An Investigation of Diseconomies of Scale in Volatile Markets under Short-term Turbulence

Analyzing the Impact of fund-specific Variables on Mutual Fund Performance during Market Turbulence

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Abstract:
This thesis explores the relationship between mutual fund size and performance during market volatility, focusing on U.S.-equity actively managed mutual funds from 2019 to 2023. Unlike findings from stable, long-term periods, no significant relationship is observed between assets under management and benchmark-adjusted returns in this turbulent time frame. Turnover ratio emerges as a key factor, showing a significant negative relationship with gross and net returns, likely due to higher trading costs, and a weak negative relationship with fund size, suggesting larger funds trade less actively. However, low R^2 values indicate limited explanatory power. These results highlight the complexity of fund performance during volatile periods and the need for broader research to better understand the interplay between fund-specific and market-level factors.

Keywords:
Mutual Funds, Turnover ratio, Expense ratio, Assets Under Management, Performance metrics

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1. Introduction

1.1 Background

Mutual funds are financial instruments that have grown to become increasingly important instruments, having their level of assets under management (AUM) more than tripled in the last two decades, according to Statista (2024), accounting for over $20 trillion in assets in 2019. This financial instrument has become a popular choice of investment, where more than 40% of American households have had holdings in mutual funds since the year 2000. As mutual funds have become popular financial instruments, their asset holdings have logically also increased.

Mutual fund size is an area of finance literature that, in comparison to other areas, is relatively unexplored. However, some research has been performed on this topic. Both Zhu (2018**)** and Yan (2008) find significant evidence for actively managed mutual funds exhibiting decreasing returns to scale when exploring the relationship between fund returns and fund size, measured in assets under management (AUM). On the contrary, Elton, Gruber, Blake (2012) find no significant evidence for a relationship between a fund's performance and size, but they find that fund fees decrease as they grow in size.

The debate regarding returns to scale is about whether there are decreasing returns to scale. The sample tested by Zhu (2018**)** ranges from January 1995 - December 2014 and uses benchmark-adjusted returns; Yan (2008) ranges from January 1993 - December 2002 and uses returns, and Elton et al. (2012) features a range from January 1999 - December 2009 and uses a Fama French Model. These sample windows represent extended time periods that are generally regarded as stable, with the exception of the 2008 financial crisis.

Unexplored is the gap in research on how mutual fund performance is correlated during a shorter timeframe with a more volatile market. Considering the popularity of this financial instrument, awareness regarding how mutual funds react to unstable market conditions should be better explored, and whether funds experience decreasing returns to scale should be examined.

In this paper, we perform sample testing on US-equity actively managed mutual funds, on a sample ranging from January 2019 to December 2023, to examine how fund size correlates with benchmark-adjusted returns and fund-specific variables, including expense ratio and turnover ratio. This period is characterized by several events that had a significant impact on the stock market, among those, COVID-19, as explored in Zhang, Hu, and Ji (2020), and the start of the Russo-Ukrainian war, as explored in Boungou, Yaité (2022).

Building on the previously identified gap in mutual fund performance research, this study aims to explore the following questions:

- Do mutual funds exhibit diseconomies of scale in shorter, turbulent periods?
- Are the effects exhibited consistent with patterns observed in more extended and stable time frames?

The rationale for the research questions is that while existing research has challenged the assumption of constant returns to scale, most studies focus on long-term, more stable periods, leaving a gap in understanding how fund size influences performance in short-term, volatile conditions. By examining fund performance in a volatile period against AUM, this research aims to clarify whether previously observed relationships persist under high-stress conditions, such as during economic shocks.

1.2 Methodology

1.2.1 Research Design

This study examines the relationship between mutual fund size and performance during periods of significant market volatility, with a particular focus on recent disruptions caused by the COVID-19 pandemic and the Russo-Ukrainian war. These events have created considerable instability in global financial markets, as explored by Zhang et al. (2020) and Boungoue and Yaité (2022), providing an opportunity to explore how mutual fund size may influence performance during such turbulent periods. By analyzing the performance of mutual funds across these volatile episodes, the study aims to assess whether fund size has a distinct impact on benchmark-adjusted returns and whether this impact differs from that observed in more stable market conditions.

1.2.2 Data Sources and Sample Construction

The data on mutual funds, fund characteristics, and performance metrics were obtained from Morningstar Direct. Performance metrics consist of gross return and net return. The data for this study was sourced from a single comprehensive file on Morningstar Direct, containing performance metrics for a sample of American US-equity mutual funds. The data was organized into multiple sheets, and calculations were performed across these sheets before the results were consolidated into separate Excel files, which were then imported into R for further analysis. These files included key performance indicators such as Assets Under Management (AUM), net returns, gross returns, expense ratios, and turnover ratios extracted from various sheets within the Excel files. The data spans multiple years, with time-series observations for each fund, identified uniquely by a FundID. This structure enables a comprehensive examination of the fund's performance across different time periods, helping to uncover patterns and trends in how fund size and other characteristics influence performance under varying market conditions.

1.2.3 Data Processing, Transformation and Imputation

1.2.3.1 Data Importing and Reshaping

Data was imported from multiple Excel sheets using the readxl package in R. The relevant performance metrics, AUM and fund-specific variables were extracted from different sheets within the Excel files. The data was then reshaped using the pivot_longer() function from the tidyr package, transforming the dataset from a wide format to a long format. This reshaping procedure allowed for the creation of a uniform dataset where each row represents a single observation for a given fund, performance metric, and time period.

Additionally, the data was extracted and organized into column groups to facilitate the use of the rowMeans() function. This method allowed for efficient data aggregation, streamlining the calculations required for Ordinary Least Squares (OLS) regression analyses.

Several key transformations were applied to the data during this reshaping process. The core performance metrics and AUM were standardized. For instance, AUM was scaled to billions of dollars (AUM / 10^9) to ensure consistency across the data and to facilitate easier comparison. To further facilitate easier comparison, each metric was labeled with its corresponding category (AUM, net returns, gross returns, expense ratios and turnover) using the mutate() function from dplyr and rows with zero values were excluded from the dataset, as zero values indicate periods before the fund's inception or after its closure, which do not contain data that is relevant to the analysis.

This reshaping and transformation process ensures that the data is in a format conducive to time-series and panel data analysis, where each metric is treated as a separate variable, and observations are correctly aligned with the time dimension.

1.2.3.2 Outlier Management and the Use of Benchmark-Adjusted Variables

To ensure the robustness of the analysis and mitigate the influence of extreme values, a Winsorization procedure was applied to key performance metrics and fund-specific variables. In financial data, outliers can disproportionately distort statistical results, as extreme values may not accurately represent typical behavior and could mask underlying trends. Winsorization addresses this issue by capping extreme values at predefined percentiles, more specifically, the 1st and 99th percentiles in this study. This approach reduces the impact of outliers without removing the data points entirely, thus preserving the dataset's integrity while ensuring that the results are not overly influenced by anomalous observations.

Mutual fund performance is assessed using benchmark-adjusted returns, while the academic Fama-French factors, though helpful in explaining return variation, are non-tradable and can lead to biased evaluations. Morningstar benchmarks, based on fund holdings rather than objectives, provide a more practical and unbiased alternative. We assume a benchmark beta of 1 and calculate performance using benchmark-adjusted gross and net returns, which reflect the manager's ability to outperform the benchmark and the investor’s return after fees.

For the performance metrics in this study, benchmark-adjusted gross returns and benchmark-adjusted net returns were computed by subtracting the respective benchmark returns from the fund’s returns. After this adjustment, extreme values in the performance metrics were capped at the 1st and 99th percentiles. This process, implemented within the R programming language using mutate() and percentile-based capping, ensures that the analysis provides a more accurate and representative view of fund performance. By mitigating the influence of outliers, the procedure helps maintain focus on typical performance patterns, which is critical for drawing valid conclusions about mutual fund behavior, especially in fluctuating market conditions.

By carefully managing outliers, this procedure improves the reliability of the analysis, offering a clearer picture of how mutual funds perform, particularly during periods of market volatility. This enhances both the accuracy of the statistical analysis and the overall validity of the study's findings.

1.2.3.3 Data Imputation Methodologies

In this study, missing data was addressed through column mean imputation. During the Ordinary Least Squares (OLS) regression analyses, R flagged missing observations with messages such as "15 observations deleted due to missingness." Upon review, it was found that missing values were not due to random omission but rather resulted from the fact that certain mutual funds in the dataset were active only for certain periods between January 2019 and December 2023. This non-random missingness arose because some funds were either incepted after January 2019 or ceased operations before December 2023, leading to gaps in the data.

Excluding observations with missing values through complete-case analysis would have significantly reduced the sample size, with some outputs indicating the removal of as few as 14 observations and, in other cases, over 1,000 observations out of a relatively small sample size of mutual funds. Such a reduction would have been extensive, impacting the statistical power of the analysis. To avoid this and preserve the integrity of the dataset, column mean imputation was applied. This method replaces missing values in each column with the mean of the available observations for that column. The decision to use column mean imputation was driven by its simplicity, computational efficiency, and minimal disruption to the overall data structure. It allowed for retaining a larger portion of the dataset and avoiding significant data loss while ensuring that the analysis remained based on a more complete sample.

The imputation was executed in R using the following code:

```
Variable[is.na(Variable)] <- mean(Variable, na.rm = TRUE)
```

This code replaces any missing values (denoted by NA) in the variable with the mean of the observed values for that variable, ensuring that the dataset remains intact.

While column mean imputation is widely used and considered efficient, it is important to acknowledge that this method may introduce some bias. Specifically, replacing missing values with the mean of observed data can underestimate variability and may not fully capture the underlying distribution of missing values, particularly if the missingness is not completely random. In this study, it was recognized that while the missingness was not random due to the nature of fund inception and closure, the imputation process may have slightly skewed the results, especially for variables where the missingness was systematic. However, given the manageable level of missing data and the need to retain a robust sample size, it was deemed that this approach was a reasonable trade-off for the analysis. The potential bias introduced by imputation was acknowledged and believed not to substantially affect the reliability of the findings.

While more advanced imputation methods, such as predictive mean matching (PMM) or Bayesian linear regression, could potentially offer more accurate imputations by modeling relationships between variables, these methods are computationally more demanding and require stronger assumptions about the data. Given the manageable level of missing data and the absence of evidence suggesting non-random missingness beyond the fund start and end dates, column mean imputation was considered an appropriate and efficient choice.

1.2.4 Statistical Analysis

To provide a comprehensive overview of the dataset, a summary statistics table was created, which included key metrics such as the number of observations, mean, standard deviation, and percentiles (1%, 25%, 50%, 75%, and 99%) for various categories, featuring gross returns, benchmark-adjusted gross returns, net returns, benchmark-adjusted net returns, expense ratios, turnover ratios, and AUM.

To investigate the relationship between mutual fund size and performance, this study employed a combination of Ordinary Least Squares (OLS) regression models, Monte Carlo simulations and Multilinear regressions (MLR). The OLS models were used to assess the strength and direction of the relationship between various metrics, such as Average Assets Under Management (AUM) and Average benchmark-adjusted fund returns (both gross and net). The Monte Carlo simulations, on the other hand, were used to assess the robustness of the findings and to explore the variability of benchmark-adjusted returns under different scenarios. Below, each method is explained in detail. The MLR model refers to a regression model with multiple predictors and independent variables. The relationship between the independent variable and each predictor is assumed to be linear.

1.2.4.1 Ordinary Least Squares (OLS) Regression Analysis

OLS regression is a fundamental statistical technique used to model the relationship between a dependent variable and an independent variable. In the context of this study, OLS regression was used to assess the impact of fund size (AUM), the independent variable, on the performance metrics, specifically benchmark-adjusted returns, the dependent variables.

The general form of the OLS regression model is:

$$Y_i=\beta_0+\beta_1 X_i+\epsilon_i$$

Where $\mathbf{Y_i}$ is the dependent variable, $\mathbf{X_i}$ is the independent variable, $\boldsymbol{\beta_0}$ is the intercept term, $\boldsymbol{\beta_1}$ is the coefficient for the independent variable, representing the relationship between AUM and fund performance and $\boldsymbol{\epsilon_i}$ is the error term.

