"Exploring the Dynamics of Hedge Fund Performance: A Regional and Typological Analysis"

Data Science Project – Final Project

at the

Faculty of Economics and Business

of the

University of Neuchâtel

with

Prof. Florian Weigert

as part of the

« Master of Science in Finance »

Author and student number:

Samuel Keiling / 22509798

Table of Content

List of Figures and Graphs

Executive Summary

This project, titled "Exploring the Dynamics of Hedge Fund Performance: A Regional and Typological Analysis," delves into the complex performance dynamics of hedge funds by examining trends, correlations, and volatilities across different regions and strategies. Utilizing data from HFR.com, the study analyzes a comprehensive dataset that encompasses a wide array of hedge fund types and geographic regions.

The research aims to provide a foundational understanding of the data characteristics and the analytical methods employed, which include time-series and correlation analyses, as well as more sophisticated volatility assessments.

The analysis section offers an empirical examination of hedge fund performance, highlighting significant trends and patterns that emerge over time and across various fund types. It explores the interdependencies between regional market events and hedge fund strategies, quantifying these relationships through correlation coefficients. Additionally, the volatility analysis provides insights into the risk profiles of each hedge fund category, offering a comparative perspective on the stability versus reward paradigms inherent in different investment strategies.

The discussion section synthesizes the findings, outlining their implications for investors and fund managers, particularly regarding investment strategies and risk management. The project concludes with a summary of the key insights, recommendations for stakeholders based on the analyzed data, and suggestions for future research directions that could further enhance the understanding of hedge fund performance dynamics.

1. Introduction

Hedge funds are pivotal entities within the financial markets, known for their diverse strategies and significant impact on investment portfolios. Understanding the dynamics of hedge fund performance is crucial for investors and fund managers who aim to optimize investment decisions and manage risks effectively. This project, "Exploring the Dynamics of Hedge Fund Performance: A Regional and Typological Analysis," provides a comprehensive data-driven analysis of hedge fund performance across various regions and strategies.

Objectives of the Study:

The primary objective of this research is to dissect and understand the performance dynamics of hedge funds by leveraging analytical techniques. The study focuses on three main aspects:

Trend Analysis: To identify and analyze performance trends of hedge funds across different regions (e.g.: North America, Europe, Asia including Japan) and strategies (e.g.: equity hedge, macro, and event-driven).

Correlation Analysis: To examine the relationships between hedge fund performances across various regions and strategies.

Volatility Analysis: To assess and compare the volatility of returns among hedge funds of different regions and strategies.

The report is structured as follows: The methodology section details the analytical approaches used. The analysis section presents empirical findings on hedge fund performance. The conclusion and discussion sections synthesize these findings, offering implications and recommendations for stakeholders.

2. Data

Descriptive Overview:

The dataset used in this study comprises 16,109 observations across five key variables: date, index name, index code, monthly returns, and index value. Sourced from HFR.com, this dataset offers 30 years of monthly hedge fund performance.

This dataset is particularly valuable if a categorization of each fund can be made. Such diversity allows for an in-depth analysis of how different strategies perform under varying economic conditions and regional influences. The structured data supports a progression from simple descriptive statistics to more precise analytical models, including time-series analysis, correlation analysis, and volatility assessment.

Key Variables:

Date: Represents the time-period of the recorded performance data, essential for time-series analysis.

Index Name: Provides the name of the hedge fund index, offering insights into the specific category or region of the fund.

Index Code: An numeric code corresponding to the index name, used for precise identification and categorization.

Monthly Returns: Measures the performance of hedge funds on a monthly basis, serving as the primary indicator of performance trends.

Index Value: Values of the individual funds included in the dataset.

The dataset's structured enables a focused analysis of hedge fund performance. Using analytical techniques in R, including time-series analysis to track performance trends, correlation analysis to explore interdependencies between regions and strategies, and volatility analysis to assess risk profiles, provides a robust framework for addressing the study objective.

Overall, the "HFR" dataset offers a solid foundation for exploring how regional and strategic factors influence hedge fund performance, providing valuable insights for investors and fund managers seeking to optimize their investment decisions and manage risks effectively.

3. Methodology

This section outlines the methodological approach adopted to analyze the performance dynamics of hedge funds across different regions and strategies. The methodology is structured into three main analytical components: trend analysis, correlation analysis, and volatility analysis. To categorize each fund by type and region, manual sorting was performed based on the provided index names and codes.

Trend Analysis

The primary objective of the trend analysis is to identify and analyze performance trends of hedge funds across different regions, including North America, Europe, and Asia (including Japan), as well as various strategies such as equity hedge, macro, and event-driven, over time.

The initial step in the trend analysis involved data preparation. This included preprocessing the dataset to ensure accuracy and consistency by handling missing values, standardizing date formats, and converting percentage returns to numeric format. Following this, each fund was manually sorted into categories based on type and region using the index names and codes provided.

Once the data was prepared and categorized, the monthly returns were aggregated into yearly returns to facilitate clearer visualization and analysis of performance trends. These yearly returns were then organized into time-series for each region and strategy, allowing for the tracking and visualization of performance trends over time. Performance trends were visualized using line charts, with time on the x-axis and yearly returns on the y-axis, helping to identify periods of significant change and overall growth rates.

Correlation Analysis

The objective of the correlation analysis is to examine the relationships between the performances of hedge funds across different regions and strategies. This helps in understanding how global events or regional dynamics affect various hedge fund strategies.

To achieve this, the dataset was segmented by region and strategy, creating subsets for detailed correlation analysis. Pearson correlation coefficients were calculated between the yearly returns of different fund indices to assess linear relationships. Additionally, correlation matrices were generated to visualize the relationships between different regions and strategies, helping to identify strong correlations and potential leading or lagging indicators.

Volatility Analysis

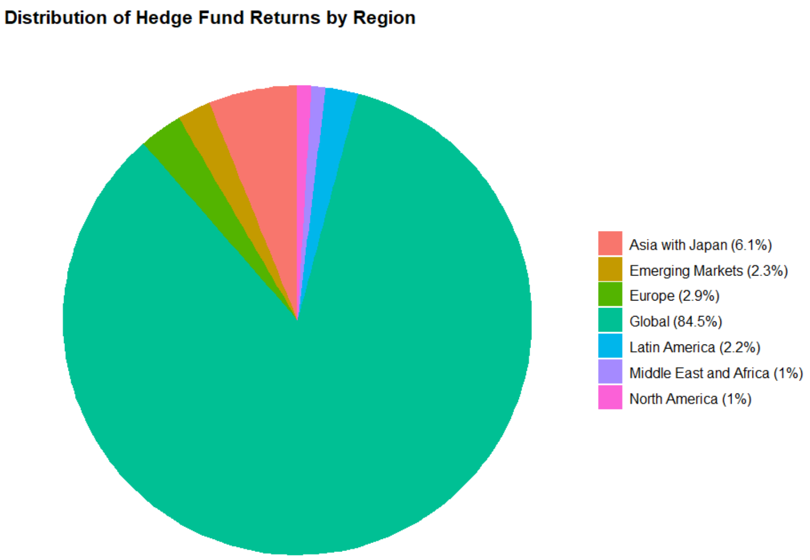
The volatility analysis aims to assess and compare the volatility of returns among hedge funds from different regions and strategies, providing insights into the risk profiles associated with each category.

In this analysis, several volatility metrics such as standard deviation, variance, and beta were computed for each fund index over the considered time period. These metrics were then compared across different regions and strategies to identify which categories exhibit higher volatility. Furthermore, the analysis included the evaluation of risk-adjusted returns using metrics such as the Sharpe ratio, which provides a balanced view of risk versus reward for each hedge fund category.

4. Analysis

Before delving deeper into each specific part, a descriptive analysis of the data is conducted to provide an overview of the general landscape. This preliminary examination sets the stage for a more detailed exploration of hedge fund performance through Trend Analysis, Correlation Analysis, and Volatility Analysis, each offering distinct insights into various regional and strategic dimensions.

Figure 1



The pie chart illustrates the distribution of hedge fund returns by region, showing the proportion each region contributes to the overall hedge fund landscape. Here's a brief analysis linking the index mapping who was created:

Global (84.5%)

- This is the largest segment, encompassing a variety of strategies and indices:
    - **Other**: HFRI Asset Weighted Composite Index, HFRI Fund Weighted Composite Index (various currencies like CHF, EUR, GBP, JPY), HFRI World Index.
    - **Credit**: HFRI Credit Index.
    - **Diversity**: HFRI Diversity Index, HFRI Women Index.
    - **Event-Driven**: HFRI ED indices (Activist, Credit Arbitrage, Distressed/Restructuring, Merger Arbitrage, Multi-Strategy, Special Situations), HFRI Event-Driven (Total) Index, HFRI Event-Driven (Total) Index - Asset Weighted.
    - **Equity Hedge**: HFRI EH indices (Equity Market Neutral, Fundamental Growth, Fundamental Value, Multi-Strategy, Quantitative Directional, Sector-specific indices), HFRI Equity Hedge (Total) Index, HFRI Equity Hedge (Total) Index - Asset Weighted.
    - **Emerging Markets**: HFRI Emerging Markets: Global Index.

    - **Fund of Funds**: HFRI FOF indices (Conservative, Diversified, Market Defensive, Strategic), HFRI Fund of Funds Composite Index.
    - **Macro**: HFRI Macro indices (Total, Active Trading, Commodity, Currency, Discretionary Thematic, Multi-Strategy, Systematic Diversified), HFRI Macro (Total) Index, HFRI Macro (Total) Index - Asset Weighted.
    - **Relative Value**: HFRI Relative Value indices (Total, Fixed Income-Asset Backed, Fixed Income-Convertible Arbitrage, Fixed Income-Corporate, Fixed Income-Sovereign, Multi-Strategy, Volatility, Yield Alternatives), HFRI Relative Value (Total) Index, HFRI Relative Value (Total) Index - Asset Weighted.

Asia with Japan (6.1%)

- **Equity Hedge**: HFRI Asia with Japan Index, HFRI Japan Index.
- **Emerging Markets**: HFRI Emerging Markets (various indices like Asia ex-Japan, China, India).

Europe (2.9%)

- **Equity Hedge**: HFRI Western/Pan Europe Index.
- **Emerging Markets**: HFRI Emerging Markets: Russia/Eastern Europe Index.

Emerging Markets (2.3%)

- This includes indices specific to emerging market economies:
    - **Other**: HFRI Emerging Markets (Total) Index.
    - **Regional Indices** : HFRI Emerging Markets (various indices like Asia ex-Japan, China, India, Latin America, MENA, Russia/Eastern Europe).

Latin America (2.2%)

- **Emerging Markets**: HFRI Emerging Markets: Latin America Index.

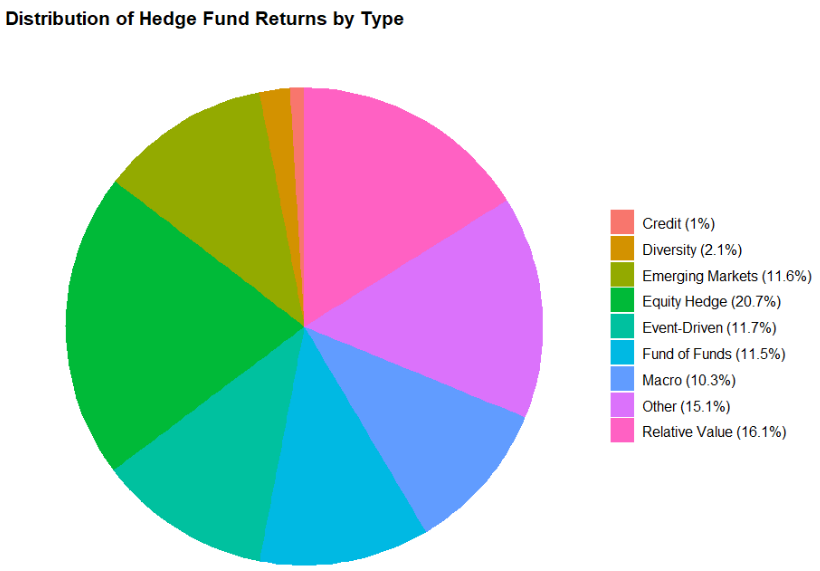
Middle East and Africa (1%)

- **Emerging Markets**: HFRI Emerging Markets: MENA Index.

