positioning beyond what is captured by the systematic factors.

This table also includes the regression results for the Credit Suisse Hedge Fund USD Index, which aggregates a diversified basket of hedge funds across strategies. For this broad index, the estimated alpha is modest (0.00392) and the R^2 is around 0.39, implying that roughly 40% of return variation is explained by the eight factors. Significant exposures to the S&P 500 and EM factors point to sustained participation in global equity markets, particularly by equity hedge, multi-strategy, and event-driven funds that maintained net long positions over much of the sample. The strong significance on the Credit Spread factor underscores the persistent role of credit and liquidity premia, especially during the 2008 GFC and subsequent credit-driven recoveries. The Bond Trend-Following factor is also significant, indicating that part of the industry's performance is linked to systematic momentum in fixed-income markets, likely reflecting CTAs and macro funds profiting from long-duration trades during prolonged declines in yields (e.g., 2008–2013, 2020). The relatively low alpha and moderate explanatory power, particularly when compared to individual strategy indices, suggest that hedge funds in aggregate have delivered limited performance beyond systematic exposures, consistent with a more institutionalized, factor-driven industry.

A comparison with Fung and Hsieh's (2004) HFR Fund of Funds index (HFRFOF) highlights the structural changes. In the earlier 1994–2004 sample, the HFRFOF displayed a higher alpha (0.00477), significant at the 1 % level, and broader sensitivity to Size, 10-year yield changes, Credit Spread, and both Bond and Commodity Trend-Following factors. At that time, hedge fund strategies were less correlated, less constrained by institutional capital, and more oriented toward idiosyncratic, niche opportunities. By 2004-2024, as represented by the Credit Suisse Hedge Fund USD Index, the industry appears more integrated with global capital markets. Its lower alpha and narrower factor exposures reflect a shift toward hedge funds acting as sophisticated allocators across well-known risk premia rather than as generators of unique, uncorrelated returns.

The cross-section of factor exposures reveals several additional patterns. Only Event-Driven hedge funds exhibit a statistically significant loading on the Size factor, capturing sensitivity to the return differential between small- and large-cap stocks. This aligns with the nature of event-driven investing, which often targets mergers, acquisitions, restructurings, and spin-offs that are disproportionately concentrated in smaller and mid-cap firms, where valuation inefficiencies and deal spreads tend to be larger. Such trades offer greater arbitrage potential but also embed systematic small-cap risk. Most other hedge fund categories, Global Macro, Fixed Income Arbitrage, Managed Futures, operate in highly liquid, large-cap or institutional markets (sovereign bonds, major equity indices, currencies, and commodities), and thus show little exposure to Size Factor.

This pattern departs from Fung and Hsieh's (2004) findings, where the Size factor was significant for HFRFOF, reflecting an industry more focused on smaller, niche equity opportunities. Over 2004–2024, the hedge fund sector has become increasingly institutionalized, with larger assets under management and a stronger emphasis on scalable, liquid strategies (Getmansky, Lee, & Lo, 2015; Barth et al., 2020). As a result, the importance of the Size factor has diminished, remaining primarily relevant for event-driven strategies that still engage with smaller firms.

Interest-rate exposure has also evolved. An unexpected result is that the 10-year Treasury yield factor is statistically insignificant for all hedge fund indices except the Credit Suisse ED Risk Arbitrage index, where it is significant at the 5 % level. This contrasts with Fung and Hsieh (2004), where changes in the 10-year yield significantly influenced HFRFOF. The lack of significance in the broader sample suggests that hedge funds have substantially reduced their net duration exposure. Post-GFC, many managers actively hedge interest-rate risk or use instruments with limited sensitivity to sovereign yields, such as credit derivatives, equity long/short positions, or macro trades implemented via futures and options. Persistent low and stable rates, combined with greater use of derivatives, have decoupled most hedge fund returns from direct interest-rate movements. The exception, ED Risk Arbitrage, can be explained by the rate sensitivity of merger financing and deal spreads: rising long-term yields raise discount rates and funding costs, lowering expected deal values and widening spreads.

A similar story emerges for the Commodity Trend-Following factor, which is insignificant across all indices. This indicates that commodity momentum has not been a meaningful driver of hedge fund returns over 2004–2024. Earlier work, including Fung and Hsieh (2004), found that commodity trend captured part of the convex, option-like payoffs of Managed Futures and Macro funds. As the industry matured, however, commodity exposure became concentrated in dedicated CTA and systematic trend-following managers, whose performance is better captured by specialized indices than by broad hedge fund composites. For most equity hedge, event-driven, and relative-value strategies, commodity price movements influence returns only indirectly, primarily through exposures to commodity-linked sectors such as energy, materials, or industrials. In the post-2008 period, the growing financialization of commodity markets and the compression of volatility under accommodative monetary policy reduced the persistence of price trends and, consequently, the profitability of long-term momentum trades.

By contrast, the Bond Trend-Following factor shows considerably more significance across the Credit Suisse hedge fund indices than the Currency or Commodity Trend factors. This reflects the central role of interest-rate dynamics in driving cross-asset performance during an era dominated by monetary-policy cycles. Following the GFC and again after the COVID-19 shock, global markets experienced extended bond bull markets driven by falling yields and large-scale QE. These multi-year declines in interest rates generated sustained directional moves in sovereign bonds, the kind of trends that the Bond Trend factor is designed to capture. Bond trends affected not only CTAs and Global Macro funds but also credit, equity, and multi-strategy managers, since interest rates influence discount rates, leverage costs, and valuations across asset classes.

In contrast, currency and commodity trends were more episodic. Currency markets were frequently influenced by policy interventions and managed exchange-rate regimes, which constrained sustained momentum and led to frequent mean reversion (Levich & Pojarliev, 2012). Commodity markets, while exhibiting pronounced directional moves during the 2003–2008 super-cycle and again in 2021–2022, experienced extended phases of low volatility and limited trend persistence during the intervening years (Hurst, Ooi, & Pedersen, 2013; IMF, 2023). Many hedge funds either hedge or avoid direct currency and commodity exposures altogether. Unlike commodity or currency momentum, bond trends exert broad and persistent spillover effects across asset classes, shaping the returns of virtually all major hedge fund strategies (Hurst, Ooi, & Pedersen, 2013; Fung & Hsieh, 2001).

5.1.2. 2004-2024 Beta Replication Analysis

To complement the regression analysis and provide a more intuitive understanding of the factor dynamics underlying hedge fund index returns, this study extends the empirical framework by implementing a beta replication approach. While the initial regressions identify the statistical significance and direction of exposure to each of the eight risk factors, the replication approach translates these sensitivities into normalized exposure proportions that illustrate the relative importance of each factor in explaining index behavior.

As shown in **Formula 1** in the Appendix, for each hedge fund index the absolute values of the estimated factor loadings are summed to obtain the total magnitude of exposure across all factors. Each individual coefficient is then divided by this total to derive a normalized weight that represents the proportion of overall exposure attributable to that factor. This normalization allows for direct comparison across indexes, irrespective of differences in factor scales or absolute beta magnitudes. Positive normalized weights correspond to long exposures, while negative values indicate short exposures to the respective factors. The resulting decomposition provides a portfolio-like representation of each index's systematic risk profile, highlighting which factors dominate performance and whether exposures are predominantly directional or hedging in nature.