The OLS model minimizes the sum of squared residuals to estimate the coefficients $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$. This is performed under the assumption that residuals are homoscedastic and normally distributed.

$$\sum(\epsilon_i\text{^}2) = \sum(y_i-\hat{y}_i)\text{^}2$$

In this study, several OLS-regression models were used to explore the relationship between Assets Under Management (AUM) and benchmark-adjusted returns. These models analyze different time periods and performance metrics. The following regression models were implemented:

Regression Model 1: This model examines the relationship between average benchmark-adjusted gross return and average AUM for the period 2019-2023. The corresponding code implementation is:

```
Regression1 <- lm(AVGBenchmarkAdjustedGrossReturn ~ AverageAllAUM)
summary(Regression1)
```

Mathematically, the model can be expressed as:

$$AVGBenchmarkAdjustedGrossReturn_i=\beta_0+\beta_1 \cdot AverageAllAUM_i+\epsilon_i \tag{1}$$

Regression Model 2: This model examines the relationship between average benchmark-adjusted net return and average AUM for the period 2019-2023. The corresponding code implementation is:

```
Regression2 <- lm(AVGBenchmarkAdjustedNetReturn ~ AverageAllAUM)
summary(Regression2)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturn}_i=\beta_0+\beta_1 \cdot \mathit{AverageAllAUM}_i+\epsilon_i \tag{2}$$

Regression Model 3: This regression examines the relationship between average benchmark-adjusted gross return and average AUM for the period 1995-2014. The corresponding code implementation is:

```
Regression3 <- lm(AVGBenchmarkAdjustedGrossReturnBaseArticleFullData ~
AverageAllAUMBaseArticleFullData)
summary(Regression3)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedGrossReturnBaseArticleFullData}=\beta_0+ \mathit{AverageAllAUMBaseArticleFullData}+\epsilon_i \tag{3}$$

Regression Model 4: This regression examines the relationship between average benchmark-adjusted net return and average AUM for the period 1995-2014. The corresponding code implementation is:

```
Regression4 <- lm(AVGBenchmarkAdjustedNetReturnBaseArticleFullData ~
AverageAllAUMBaseArticleFullData)
summary(Regression4)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturnBaseArticleFullData}=\beta_0+ \mathit{AverageAllAUMBaseArticleFullData}+\epsilon_i \tag{4}$$

Regression Model 5: This regression examines the relationship between average benchmark-adjusted gross return and average AUM for the period 2006-2010. The corresponding code implementation is:

```
Regression5 <- lm(AVGBenchmarkAdjustedGrossReturnBaseArticle ~ AverageAllAUMBaseArticle)
summary(Regression5)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedGrossReturnBaseArticle}=\beta_0+ \mathit{AverageAllAUMBaseArticle}+\epsilon_i \tag{5}$$

Regression Model 6: The model examines the relationship between average benchmark-adjusted net return and average AUM for the period 2006-2010. The corresponding code implementation is:

```
Regression6 <- lm(AVGBenchmarkAdjustedNetReturnBaseArticle ~ AverageAllAUMBaseArticle)
summary(Regression6)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturnBaseArticle}=\beta_0+ \mathit{AverageAllAUMBaseArticle}+\epsilon_i \tag{6}$$

Regression Model 7: The model examines the relationship between average benchmark-adjusted gross return and average expense ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression7 <- lm(AVGBenchmarkAdjustedGrossReturn ~ AverageALLExpenseRatio)
summary(Regression7)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturnBaseArticle}=\beta_0+\mathit{AverageALLExpenseRatio}+\epsilon_i \tag{7}$$

Regression Model 8: The model examines the relationship between average benchmark-adjusted net return and average expense ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression8 <- lm(AVGBenchmarkAdjustedNetReturn ~ AverageALLExpenseRatio)
summary(Regression8)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturn}=\beta_0+\mathit{AverageALLExpenseRatio}+\epsilon_i \tag{8}$$

Regression Model 9: The model examines the relationship between average benchmark-adjusted gross return and average turnover ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression9 <- lm(AVGBenchmarkAdjustedGrossReturn ~ AverageAllTurnoverRatio)
summary(Regression9)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedGrossReturn}=\beta_0+\mathit{AverageAllTurnoverRatio}+\epsilon_i \tag{9}$$

Regression Model 10: The model examines the relationship between average benchmark-adjusted net return and average turnover ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression10 <- lm(AVGBenchmarkAdjustedNetReturn ~ AverageAllTurnoverRatio)
summary(Regression10)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturn}=\beta_0+\mathit{AverageAllTurnoverRatio}+\epsilon_i \tag{10}$$

Regression Model 11: The model examines the relationship between the average turnover ratio and average AUM for the period 2019-2023. The corresponding code implementation is:

```
Regression11 <- lm(AverageAllTurnoverRatio ~ AverageAllAUM)
summary(Regression11)
```

Mathematically, the model can be expressed as:

$$\mathit{AverageAllTurnoverRatio}=\beta_0+\mathit{AverageAllAUM}+\epsilon_i \tag{11}$$

For the regression models, the summary output includes the coefficients, p-values, and R-squared values, which help assess the statistical significance and explanatory power of the models. Moreover, each regression was accompanied by scatterplots. In these scatterplots, the independent variable was plotted on a logarithmic scale for the x-axis. This transformation helps to better visualize the relationship between the dependent and the independent variable. By applying a logarithmic scale, we ensure that the independent variables across a broad range are more appropriately represented, making it easier to observe patterns and trends in the data.

1.2.4.2 Monte Carlo Simulations

Monte Carlo simulations are used to model the uncertainty and variability of mutual fund benchmark-adjusted returns under different scenarios. This technique involves generating random samples from the distribution of benchmark-adjusted returns and simulating possible outcomes. By running a large number of simulations, for this instance, 1000, it allows for estimating the range of possible outcomes and assesses the risk and return profiles under various conditions.

In this study, the Monte Carlo simulation is employed to evaluate the robustness of the regression models and to examine how variations in AUM may influence benchmark-adjusted returns under different market conditions. The process involves several steps: sampling, simulation, repetition, and analysis. For the Monte Carlo analysis, data from Tzu (2018), which spans 20 years, was readily available, as explained by the data extraction in the Data Description, and used for the simulation. A total of 1,000 iterations were conducted to assess the potential impact of changes in AUM on benchmark-adjusted returns.

Randomly sampled data points were drawn from the distribution of historical AUM and benchmark-adjusted return values. The regression coefficients derived from the OLS models were then applied to each set of sampled data, generating simulated return outcomes. This process was repeated for 1,000 iterations to simulate a wide range of possible returns. The results of these iterations were aggregated to create a distribution of simulated returns. From this distribution, key statistics such as the mean and standard deviation were calculated to estimate the potential range of outcomes and understand the variability in returns across different market conditions. Additionally, histograms were used to visualize the distribution of simulated returns, providing insight into the spread and frequency of potential outcomes, and the mean and standard deviation for each histogram were calculated to receive accurate results regarding the histogram data.

To test the robustness of the Monte Carlo simulation, we repeated all of the previous steps to ensure the results remained accurate when not applying column means, which had been continuously used up until that point and was continuously used after the robustness test.

The Monte Carlo simulations provide insights into the potential risk and return profiles of mutual funds under varying market conditions, especially during periods of heightened market volatility. This approach helps to quantify the uncertainty in the relationship between AUM and fund performance and allows for a better understanding of how these variables interact in the face of market disruptions such as the COVID-19 pandemic and the Russo-Ukrainian wars market impact.

1.2.4.2 Multivariable Regression Analysis

Regression model 12: The model examines the relationship between average benchmark-adjusted gross returns on the three variables, average AUM, average expense ratio and average turnover ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression12 <- lm(AVGBenchmarkAdjustedGrossReturn ~ AverageAllAUM + AverageALLExpenseRatio +
AverageALLTurnoverRatio)
summary(Regression12)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedGrossReturn}=\beta_0+ \mathit{AverageAllAUM} + \mathit{AverageALLExpenseRatio} + \mathit{AverageALLTurnoverRatio} +\epsilon_i \tag{12}$$

Regression model 13: The model examines the relationship between average benchmark-adjusted net returns on the three variables, average AUM, average expense ratio and average turnover ratio for the period 2019-2023. The corresponding code implementation is:

