# Demystifying Derivatives: How Equity, Fixed-Income, and Asset Allocation Mutual Funds Employ Derivatives.

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**ABSTRACT:** After the 2008 crisis and the COVID-19 pandemic-related financial downturn, attention to the use of derivatives by mutual funds has increased both from investors and regulatory bodies. This paper uses SEC N-PORT and CRSP data on equity, fixed-income, and asset allocation mutual funds from 2021 to 2023 to investigate the primary use case of derivatives by these mutual funds. We find that while equity and asset allocation funds primarily use derivatives to amplify returns, fixed-income funds use them mainly for hedging risks. We also show how all 3 types of mutual funds use derivatives on a contract level. Equity funds tend to use equity derivatives for amplification and use foreign exchange and credit derivatives for hedging. On the other hand, fixed-income funds mainly utilize foreign exchange and interest rate derivatives for hedging. Asset allocation funds use foreign exchange derivatives for hedging and interest rate derivatives for amplification.

**Keywords:** Derivatives, Mutual Funds, Risk Hedging, Amplification

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# 1 Introduction

Derivatives have been integral to mutual fund strategies for decades. However, the aftermath of the 2008 global financial crisis and the COVID-19 crisis has intensified scrutiny on their use, particularly concerning the risks they pose to investors. These events have prompted tighter regulations by the SEC to protect unsophisticated investors, underscoring the need for a deeper understanding of mutual fund derivative practices. Existing research on derivative use by mutual funds dates back from 1999 and has primarily focused on derivative use by equity mutual funds. Despite over two decades of research, no consensus has emerged on whether mutual funds primarily use derivatives for hedging or for return amplification. This uncertainty complicates investor decision-making and regulatory oversight. While some of the research papers argue that derivatives are primarily used for hedging (Cao et al. (2011), Koski & Pontiff (1999)), others argue that mutual funds use derivatives for return amplification and profit seeking purposes (Kaniel & Wang, 2024).

Prior research has relied on various data sources such as balance sheet data (Cao et al., 2011), survey data from mutual funds (Koski and Pontiff, 1999), and other non-granular data sources to make their research – not able to empirically measure the performance of derivatives of mutual funds to make more accurate research.

It wasn't until SEC N-PORT data became available that the exact use case of derivatives by equity mutual funds was researched using granular data. Notably, the first research utilizing N-PORT data by Kaniel and Wang has revised the perspective on usage of derivatives by equity mutual funds – utilizing granular derivative data to show that equity mutual funds on average use derivatives to amplify their returns (Kaniel & Wang, 2024).

Despite these insights, there remains a major gap in the literature concerning the usage of derivatives by mutual funds in other asset classes. This gap is particularly noteworthy given the substantial assets under management in fixed-income and asset allocation mutual funds. Moreover, there is sparse research on how exactly different contract types are used by mutual funds. Our research aims to fill this gap by investigating whether equity, fixed-income and asset allocation funds use derivatives primarily for hedging or to enhance returns as well as how each derivative contract is utilized by these mutual funds.

We look at a total of 4346 mutual funds with 2391 equity mutual funds, 1149 fixed-income mutual funds, and 806 asset allocation (blending equity & fixed-income strategies) mutual funds. Data spans from the first quarter of 2021 to the last quarter of 2023 analyzing the results on quarterly level. Equity mutual funds from our dataset have around $12.04 trillion total net assets as of end of 2023, while fixed income funds have $4.47 trillion total net assets and asset allocation mutual funds have $3.37 trillion net assets respectively.

After obtaining the data for 3 different fund categories (equity, fixed-income, asset allocation), we first start by calculating fund returns for the given period. We divide the returns into derivative induced returns (DIR) and non-derivative induced returns (non-DIR). DIR refers to part of returns that comes from derivative positions of the company and was introduced as a novel measure by Kaniel & Wang (2024). We utilized this measure for our analysis further extending it to other fund categories including fixed-income and asset allocation funds. Fund level correlation analysis is conducted between DIR and non-DIR for the sample period to find how each fund in a different asset class uses derivatives. We then take average of fund level correlation for funds in each asset class to determine how funds use derivatives on average in each asset class. One-Sample t-Test is then implemented to test whether the derivative usage is systematic in mutual funds across different asset classes. Additionally, we examine the usage of various types of derivative contracts – such as equity, commodity, credit, foreign exchange, interest rate and other contracts – by performing correlation analyses and One-Sample t-Tests at the derivative contract level, similar to the overall derivative analysis we performed before. This approach helps us understand how mutual funds typically employ different types of derivative contracts within each asset class.

Our findings suggest that mutual funds use derivatives differently depending on the asset class. Equity and asset allocation funds primarily use derivatives to amplify returns, whereas fixed-income funds use them mainly for hedging risks. Specifically, equity funds tend to use equity derivatives for amplification and use foreign exchange and credit derivatives for hedging. On the other hand, fixed income funds mainly utilize foreign exchange and interest rate derivatives for hedging. Asset allocation funds use foreign exchange derivatives for hedging and interest rate derivatives for amplification. By clarifying the derivative usage strategies of mutual funds, this study aims to provide valuable insights that can influence future regulatory frameworks and investment strategies.

Following this introduction, Section 2 reviews the literature, providing a backdrop for the hypotheses developed in Section 3. Section 4 details our data sources and methodology, leading into Section 5 where we present and discuss our findings. The implications and limitations of our research are explored in Sections 6 and 7, respectively, before concluding in Section 8

# 2 Literature Review

Current existing literature on usage of derivatives by mutual funds is divided by regions and primarily focused on equity mutual funds.

Starting from Koski and Pontiff (1999), with focus on derivatives usage by the US equity mutual funds, there has been extended focus on studying derivative usage across mutual funds in Europe from European Securities and Markets Authority paper on European equity mutual funds (Bias et al., 2021), and latest on the US mutual funds again with a new N-PORT filing system of SEC that makes it easier to retrieve deeper company specific data (Kaniel & Wang, 2024).

## Derivative use by mutual funds

The first major research into the use of derivatives by mutual funds can be traced back to the pioneering study by Koski and Pontiff in 1999. Their research was only limited to US equity mutual funds. Koski and Pontiff looked at 679 mutual funds and found that around 21% of mutual funds employed derivatives. According to their paper, this figure might be underrepresented due to undeclared positions and data acquisition challenges during the interviews they were conducting. They found that managers using derivative assets tended to combine them with non-derivative assets to deliver returns and risk profiles comparable to those funds not using derivatives, suggesting a focus on risk minimization (hedging) rather than return amplification (Koski & Pontiff, 1999). Lastly, the authors of the paper discovered that managers adjusted their derivative positions in response to events of the past events which resulted in lower risk measures, indicating that this might be representative of funds using derivatives to reduce impact of performance on the risk levels of the fund.

In 2006, Marín and Rangel conducted an extensive study on the Spanish mutual fund industry. Their research looked at 1707 funds across 8 different classifications ranging from European equity to global mutual funds. According to their research a more significant adoption of derivatives in Spain could be observed compared to the U.S., with about 60% of funds having allocations in these financial instruments. Additionally, over a decade, they observed an increase from 2.7% to more than 15% of net asset value in derivatives holdings among these funds. Marín and Rangel (2006) show increased derivative use in Spain, suggesting market-wide acceptance and differing dynamics compared to the U.S. This implies that regulatory environments and market conditions might significantly influence derivative strategies, a factor that should be considered in comparative studies. Looking at the potential fund characteristics that might influence derivative adoption for the mutual funds, the research discovered that funds belonging to larger family where derivatives are already used, funds charging higher fees, and large funds were more likely to use derivatives. Particularly, research concluded that in most cases mutual funds use derivatives for speculative purposes (amplification).

Cao et al. (2011) analyzed 300 funds over a period of 5 years to see how their use of derivatives affects performance furthermore digging into effect of derivative usage on performance in high volatility crisis times like during 1998 Russian financial crisis. They discovered that while 77% of companies were permitted to use derivative instruments, only 14% did so. Even then, most of the derivative users use these financial instruments very sparingly which justifies their lack of considerable risk-adjusted returns. Their study showed that funds with considerable foreign holdings and those using foreign exchange contracts had a more significant portion of their assets in derivatives compared to domestic equity funds, which held less than 1% of their assets in these instruments. Funds that were in top decile for allocation of derivatives relative to their net assets, showed considerable returns differences compared to non-users and light users of derivatives. Authors argued that one reason for this might be because derivatives were primarily used for hedging against extreme events instead of profit seeking. Lastly, the paper concluded that there was a tendency among funds to manage their positions based on historical crises rather than prospective future events (Cao et al., 2011).

Cici and Palacios (2015) looked at one specific type of derivative use across mutual funds. Their dataset that looked at 250 U.S based mutual funds from 2003-2010 period analyzed how funds use options to either amplify, hedge, or even potentially just create income source for the mutual funds. The research found that most of the funds used call options to for income generation for the fund, while put options were primarily used to hedge the risk of the funds. Further looking into some funds characteristics that might impact option use, Cici and Palacios find that funds with higher expense ratio and managers with less tenure tend to use options more frequently. This paper also finds that funds that primarily focus on hedging by purchasing put options end up with lower systemic risk compared to non-users of those derivatives.

A research paper by Natter et al. (2016) on benefits of using options for mutual funds also reveals similar results as earlier paper by Cici and Palacios. Use of options by mutual funds yields higher risk adjusted returns. On top of it, the paper finds that mutual funds primarily use options for hedging purposes which helps them get lower systemic risk on average. Just like in earlier research the paper confirms that while put options are the primary contributor to the lower risk for the mutual funds, call options are the main drivers of increased risk adjusted returns of 184 basis points annually. The viability of options as hedging mechanisms for the funds is also confirmed by the authors with the discovery that mutual funds consistently get lower systemic risk while using options compared to the times, they do not employ these derivatives.

Bias et al. (2021) explored the prevalence of derivative usage among European mutual funds looking at 4555 equity mutual funds. The findings suggest that over 46% of these funds regularly engaged in derivatives trading with the most utilized derivatives being forwards, futures, and options.  These derivatives are primarily used for two purposes: to minimize risk and to save on transaction costs. The research concludes that return amplification and speculation are not the driving motives behind derivative use by the funds. On top of it, their study concluded that, on average, while derivative users had a 75-basis point higher return, the risk-adjusted return was comparable to that of non-users.

Choi et al. (2023) analyzed specific types of derivative contracts for fixed-income mutual funds – interest rate derivatives. By looking through the newly available SEC N-PORT database, authors observed high level adoption of interest rate contracts by the fixed-income funds. The paper concludes that interest rate derivatives are usually used not only to hedge interest rate risk by the funds but also to speculate on and amplify that risk. A pattern could be observed within the main user group of interest rate derivatives with most of the funds being either larger, younger, or charging a larger expense ratio. Unlike some of the literature reviewed earlier, Choi et al. (2023) find that interest rate derivatives are not totally integrated with the rest of the portfolio, sometimes used as a separate revenue source by the funds. Authors also state that because of older relaxed regulations on the derivative use, most of the funds would not use notional value of the derivative in their declarations and risk calculations, frequently understating risk exposure of the stakeholders which caused SEC to standardize and tighten the regulations around this matter.

Unlike earlier studies that focused primarily on retrieving derivative data based on centralized data providers like CRSP and Morningstar, Kaniel and Wang (2024) used new type of dataset that was accessible only recently through SEC N-PORT. Differently from earlier data sources, N-PORT allowed authors to get more granular data about derivative usage by looking at derivative unrealized/realized PnL and gave better insight on total derivative positions that were not available through any other source earlier. Analyzing particularly US equity mutual funds, the authors noted that while 35% of 3106 funds had derivative allocations, 36% of total net assets of these funds were invested in derivatives. Since options and futures comprise the biggest chunk of derivative usage, most of the research until now has been focused on these two derivative forms. Meanwhile, Kaniel and Wang (2024) dive deeper into looking at swap and foreign exchange contract derivatives as well. Analyzing derivative induced returns versus non-derivative induced returns across all the funds, the research proposed that derivative instruments are being utilized as a leverage mechanism to enhance fund returns, particularly with long index funds being the most avid users (Kaniel & Wang, 2024). Findings imply that even though the main purpose of the derivative usage is return amplification, positive results are only considerable for the funds that have large allocations in derivatives. The rest of the funds yield comparable risk adjusted returns to non-users of derivatives.

## Our Contributions

Our research contributes to the existing literature especially to the research by Kaniel & Wang (2024) and Choi et al. (2023) by shedding light on how derivatives are used overall and at contract level by mutual funds in different asset classes. While Kaniel & Wang (2024) analyzed how equity mutual funds use derivatives and Choi et al. (2023) analyzed usage of interest rate contract by fixed-income mutual funds, in our study we extend the analysis by showing how derivatives are used by mutual funds in 3 asset classes and whether they are used systematically. We further contribute to the literature by analyzing how 6 different types of derivative contracts are used by mutual funds in equity, fixed-income, and allocation funds and explaining whether they are used systematically and for what purposes. Overall, there are a lot more research avenues in this space given increasing transparency due to regulation and open/ easier access to SEC digital filings, and our research sets good starting ground for further analysis.