This beta replication perspective aligns with the hedge fund replication literature (e.g., Fung and Hsieh, 2004; Hasanhodzic and Lo, 2007), in which factor sensitivities are interpreted as implicit positions in tradable risk premia. It therefore serves as a bridge between statistical inference and economic interpretation, offering insights into the structure and stability of hedge fund strategies across market environments. By comparing the normalized exposure patterns across subperiods, such as the GFC and the COVID-19 pandemic, this analysis also enables the assessment of how hedge fund style exposures evolve under varying market conditions.

Appendix Table 2 presents the normalized factor exposures for the eleven hedge fund indexes over the full sample period (2004–2024), incorporating both the magnitude and direction of sensitivities to the eight Fung and Hsieh factors. The results confirm that hedge fund strategies remain highly heterogeneous, yet credit and rate exposures dominate much of the industry's systematic risk profile.

Credit spread risk stands out as the principal driver, with large negative loadings across nearly all strategies, ranging from roughly −60% to −95%. This pattern reflects the heavy reliance of Event Driven, Multi-Strategy, and Convertible Arbitrage funds on credit and liquidity premia. Conversely, Managed Futures show a strong positive loading, reflecting their tendency to benefit from risk-off environments in which credit spreads widen. Although CTAs do not hold credit instruments directly, widening spreads typically coincide with bond rallies, equity sell-offs, and pronounced macro trends — conditions under which trend-following strategies historically perform well.

Interest rate sensitivity, captured by the monthly change in the 10-year Treasury yield, also plays a notable role, particularly for Risk Arbitrage and Emerging Markets, which show sizable negative coefficients indicating adverse impacts from rising yields. Managed Futures, by contrast, display a large positive loading (around 42%) on this factor, suggesting that they benefited from directional movements in interest rates, likely through trend-following or duration-based positioning that profited from pronounced shifts in bond yields rather than from stable rate environments.

Equity-related factors, S&P returns, Size, and EM, show mixed but generally modest effects. Equity exposures are most evident in ED and Emerging Market funds. Negative coefficients for some strategies, such as Equity Market Neutral, imply mild short exposure or hedging against broad market direction.

The three trend-following factors (bond, currency, and commodity trends) contribute only marginally for most strategies, except for Managed Futures, where all three are positive, consistent with their momentum-based, cross-asset trading style.

In summary, the 2004–2024 beta replication results reveal that hedge fund returns remain concentrated in credit and interest rate risk, with limited diversification across other factors.

Only Managed Futures demonstrates a balanced exposure profile, while most other strategies derive their systematic returns primarily from variations in credit and funding conditions.

To capture the evolution of hedge fund behavior across distinct market environments, the analysis divides the sample into three subperiods: 2004–2011, 2012–2019, and 2020–2024. Each interval represents a unique macro-financial regime with different implications for risk-taking, liquidity, and factor exposures.

5.2. 2004-2011 Period Analysis

5.2.1. 2004-2011 Regression Analysis

We begin this subperiod analysis by examining the model's explanatory power, measured by the coefficient of determination (R^2). As shown in **Appendix Table 3**, during 2004–2011 the average R^2 of the eight-factor model rose from 35.2% in the full sample to roughly 45%, indicating greater systematic explainability of hedge fund returns. This suggests that, during the crisis and its aftermath, hedge fund performance was more influenced by common risk factors than in the broader 2004–2024 period.

The elevated R^2 values align with the macro-financial backdrop of the GFC, which brought heightened market integration, soaring asset correlations, and reduced diversification benefits. As liquidity dried up and credit risk became the main source of return variation, strategies converged toward similar exposures, particularly to credit spread and interest-rate factors, raising the share of return variability captured by the model.

Across strategies, Convertible Arbitrage and Distressed Debt maintained the highest R^2 values, rising from 55.4% to 61.9% and 53.3% to 64.8%, respectively, reflecting their dependence on credit and interest-rate dynamics during the crisis. At the opposite end, Managed Futures and Global Macro continued to show the lowest explanatory power (R^2 = 14.4% and 20.6%), though both increased from prior levels, suggesting that even flexible, cross-asset strategies were influenced by the dominant risk-on/risk-off environment.

The largest change occurred in the Multi-Strategy category, where R^2 rose from 42.7% to 61.0%, underscoring how portfolio diversification offered limited insulation as liquidity pressures and cross-market contagion intensified. Overall, higher R^2 values across most strategies indicate that hedge fund returns became more synchronized with broader markets, driven by collapsing liquidity, rising correlations, and policy interventions.

During this period, hedge fund alphas were generally positive, reflecting strong manager performance through both the pre-crisis boom and the subsequent turmoil. The highest alphas were observed for Global Macro (0.0070) and Event Driven Multi Strategy (0.00398), while Distressed Debt, Event Driven, and Multi-Strategy also delivered moderate positive constants (around 0.0038–0.004). By contrast, Equity Market Neutral posted a negative alpha, indicating weaker performance amid equity turbulence. Overall, 2004–2011 reflects a phase of active alpha generation during an unstable macro environment, as skilled managers capitalized on crisis-related inefficiencies.

Relative to the full 2004–2024 period, the 2004–2011 subperiod shows stronger and more widespread statistical significance across key risk factors, reflecting the systemic pressures of the GFC.

The Credit Spread factor remained a key driver of hedge fund returns but became more selective in its significance. It remained statistically significant for Convertible Arbitrage, Distressed Debt, Risk Arbitrage, Equity Market Neutral, Hedge Fund Composite, and Multi-Strategy, while losing significance for ED Multi-Strategy, Emerging Markets, and Event Driven. As in the full sample, Global Macro and Managed Futures continued to show no statistical significance for credit spreads. This pattern suggests that credit exposure was concentrated in strategies directly tied to corporate and capital-structure opportunities, while macro and trend-following styles were largely insulated from credit market stress.

The 10-year Treasury yield change also gained importance, becoming significant for Distressed Debt, ED Multi-Strategy, and Event Driven funds, unlike the total sample, where it only influenced Risk Arbitrage. This reflects the heightened rate volatility and funding pressure faced by leveraged strategies during the crisis.

Equity-related factors became more influential as well. The S&P 500 coefficient was significant for Distressed Debt, Event Driven, and Multi-Strategy strategies, showing participation in market direction, while the EM factor gained relevance for Risk Arbitrage, as it maintained significance for the remaining strategies for which it was already relevant for in the full sample. The Size effect remained mostly insignificant, apart from ED Risk Arbitrage and Equity Market Neutral, indicating that small-cap exposure played little role in this liquidity-constrained environment.

Among trend-following variables, the Bond Trend factor stood out as broadly significant, consistent with the total sample, suggesting that fixed-income momentum captured part of the crisis-driven volatility. Currency and Commodity Trend factors remained largely insignificant.

Overall, the 2004–2011 period was characterized by systematic exposures to credit, rate, and equity risk, which jointly explained much of hedge fund performance. The concentration of significance in these factors reflects how strategies converged under the liquidity stress and macro shocks of the GFC.

5.2.2. 2004-2011 Beta Replication Analysis

During the 2004–2011 period, hedge fund exposures displayed distinct patterns compared with the overall 2004–2024 sample, reflecting the impact of the GFC and the market conditions that preceded and followed it.

