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Revisiting Refocusing Costs: A Causal Machine Learning Approach to Hedge Fund Closures

for a Thesis

Hendrik van den Broek

Supervisors:
Miros Zohrehvand & Saber Salehkaleybar

BACHELOR THESIS

Leiden Institute of Advanced Computer Science (LIACS)
www.liacs.leidenuniv.nl

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Abstract

In this thesis, I set out to conduct an exploratory study on refocusing costs (the costs of corporate scope reduction) in hedge funds by investigating the effects of hedge fund closures during the financial crisis of 2007-2009 on the performance of continuing funds. The thesis seeks to contribute to the literature on refocusing costs by using traditional econometric tools and a novel causal machine learning technique, differences-in-differences regression and CausalForestDML to analyse hedge fund performance after refocusing. In this exploratory thesis I observed results that vary from those in the original study, after implementing the methods on an alternative dataset I found indications of positive effects of fund closures on performance of remaining funds. These findings are not intended to either validate or challenge the original study's conclusions, and they are specific to the characteristics and limitations of the data sample used. The implementation of the causal machine learning analysis reveals possible heterogeneity in treatment effects, indicating that the likely effect of fund closures depends on firm and fund characteristics, such as the scope of a firm. This exploration research supplies context-specific insights that may be useful for scholars striving to develop theories of corporate strategy, as well as for managers facing strategic decisions about the future of their firm.

Contents

1 Introduction

This thesis set out to replicate and extend research on refocusing costs in hedge funds, specifically examining the effects of fund closures during the 2007-2009 financial crisis. The study is important because it addresses crucial questions pertaining corporate strategy and scope, particularly how reducing a firm's scope by refocusing impacts performance. Through my usage of a unique dataset and both traditional econometric and novel causal machine learning methods, I try to offer supplementary insights to the costs associated with refocusing. Not only for scholars seeking to build robust theories of corporate strategy but equally managers making critical decisions about firm scope and structure could benefit from this study.

The key study in this area by de Figueiredo, Feldman, and Rawley (2019) leveraged the 2007-2009 financial crisis as an exogenous shock to examine refocusing costs in hedge funds. They found significant negative impacts of fund closures on the performance of remaining funds within hedge fund firms, with these effects being more pronounced for closely related funds.

There are however still matters to explore in this area of research. First of all, the source of the refocusing costs are not yet fully discovered, this holds back the ability to give advice to managers on minimising the costs effectively. Furthermore, replication studies using different data sources can be useful to extend the understanding of refocusing costs in various contexts. This can help the development of robust theories of corporate strategy and improve my ability to provide actionable insights to managers making crucial decisions about firm scope.

That is why I set out to explore the ideas of the de Figueiredo Jr et al. (2019) study using a different dataset. As well as supplementing the analysis by employing both the original study's econometric methods and causal machine learning algorithms. This dual approach enables us to compare insights gained from each method and evaluate their relative strengths in analyzing complex strategic phenomena. Through the usage of this new dataset and new analysis techniques, I seek to provide additional insights into refocusing costs. Due to the significant differences in datasets used my research is meant as an exploration of the ideas and methodologies of the original research and these findings are not intended to either validate or challenge the original study's conclusions.

1.1 Thesis Structure

This thesis is set up through a number of chapters that build form each other to accomplish a comprehensive analysis. Chapter one introduces the problem statement, significance of the research, and the conceptual framework. Chapter two provides the theoretical framework and hypotheses. Chapter three describes the data and sample. In chapter four, the methodology that includes the original econometric approach and the novel causal machine learning method is explained and the results are presented. Chapter five discusses findings and implications. Chapter six discusses limitations and further suggests avenues of future research. Lastly, Chapter Seven concludes this thesis by summarizing the findings and their contributions that can be made from it to the field of Corporate Strategy and Hedge fund management.

1.2 Key Concepts and Definitions

1.2.1 Refocusing

Refocusing in my study refers to the reduction of corporate scope, where a multi-business decides to close, sell or spin-off line off business, leading to a refocusing within the business structure (Brauer, 2006; Johnson, 1996; Lee and Madhavan, 2010; Markides, 1992, 1995). In this study I will focus on Hedge Funds, and in multi-fund firms, refocusing implies the closing, selling or spinning off of a fund within the firm.

1.2.2 Refocusing Costs

Economic costs that arise due to the reduction of scope by a firm. These costs can as an example be the result of a loss of synergies between businesses, or adjustment costs caused by reorganization.

1.2.3 Fund Reduction

As stated earlier, fund reduction can occur through three primary mechanisms:

Closing: This means the termination of a funds operations, typically resulting in the liquidation of its assets and the return of capital to the investors.
Selling: Also referred to as a divestiture, meaning the transfer of ownership of a fund to another firm or company.
Spinning off: In this case the fund is cut loose from the firm and becomes an independent company.

1.2.4 Relatedness

The relatedness describes the relationship between businesses within the same firm, this interconnectedness between funds can be the result of sharing resources, strategies, or other operational elements.

1.2.5 Fund Performance

Fund performance refers to the financial results achieved by a hedge fund over a specified period. In this study, I specifically measure performance using the Information Ratio, a risk-adjusted metric (Goodwin, 2009).

1.2.6 Treatment Effect

In the context of this study, the treatment effect refers to the impact of fund closure (the 'treatment') on the performance of remaining funds within the same firm.

1.2.7 Causal Machine Learning

Causal Machine learning refers to a set of techniques that combine machine learning algorithms with causal inference frameworks to estimate causal effects Chernozhukov et al. (2018a).

1.3 Classic vs Modern Causal Models

My study sets out to not only replicate the classic models used in the de Figueiredo Jr et al. (2019) but additionally explore modern causal models, because the methods of establishing causal relationships have progressed quickly throughout recent years and could give meaningful new insights. Classical methods have allowed researchers to estimate causal effects in observational studies for decades and usually consist of statistical techniques such as Differences-in-Differences(DiD), Instrumental Variables (IV), or Regression Discontinuity (RD)(Angrist and Pischke, 2008). A couple things that have held back these models however is that they often rely on strong assumptions about the data-generating process and can struggle with high-dimensional data or complex, non-linear relationships (Athey and Imbens, 2017).

Because of advances in machine learning, modern causal models have emerged that can overcome some limitations of the classic approaches. These include methods such as Causal Forests (Wager and Athey, 2018), Double Machine Learning (Chernozhukov et al., 2018b), and Causal Boosting (Powers et al., 2018). These models brought new abilities to the table such as the ability to handle high-dimensional data, capture complex relationships, and estimate heterogeneous treatment effects. On top of that they provide more flexibility in modeling and can provide more detailed results for causal relationships (Athey and Imbens, 2019).