# 3 Hypothesis Development

Literature on derivative usage by mutual funds has mostly focused on equity mutual funds for a long time. Some of the reasons behind it were access to a larger number of equity funds, inaccessibility of derivative usage data for funds other than equity mutual funds as well as complexity of derivatives used by different funds that have made it challenging for researchers to quantify derivative usage and its impact on mutual funds. For a long time, most researchers have claimed that equity mutual funds use derivatives for hedging purposes (Cao et al. (2011), Koski and Pontiff (1999), Cici & Palacios (2015), Natter et al. (2016)). The research of Kaniel and Wang (2024) was the first to question predominant claims by using granular N-PORT data to prove that equity mutual funds mostly use derivatives for amplification. Our research, inspired by their new finding, investigates how equity mutual funds use derivatives and expands the scope to analyze how asset allocation and fixed-income mutual funds use derivatives overall as well as at the derivative contract level.

In developing our hypotheses, we begin by articulating our primary research question, which is then analyzed through a series of hypotheses addressing specific components of the questions. Especially, we want to understand how derivatives are used by mutual funds in equity, fixed-income, and asset allocation assets as well as dive deeper to understand how those funds use specific derivative contracts. Furthermore, our research aims to investigate whether derivatives are used by mutual funds systematically/regularly (in a planned & strategic way) or not. We split our central research question into smaller questions to be able to answer each part more thoroughly through hypothesis testing.

Our research question: how do mutual funds in equity, fixed-income, and asset allocation asset classes utilize derivatives?

- Do mutual funds use derivatives for amplification or hedging?
- Is there a systematic relationship between derivative returns and non-derivative returns – signaling systematic use of derivatives in different mutual fund asset classes?
- How is each derivative contract utilized by the mutual funds?

We develop the following 3 hypotheses to research how funds use derivatives and whether their use is systematic. First, by replicating the methods of Kaniel and Wang (2024) we aim to understand how equity mutual funds use derivatives, especially, what type of derivatives are used by equity mutual funds. According to most prior literature equity mutual funds used to use derivatives for hedging (Koski and Pontiff (1999), Cao et al. (2011), Natter et al. (2016)). The time span of prior research has been different and has witnessed different economic events, crises as well as different monetary policies. While Kaniel and Wang (2024) claimed that derivatives are used for amplification, their research period started with the start of COVID-19 and encompassed a period of different major changes to economic and monetary policies. Cao et al. have proven that the effects of derivatives are more visible during the time of crisis (2011).

That may mean that Kaniel and Wang's research may be influenced by black swan events and may not be representative of normal derivative usage for equity mutual funds. Since economic conditions/uncertainty during our research period are different and don't include COVID-19, we believe our research can be representative of "average" derivative usage by equity mutual funds. To test how equity mutual funds use derivatives, we develop our first hypothesis as follows:

H1: *Equity mutual funds use derivatives systematically and on average to amplify their returns rather than to hedge against downside risk.*

Differently from equity mutual funds, fixed-income funds are known for their more conservative investment strategy since the asset class those funds invest into is mainly focused on capital preservation and income generation (Wall Street Prep, 2024). Prior research on fixed-income mutual funds (Sialm & Zhu, 2022) showed that 90% of fixed-income funds use foreign exchange contracts to hedge against their currency exposure. Even though the use of all other derivative contracts by fixed-income mutual funds hasn't been majorly explained by prior research, foreign exchange contracts take a major share of derivative usage of fixed-income funds (Sialm & Zhu, 2022). Consequently, we expect the overall derivative strategy of fixed-income funds to focus on risk management to minimize the volatility of returns compared to equity funds which may focus on amplification. Therefore, we develop our second hypothesis as follows:

H2: *Fixed-income mutual funds utilize derivatives systematically for hedging rather than for amplification/speculation.*

Literature on asset allocation mutual fund usage of derivatives is almost non-existent, while there are more than 1000 asset allocation mutual funds operating just in the United States that hold extensive amounts of assets under management according to Morningstar data - making asset allocation mutual funds the third largest mutual fund asset class after equity and fixed income mutual funds. Asset allocation mutual funds are known for their diversification strategy of investing both in equity and bond markets (Charles Schwab, n.d). Therefore, there is no straightforward way to predict how derivatives will be used by Allocation mutual funds. Thus, to check how Allocation mutual funds use derivatives, we develop our next hypothesis as follows:

H3. *Asset allocation mutual funds use derivatives systematically to amplify their exposure to their underlying assets*.

To further investigate how mutual funds in each asset class utilize derivatives and to answer the last part of our research question, we develop 3 hypotheses. Kaniel and Wang research illustrated that equity mutual funds use equity derivative contracts for amplification purposes (2024), while Choi et al., showed that fixed-income mutual funds can use interest rate derivatives for hedging as well as speculation (2023). Aside from those 2 researchers, there is limited investigation into how specific derivative contracts are used by mutual funds. Consequently, we develop the following 3 hypotheses, assuming underlying derivative contracts will be used in line with the overall derivative strategy (hedging or amplification). Through each hypothesis, we test how funds in different asset classes utilize equity, interest, credit, commodity, foreign exchange, and other derivative contracts.

H4. *Equity mutual funds use each derivative contract systematically to amplify their exposure to their underlying assets*.

H5. *Fixed-income mutual funds use each derivative contract systematically to hedge their exposure to their underlying assets*.

H6. *Asset allocation mutual funds use each derivative contract systematically to amplify their exposure to their underlying assets*.

Through these hypotheses, we will systematically explore the detailed behaviors of mutual funds in their use of derivatives. Hypotheses 1-3 will investigate and answer whether derivatives are on average used systematically for hedging or amplification across different mutual fund asset classes, answering a major part of our research question. Using hypotheses 4-6, we will answer the remaining part of our research question – illustrating how mutual funds in different asset classes utilize each derivative contract. Moreover, the absence of black swan events such as COVID-19 that not only struck businesses but sent a shock wave across stock markets in our sample period, will enable us to prepare representative views about the usage of derivatives by mutual funds.

# 4 Data and Methodology

## 4.1 Data Sample

Our analysis investigates the use of derivatives by mutual funds, using three principal data sources to capture a comprehensive view of mutual fund activities in the United States. The period of analysis spans from Q1 2021 to Q4 2023, containing 3 years and 12 quarters of financial data. These sources include the Morningstar Database for information on active mutual in the United States, the SEC's Form N-PORT for detailed derivative positions, and the CRSP database for fund Net Asset Value (NAV) and Total Net Assets (TNA) of the mutual funds.

### Mutual Fund Data

Initially, we retrieve a list of all active mutual funds in the United States from Morningstar Direct. It is noteworthy that Morningstar reports not only unique funds but also their classes (institutional, retail, advisory, etc.). Despite differing tickers, management fees, and expense ratios, each fund class reports almost identical returns and derivative holdings within the same N-PORT filings. Utilizing the 'FundID' number that is unique to each mutual fund regardless of the asset class, we aggregate data from different classes under one ticker/FundID to analyze each mutual fund overall. The Morningstar dataset also includes valuable metadata for each fund, such as the Global Broad Category Group (classifying funds into equity, fixed income, and allocation categories), name of firm owning the fund family, Primary Prospectus Benchmark, expense ratio, and fund size.

## Derivative Data

To get derivative holdings of the funds, we use the novel Form N-PORT database of the SEC. The N-PORT database has some advantages compared to other data sources for mutual funds. Structured reporting requirements provide a complete view of the derivative holdings as well as derivative position appreciation/depreciation value for each fund per quarter, split into 6 different derivative contract categories: equity, interest rate, commodity, credit, foreign exchange, and other. This richness of data not only helps us measure how derivatives are used by mutual funds but also allows us to measure how each derivative contract type is used by mutual funds in different asset classes.

SEC finalized the reporting requirements for Form N-PORT in June 2018, while funds started filing Form N-PORT in different periods, based on their net assets (U.S. Securities and Exchange Commission, 2019). Funds with net assets of $1 billion or more began filing Form N-PORT quarterly by June 1, 2018, while funds with net assets of less than $1 billion but at least $400 million began filing by June 1, 2019 (U.S. Securities and Exchange Commission, 2019). Lastly, funds with net assets of less than $400 million were initially granted an additional year, with a compliance date of June 1, 2020 (U.S. Securities and Exchange Commission, 2019).

We use the N-PORT database to get data on quarterly net assets for each mutual fund and monthly realized and unrealized appreciation for derivative positions under each derivative contract category (equity, credit, interest rate, commodity, foreign exchange, and other) for each mutual fund from Q4 2020 till Q4 2023. We use Q4 2020 net asset value for calculations of derivative returns (used when calculating Q1 2021 returns), but our main analysis covers the research period from Q1 2021 till Q4 2023.

### NAV and TNA Data

We use fund tickers from Morningstar data to get monthly Net Asset Value (NAV) and yearly Total Net Asset (TNA) data for each fund starting from Q4 2020 till Q4 2023. We use NAV instead of share price to calculate fund quarterly return, similar to the approach used by Kaniel and Wang (2024).

## 4.2. Data Collection

After aggregating unique funds using their FundID, we split funds into 3 datasets based on 3 main asset classes for our analysis: equities, fixed-income, and asset allocation (a blend of equity and fixed-income strategies). Our initial data set for equity funds consisted of 3327 unique funds, while the fixed-income data set had 1783 mutual funds, and the asset allocation data set had 1148 mutual funds.

After splitting mutual funds into separate data frames based on their asset class (equity, fixed-income, and asset allocation) (we use Morningstar category column), the main aim is to gather a comprehensive set of metadata for these funds, particularly to extract their N-PORT reports, which would be pivotal in the following analysis. We use Sec-Api to retrieve N-PORT reports for all funds in different asset class data frames. We set a critical filtering criterion to ensure our data is organized smoothly for analysis: to include only funds that had consistently reported from 2021 to 2023, encapsulating all 12 quarterly reports within this span (plus, Q4 2020 report to get TNA for later calculations).

Application of selection criteria after data retrieval criterion resulted in the dataset for funds getting smaller. It led to equity funds data decreasing to 2391, while fixed-income funds and allocation funds numbers decreased to 1149 and 806, respectively. This reduction is attributable to several factors: some funds did not report in that period, some were absent from the N-PORT database, some funds did not exist throughout the whole analysis period, while others had not reported consistently throughout the designated research period. Our manual investigation of some missing funds supports our expectations that either those funds tickers were missing from the N-PORT database, they did not report for the whole sample period, or they reported several N-PORT forms for the period – creating ambiguity regarding their N-PORT results.

## 4.3 Data Representativeness

To investigate potential selection bias that could be introduced through this filtering, we decided to make a few tests to see whether the data we have is representative of the population since wrong/unrepresentative data could skew the study's outcomes. Considering that equity, fixed-income, and asset allocation sample datasets all have around 70-80% of the population data, we cannot compare full population data with sample data, since sample data could skew the population data, thus, leading to incorrect statistical inferences. Therefore, we conduct statistical tests on the sample data set and the data not included in the sample data (data for which we could not retrieve full N-PORT data – leftover sample henceforth) to see whether they are statistically different from each other.

### 4.3.1 Statistical Tests for Representativeness

We check the representativeness of the data using two categorical and four numerical variables. To evaluate the categorical variables – global category and prospectus objective – a Chi-Square test was employed. We use the Chi-Square test for its ability to compare observed frequencies in each category with expected frequencies under the assumption of no association between the variables (Singhal and Rana, 2015). The null hypothesis for the Chi-Square test is that the sample data is representative of the population (Singhal and Rana, 2015). The alternative hypothesis states that sample data is not representative of the population (proportions of data are not similar) (Singhal and Rana, 2015). Low p-values (we use a 5% threshold) for both categorical variables would signify that the null hypothesis should be rejected, implying that we cannot claim that our sample is representative of the population.

Furthermore, we used T-test for numerical variables, specifically average expense ratio, risk score (provided by Morningstar), average management fee, and total net assets (from CRSP and for 2023 Q4) to understand whether the means of these variables in the sample we have were significantly different from those in the leftover sample. The null hypothesis stated that no such difference existed, and any observed variance was a result of sampling error or chance occurrences. However, the alternative hypothesis would suggest a substantial divergence in means. P-values from the T-test below the threshold of 0.05, would mean we have to reject the null hypothesis – showing that the subsample is not a good representation of the full sample (in our case leftover sample) with respect to these numerical variables.

We made these tests for equity funds, fixed-income funds, and asset allocation funds. Overall, based on some variables our sample is similar to the leftover population – a good representation of the population, while based on TNA for all 3 asset classes, our sample is not similar to the leftover population.

### 4.3.2 Interpretation of Results

**Equity funds**:

We use the Chi-Square test to check for sample selection bias for equity funds and get low p-values for both categorical variables as can be seen from Table 1 (we use 5% statistical significance). Thus, we show that there is a statistically significant difference between the distributions of these variables in the equity funds sample and leftover dataset.

We implement a T-test when analyzing four numerical values to find whether there is a difference between our sample and leftover sample. As can be seen from Table 1, the average management fee and average expense ratio columns are not statistically different between the sample and leftover sample. However, TNA and portfolio risk scores test results show statistically significant differences in the sample and the leftover sample.