As shown in **Appendix Table 4**, credit-related sensitivities were prominent across most strategies, but the magnitude and direction of exposures shifted notably. For instance, Convertible Arbitrage, Distressed, and Risk Arbitrage funds showed strong negative exposure to the Credit Spread factor (−50% to −80%), consistent with their reliance on credit market stability. These exposures were generally less extreme than in the full sample, suggesting a reduction in effective credit beta after the crisis, likely as funds deleveraged or adjusted exposures to tightening credit conditions.

Interest rate sensitivity, represented by the Monthly Change in 10-year yields, was more pronounced during 2004–2011, particularly for Event Driven, Distressed, and ED Multi Strategy funds, which exhibited large absolute betas to rate movements (often exceeding 40–50%). This pattern aligns with the turbulent fixed-income environment of the crisis period, when yields experienced sharp swings.

Across the full 2004–2024 sample, exposures to the S&P 500, Size, and EM factors are generally stronger and more pervasive, but the 2004–2011 subperiod already reveals a clear equity imprint on hedge fund returns. Event Driven, ED Multi-Strategy, and Emerging

Markets display the largest loadings on the S&P 500 and MSCI EM, consistent with their partial participation in the pre-crisis equity rally and the subsequent drawdown. Several event-driven categories also exhibit sizable (and mostly negative) Size coefficients, indicating a tilt away from smaller-cap names during this phase. Taken together, these patterns suggest that equity beta was an important driver of hedge fund performance even before 2011, with the longer 2004–2024 window amplifying and extending this equity linkage as the post-crisis bull market unfolds.

ED Risk Arbitrage provides a particularly stark example of how equity-factor exposures evolve between the two samples. Over 2004–2011, the strategy is characterised by a considerable short exposure on the Size factor (around −7%) and a meaningful long exposure to EM returns, consistent with a preference for larger, more liquid names and a degree of sensitivity to global equity risk during the crisis period. In the full 2004–2024 sample, however, the Size coefficient turns modestly positive and the EM loading falls back, while S&P 500 sensitivity remains small. This shift points to a more balanced and less one-sided equity profile over the longer horizon, with ED Risk Arbitrage becoming less dominated by a single equity dimension and its returns increasingly reflecting a mix of deal-specific risk and more moderate, diversified equity-factor exposures.

Overall, the 2004–2011 sub-period highlights a stronger dependence on traditional risk factors, credit, rates, and equity, across most hedge fund styles, compared with the more credit focused exposures seen in the total sample. The patterns are consistent with a period characterized by systemic deleveraging and factor crowding, followed by gradual normalization in the subsequent years.

5.3. 2012-2019 Analysis

5.3.1. 2012-2019 Regression Analysis

As market conditions stabilized after 2011, hedge fund exposures evolved alongside the recovery in global risk appetite. The 2012–2019 sub-period corresponded to an environment of prolonged QE, low interest rates, and a sustained equity rally. This context is expected to reveal reduced credit and rate sensitivities and greater alignment with equity factors, as managers re-engaged in directional strategies and cross-asset correlations normalized.

Analyzing this period thus provides insight into how hedge funds adjusted factor exposures in a less volatile yet liquidity-driven regime.

Appendix Table 5 shows a notable decline in the explanatory power of the eight-factor model during 2012–2019 compared with both the full sample and the 2004–2011 sub-period. Lower R^2 values across most categories indicate that common systematic factors explained a smaller share of return variation during the post-crisis expansion. The average R^2 fell to roughly 0.35, down from 0.45 in 2004–2011, signaling a period when the usual macroeconomic forces that drove hedge fund returns during the crisis years (like sharp moves in rates, spreads, and global equities) became much less volatile and less influential.

Across individual strategies, Convertible Arbitrage, Event Driven, and Distressed Debt, all of which previously exhibited high explanatory power (above 0.60), experienced visible declines. This shift reflects the normalization of markets after the crisis: as spreads tightened and volatility fell, performance became less tied to broad credit and rate movements and more influenced by deal flow, security selection, and relative-value opportunities.

Global Macro and Managed Futures showed modest R^2 increases from previously observed low levels but remained among the least explained by the model (0.30 and 0.32). This aligns with their discretionary, adaptive nature, which tends to perform independently of standard market betas, especially amid low macro volatility and few persistent trends. Equity Market Neutral and Risk Arbitrage recorded the lowest R^2 values (0.04 and 0.26), suggesting returns driven largely by micro-level relationships rather than broad exposures.

Overall, the 2012–2019 decline in R^2 underscores a decoupling between hedge fund performance and traditional risk factors. Prolonged low volatility, accommodative policy, and narrow spreads reduced the role of macro variables, allowing manager discretion and strategy-specific alpha to explain more of the variation in returns. The model's weaker fit reflects a market phase where dispersion and security-level opportunities replaced systematic risk as primary return drivers.

Comparing the full 2004–2024 sample with the 2012–2019 period, average manager alpha declined notably across most strategies. During the full sample, alphas were consistently positive (0.0026–0.0049), but in 2012–2019 they fell to roughly -0.0000542 to 0.0037, indicating reduced outperformance. The decline was most evident for Event Driven and

Equity Market Neutral funds. Multi-Strategy funds were the main exception, maintaining a relatively strong alpha (0.0037), suggesting that diversification and tactical flexibility still added value. Managed Futures recorded a slightly negative constant, consistent with weaker trend-following in a low-volatility setting.

The pattern of significant coefficients in 2012–2019 reveals a marked change from 2004–2011. While overall explanatory power fell, the structure of significance also shifted, indicating that hedge funds became less uniformly exposed to broad risks and more heterogeneous in performance sources.

The most notable change was in the Credit Spread factor, previously significant across nearly all strategies (often at 1%). During 2012–2019 it remained significant only at 5% for ED Distressed Debt. This decline in significance implies that credit markets became a less dominant performance driver as liquidity improved and spreads compressed. In this environment, meaningful credit exposure was largely concentrated in explicitly distressed, restructuring-oriented mandates rather than being a broad industry-wide driver.

The S&P 500 factor evolved more subtly. It stayed significant for ED Multi-Strategy funds (at 5%, down from 1%), suggesting persistent but weaker equity exposure. Conversely, its significance rose for Fund of Funds, from 5% to 1%, indicating a stronger and more stable equity link for diversified portfolios. The S&P 500 factor also became significant for Global Macro, Multi-Strategy, and Managed Futures, showing that even typically non-equity-dependent strategies gained measurable market sensitivity during the prolonged bull run. Meanwhile, Distressed Debt and Equity Market Neutral funds lost their prior equity significance, emphasizing a shift toward idiosyncratic, security-specific returns.

Together, these results indicate a structural transition in hedge fund dynamics: from broad dependence on macro-financial factors, particularly credit conditions, to more differentiated, strategy-specific performance. The emergence of highly significant equity exposure for diversified and macro strategies reflects abundant liquidity and persistent market strength, while the fading significance of credit factors highlights the stability of the QE era.

Within equity-related factors, the Size effect actually lost prominence during 2012–2019. The only strategy showing a statistically significant relationship with this factor was Convertible Arbitrage, where small-cap exposure remained relevant. In contrast, the Size effect lost significance for ED Distressed Debt and ED Multi-Strategy funds, suggesting that these strategies shifted away from smaller or less liquid equities toward larger-cap positions. Overall, the diminished importance of the Size factor indicates that hedge fund returns became less dependent on small-cap risk during this period.