North America (1%)

- **Equity Hedge**: HFRI North America Index.

Figure 2



This second pie chart provides a visual distribution of hedge fund returns by type, showing the proportion each strategy contributes to the overall hedge fund landscape.

Equity Hedge (20.7%)

- Indices: HFRI Asia with Japan Index, HFRI Japan Index, HFRI EH (various indices like Equity Market Neutral, Fundamental Growth, Fundamental Value, Multi-Strategy, Quantitative Directional, Sector-specific indices), HFRI Equity Hedge (Total) Index, HFRI Equity Hedge (Total) Index - Asset Weighted, HFRI North America Index, HFRI Western/Pan Europe Index.

Relative Value (16.1%)

- Indices: HFRI Relative Value (Total) Index, HFRI Relative Value (Total) Index - Asset Weighted, HFRI RV (various indices like Fixed Income-Asset Backed, Fixed Income-Convertible Arbitrage, Fixed Income-Corporate, Fixed Income-Sovereign, Multi-Strategy, Volatility, Yield Alternatives).

Other (15.1%)

- Indices: HFRI Asset Weighted Composite Index, HFRI Fund Weighted Composite Index (various currencies like CHF, EUR, GBP, JPY), HFRI World Index.

Emerging Markets (11.6%)

- Indices: HFRI Emerging Markets (Total) Index, HFRI Emerging Markets (various indices like Asia ex-Japan, China, Global, India, Latin America, MENA, Russia/Eastern Europe).

Event-Driven (11.7%)

- Indices: HFRI ED (various indices like Activist, Credit Arbitrage, Distressed/Restructuring, Merger Arbitrage, Multi-Strategy, Special Situations), HFRI Event-Driven (Total) Index, HFRI Event-Driven (Total) Index - Asset Weighted.

Fund of Funds (11.5%)

- Indices: HFRI FOF (various indices like Conservative, Diversified, Market Defensive, Strategic), HFRI Fund of Funds Composite Index.

Macro (10.3%)

- Indices: HFRI Macro (Total) Index, HFRI Macro (Total) Index - Asset Weighted, HFRI Macro (various indices like Active Trading, Commodity, Currency, Discretionary Thematic, Multi-Strategy, Systematic Diversified).

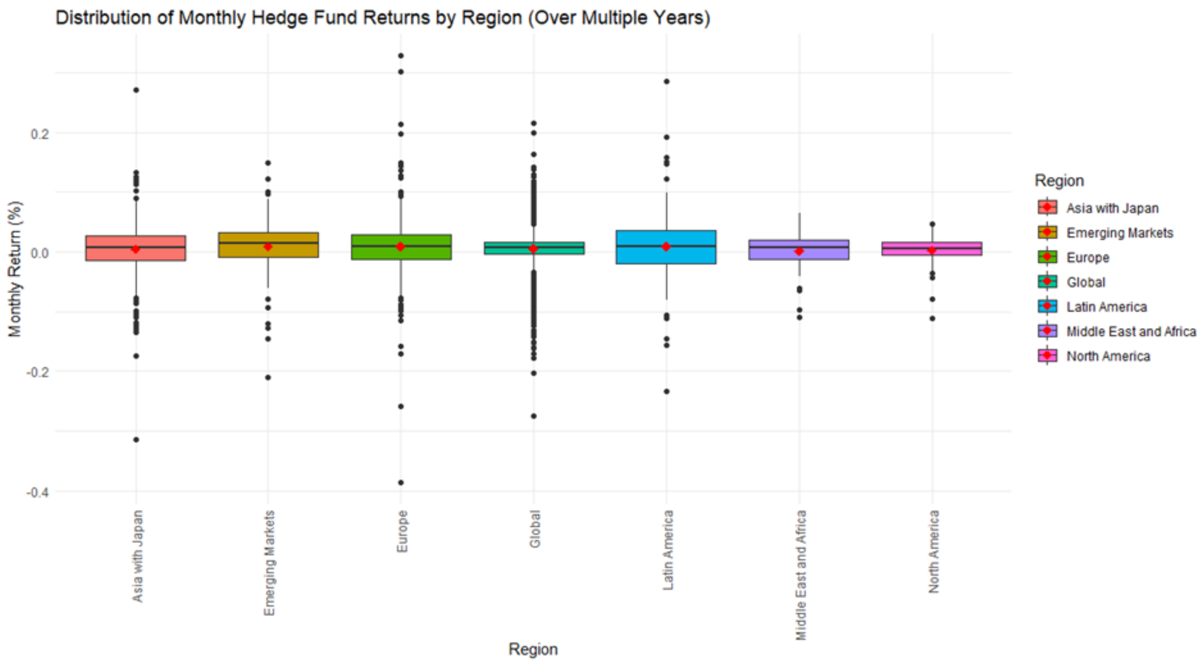
Diversity (2.1%)

- Indices: HFRI Diversity Index, HFRI Women Index.

Credit (1%)

- Indices : HFRI Credit Index.

Figure 3



The box plot above illustrates the distribution of monthly returns for hedge funds across different regions over multiple years, providing insights into their performance characteristics in terms of central tendency, dispersion, and the presence of outliers.

Central Tendency and Variability:

- The median monthly returns for all regions are closely clustered around the zero mark, indicating that, on average, the monthly returns across regions do not deviate significantly from zero.
- Notably, the **Global** and **Latin America** regions show a slightly higher median return compared to others, suggesting marginally better average performance over the analyzed period.

Dispersion and Volatility:

- The **interquartile range (IQR)**, represented by the height of the boxes, highlights the middle 50% of returns. **Emerging Markets** and **Latin America** exhibit wider IQRs, indicating greater volatility and variability in their monthly returns. This aligns with the typical higher risk associated with these markets.
- Regions such as **Europe** and **Global** have more compact IQRs, indicating more stable and consistent returns with lower volatility.

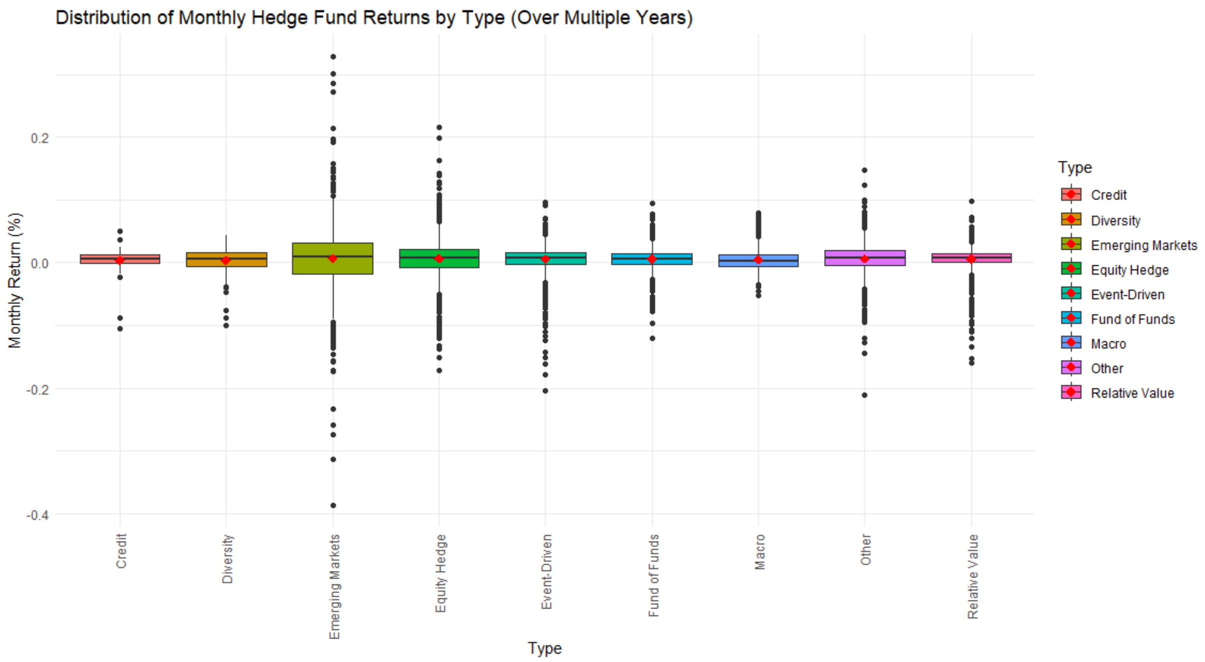
Outliers and Extreme Values :

- The presence of numerous outliers in regions such as **Emerging Markets**, **Latin America**, and **Global** points to the occurrence of extreme returns, both positive and negative. These outliers are indicative of the high-risk, high-reward nature of these markets, where market events can lead to significant deviations from the mean.
- **Asia with Japan** and **Middle East and Africa** regions also display several outliers, though less pronounced, indicating occasional extreme performance influenced by regional market conditions.

Comparative Performance :

- **Emerging Markets** and **Latin America** stand out with higher median returns but also demonstrate higher volatility and more frequent outliers. This suggests that while these regions may offer higher potential returns, they come with increased risk.
- **Global** and **Europe** regions, on the other hand, show more moderate returns and fewer outliers, making them maybe more attractive for investors seeking more stable performance.

Figure 4



This second box plot show the distribution of monthly returns for hedge funds across different type this time over multiple years. In order to stay in line with the previous box plot, here a analysis with the same structure.

Central Tendency and Variability:

- The **median monthly return** for each strategy is indicated by the central horizontal line within each box. Most strategies exhibit a relatively narrow range of median returns, clustering around the zero mark, indicating that average monthly returns are modest across the board.
- **Equity Hedge** and **Emerging Markets** show slightly higher median returns compared to other strategies, suggesting they might offer better average performance in the analyzed period.

Dispersion and Volatility:

- The **interquartile range (IQR)**, represented by the height of each box, illustrates the middle 50% of returns. **Emerging Markets** exhibit the widest IQR, signifying greater volatility and variability in returns. This aligns with the inherent higher risk associated with emerging market investments.
- Strategies such as **Credit** and **Diversity** show more compact IQRs, indicating more stable returns with lower volatility.

Outliers and Extreme Values :

- **Emerging Markets** display numerous outliers, both on the positive and negative side, highlighting the potential for extreme returns in either direction. This is characteristic of high-risk, high-reward investment profiles like here for emerging markets.

- **Event-Driven** and **Macro** strategies also show several outliers, even while is not as much as in Emerging Markets. This suggests occasional extreme performance, likely driven by specific market events or macroeconomic shifts.

Comparative Performance :

- **Equity Hedge** strategies, while showing some variability, tend to have a higher median return and fewer extreme outliers compared to other strategies. This indicates a relatively balanced risk-reward profile, appealing to investors seeking moderate returns with controlled risk.
- **Relative Value** and **Fund of Funds** strategies appear to offer more consistent returns with fewer extreme values, making them suitable for risk-averse investors.