```
Regression13 <- lm(AVGBenchmarkAdjustedNetReturn ~ AverageAllAUM + AverageALLExpenseRatio +
AverageALLTurnoverRatio)
summary(Regression13)
```

Mathematically, the model can be expressed as:

$$\mathit{AVGBenchmarkAdjustedNetReturn}=\beta_0+ \mathit{AverageAllAUM} + \mathit{AverageALLExpenseRatio} + \mathit{AverageALLTurnoverRatio} +\epsilon_i \tag{13}$$

1.2.4.4 Model Evaluation

The models were evaluated using several statistical measures. The R-squared values provide insight into how well the independent variable accounts for the dependent variables. The coefficients reflect the strength and direction of the relationship between the dependent and the independent variable, with t-values showing the significance of these coefficients. P-values below 0.05 suggest a statistically significant relationship between the independent and dependent variables. These metrics collectively demonstrate the degree to which the independent variable influences the dependent variable.

2. Results

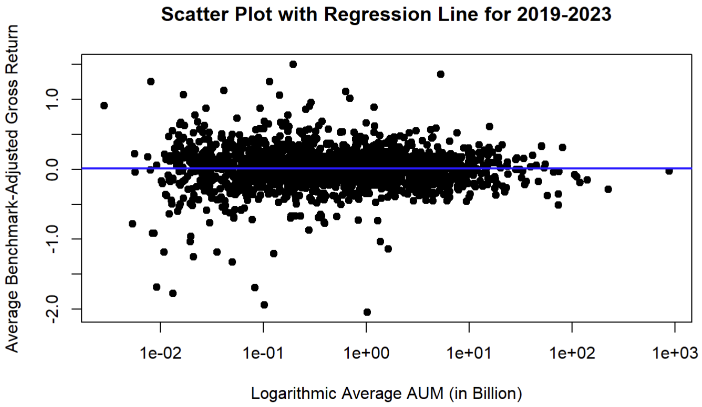


Figure 1: OLS Regression of Average Benchmark-adjusted Gross Return vs. Average AUM (2019–2023)
The figure illustrates the relationship between the Average Benchmark-adjusted Gross Return and the logarithmic Average AUM (in billions) from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 18), where the R output shows that the relationship is not statistically significant (p = 0.4345), with a negative near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (1).

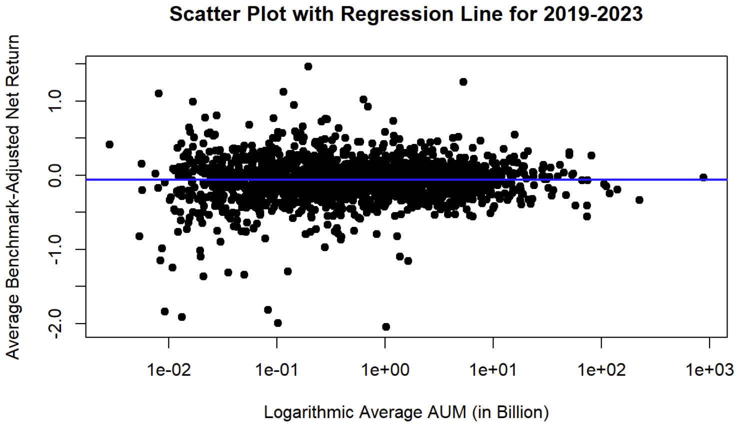


Figure 2: OLS Regression of Average Benchmark-adjusted Net Return vs. Average AUM (2019–2023)
The figure illustrates the relationship between the Average Benchmark-adjusted Net Return and the logarithmic Average AUM (in billions) from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 19), where the R output shows that the relationship is not statistically significant (p = 0.8821) with a negative near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (2).

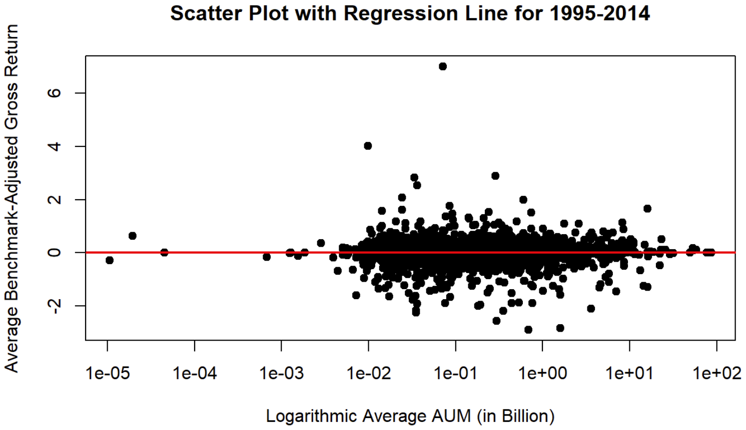


Figure 3: OLS Regression of Average Benchmark-adjusted Gross Return vs. Average AUM (1995–2014)
The figure illustrates the relationship between the Average Benchmark-adjusted Gross Return and the logarithmic Average AUM (in billions) from January 1995 to December 2014. The regression analysis underlying the plot is detailed in the Appendix (Figure 20), where the R output shows that the relationship is not statistically significant ($p = 0.7002$) with a positive near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (3).

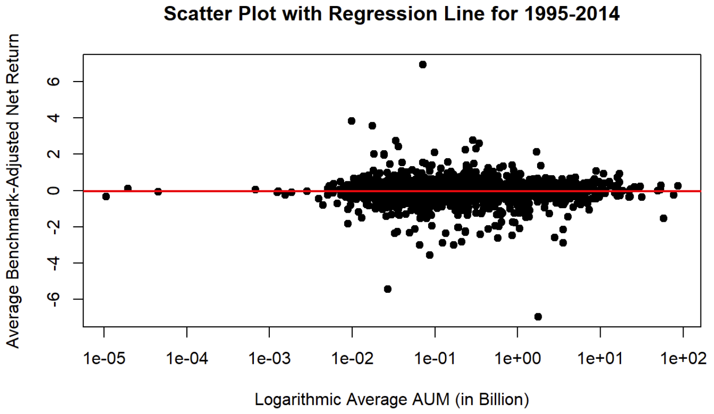


Figure 4: OLS Regression of Average Benchmark-adjusted Net Return vs. Average AUM (1995–2014)
The figure illustrates the relationship between the Average Benchmark-adjusted Net Return and the logarithmic Average AUM (in billions) from January 1995 to December 2014. The regression analysis underlying the plot is detailed in the Appendix (Figure 21), where the R output shows that the relationship is not statistically significant ($p = 0.7209$) with a negative near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (4).

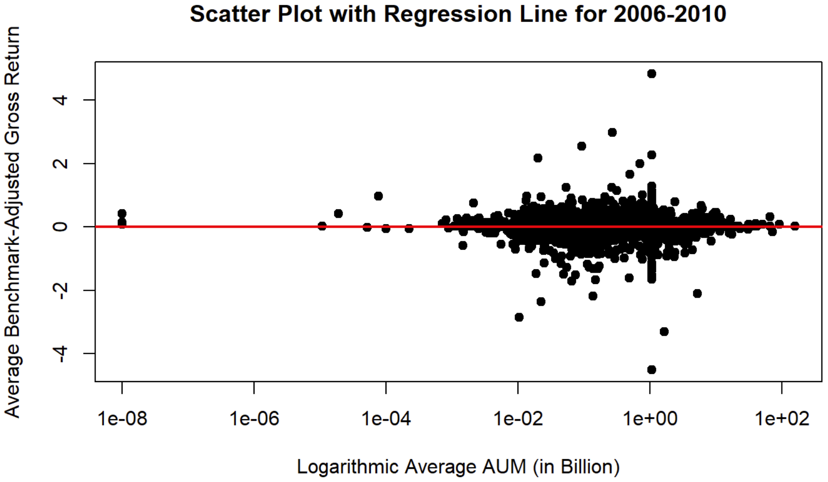


Figure 5: OLS Regression of Average Benchmark-adjusted Gross Return vs. Average AUM (2006–2010)
The figure illustrates the relationship between the Average Benchmark-adjusted Gross Return and the logarithmic Average AUM (in billions) from January 2006 to December 2010. The regression analysis underlying the plot is detailed in the Appendix (Figure 22), where the R output shows that the relationship is not statistically significant ($p = 0.7625$) with a positive near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (5).

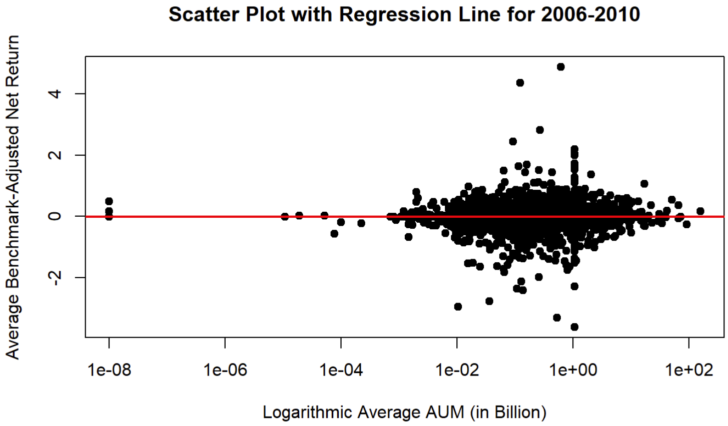


Figure 6: OLS Regression of Average Benchmark-adjusted Net Return vs. Average AUM (2006–2010)
The figure illustrates the relationship between the Average Benchmark-adjusted Net Return and the logarithmic Average AUM (in billions) from January 2006 to December 2010. The regression analysis underlying the plot is detailed in the Appendix (Figure 23), where the R output shows that the relationship is not statistically significant ($p = 0.4343$), with a positive near-zero coefficient for Average AUM, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (6).

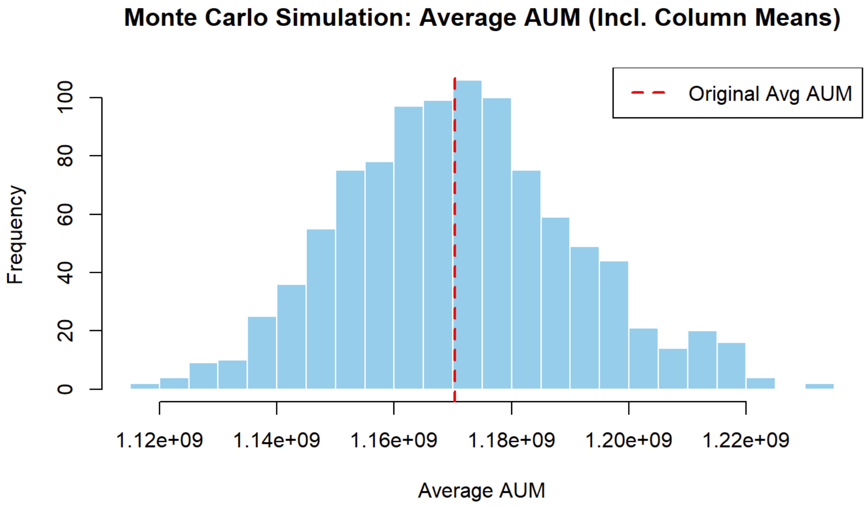


Figure 7: A histogram for the distribution of Average AUM (Including Column Mean)
This histogram shows the distribution of average AUM values across 1,000 Monte Carlo iterations, with the red dashed line indicating the original average AUM (Original Avg AUM = Calculated Value). The comparison highlights whether the observed AUM falls within a typical range of the simulated outcomes or if it deviates significantly. The distribution is approximately symmetric, centered around the observed average AUM ($\approx 1.1709*10^9$) . This alignment of the observed value with the center of the simulated distribution suggests that the original average AUM is typical and consistent with what is expected under random sampling of 5-year periods. This simulation takes into consideration column means imputation.

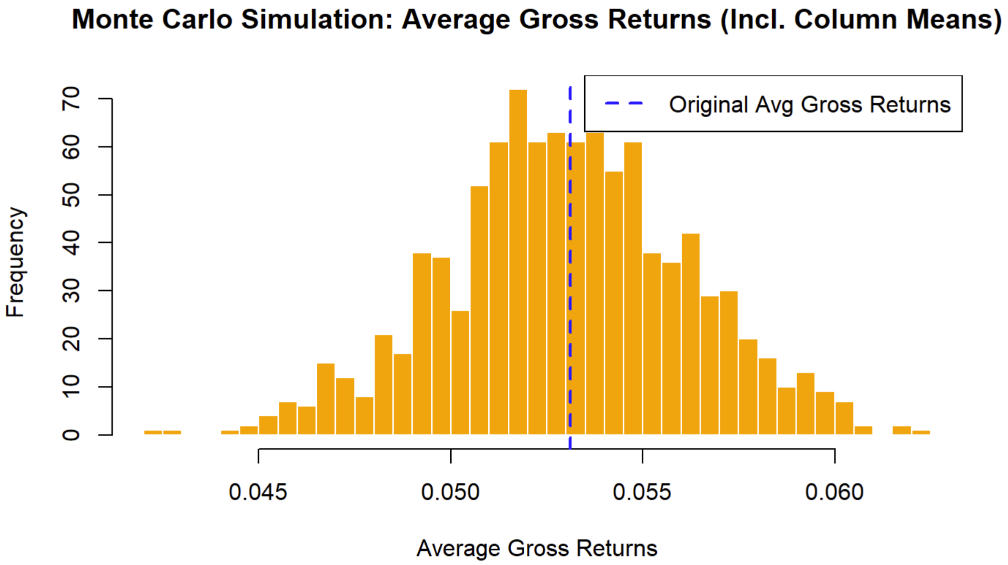


Figure 8: A histogram for the distribution of Average Gross Returns (Including Column Mean)
This histogram illustrates the distribution of simulated average benchmark-adjusted gross returns across 1,000 Monte Carlo iterations based on randomly sampled 5-year periods from the dataset. The blue dashed line marks the observed average benchmark-adjusted gross return from the original data (≈ 0.0530). The distribution is centered around a value close to the observed average, suggesting that the original benchmark-adjusted gross return is typical within the simulated context. The range of simulated values indicates variability in benchmark-adjusted gross returns due to differences in sampled periods, and the alignment of the observed average with the peak of the distribution reinforces its consistency with the underlying data. Outliers or deviations in the tails highlight less likely scenarios. This simulation takes into consideration the column means imputation.

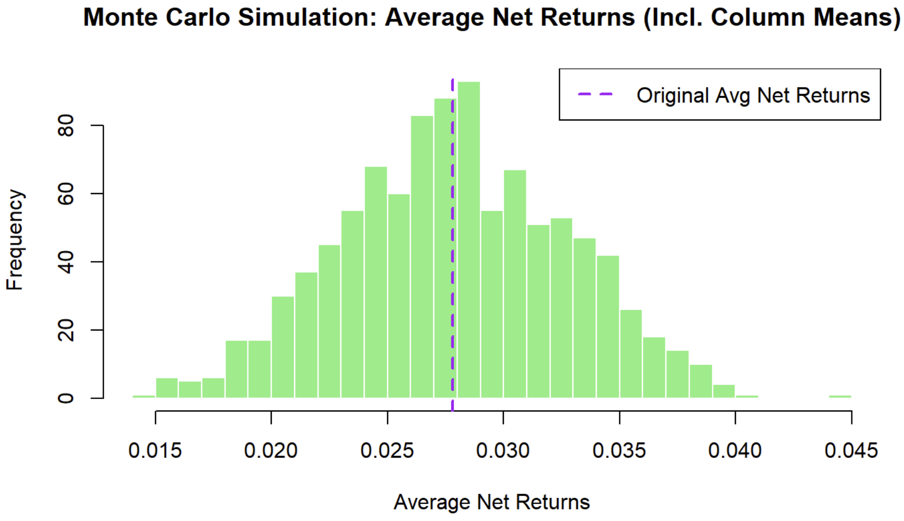


Figure 9: A histogram for the distribution of Average Net Returns (Including Column Mean)
This histogram shows the distribution of simulated average benchmark-adjusted net returns across 1,000 Monte Carlo iterations derived from randomly sampled 5-year periods. The purple dashed line represents the observed average benchmark-adjusted net return (≈ 0.02788) from the original data. The distribution appears symmetric and is centered around a value close to the observed average, indicating that the original benchmark-adjusted net return is typical within the context of the simulated scenarios. The spread of the histogram reflects the variability in benchmark-adjusted net returns due to different combinations of sampled periods, with the observed average aligning closely with the peak of the simulated distribution, suggesting consistency with the underlying data. Outliers on the tails highlight less frequent outcomes. This simulation takes into consideration column means imputation.

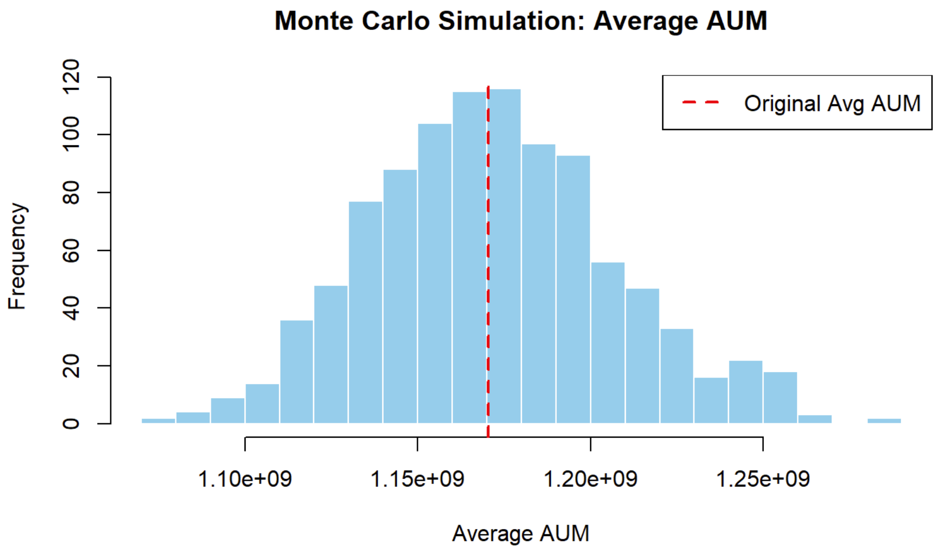


Figure 10: A histogram for the distribution of Average AUM (Excluding Column Mean)
This histogram shows the distribution of average AUM values across 1,000 Monte Carlo iterations, with the red dashed line indicating the original average AUM (Original Avg AUM = Calculated Value). The comparison highlights whether the observed AUM falls within a typical range of the simulated outcomes or if it deviates significantly. The distribution is approximately symmetric, centered around the observed average AUM (≈ 1.1719 * 10^9) . This alignment of the observed value with the center of the simulated distribution suggests that the original average AUM is typical and consistent with what is expected under random sampling of 5-year periods. This simulation does not take into consideration column means imputation.

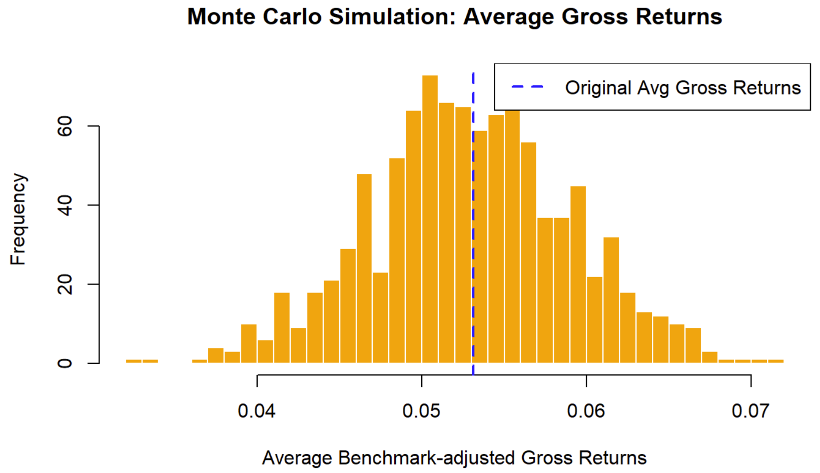


Figure 11: A histogram for the distribution of Average Gross Returns (Excluding Column Mean)
This histogram illustrates the distribution of simulated average benchmark-adjusted gross returns across 1,000 Monte Carlo iterations based on randomly sampled 5-year periods from the dataset. The blue dashed line marks the observed average benchmark-adjusted gross return from the original data (≈ 0.0529). The distribution is centered around a value close to the observed average, suggesting that the original benchmark-adjusted gross return is typical within the simulated context. The range of simulated values indicates variability in benchmark-adjusted gross returns due to differences in sampled periods, and the alignment of the observed average with the peak of the distribution reinforces its consistency with the underlying data. Outliers or deviations in the tails highlight less likely scenarios. This simulation does not take into consideration the column means imputation.

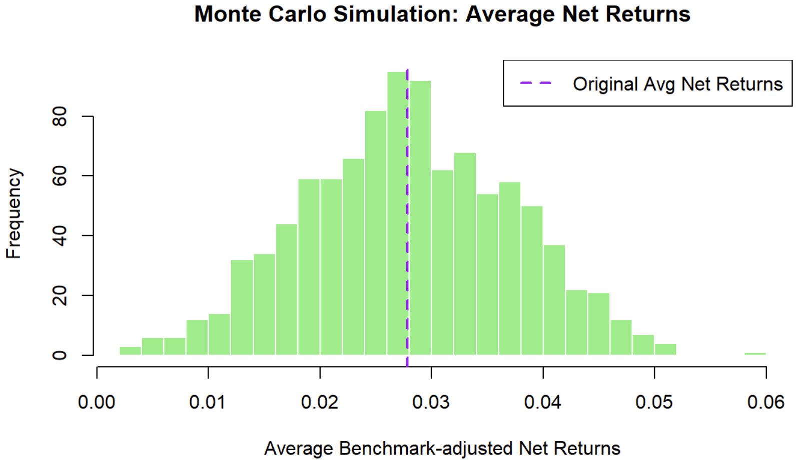


Figure 12: A histogram for the distribution of Average Net Returns (Excluding Column Mean)
This histogram shows the distribution of simulated average benchmark-adjusted net returns across 1,000 Monte Carlo iterations derived from randomly sampled 5-year periods. The purple dashed line represents the observed average benchmark-adjusted net return (≈ 0.02796) from the original data. The distribution appears symmetric and is centered around a value close to the observed average, indicating that the original benchmark-adjusted net return is typical within the context of the simulated scenarios. The spread of the histogram reflects the variability in benchmark-adjusted net returns due to different combinations of sampled periods, with the observed average aligning closely with the peak of the simulated distribution, suggesting consistency with the underlying data. Outliers on the tails highlight less frequent outcomes. This simulation does not take into consideration column means imputation.

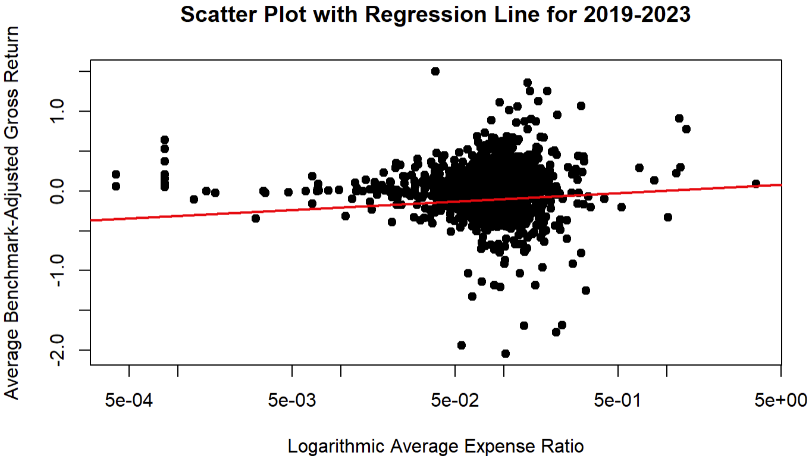


Figure 13: OLS Regression of Average Benchmark-adjusted Gross Return vs. Average Expense Ratio (2019–2023)
The figure illustrates the relationship between the Average Benchmark-adjusted Gross Return and the logarithmic average expense ratio from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 24), where the R output shows that the relationship is near statistically significant ($p = 0.09385$) with a positive coefficient (0.104801) for Benchmark-Adjusted gross return, indicating near strong linear correlation. The OLS equation corresponding to this scatterplot is equation (7).

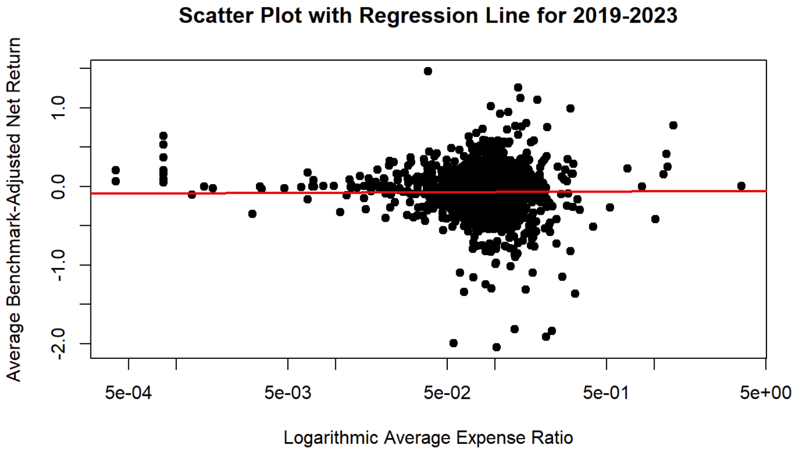


Figure 14: OLS Regression of Average Benchmark-adjusted NetReturn vs. Average Expense Ratio (2019–2023) The figure illustrates the relationship between the Average Benchmark-adjusted Net Return and the logarithmic average expense ratio from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 25), where the R output shows that the relationship is not statistically significant (p = 0.9011) with a positive coefficient (0.007763) for Benchmark-Adjusted net return, indicating no strong linear correlation. The OLS equation corresponding to this scatterplot is equation (8).

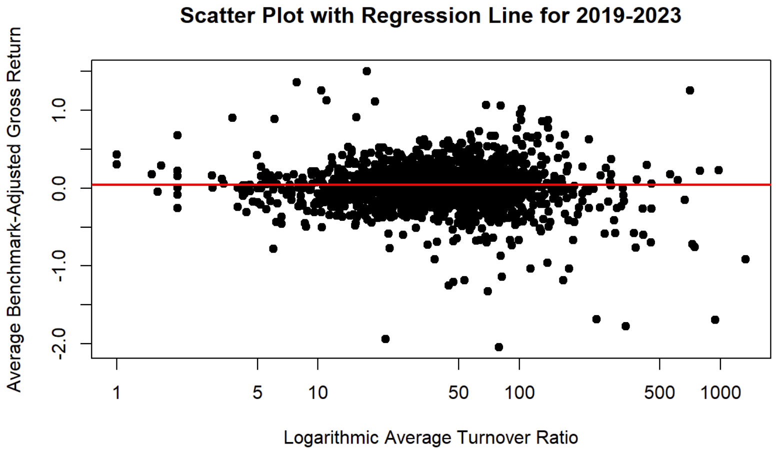


Figure 15: OLS Regression of Average Benchmark-adjusted Gross Return vs. Average Turnover Ratio (2019–2023) The figure illustrates the relationship between the Average Benchmark-adjusted Gross Return and the logarithmic average turnover ratio from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 26), where the R output shows that the relationship is statistically significant (p = 1.383*10^-7) with a negative coefficient (-4.689*10^-4) for Benchmark-Adjusted gross return, indicating strong linear correlation. The OLS equation corresponding to this scatterplot is equation (9).

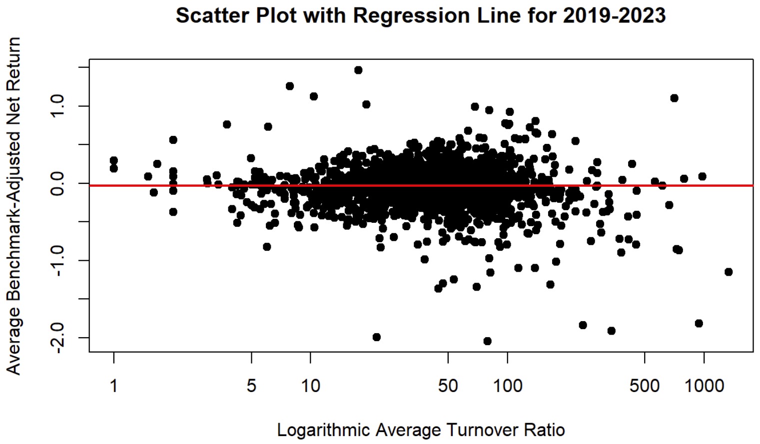


Figure 16: OLS Regression of Average Benchmark-adjusted Net Return vs. Average Expense Ratio (2019–2023)
The figure illustrates the relationship between the Average Benchmark-adjusted net Return and the logarithmic average turnover ratio from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 27), where the R output shows that the relationship is statistically significant (p = 1.887*10^-10)) with a positive coefficient (0.02393) for Benchmark-Adjusted net return, indicating strong linear correlation. The OLS equation corresponding to this scatterplot is equation (10).

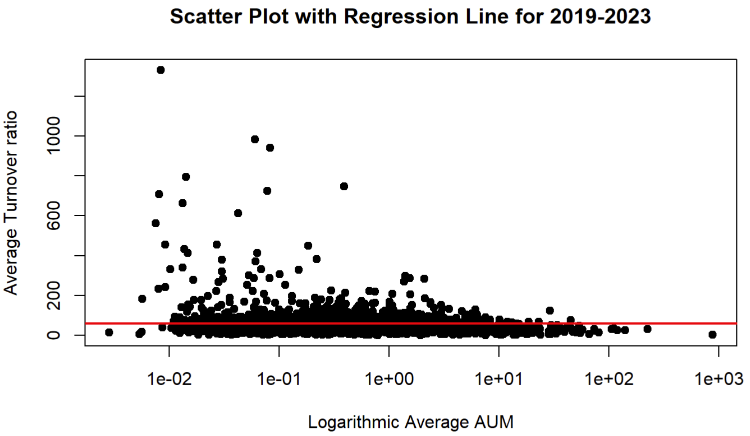
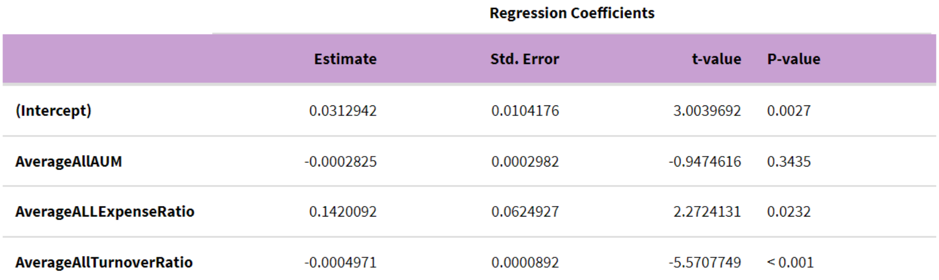


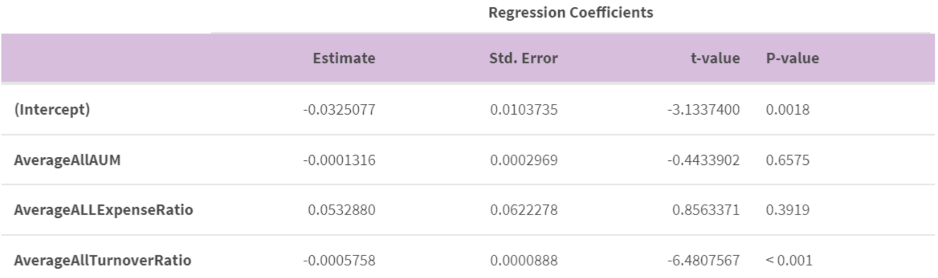
Figure 17: OLS Regression of Average Turnover Ratio vs. Average AUM (2019–2023)
The figure illustrates the relationship between the Average turnover ratio and the logarithmic average AUM from January 2019 to December 2023. The regression analysis underlying the plot is detailed in the Appendix (Figure 28), where the R output shows that the relationship is statistically significant (p = 0.03011)) with a negative coefficient (-0.17783) for Benchmark-Adjusted net return, indicating strong linear correlation. The OLS equation corresponding to this scatterplot is equation (11).



Regression Coefficients

	Estimate	Std. Error	t-value	P-value
(Intercept)	0.0312942	0.0104176	3.0039692	0.0027
AverageAllAUM	-0.0002825	0.0002982	-0.9474616	0.3435
AverageALLExpenseRatio	0.1420092	0.0624927	2.2724131	0.0232
AverageAllTurnoverRatio	-0.0004971	0.0000892	-5.5707749	< 0.001

Table 1: Regression Coefficients for benchmark-adjusted gross return and three independent variables
This table presents the results of the Multilinear regression used to analyze the relationship between benchmark-adjusted gross returns (AVGBenchmarkAdjustedGrossReturn) and three independent variables: fund size (AverageAllAUM), cost structure (AverageALLExpenseRatio), and trading activity (AverageAllTurnoverRatio). The OLS equation corresponding to this scatterplot is equation (12) and the regression analysis underlying the plot is detailed in the Appendix (Figure 29).



Regression Coefficients

	Estimate	Std. Error	t-value	P-value
(Intercept)	-0.0325077	0.0103735	-3.1337400	0.0018
AverageAllAUM	-0.0001316	0.0002969	-0.4433902	0.6575
AverageALLExpenseRatio	0.0532880	0.0622278	0.8563371	0.3919
AverageAllTurnoverRatio	-0.0005758	0.0000888	-6.4807567	< 0.001

Table 2: Regression Coefficients for benchmark-adjusted Net return and three independent variables
This table presents the results of the Multilinear regression used to analyze the relationship between benchmark-adjusted net returns (AVGBenchmarkAdjustedNetReturn) and three independent variables: fund size (AverageAllAUM), cost structure (AverageALLExpenseRatio), and trading activity (AverageAllTurnoverRatio). The OLS equation corresponding to this scatterplot is equation (13) and the regression analysis underlying the plot is detailed in the Appendix (Figure 30).

3. Literature Review

Previous studies have conducted returns to scale analyses and consistently concluded that U.S. equity mutual funds exhibit decreasing returns to scale. However, these analyses are typically conducted over extended investment horizons, often spanning around 10–20 years, which frames them as longer-term periods capturing average performance and volatility over relatively stable market periods. This long-term approach provides valuable insights but may overlook how returns to scale behave during shorter, more volatile periods, such as the 2008 financial crisis or the COVID-19 pandemic.

This paper primarily builds on Zhu (2018), who examined U.S. equity mutual funds from January 1995 to December 2014. Zhu finds evidence for mutual funds to experience decreasing returns to scale on an individual fund level. Zhu performs testing on fund size using OLS regressions, a fixed-effects model, as well as two econometric models from Berk and Van Binsbergen (2015). To further extend the analysis, Zhu finds that fund managers decrease performance as fund size increases due to suboptimal behavior from managing more than optimal capital. Zhu attributes this suboptimal behavior to be a major source of the difference between optimal and actual fund performance. However, Zhu does not address the question if there exist other variables than value-added, that would indicate how and if a fund changes behavior as size differs.

Elton et al. (2012) argue that there are no, or insignificant, diseconomies of scale as fund size increases. They perform their testing on a sample of mutual funds during 1999-2009 and they perform testing on fund size by modeling an estimated predicted alpha and comparing the predicted alpha with actual alpha. The results are driven by the fact that if funds returns would decrease with size, then it would not be possible to predict future returns. Furthermore, they perform testing on expense ratios and find that as funds grow in size and/or perform better, they decrease expense ratios and management fees. Meanwhile, as funds decrease in size and/or perform worse, they increase their expense ratios and management fees. The addition of performing a similar analysis on expense ratio and turnover during a more volatile period, which this paper intends to do, will shed more light on how funds behave as size differs and when markets become unstable.

This thesis extends the literature by examining the relationship between fund size and returns during volatile periods, with a particular focus on expense ratios and turnover. By addressing these gaps, this study aims to provide a more nuanced understanding of mutual fund behavior under varying market conditions, challenging and complementing existing findings on returns to scale.