The Bond Trend factor became far less influential, with significance disappearing across most strategies, only Emerging Markets retained significance at 5%, reflecting continued sensitivity to yield momentum. Among trend-following exposures, Managed Futures showed significance only in the Currency Trend factor at 1%, revealing dependence on FX momentum as a remaining systematic source of return during an otherwise low-volatility period.

The 2012–2019 phase thus represents a clear transition from the crisis-driven dynamics of 2004–2011. Extended monetary accommodation, subdued volatility, and steady equity appreciation are all mirrored in the evolving composition of hedge fund betas.

5.3.2. 2012-2019 Beta Replication Analysis

Evidence from **Appendix Table 6** shows that, across nearly all styles, exposures to equity-related factors increased markedly. Sensitivity to the S&P 500 rose for most categories, particularly for the various Event Driven strategies and Multi Strategy funds, indicating a stronger participation in directional market risk. Similarly, positive loadings on Emerging Market returns became more widespread, implying that managers actively re-engaged in growth and momentum oriented trades as market sentiment improved.

By contrast, the Credit Spread and interest rate factors showed more mixed and less dominant roles than in the earlier period. While certain strategies such as Distressed and Event Driven retained moderate short exposures to credit spreads, others, most notably Risk Arbitrage, shifted towards long positions, suggesting that these funds benefited from tightening spreads and improved deal activity in a low-rate environment. However, Managed Futures displayed substantial short exposure to rate changes (−93.5%), highlighting its sensitivity to movements in long-term interest rates and its relatively defensive positioning within an otherwise risk-on environment. The reduction in credit sensitivity is consistent with the normalization of funding conditions and the compression of spreads during the QE era.

Exposure to bond and commodity trend factors remained minimal, reinforcing the view that systematic trend-following played a limited role during this period of subdued macro volatility.

Overall, the 2012–2019 sub-period reflects a re-risking phase for hedge funds, characterized by stronger equity market participation and reduced dependence on credit exposures. The pattern aligns with a market regime driven by central bank liquidity and sustained risk appetite, where equity-related strategies most notably thrived under stable financial conditions.

5.4. 2020-2024 Analysis

5.4.1. 2020-2024 Regression Analysis

The transition from 2012–2019 to 2020–2024 marks a fundamental shift in global financial conditions and hedge fund behavior. The onset of the COVID-19 pandemic, followed by unprecedented fiscal and monetary interventions, disrupted the low-volatility regime that had prevailed throughout the previous decade. Subsequent years were defined by rapid inflation, rising interest rates, and geopolitical tensions, all of which reintroduced macroeconomic uncertainty as a key driver of returns. In this environment, hedge fund strategies were once again tested by sharp market dislocations and shifting risk premia. The 2020–2024 sub-period therefore offers valuable insight into how managers adjusted exposures in response to renewed volatility and structural regime change, contrasting sharply with the liquidity-driven stability of the preceding era.

As reported in **Appendix Table 7**, the relationship between hedge fund returns and the model's systematic risk factors strengthened considerably during the 2020–2024 period. After a decade marked by weak explanatory power, the eight-factor model once again captured a significant portion of return variability across most strategies. This rebound in R^2 values reflects a market environment dominated by macro shocks and regime transitions, where broad risk factors, particularly those linked to interest rates, credit spreads, and equity volatility, reasserted their influence on hedge fund performance.

Several strategies exhibited particularly high goodness of fit. Event Driven and ED Multi Strategy both reached R^2 values above 0.70, suggesting that their returns became strongly aligned with the model's factors. Distressed Debt and Convertible Arbitrage also recorded elevated R^2s around 0.65, comparable to levels last observed during the 2004–2011 period, implying renewed dependence on credit and rate movements.

In contrast, Global Macro and Managed Futures maintained relatively low explanatory power (R^2 of 0.24 and 0.31, respectively), consistent with their opportunistic and trend-based profiles. These strategies tend to exploit cross-asset dislocations or persistent market trends that are not fully captured by static linear factor models.

Overall, the widespread increase in R^2 values during 2020–2024 indicates that systematic macroeconomic forces once again dominated hedge fund returns. The post-pandemic period's combination of policy normalization, inflation shocks, and rate volatility effectively re-coupled hedge fund performance with traditional risk factors, reversing the pattern of reduced factor dependence and idiosyncratic behavior observed in the preceding decade.

Manager alphas increased markedly during 2020–2024, reversing the decline observed in the 2012–2019 period. Most strategies show higher constants, indicating stronger idiosyncratic performance amid heightened volatility and market dislocation. ED Multi Strategy, Event Driven, and Risk Arbitrage recorded the highest alphas (0.007–0.010), reflecting successful tactical allocation and exploitation of pricing inefficiencies. Distressed Debt, Convertible Arbitrage, and Emerging Markets also improved, consistent with wider credit spreads and greater dispersion across asset classes.

In contrast, Managed Futures remained slightly negative, suggesting limited alpha generation beyond systematic trend exposures. Overall, the period reflects a clear rebound in manager-specific value creation, driven by macro uncertainty and increased cross-market dispersion.

The 2020–2024 period marked a clear reconfiguration of factor relevance within hedge fund returns, reflecting the disruptive macroeconomic environment following the pandemic. Unlike the 2012–2019 phase, when equity exposure was a key explanatory component, the S&P 500 return factor became statistically insignificant across all hedge fund indexes, even at the 5% level. This indicates a decisive decoupling of hedge fund performance from broad equity market movements. The loss of significance suggests that hedge funds either reduced directional equity exposure or that equity market dynamics became too volatile and policy-dependent to explain performance consistently.

Perhaps the most unexpected outcome is that the EM factor ceased to be significant even for the EM hedge fund index. This result implies a substantial structural shift within emerging market strategies, which may have diversified exposures beyond their traditional benchmarks or adopted more market-neutral and macro-hedged positions in response to rising geopolitical and rate-driven risks during this period.

In contrast, the Monthly Change in 10-year Treasury yield factor gained prominence, showing an increase in significance across most strategies. This heightened sensitivity reflects the sharp repricing of fixed-income markets amid the transition from ultra-low to higher interest rates. Only a few categories, Global Macro, Fund of Funds, Multi Strategy, and ED Distressed Debt, did not display significant relationships with this factor, suggesting that the majority of hedge fund styles became more reactive to rate volatility and duration risk during this regime shift.

A further notable change occurred within the trend-following factors: Managed Futures exhibited moderate statistical significance at the 5% level for the Commodity Trend factor, a relationship not previously observed. This aligns with the resurgence of commodity price trends during the inflationary phase of 2021–2023, which created favorable conditions for momentum-based trading systems.

Overall, the coefficient significance patterns in 2020–2024 indicate a broad realignment of hedge fund factor sensitivities toward interest rate dynamics, accompanied by a diminished role for equity and regional market factors. These changes mirror the macroeconomic turbulence of the period, defined by inflation shocks, policy tightening, and market rotation, and demonstrate how hedge fund strategies recalibrated exposures in response to a fundamentally altered investment landscape.