**Table 1:** *Chi-Square Test and T-Test results for Equity Mutual Funds*

| Variable | T-statistic | P-value |
|---|---|---|
| Global Category | 71.7992 | 0.0001 |
| Prospectus Objective | 42.9042 | 0.0010 |
| Portfolio Risk Score | 2.2534 | 0.0243 |
| Average Management Fee | -1.1482 | 0.2510 |
| Average Expense Ratio | -0.6051 | 0.5452 |
| TNA Latest | -4.4672 | 0.0000 |

**Fixed-income funds**:

We utilize the Chi-Square test for fixed-income funds and get low p-values for both categorical variables as can be seen from Table 2. Thus, we show that there is a statistically significant difference between the distributions of these variables in the fixed-income mutual funds sample and the leftover sample.

We conduct a T-test to 4 numerical variables for fixed-income funds as well. As can be seen from Table 2, the average management fee, average expense ratio, and portfolio risk score columns are not statistically different between the sample and the leftover sample. However, TNA test results show statistically significant difference in the sample and the leftover sample (low p-value).

**Table 2:** *Chi-Square Test and T-Test results for Fixed Income Mutual Funds*

| Variable | T-statistic | P-value |
|---|---|---|
| Global Category | 12.1533 | 0.0162 |
| Prospectus Objective | 50.4551 | 0.0001 |
| Portfolio Risk Score | 1.3454 | 0.1787 |
| Average Management Fee | 0.4819 | 0.6299 |
| Average Expense Ratio | 0.0183 | 0.9853 |
| TNA Latest | 2.2737 | 0.0231 |

**Asset Allocation funds**:

We perform the Chi-Square test for asset allocation funds and get high p-values for both categorical variables as can be seen from the results in Table 3. Thus, our asset allocation sample is not statistically different from leftover data according to the two categorical variables.

We implement a T-test to 4 numerical variables for asset allocation funds as well. As can be seen from Table 3, similar to the case of fixed-income funds, average management fee, average expense ratio, and portfolio risk score columns are not statistically different between our sample and the leftover sample. However, TNA test results illustrate a statistically significant difference in the sample and the leftover sample (low p-value).

**Table 3:** *Chi-Square Test and T-Test results for Asset Allocation Mutual Funds*

| Variable | T-statistic | P-value |
|---|---|---|
| Global Category | 7.3450 | 0.3938 |
| Prospectus Objective | 0.3938 | 0.3055 |
| Portfolio Risk Score | -1.0596 | 0.2897 |
| Average Management Fee | -1.7866 | 0.0744 |
| Average Expense Ratio | 1.2217 | 0.2222 |
| TNA Latest | 4.7436 | 0.0000 |

Furthermore, we check the average TNA for leftover and sample data for funds from all 3 asset classes and find that the average TNA is lower for leftover sample data compared to the sample data we have (see Table 4). Therefore, we can observe that our samples of mutual funds for all three classes are less representative of mutual funds with small TNA.

**Table 4:** *Mean TNA for sample and Leftover sample (in millions of USD)*

| Variable | Sample Mean | Leftover Sample Mean |
|---|---|---|
| Equity | 2150.03 | 649.76 |
| Fixed Income | 1337.57 | 741.40 |
| Asset Allocation | 1920.17 | 363.30 |

Since our datasets for all 3 asset classes cover 70-80% of US mutual funds in those asset classes, we continue our analysis but keep in mind that our data is less representative of smaller mutual funds.

## 4.4 Variable Construction

We construct new variables from the raw data we get from 3 data sources to use in the model for analysis. All the variables are constructed for the mutual funds from 3 different asset classes: equity, fixed-income, and asset allocation. In our research, we adapt and extend some formulas originally proposed by Kaniel and Wang (2024) to construct our variables.

### 4.4.1 Quarterly returns

To calculate quarterly returns for funds we use NAV data from CRSP. Quarterly returns will be used to calculate derivative and non-derivative returns in the following sections.

$$Quarterly\ Return_t = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} \quad (1.1)$$

where:

*NAVt* is the Net Asset Value at the end of the current quarter,

*NAVt-1* is the Net Asset Value at the end of the previous quarter.

### 4.4.2 Derivative Variable Construction

Since this paper analyzes the relationship between derivative and non-derivative returns, below we construct derivative-related variables using quarterly N-PORT filings, which provide granular data on the monthly realized and unrealized derivative appreciation for various derivative contracts for each fund for every quarter as well as quarterly net asset information. The variables are constructed as follows:

**Derivative Induced Return (DIR)**:

To account for the impact of derivatives on fund quarterly performance, we calculate the DIR variable. We calculate DIR using two variables: quarterly derivative appreciation/depreciation and TNA for the prior quarter. N-PORT report for each fund reports monthly realized and unrealized appreciation/depreciation (PnL) for each derivative contract type. Therefore, we first sum up monthly (sum up for 3 months) derivative realized and unrealized PnL for all the derivative contract types to get the total quarterly derivative PnL for each fund. This aggregate sum is then standardized by the Net Assets of the mutual fund as reported at the end of the previous quarter, yielding the *Derivative Induced Return* (DIR) for the quarter. This measure captures the proportional effect of derivative positions on fund returns, independent of the fund's scale. Following the Wang and Kaniel (2024) formula we build our derivative return variables as follows:

$$DIR_t = \frac{PnL_t^{Realized} + PnL_t^{Unrealized}}{TNA_{t-1}} \quad (1.2)$$

where:

$PnL_t^{Realized}$ is the total quarterly realized appreciation/depreciation from derivative positions in the current quarter,

$PnL_t^{Unrealized}$ is the total quarterly unrealized appreciation/depreciation from derivative positions in the current quarter,

$TNA_{t-1}$ is total net asset of the previous quarter.

**Non-Derivative Induced Return (non-DIR)**:

Using quarterly return data from CRSP, we calculate *Non-Derivative Induced Return* (non-DIR) for the mutual funds by subtracting DIR (formula 1.2) for the quarter from the quarterly returns of the fund (formula 1.1). Non-DIR captures fund returns not related to derivative positions.

$$nonDIR_t = Quarterly\ Return_t - DIR_t \quad (1.3)$$

**Signed Derivative Relative Contribution:**

To understand the effect of derivative returns on the total quarterly returns, we calculate *Signed Derivative Relative Contribution*.

$$Signed\ Derivative\ Relative\ Contribution = \frac{DIR_t}{nonDIR_t} \quad (1.4)$$

**Derivative Relative Contribution:**

Finally, we calculate the *Derivative Relative Contribution* to capture the relative size difference between derivative and non-derivative returns.

$$Derivative\ Relative\ Contribution = |Signed\ Derivative\ Relative\ Contrubution| \quad (1.5)$$

**Derivative Usage Variables**:

To capture the information about derivative usage, we construct two binary variables:

*Derivative User*: This variable takes a value of 1 if the fund engages in any derivative transactions within the specific quarter, otherwise 0. It provides a discrete indication of derivative activity within each reporting period.

*Derivative User Overall*: This variable indicates whether the fund has utilized derivatives at any point across the examined 12-quarter span. It is assigned a value of 1 if the fund has used derivatives during any of the quarters, and 0 otherwise. This variable serves as a longitudinal indicator of derivative engagement.

**Derivative Contract Type Variables**:

For a detailed understanding of derivative usage, we create a set of variables to represent the types of derivative contracts employed by the fund in each quarter for 6 different derivative contract types based on the N-PORT report of the funds: equity, commodity, credit, foreign exchange, interest rate, and other derivative contracts. A value of 1 is assigned to a variable if the corresponding type of derivative contract was used during the quarter, and 0 otherwise (same meaning as the *Derivative User* variable but for each contract type). For descriptive analytics, we create an additional 6 new binary variables to show whether funds used any of these 6 contract types across the examined 12-quarter span. A value of 1 is assigned to a variable if the corresponding type of derivative contract was used at least once during the research period, and 0 otherwise (same meaning as *Derivative User Overall* variable but for each contract type).

**DIR and non-DIR for each contract type:**

Using formulas similar to formulas 1.2 and 1.3 we build DIR and non-DIR values for each contract type. While in formula 1.2 we summed up all derivative contracts' unrealized and realized appreciation/depreciation to get a total derivative return for each fund, to calculate derivative returns for each derivative contract type, we simply sum up specific derivative contract realized and unrealized appreciation and follow the same steps thereafter. We calculate the return from each derivative contract as can be seen in formula 1.6. Then, we simply use Contract Return instead of DIR for the calculation of returns not coming from specific derivative contracts (similar to formula 1.3).

$$ContractReturn_t = \frac{PnLContract_t^{Realized} + PnLContract_t^{Unrealized}}{TNA_{t-1}} \quad (1.6)$$

where:

$PnLContract_t^{Realized}$ is the total quarterly realized appreciation/depreciation from specific derivative contract positions in the current quarter,

$PnLContract_t^{Unrealized}$ is total quarterly unrealized appreciation/depreciation from derivative positions in the current quarter,

$TNA_{t-1}$ is total net asset of the previous quarter.

### 4.4.3 Descriptive Statistics

Figure 1 illustrates the variation in the use of derivatives among funds across different quarters, categorized by asset class. We observe that fixed-income mutual funds exhibit the highest engagement with derivatives – almost half of the funds within this asset class funds utilize such instruments each quarter. In contrast, approximately 30% of equity mutual funds engage in derivative usage, with a downward trend over successive quarters – similar to findings of Kaniel and Wang (2024). The asset allocation class presents a distinct pattern, showing a gradual increase in derivative usage quarter-over-quarter, averaging 35% of funds using derivatives for each quarter.

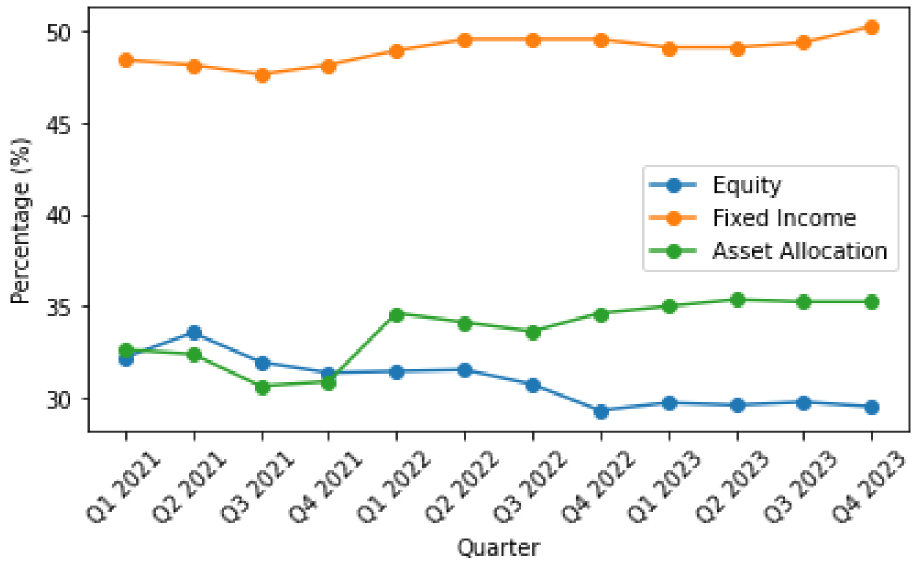


**Figure 1**: Percentage of mutual funds using derivatives per quarter and for each asset class

*Note:* The figure plots what percentage of funds in our sample mutual fund dataset that use derivatives in each quarter of interest for each asset class.

To delve deeper into the temporal dynamics of derivative usage, Appendices 1 through 3 detail the frequency of derivative utilization over the quarters (how many funds have used derivatives for how many quarters in a 12-quarter research period). For fixed-income (see Appendix 2) and asset allocation funds (see Appendix 3), a predominant number of funds consistently use derivatives throughout all 12 quarters. However, equity funds (see Appendix 1) demonstrate a more varied pattern, with a notable segment utilizing derivatives for a single or just a few quarters only.

Table 5 depicts the types of derivative contracts employed by mutual funds within each asset class. A single instance of usage of a specific derivative contract within the research period qualifies a fund as a user of that derivative type. Equity mutual funds predominantly use equity (766 funds) and foreign exchange contracts (376 funds), indicating a strategy with limited diversification across derivative types. Conversely, fixed-income mutual funds employ a more varied approach, integrating different types of derivative contracts, with interest rate contracts being the most utilized (551 funds), followed by foreign exchange (295) and credit contracts

(276). Notably, approximately 163 fixed-income mutual funds engaged with equity derivatives during the research period. Asset allocation funds, reflective of their hybrid nature, exhibit a balanced approach to derivative usage, predominantly employing equity (265) and interest rate derivative contracts (229), with foreign exchange (96) contracts as a secondary preference.

**Table 5:** *Usage of Derivative Contracts in Mutual Funds Across Asset Classes*

| Contract Type | Equity Funds | Fixed Income Funds | Asset Allocation Funds |
|---|---|---|---|
| Equity | 766 | 163 | 265 |
| Credit | 14 | 276 | 53 |
| Foreign Exchange | 376 | 295 | 96 |
| Interest Rate | 32 | 551 | 229 |
| Other | 25 | 71 | 23 |
| Commodity | 4 | 15 | 19 |

*Note:* The table reports how many funds have used each type of derivative contract. If a fund uses a derivative contract for at least one quarter, we consider that fund a user of that specific type of derivative contract.