4. Data description

The dataset, imported from Morningstar Direct, consists of 6,855 records of U.S.-equity mutual funds share classes over a 5-year period from January 2019 to December 2023. This time reflects an initially stable period, later on experiencing high rates of volatility due to the COVID-19 pandemic, among other events, that offers insights into how funds have performed through various market conditions. By including only actively managed domestic equity funds in the U.S. market, the dataset allows us to assess the relationship of AUM to performance metrics in a controlled environment, avoiding the noise that could arise from including passive funds or funds with international exposures. An essential feature of our dataset is the inclusion of both live (currently active) and dead (inactive) funds. This inclusion mitigates survivorship bias, a common issue in financial studies where only currently active funds are analyzed, thereby omitting funds that may have closed due to poor performance. By including inactive funds, the dataset provides a more balanced view of the mutual fund markets over time, capturing the entire landscape of funds available during the period. To further refine the analysis, the dataset is restricted to specific Morningstar categories, representing various investment styles and holdings. These include Small Value, Small Growth, Small Blend, Mid-cap Value, Mid-Cap Growth, Mid-Cap Blend, Large-Value, Large growth, and Large Blend. This categorization allows us to explore performance nuances across different fund types.

Morningstar Direct is a leading data platform for mutual fund research. It offers comprehensive datasets on fund performance, expense ratios, AUM, among others. Additionally, its robust analytical tools allow for precise filtering and benchmarking, further increasing its reliability. However, missing data exists and is more apparent among older or less popular funds, which affects the whole dataset and requires imputation methods that may introduce bias. We apply methods to address these biases, as explained in 4.3 Sample Inclusion Criteria. In addition, fund classifications might sometimes lack clarity, posing a threat for potential inaccuracies.

4.1 Data Refinement

Once the data was imported into Microsoft Excel, the dataset underwent additional filtering to ensure that only actively managed funds were retained. Funds identified by Morningstar as “passively managed” were removed, as were any funds with “index” or “enhanced-index” in their names. This step was critical in isolating actively managed funds, and aligning the dataset with the goal to assess the performance of active management as opposed to passive strategies.

4.2 Handling Share Classes and Aggregating Data

Mutual funds often provide multiple share classes, but treating each share class as a separate fund in analysis can lead to misleading results. Share classes represent claims on the same underlying assets and typically differ only in their fee structures and target clientele. Apart from these differences, they share identical returns before accounting for expenses and loads. Therefore, failing to account for this distinction would skew the analysis and produce inaccurate findings.

This paper addresses this by grouping these share classes together. Morningstar assigns each fund a FundID and a SecID, which we use to aggregate these share classes. Funds with a single FundID but multiple SecID totaled 1477 groups and funds with one SecID accounted for 576 mutual.

When aggregating returns, turnover ratios, and expense ratios across different share classes, an AUM-weighted average is used, calculated across all non-missing values to ensure a representative measure of the fund's performance. To standardize the expense ratio, the monthly expense ratio, as reported by Morningstar, is derived by dividing the reported annual gross expense ratio by twelve. The turnover ratio is calculated by dividing the minimum of the aggregate purchases and sales by the average annual AUM, expressed as a percentage, to reflect the fund's trading activity relative to its size. All returns and expense ratios are expressed on a monthly basis, ensuring consistency in temporal measurement across the fund's performance metrics. This approach allows for a comprehensive and accurate evaluation of the fund's financial health and operational efficiency.

4.3 Sample Inclusion Criteria

In accordance with Zhu (2018), each fund is required to have at least $15 million in net assets at some point during the period to be included in the sample. This is to avoid sample selection bias. This screening criteria was followed in the new dataset as well. Furthermore, each fund was required to have at least two years of data, ensuring a stable panel data structure that captures within-fund variation over time. These criteria were chosen as a precaution to avoid sample selection bias.

These criteria ensured that only funds with a notable market presence and sufficient data points were included, enhancing the reliability of our performance metrics and ensuring our results were based on funds of practical relevance to investors.

4.4 Benchmarking

Morningstar assigns each fund a benchmark portfolio based on its actual holdings, known as the "FTSE/Russell Benchmark." By categorizing funds based on actual asset composition rather than reported objectives, this approach reduces cherry-picking bias, as it aligns each fund with a realistic benchmark that reflects its actual holdings. Data on the benchmark returns were retrieved from Morningstar Direct.

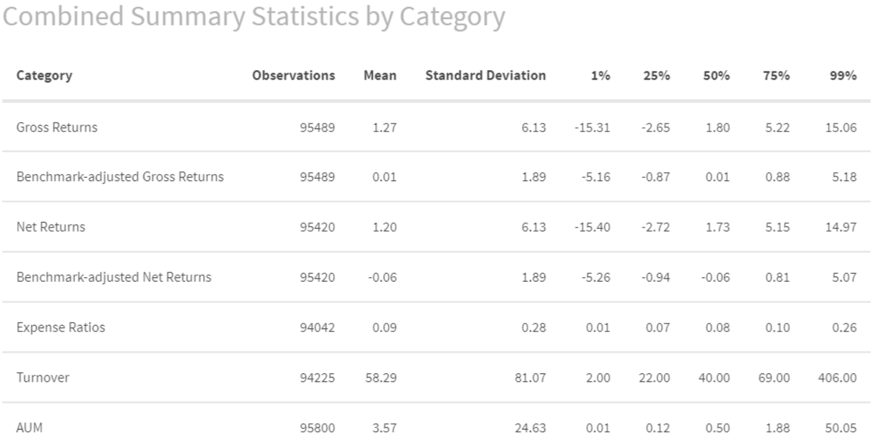
4.6 Performance Measures

Two key performance measures were created to evaluate fund management effectiveness. The first measure is the benchmark-adjusted gross return, which reflects the fund manager's skill in generating returns before fees and expenses and is calculated as the difference between a fund's gross return and the benchmark return, isolating the impact of the manager's decision-making. The second is the benchmark-adjusted net return. This measure reflects the actual return investors receive after all fees and expenses. It is calculated as the difference between a fund's net return and its benchmark return and offers a realistic view of net returns from the investor's perspective.

For defining Benchmark-adjusted returns, we denote the return for the *i*-th fund at time *t* as R_t and the corresponding Morningstar benchmark return as B_{it}. The benchmark-adjusted returns for the *i*-th fund at time *t* is:

$$\boldsymbol{r_{it} = R_{it} - B_{it}}$$

For summary statistics, the dataset included monthly figures for gross returns, benchmark-adjusted gross returns, net returns, benchmark-adjusted net returns, AUM and expense ratios, while the turnover ratio was reported annually. The table includes key descriptive statistics, such as the mean, median, standard deviation, and winsorized minimum and maximum values for each variable. Each category, except for AUM, is computed in percentage. AUM is computed as an absolute value in Dollars.



Combined Summary Statistics by Category

Category	Observations	Mean	Standard Deviation	1%	25%	50%	75%	99%
Gross Returns	95489	1.27	6.13	-15.31	-2.65	1.80	5.22	15.06
Benchmark-adjusted Gross Returns	95489	0.01	1.89	-5.16	-0.87	0.01	0.88	5.18
Net Returns	95420	1.20	6.13	-15.40	-2.72	1.73	5.15	14.97
Benchmark-adjusted Net Returns	95420	-0.06	1.89	-5.26	-0.94	-0.06	0.81	5.07
Expense Ratios	94042	0.09	0.28	0.01	0.07	0.08	0.10	0.26
Turnover	94225	58.29	81.07	2.00	22.00	40.00	69.00	406.00
AUM	95800	3.57	24.63	0.01	0.12	0.50	1.88	50.05

Table 3: Summary statistics of financial metrics, including the number of observations, mean, standard deviation, and percentiles for returns, expense ratios, turnover ratios, and AUM.

A second, similar dataset was retrieved from Morningstar Direct and the aforementioned screening processes were applied again. This sample is from Zhu (2018) and features a time range from January 1995 to December 2014, used to assess and compare the shorter, more volatile market against a longer, more stable market.

5. Empirical Analysis

5.1 Decreasing Returns to Scale

Basing the time frame on a volatile period, specifically 2019–2023, the aim was to assess whether the decreasing returns to scale relationship from Zhu's (2018) and Elton et al. (2012) articles persisted even when examining a five-year period characterized by volatility. Regarding Figure 1, the OLS regression was plotted with the average AUM for all years (coded as the vector *AverageAllAUM*, the independent variable, scaled by 10^9) and the average benchmark-adjusted gross return (coded as *AVGBenchmarkAdjustedGrossReturn*, the dependent variable).

The results of the regression indicated that for every additional unit of AUM (in Billions), the *AVGBenchmarkAdjustedGrossReturn* decreased by -0.0002346, or -2.3464*10^−4. The t-value of -0.782 indicates that the coefficient is not significantly different from zero, meaning there is no strong evidence of a linear relationship between AUM and benchmark-adjusted returns. This interpretation is further reinforced by the p-value of 0.4345, which is substantially higher than typical significance thresholds. A p-value this large confirms that there is insufficient evidence to reject the null hypothesis (H_0: $\beta=0$), indicating the predictor variable does not significantly explain variation in the dependent variable.

In Figure 2, the Ordinary Least Squares (OLS) regression follows a similar structure to the previous analysis but introduces a change: the dependent variable is now the benchmark-adjusted net return, coded as *AVGBenchmarkAdjustedNetReturn*, rather than the benchmark-adjusted gross return. The independent variable remains the average AUM, scaled by 10^9, allowing for comparability between the two regressions. This shift in focus leads to some unexpected and thought-provoking results.

The regression output revealed a coefficient indicating that for every additional unit of 10^9 AUM, the benchmark-adjusted net return increased by -0.00004444, or -4.444*10^-5. Surprisingly, this is a more pronounced effect than observed in the benchmark-adjusted gross return regression, where the coefficient was only -2,3464*10^−4. The result appears counterintuitive because, in a world of decreasing returns to scale, net returns, which account for relatively stable costs such as management fees and trading expenses, are expected to decline more significantly compared to benchmark-adjusted gross returns as AUM increases due to the added impact of these fees on the already diminishing benchmark-adjusted gross returns.

Adding to the complexity, the regression's t-value of -0.148 and p-value of 0.8821 indicate that the coefficient for average AUM is not statistically significant. A t-value so close to zero, paired with a p-value well above common significance thresholds, provides insufficient evidence to reject the null hypothesis that the coefficient is zero. This suggests that the observed relationship between AUM and net returns could be attributed to random variation rather than a meaningful underlying relationship. Alternatively, it may stem from the influence of another factor, such as a mediating variable, that affects both AUM, benchmark-adjusted net returns and benchmark-adjusted gross returns, or an omitted relationship that has yet to be identified.

The adjusted R^2 value for the model further compounds the unexpected nature of the results. At -0.0005835, the adjusted R^2 suggests that the regression model explains less of the variation in benchmark-adjusted net returns than a simple average of the dependent variable would. Negative adjusted R^2 values are rare and typically indicate that the model is not only failing to fit the data but is actively underperforming relative to a baseline model. This raises significant concerns about the model's suitability, suggesting that key variables influencing benchmark-adjusted net returns may be missing or improperly specified.

Additionally, the use of a sample period of only 5 years could exacerbate these issues, as a short time frame increases the likelihood that the observed relationship between AUM and benchmark-adjusted net returns or AUM and benchmark-adjusted gross returns is influenced by random variation or market dynamics. This limitation strengthens the argument that the relationship might not be meaningful but rather driven by unobserved factors, such as a mediating variable that impacts both AUM and benchmark-adjusted net returns or an omitted variable yet to be identified. Incorporating longer-term data could help establish greater clarity, reduce noise, and provide a more robust foundation for the analysis.

Using the same timeframe as in Zhu (2018), allows for a direct evaluation of whether the claimed effects are observed when applying the identical regression model over their specified timeframe, January 1995 to December 2014. Additionally, this comparison provides insight into whether the model produces results consistent with those found in previous analyses. Regression outputs for the timeframe spanning January 1995 to December 2014, displayed in Figure 20 and Figure 21 in the appendix and as scatterplots in Figures 3 and 4, reveal notable differences between the datasets. When comparing the previous regression outputs to those based on the article’s dataset, it becomes evident that in the regressions aligned with the article’s data, the benchmark-adjusted gross return exhibits a higher value than the benchmark-adjusted net return for each additional unit increase in AUM (in billions).

The unexpected results between the regressions, specifically the higher coefficient for benchmark-adjusted net returns compared to benchmark-adjusted gross returns, will be referred to as the *"discrepancy"* from this point onward.

The discrepancy between the regressions is hypothesized to arise from differences in the timeframe, as the first two regressions cover a 5-year period (2019–2023), while the two subsequent regressions span 20 years (1995–2014). To further investigate this discrepancy, the same model was applied to Zhu's (2018) timeframe but restricted to a 5-year period. The years 2006–2010 were selected for analysis, as this period also captures the effects of a highly volatile market environment, the financial crisis of 2008.

This analysis aimed to determine whether the difference in output from the 2019–2023 data could be attributed to the shorter timeframe, another variable, or some other underlying factor.

The output from the 2006-2010 regression revealed that for each additional unit increase in AUM (in billions), the benchmark-adjusted gross return increased by a smaller margin compared to the benchmark-adjusted net return. This suggests that the discrepancy may indeed be influenced by the time frame, as the shorter periods appear to produce outputs distinct from those observed in longer timeframes, potentially due to heightened sensitivity to fluctuating market conditions or other unobserved factors.

5.2 Monte Carlo

To evaluate whether the observed discrepancy between the regression outputs for different time frames can be attributed to the inherent sensitivity of shorter periods to volatile market conditions, Monte Carlo Simulations were introduced. The Monte Carlo simulations provided a crucial tool for understanding the variability introduced by shorter timeframes. By generating 1,000 random iterations on 5-year samples on the dataset from January 1995 - December 2014, which was readily available and comparing their average metrics to the original dataset, the simulations highlighted the potential for variability in AUM, benchmark-adjusted gross returns, and benchmark-adjusted net returns. The hypothesis regarding discrepancies in regression outputs between shorter (5-year) and longer (20-year) timeframes suggested that fluctuating market conditions and variability inherent in shorter periods might explain the observed differences. However, the Monte Carlo simulations conducted on average AUM, benchmark-adjusted gross returns, and benchmark-adjusted net returns offer new insights.

The simulated distributions for the three metrics revealed relatively narrow ranges centered around their respective averages, as highlighted by the histograms in Figures 7, 8 and 9. This suggests that variability in shorter timeframes, while present, is not as substantial as hypothesized. Instead, the results demonstrate a degree of consistency between the sampled 5-year averages and the original dataset's values. This observation challenges the notion that random variation during shorter periods significantly skews outputs.

The revised interpretation points toward fluctuating market conditions, other interfering variables, or unique events, such as the financial crisis of 2008, as more plausible drivers of the discrepancies. These conditions introduce structural shifts in relationships, such as between AUM and returns that are less likely to smooth out over shorter intervals. For instance, during periods of heightened volatility, fund managers may adjust strategies in response to capital flows, causing variations in benchmark-adjusted gross and net returns relative to AUM.