5.4.2. 2020-2024 Beta Replication Analysis

Appendix Table 8 highlights a substantial decline in equity-related exposures across most hedge fund styles compared with the 2012–2019 period. Coefficients on the S&P 500 factor were muted or even negative for several categories, most notably Emerging Markets, Equity

Market Neutral, and Risk Arbitrage, indicating a shift to short exposure. Similarly, exposures to the Size and EM factors weakened or turned negative, suggesting that hedge funds sought to minimize equity beta and regional risk amid heightened global uncertainty. This reduction in equity sensitivity reflects a more defensive portfolio stance following the initial pandemic shock and the later shift in market dynamics associated with rising interest rates and changing sector performance.

Credit spread exposures became markedly more negative across nearly all hedge fund strategies during 2020–2024. As shown in **Appendix Table 8**, the average short exposure on the Credit Spread Factor increased from −46%, in 2012–2019, to roughly −72% in 2020-2024, highlighting a renewed and widespread sensitivity to credit market risk. The most pronounced exposures were observed in the Fund of Funds, Global Macro, Multi Strategy, and Distressed Debt indexes (ranging from −79% to −82%), underscoring how tightening financial conditions and widening corporate spreads during 2022–2023 affected both opportunistic and multi-asset managers. This pattern reflects the sector-wide impact of higher funding costs, diminished liquidity, and a broader repricing of credit risk (IMF, 2023)

By comparison, exposures to the 10-year Treasury yield became less pronounced overall, with the average short exposure declining from −27% to −11%. This suggests that rate risk, while still relevant, played a more asymmetric role (with some strategies switching from short to long exposures) in explaining hedge fund performance relative to credit conditions. Notably, only Managed Futures maintained significant rate sensitivity, consistent with its systematic trading approaches that respond directly to shifts in long-term yields.

The Global Macro and Managed Futures categories displayed distinctive behavior during this period. Global Macro maintained long exposure to both interest rate and commodity trend factors, consistent with its opportunistic positioning during periods of macro dislocation. Managed Futures, meanwhile, showed the strongest long exposures to interest rate changes (44.7%) and commodity trends (0.69%), indicating that trend-following strategies successfully captured momentum in rising yields and commodity price surges.These patterns reaffirm the defensive and adaptive nature of systematic macro strategies, which tend to benefit from strong, directional market moves that re-emerged after years of suppressed volatility (Hurst, Ooi, & Pedersen, 2013)

Overall, the 2020–2024 sub-period reflects a return to macro-driven performance across the hedge fund industry. The reduction in equity exposure and resurgence of rate and credit sensitivities suggest that managers reoriented their portfolios toward risk mitigation and opportunistic trading in an environment dominated by policy uncertainty and regime shifts. The evolution of hedge fund factor exposures across the three sub-periods reveals a clear adaptation of strategies to shifting macroeconomic environments and risk regimes. From the pre- and post-crisis turbulence of 2004–2011, through the liquidity-driven expansion of 2012–2019, to the inflationary and policy-driven uncertainty of 2020–2024, hedge funds consistently recalibrated their exposures in line with prevailing market dynamics.

During 2004–2011, hedge fund returns were primarily influenced by credit and interest rate factors, reflecting the dominance of leverage, liquidity constraints, and systemic stress during the GFC. Negative exposures to credit spreads and heightened sensitivity to bond yields indicated that hedge fund performance was closely tied to the availability and cost of funding. Equity exposures were relatively moderate, suggesting a defensive orientation amid widespread deleveraging and market instability.

In contrast, the 2012–2019 period represented a re-risking phase, as abundant liquidity and QE compressed volatility and revived equity market participation. Hedge funds increased their exposure to equity-related factors (S&P 500, Size, and EM) and reduced dependence on credit risk. This shift illustrated a return to relative-value and event-driven strategies under conditions of policy stability and sustained risk appetite. The subdued macro volatility of this era limited opportunities for systematic trend-following, while favoring discretionary and equity-linked approaches.

The final period, 2020–2024, marked a re-emergence of macro-driven performance following the unprecedented disruptions caused by the COVID-19 pandemic. Hedge funds exhibited sharply reduced equity betas and renewed sensitivity to interest rate and credit factors, consistent with the rapid repricing of duration risk and widening credit spreads during the tightening cycle. Systematic macro and managed futures strategies benefited from this environment, capitalizing on directional trends in bond yields and commodities (Hurst, Ooi, & Pedersen, 2013; Kaminski & Zhao, 2023). The reappearance of these large-scale macro trends underscored the adaptive and defensive qualities of such strategies after years of suppressed volatility.

The evolution of factor exposures across periods illustrates the hedge fund industry’s capacity to adjust dynamically to shifting market conditions. Rather than relying on a single source of systematic risk, hedge funds recalibrate their exposure profiles across equity, credit, and macro factors as prevailing return drivers change. This adaptability underscores their role as active managers of factor risk, capable of both mitigating and capitalizing on evolving macro-financial environments.

6. Conclusion

This thesis set out to explore how hedge fund strategies behave across different market environments and to what extent their returns can be explained by systematic risk factors rather than unique alpha generation. Using the extended Fung–Hsieh eight-factor model, it analyzed eleven Credit Suisse Hedge Fund Indexes between 2004 and 2024, a period that includes both stability and major disruptions such as the GFC and the COVID-19 pandemic. The goal was to better understand how hedge funds adapt to uncertainty, how their factor exposures evolve, and whether their performance reflects skill or systematic risk-taking.

The results suggest that hedge fund performance is strongly linked to common risk factors, particularly during periods of market stress. Across strategies, the model's explanatory power (R^2) increased notably during crisis years, indicating that returns became more synchronized with broad market movements. This pattern supports the idea that diversification benefits within the hedge fund universe tend to weaken when markets are most volatile. During calmer periods, however, exposures were more differentiated, with certain strategies showing distinct behavior that may reflect active management or timing ability.

Differences across strategies were also evident. Event Driven and Emerging Markets funds exhibited higher sensitivity to traditional equity market and EM factors, reflecting their exposure to corporate activity and global growth dynamics.In contrast, Managed Futures strategies maintained more stable and often contrarian exposures, benefiting from trend-following factors during both crisis and recovery phases. These patterns highlight the heterogeneity of hedge fund strategies and suggest that some may offer better protection or adaptability under stress than others.

Overall, the findings support the hypothesis that systematic risk exposures are the dominant drivers of hedge fund returns, particularly in turbulent times when markets become more correlated. While genuine manager skill likely plays a role, much of what appears as alpha can often be traced back to dynamic factor exposures. This reinforces the relevance of the Fung–Hsieh framework and demonstrates its continued ability to explain hedge fund behavior even two decades after it was first introduced.

Nevertheless, the study has some limitations. It relies on index-level data, which smooths out fund-specific differences and may understate idiosyncratic performance. Additionally, the linear structure of the factor model cannot fully capture nonlinear exposures or dynamic trading behavior that many hedge funds employ. Future research could address these issues by incorporating fund-level data, higher-frequency observations, or more flexible modeling approaches, such as time-varying betas or machine learning techniques.

Ultimately, this thesis does not aim to solve the mystery of hedge funds but to make it a little clearer. By revisiting the Fung–Hsieh model with two decades of new data, it shows how much of hedge fund performance can be explained by systematic risks and how these relationships evolve under different financial conditions. In an industry that often values secrecy over transparency, even a small step toward understanding what truly drives returns can bring meaningful insight, and perhaps a bit of the "radical transparency" that Ray Dalio once called for.