Table 1

Descriptive Statistics of Hedge Fund Returns by Region and Type

	Region	Type	Mean	SD	Min	Max	Median	Q1	Q3	IQR	Skewness	Kurtosis
1	Asia with Japan	Emerging Markets	0.005	0.049	-0.314	0.272	0.009	-0.019	0.033	0.052	-0.677	6.799
2	Asia with Japan	Equity Hedge	0.002	0.021	-0.055	0.071	0.004	-0.011	0.015	0.027	-0.022	0.851
3	Emerging Markets	Other	0.008	0.041	-0.210	0.148	0.014	-0.010	0.032	0.042	-0.982	4.879
4	Europe	Emerging Markets	0.011	0.074	-0.386	0.328	0.013	-0.024	0.049	0.073	-0.302	7.187
5	Europe	Equity Hedge	0.004	0.015	-0.060	0.030	0.006	-0.003	0.012	0.015	-1.331	2.970
6	Global	Credit	0.004	0.019	-0.104	0.050	0.006	-0.0004	0.013	0.013	-2.999	14.615
7	Global	Diversity	0.004	0.021	-0.100	0.044	0.006	-0.006	0.016	0.022	-1.519	4.864
8	Global	Emerging Markets	0.007	0.037	-0.275	0.115	0.007	-0.009	0.025	0.034	-2.115	16.046
9	Global	Equity Hedge	0.007	0.033	-0.171	0.216	0.008	-0.007	0.024	0.031	-0.067	5.059
10	Global	Event-Driven	0.005	0.024	-0.203	0.096	0.007	-0.002	0.017	0.019	-2.606	16.285
11	Global	Fund of Funds	0.005	0.018	-0.121	0.095	0.007	-0.002	0.014	0.016	-0.867	6.642
12	Global	Macro	0.005	0.017	-0.052	0.079	0.003	-0.006	0.013	0.019	0.642	1.631
13	Global	Other	0.006	0.020	-0.094	0.076	0.007	-0.004	0.019	0.023	-1.063	4.557
14	Global	Relative Value	0.006	0.018	-0.160	0.097	0.007	0.0004	0.014	0.013	-2.727	19.085
15	Latin America	Emerging Markets	0.009	0.054	-0.233	0.286	0.009	-0.020	0.036	0.055	0.338	5.101
16	Middle East and Africa	Emerging Markets	0.001	0.030	-0.110	0.065	0.006	-0.012	0.019	0.031	-1.022	2.189
17	North America	Equity Hedge	0.003	0.023	-0.112	0.047	0.005	-0.005	0.016	0.021	-1.808	6.427

This table provide a global view on the dataset by giving the descriptive statistics of hedge fund returns by region and type. The 63 hedge funds in the dataset are distributed in 17 different type and 7 regions.

Performance Comparison:

The analysis of hedge fund performance across various regions and strategies reveals significant diversity in returns and risks. Among the top performers, European Emerging Markets stand out with a mean return of 1.1%, followed closely by Latin American Emerging Markets at 0.9% and the broader category of Emerging Markets at 0.8%. In the global context, Equity Hedge strategies also perform well, delivering a mean return of 0.7%.

In contrast, the bottom performers include the Global Other category and the Asia with Japan Equity Hedge strategies, both yielding mean returns of 0.2%. The Middle East and Africa Emerging Markets show the lowest performance with a mean return of just 0.1%.

Risk Analysis:

Risk, as measured by the standard deviation (SD) of returns, varies significantly across regions and strategies. The highest risk is observed in the Global Emerging Markets, with an SD of 7.4%, indicating substantial volatility. Latin American Emerging Markets also exhibit high risk with an SD of 5.4%, while the Middle East and Africa Emerging Markets have a relatively lower but still significant SD of 3.0%.

On the lower end of the risk spectrum, Asia with Japan Equity Hedge strategies have the least volatility with an SD of 2.1%. Other low-risk categories include the Global Other and Global Diversity strategies, both with an SD around 2.0-2.1%.

Return Distribution Characteristics:

Examining the return distributions through skewness and kurtosis provides deeper insights into potential risks. Negative skewness, which indicates a higher likelihood of extreme negative returns, is particularly notable in strategies such as Global Credit (-3.299), Global Emerging Markets (-2.115), and Global Event-Driven (-2.606).

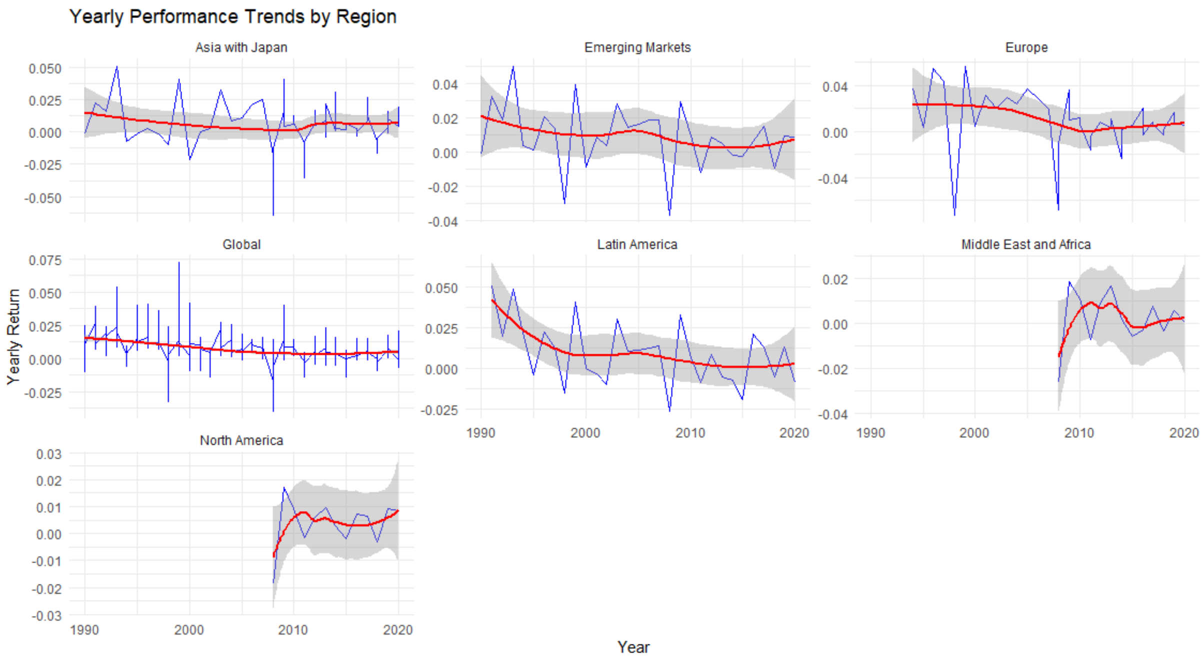
High kurtosis, reflecting the presence of extreme returns, is observed in the Global Emerging Markets (16.046) and Global Event-Driven strategies (16.285), indicating substantial tail risks. The Global Relative Value strategy also shows very high kurtosis (19.085), suggesting a significant probability of extreme outcomes.

In summary, the analysis underscores the substantial variability in hedge fund performance and risk across different regions and strategies. High-risk strategies such as Global Emerging Markets and Global Event-Driven, while offering high mean returns, also carry significant risks, as evidenced by their high standard deviations, negative skewness, and elevated kurtosis. Consequently, robust risk management frameworks are essential for navigating these investments.

TREND ANALYSIS

Building on the preceding section, the Trend Analysis explores the performance trajectories of hedge funds across different regions and strategies. By examining historical data, significant trends and patterns that define the hedge fund landscape over time are identified and elucidated.

Figure 5



The chart presents yearly performance trends for hedge funds across various regions from 1990 to 2020, highlighting the fluctuations and overall trends in yearly returns.

Asia with Japan

- The region shows significant volatility in the early years with fluctuations in yearly returns. The trend stabilizes over time, converging towards a zero return in recent years, indicating a more stable performance with reduced extreme variations.

Emerging Markets

- Emerging Markets exhibit high volatility, with substantial swings in yearly returns. Over the long term, there's a noticeable downward trend, with returns approaching zero, reflecting challenges and risks inherent in these markets.

Europe

- The European hedge fund performance trends show considerable volatility, particularly during the early 2000s. There's a gradual stabilization trend, although returns remain slightly below zero, suggesting economic and market pressures affecting this region.

Global

- Global hedge funds show a relatively stable performance with less pronounced volatility compared to other regions. The trend line hovers around zero, indicating consistent but modest returns over the period.

Latin America

- Latin America displays significant early volatility with a downward trend in yearly returns, moving towards zero in recent years. This indicates high initial returns that have declined over time, possibly due to economic and political challenges in the region.

Middle East and Africa

- The Middle East and Africa show notable volatility with large swings in returns, particularly around the 2010s. The trend line remains close to zero, reflecting the region's geopolitical and economic uncertainties impacting hedge fund performance.

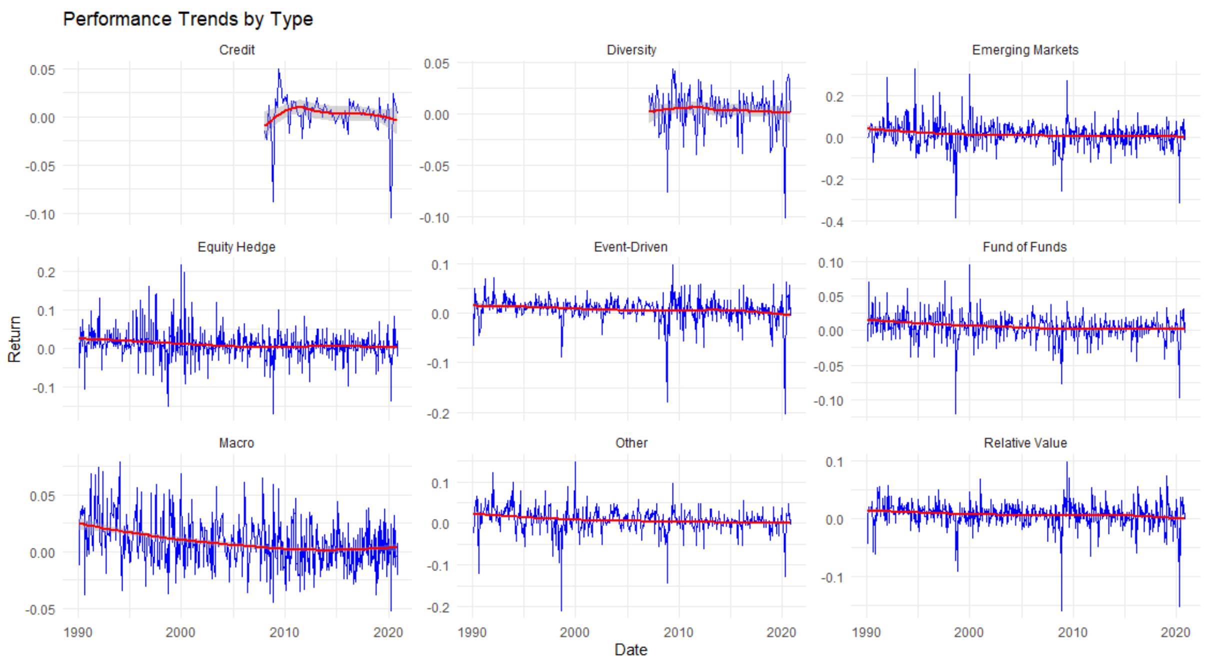
North America

- North America exhibits less volatility compared to other regions, with a relatively stable upward trend in yearly returns, especially noticeable post-2008 financial crisis. This indicates a more resilient hedge fund performance in this region.