2 Theoretical Framework

2.1 Hypotheses

Based on the original study by de Figueiredo Jr et al. (2019) I explore the following hypotheses:

1. **H1:** Closing a fund within multi-fund firms leads to refocusing costs that negatively impact the performance of the remaining funds within the same firm.

   This hypothesis is based on the previous study, that found that firms incur costs when they refocus. I will investigate whether this effect is visible in my new dataset.

2. **H2:** Funds that have a closer relationship to the closed sister fund will be more significantly affected by the closure.

   Same as the first hypothesis I will be testing whether this effect holds in my new dataset.

2.2 Theory - Relatedness and Refocusing Costs

When analysing the costs associated with refocusing within multi-business firms the concept of relatedness plays a crucial role. This concept is rooted in strategic management literature, as seen back in Penrose (1959), in this literature synergy is identified as a key benefit of diversification.
In this context synergy is referred to as intra-temporal economies of scope that stem from firm's abilities to share resources across other businesses (Helfat and Eisenhardt, 2004). Synergies can come in various forms:

1. Sharing of common technologies (Silverman, 1999)

2. Utilization of similar managerial competences (Prahalad and Bettis, 1986)

3. Leveraging of knowledge residing in human capital (Tanriverdi and Venkatraman, 2005)

Moreover, operational interdependencies can also develop across businesses, in this case one business depends on another businesses activity (Capron et al., 1998; Kaul, 2012; Teece et al., 1994). In earlier research by (Bryce and Winter, 2009; Levinthal and Wu, 2010; Sakhartov, 2017), it is said that related diversification tends to add more value for firms than unrelated diversification because of potential synergies that can occur in related businesses.
By using these insights in the context of refocusing, it can be suggested that removing a business that is generally more closely related to the other divisions within said firm will be more costly than removing a less related business. This is due to the fact that refocusing inherently diminishes a firm's ability to share resources that are used by multiple businesses, these resources can range from knowledge, capabilities, and operating processes across businesses (Feldman, 2014; Natividad and Rawley, 2016).
When businesses however are less related, this should also mean that the extent of synergy destruction is less pronounced, because capabilities, routines, and knowledge are shared less in such cases. When taking an extreme case, for example when a firm removes a business that runs completely independently, adjustment costs will be mostly related to corporate oversight and financial resources, instead of operational interdependencies (Chatterjee and Wernerfelt, 1991).
The theoretical framework surrounding relatedness provides the basis for our second hypothesis (H2), which entails that the costs caused by fund closures will be larger for sister funds that are more closely related to the closed fund.

2.3 Previous Research on Refocusing

Refocusing costs in multi-business firms has been an important area of research in the corporate strategy area. Among the works in this area is the article of de Figueiredo Jr et al. (2019), which analyses the influence of the closure of funds on the performance of the remaining funds within hedge fund firms.
Using data from Lipper TASS, de Figurerido et al. analyzed a sample of 7,201 hedge funds across 3,141 firms. They utilized the quasi-exogenous shock of the financial crisis in 2007-2009 to identify causal treatment effects by employing a difference-in-differences regression approach. Their key findings included:

1. Refocusing Costs: The authors focused on whether fund liquidations during the crisis had adverse effects on the risk-adjusted operating performance of the remaining funds within firms. They showed a negative effect of roughly 0.14-0.15% per month on the information ratio of the remaining funds.

2. Relatedness Effects: For the set of fund closures that were on average more related to their sister funds, there was an additional detrimental effect of 0.06-0.08% per month at the mean level of relatedness beyond the baseline effect described above.

3. Persistence of Costs: The authors found that refocusing costs associated with the closure of an uncorrelated fund reduced, while costs associated with the closure of a closely related fund

were more persistent. In the long run, 3-6 years after the crisis-the effect for uncorrelated fund, closures became statistically indistinguishable from zero, while for related fund closures, at the mean level of relatedness, the effect stayed at about 0.01% per month.

Combined, these results suggested that declines in firm scope via refocusing come with costs and are not an unambiguously positive activity. The study also showed the importance of the relatedness in the identification and understanding of refocusing costs. The authors measured relatedness as a correlation of excess returns between funds and found that closing more closely related funds resulted in higher levels of refocusing costs.

2.4 Research Context: Hedge Funds

Hedge funds are investment vehicles that pool capital from institutional investors and high net worth individuals. Unlike traditional mutual funds, hedge funds have more flexibility in their investment strategies, usually employing leverage, short-selling, and derivatives to generate returns (Liang, 1999). The hedge fund industry has grown significantly in recent decades, managing trillions of dollars globally.

Hedge funds create a useful environment for researching the costs associated with refocusing in multi-business enterprises. Because they are generally straightforward businesses in terms of operations, with portfolio managers—who are frequently also company principals—in charge of them.

Numerous hedge fund companies manage several funds at once, each operating as a separate product with its own financial statements, staff, and clients. Nonetheless, these funds frequently pool resources and handle tasks like risk management, information technology, and human resources. Given that this arrangement is consistent with Teece's (1980) description of diversified organizations as "multi-product firms," multi-fund hedge fund firms can be compared to multi-business firms that participate in intra-industry diversification. Hedge funds have traditionally been funded through two kinds of fees: management fees and incentive fees. Management fees are calculated as a percentage of assets under management(AUM), while incentive fees depend on the performance of the fund. This fee structure aligns the interests of fund managers with investors.

Studying refocusing costs is especially appropriate for the hedge fund sector because:

1. Hedge fund companies are structurally similar to multi-product firms, with individual funds acting as operational divisions that are somewhat independent.

2. It is relatively simple to measure important aspects like relatedness and performance.

3. The financial crisis of 2007–2009 produced a quasi-natural experiment in business scope reduction, offering a special chance to watch costs being refocused.

I investigate the effects of fund closures on the performance of remaining funds in this setting, as well as how these effects differ according to fund relatedness and other business characteristics.

3 Data and Sample Description

3.1 Data Source and Sample Description

This study employs a unique dataset obtained from The Hedge Fund Data Engine, which is overseen by Aurum Research Limited ('ARL'). The sample I employed in my investigation is very different from the one used in the original study conducted by de Figueiredo, Feldman, and Rawley (2019). The original study relied on data obtained from Lipper TASS.