The Monte Carlo results highlight the importance of considering market-specific dynamics when analyzing short timeframes rather than attributing discrepancies to random variability alone. By emphasizing the role of external factors, such as mediating variables or other underlying relationships, this approach strengthens the argument that the discrepancies observed in the 2019–2023 regression outputs are likely driven by transient market conditions rather than inherent variability in shorter time periods. To further validate these findings, we will replicate the analysis without using column mean imputation for missing data. This will help determine whether the imputation process had any significant impact on the results, adding an extra layer of robustness to the analysis.

This relationship, explored through Monte Carlo simulations and regression analyses, offers deeper insights into the underlying drivers of variability in the relationship between AUM and benchmark-adjusted returns. By synthesizing the results of the simulations with earlier regression analyses, a clearer picture emerges regarding the role of timeframe and volatility in shaping these discrepancies.

As a robustness check for the previous Monte Carlo simulations, we repeated the analysis without applying column mean imputation to the missing data. This allowed us to assess whether the imputation had any significant effect on the results. However, the new simulations yielded results that were nearly identical to those obtained with the column mean imputation, as seen in figures 9, 1,0 and 11. This suggests that the original findings were not significantly influenced by the imputation process, reinforcing the accuracy and reliability of the results from the initial Monte Carlo analysis. The consistency between both sets of simulations supports the conclusion that the findings are robust and that the use of column mean imputation did not distort the overall patterns observed. Therefore, the original Monte Carlo results are likely to be accurate, and the conclusions drawn from them can be more confidently upheld.

5.3 Extended analysis

Following this, an evaluation of the relationship between expense ratios and returns may allow for a deeper understanding of the discrepancy. Specifically, an assessment of how the benchmark-adjusted gross return and benchmark-adjusted net return are influenced by the expense ratio. The expense ratio, a measure of the cost of managing the fund, can have a direct impact on returns, and understanding its effect on both benchmark-adjusted gross and net returns will provide further insights into the dynamics of fund performance.

An OLS-regression was performed between the expense ratio and the benchmark-adjusted returns using AverageALLExpenseRatio as the independent variable, while keeping the returns as the dependent variables. This will allow us to determine whether a higher expense ratio leads to a more significant reduction in returns, and whether the effect differs between benchmark-adjusted gross and net returns.

The regression for benchmark-adjusted gross returns yielded a coefficient of 0.104801, accompanied by a p-value of 0.09385. The positive coefficient suggests that for each unit increase in the expense ratio, the benchmark-adjusted gross return is expected to increase by approximately 0.104801. While this indicates a positive relationship, the statistical significance of the result is weak. The p-value of 0.09385 is just below the commonly used threshold of 0.1, which implies that while the relationship may be statistically meaningful, it is not robust enough to confidently assert a causal effect. In other words, the observed positive relationship between the expense ratio and benchmark-adjusted gross returns may be due to random variation or external factors not accounted for in the model.

In analyzing the relationship between expense ratio and benchmark-adjusted net return, the regression results show that the coefficient for Expense Ratio is 0.007763, with a p-value of 0.9011. This suggests a weak, positive relationship between the two variables. Specifically, for every unit of increase in the expense ratio, the benchmark-adjusted net return is expected to increase by 0.007763. However, the very high p-value indicates that this relationship is not statistically significant.

These results indicate that the expense ratio has a limited effect on returns, and the weak significance calls for further exploration of other factors, such as the turnover ratio. Moving on to test turnover ratio could provide more insight into the key drivers of fund performance and help strengthen the analysis.

When performing OLS-regressions on the turnover ratio in relation to both benchmark-adjusted gross and net return. The regression results revealed a coefficient of -4.689e-04 and a p-value of 1.383e-07 for benchmark-adjusted gross return and a coefficient of -5.648e-04 and a p-value of 1.887e-10 for benchmark-adjusted net return. These results suggest a significant negative relationship between tthe urnover ratio and both types of returns, with higher turnover associated with lower returns. The strong statistical significance (p-values much smaller than 0.05) indicates that the turnover ratio is a meaningful predictor of both benchmark-adjusted gross and net returns.

This could help explain the discrepancy. Turnover likely increases trading costs more for net returns than for benchmark-adjusted gross returns, which makes benchmark-adjusted net returns more sensitive to factors such as AUM and expense ratios. The higher coefficient for benchmark-adjusted net returns suggests that these factors are playing a larger role in the determination of net returns than in gross returns, possibly due to the added impact of turnover and related costs. Moving forward, two multivariable regression models were used to assess how the variables in tandem explain the variation in benchmark-adjusted returns and to better understand the role of turnover as a mediating factor in this discrepancy.

In order to explore the relationships between benchmark-adjusted returns, AUM, expense ratios, and turnover, we conducted two multivariable regression analyses, one for benchmark-adjusted gross returns and another for benchmark-adjusted net returns. The findings are displayed in table 1 and 2. These regressions incorporate AUM, expense ratio, and turnover ratio as independent variables to assess their impact on the dependent variable, benchmark-adjusted returns.

For the benchmark-adjusted gross return regression, it revealed that AUM showed a negative coefficient of -0.0002825, with a p-value of 0.3435, indicating that AUM does not have a statistically significant relationship with gross returns. This suggests that changes in AUM do not significantly affect gross returns when controlling for other variables. The expense ratio had a positive coefficient of 0.1420, with a p-value of 0.0232, which is statistically significant at the 5% level. This suggests that an increase in the expense ratio is associated with a higher gross return, which aligns with expectations that higher costs may correlate with higher risk and, thus, higher returns. The turnover ratio displayed a negative coefficient of -0.0004970, with a highly significant p-value of 2.95*10^-08. This implies that as turnover increases, gross returns decrease, likely due to the higher transaction costs associated with frequent trading.

For the benchmark-adjusted net return regression, it revealed that AUM had a negative coefficient of -0.0001316, but with a p-value of 0.65754. This relationship was not statistically significant. Similar to the gross return regression, AUM does not have a meaningful impact on net returns. Regarding the expense ratio, it showed a positive coefficient of 0.05329, but with a p-value of 0.39193, the relationship was not statistically significant. Unlike the gross return model, the expense ratio did not seem to have a strong impact on net returns. Additionally, regarding tthe urnover ratio, it had a negative coefficient of -0.0005758, with a highly significant p-value of 1.2*10^-10. This confirms that turnover continues to negatively affect net returns, which is expected as higher turnover usually leads to higher transaction costs that eat into the net return.

The model for net returns exhibited a slightly higher R-squared value of 0.0245, indicating that it explains around 2.5% of the variation in net returns. Although this remains low, the significance of Turnover Ratio in this model is striking and underscores its importance as a factor affecting net returns more so than other variables.

The results from the gross and net return regressions help illuminate the discrepancy observed between these two return types. Despite both models showing a negative relationship between turnover and returns, the impact of turnover on net returns is far more pronounced and statistically significant. The negative coefficient for turnover in both models suggests that turnover reduces both gross and net returns. However, the fact that turnover has a stronger and more significant effect on net returns can explain the discrepancy observed between gross and net return coefficients.

This could be due to turnover's direct impact on transaction costs, which reduces the net returns more than gross returns. Since gross returns are calculated before transaction costs are subtracted, the added impact of turnover in the context of net returns may explain why the net return regression yields a higher coefficient for Expense Ratio and a much more significant result for turnover, suggesting that turnover is a larger factor influencing net returns than gross returns.

Finally, testing the relationship between Turnover Ratio and AUM is a crucial next step in understanding the discrepancy between the benchmark-adjusted gross and net returns. If turnover acts as a mediating variable, it could explain how AUM indirectly impacts returns. By testing this relationship, we can determine whether AUM drives turnover and how turnover might influence the returns. This will help clarify whether turnover contributes to the unexpected discrepancy in the regression results, offering a more comprehensive understanding of the dynamics at play between AUM, turnover, and returns.

The test between Turnover Ratio and AUM reveals a statistically significant negative relationship, with a coefficient of -0.17783 and a p-value of 0.0301, suggesting that as AUM increases, turnover tends to decrease. While this relationship is statistically significant, it is relatively weak, as indicated by the low R-squared value of 0.0028, meaning that AUM explains only a small portion of the variation in turnover. Nonetheless, the significant p-value confirms that the relationship is unlikely to be due to random chance.

This negative relationship could offer some insight into the unexpected discrepancy observed in earlier regressions, where net returns appeared to be more sensitive to factors like AUM and expense ratios than gross returns. The negative link between turnover and AUM suggests that larger AUM may result in less frequent trading, potentially reducing trading costs, which could impact net returns differently than gross returns. In particular, the costs associated with turnover, such as trading fees and expenses, are more directly reflected in net returns, which could explain why net returns were more responsive to AUM and expense ratios.

6. Conclusion

This thesis set out to explore the relationship between mutual fund size and performance during volatile periods, focusing on U.S.-equity actively managed mutual funds from 2019 to 2023. While prior research often identifies clear trends of decreasing returns to scale over longer, stable periods, our analysis during this shorter, turbulent time frame did not yield similarly definitive results. Specifically, the findings indicate no significant direct relationship between assets under management and benchmark-adjusted returns, diverging from long-term studies such as Zhu (2018). One notable outcome, however, is the identification of turnover ratio as a critical explanatory variable. Turnover ratio demonstrated a consistent and statistically significant negative relationship with both benchmark-adjusted gross and net returns. This suggests that higher turnover, likely associated with increased trading costs, diminishes fund performance, particularly net returns. Additionally, the analysis revealed a statistically significant, albeit weak, negative relationship between turnover ratio and fund size, indicating that larger funds tend to trade less actively. Despite these findings, it is important to note that the R^2 values remain low across these regression models, suggesting limited explanatory power of these variables. Nevertheless, it is important to recognize the limitations of turnover ratio as a standalone explanatory variable. While it provides insight into how funds behave during volatile periods, it does not fully account for the observed variability in returns. Other factors, including broader market conditions, fund management strategies, and external shocks, may also play significant roles but were beyond the scope of this study.

Ultimately, this thesis highlights the complexity of mutual fund performance during volatile periods and raises questions for further research. The findings suggest that turnover ratio warrants closer examination as part of a broader framework of explanatory variables, but it remains insufficient on its own to draw robust conclusions about fund performance. Future studies may benefit from incorporating additional fund-specific and market-level variables to develop a more comprehensive understanding of mutual fund dynamics during market instability. By focusing on a short-term, volatile period, this thesis contributes to the literature by exploring mutual fund performance in a context that remains under-researched. While the results do not provide definitive conclusions, they challenge assumptions about constant returns to scale and emphasize the need to consider the role of fund-specific variables, particularly turnover, during periods of market disruption. For fund managers, the findings suggest that reducing trading activity in volatile markets could help mitigate performance losses. For researchers, this study underscores the importance of investigating performance over varying timeframes and contexts, paving the way for more nuanced analyses of mutual fund behavior. This thesis underscores the importance of continued research into the intricate relationship between fund-specific variables and market conditions. The turnover ratio stands out as a significant factor influencing fund performance, yet the findings also highlight the complexity of navigating fund performance during periods of market turbulence. By contributing valuable insights into mutual fund behavior under stress, this study provides a solid foundation for future research aimed at equipping investors and fund managers with strategies to navigate the growing uncertainty in financial markets.

7. Definitions of Variables

The following definitions outline the key variables used in the statistical models and analysis:

AverageALLExpenseRatio: The average expense ratio for all funds in the dataset.

AverageAllAUM: The average of all assets under management (AUM) across the dataset for the period January 2019 - December 2023. This represents the mean value of the total assets managed by all funds in the dataset.

AverageAllAUMBaseArticle: The average assets under management (AUM) for Zhu’s (2018) article’s dataset. More specifically, the subset of the dataset is the years 2006-2010.

AverageAllAUMBaseArticleFullData: The average assets under management (AUM) for all funds across the full dataset of Zhu’s article.

AverageAllTurnoverRatio: The average turnover ratio for all funds, indicating how frequently portfolio assets are traded, averaged across all funds in the dataset.

AVGBenchmarkAdjustedGrossReturn: The average gross return of funds, adjusted for performance relative to a benchmark index. This measures the funds' raw returns before expenses or fees are deducted and benchmarked against a comparable index.

AVGBenchmarkAdjustedGrossReturnBaseArticle: The average gross return of funds, adjusted for performance relative to a benchmark index for Zhu’s article’s subset of years 2006-2010 of her time frame.

AVGBenchmarkAdjustedGrossReturnBaseArticleFullData: The average gross return of funds, adjusted for performance relative to a benchmark index for Zhu’s article’s full set of data.

AVGBenchmarkAdjustedNetReturn: The average net return of funds, adjusted for performance relative to a benchmark index. This captures the funds' returns after expenses and fees have been deducted, providing a more realistic view of investor returns.

AVGBenchmarkAdjustedNetReturnBaseArticle: The average net returns of funds for Zhu’s article’s dataset. More specifically, the subset of the dataset that is the years 2006-2010, adjusted for performance relative to a benchmark index.

AVGBenchmarkAdjustedNetReturnBaseArticleFullData: The average net return of funds, adjusted for performance relative to a benchmark index for Zhu’s article’s full set of data.

8. References

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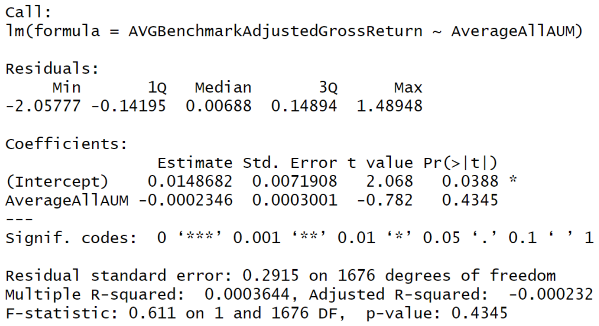
9. Appendix



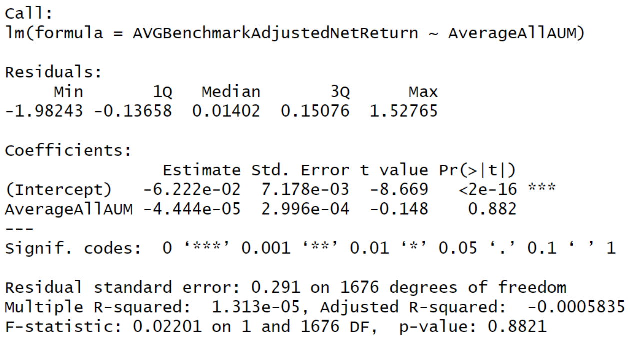
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturn ~ AverageAllAUM)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.05777 -0.14195  0.00688  0.14894  1.48948 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)  
(Intercept)    0.0148682  0.0071908   2.068   0.0388 *
AverageAllAUM -0.0002346  0.0003001  -0.782   0.4345  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2915 on 1676 degrees of freedom
Multiple R-squared:  0.0003644,	Adjusted R-squared:  -0.000232 
F-statistic: 0.611 on 1 and 1676 DF,  p-value: 0.4345
```