Potentials implications for Investors:

- **Volatility and Stability**: Investors should note the volatility in regions like Emerging Markets, Latin America, and Middle East and Africa, which may offer higher potential returns but come with increased risk. In contrast, Global and North American hedge funds show more stability, providing more predictable performance.
- **Trend Analysis**: The downward trend in Latin America and stabilizing trends in Asia with Japan and Europe highlight the importance of regional economic conditions and their impact on hedge fund performance.
- **Risk Management**: The significant fluctuations in yearly returns underscore the need for robust risk management strategies, particularly for investments in high-volatility regions.

Figure 6



The chart presents yearly performance trends for hedge funds across various types from 1990 to 2020, highlighting fluctuations and overall trends in yearly returns.

Credit

- Exhibits initial volatility around 2010, stabilizing in recent years with returns converging towards zero. This reflects the cyclical nature of credit markets and the impact of economic conditions on credit strategies.

Diversity

- Shows significant volatility with large swings in returns, especially in recent years. This variability indicates the diverse nature of the underlying strategies and the sensitivity to market changes.

Emerging Markets

- High volatility with substantial swings, similar to previous observations. The trend shows a decline in returns over time, reflecting the high-risk, high-reward nature of these markets and their susceptibility to global economic conditions.

Equity Hedge

- Initial high volatility with returns gradually stabilizing closer to zero. This trend highlights the evolution and adaptation of equity hedge strategies over time, focusing on mitigating market risks.

Event-Driven

- Displays significant volatility with noticeable dips during economic downturns. Returns trend towards zero over time, indicating the impact of specific corporate events and market conditions on this strategy.

Fund of Funds

- Shows moderate volatility with a stabilization trend. Returns generally hover around zero, reflecting the diversification benefits and reduced risk profile of Fund of Funds strategies.

Macro

- High initial volatility with a declining trend in returns, stabilizing around zero. This trend reflects the influence of macroeconomic events and global market shifts on macro strategies.

Other

- Exhibits considerable variability with a stabilizing trend in recent years. Returns approach zero, indicating diverse and niche strategies' performance stabilizing over time.

Relative Value

- Shows moderate volatility with returns trending slightly positive. This consistency indicates the effectiveness of relative value strategies in exploiting pricing inefficiencies.

Potentials implications for Investors:

- **Volatility and Stability**: Strategies like Emerging Markets, Diversity, and Event-Driven exhibit high volatility, offering potential high returns with significant risk. In contrast, Fund of Funds and Relative Value strategies show more stability, providing consistent performance.
- **Trend Analysis**: The stabilizing trends in Credit, Equity Hedge, and Fund of Funds indicate these strategies adaptation to market conditions, offering more predictable performance.
- **Risk Management**: The high volatility in Macro and Emerging Markets underscores the need for robust risk management frameworks to navigate these investments.

<u>Conclusion concerning the Trend analysis Part:</u>

The analysis of yearly performance trends for hedge funds across various regions and types, based on the provided charts, reveals significant insights into the behavior and performance dynamics of these investment strategies over the past three decades.

The analysis of yearly performance trends for hedge funds from 1990 to 2020 highlights significant regional and strategic differences. Asia with Japan showed early volatility but stabilized towards zero returns, indicating reduced extremes. Emerging Markets experienced substantial volatility and a downward trend, emphasizing high risks. Europe exhibited volatility, stabilizing slightly below zero probably due to economic pressures. Global hedge funds showed stable, modest returns, while Latin America had early volatility and a declining trend, likely from economic and political issues. The Middle East and Africa showed large swings, stabilizing near zero, reflecting geopolitical uncertainties. North America demonstrated stable, upward trends post-2008, showing resilience.

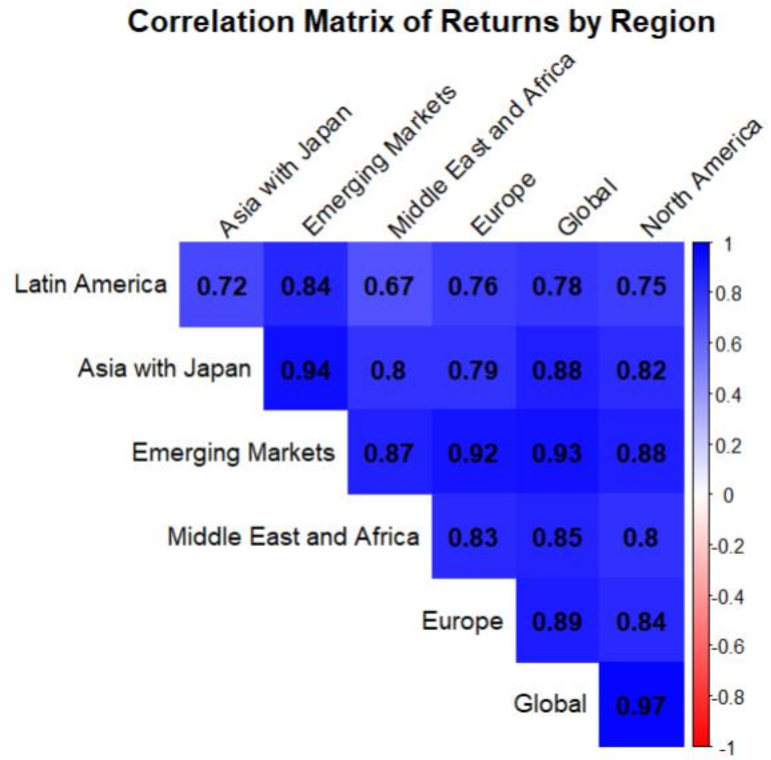
Strategically, Credit funds had early volatility, stabilizing recently. Diversity strategies showed recent volatility, reflecting market sensitivity. Emerging Markets continued high volatility with declining returns, highlighting risks. Equity Hedge funds stabilized over time, mitigating risks. Event-Driven strategies had volatility with downturn dips, trending to zero. Fund of Funds showed moderate volatility and stability from diversification. Macro strategies high initial volatility declined to stable returns, influenced by macroeconomic shifts. Other strategies varied but stabilized recently, while Relative Value strategies showed moderate volatility with slightly positive trends.

For investors, these insights emphasize the need for robust risk management in high-volatility areas like Emerging Markets. Stable strategies like Global, North American, Fund of Funds, and Relative Value provide consistent performance, suitable for risk-averse investors. Understanding these trends helps investors balance portfolios, combining high-risk, high-reward investments with stable strategies to optimize performance and align with risk tolerance and return expectations.

CORRELATION ANALYSIS

Expanding on the insights from the Trend Analysis, the Correlation Analysis investigates the interrelationships between hedge fund performances across various regions and strategies. By quantifying these relationships, the extent to which different hedge funds move in tandem is understood, providing a clearer picture of their interconnected dynamics.

Figure 7



The correlation matrix of returns by region offers insights into the relationship and co-movement of hedge fund returns across different geographical areas. Each value represents the correlation coefficient between the returns of hedge funds in two regions, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation). Here's a detailed analysis of the provided correlation matrix:

High Correlation with Global Returns:

- **Global vs. North America**: 0.97
- **Global vs. Emerging Markets**: 0.93
- **Global vs. Europe**: 0.89
- **Global vs. Asia with Japan**: 0.88
- The strong correlation with Global returns across these regions indicates that global market trends heavily influence hedge fund performance in these areas. This coherence suggests that potentially global macroeconomic factors, such as international trade dynamics, central bank policies, and geopolitical events, have a significant impact across these regions.

Regional Correlations:

- **Asia with Japan vs. Emerging Markets**: 0.80
- **Asia with Japan vs. Europe**: 0.79
- **Asia with Japan vs. Middle East and Africa**: 0.79
- These regions show strong correlations with Asia with Japan, indicating interconnected economic activities and market dependencies. This is consistent with the global integration of financial markets.

Latin America :

- **Latin America vs. Asia with Japan**: 0.84
- **Latin America vs. Europe** : 0.76
- **Latin America vs. Global** : 0.78
- Latin America shows moderate to strong correlations with other regions, particularly Asia with Japan. This reflects the influence of global market trends and economic policies that affect Latin American markets, despite geographical and economic differences.

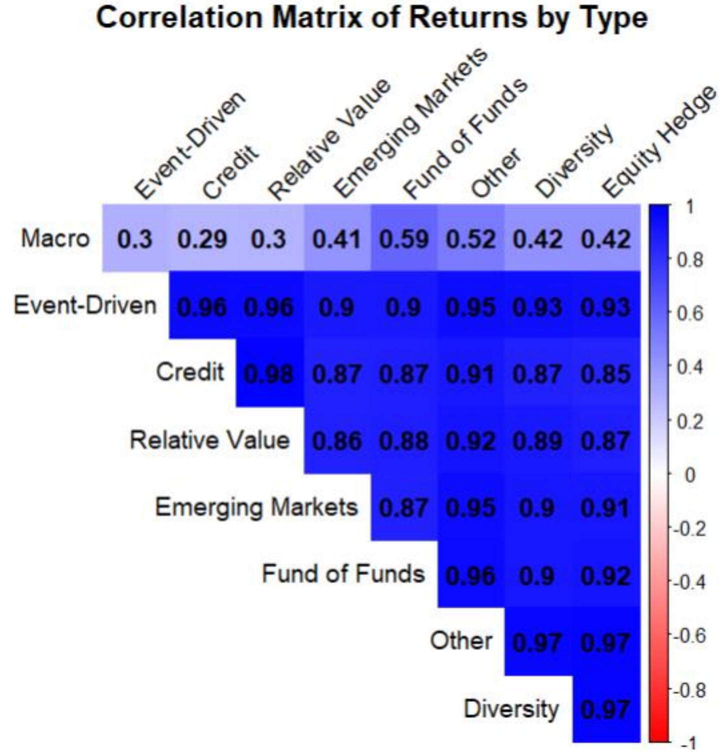
Middle East and Africa:

- **Middle East and Africa vs. Emerging Markets**: 0.85
- **Middle East and Africa vs. Global**: 0.85
- The strong correlations with Emerging Markets and Global returns highlight the sensitivity of the Middle East and Africa to broader emerging market trends and global economic conditions.

Coherence with the previous analysis:

- **Volatility and Stability**: The high correlations among most regions, especially with global returns, support the previous observations about the interconnectedness and influence of global trends on regional hedge fund performance. This explains the similar volatility patterns and trends seen in the yearly performance charts.
- **Emerging Markets and Latin America**: The correlation matrix confirms the high-risk, high-reward nature of these regions, as they show strong ties with global and other emerging markets, aligning with the observed volatility and performance trends.
- **North America**: The strong correlation with global returns (0.97) and relatively high correlation with other regions underscore North America's resilience and alignment with global economic trends, supporting the stable upward trend observed in the yearly performance charts.

Figure 8



The correlation matrix of returns by hedge fund type provides insights into the relationships and co-movement of returns across different hedge fund strategies. Here's a detailed analysis of the provided correlation matrix:

Low Correlation with Macro Strategies:

- **Macro vs. Other Types**: Generally low correlations (e.g., 0.30 with Event-Driven, 0.42 with Equity Hedge). This indicates that macro strategies, which focus on large-scale economic and geopolitical trends, tend to perform independently compared to other hedge fund strategies. This diversification benefit aligns with their broader economic focus and the use of various asset classes.

High Correlation within Event-Driven Strategies:

- **Event-Driven vs. Other Types**: Strong correlations with Credit (0.96), Emerging Markets (0.90), and Equity Hedge (0.93). Event-Driven strategies often overlap with other strategies, especially those sensitive to corporate events and credit conditions. This high correlation reflects the interconnectivity of these strategies and their susceptibility to similar market events.