The research specifically examines a group of 1,728 hedge funds from 804 organizations that are left after data processing. The total funds in the database collectively managed roughly $1.5 trillion in assets at the beginning of the 2007-2009 financial crisis. This sample has a total of 94,311 fund-month observations, offering a complete perspective on the dynamics of hedge funds over a prolonged duration.

The analysis is performed at the level of individual funds and months, using data that covers the period from 1994 to 2015. Consistent with the original work the sample I use consists of funds that were operating for a minimum of one year before the financial crisis started, and continued to operate during it.
The financial crisis, as designated by the National Bureau of Economic Research (NBER), spanned from December 2007 to June 2009. In order to guarantee the precision of my results and to differentiate the impact of relatedness on operations from the implications of common investment portfolios, same as in the original study I have chosen to remove data from the months of peak crisis in my research. This exclusion is essential because of the difficulties in determining the value and the lack of available funds in the capital markets at this time.

Although my dataset includes data until the end of 2015, my baseline analysis, which I use to compare with the original study, specifically examines fund returns for a period of up to two years after the crisis, until June 2011.

3.2 Summary Statistics

Table 1 presents the summary statistics for my sample.

3.3 Comparison with Original Sample

In order to contextualise my sample I compare key characteristics, in Table 2 I find the characteristics of my sample and the sample used in the original study.
Within this table there are several significant distinctions between the two samples that should be addressed:

- **Sample Size:** In comparison to the sample used in the original research my sample comprises a significantly smaller number of funds of 1,728 and fims of 804 in comparison to the originals 7,201 funds and 3,141 firms.

Table 1: Summary Statistics (n = 94,311)

	Mean	Std. Dev.	Min	25%	Median	75%	Max
Information Ratio	0.0568	1.170	−4.799	−0.206	0.0100	0.258	5.825
TREATED	0.0118	0.1079	0	0	0	0	1
Other Closures	0.0580	0.356	0	0	0	0	4
Relatedness_TREATED	0.0031	0.0411	−0.709	−0.010	0	0.010	0.932
AUM ($)	668 M	1.58 B	1 M	61.7 M	238.1 M	676 M	59.7 B
Firm AUM ($)	1.7 B	4.08 B	1 M	83.2 M	384 M	1.44 B	101 B
Firm Scope (# Funds)	2.37	2.71	1	1	1	3	29
Firm Age (months)	71	49.91	1	30	62	103	210
Fund Age (months)	66	45.03	1	30	60	100	210

Notes: This table provides a detailed overview of the sample characteristics used in my study.

Table 2: Comparison of Summary Statistics with Original Sample

	My Sample	Original Sample
Number of Funds	1,728	7,201
Number of Firms	804	3,141
Fund-Month Observations	94,311	489,037
Information Ratio (Mean)	0.057	0.25
TREATED (Mean)	0.012	0.04
Other Closures (Mean)	0.058	0.09
Relatedness_TREATED (Mean)	0.0031	0.02
AUM (Mean)	$668 M	$215 M
Firm AUM (Mean)	$1.7 B	$591 M
Firm Scope (Mean)	2.37	6.0
Firm Age (Mean)	71	70
Fund Age (Mean)	66	51

Notes: This table highlights similarities and differences in sample characteristics between my study and the original research, providing context for interpreting the results of my analysis.

- **Performance Metrics:** My samples average information ratio of 0.057 is considerably lower than the original samples 0.25, this would suggest that on average the funds in my database have less risk-adjusted monthly returns.
- **The Impact of the Crisis:** In my sample, the average value for the TREATED variable is lower with 0.012 compared to 0.04, indicating that a smaller proportion of funds in my sample were affected by closures resulting from crises.
- **Fund and Firm Size** The average assets under management (AUM) is considerably higher in my sample, for both fund size and firm size.
- **Firm Structure:** In my sample, the average firm scope of 2.37 funds per firm is lower compared to 6.0. Indicating that the firms in my study usually manage a smaller number of funds.
- **Fund Age:** With a higher average fund age of 66 months compared to 51 months for my sample and the original sample respectively, relatively more established funds within my database are suggested.

  Understanding the differences in sample characteristics is crucial for interpreting my findings and detecting any discrepancies from the original study. This is of major importance when carrying out replication studies in finance to underscore the potential influence of dataset composition has on research outcomes.

4 Methodology

4.1 Measures

4.1.1 Overview of Measures

In order to evaluate the impact of fund closures on the performance of remaining hedge funds before and after the 2007-2009 financial crisis I have employed a couple of distinct measures that are explained in this section. The employed measures in my study are exactly the same as in the original study, I will however go a bit more in depth in this section. The primary dependent variable that I use is the Information Ratio (IR), which assesses risk-adjusted performance (Goodwin, 2009). On the other hand the key independent variable is *TREATED*, this variable identifies funds that are affected due to closures during the crisis, meanwhile Relatedness captures the correlation in excess returns between funds within the same firm.
With these measures I am able to capture the effects fund closures, and by using risk-adjusted performance measures, I aim to control for the heterogeneity in behavior among different hedge funds and strategies (Fung and Hsieh, 2001), whilst taking into account other factors that might influence returns.

4.1.2 Dependent Variable: Information Ratio (IR)

Definition: The Information Ratio (IR) is used to measure a fund's performance relative to the amount of risk taken. These returns that have been adjusted for risk are calculated by dividing a fund's excess returns by the standard deviation of said returns, this standard deviation is also referred to as risk:

$$\text{Information Ratio} = \frac{\alpha_i}{\sigma_i} \tag{1}$$

- α_i: Excess returns of a firm over a set benchmark (often referred to as "alpha").
- σ_i: The standard deviation of the excess returns, indicating the risk taken by the fund.

For a while now the Information ratio has been a standard performance measure used both in academia and in industry (Goodwin, 2009). It is a very useful measure because it can capture "real-time" changes in the fund's portfolio returns and provides a normalized metric, which lets you compare performance easily across different funds and time periods. Due to the fact that the returns are risk-adjusted, the IR also provides a measure that takes the variability of returns into account.
To calculate the excess returns, I use the following regression model:

$$R_{it} = \alpha_i + R_{ft} + X_t\beta_i + \epsilon_{it} \tag{2}$$

- R_{it}: Raw return of fund i at time t.
- α_i: Excess returns of a firm over a set benchmark.
- R_{ft}: Risk-free rate at time t (e.g., the yield on a Treasury Bill).
- X_t: Vector of market factors (e.g., market risk premium, size, value, etc.).
- β_i: Coefficients for the market factors (betas).
- ϵ_{it}: Mean-zero residual term for fund i and time t.