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8. Appendix

Table 1 - 2004-2024 Regression Table

2004-2024	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.00623	0.0529*	0.101**	0.00292	0.0320	-0.144*	0.0820**	0.0417	0.0506*	0.0396	0.0845
St. Deviation	(0.0263)	(0.0236)	(0.0347)	(0.0231)	(0.0422)	(0.0578)	(0.0293)	(0.0379)	(0.0256)	(0.0239)	(0.0621)
Size effect	0.00873	0.0678*	0.121**	0.0449	-0.0382	0.108	0.104**	-0.0154	0.0184	-0.00864	0.0204
St. Deviation	(0.0303)	(0.0272)	(0.0400)	(0.0267)	(0.0488)	(0.0668)	(0.0338)	(0.0438)	(0.0295)	(0.0276)	(0.0717)
MSCI EM Returns	0.0751***	0.0282	0.00662	0.0319	0.168***	0.0382	0.0150	0.0188	0.0391*	0.0381*	-0.00468
St. Deviation	(0.0188)	(0.0168)	(0.0248)	(0.0165)	(0.0302)	(0.0413)	(0.0209)	(0.0271)	(0.0182)	(0.0171)	(0.0443)
Monthly Change 10y	-0.832	0.508	0.0925	-0.978*	-1.272	-1.122	0.147	0.145	0.00597	0.282	0.491
St. Deviation	(0.429)	(0.386)	(0.567)	(0.378)	(0.691)	(0.946)	(0.479)	(0.620)	(0.418)	(0.391)	(1.015)
Credit Spread Factor	-4.511***	-2.383***	-2.691***	-1.720**	-2.607**	-5.450***	-2.613***	-1.487	-2.212***	-2.602***	0.512
St. Deviation	(0.604)	(0.542)	(0.797)	(0.532)	(0.971)	(1.330)	(0.674)	(0.872)	(0.588)	(0.550)	(1.427)
Bond Trend	0.000696	-0.0159***	-0.0228***	-0.00887*	-0.0226**	-0.0244*	-0.0205***	-0.00173	-0.0102*	-0.00820*	0.0209*
St. Deviation	(0.00438)	(0.00394)	(0.00579)	(0.00386)	(0.00705)	(0.00965)	(0.00489)	(0.00632)	(0.00426)	(0.00399)	(0.0104)
Currency Trend	-0.0103*	-0.00549	-0.00637	-0.00437	0.000383	0.0133	-0.00626	0.00325	-0.000652	-0.000786	0.0256*
St. Deviation	(0.00476)	(0.00427)	(0.00628)	(0.00419)	(0.00765)	(0.0105)	(0.00530)	(0.00686)	(0.00463)	(0.00433)	(0.0112)
Commodity Trend	-0.00823	-0.00663	-0.0121	-0.00353	-0.0128	0.0112	-0.00971	0.00836	-0.00258	-0.00369	0.0194
St. Deviation	(0.00585)	(0.00525)	(0.00772)	(0.00515)	(0.00940)	(0.0129)	(0.00652)	(0.00843)	(0.00569)	(0.00532)	(0.0138)
Constant	0.00298***	0.00418***	0.00425***	0.00356***	0.00422***	0.00257	0.00422***	0.00493***	0.00392***	0.00443***	0.00296
St. Deviation	(0.000787)	(0.000707)	(0.00104)	(0.000694)	(0.00127)	(0.00173)	(0.000878)	(0.00114)	(0.000766)	(0.000716)	(0.00186)
R-squared	0.554	0.533	0.457	0.266	0.434	0.134	0.501	0.0824	0.392	0.427	0.0916

Standard errors in parentheses(5%)	1%	0.1%
* p<0.05	** p<0.01	*** p<0.001"

Table 1- 2004-2024 Regression Table
Source: Author's computation

Table 2 - 2004-2024 Beta Replication Table

2004-2024	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.11%	1.72%	3.31%	0.10%	0.77%	-2.08%	2.74%	2.42%	2.16%	1.33%	7.17%
Size effect	0.16%	2.21%	3.96%	1.61%	-0.92%	1.56%	3.47%	-0.89%	0.79%	-0.29%	1.73%
MSCI EM Returns	1.38%	0.92%	0.22%	1.14%	4.05%	0.55%	0.50%	1.09%	1.67%	1.28%	-0.40%
Monthly Change 10y	-15.26%	16.56%	3.03%	-35.00%	-30.63%	-16.23%	4.90%	8.42%	0.26%	9.45%	41.66%
Credit Spread Factor	-82.74%	-77.67%	-88.13%	-61.55%	-62.77%	-78.86%	-87.17%	-86.39%	-94.55%	-87.23%	43.45%
Bond Trend	0.01%	-0.52%	-0.75%	-0.32%	-0.54%	-0.35%	-0.68%	-0.10%	-0.44%	-0.27%	1.77%
Currency Trend	-0.19%	-0.18%	-0.21%	-0.16%	0.01%	0.19%	-0.21%	0.19%	-0.03%	-0.03%	2.17%
Commodity Trend	-0.15%	-0.22%	-0.40%	-0.13%	-0.31%	0.16%	-0.32%	0.49%	-0.11%	-0.12%	1.65%

Table 2- 2004-2024 Beta Replication Table
Source: Author's computation

Table 3 - 2004-2011 Regression Table

2004-2011	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.0131	0.0904*	0.136**	0.00723	0.114	-0.267*	0.116**	0.0478	0.0649	0.0279	0.0987
St. Deviation	(0.0536)	(0.0354)	(0.0511)	(0.0293)	(0.0752)	(0.123)	(0.0421)	(0.0491)	(0.0436)	(0.0382)	(0.102)
Size effect	-0.0560	-0.0664	-0.0688	-0.128**	-0.186	0.381*	-0.0687	-0.102	-0.0603	-0.0329	0.00543
St. Deviation	(0.0805)	(0.0531)	(0.0768)	(0.0440)	(0.113)	(0.184)	(0.0632)	(0.0738)	(0.0655)	(0.0574)	(0.153)
MSCI EM Returns	0.0719*	0.0366	0.0288	0.0428*	0.139**	0.0699	0.0322	0.0519	0.0587*	0.0609*	0.0182
St. Deviation	(0.0351)	(0.0232)	(0.0335)	(0.0192)	(0.0493)	(0.0804)	(0.0276)	(0.0322)	(0.0286)	(0.0250)	(0.0667)
Monthly Change 10y	-1.176	1.380*	1.879*	-0.350	-0.983	-3.348	1.660*	-0.117	0.399	0.248	2.062
St. Deviation	(0.914)	(0.603)	(0.872)	(0.500)	(1.283)	(2.091)	(0.718)	(0.838)	(0.744)	(0.651)	(1.735)
Credit Spread Factor	-5.305***	-1.637*	-1.082	-1.272*	-1.790	-7.303**	-1.305	-0.753	-1.797*	-2.750***	1.968
St. Deviation	(1.067)	(0.705)	(1.018)	(0.584)	(1.498)	(2.441)	(0.838)	(0.979)	(0.869)	(0.761)	(2.026)
Bond Trend	-0.0212	-0.0449***	-0.0488***	-0.0249**	-0.0579**	-0.103**	-0.0471***	-0.00130	-0.0352**	-0.0345**	0.0313
St. Deviation	(0.0149)	(0.00982)	(0.0142)	(0.00814)	(0.0209)	(0.0340)	(0.0117)	(0.0136)	(0.0121)	(0.0106)	(0.0282)
Currency Trend	-0.0134	0.0124	0.0183	0.0139*	0.00575	0.0189	0.0160	0.00146	0.00868	0.00401	0.0295
St. Deviation	(0.0112)	(0.00740)	(0.0107)	(0.00613)	(0.0157)	(0.0256)	(0.00880)	(0.0103)	(0.00913)	(0.00799)	(0.0213)
Commodity Trend	-0.0136	-0.00106	-0.00238	-0.00486	0.00170	0.0357	-0.00218	0.0198	0.00779	-0.00203	0.0414
St. Deviation	(0.0134)	(0.00886)	(0.0128)	(0.00735)	(0.0188)	(0.0307)	(0.0105)	(0.0123)	(0.0109)	(0.00957)	(0.0255)
Constant	0.00240	0.00375**	0.00398*	0.00270**	0.00316	-0.00420	0.00382**	0.00700***	0.00326*	0.00325*	0.00544
St. Deviation	(0.00182)	(0.00120)	(0.00174)	(0.000998)	(0.00256)	(0.00417)	(0.00143)	(0.00167)	(0.00148)	(0.00130)	(0.00346)
R-squared	0.619	0.648	0.509	0.353	0.474	0.301	0.585	0.206	0.497	0.61	0.144