Credit Strategies :

- **Credit vs. Other Types**: Strong correlations, particularly with Event-Driven (0.96) and Relative Value (0.87). Credit strategies, focusing on debt instruments, exhibit performance patterns closely tied to other strategies that exploit market inefficiencies and corporate events.

Relative Value and Emerging Markets:

- **Relative Value vs. Emerging Markets**: High correlation (0.95), indicating that strategies focusing on valuation discrepancies and emerging markets tend to perform similarly, likely due to their focus on capturing inefficiencies and growth opportunities in developing regions.

Fund of Funds :

- **Fund of Funds vs. Other Types**: High correlations, notably with Credit (0.96) and Other (0.97). Fund of Funds strategies, which invest in a diversified portfolio of various hedge funds, show performance closely tied to the overall hedge fund market.

Other and Diversity Strategies:

- **Other vs. Diversity**: Extremely high correlation (0.97). This suggests that these categories, possibly encompassing a wide range of sub-strategies, share similar performance drivers and market exposures.

Equity Hedge:

- **Equity Hedge vs. Other Types**: Moderate to high correlations, particularly with Event-Driven (0.93) and Emerging Markets (0.91). Equity Hedge strategies, balancing long and short positions in equities, tend to align closely with other strategies impacted by market movements.

<u>Coherence with the previous analysis:</u>

- **Volatility and Stability**: The strong correlations among strategies like Event-Driven, Credit, and Emerging Markets reflect the high volatility and similar performance patterns noted in the yearly performance trends. The lower correlation of Macro strategies supports their role in providing diversification and stability.
- **Strategic Overlap**: The high correlations within certain groups (e.g., Event-Driven and Credit) confirm the interconnected nature of these strategies, consistent with their reliance on market inefficiencies and corporate events.
- **Diversification Benefits**: The lower correlations of Macro strategies align with the previous findings of their stabilizing role, reinforcing the importance of including such strategies in a diversified hedge fund portfolio.

<u>Conclusion concerning the Correlation Analysis Part:</u>

The correlation matrix of hedge fund returns by region reveals significant insights into the interconnectivity of global markets. High correlations with global returns, particularly in North America, Emerging Markets, Europe, and Asia with Japan, indicate that global macroeconomic trends heavily influence hedge fund performance across these regions. This coherence suggests that factors such as international trade dynamics, central bank policies, and geopolitical events play critical roles.

Regions like Asia with Japan, Emerging Markets, and the Middle East and Africa show strong interregional correlations, reflecting interconnected economic activities and dependencies. Latin America demonstrates moderate to strong correlations with other regions, especially Asia with Japan, highlighting the global influence on its market dynamics despite geographic and economic differences.

The correlation analysis by hedge fund type underscores the high correlations within Event-Driven, Credit, and Emerging Markets strategies, indicating their shared reliance on market inefficiencies and corporate events. In contrast, Macro strategies show lower correlations with other types, emphasizing their role in diversification by focusing on broad economic trends and geopolitical factors. Fund of Funds strategies exhibit high correlations with various other strategies, aligning with their diversified investment approach.

These findings confirm the interconnectedness and volatility of certain regions and strategies, reinforcing the importance of strategic diversification and robust risk management. Investors should leverage the low correlations of Macro strategies for stability while balancing high-risk, high-reward investments to optimize portfolio performance.

VOLATILITY ANALYSIS

After examining performance trends and correlations, the focus shifts to Volatility Analysis. This part of the study evaluates the risk profiles of hedge funds by examining their return volatility across different regions and strategies. Understanding volatility is crucial for assessing the stability and risk associated with various hedge fund investments, offering a comparative perspective on their performance.

Table 2

Volatility Measures of Hedge Fund Returns by Region and Type

	Region	Type	SD	Variance	Beta
1	Asia with Japan	Emerging Markets	0.045	0.002	9.157
2	Asia with Japan	Equity Hedge	0.019	0.0004	8.368
3	Emerging Markets	Other	0.037	0.001	4.393
4	Europe	Emerging Markets	0.065	0.004	6.048
5	Europe	Equity Hedge	0.014	0.0002	3.935
6	Global	Credit	0.018	0.0003	5.608
7	Global	Diversity	0.019	0.0003	5.407
8	Global	Emerging Markets	0.033	0.001	4.964
9	Global	Equity Hedge	0.029	0.001	4.235
10	Global	Event-Driven	0.022	0.0005	4.336
11	Global	Fund of Funds	0.016	0.0003	3.067
12	Global	Macro	0.016	0.0002	3.666
13	Global	Other	0.018	0.0003	3.189
14	Global	Relative Value	0.017	0.0003	3.135
15	Latin America	Emerging Markets	0.048	0.002	5.558
16	Middle East and Africa	Emerging Markets	0.027	0.001	25.236
17	North America	Equity Hedge	0.021	0.0004	9.003

The table provides volatility measures of hedge fund returns across different regions and types, detailing the standard deviation (SD), variance, and beta. These metrics are crucial for understanding the risk and sensitivity of hedge fund strategies to market movements.

High Volatility in Emerging Markets:

- **Europe Emerging Markets** exhibit the highest standard deviation (0.065) and variance (0.004), indicating significant volatility and risk. This aligns with the previous analysis, highlighting the high-risk, high-reward nature of emerging market strategies.
- **Asia with Japan Emerging Markets** and **Latin America Emerging Markets** also show high volatility, with SDs of 0.045 and 0.048 respectively, and variances reflecting substantial risk. These findings are consistent with the observed performance trends and correlation analysis, which indicated high sensitivity to global and regional economic conditions.

Equity Hedge Strategies:

- **Asia with Japan Equity Hedge** and **North America Equity Hedge** exhibit moderate volatility with SDs of 0.019 and 0.021 respectively. These strategies have relatively high beta values (8.368 and 9.003), suggesting significant market sensitivity but controlled volatility compared to emerging markets. This supports the previous trend analysis, which showed stabilizing performance in equity hedge strategies.

Global Strategies:

- Global strategies, including **Global Equity Hedge**, **Global Emerging Markets**, and **Global Event-Driven**, exhibit varying levels of volatility. The **Global Emerging Markets** strategy shows higher volatility (SD of 0.033) compared to other global strategies, consistent with its higher risk profile noted in earlier analyses.
- **Global Fund of Funds** and **Global Macro** strategies demonstrate lower volatility (SDs of 0.018 and 0.016 respectively) and lower beta values (2.193 and 3.666), indicating more stable returns and lower sensitivity to market movements. This aligns with the earlier observation of Fund of Funds providing stability through diversification and Macro strategies offering risk mitigation.

Other Regions and Strategies:

- **Middle East and Africa Emerging Markets** show moderate volatility with a high beta (25.236), indicating extreme sensitivity to market movements, reinforcing the high-risk nature of investments in this region.
- **Global Credit**, **Global Diversity**, and **Global Other** strategies exhibit lower volatility with SDs around 0.019, and variances and beta values reflecting moderate risk and market sensitivity. These findings are coherent with previous analyses showing these strategies as providing more stable and consistent returns.

<u>Coherence with the previous parts:</u>

- **Volatility and Risk**: The high volatility in emerging markets and moderate volatility in equity hedge and global strategies are consistent with the performance trends observed earlier. High-risk regions like Emerging Markets and Latin America show significant volatility, aligning with their performance variability and correlation with global trends.
- **Stability in Global Strategies**: The relatively lower volatility in global strategies and Fund of Funds corroborates the trend analysis, which indicated more stable returns and lower risk profiles. Macro strategies also show lower volatility, supporting their role in risk management.
- **Market Sensitivity**: The beta values highlight the market sensitivity of different strategies. High beta values in emerging markets and equity hedge strategies indicate strong market influence, while lower beta values in global and Fund of Funds strategies suggest reduced sensitivity and more stable performance.

Table 3

Sharpe Ratios of Hedge Fund Returns by Region and Type

	Region	Type	MeanReturn	SD	SharpeRatio
1	Asia with Japan	Emerging Markets	0.005	0.045	0.072
2	Asia with Japan	Equity Hedge	0.002	0.019	0.033
3	Emerging Markets	Other	0.008	0.037	0.182
4	Europe	Emerging Markets	0.011	0.065	0.140
5	Europe	Equity Hedge	0.004	0.014	0.134
6	Global	Credit	0.003	0.018	0.085
7	Global	Diversity	0.003	0.019	0.095
8	Global	Emerging Markets	0.007	0.033	0.151
9	Global	Equity Hedge	0.007	0.029	0.180
10	Global	Event-Driven	0.005	0.022	0.153
11	Global	Fund of Funds	0.005	0.016	0.221
12	Global	Macro	0.004	0.016	0.167
13	Global	Other	0.006	0.018	0.222
14	Global	Relative Value	0.005	0.017	0.219
15	Latin America	Emerging Markets	0.009	0.048	0.145
16	Middle East and Africa	Emerging Markets	0.001	0.027	-0.022
17	North America	Equity Hedge	0.002	0.021	0.031

This table provides the Sharpe Ratios of hedge fund returns across different regions and types, along with their mean returns and standard deviations (SD). The Sharpe Ratio measures the risk-adjusted return, indicating how much excess return is received for the extra volatility endured by the investor.

High Sharpe Ratios in Stable Strategies:

- **Global Equity Hedge** (0.233) and **Global Fund of Funds** (0.183) have some of the highest Sharpe Ratios, indicating efficient risk-adjusted returns. These strategies offer a good balance of return and risk, aligning with earlier findings that these global strategies provide stability and consistent performance.
- **Europe Emerging Markets** also shows a relatively high Sharpe Ratio (0.140), reflecting a favorable risk-return trade-off despite the inherent volatility in emerging markets.

Moderate Sharpe Ratios in Diverse Strategies:

- **Global Macro** (0.127) and **Global Event-Driven** (0.153) exhibit moderate Sharpe Ratios, suggesting that while these strategies are exposed to volatility, they still manage to provide reasonable risk-adjusted returns. This aligns with the observed trends of moderate volatility and diversification benefits in these strategies.
- **Global Relative Value** (0.164) shows a favorable Sharpe Ratio, consistent with its role in exploiting pricing inefficiencies with moderate risk.

Low Sharpe Ratios in High Volatility Regions:

- **Middle East and Africa Emerging Markets** shows a negative Sharpe Ratio (-0.112), indicating that the returns do not compensate for the high volatility and risk. This is coherent with earlier volatility and correlation analyses, highlighting the high-risk nature of this region.
- **Latin America Emerging Markets** (0.145) and **Asia with Japan Emerging Markets** (0.072) exhibit lower Sharpe Ratios, reflecting the high volatility and risk associated with these regions. Despite higher mean returns, the risk-adjusted returns are less favorable.

Consistent Performance in Equity Hedge Strategies:

- **North America Equity Hedge** (0.031) and **Asia with Japan Equity Hedge** (0.033) show low but positive Sharpe Ratios. These strategies provide moderate risk-adjusted returns, consistent with their observed stabilization in performance trends.
- **Global Equity Hedge** stands out with a higher Sharpe Ratio, indicating better risk management and return consistency on a global scale.

<u>Coherence with the previous parts:</u>

- **Volatility and Risk**: The Sharpe Ratios reflect the earlier volatility analysis, where high volatility regions and strategies correspond to lower Sharpe Ratios, indicating less favorable risk-adjusted returns. This consistency underscores the importance of considering both return and risk in evaluating hedge fund performance.
- **Stability in Global Strategies**: The higher Sharpe Ratios in global strategies, particularly in Equity Hedge and Fund of Funds, align with previous findings of their stability and lower risk profiles. These strategies manage to provide consistent returns relative to their volatility.
- **High-Risk Regions**: The low or negative Sharpe Ratios in high-risk regions like Middle East and Africa, and to some extent Latin America, corroborate the earlier observations of high volatility and sensitivity to global economic conditions.