Figure 18: OLS-Regression Output One
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturn and AverageAllAUM (in Billions) for the period January 2019 - December 2023.



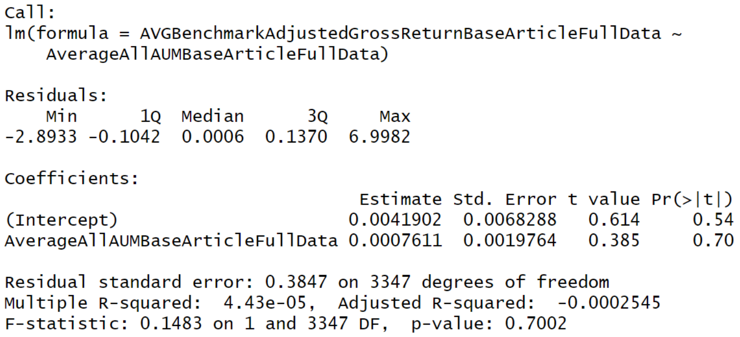
```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturn ~ AverageAllAUM)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.98243 -0.13658  0.01402  0.15076  1.52765 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)   -6.222e-02  7.178e-03  -8.669   <2e-16 ***
AverageAllAUM -4.444e-05  2.996e-04  -0.148    0.882    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.291 on 1676 degrees of freedom
Multiple R-squared:  1.313e-05,	Adjusted R-squared:  -0.0005835 
F-statistic: 0.02201 on 1 and 1676 DF,  p-value: 0.8821
```