Standard errors in parentheses(5%)	1%	0.1%
* p<0.05	** p<0.01	*** p<0.001"

Table 3- 2004-2011 Regression Table
Source: Author’s computation

Table 4 - 2004-2011 Beta Replication Table

2004-2011	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.20%	2.77%	4.17%	0.39%	3.48%	-2.32%	3.57%	4.37%	2.67%	0.88%	2.32%
Size effect	-0.84%	-2.03%	-2.11%	-6.94%	-5.68%	3.31%	-2.12%	-9.32%	-2.48%	-1.04%	0.13%
MSCI EM Returns	1.08%	1.12%	0.88%	2.32%	4.24%	0.61%	0.99%	4.74%	2.41%	1.93%	0.43%
Monthly Change 10y	-17.63%	42.22%	57.57%	-18.98%	-29.99%	-29.05%	51.12%	-10.69%	16.41%	7.85%	48.47%
Credit Spread Factor	-79.53%	-50.08%	-33.15%	-68.99%	-54.62%	-63.36%	-40.19%	-68.81%	-73.90%	-87.02%	46.26%
Bond Trend	-0.32%	-1.37%	-1.50%	-1.35%	-1.77%	-0.89%	-1.45%	-0.12%	-1.45%	-1.09%	0.74%
Currency Trend	-0.20%	0.38%	0.56%	0.75%	0.18%	0.16%	0.49%	0.13%	0.36%	0.13%	0.69%
Commodity Trend	-0.20%	-0.03%	-0.07%	-0.26%	0.05%	0.31%	-0.07%	1.81%	0.32%	-0.06%	0.97%

Table 4- 2004-2011 Beta Replication Table
Source: Author’s computation

Table 5 - 2012-2019 Regression Table

2012-2019	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.00866	0.0658	0.139*	0.0312	0.0866	0.0372	0.116*	0.105*	0.122**	0.108**	0.289*
St. Deviation	(0.0346)	(0.0421)	(0.0609)	(0.0344)	(0.0722)	(0.0634)	(0.0524)	(0.0490)	(0.0407)	(0.0355)	(0.126)
Size effect	0.124**	0.0548	0.110	0.0636	-0.0242	0.0164	0.0932	0.0262	0.0484	0.0384	0.0560
St. Deviation	(0.0367)	(0.0447)	(0.0646)	(0.0365)	(0.0767)	(0.0673)	(0.0557)	(0.0520)	(0.0432)	(0.0376)	(0.134)
MSCI EM Returns	0.0937***	0.0416	0.0758	0.0509*	0.186***	-0.0339	0.0674	0.0496	0.0435	0.0186	-0.0770
St. Deviation	(0.0242)	(0.0295)	(0.0427)	(0.0241)	(0.0507)	(0.0444)	(0.0368)	(0.0344)	(0.0286)	(0.0249)	(0.0882)
Monthly Change 10y	-0.311	0.257	-0.0909	0.405	-1.572	-0.463	0.0266	-1.518	-1.387*	-1.321*	-9.890***
St. Deviation	(0.581)	(0.707)	(1.023)	(0.578)	(1.213)	(1.064)	(0.880)	(0.823)	(0.684)	(0.596)	(2.113)
Credit Spread Factor	-1.539	-2.077*	-2.388	0.700	-1.069	-1.619	-2.255	-0.990	-1.228	-1.245	-0.174
St. Deviation	(0.849)	(1.034)	(1.496)	(0.845)	(1.774)	(1.556)	(1.288)	(1.203)	(1.000)	(0.871)	(3.090)
Bond Trend	0.00333	-0.0121	-0.000791	0.00397	-0.0244*	-0.00289	-0.00371	0.00239	-0.00442	-0.00121	-0.00666
St. Deviation	(0.00568)	(0.00692)	(0.0100)	(0.00565)	(0.0119)	(0.0104)	(0.00862)	(0.00805)	(0.00669)	(0.00583)	(0.0207)
Currency Trend	-0.00936	-0.00530	-0.0119	-0.00822	0.0134	-0.00161	-0.0101	0.0212**	0.00503	0.00342	0.0610**
St. Deviation	(0.00498)	(0.00606)	(0.00877)	(0.00495)	(0.0104)	(0.00912)	(0.00755)	(0.00705)	(0.00586)	(0.00510)	(0.0181)
Commodity Trend	-0.00530	-0.00632	-0.00544	-0.00906	-0.0245*	-0.0111	-0.00550	-0.00801	-0.0114	-0.0104	-0.0209
St. Deviation	(0.00540)	(0.00657)	(0.00951)	(0.00537)	(0.0113)	(0.00990)	(0.00819)	(0.00765)	(0.00636)	(0.00554)	(0.0196)
Constant	0.00258**	0.00244*	0.00112	0.00194*	0.00262	0.000457	0.00153	0.00218	0.00206*	0.00372***	-0.0000542
St. Deviation	(0.000810)	(0.000985)	(0.00143)	(0.000805)	(0.00169)	(0.00148)	(0.00123)	(0.00115)	(0.000953)	(0.000830)	(0.00295)
R-squared	0.489	0.424	0.404	0.260	0.441	0.0418	0.427	0.299	0.381	0.323	0.320

Standard errors in parentheses(5%)	1%	0.1%
* p<0.05	** p<0.01	*** p<0.001"