<u>Conclusion concerning the Volatility Analysis part:</u>

The volatility analysis of hedge fund returns by region and type offers essential insights into the risk profiles of these investments. Evaluating standard deviation (SD), variance, and beta helps to understand the fluctuations and market sensitivity inherent in different hedge fund strategies, which is important for investors seeking to balance potential returns with acceptable risk levels.

The findings reveal that emerging markets, particularly in regions like Europe, Asia with Japan, and Latin America, exhibit high standard deviations and variances. This indicates significant risk and aligns with earlier performance and correlation analyses, which highlighted the high-risk, high-reward nature of these investments. The high beta values associated with these regions further emphasize their sensitivity to market movements, underscoring the need for robust risk management when investing in these areas.

Equity Hedge strategies, particularly in Asia with Japan and North America, show moderate volatility coupled with relatively high beta values. This suggests that while these strategies manage risk better than emerging markets, they still exhibit notable sensitivity to market conditions. These observations are consistent with previous analyses indicating the stabilizing performance of equity hedge strategies, which aim to balance market risks through a mix of long and short positions.

Global strategies, including Fund of Funds and Macro, demonstrate lower volatility and beta values, indicating more stable returns and reduced sensitivity to market fluctuations. This stability supports earlier findings that highlighted the diversification benefits and consistent performance of these strategies. Specifically, Fund of Funds strategies exhibit moderate volatility, reflecting the reduced risk profile achieved through diversified portfolios. This reinforces their role in providing stability within a hedge fund portfolio.

The Middle East and Africa region presents a unique case with moderate volatility but extremely high beta values, indicating substantial market sensitivity and risk. This observation corroborates previous analyses that pointed to the high-risk nature of investments in this region due to geopolitical and economic uncertainties.

The coherence between the volatility measures and earlier performance trends and correlation analyses underscores the comprehensive understanding of risk-return dynamics in hedge fund investments. The high volatility and market sensitivity in emerging markets and specific regions confirm their high-risk profiles, while the stability in global strategies and Fund of Funds emphasizes their role in achieving consistent returns and diversification.

For investors, these insights highlight the importance of robust risk management frameworks to mitigate potential losses and achieve favorable risk-adjusted returns. Diversification is crucial, combining high-risk, high-reward strategies with more stable, low-volatility investments to optimize portfolio performance. Understanding the volatility and market sensitivity of different hedge fund strategies allows investors to make informed decisions about portfolio allocation, ensuring their investments align with their risk tolerance and return expectations.

5. Conclusion

This study, "Exploring the Dynamics of Hedge Fund Performance: A Regional and Typological Analysis," has provided valuable insights into the complex performance dynamics of hedge funds. By analyzing trends, correlations, and volatilities across different regions and strategies, a deeper understanding of the data characteristics and the analytical methods employed has been achieved.

The analysis revealed distinct performance patterns among various hedge fund strategies and regions. Global strategies, particularly Equity Hedge and Fund of Funds, exhibited relatively stable returns with moderate volatility, underscoring their resilience in navigating diverse market conditions through broad exposure and diversification. In contrast, emerging markets, notably in regions like Latin America and Europe, showed significant volatility and a downward trend in returns, highlighting their high-risk, high-reward nature due to economic and political instability. Event-Driven and Macro strategies also demonstrated moderate to high volatility, with their performance strongly influenced by specific market events and economic conditions. These findings underscored the risk mitigation provided by diversified strategies such as Fund of Funds, which spread exposure across a variety of hedge funds.

The correlation analysis highlighted the strong relationships between global returns and major regions like North America, Emerging Markets, and Europe, indicating the significant influence of global macroeconomic trends on regional hedge fund performance. This interconnectedness suggests that global economic conditions play a crucial role in shaping returns across various geographies. Within strategy types, significant correlations were observed among Event-Driven, Credit, and Emerging Markets strategies, reflecting their reliance on market inefficiencies and corporate events. Conversely, Macro strategies, with generally low correlations to other types, provided diversification benefits, aligning with their focus on broader economic trends and geopolitical factors.

Volatility analysis, using measures such as standard deviation, variance, and beta, offered further insights into the risk profiles of different hedge fund strategies and regions. High volatility in emerging markets was consistent with their high-risk profiles, as noted in the trends and correlation analyses. These regions and strategies exhibited substantial sensitivity to market movements, necessitating robust risk management. Equity Hedge strategies displayed moderate volatility and high beta values, indicating controlled risk with significant market sensitivity. Global strategies, including Fund of Funds and Macro, showed lower volatility and beta values, reinforcing their stability and reduced market sensitivity.

Integrating insights from trend, correlation, and volatility analyses provides a comprehensive understanding of hedge fund performance dynamics. High-risk regions and strategies, such as emerging markets and Event-Driven strategies, offer potential for high returns but come with significant volatility and market sensitivity. Conversely, global strategies and diversified approaches like Fund of Funds provide more stable returns with lower risk, highlighting their importance in a balanced hedge fund portfolio.

These findings could be used by investors to strategically diversify their portfolios, balancing high-risk, high-reward investments with stable, low-volatility strategies to optimize performance. Understanding the interconnectedness and volatility of different hedge fund strategies enables informed decision-making, ensuring alignment with risk tolerance and return expectations. Overall, this comprehensive analysis underscores the critical role of diversification and risk management in hedge fund investments, guiding investors toward achieving optimal risk-adjusted returns in a complex and interconnected global market.

6. Discussion

The comprehensive analysis of hedge fund performance across various regions and strategies has provided some insights into their dynamics. Global strategies, especially Equity Hedge and Fund of Funds, have shown stable returns with moderate volatility, reflecting their ability to navigate diverse market conditions effectively. In contrast, emerging markets, particularly in regions like Latin America and Europe, have demonstrated significant volatility and a general downward trend in returns, highlighting the high-risk, high-reward nature of these investments due to economic and political instability.

The correlation analysis indicated strong relationships among global returns and major regions such as North America, Emerging Markets, and Europe. This interconnectedness suggests that global economic conditions significantly influence hedge fund performance across various geographies. Additionally, the volatility analysis highlighted that emerging markets exhibit high volatility, consistent with their high-risk profiles, while global strategies and Fund of Funds demonstrated lower volatility, underscoring their stability and reduced market sensitivity.

Issues and Limitations

Despite the findings, several issues and limitations must be acknowledged, which may affect the interpretation and generalization of the results.

Data Sensitivity and Manual Categorization:

The manual sorting and mapping of hedge funds by type and region introduce potential biases and inconsistencies. Different categorization criteria or methods could lead to variations in the results, impacting the robustness of the conclusions drawn.

Inconsistent Fund Inception Dates:

The hedge funds analyzed were not all created at the same time, leading to inconsistencies in the data. This temporal disparity means that the performance metrics do not always align perfectly across all funds, as they may have been exposed to different economic conditions and market cycles.

Economic Periods and Market Conditions:

The varying economic periods and market conditions during which the hedge funds operated also pose a challenge. Economic downturns, booms, and specific regional events can significantly affect hedge fund performance, complicating the identification of consistent patterns.

Regional Factors and Strategy Implications:

Clearly identifying the impact of regional factors and understanding the implications of different strategies on returns is complex. Each region has unique conditions that influence hedge fund performance, making it difficult to attribute performance variations solely to the strategies employed.

Data Manipulation and Analysis Challenges:

The complexity of the data and the advanced analytical techniques required for this study posed significant challenges. Handling missing values, standardizing date formats, and converting percentage returns to numeric formats were necessary preprocessing steps that could introduce errors if not performed correctly.