Tables 6 through 8 present detailed statistics on Derivative Relative Contribution (DRC), Signed Derivative Relative Contribution (SDRC), DIR, and non-DIR for equity, fixed-income, and asset allocation mutual funds, respectively. As shown in Table 6, equity mutual funds display an average DIR of 0.064 and a non-DIR of 0.088, with corresponding standard deviations of 1.59 and 12.746. The mean DRC for equity funds is 0.19, with a median of 0.02, indicating the presence of outliers with significantly high DRCs that elevate the mean. The mean SDRC stands at 0.013 with a median of zero, suggesting that the contributions of derivative returns to non-derivative returns are typically marginal on average while there are some funds with high derivative relative contributions.

**Table 6:** *Summary Statistics of key variables for Equity Mutual Funds*

| Variable | Mean | StdDev | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|
| DRC[1] | 0.19 | 1.88 | 0 | 0 | 0.002 | 0.17 | 69.165 |
| SDRC[2] | 0.013 | 1.892 | -68.016 | 0 | 0 | 0.006 | 69.165 |
| DIR[3] | 0.064 | 1.596 | -30.753 | -0.005 | 0 | 0.213 | 36 |
| non-DIR[4] | 0.088 | 12.746 | -76.745 | -5.870 | 0.312 | 6.042 | 684.815 |

[1] DRC: Derivative Relative Contribution
[2] SDRC: Signed Derivative Relative Contribution
[3] DIR: Derivative-Induced Returns (values in %)
[4] non-DIR: Non-Derivative-Induced Returns (values in %)

Note: For the purpose of better descriptive statistics, we require the absolute value of non-DIR to be greater than or equal to 10 basis points. This threshold prevents DRC and SDRC from appearing disproportionately large due to very small non-DIR values. However, in calculations we use all non-DIR values.

For fixed-income funds (Table 7), the average DIR is 0.03, and the non-DIR is -1.218, with standard deviations of 2.168 and 7.201, respectively. Moreover, fixed-income funds exhibit a higher average DRC of 0.273, with a median of 0.056, when compared to equity mutual funds. The average SDRC is -0.014, with a median of zero.

**Table 7:** *Summary Statistics of Key Variables for Fixed Income Mutual Funds*

| Variable | Mean | StdDev | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|
| DRC[1] | 0.273 | 0.978 | 0 | 0.062 | 0.056 | 0.216 | 30.689 |
| SDRC[2] | -0.014 | 1.015 | -17.034 | -0.082 | 0 | 0.032 | 30.689 |
| DIR[3] | 0.030 | 2.168 | -57.574 | -0.099 | 0 | 0.105 | 99.736 |
| non-DIR[4] | -1.218 | 7.201 | -101.617 | -3.207 | -0.875 | 0.066 | 331.102 |

[1] DRC: Derivative Relative Contribution
[2] SDRC: Signed Derivative Relative Contribution
[3] DIR: Derivative-Induced Returns (values in %)
[4] non-DIR: Non-Derivative-Induced Returns (values in %)

Note: For the purpose of better descriptive statistics, we require the absolute value of non-DIR to be greater than or equal to 10 basis points. This threshold prevents DRC and SDRC from appearing disproportionately large due to very small non-DIR values. However, in calculations we use all non-DIR values.

Asset allocation funds, as reported in Table 8, have an average DIR of 0.011 and a non-DIR of -0.56, with standard deviations of 1.547 and 7.257, respectively. The mean DRC is

0.3227 with a near-zero median, while the mean SDRC is 0.029, again with a median of zero, aligning with the trend of derivatives playing a negligible role in the contribution to total returns.

**Table 8:** *Summary Statistics of Key Variables for Asset Allocation Mutual Funds*

| Variable | Mean | StdDev | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|
| DRC[1] | 0.3227 | 2.2863 | 0 | 0.004 | 0.002 | 0.093 | 98.331 |
| SDRC[2] | 0.029 | 2.388 | -98.331 | -0.017 | 0 | 0.024 | 48.438 |
| DIR[3] | 0.011 | 1.547 | -21.789 | -0.128 | 0 | 0.061 | 32.439 |
| non-DIR[4] | -0.560 | 7.257 | -28.672 | -1.898 | 0.233 | 4.183 | 230.997 |

[1] DRC: Derivative Relative Contribution
[2] SDRC: Signed Derivative Relative Contribution
[3] DIR: Derivative-Induced Returns (values in %)
[4] non-DIR: Non-Derivative-Induced Returns (values in %)

Note: For the purpose of better descriptive statistics, we require the absolute value of non-DIR to be greater than or equal to 10 basis points. This threshold prevents DRC and SDRC from appearing disproportionately large due to very small non-DIR values. However, in calculations we use all non-DIR values.

DRC standing for absolute weight of non-DIR over DIR, shows us how large derivative returns have been compared to non-derivative returns in scale. In Appendices 4, 5, and 6 we look at how average DRC changes over time to understand whether there has been temporal change in the average relative weight of derivative returns compared to non-derivative returns. For equity mutual funds average DRC peaked in Q2 of 2022 (see Appendix 4) with the start of Ukraine war (Murphy, 2022), showing that some equity mutual funds got excessively high derivative returns for the period. For fixed-income funds the average DRC started dropping after Q1 2021 while peaking at Q4 2021 (see Appendix 5). Asset allocation funds saw a sharp rise in average DRC in Q4 2022 while being stable and low for most of the time (see Appendix 6).

## 4.5 Data Handling

Our descriptive analytics reveals presence of some outliers in the DIR and non-DIR values across the dataset. Given that our data is structured as a time series for various tickers/funds, discarding individual outliers is not feasible without disrupting the continuity of our quarterly data, which is crucial for reliable correlation analysis.

While considering options to mitigate the influence of outliers, we face a decision between winsorizing and truncating these extreme values. Winsorizing stands for replacing outliers with nearest non-outliers (Chambers & Kokic, 2000). Winsorizing, while it limits the effect of outliers, is unsuitable for our analysis. The primary concern here is the potential distortion of our data's true variability. Mutual fund returns, particularly for the DIR and non-DIR components, inherently possess a level of volatility that is indicative of market dynamics. By winsorizing, we risk distorting genuine market signals with substituted figures and introduce bias into our dataset (Brownen-Trinh, 2016), potentially leading to misinterpretations of relationship between DIR and non-DIR. Since tails of the distributions are crucial for the proper analysis, modifying them through winsorization will result in invalidation of a lot of statistical analysis and measures.

Consequently, we proceed to truncate outliers – specifically, by eliminating all data for a given ticker if any single DIR or non-DIR value falls outside the 5th to 95th percentile range. This approach preserves the integrity of the time series but dramatically reduces the dataset's volume. Post-truncation, the number of equity funds using derivatives drops from 1,032 to 260, and for fixed-income and asset allocation funds, the number falls from 658 to 225 and from 303 to 74, respectively. The significant reduction in data quantity shows that these outliers are not mere noise; rather, they appear to be a systematic component of the mutual fund DIR and non-DIR returns, reflecting inherent market structural movements. By calculating the correlation coefficient for each fund individually and then calculating mean correlation (and median) (discussed in Empirical Methods section) for the whole asset class, we plan to partially mitigate the impact of outliers on our overall analysis. In the end, we decide not to implement truncation to be able to make more thorough and representative analysis.

## 4.6 Empirical Methods

Our objective is to assess how derivative-using mutual funds in equity, fixed-income and asset allocation asset classes utilize derivatives. Therefore, we employ 2 main models to assess not only whether there is a high correlation between derivative returns and non-derivative returns but also whether the relationship of derivative and non-derivative returns is systematic. We combine those 2 models to test our hypotheses and answer our research questions.

### 4.6.1 Correlation Analysis

Following the methodology of Kaniel and Wang (2024), we employ Pearson correlation analysis to assess each fund's data over a period of 12 quarters (3 years). This analysis aims to determine whether funds utilize derivatives primarily for amplification or hedging purposes. The analysis involves using the DIR to represent returns from derivative positions of funds, and non-DIR to represent returns from non-derivative positions.

Initially, we compute the Pearson correlation coefficient (formula 1.7) for each fund over the specified analysis period using DIR and non-DIR value from formula 1.2 and 1.3. This coefficient quantifies the degree of linear association between the DIR and non-DIR for each fund in each asset class for the research period. The strength and direction of this correlation provide insights into the strategic use of derivatives by the funds. A positive correlation suggests that derivatives are used in a manner that amplifies the overall fund returns, aligning with the fund's performance objectives. On the contrary, a negative correlation may indicate a hedging strategy, where derivatives are employed to mitigate risk rather than enhance returns.

$$Corr_i = \frac{\sum_{t=1}^{T}\left(DIR_{it} - \overline{DIR_i}\right)\left(nonDIR_{it} - \overline{nonDIR_i}\right)}{\sqrt{\sum_{t=1}^{T}\left(DIR_{it} - \overline{DIR_i}\right)^2}\sqrt{\sum_{t=1}^{T}\left(nonDIR_{it} - \overline{nonDIR_i}\right)^2}} \quad (1.7)$$

where:

$DIR_{it}$ is the value of derivative induced return for fund *i* at time *t*,

$nonDIR_{it}$ is the value of non-derivative induced return for fund *i* at time *t*,

$\overline{DIR_i}$ is the mean of DIR for fund *i* over the period T,

$\overline{nonDIR_i}$ is the mean of non-DIR for fund *i* over the period T,

T is the number of time periods for which data is available for fund *i*.

Once we calculate correlation between DIR and non-DIR for each fund, we calculate the average correlation for each asset class as follows:

$$\overline{C} = \frac{1}{N}\sum_{t=1}^{N} C_i \quad (1.8)$$

where:

N is the total number of funds,

$C_i$ denotes Pearson correlation coefficient for each fund,

$\overline{C}$ denotes average correlation across all funds.

To assess whether on average mutual funds from different asset classes use derivatives for hedging or amplification, we calculate and evaluate average correlation for each asset class. Correlation coefficient informs us on how extensively derivatives are used in specific direction, while direction of the coefficient informs us on how specifically derivatives are used. Kaniel and Wang (2024) consider that if the average correlation is positive then the average correlation coefficient number is not essential – only the sign of the correlation coefficient is essential to make the claim about how derivatives are used by mutual funds in each asset class. In line with Kaniel and Wang (2024), we focus on directionality rather than extent to make our conclusions on how derivatives are used. However, averaging fund level correlations for making a claim about how funds use derivatives, Kaniel and Wang (2024) do not assume that the average could be diverted because of few funds with high correlation coefficients while most of the funds could have correlation coefficients of 0. Therefore, since the direction of the correlation can be diverted by funds with large correlations, we decide to make one more analysis to investigate whether there is systematic relationship between DIR and non-DIR.

### 4.6.2 One-Sample t-Test

In the analysis of mutual fund behaviors, particularly regarding the use of derivatives, it is critical to recognize the limitations of relying solely on average of fund-level correlations as conclusive evidence of systematic derivative usage. Average of the correlations provide a broad overview of general trends within the data but fail to account for variability or the distribution of individual fund behaviors (Pernet, Wilcox, & Rousselet, 2013). This oversight is significant as it can obscure underlying patterns or anomalies that might contradict the apparent general trend or suggest more complex strategic behaviors that a simple average correlation coefficient cannot adequately capture. To address these concerns and establish a more robust statistical foundation for asserting systematic usage of derivatives among funds, we employ One-Sample t-Test after calculating fund level correlations in each asset class. Normally, One-Sample t-Test is used to test whether the average of a population is different from specified value (Kent State University Libraries, n.d.). The primary rationale for using this test in our case stems from the need to test the significance of the mean correlation coefficient obtained from fund-level correlations between the DIR and non-DIR to understand whether there is systematic relationship between DIR and non-DIR for funds using derivatives.

To be able to apply the One-Sample t-Test accurately, certain conditions of the Central Limit Theorem must be met. Firstly, the sample size must be sufficiently large. Secondly, there should be no major outliers in the dataset (Kwak & Kim, 2017). When these conditions are fulfilled, the distribution of sample means will approximate normality, regardless of the data's underlying distribution. Our fund level correlation datasets meet the first requirement, since each data set is large enough. Moreover, our preliminary distribution check shows no major outliers exist in each fund level correlation dataset. Therefore, we believe One-Sample t-Test is well suited for our analysis and develop our hypotheses for One-Sample t-Test as follows:

*Null Hypothesis (H0)*: The mean correlation between DIR and non-DIR is zero, indicating no systematic relationship.

*Alternative Hypothesis (H1)*: The mean correlation between DIR and non-DIR is not zero, indicating a systematic relationship.

By applying the One-Sample t-Test on the fund level correlations we calculated before, we aim to assess whether the correlation results can indeed inform us about whether funds use derivatives predominantly for amplification or hedging. A significant result, where the mean correlation for specific asset class significantly deviates from zero, supports the existence of a systematic usage of derivatives by mutual funds in specific asset class. Conversely, a non-significant result suggests that the use of derivatives across funds in that asset class might not be systematic – thus, we can't make a generalized claim that derivatives are used for specific purposes by mutual funds in some asset class.

Furthermore, by analyzing the direction – whether positive or negative – of the T-statistic obtained from the One-Sample t-Test, we can derive insights into the strategic use of derivatives by funds. Specifically, this analysis allows us to understand whether derivatives are predominantly utilized for hedging or amplifying returns – that in line with fund level correlation analysis can improve our claim of how funds in different asset classes use derivatives. Overall, One-Sample t-Test offers us a statistically robust model that not only confirms the presence of systematic relationships but also clarifies the strategic intentions behind derivative usage within mutual funds.