Table 5- 2012-2019 Regression Table
Source: Author’s computation

Table 6 - 2012-2019 Beta Replication Table

2012-2019	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.41%	2.61%	4.93%	2.45%	2.89%	1.70%	4.50%	3.86%	4.28%	3.93%	2.73%
Size effect	5.92%	2.17%	3.90%	5.00%	-0.81%	0.75%	3.62%	0.96%	1.70%	1.40%	0.53%
MSCI EM Returns	4.47%	1.65%	2.69%	4.00%	6.20%	-1.55%	2.61%	1.82%	1.53%	0.68%	-0.73%
Monthly Change 10y	-14.85%	10.20%	-3.22%	31.84%	-52.40%	-21.19%	1.03%	-55.80%	-48.67%	-48.11%	-93.53%
Credit Spread Factor	-73.48%	-82.42%	-84.63%	55.03%	-35.63%	-74.09%	-87.49%	-36.39%	-43.09%	-45.34%	-1.65%
Bond Trend	0.16%	-0.48%	-0.03%	0.31%	-0.81%	-0.13%	-0.14%	0.09%	-0.16%	-0.04%	-0.06%
Currency Trend	-0.45%	-0.21%	-0.42%	-0.65%	0.45%	-0.07%	-0.39%	0.78%	0.18%	0.12%	0.58%
Commodity Trend	-0.25%	-0.25%	-0.19%	-0.71%	-0.82%	-0.51%	-0.21%	-0.29%	-0.40%	-0.38%	-0.20%

Table 6 - 2012-2019 Beta Replication Table
Source: Author's computation

Table 7 - 2020-2024 Regression Table

2020-2024	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.0232	0.0473	0.0179	-0.0283	-0.154	-0.0750	0.0197	0.0935	0.0310	0.0919	0.117
St. Deviation	(0.0431)	(0.0616)	(0.0811)	(0.0649)	(0.0964)	(0.0546)	(0.0701)	(0.125)	(0.0585)	(0.0660)	(0.116)
Size effect	0.0311	0.115*	0.189**	0.115*	-0.0209	-0.0440	0.168**	0.0385	0.0407	-0.00678	-0.0474
St. Deviation	(0.0344)	(0.0492)	(0.0647)	(0.0518)	(0.0769)	(0.0436)	(0.0559)	(0.0999)	(0.0466)	(0.0527)	(0.0925)
MSCI EM Returns	0.00558	-0.0710	-0.115	-0.0201	0.152	-0.00869	-0.0950	-0.271*	-0.103*	-0.0945	-0.195*
St. Deviation	(0.0359)	(0.0513)	(0.0674)	(0.0540)	(0.0801)	(0.0454)	(0.0583)	(0.104)	(0.0486)	(0.0549)	(0.0965)
Monthly Change 10y	-1.292*	-0.999	-2.969**	-2.772**	-3.026*	-2.224**	-2.549**	1.156	-0.876	0.517	4.076*
St. Deviation	(0.570)	(0.814)	(1.071)	(0.857)	(1.272)	(0.721)	(0.925)	(1.653)	(0.772)	(0.872)	(1.531)
Credit Spread Factor	-4.336***	-4.791**	-7.801***	-6.408***	-8.344**	-4.495**	-6.911***	-7.065*	-5.042**	-3.348	-4.592
St. Deviation	(1.126)	(1.609)	(2.116)	(1.694)	(2.515)	(1.426)	(1.829)	(3.268)	(1.526)	(1.723)	(3.027)
Bond Trend	-0.00126	-0.00509	-0.0175	-0.00747	-0.0155	-0.00488	-0.0140	-0.00347	-0.00562	-0.00526	0.0271*
St. Deviation	(0.00467)	(0.00668)	(0.00878)	(0.00703)	(0.0104)	(0.00592)	(0.00759)	(0.0136)	(0.00633)	(0.00715)	(0.0126)
Currency Trend	-0.00440	-0.0259**	-0.0361**	-0.0245*	-0.0101	0.000633	-0.0326**	-0.0195	-0.0196*	-0.0121	-0.00736
St. Deviation	(0.00637)	(0.00910)	(0.0120)	(0.00958)	(0.0142)	(0.00806)	(0.0103)	(0.0185)	(0.00863)	(0.00974)	(0.0171)
Commodity Trend	0.00173	-0.00703	-0.0263	0.0341*	0.00462	-0.00723	-0.0175	0.0598	0.00351	0.00848	0.0634*
St. Deviation	(0.0105)	(0.0150)	(0.0198)	(0.0158)	(0.0235)	(0.0133)	(0.0171)	(0.0305)	(0.0143)	(0.0161)	(0.0283)
Constant	0.00425**	0.00600**	0.0102***	0.00783***	0.00708*	0.00548**	0.00913***	0.00453	0.00603**	0.00431*	-0.000654
St. Deviation	(0.00134)	(0.00191)	(0.00251)	(0.00201)	(0.00298)	(0.00169)	(0.00217)	(0.00388)	(0.00181)	(0.00204)	(0.00359)
R-squared	0.633	0.646	0.725	0.589	0.523	0.320	0.729	0.244	0.537	0.390	0.311

Standard errors in parentheses(5%)	1%	0.1%
* p<0.05	** p<0.01	*** p<0.001"

Table 7 - 2020-2024 Regression Table
Source: Author’s computation

Table 8 - 2020-2024 Beta Replication Table

2020-2024	Cvtb Arbt	ED Dst Debt	ED Mlt Stg	ED Rsk Arbt	Emg Mkt	Eqt Mkt Ntral	Evnt Driven	Glb Macro	Hedge Fnd	Mlt Strategy	Mng Ftr
SP Returns	0.41%	0.78%	0.16%	-0.30%	-1.31%	-1.09%	0.20%	1.07%	0.51%	2.25%	1.28%
Size effect	0.55%	1.90%	1.69%	1.22%	-0.18%	-0.64%	1.71%	0.44%	0.66%	-0.17%	-0.52%
MSCI EM Returns	0.10%	-1.17%	-1.03%	-0.21%	1.30%	-0.13%	-0.97%	-3.11%	-1.68%	-2.31%	-2.14%
Monthly Change 10y	-22.69%	-16.48%	-26.58%	-29.46%	-25.80%	-32.42%	-25.99%	13.28%	-14.31%	12.66%	44.67%
Credit Spread Factor	-76.13%	-79.04%	-69.83%	-68.10%	-71.15%	-65.53%	-70.47%	-81.14%	-82.37%	-81.98%	-50.32%
Bond Trend	-0.02%	-0.08%	-0.16%	-0.08%	-0.13%	-0.07%	-0.14%	-0.04%	-0.09%	-0.13%	0.30%
Currency Trend	-0.08%	-0.43%	-0.32%	-0.26%	-0.09%	0.01%	-0.33%	-0.22%	-0.32%	-0.30%	-0.08%
Commodity Trend	0.03%	-0.12%	-0.24%	0.36%	0.04%	-0.11%	-0.18%	0.69%	0.06%	0.21%	0.69%

Table 8 - 2020-2024 Beta Replication Table
Source: Author’s computation

Formula 1 - Beta Replication Formula

$$w_{ik} = \frac{\beta_{ik}}{\sum_{j=1}^{8} \left|\beta_{ij}\right|}$$

Formula 1 - Beta Replication Formula
Source: Author's work

i → Represents the specific Hedge Fund index or strategy.

k → Represents the specific Risk Factor being evaluated
βik→ The estimated regression coefficient (loading) of strategy i on factor k

wik→ The normalized exposure (beta replication weight) of strategy i to factor k, expressed as a proportion of the total absolute exposure.
K → The total number of factors in the model (in this case, $K = 8$).

j → The index of summation, used in the denominator to iterate through all risk factors (1 to K) for strategy i