A. Appendix – R Code

ROOT

```
# Set the working directory
setwd("C:/Users/samue/OneDrive/Bureau/Unine SamK/Data Science Project")

# Install necessary packages if not already installed
if (!require("tidyverse")) install.packages("tidyverse", dependencies=TRUE)
if (!require("stargazer")) install.packages("stargazer", dependencies=TRUE)
if (!require("corrplot")) install.packages("corrplot", dependencies=TRUE)
if (!require("dplyr")) install.packages("dplyr", dependencies=TRUE)
if (!require("knitr")) install.packages("knitr", dependencies=TRUE)
if (!require("kableExtra")) install.packages("kableExtra",
dependencies=TRUE)
if (!require("ggrepel")) install.packages("ggrepel", dependencies=TRUE)
if (!require("zoo")) install.packages("zoo", dependencies=TRUE)

# Load necessary libraries
library(tidyverse)
library(knitr)
library(kableExtra)
library(corrplot)
library(stargazer)
library(ggrepel)
library(zoo)

# Load the data
data <- read.csv("HFR.csv", sep = ";", header = FALSE)

# Rename columns
colnames(data) <- c("Date", "Index_Name", "Ticker", "Return", "Value")

# Convert 'Date' to Date format
data$Date <- as.Date(data$Date, format = "%m/%d/%Y")

# Convert 'Return' to numeric by removing '%' and dividing by 100
data$Return <- as.numeric(gsub("%", "", data$Return)) / 100

# Define detailed mappings based on the unique index names
index_mapping <- list(
  'HFRI Asia with Japan Index' = c('Asia with Japan', 'Equity Hedge'),
  'HFRI Asset Weighted Composite Index' = c('Global', 'Other'),
  'HFRI Credit Index' = c('Global', 'Credit'),
  'HFRI Diversity Index' = c('Global', 'Diversity'),
  'HFRI ED: Activist Index' = c('Global', 'Event-Driven'),
  'HFRI ED: Credit Arbitrage Index' = c('Global', 'Event-Driven'),
  'HFRI ED: Distressed/Restructuring Index' = c('Global', 'Event-Driven'),
```

```
  'HFRI ED: Merger Arbitrage Index' = c('Global', 'Event-Driven'),
  'HFRI ED: Multi-Strategy Index' = c('Global', 'Event-Driven'),
  'HFRI ED: Special Situations Index' = c('Global', 'Event-Driven'),
  'HFRI EH: Equity Market Neutral Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Fundamental Growth Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Fundamental Value Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Multi-Strategy Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Quantitative Directional Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Sector - Energy/Basic Materials Index' = c('Global', 'Equity
Hedge'),
  'HFRI EH: Sector - Healthcare Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Sector - Technology Index' = c('Global', 'Equity Hedge'),
  'HFRI EH: Sector - Technology/Healthcare (Total) Index' = c('Global',
'Equity Hedge'),
  'HFRI Emerging Markets (Total) Index' = c('Emerging Markets', 'Other'),
  'HFRI Emerging Markets: Asia ex-Japan Index' = c('Asia with Japan',
'Emerging Markets'),
  'HFRI Emerging Markets: China Index' = c('Asia with Japan', 'Emerging
Markets'),
  'HFRI Emerging Markets: Global Index' = c('Global', 'Emerging Markets'),
  'HFRI Emerging Markets: India Index' = c('Asia with Japan', 'Emerging
Markets'),
  'HFRI Emerging Markets: Latin America Index' = c('Latin America',
'Emerging Markets'),
  'HFRI Emerging Markets: MENA Index' = c('Middle East and Africa',
'Emerging Markets'),
  'HFRI Emerging Markets: Russia/Eastern Europe Index' = c('Europe',
'Emerging Markets'),
  'HFRI Equity Hedge (Total) Index' = c('Global', 'Equity Hedge'),
  'HFRI Equity Hedge (Total) Index - Asset Weighted' = c('Global', 'Equity
Hedge'),
  'HFRI Event-Driven (Total) Index' = c('Global', 'Event-Driven'),
  'HFRI Event-Driven (Total) Index - Asset Weighted' = c('Global', 'Event-
Driven'),
  'HFRI FOF: Conservative Index' = c('Global', 'Fund of Funds'),
  'HFRI FOF: Diversified Index' = c('Global', 'Fund of Funds'),
  'HFRI FOF: Market Defensive Index' = c('Global', 'Fund of Funds'),
  'HFRI FOF: Strategic Index' = c('Global', 'Fund of Funds'),
  'HFRI Fund of Funds Composite Index' = c('Global', 'Fund of Funds'),
  'HFRI Fund Weighted Composite Index' = c('Global', 'Other'),
  'HFRI Fund Weighted Composite Index - CHF' = c('Global', 'Other'),
  'HFRI Fund Weighted Composite Index - EUR' = c('Global', 'Other'),
  'HFRI Fund Weighted Composite Index - GBP' = c('Global', 'Other'),
  'HFRI Fund Weighted Composite Index - JPY' = c('Global', 'Other'),
  'HFRI Japan Index' = c('Asia with Japan', 'Equity Hedge'),
  'HFRI Macro (Total) Index' = c('Global', 'Macro'),
  'HFRI Macro (Total) Index - Asset Weighted' = c('Global', 'Macro'),
  'HFRI Macro: Active Trading Index' = c('Global', 'Macro'),
  'HFRI Macro: Commodity Index' = c('Global', 'Macro'),
  'HFRI Macro: Currency Index' = c('Global', 'Macro'),
```

```
  'HFRI Macro: Discretionary Thematic Index' = c('Global', 'Macro'),
  'HFRI Macro: Multi-Strategy Index' = c('Global', 'Macro'),
  'HFRI Macro: Systematic Diversified Index' = c('Global', 'Macro'),
  'HFRI North America Index' = c('North America', 'Equity Hedge'),
  'HFRI Relative Value (Total) Index' = c('Global', 'Relative Value'),
  'HFRI Relative Value (Total) Index - Asset Weighted' = c('Global',
'Relative Value'),
  'HFRI RV: Fixed Income-Asset Backed Index' = c('Global', 'Relative
Value'),
  'HFRI RV: Fixed Income-Convertible Arbitrage Index' = c('Global',
'Relative Value'),
  'HFRI RV: Fixed Income-Corporate Index' = c('Global', 'Relative Value'),
  'HFRI RV: Fixed Income-Sovereign Index' = c('Global', 'Relative Value'),
  'HFRI RV: Multi-Strategy Index' = c('Global', 'Relative Value'),
  'HFRI RV: Volatility Index' = c('Global', 'Relative Value'),
  'HFRI RV: Yield Alternatives Index' = c('Global', 'Relative Value'),
  'HFRI Western/Pan Europe Index' = c('Europe', 'Equity Hedge'),
  'HFRI Women Index' = c('Global', 'Diversity'),
  'HFRI World Index' = c('Global', 'Other')
)

# Define a function to categorize each index based on the detailed mapping
categorize_index_detailed <- function(index_name) {
  if (index_name %in% names(index_mapping)) {
    return(index_mapping[[index_name]])
  } else {
    return(c('Other', 'Other'))
  }
}

# Apply the detailed categorization
categories <- t(apply(data, 1, function(row)
categorize_index_detailed(row["Index_Name"])))
data <- cbind(data, Region = categories[, 1], Type = categories[, 2])

# Identify the creation and closure dates for each fund
fund_dates <- data %>%
  group_by(Index_Name) %>%
  summarize(
    Creation_Date = min(Date, na.rm = TRUE),
    Closure_Date = max(Date, na.rm = TRUE),
    .groups = 'drop'
  )

# Print the creation and closure dates of funds
print(fund_dates)

# Create a complete grid of all dates and funds
complete_data <- expand.grid(Date = seq(min(data$Date), max(data$Date), by
= "month"), Index_Name = unique(data$Index_Name))
```

```
# Merge with the actual data to identify missing observations
merged_data <- merge(complete_data, data, by = c("Date", "Index_Name"),
all.x = TRUE)

# Perform linear interpolation to impute missing values
merged_data <- merged_data %>%
  group_by(Index_Name) %>%
  arrange(Date) %>%
  mutate(Return = na.approx(Return, na.rm = FALSE)) %>%
  ungroup()

# Ensure no duplicates of region and type columns exist
merged_data <- merged_data %>%
  select(Date, Index_Name, Ticker, Return, Value) %>%
  mutate(Region = categories[, 1], Type = categories[, 2])

# Filter out rows with NA returns after interpolation
merged_data <- merged_data %>% filter(!is.na(Return))

# Descriptive Statistics
descriptive_stats <- merged_data %>%
  filter(!is.na(Region) & !is.na(Type)) %>%
  group_by(Region, Type) %>%
  summarize(
    Mean = mean(Return, na.rm = TRUE),
    SD = sd(Return, na.rm = TRUE),
    Min = min(Return, na.rm = TRUE),
    Max = max(Return, na.rm = TRUE),
    Median = median(Return, na.rm = TRUE),
    Q1 = quantile(Return, 0.25, na.rm = TRUE),
    Q3 = quantile(Return, 0.75, na.rm = TRUE),
    IQR = IQR(Return, na.rm = TRUE),
    .groups = 'drop'
  )

# Convert descriptive_stats to a data frame for stargazer
descriptive_stats_df <- as.data.frame(descriptive_stats)

# Use stargazer to create a formatted table
stargazer(descriptive_stats_df, type = "text", summary = FALSE, title =
"Descriptive Statistics of Hedge Fund Returns by Region and Type", digits =
3)

# Calculate mean returns for each region
mean_returns <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Region) %>%
  summarize(MeanReturn = mean(Return, na.rm = TRUE))
```

```
# Boxplot of Monthly Returns by Region with mean points
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Region)), aes(x =
Region, y = Return, fill = Region)) +
  geom_boxplot() +
  geom_point(data = mean_returns, aes(x = Region, y = MeanReturn), color =
"red", size = 3, shape = 18) +
  labs(
    title = "Distribution of Monthly Hedge Fund Returns by Region (Over
Multiple Years)",
    x = "Region",
    y = "Monthly Return (%)"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Calculate mean returns for each type
mean_returns_type <- merged_data %>%
  filter(!is.na(Return) & !is.na(Type)) %>%
  group_by(Type) %>%
  summarize(MeanReturn = mean(Return, na.rm = TRUE))

# Boxplot of Returns by Type with mean points
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Type)), aes(x = Type,
y = Return, fill = Type)) +
  geom_boxplot() +
  geom_point(data = mean_returns_type, aes(x = Type, y = MeanReturn), color
= "red", size = 3, shape = 18) +
  labs(
    title = "Distribution of Monthly Hedge Fund Returns by Type (Over
Multiple Years)",
    x = "Type",
    y = "Monthly Return (%)"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Pie Chart of Returns by Region
region_counts <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Region) %>%
  summarize(Count = n()) %>%
  mutate(Percentage = Count / sum(Count) * 100)

# Create custom legend labels
region_counts <- region_counts %>%
  mutate(Legend = paste0(Region, " (", round(Percentage, 1), "%)"))

# Create the pie chart
ggplot(region_counts, aes(x = "", y = Percentage, fill = Legend)) +
  geom_col(width = 1) +
```

```
  coord_polar(theta = "y") +
  labs(
    title = "Distribution of Hedge Fund Returns by Region",
    x = "",
    y = ""
  ) +
  theme_void() +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    legend.title = element_blank(),  # Remove legend title
    legend.text = element_text(size = 12),
    legend.key.size = unit(1.5, "lines")  # Increase legend key size
  )

# Pie Chart of Returns by Type
type_counts <- merged_data %>%
  filter(!is.na(Return) & !is.na(Type)) %>%
  group_by(Type) %>%
  summarize(Count = n()) %>%
  mutate(Percentage = Count / sum(Count) * 100)

# Create custom legend labels
type_counts <- type_counts %>%
  mutate(Legend = paste0(Type, " (", round(Percentage, 1), "%)"))

# Create the pie chart
ggplot(type_counts, aes(x = "", y = Percentage, fill = Legend)) +
  geom_col(width = 1) +
  coord_polar(theta = "y") +
  labs(
    title = "Distribution of Hedge Fund Returns by Type",
    x = "",
    y = ""
  ) +
  theme_void() +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    legend.title = element_blank(),  # Remove legend title
    legend.text = element_text(size = 12),
    legend.key.size = unit(1.5, "lines")  # Increase legend key size
  )

if (!require("moments")) install.packages("moments", dependencies=TRUE)

# Charger la bibliothèque moments pour les calculs de skewness et kurtosis
library(moments)

# Calcul des statistiques descriptives, y compris skewness et kurtosis
descriptive_stats <- merged_data %>%
  filter(!is.na(Region) & !is.na(Type)) %>%
```

```
  group_by(Region, Type) %>%
  summarize(
    Mean = mean(Return, na.rm = TRUE),
    SD = sd(Return, na.rm = TRUE),
    Min = min(Return, na.rm = TRUE),
    Max = max(Return, na.rm = TRUE),
    Median = median(Return, na.rm = TRUE),
    Q1 = quantile(Return, 0.25, na.rm = TRUE),
    Q3 = quantile(Return, 0.75, na.rm = TRUE),
    IQR = IQR(Return, na.rm = TRUE),
    Skewness = skewness(Return, na.rm = TRUE),
    Kurtosis = kurtosis(Return, na.rm = TRUE) - 3,  # Excess kurtosis
    .groups = 'drop'
  )

# Convert descriptive_stats to a data frame for stargazer
descriptive_stats_df <- as.data.frame(descriptive_stats)

# Utiliser stargazer pour créer une table formatée
stargazer(descriptive_stats_df, type = "text", summary = FALSE, title =
"Descriptive Statistics of Hedge Fund Returns by Region and Type", digits =
3)
```

TREND ANALYSIS

```
# Apply the detailed categorization
categories <- t(apply(data, 1, function(row)
categorize_index_detailed(row["Index_Name"])))
data <- cbind(data, Region = categories[, 1], Type = categories[, 2])

# Extract the year from the Date
data$Year <- format(data$Date, "%Y")

# Calculate yearly returns
yearly_data <- data %>%
  group_by(Index_Name, Year, Region, Type) %>%
  summarize(
    Yearly_Return = mean(Return, na.rm = TRUE),
    .groups = 'drop'
  )

# Convert Year back to Date format for plotting purposes
yearly_data$Year <- as.Date(paste0(yearly_data$Year, "-01-01"))
```

```
# Separate plots for each region
for (region in unique(yearly_data$Region)) {
  p <- ggplot(yearly_data %>% filter(Region == region), aes(x = Year, y =
Yearly_Return, color = region)) +
    geom_line() +
    geom_smooth(method = "loess") +  # Add a smoothing line
    labs(title = paste("Yearly Performance Trends in", region), x = "Year",
y = "Yearly Return") +
    theme_minimal() +
    scale_color_brewer(palette = "Set1")

  print(p)
}

# Separate plots for each type
for (type in unique(yearly_data$Type)) {
  p <- ggplot(yearly_data %>% filter(Type == type), aes(x = Year, y =
Yearly_Return, color = type)) +
    geom_line() +
    geom_smooth(method = "loess") +  # Add a smoothing line
    labs(title = paste("Yearly Performance Trends for", type), x = "Year",
y = "Yearly Return") +
    theme_minimal() +
    scale_color_brewer(palette = "Set2")

  print(p)
}

# Facet wrapping by region
p_region <- ggplot(yearly_data, aes(x = Year, y = Yearly_Return)) +
  geom_line(color = "blue") +
  geom_smooth(method = "loess", color = "red") +  # Add a smoothing line
  facet_wrap(~ Region, scales = "free_y") +
  labs(title = "Yearly Performance Trends by Region", x = "Year", y =
"Yearly Return") +
  theme_minimal()

print(p_region)

# Facet wrapping by type
p_type <- ggplot(yearly_data, aes(x = Year, y = Yearly_Return)) +
  geom_line(color = "blue") +
  geom_smooth(method = "loess", color = "red") +  # Add a smoothing line
  facet_wrap(~ Type, scales = "free_y") +
  labs(title = "Yearly Performance Trends by Type", x = "Year", y = "Yearly
Return") +
  theme_minimal()

print(p_type)
```

```
# Interactive plot example by region
p_interactive_region <- ggplot(yearly_data, aes(x = Year, y =
Yearly_Return, color = Region)) +
  geom_line() +
  geom_smooth(method = "loess") +  # Add a smoothing line
  labs(title = "Interactive Yearly Performance Trends by Region", x =
"Year", y = "Yearly Return") +
  theme_minimal()

# Convert ggplot to plotly for interactivity
ggplotly(p_interactive_region)

# Interactive plot by type
p_interactive_type <- ggplot(yearly_data, aes(x = Year, y = Yearly_Return,
color = Type)) +
  geom_line() +
  geom_smooth(method = "loess") +  # Add a smoothing line
  labs(title = "Interactive Yearly Performance Trends by Type", x = "Year",
y = "Yearly Return") +
  theme_minimal()

# Convert ggplot to plotly for interactivity
ggplotly(p_interactive_type)
```