# 5 Findings and Discussion

To test H1-H3, we analyze and discuss findings in sections 5.1 and 5.2. The first section similar to research of Kaniel and Wang (2024) discusses whether mutual funds in different asset classes use derivatives differently and how they use it. In the second section we analyze whether there is a systematic relationship between DIR and non-DIR for mutual funds in different asset classes, so that we can test out each hypothesis. In section 5.3 we analyze how different derivative contracts are used by mutual funds and whether they are used systematically to test H4-H6 and answer our research question.

## 5.1 How funds use derivatives

Below we analyze derivative contribution to fund returns for funds from three different asset classes. While the goal of analysis into equity mutual funds is to replicate and update the research of Kaniel and Wang (2024), research into fixed-income and asset allocation mutual funds is the first of its type: using granular data to show how derivatives are used by mutual funds from those asset classes.

### 5.1.1 Equity Mutual Funds

The correlation results, presented in Table 9, reveal interesting findings on the utilization of derivatives by equity mutual funds. These results are consistent with the findings of Kaniel and Wang (2024), who documented that equity mutual funds employ derivatives primarily for amplification purposes. Although the mean correlation coefficient of 0.2392 may appear modest, it is crucial to recognize that this figure represents the average of individual fund-level correlations. Importantly, as outlined in the methodology section, the assessment of whether funds utilize derivatives for amplification or hedging does not rely solely on the numeric value of the correlation coefficient; rather, the direction of the coefficient is of paramount importance.

Our further analysis reveals that the median correlation coefficient for equity mutual funds exceeds the mean, suggesting a slight negative skewness in the distribution of the data. This observation is substantiated by the distribution graph of equity mutual fund correlations (see Appendix 7), which shows that a substantial majority of these funds exhibit high positive correlation coefficients. While a minority of funds exhibit negative coefficients and utilize derivatives for hedging, these are less common. Overall, these findings support part of our hypothesis H1: equity mutual funds predominantly use derivatives for amplification rather than for hedging purposes.

### 5.1.2 Fixed-Income Funds

We observe interesting findings for fixed-income mutual funds as well (see Table 9). The average correlation coefficient, recorded at -0.1542, indicates that fixed-income mutual funds predominantly employ derivatives for hedging purposes. This finding supports part of our hypothesis H2, confirming that, on average, fixed-income mutual funds leverage derivatives more for hedging than for amplifying returns.

Further examination of the distribution characteristics reveals that the median correlation coefficient is greater than the mean, indicating a rightward skew (positive skewness) in the data. This skew suggests that while the predominant strategy involves hedging, there exists a notable proportion of funds that utilize derivatives for amplification. The distribution graph for the correlations of fixed-income mutual funds, as detailed in Appendix 8, reinforces this observation. Although a minority of funds demonstrate the use of derivatives for amplification purposes, characterized by positive correlation coefficients, most fixed-income mutual funds exhibit high negative correlations, emphasizing an overall strategic preference for hedging.

### 5.1.3 Asset Allocation Funds

The analysis of derivatives usage by asset allocation mutual funds represents a novel area of research, as prior research has not covered this fund category. Our findings indicate a positive average correlation coefficient between DIR and non-DIR for asset allocation funds (see Table 9), suggesting that asset allocation mutual funds typically employ derivatives to amplify returns. This positive correlation supports part of our hypothesis H3 that derivatives are used for amplification rather than hedging in asset allocation funds.

An interesting aspect of our analysis is the relationship between the mean and median correlation values. While the mean correlation is positive, we observe that the median is lower than the mean, which initially suggests a rightward skew in the data. However, upon examining the distribution graph of correlation coefficients for asset allocation funds (see Appendix 9), it appears that a significant portion of asset allocation funds has correlation coefficients ranging between 0 and 0.1. This concentration near the lower end of the positive range effectively shifts the median rightward but does not necessarily indicate a broad rightward skew across all data points. Contrary to the initial assumption of rightward skew based on median and mean discrepancies, the overall distribution predominantly demonstrates positive correlations. This confirms that most asset allocation funds are using derivatives to increase potential returns rather than hedge against losses. In conclusion, these results validate our third hypothesis: asset allocation funds, on average, utilize derivatives for amplification rather than hedging.

**Table 9:** *Correlation results for funds from different asset classes*

| Asset Classes | Mean | Median | Std.Error |
|---|---|---|---|
| Equity | 0.2392 | 0.2417 | 0.0152 |
| Fixed Income | -0.1542 | -0.1845 | 0.0195 |
| Asset Allocation | 0.1264 | 0.1005 | 0.0255 |

## 5.2 Systematic Use of Derivatives

As described in section 4.6.2 of the paper, the presence of high or low average correlations does not inherently establish a systematic relationship between DIR and non-DIR. Consequently, we analyze the One Sample T-test results to understand whether such a systematic relationship exists.

Table 10 reveals that equity mutual funds exhibit a high T-statistic alongside an exceedingly low p-value. These results allow us to affirm the presence of a systematic relationship between DIR and non-DIR within this asset class. Furthermore, the positive and substantial T-statistic corroborates the findings from our correlation analysis, substantiating that equity mutual funds predominantly utilize derivatives to amplify their returns.

Similarly, the One Sample T-test results for fixed-income mutual funds confirm the existence of a systematic relationship between DIR and non-DIR. The high absolute value of the T-statistic, coupled with an extremely low p-value, as detailed in Table 10, validates this systematic relationship. Additionally, the direction of the T-statistic is consistent with our correlation analysis, indicating that fixed-income mutual funds primarily employ derivatives for hedging purposes rather than for amplification of returns.

The test results for asset allocation funds, as reported in Table 10, likewise affirm the existence of a systematic relationship between DIR and non-DIR, similar to the findings for equity and fixed-income funds. Although the T-statistic for asset allocation funds is lower in comparison to that of equity funds, it remains significantly high and has statistically significant p-value. This significant result supports the hypothesis of a systematic relationship within this fund category. Furthermore, the positive value of the T-statistic aligns with our earlier correlation analysis, corroborating that asset allocation funds typically use derivatives to amplify their returns.

**Table 10:** *One Sample T-test Results*

| Asset Classes | T-statistic | P-value |
|---|---|---|
| Equity | 15.7284 | $3.9902 \times 10^{-50}$ |
| Fixed Income | -7.8829 | $1.3327 \times 10^{-14}$ |
| Asset Allocation | 4.9445 | $1.2685 \times 10^{-6}$ |

## 5.3 Usage of different derivative contracts by mutual funds

In this section, we analyze the usage of derivative contracts by mutual funds to test our hypotheses 4-6. We start by analyzing contract usage by mutual funds in different asset classes using derivative contract usage data at each correlation level. Then, we discuss how mutual funds use different derivative contracts and whether there is a systematic relationship between returns from those derivative contracts and returns coming outside those contracts.

### 5.3.1 What contracts are used at different correlation levels?

Building upon the understanding of how mutual funds employ derivatives across three distinct asset classes, our analysis now extends to examining the usage patterns of different types of derivative contracts. By analyzing what types of derivative contracts funds use across various correlation levels (correlation between DIR and non-DIR calculated before), we aim to find out which derivative contracts are predominantly used by mutual funds for their strategies.

From the data visualized in Figure 2, it becomes evident that equity mutual funds exhibit a high use of equity contracts at higher positive correlation levels. This indicates a strategy focused on amplification, aiming to capitalize on equity market trends to boost returns. This finding is particularly significant in light of the research by Kaniel and Wang (2024), which noted that users of equity contracts—especially those engaging in equity swaps—tend to exhibit a higher positive correlation between DIR and non-DIR. Our analysis corroborates the observations made by Kaniel and Wang (2024). We find that the funds displaying the highest positive correlations between DIR and non-DIR are predominantly users of equity contracts. This trend indicates that when equity funds employ equity contracts, they are more inclined to use these derivatives to enhance their returns, aligning with the broader strategy of amplification observed in these funds. Foreign exchange contracts appear consistently across various levels of correlation, possibly indicating their use as both a hedge against currency risk and a speculative tool to take advantage of currency fluctuations. Overall, we can see that other derivative contracts are not used as much by equity mutual funds.

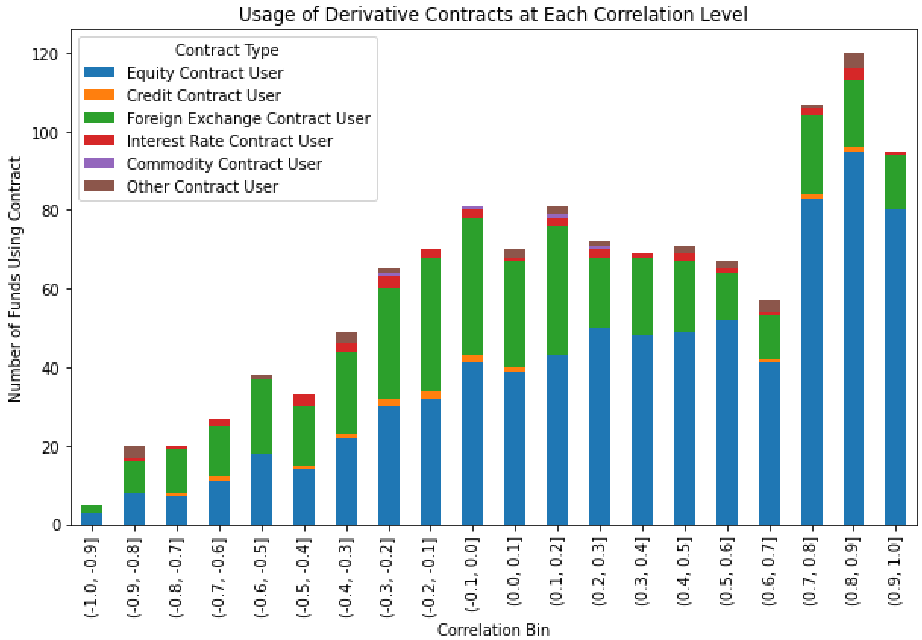


**Figure 2**: Usage of specific derivative contracts at each correlation level for equity mutual funds

*Note:* The figure plots which contracts have been used by mutual funds that have specific correlation coefficient between their DIR and non-DIR.

Fixed-income mutual funds have a relatively uniform distribution across correlation levels for credit, foreign exchange, and interest rate contracts, with a noteworthy cluster in the negative correlation bins (Figure 3). This pattern suggests a strategy with a preference for hedging, especially given the nature of fixed-income securities and their sensitivity to interest rate changes. The use of equity contracts is less prevalent, which aligns with the typical investment strategy of fixed-income funds that traditionally have lower exposure to equity markets.

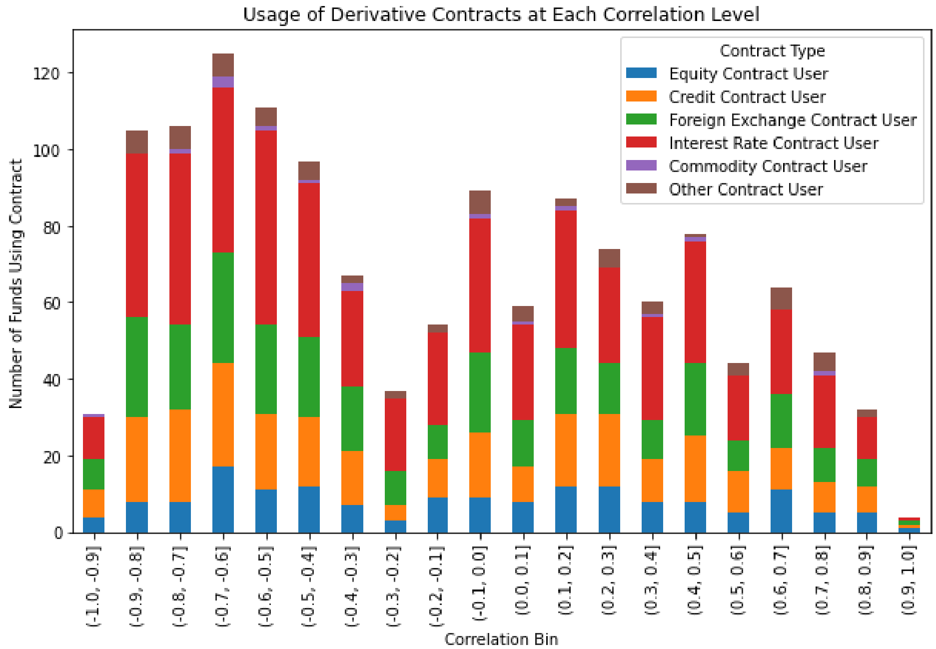


**Figure 3**: Usage of specific derivative contracts at each correlation level for fixed-income mutual funds

*Note:* The figure plots which contracts have been used by mutual funds that have specific correlation coefficient between their DIR and non-DIR.

For asset allocation funds, the data in Figure 4 suggests a predominant use of equity and interest rate contracts across all correlation levels, indicating a versatile approach to using derivatives for both hedging (evidenced by contracts in negative correlation bins) and amplification purposes (evidenced by contracts in positive correlation bins). The presence of a substantial number of funds in the mid-correlation bins could imply a balanced approach to managing risks and leveraging market movements.