Figure 19: OLS-Regression Output Two
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturn and AverageAllAUM (in Billions) for the period January 2019 - December 2023.



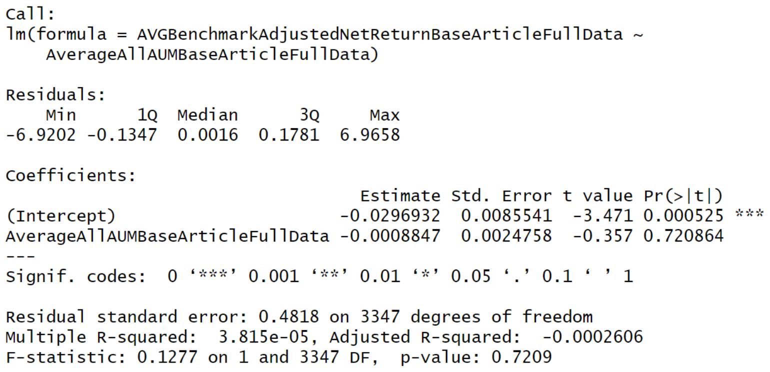
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturnBaseArticleFullData ~ 
    AverageAllAUMBaseArticleFullData)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.8933 -0.1042  0.0006  0.1370  6.9982 

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                      0.0041902  0.0068288   0.614     0.54
AverageAllAUMBaseArticleFullData 0.0007611  0.0019764   0.385     0.70

Residual standard error: 0.3847 on 3347 degrees of freedom
Multiple R-squared:  4.43e-05,	Adjusted R-squared:  -0.0002545 
F-statistic: 0.1483 on 1 and 3347 DF,  p-value: 0.7002
```

Figure 20: OLS-Regression Output Three
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturnBaseArticleFullData and AverageAllAUMBaseArticleFullData (in Billions) for the period January 1995- December 2014.



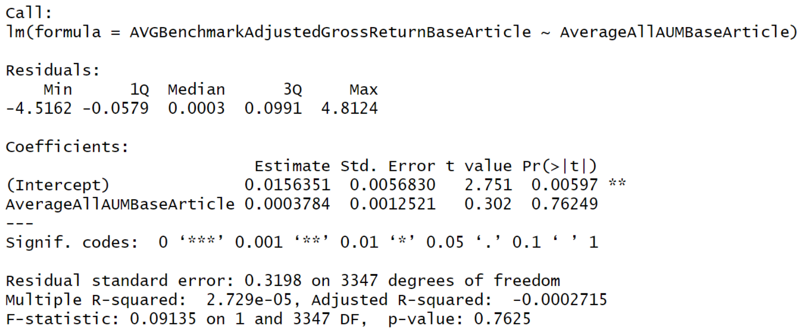
```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturnBaseArticleFullData ~ 
    AverageAllAUMBaseArticleFullData)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.9202 -0.1347  0.0016  0.1781  6.9658 

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)                      -0.0296932  0.0085541  -3.471 0.000525 ***
AverageAllAUMBaseArticleFullData -0.0008847  0.0024758  -0.357 0.720864    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4818 on 3347 degrees of freedom
Multiple R-squared:  3.815e-05,	Adjusted R-squared:  -0.0002606 
F-statistic: 0.1277 on 1 and 3347 DF,  p-value: 0.7209
```

Figure 21: OLS-Regression Output Four
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturnBaseArticleFullData and AverageAllAUMBaseArticleFullData (in Billions) for the period January 1995- December 2014.



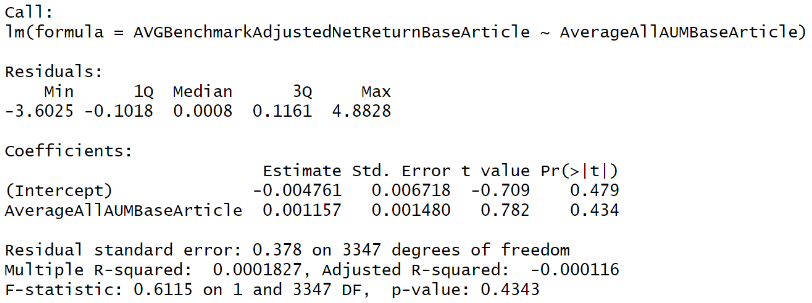
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturnBaseArticle ~ AverageAllAUMBaseArticle)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.5162 -0.0579  0.0003  0.0991  4.8124 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)   
(Intercept)              0.0156351  0.0056830   2.751  0.00597 **
AverageAllAUMBaseArticle 0.0003784  0.0012521   0.302  0.76249   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3198 on 3347 degrees of freedom
Multiple R-squared:  2.729e-05,	Adjusted R-squared:  -0.0002715 
F-statistic: 0.09135 on 1 and 3347 DF,  p-value: 0.7625
```

Figure 22: OLS-Regression Output Five
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturnBaseArticle and AverageAllAUMBaseArticle (in Billions) for the period January 2006 - December 2010.