CORRELATION ANALYSIS

```
# Load necessary libraries
if (!require("moments")) install.packages("moments", dependencies=TRUE)
if (!require("corrplot")) install.packages("corrplot", dependencies=TRUE)
if (!require("ggplot2")) install.packages("ggplot2", dependencies=TRUE)
library(moments)
library(dplyr)
library(tidyr)
library(corrplot)
library(ggplot2)

# Check for duplicate entries
duplicate_entries <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Date, Region) %>%
  filter(n() > 1)

# Handle duplicates by taking the mean of the Returns for each Date and
Region combination
```

```r
merged_data_unique <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Date, Region) %>%
  summarise(Return = mean(Return, na.rm = TRUE), .groups = 'drop')

# Reshape the data to wide format for correlation analysis by region
data_wide_region <- merged_data_unique %>%
  select(Date, Region, Return) %>%
  spread(key = Region, value = Return)

# Print the resulting wide data to verify
print(head(data_wide_region))

# Ensure all columns except Date are numeric for correlation calculation
numeric_columns <- data_wide_region %>%
  select(-Date) %>%
  mutate_if(is.character, as.numeric)

# Calculate the correlation matrix
correlation_matrix <- cor(numeric_columns, use = "complete.obs")

# Print the correlation matrix to verify
print(correlation_matrix)

# Plot the correlation matrix
corrplot(correlation_matrix, method = "color",
         type = "upper", order = "hclust",
         addCoef.col = "black", # Add coefficient of correlation
         tl.col = "black", tl.srt = 45, # Text label color and rotation
         diag = FALSE, # Hide the diagonal
         title = "Correlation Matrix of Returns by Region",
         mar = c(0,0,2,0), # Adjust margin
         col = colorRampPalette(c("red", "white", "blue"))(200)) # Color
palette


# Handle duplicates by taking the mean of the Returns for each Date and
Type combination
merged_data_unique_type <- merged_data %>%
  filter(!is.na(Return) & !is.na(Type)) %>%
  group_by(Date, Type) %>%
  summarise(Return = mean(Return, na.rm = TRUE), .groups = 'drop')

# Reshape the data to wide format for correlation analysis by type
data_wide_type <- merged_data_unique_type %>%
  select(Date, Type, Return) %>%
  spread(key = Type, value = Return)

# Print the resulting wide data for verification
print(head(data_wide_type))
```

```
# Ensure all columns except Date are numeric for correlation calculation
numeric_columns_type <- data_wide_type %>%
  select(-Date) %>%
  mutate_if(is.character, as.numeric)

# Calculate the correlation matrix
correlation_matrix_type <- cor(numeric_columns_type, use = "complete.obs")

# Print the correlation matrix in order to check
print(correlation_matrix_type)

# Plot the correlation matrix
corrplot(correlation_matrix_type, method = "color",
         type = "upper", order = "hclust",
         addCoef.col = "black", # Add coefficient of correlation
         tl.col = "black", tl.srt = 45, # Text label color and rotation
         diag = FALSE, # Hide the diagonal
         title = "Correlation Matrix of Returns by Type",
         mar = c(0,0,2,0), # Adjust margin
         col = colorRampPalette(c("red", "white", "blue"))(200)) # Color
palette
```

VOLATILITY ANALYSIS

```
# Create a complete grid of all dates and funds
complete_data <- expand.grid(Date = seq(min(data$Date), max(data$Date), by
= "month"), Index_Name = unique(data$Index_Name))

# Merge with the actual data to identify missing observations
merged_data <- merge(complete_data, data, by = c("Date", "Index_Name"),
all.x = TRUE)

# Perform linear interpolation to impute missing values
merged_data <- merged_data %>%
  group_by(Index_Name) %>%
  arrange(Date) %>%
  mutate(Return = na.approx(Return, na.rm = FALSE)) %>%
  ungroup()

# Apply the detailed categorization after merging
categories <- t(apply(merged_data, 1, function(row)
categorize_index_detailed(row["Index_Name"])))
merged_data <- cbind(merged_data, Region = categories[, 1], Type =
categories[, 2])

# Filter out rows with NA returns after interpolation
```

```r
merged_data <- merged_data %>% filter(!is.na(Return))

# Descriptive Statistics
descriptive_stats <- merged_data %>%
  filter(!is.na(Region) & !is.na(Type)) %>%
  group_by(Region, Type) %>%
  summarize(
    Mean = mean(Return, na.rm = TRUE),
    SD = sd(Return, na.rm = TRUE),
    Min = min(Return, na.rm = TRUE),
    Max = max(Return, na.rm = TRUE),
    Median = median(Return, na.rm = TRUE),
    Q1 = quantile(Return, 0.25, na.rm = TRUE),
    Q3 = quantile(Return, 0.75, na.rm = TRUE),
    IQR = IQR(Return, na.rm = TRUE),
    .groups = 'drop'
  )

# Convert descriptive_stats to a data frame for stargazer
descriptive_stats_df <- as.data.frame(descriptive_stats)

# Use stargazer to create a formatted table
stargazer(descriptive_stats_df, type = "text", summary = FALSE, title =
"Descriptive Statistics of Hedge Fund Returns by Region and Type", digits =
3)

# Calculate mean returns for each region
mean_returns <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Region) %>%
  summarize(MeanReturn = mean(Return, na.rm = TRUE))

# Boxplot of Monthly Returns by Region with mean points
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Region)), aes(x =
Region, y = Return, fill = Region)) +
  geom_boxplot() +
  geom_point(data = mean_returns, aes(x = Region, y = MeanReturn), color =
"red", size = 3, shape = 18) +
  labs(
    title = "Distribution of Monthly Hedge Fund Returns by Region (Over
Multiple Years)",
    x = "Region",
    y = "Monthly Return (%)"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Calculate mean returns for each type
mean_returns_type <- merged_data %>%
  filter(!is.na(Return) & !is.na(Type)) %>%
```

```
  group_by(Type) %>%
  summarize(MeanReturn = mean(Return, na.rm = TRUE))

# Boxplot of Returns by Type with mean points
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Type)), aes(x = Type,
y = Return, fill = Type)) +
  geom_boxplot() +
  geom_point(data = mean_returns_type, aes(x = Type, y = MeanReturn), color
= "red", size = 3, shape = 18) +
  labs(
    title = "Distribution of Monthly Hedge Fund Returns by Type (Over
Multiple Years)",
    x = "Type",
    y = "Monthly Return (%)"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Pie Chart of Returns by Region
region_counts <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region)) %>%
  group_by(Region) %>%
  summarize(Count = n()) %>%
  mutate(Percentage = Count / sum(Count) * 100)

# Create custom legend labels
region_counts <- region_counts %>%
  mutate(Legend = paste0(Region, " (", round(Percentage, 1), "%)"))

# Create the pie chart
ggplot(region_counts, aes(x = "", y = Percentage, fill = Legend)) +
  geom_col(width = 1) +
  coord_polar(theta = "y") +
  labs(
    title = "Distribution of Hedge Fund Returns by Region",
    x = "",
    y = ""
  ) +
  theme_void() +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    legend.title = element_blank(),  # Remove legend title
    legend.text = element_text(size = 12),
    legend.key.size = unit(1.5, "lines")  # Increase legend key size
  )

# Pie Chart of Returns by Type
type_counts <- merged_data %>%
  filter(!is.na(Return) & !is.na(Type)) %>%
  group_by(Type) %>%
```

```
  summarize(Count = n()) %>%
  mutate(Percentage = Count / sum(Count) * 100)

# Create custom legend labels
type_counts <- type_counts %>%
  mutate(Legend = paste0(Type, " (", round(Percentage, 1), "%)"))

# Create the pie chart
ggplot(type_counts, aes(x = "", y = Percentage, fill = Legend)) +
  geom_col(width = 1) +
  coord_polar(theta = "y") +
  labs(
    title = "Distribution of Hedge Fund Returns by Type",
    x = "",
    y = ""
  ) +
  theme_void() +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    legend.title = element_blank(),  # Remove legend title
    legend.text = element_text(size = 12),
    legend.key.size = unit(1.5, "lines")  # Increase legend key size
  )

# Volatility Analysis
# Calculate volatility measures
volatility_stats <- merged_data %>%
  filter(!is.na(Return) & !is.na(Region) & !is.na(Type)) %>%
  group_by(Region, Type) %>%
  summarize(
    SD = sd(Return, na.rm = TRUE),
    Variance = var(Return, na.rm = TRUE),
    Beta = sd(Return, na.rm = TRUE) / mean(Return, na.rm = TRUE),
    .groups = 'drop'
  )

# Convert to a data frame
volatility_stats_df <- as.data.frame(volatility_stats)

# Use stargazer to create a formatted table
stargazer (volatility_stats_df, type = "text", summary = FALSE, title =
"Volatility Measures of Hedge Fund Returns by Region and Type", digits = 3)

# Sharpe Ratio Calculation
risk_free_rate <- 0.02 / 12 # risk-free rate, adjusted for monthly returns
sharpe_ratio <- merged_data %>%
  group_by(Region, Type) %>%
  summarize(
    MeanReturn = mean(Return, na.rm = TRUE),
    SD = sd(Return, na.rm = TRUE),
```

```
    SharpeRatio = (MeanReturn - risk_free_rate) / SD,
    .groups = 'drop'
  )

# Convert to a data frame
sharpe_ratio_df <- as.data.frame(sharpe_ratio)

# Use stargazer to create a formatted table
stargazer(sharpe_ratio_df, type = "text", summary = FALSE, title = "Sharpe
Ratios of Hedge Fund Returns by Region and Type", digits = 3)

# Plot volatility trends by region
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Region)), aes(x =
Date, y = Return, color = Region)) +
  geom_line() +
  labs(title = "Volatility Trends by Region", x = "Date", y = "Return") +
  theme_minimal()

# Plot volatility trends by type
ggplot(merged_data %>% filter(!is.na(Return) & !is.na(Type)), aes(x = Date,
y = Return, color = Type)) +
  geom_line() +
  labs(title = "Volatility Trends by Type", x = "Date", y = "Return") +
  theme_minimal()
```