To adjust for autocorrelation, which is correlation of a return with a delayed copy of itself, in returns, I calculate *ret_star*, an adjusted return that accounts for this autocorrelation, using the autocorrelation coefficient (ρ) :

$$\text{ret\_star} = \frac{\text{ret}_t - \rho \cdot \text{ret}_{t-1}}{1 - \rho} \tag{3}$$

- ret_t: The raw return of the fund.
- ρ: The autocorrelation coefficient of the returns.
- ret_{t-1}: The return of the fund in the previous period.

Instead of raw returns I will be using *ret_star*, because this mitigates the effects of serial correlation in the data and thus leads to the returns more accurately reflecting the fund's true performance. This works by removing the influence from the past returns on the current returns. Especially in financial time series data this adjustment is quite important, due to the ability of autocorrelation to distort performance metrics and lead to biased estimates.

4.1.3 Independent Variable: TREATED

Definition: The *TREATED* variable, which is referred to as *CLOSED_CRISIS* in the original study, is used as an indicator variable that is set to 0 but takes on the value of 1 in the months after the financial crisis (starting from July 2009) if a particular fund is the sister fund of a fund that was closed during the crisis (December 2007 to June 2009).
Purpose: The purpose of this variable is to identify the funds that have been affected by the refocusing and in doing so it will allow us to measure the impact of the closures on the performance of the remaining funds. This variable creates the the eventual treated group(1) which will be compared to the control group(0).

4.1.4 Relatedness Measure

Definition: The Relatedness is measured by taking the pairwise correlation of the excess returns between every pair of funds in a firm. Using this variable I can measure how intensively firms share resources and activities across funds.
Purpose: The purpose of the relatedness measure is to help us assess the extent in which funds within the same firm are interconnected. The importance of this measure is that high relatedness indicates greater interdependence, which can increase the costs of refocusing due to the loss of synergies once a sister fund closes.
I calculate relatedness by taking the pairwise correlation of excess returns between every pair of funds in a firm. The idea behind this is that by definition correlation in excess returns is due to correlation in idiosyncratic fund-specific investments, thus this variable gives a good indication of how intensively firms share resources across funds.

4.2 Original Approach

4.2.1 Empirical Approach

Overview

The empirical strategy that I employ mirrors the methodology used in the original study. In both the original study and in my study I utilize a differences-in-differences (DiD) regression. This regression allows us to use both fund and time fixed effects, thus allowing us to control for unobserved, time-invariant characteristics, on top of that I can control for common time-related shocks.

Regression Specification

For each fund i at time t (month), I regress the information ratio (Y) on *TREATED* using the following model:

$$Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it} \tag{4}$$

- α is the intercept term.
- λ_i represents fund-specific fixed effects.

- $TREATED_{it}$ is a binary treatment variable set to 1 for funds from firms that closed at least one fund during the crisis period and 0 otherwise.
- T_t includes time fixed effects to control for time-specific factors.
- X_{it} is a vector of control variables, including:
  - Fund and firm size decile dummies based on assets under management (AUM)
  - A dummy for non-reporting of AUM
  - Decile splines for age (measured in months since inception)
  - Quartiles splitting up the scope
- ϵ_{it} is the error term.

I cluster standard errors at the fund level in order to account for potential serial correlation within funds.

Difference-in-Difference Estimation

Using a differences-in-differences model I am able to estimate β_{cc}, which is the coefficient that is used to measure the differential effect on performance for the funds affected by the crisis ($TREATED = 1$) compared to those not affected ($TREATED = 0$). By utilising this method I can isolate the specific impact of refocusing on the remaining sister funds.

Logarithmic Control Variables

Given the smaller sample size and lower percentage of treated funds in my dataset compared to the original study, I also explore an alternative specification, this is not used in the original study, using logarithmic transformations of my control variables instead of creating deciles or quartiles. This approach helps to avoid potential issues with sparsely populated categories and provides a continuous measure of these variables Deltas (2003).

4.2.2 Identification Strategy

Quasi-Exogenous Shock

My identification strategy leverages the 2007-2009 global financial crisis as a quasi-exogenous shock that forced many firms to close underperforming funds. This approach follows the original study in using the crisis as a source of exogenous variation in fund closures.

Addressing Selection Bias

While the financial crisis provides a strong exogenous shock, I acknowledge that firms still retained some discretion in their fund closure decisions. To address potential selection bias, I follow the argument presented in the original study: any bias from strategic fund closures would likely underestimate the true costs of refocusing, as firms would preferentially close funds with the least negative impact on remaining funds.

4.2.3 Results of the Replication

Results Summary
Key results of my analysis include:

- **Marginal Positive Effects**: My base regression (column 1) suggests potential positive effects on performance, although these effects have marginal significance and are especially not robust when including fixed fund effects.
- **Relatedness Hypothesis Not Supported**: From my data I do not find strong evidence supporting the hypothesis that fund closures that are more closely related to each other lead to higher refocusing costs.
- **Limited Model Explanatory Power**: The relatively low R-squared values in my models suggest that other factors influencing fund performance are not captured in my analysis.

Baseline Regressions

In Table 3 the results of my baseline regression are displayed, the regression examines the impact of fund closure during the 2007-2009 financial crisis and the performance of the remaining funds within firms.

Table 3: Baseline Regression Results

	(1)	(2)	(3)
TREATED	0.2605*	0.0571	0.211
	(0.071)	(0.825)	(0.534)
Relatedness × TREATED			-0.586
			(0.617)
Controls	Yes	Yes	Yes
Fund FE	No	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	94,311	94,311	94,311
R-squared	0.044	0.0761	0.0763

P-values in parentheses underneath the coefficients
**** p<0.01, ** p<0.05, * p<0.1*
Model specifications are as follows:
Model (1): $Y_{it} = \alpha + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$.
Model (2): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$.
Model (3): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + Relatedness_i \times TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$.

After reviewing the results that were produced by the baseline regression I can observe that in column 1, the coefficient is positive and marginally significant on TREATED. This result suggests that firms in my sample, that had funds close during the crisis, saw no costs but rather only gains in performance in their remaining funds. The fixed effects models in column 2 and 3 show similar trends however these results lack statistical significance, indicating that the results are sensitive to the model specification.

Control Variables and Model Fit

Even though I do not address all of the coefficients from all of the control variables in Table 3, my analysis does include the following controls; fund and firm size (using AUM deciles), fund and firm age (using decile splines), and firm scope (using quartiles). These controls have been mirrored exactly from the original study by Figuerido et al.
In the Table 3 I can observe the R-squared value of my models, with 0.044 for column 1 and 0.076 for column 2 and 3 this suggests that my model only explains a small portion of the total variation in fund performance.