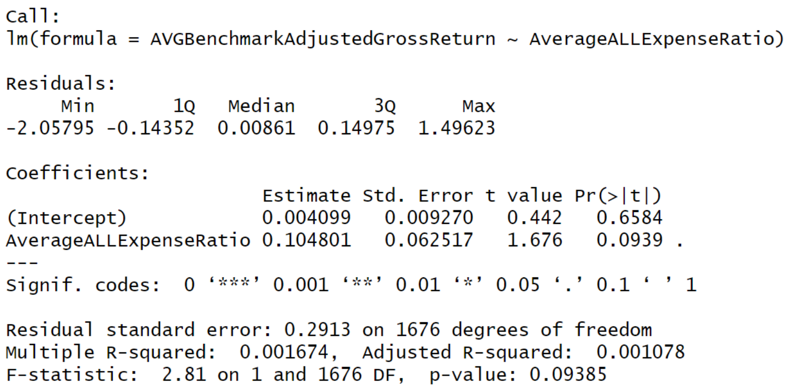
```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturnBaseArticle ~ AverageAllAUMBaseArticle)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.6025 -0.1018  0.0008  0.1161  4.8828 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              -0.004761   0.006718  -0.709    0.479
AverageAllAUMBaseArticle  0.001157   0.001480   0.782    0.434

Residual standard error: 0.378 on 3347 degrees of freedom
Multiple R-squared:  0.0001827,	Adjusted R-squared:  -0.000116 
F-statistic: 0.6115 on 1 and 3347 DF,  p-value: 0.4343
```

Figure 23: OLS-Regression Output Six
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturnBaseArticle and AverageAllAUMBaseArticle (in Billions) for the period January 2006 - December 2010.



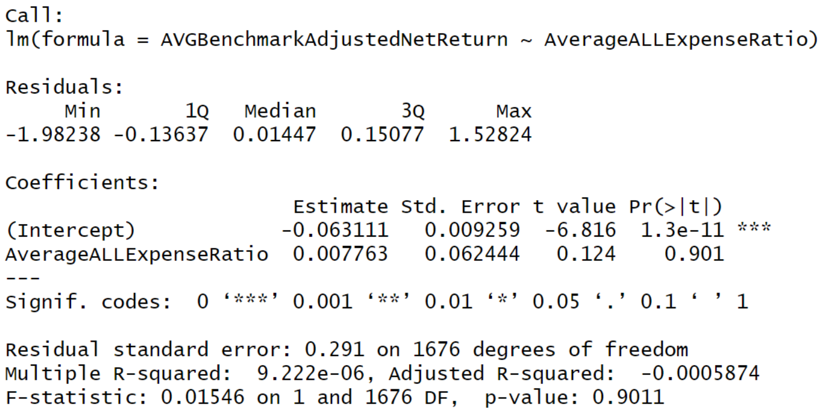
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturn ~ AverageALLExpenseRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.05795 -0.14352  0.00861  0.14975  1.49623 

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)  
(Intercept)            0.004099   0.009270   0.442   0.6584  
AverageALLExpenseRatio 0.104801   0.062517   1.676   0.0939 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2913 on 1676 degrees of freedom
Multiple R-squared:  0.001674,  Adjusted R-squared:  0.001078 
F-statistic:  2.81 on 1 and 1676 DF,  p-value: 0.09385
```

Figure 24: OLS-Regression Output Seven
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturn and AverageALLExpenseRatio for the period January 2019 - December 2023.



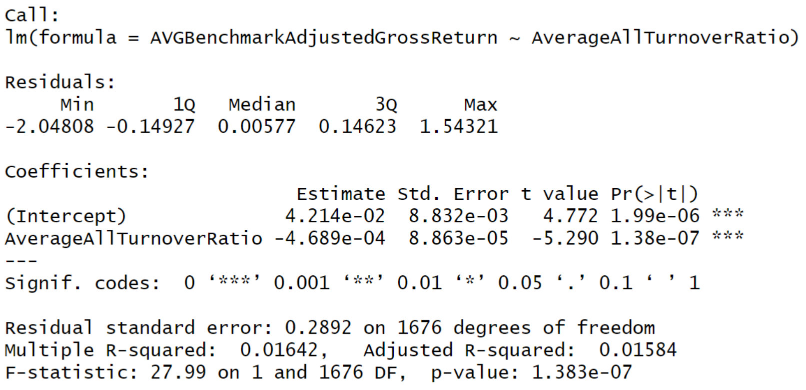
```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturn ~ AverageALLExpenseRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.98238 -0.13637  0.01447  0.15077  1.52824 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -0.063111   0.009259  -6.816  1.3e-11 ***
AverageALLExpenseRatio  0.007763   0.062444   0.124    0.901    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.291 on 1676 degrees of freedom
Multiple R-squared:  9.222e-06, Adjusted R-squared:  -0.0005874 
F-statistic: 0.01546 on 1 and 1676 DF,  p-value: 0.9011
```

Figure 25: OLS-Regression Output Eight
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturn and AverageALLExpenseRatio for the period January 2019 - December 2023.



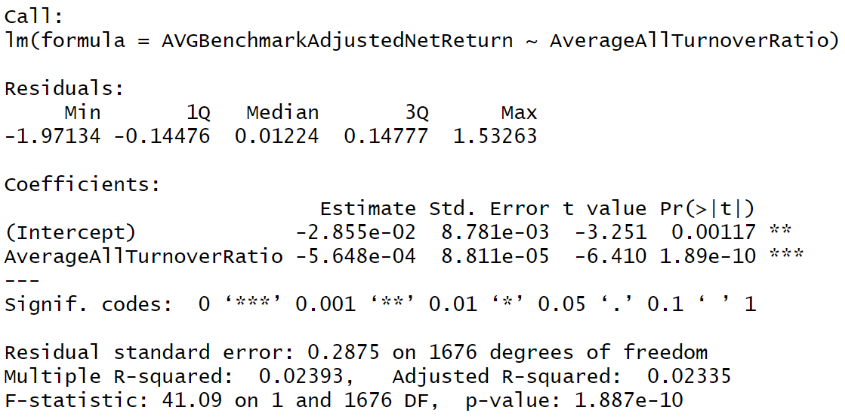
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturn ~ AverageAllTurnoverRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.04808 -0.14927  0.00577  0.14623  1.54321 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              4.214e-02  8.832e-03   4.772 1.99e-06 ***
AverageAllTurnoverRatio -4.689e-04  8.863e-05  -5.290 1.38e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2892 on 1676 degrees of freedom
Multiple R-squared:  0.01642,   Adjusted R-squared:  0.01584 
F-statistic: 27.99 on 1 and 1676 DF,  p-value: 1.383e-07
```

Figure 26: OLS-Regression Output Nine
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturn and AverageAllTurnoverRatio for the period January 2019 - December 2023.



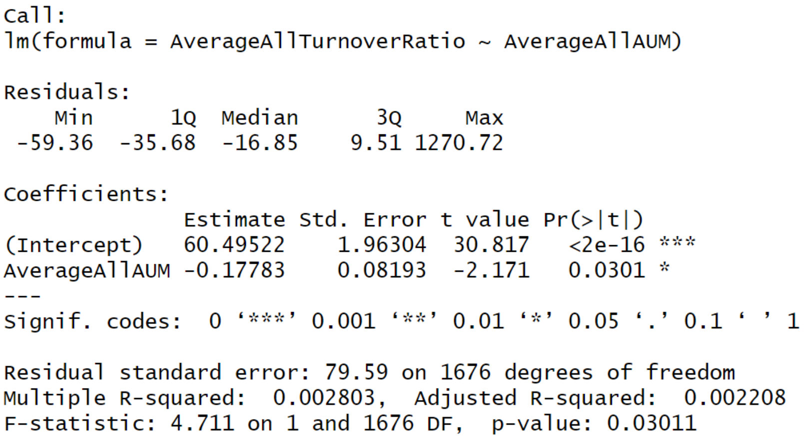
```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturn ~ AverageAllTurnoverRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.97134 -0.14476  0.01224  0.14777  1.53263 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)             -2.855e-02  8.781e-03  -3.251  0.00117 ** 
AverageAllTurnoverRatio -5.648e-04  8.811e-05  -6.410 1.89e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2875 on 1676 degrees of freedom
Multiple R-squared:  0.02393,	Adjusted R-squared:  0.02335 
F-statistic: 41.09 on 1 and 1676 DF,  p-value: 1.887e-10
```

Figure 27: OLS-Regression Output Ten
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturn and AverageAllTurnoverRatio for the period January 2019 - December 2023.



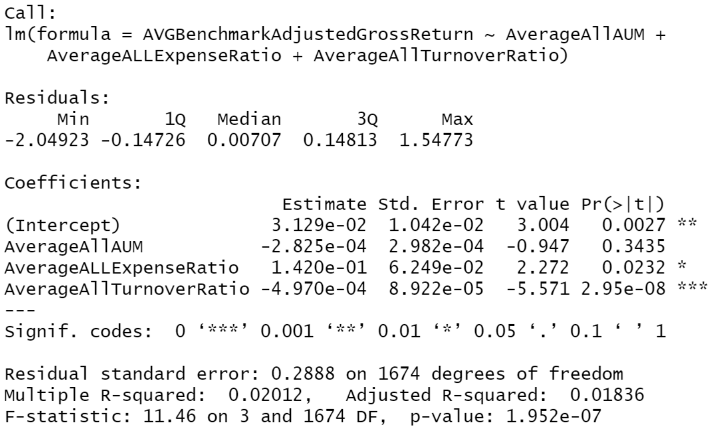
```
Call:
lm(formula = AverageAllTurnoverRatio ~ AverageAllAUM)

Residuals:
    Min      1Q  Median      3Q     Max 
 -59.36  -35.68  -16.85    9.51 1270.72 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   60.49522    1.96304  30.817   <2e-16 ***
AverageAllAUM -0.17783    0.08193  -2.171   0.0301 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 79.59 on 1676 degrees of freedom
Multiple R-squared:  0.002803,	Adjusted R-squared:  0.002208 
F-statistic: 4.711 on 1 and 1676 DF,  p-value: 0.03011
```

Figure 28: OLS-Regression Output Thirteen
An OLS-regression output for the relationship between AverageAllTurnoverRatio and AverageAllAUM for the period January 2019 - December 2023.



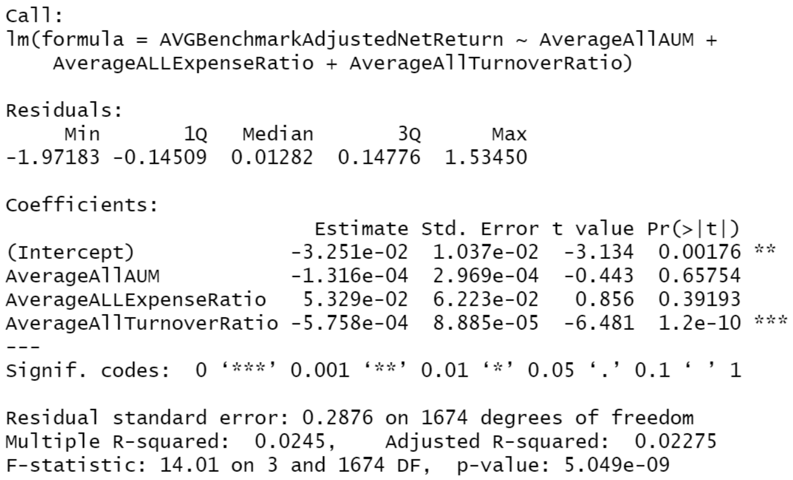
```
Call:
lm(formula = AVGBenchmarkAdjustedGrossReturn ~ AverageAllAUM + 
    AverageALLExpenseRatio + AverageAllTurnoverRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.04923 -0.14726  0.00707  0.14813  1.54773 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              3.129e-02  1.042e-02   3.004   0.0027 ** 
AverageAllAUM           -2.825e-04  2.982e-04  -0.947   0.3435    
AverageALLExpenseRatio   1.420e-01  6.249e-02   2.272   0.0232 *  
AverageAllTurnoverRatio -4.970e-04  8.922e-05  -5.571 2.95e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2888 on 1674 degrees of freedom
Multiple R-squared:  0.02012,	Adjusted R-squared:  0.01836 
F-statistic: 11.46 on 3 and 1674 DF,  p-value: 1.952e-07
```

Figure 29: OLS-Regression Output Eleven
An OLS-regression output for the relationship between AVGBenchmarkAdjustedGrossReturn, AverageAllAUM, AverageALLExpenseRatio and AverageAllTurnoverRatio for the period January 2019 - December 2023.



```
Call:
lm(formula = AVGBenchmarkAdjustedNetReturn ~ AverageAllAUM + 
    AverageALLExpenseRatio + AverageAllTurnoverRatio)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.97183 -0.14509  0.01282  0.14776  1.53450 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)             -3.251e-02  1.037e-02  -3.134  0.00176 ** 
AverageAllAUM           -1.316e-04  2.969e-04  -0.443  0.65754    
AverageALLExpenseRatio   5.329e-02  6.223e-02   0.856  0.39193    
AverageAllTurnoverRatio -5.758e-04  8.885e-05  -6.481  1.2e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2876 on 1674 degrees of freedom
Multiple R-squared:  0.0245,	Adjusted R-squared:  0.02275 
F-statistic: 14.01 on 3 and 1674 DF,  p-value: 5.049e-09
```

Figure 30: OLS-Regression Output Twelve
An OLS-regression output for the relationship between AVGBenchmarkAdjustedNetReturn, AverageAllAUM, AverageALLExpenseRatio and AverageAllTurnoverRatio for the period January 2019 - December 2023.

10. AI-disclosure

- **AI spelling and grammar assistance**

Artificial Intelligence (AI) was used to assist the writers of this thesis with spelling and grammar. This precaution was taken to enhance the paper's quality by making it more adaptable to the reader.

- **AI programming assistance**

AI was further used to assist the authors with programming. The programming was performed in R, which sometimes requires extensive knowledge of coding language and packages, among other things. Hence, AI was used to assist the authors in producing the correct code when facing a roadblock, which, in turn, generated the correct output.