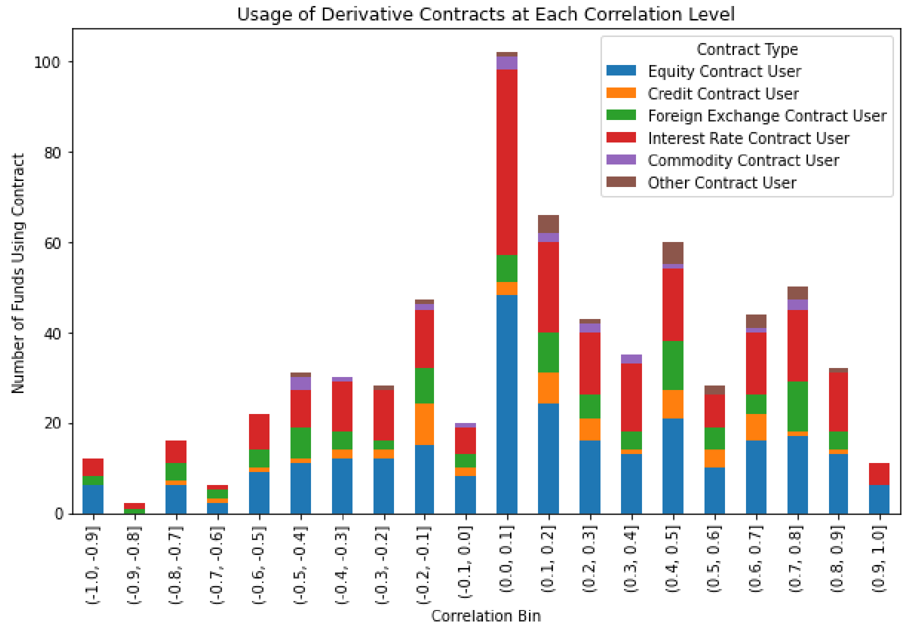


**Figure 4**: Usage of specific derivative contracts at each correlation level for asset allocation mutual funds

*Note:* The figure plots which contracts have been used by mutual funds that have specific correlation coefficient between their DIR and non-DIR.

The findings about the contract usage by mutual funds at each correlation level in the section above help us dive deeper into specific derivative contract usage strategies of mutual funds. Expanding upon research of Choi et al., (2023) our study investigates how mutual funds across equity, fixed-income and asset allocation asset classes utilize different derivative contracts.

### 5.3.2 Contract level analysis

In this section, we apply formula 1.6 to determine the returns from various derivative contracts and calculate the corresponding returns not related to those derivative contracts. We calculate the average correlation coefficient for DIR and non-DIR for each contract type used by equity, fixed-income, and asset allocation mutual funds. We conduct One Sample T-test to check whether there is systematic relationship between derivative contract induced returns and non-contract induced returns.

The results, presented in Table 11 and Appendix 10, indicate that a systematic relationship between derivative and non-derivative returns is present only for certain types of derivative contracts within the equity mutual funds category: only equity, foreign exchange and credit derivative contracts are used systematically. Consistent with our previous findings, we note that equity mutual funds typically use equity contracts for return amplification. In contrast, foreign exchange contracts are utilized for hedging purposes. For credit contracts, a lower mean correlation relative to the median suggests that while some equity funds may use these contracts for hedging, a sizable number employ them for amplification purposes. Consequently, we can reject hypothesis H4 – not all derivative contracts are used systematically and for amplification by equity mutual funds.

**Table 11:** *Average Correlation Coefficients by Contract Type for Equity Mutual Funds*

| Derivative Contract Type | Mean | Median |
|---|---|---|
| Commodity | -0.0969 | 0.1426 |
| Credit | -0.2529 | 0.1696 |
| Equity | 0.3541 | 0.4185 |
| Foreign Exchange | -0.1004 | -0.0954 |
| Interest Rate | -0.0836 | -0.1527 |
| Other | -0.0184 | 0.0471 |

For the fixed-income funds, our results reveal a systematic use of foreign exchange and interest rate derivative contracts for hedging purposes (p-value lower than 5% for both in One-Sample t-Test) (see Table 12 and Appendix 11). This hedging focus aligns with the conservative nature of fixed-income investments and their vulnerability to interest rate movements. Conversely, there is no significant relationship identified for other derivative contract types, indicating a more selective and less systematic use of other derivative contracts. Thus, we can refute hypothesis H5 – not all derivative contracts are used systematically and for hedging by fixed-income mutual funds.

**Table 12:** *Average Correlation Coefficients by Contract Type for Fixed Income Mutual Funds*

| Derivative Contract Type | Mean | Median |
|---|---|---|
| Commodity | -0.0197 | 0.0082 |
| Credit | -0.0064 | -0.0337 |
| Equity | -0.0207 | -0.0488 |
| Foreign Exchange | -0.3479 | -0.4204 |
| Interest Rate | -0.0810 | -0.0791 |
| Other | 0.0613 | 0.0811 |

We conduct the same analysis for asset allocation mutual funds and find out that only foreign exchange, interest rates and other derivative contracts are used systematically by mutual funds in this asset class (see Table 13 and Appendix 12). Our research findings show that while asset allocation funds use foreign exchange contracts for hedging, they use interest rate contracts and other derivative contracts for amplification of returns (see average correlation scores from Table 13). We can't find a systematic relationship between derivative contract returns and returns not-from derivative contracts for commodity, credit and equity derivative contracts (see high p-value in Appendix 12). Overall, we reject hypothesis H6: not all derivative contracts are used systematically and for amplification by asset allocation mutual funds.

**Table 13:** *Average Correlation Coefficients by Contract Type for Asset Allocation Mutual Funds*

| Derivative Contract Type | Mean | Median |
|---|---|---|
| Commodity | 0.0071 | -0.0361 |
| Credit | 0.0766 | -0.0205 |
| Equity | -0.0080 | -0.0052 |
| Foreign Exchange | -0.1213 | -0.1809 |
| Interest Rate | 0.2754 | 0.3555 |
| Other | 0.1826 | 0.1660 |

To sum up, our findings align with prior research of Wang and Kaniel (2024) on how equity mutual funds predominantly use equity derivative contracts for amplification, while we also demonstrate what type of derivative contracts are used systematically by fixed-income and asset allocation mutual funds.

## 5.4 Hypothesis testing

The integration of One Sample t-Test results with the correlation analysis findings provides a robust framework for testing our hypotheses concerning the use of derivatives by mutual funds across different asset classes. By examining derivative usage for all three asset classes – equity, fixed-income, and asset allocation funds – we have demonstrated a systematic relationship between DIR and non-DIR for mutual funds in all 3 asset classes. Consequently, our analysis approves our Hypotheses 1 through 3.

For equity mutual funds, both the One-Sample t-Test and correlation analysis consistently indicate a use of derivatives primarily for amplification of returns. For fixed-income mutual funds, the analyses suggest a predominant use of derivatives for hedging purposes, as evidenced by the nature of the T-statistic and correlation coefficients. Asset allocation funds also show a systematic use of derivatives to amplify returns, although with a lesser magnitude of the T-statistic compared to equity funds, yet still significant.

Furthermore, our derivative contract level analysis allows us to reject hypotheses 4-6: not all derivative contracts are used systematically by mutual funds in 3 asset classes. Additionally, mutual funds across all three asset classes may use derivative contracts for purposes that do not consistently align with their overarching derivative usage strategy. While some contracts are employed for hedging, the primary focus of their strategy may be on amplification (case of equity mutual funds).

Overall, through our analysis we answer our research question by showing how funds in different asset classes utilize derivatives and that derivatives are used systematically. We also find out that only some derivative contracts are used systematically by mutual funds in 3 asset classes, and specific derivative contract usage strategies do not always align with the overarching derivative usage strategy of the mutual funds.

# 6 Implications

Our research develops current financial literature by shedding light on how derivatives are used by mutual funds in equity, fixed-income, and asset allocation funds. Research findings have major economic implications not only for mutual funds but more importantly for investors and regulators.

Investors need to be aware of the economic implications of derivative use by mutual funds. When selecting mutual funds for investments, investors should thoroughly evaluate the underlying derivative strategies used by funds. Equity and asset allocation funds – using amplification strategy when using derivatives, can expose investors to increased risk while trying to get additional returns. One the other hand, fixed-income funds can lower their risk profile while using derivatives for hedging. Thus, our findings showing that funds use derivatives with different strategies, imply that investors can be exposed to different hidden risk and return that they normally aren't aware of – thus, they should do careful research before choosing to invest into specific mutual fund. Furthermore, understanding usage of each derivative contract by mutual funds will enable investors to evaluate whether they want to be exposed to risks coming from specific derivative contracts or from complexity of derivative contracts used by the mutual funds in all 3 asset classes. While investors may normally see mutual funds as a safe investment choice to get exposure to specific assets, our findings show that mutual funds have complex derivative strategies. Simply being aware of this complexity can be a determinant for investors that may choose to invest into mutual funds that do not use derivatives.

As the 2008 financial crisis demonstrated, derivatives can introduce significant complexity into financial markets. Recent financial failures have further illustrated this point, as hidden leverage and changes in interest rates in U.S. and UK contributed to notable financial failures, such as those of Silicon Valley Bank and LDI crisis (Choi et al., 2023). While derivatives can be efficient tools to maximize returns or minimize risk, they can also, like leverage, introduce additional risks to both their users and the broader financial system. Therefore, regulators must closely monitor the types of derivatives used by mutual funds and the purposes for which they are employed. As our findings demonstrate, the predominant number of funds within specific asset classes systematically utilize derivatives for similar strategic purposes – equity and asset allocation funds for amplification and fixed-income funds for hedging. Moreover, analysis of underlying derivative contracts for mutual funds in each asset class illustrates complexity in derivative strategies of the funds. Therefore, regulators should be aware of the complexity of the derivative strategies used by the mutual funds to make sure that mutual funds do not introduce implicit or latent risks into their portfolios that diverge from their publicly declared investment strategies because of the usage of derivatives. Regulatory oversight is important, not only for the protection of the individual investors but also for preserving the stability of the broader financial market. Ensuring transparency and adherence to declared strategies can help regulators mitigate systemic risks that might arise from complex derivative engagements (Markose, 2012).

# 7 Limitations and Further Research

Our study has several limitations that require consideration. The first major limitation, detailed in sections 4.2 and 4.3 of our paper, is the incomplete reporting of derivative usage to the SEC's N-PORT database. Not all funds consistently reported their derivative activities, and some did not exist during the entire duration of our study period. We found that funds excluded from our dataset, due to these reporting issues, tended to have a smaller total net asset than those included. This suggests that smaller funds may not use or report derivatives as frequently. Consequently, our findings cannot be universally applied to all U.S. mutual funds, but they are relevant to the subset of funds included in our study.

Secondly, our research is confined to the specific period from 2021 to 2023. As such, the results may not be representative of other time periods. This temporal limitation mirrors challenges faced in earlier studies, such as those by Kaniel and Wang (2024), which also focused on time periods potentially influenced by external factors like COVID-19 and shifts in monetary policy. Thus, while our findings provide insights into derivative usage during this specific period, they should not be extrapolated beyond it.

Further research can use our findings to examine how derivative strategies evolve in response to various economic scenarios and unexpected global events, such as Ukraine War and the COVID-19 pandemic. While our research has shown general derivative strategies of mutual funds over the period and has shown how derivative usage changes in different quarters, we did not touch upon case studies of how specific global events impact the overall derivative strategies. Therefore, understanding how mutual funds adapt their derivative use during crises can contribute significantly to the literature on financial risk management and derivative usage in turbulent times.

# 8 Conclusion

Derivatives usage by institutions and mutual funds has historically been a complex and opaque area, often leading investors to make suboptimal investment decisions due to a lack of clear information. The introduction of the SEC's N-PORT reporting requirements has significantly demystified this aspect of the mutual fund industry, offering investors a transparent view of the types of derivatives utilized by mutual funds. Our research contributes to expanding the financial literature on how mutual funds employ derivatives within equity, fixed-income, and asset allocation classes by examining the types of derivatives used as well as investigating and analyzing how each derivative contracts are used by mutual funds.

We begin with the hypotheses that mutual funds across different asset classes employ derivatives in distinct and systematic ways. Our findings confirm our initial hypotheses, demonstrating that while equity and asset allocation funds typically use derivatives for amplification purposes, fixed-income funds primarily employ them for hedging.

We later develop hypotheses 4-6 to check how mutual funds use specific derivative contracts. Our analysis reveals nuanced patterns in the usage of different types of derivative contracts. Equity funds systematically use equity derivatives for amplification, and foreign exchange and credit derivatives for hedging. In contrast, fixed-income funds predominantly use foreign exchange and interest rate derivatives for hedging purposes. Asset allocation funds, interestingly, tend to use foreign exchange derivatives for hedging and interest rate derivatives for amplification. Using our findings we reject our hypotheses H4-H6.

Overall, our paper not only improves the existing body of knowledge on derivative usage in mutual funds but also sets a foundation for future inquiries into how these strategies evolve over time and across different economic conditions. By gathering granular data on mutual fund derivative usage and providing detailed insights into the derivative practices of fixed-income and asset allocation funds – areas previously less explored in financial research – we pave the way for more informed investment decisions and further research into the strategic use of derivatives by mutual funds.