Supplementary Analysis: Logarithmic Approach

In our baseline regression deciles and quartiles are used in order to improve the robustness against outliers, however the drawback is that deciles and quartiles do not work optimally in samples with fewer datapoints (Long and Freese, 2006). Due to the fact that my sample has a lot less datapoints I have decided to add an alternative approach using logarithmic scaling on the control variable. This approach has resulted statistically significant coefficient for TREATED column (1), further suggesting that in my sample fund closure has positive effects on the performance of the remaining funds. Table 4 presents the results of this supplementary analysis.
The results from this logarithmic approach are consistent with my main findings:

- The base model (Column 1) shows a positive and significant effect of fund closures on the performance of remaining funds.
- The fixed effects models (Columns 2 and 3) show positive but insignificant effects of fund closures.
- The interaction term between TREATED and Relatedness is negative but not statistically significant.

These results further support my main findings and provide additional context for understanding the relationships between fund characteristics and performance in my sample.

4.3 Causal Machine Learning Approach

4.3.1 Introduction to Causal Machine Learning

Causal machine learning (CML) is a development in the field of econometrics and data science. It effectively combines conventional causal inference methods with modern machine learning techniques. Contrary to conventional predictive machine learning, which emphasizes correlations, Causal Machine Learning (CML) aims to reveal causal relationships and estimate treatment effects. This makes it highly valuable for various applications, such as policy evaluation and decision-making in intricate environments (Athey and Imbens, 2019), as well as economic forecasting and planning

Table 4: Logarithmic Approach Results

	(1)	(2)	(3)
TREATED	0.303**	0.081	0.227
	(0.047)	(0.761)	(0.524)
Relatedness × TREATED			-0.556
			(0.648)
Log Firm Scope	Yes	Yes	Yes
Log Fund AUM	Yes	Yes	Yes
Log Firm AUM	Yes	Yes	Yes
Log Firm Age	Yes	Yes	Yes
Log Fund Age	Yes	Yes	Yes
Fund FE	No	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	94,311	94,311	94,311
R-squared	0.034	0.0581	0.0583

P-values in parentheses underneath the coefficients
**** p<0.01, ** p<0.05, * p<0.1*
Model specifications are as follows:
Model (1): $Y_{it} = \alpha + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$.
Model (2): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$.
Model (3): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + Relatedness_i \times TREATED_{it} + T_t + X_{it}\beta_c + \epsilon_{it}$.

(Chernozhukov et al., 2018a). The advancement of CML (causal machine learning) methods has been motivated by the necessity to accurately capture diverse treatment effects in datasets with a large number of variables, as this can pose difficulties for conventional econometric approaches. The CML methods use the flexibility and predictive power of machine learning algorithms and combining this with the rigorous causal framework necessary for valid inference (Chernozhukov et al., 2018a)
Several CML techniques have become prominent in recent years:

- Causal Forests (Wager and Athey, 2018) is a modified version of random forests that is used to estimate treatment effects that vary across different groups (heterogeneous treatment effects).
- Double Machine Learning (Chernozhukov et al., 2018a) is a technique that addresses the issue of regularization bias in high-dimensional scenarios by employing sample splitting and orthogonalization.
- Causal Boosting (Powers et al., 2018) is a modified version of gradient boosting designed specifically for challenges related to causal inference.
- BART (Bayesian Additive Regression Trees) (Hill, 2011) is a Bayesian nonparametric method used to estimate treatment effects.

4.3.2 CausalForestDML: A Synthesis of Causal Forests and Double Machine Learning

My analysis utilizes the CausalForestDML approach, which combines the strengths of Causal Forests and Double Machine Learning. The method used in the econml package by Microsoft Research (2019) is highly suitable for my study on refocusing costs in hedge funds for several reasons:

1. **Heterogeneous Treatment Effects**: CausalForestDML allows us to estimate the Conditional Average Treatment Effects (CATE) and gain insights into how the impact of fund closures may vary depending on different fund characteristics.

2. **Robustness to Confounding**: The double machine learning approach enhances resilience to potential confounding variables, which is a concern in observational studies similar to ours (Chernozhukov et al., 2018a).

3. **Extensive Covariate Space**: My dataset contains a wide range of fund and firm characteristics. CausalForestDML effectively addresses the high-dimensional setting, enabling control for a broad range of potential confounders without the risk of overfitting (Wager and Athey, 2018).

4. **Enhanced Flexibility**: CausalForestDML can capture complex and non-linear relationships between variables without relying on predefined assumptions about their functional form (Athey and Imbens, 2016).

I have selected CausalForestDML to gain deeper insights into the impact of fund closures on the remaining sister funds. This method allows us to move beyond average treatment effects and examine how the costs and benefits of scope reduction vary across different fund characteristics.

4.3.3 Estimating and Interpreting CATE

In my analysis, I measure the Conditional Average Treatment Effect (CATE) of fund closures on the performance of remaining funds using CausalForestDML.
CATE is defined as:

$$CATE(X) = E[Y(1) - Y(0)|X]$$

Y(1) and Y(0) are the potential outcomes under treatment and control conditions respectively, while X stands for the covariates (Künzel et al., 2019).
CATE enables us to understand how the effect of fund closures differs by a variety of fund and firm characteristics. Under this framework, one can explore whether firm size moderates the effect of fund closures or whether funds of varying ages are affected differently.

My estimates of CATEs indicate a heterogeneity in treatment effects that gives a different interpretation of refocusing costs than traditional average treatment effect estimates. This enables to explore when refocusing might be most costly depending on funds' characteristics.

4.3.4 Causality in the Original Research

In the work of (de Figueiredo Jr et al., 2019), after the baseline regression approach, a propensity score matching model (PSM) is used. This PSM model was used in an attempt to estimate the 'true' causal effect of fund closures on sister funds, by taking out the bias (Rosenbaum and Rubin, 1983). Like in my study, the causality is being researched, however there are key differences in the approach and results that I will highlight here. Both the PSM and causal machine learning (CML) approach attempt to estimate the true causal effect of the closure of sister funds, however they are very different in both methodology and capabilities. The PSM method works by creating a balanced treatment group and control groups based on observed characteristics, afterwards it estimates the average treament effects by typically utilising traditional regression techniques(Stuart, 2010). The CML approach, specifically the CausalForestDML, uses a more flexibel non-linear way of estimating treatment effects for each individual observation.

The main difference seperating the two methods lies in their handling of heterogeneity. The PSM model is mainly able to account for pre-specified sources of heterogeneity where the CML method is able to automatically captures complex interactions and heterogeneous treatment effects across multiple dimensions (Künzel et al., 2019). This advantage allows the CML model to get a more nuanced understanding of the way in which refocusing costs can vary and the importance of different fund and firm characteristics.

On top of that the CML model provides robustness to high dimensional confounding and typically generates richer insights into the complexity of treatment effects (Chernozhukov et al., 2018a). All of these benefits allow the CML approach to find nuanced patterns and relationships that might otherwise be overlooked when using traditional methods, thus creating new insights for my research.

4.3.5 Causal Approach Flowchart

To help illustrate my causal approach more clearly, I also developed a flowchart, detailing the steps taken to arrive at the final findings. The flowchart in Figure 1 combines conventional econometric techniques with advanced causal machine learning methods to analyze the performance of remaining funds after experiencing refocusing within the firm.

The process begins with my input data provided by Aurum Research Limited. This data undergoes considerable preprocessing to prepare it for use. The next step is to define my variables, starting with the outcome variable (Y) as the Information Ratio, the treatment variable (T) as "TREATED" and the covariates (X) consisting of various fund characteristics. I also include control variables (W) to account for time-fixed effects.

After the feature scaling, I employ sample splitting, an important step for the validity of my causal model. I perform this by splitting my data into a training set and a test set. One set is used to fit my model, while the other is used to evaluate its performance, helping to prevent overfitting.

Next, I proceed to the `CausalForestDML` model, which includes multiple stages because it is a double machine learning technique. First, two random forests are created: one for the outcome (model_y) and another for the treatment (model_t). The double machine learning step then combines

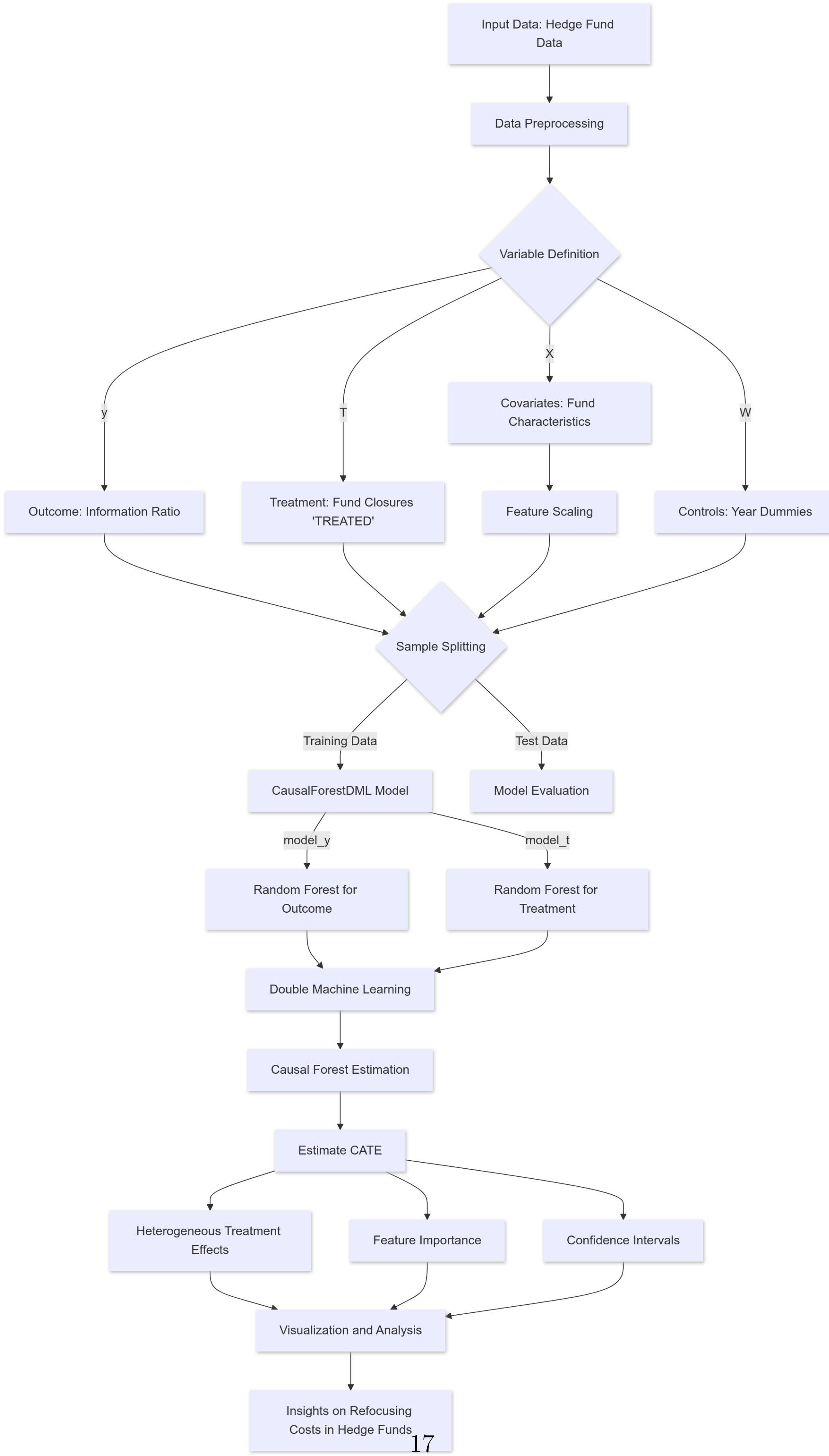

Figure 1: Causal Approach Flowchart

these two models and estimates the causal effect that fund closures have on performance.

This process provides us with estimates of the Conditional Average Treatment Effects (CATE). Using these estimates, I can gain insight into how the impact of fund closure varies across different fund characteristics. I then analyze these results by analysing three different outputs:

1. **Heterogeneous Treatment Effects**: These effects are useful to see differences on the effects of fund closure by characteristics of funds.

2. **Feature Importance**: Used to find out the amount that the fund characteristics influences the heterogeneity.

3. **Confidence Intervals**: This will show us whether my estimates are statistically significant.

By analyzing and visualizing these results, I can find results into refocusing costs in hedge funds that were previously inaccessible. Utilizing this approach allows us to explore beyond average treatment effects and find the nuanced ways in which refocusing within firms impacts performance across different fund and firm characteristics.