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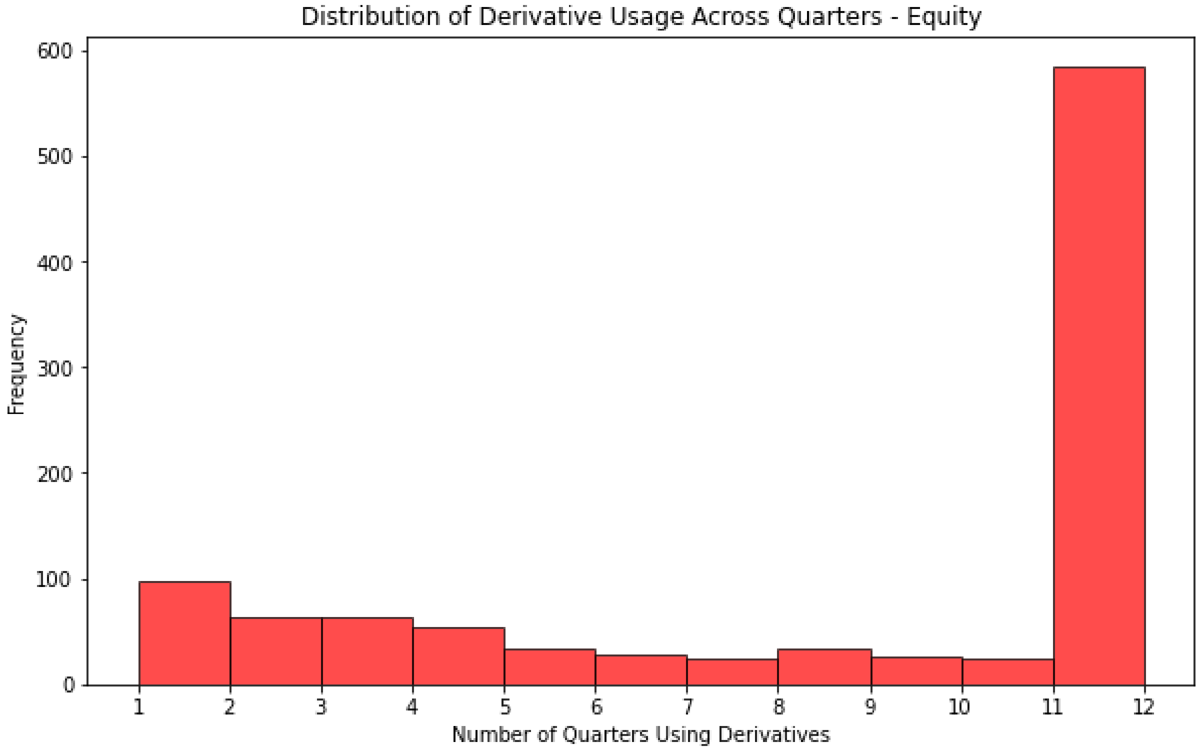
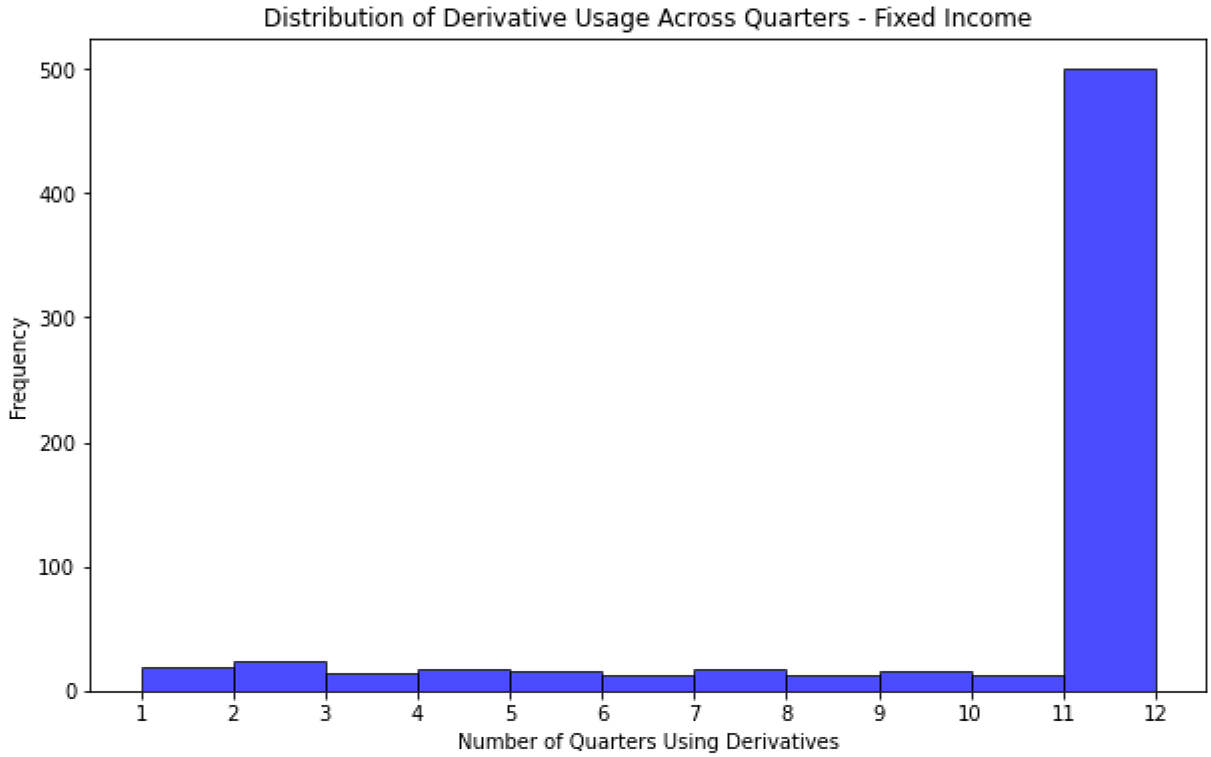
# 10 Appendix:

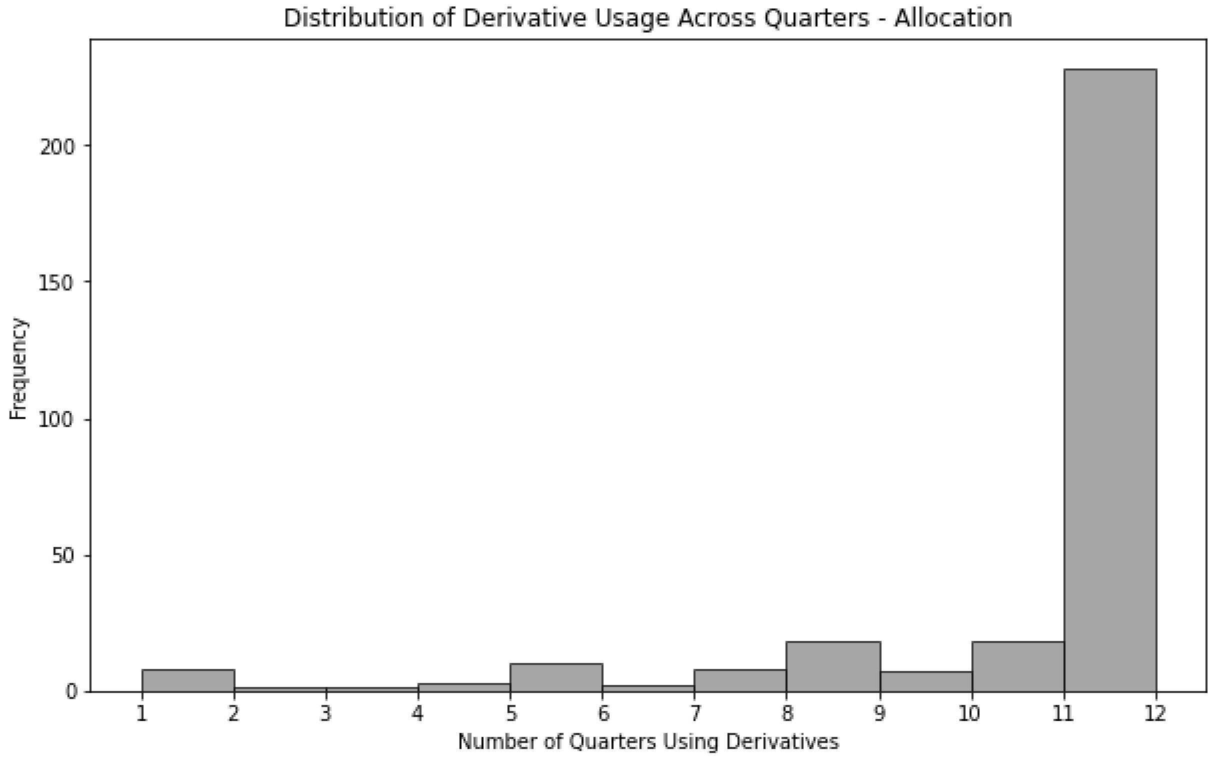
**Appendix 1** Equity funds usage of derivatives



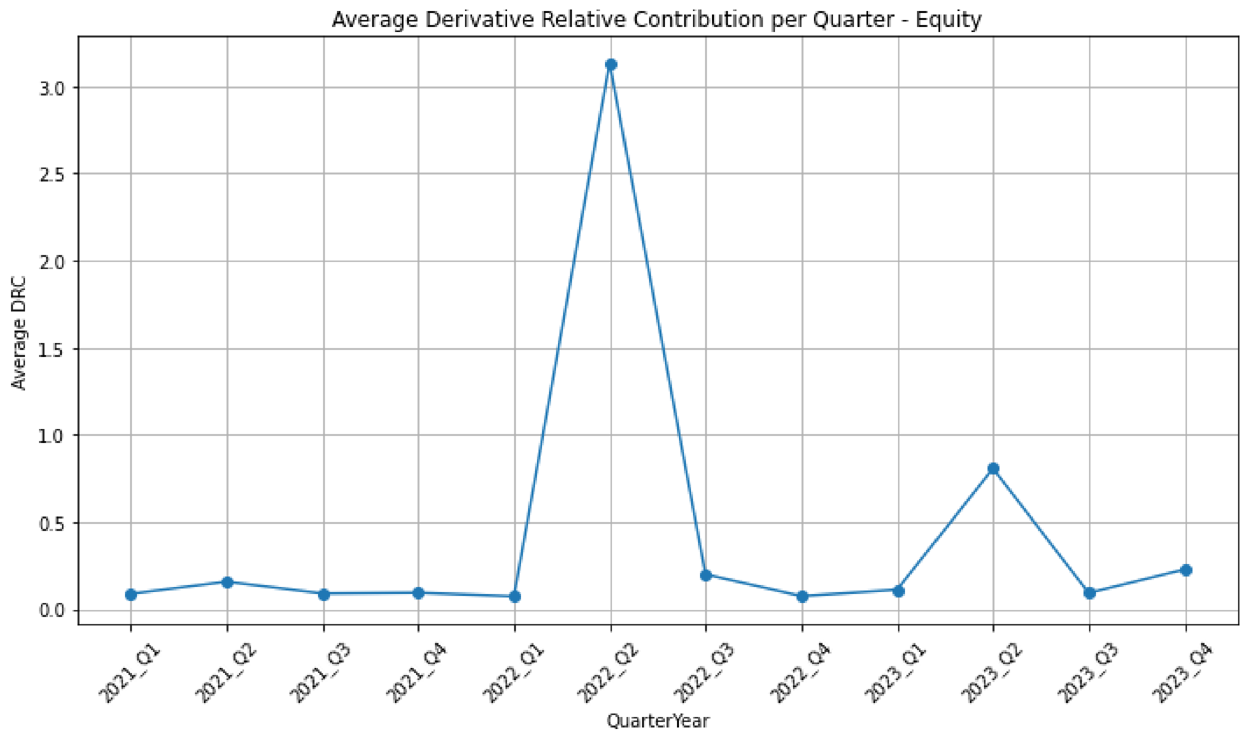
**Appendix 2** Fixed-income funds usage of derivatives



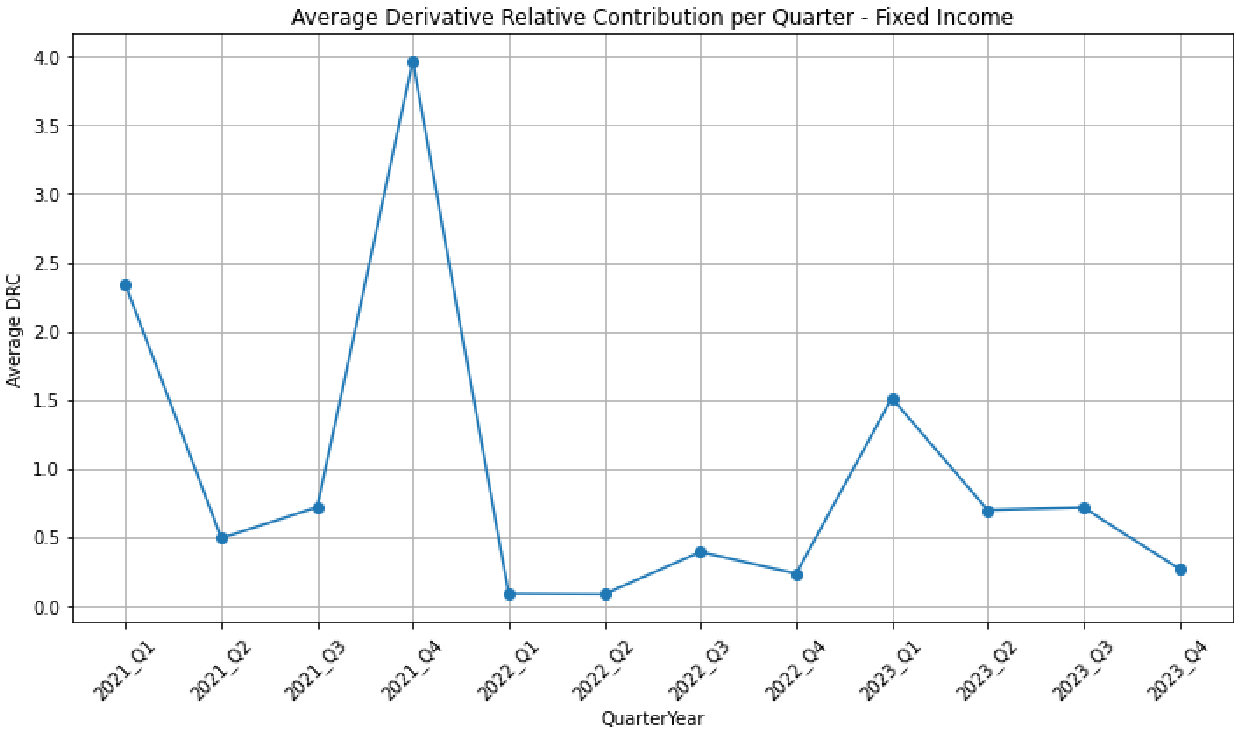
**Appendix 3** Asset allocation funds usage of derivatives



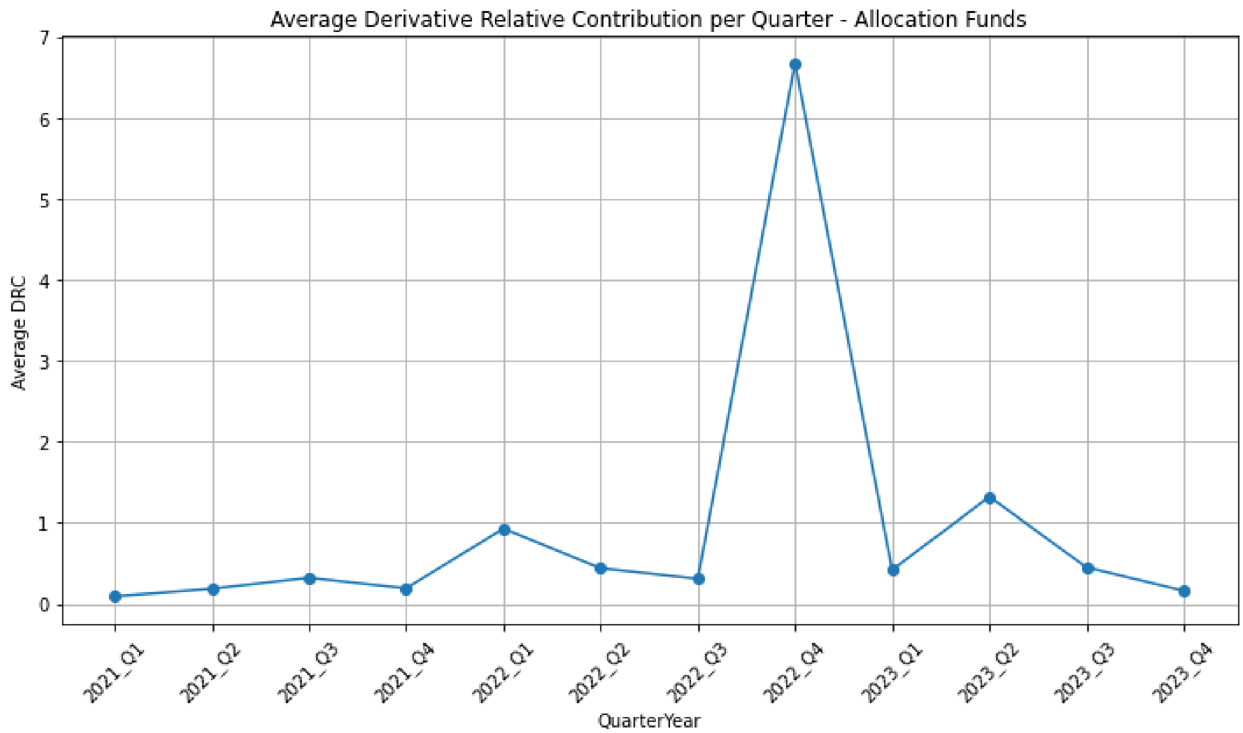
**Appendix 4** Average Derivative Relative Contribution (DRC) per quarter for Equity Mutual Funds



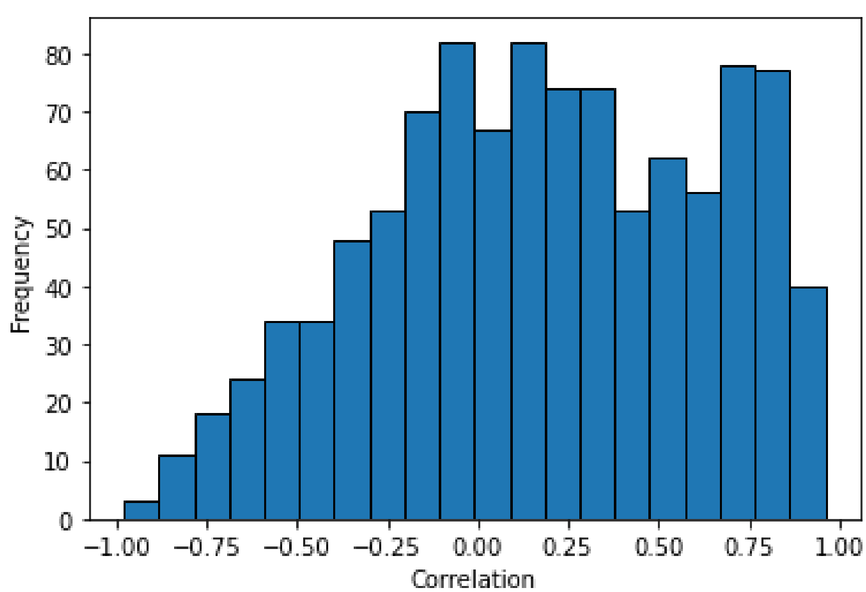
**Appendix 5** Average Derivative Relative Contribution (DRC) per quarter for Fixed Income Mutual Funds



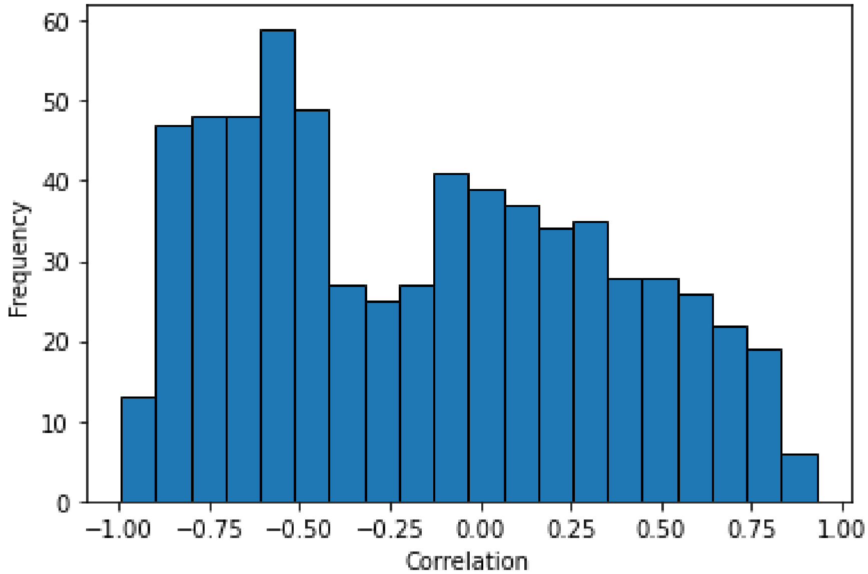
**Appendix 6** Average Derivative Relative Contribution (DRC) per quarter for Asset Allocation Mutual Funds



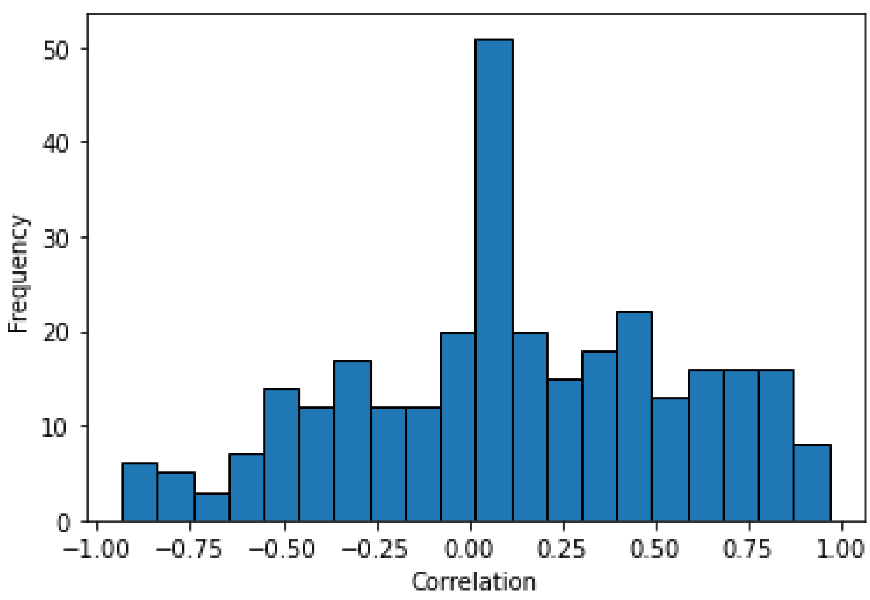

**Appendix 7** Distribution of Correlations for Equity Funds



**Appendix 8** Distribution of Correlations for Fixed Income Funds




**Appendix 9** Distribution of Correlations for Asset Allocation Funds



**Appendix 10** One Sample T-test for Equity Mutual Fund Derivative Contract Usage

| Contract Type | T-Statistic | P-Value |
|---|---|---|
| Commodity | 0.6398 | 0.5678 |
| Credit | 2.9944 | 0.0086 |
| Equity | 21.9319 | $< 0.0001$ |
| Foreign Exchange | -5.5395 | $< 0.0001$ |
| Interest Rate | -1.5657 | 0.1269 |
| Other | -0.2728 | 0.7865 |

**Appendix 11** One Sample T-test for Fixed Income Mutual Fund Derivative Contract Usage

| Contract Type | T-Statistic | P-Value |
|---|---|---|
| Commodity | -0.3492 | 0.7306 |
| Credit | -0.2376 | 0.8124 |
| Equity | -0.8042 | 0.4224 |
| Foreign Exchange | -14.9503 | $< 0.0001$ |
| Interest Rate | -3.7980 | 0.0002 |
| Other | 1.6925 | 0.0946 |

**Appendix 12** One Sample T-test for Asset Allocation Mutual Fund Derivative Contract Usage

| Contract Type | T-Statistic | P-Value |
|---|---|---|
| Commodity | 0.1013 | 0.9203 |
| Credit | 1.3415 | 0.1852 |
| Equity | -0.2467 | 0.8054 |
| Foreign Exchange | -2.7689 | 0.0066 |
| Interest Rate | 13.4139 | $< 0.0001$ |
| Other | 3.6997 | 0.0003 |

**Appendix 13** AI Usage in thesis writing

In our thesis process we utilized ChatGPT 4 AI tool. We used ChatGPT for coding. Especially, we used it to improve efficiency of our code and to look for some possible errors in the analysis. ChatGPT enhanced the efficiency of our code by helping us identify potential errors and streamline our data analysis. Instead of building code from scratch or searching through various websites, using AI significantly reduced the time we spent. Additionally, it helped us minimize coding errors, thus cutting down on debugging time. However, there were instances when ChatGPT generated incorrect code, deleted parts of our code, or inserted irrelevant code segments. We noticed these issues early on and made sure to check each code produced by ChatGPT manually. Some of the code we wrote has not been used/seen before by ChatGPT. Since it is a black box that learns from the prior data it had, we already knew that in those instances we would get some code that would not work properly. Therefore, we made sure to ask ChatGPT mostly for small functional parts of the code while writing the main code snippets ourselves.

We considered using ChatGPT for the writing process. However, when we started asking AI for paraphrasing some content, it would completely change the meaning of our sentences leading to incorrect statements. Therefore, we decided to restrict ChatGPT's role to technical aspects of the thesis work.

Overall, what we understood from the usage of ChatGPT in thesis writing process is that AI, while a good tool for improving efficiency, is not perfectly suited for creative parts of academic writing. Even in technical parts of the thesis process (coding), one needs to be knowledgeable of the task to understand the errors of the AI.