4.3.6 Causal Directed Acyclic Graph (DAG)

To better understand the causal relationships in my analysis, I constructed a Directed Acyclic Graph (DAG) as shown in Figure 2.
This DAG presents the hypothesized causal relationships between important variables in my study:

1. **Fund Closure**: This variable represents the closure of a fund within a multi-fund firm and serves as my treatment variable. In the DAG, Fund Closure directly affects Fund Performance, which is the primary relationship defining my study.

2. **Firm Assets Under Management (AUM) and Fund AUM**: Both of these variables influence the probability of fund closure and fund performance. In general, larger funds or firms may be better equipped to withstand significant market shocks that could pressure them, potentially affecting decisions concerning refocusing and leading to different performance outcomes. Fund AUM also has a direct influence on Firm AUM because as the assets of a fund grow larger, the firm's assets will grow as well.

3. **Firm Scope**: If a firm is managing a larger number of funds, this may influence its decision on whether to refocus. Having a broader scope could make it easier to close underperforming funds, as these funds may not be central to the firm's core operations. Moreover, the performance of the remaining funds can be affected by potential synergies or inefficiencies resulting from the firm's scale, thus the relationship with fund performance.

4. **Firm Age and Fund Age**: Both of these variables influence both fund closure and fund performance. This could be due to accumulated experience or established track records, which can influence decision-making and performance. Additionally, natural age is associated with natural growth, which influences both Firm AUM and Fund Age.

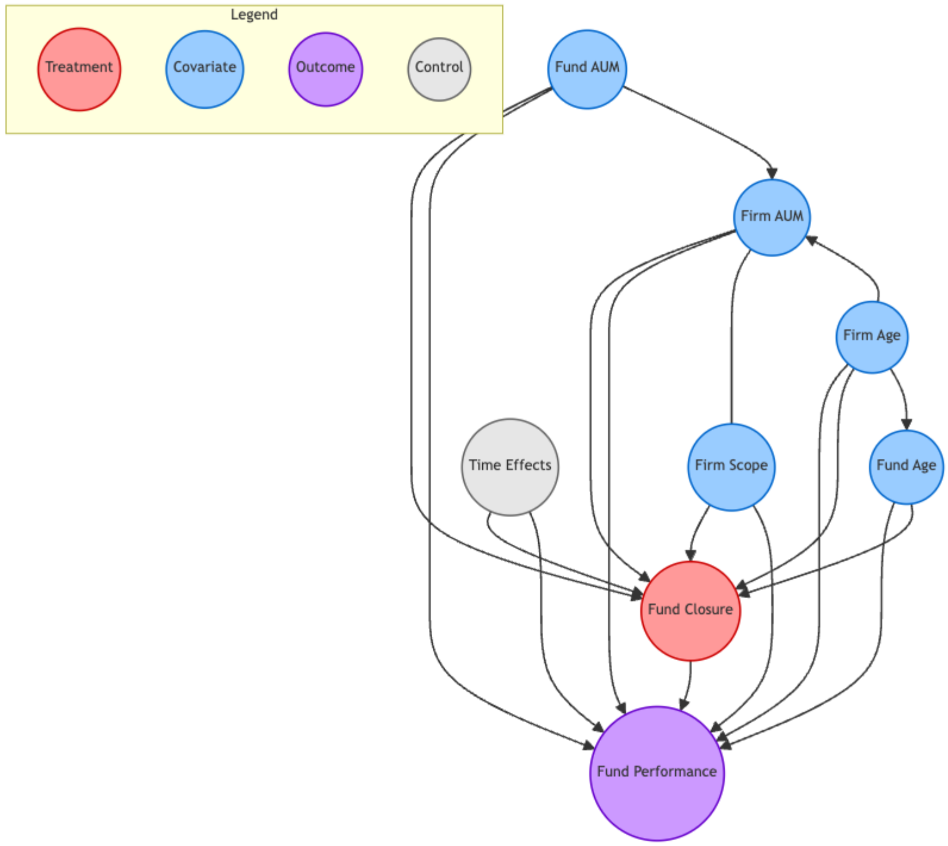

Figure 2: Causal Directed Acyclic Graph (DAG) for Refocusing Costs Analysis

5. **Time Effects**: These effects are included to capture any temporal factors that might affect both fund closures and performance, such as market-wide trends or regulatory changes.

The imperative feature of the DAG is that it graphically illustrates the causal relationships between variables, making us think about the potential confounders that I need to control for in my analysis. For example, the DAG shows that there are directed edges flowing from both Firm AUM and Fund AUM to Fund Closure and Fund Performance, suggesting their importance as control variables in my model.
Although I have not used the DAG for formal causal identification in this study, it is a useful resource for transparent communication of my assumptions and could be used more actively in future research to help in with causal identification strategies (Pearl, 2009).

4.3.7 Findings from CausalForestDML Analysis

After implementing my CausalForestDML approach I have been able to find valuable insights into the diverse treatment effects of fund closures on the performance of the remaining funds. Underneath is a summary displayed with the Conditional Average Treatment Effects (CATE) which has been estimated by my model in Table 5.

Table 5: Summary Statistics of Conditional Average Treatment Effects (CATE)

Statistic	CATE	Lower Bound	Upper Bound
Count	28,294	28,294	28,294
Mean	-0.041	-0.466	0.385
Std. Dev.	0.545	1.197	0.637
Min	-12.863	-37.546	-0.497
25%	-0.439	-0.768	-0.085
Median	0.060	-0.259	0.386
75%	0.323	0.044	0.679
Max	1.859	0.817	13.473

Interpretation of CATE Results

1. **Average Effect**: The mean CATE is -0.041, which is a slight negative effect on the performance of the remaining funds after fund closure. However the confidence interval on this includes zero which indicates that the average effect is not statistically significant.
2. **Heterogeneity**: The standard deviation of CATE is a substantial 0.545 and combined with the wide range, from -12.86 to 1.86, this would indicate a major amount of heterogeneity within the treatment effects.
3. **Distribution**: With a positive median CATE of 0.060 in contrast to the negative mean, a left-skewed distribution of the treatment effects is suggested.
This is caused by a subset of funds experiencing very large negative effects, while the majority of funds experience a small positive effect from closures, this is pulling the mean into negative territory.
4. **Confidence Intervals**: When looking into the confidence intervals it is clear that they range far, from lower to upper bound, suggesting large uncertainty in the point estimates of the treatment effects for individual observations.

Feature Importance

Included in my analysis are insights into which factors are the most important in determining the heterogeneity of treatment effects.
Figure 3, in this figure the relative importance of the different features in my model are included. The key findings from the feature importance analysis are:
1. **Firm AUM**: The first score that sticks out is the Firm AUM with an importance score of 0.33, this score is the highest of all covariates and signifies that the Firm AUM is the most crucial factor when I am trying to determine the effects of fund closures on the performance of the funds that remain within the firm.
2. **Fund AUM**: The size of the individual fund has an importance score of 0.320, which is almost equally important as the firm size, this suggests that both firm-level and fund-level characteristics play significant roles in determining the impact.
3. **Firm Scope**: As the third largest with a score of 0.16, the scope is significantly less important than the size, however it still suggests that the scope has an influence on the impact generated by

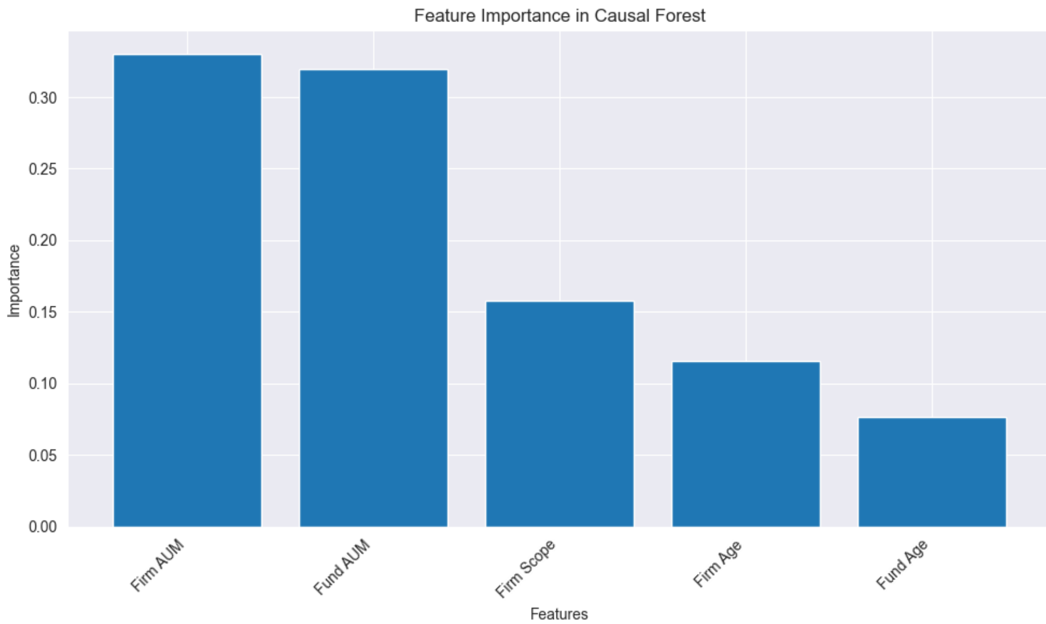

Figure 3: Feature Importance in Causal Forest Model

fund closure and therefore should not be overlooked.
4. **Firm Age and Fund Age**: These features have lower importance scores of 0.12 and 0.077 respectively, suggesting that the age of the firm and the fund play less crucial roles in determining the heterogeneity of treatment effects compared to the size and scope factors.

Heterogeneous Effects by Firm Scope

Figure 4 illustrates how the estimated treatment effects vary with Firm Scope.
The visualization found below reveals several important patterns:
1. When analysing the figure the difference in values of treatment effects across different levels of firm scope stands out. This reinforces my findings of heterogeneous impacts of fund closures.
2. In observing the relationship of firm scope and treatment effects I find that it is non-linear. Both very low and very high scope firms have different patterns when compared to firms with a moderate scope.
3. The figure shows a cluster of firms with lower scope that experiences a more negative treatment effect, this observation indicates that a fund closure for a firm with a smaller scope could have a larger negative impact.

4.3.8 Extended Results of CausalForestDML Analysis

Heterogeneity in Treatment Effects

My analysis reveals significant heterogeneity in the treatment effects of fund closures. Figure 5 and Figure 6 illustrate how the Conditional Average Treatment Effects (CATE) vary with firm-level and fund-level Assets Under Management (AUM), respectively.

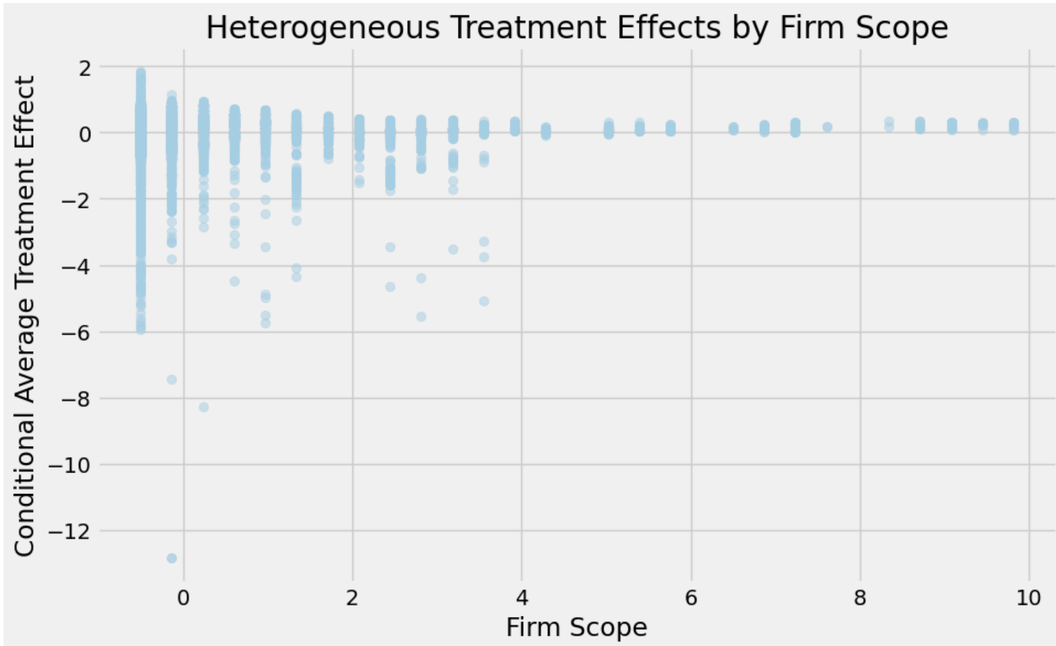

Figure 4: Heterogeneous Treatment Effects by Firm Scope

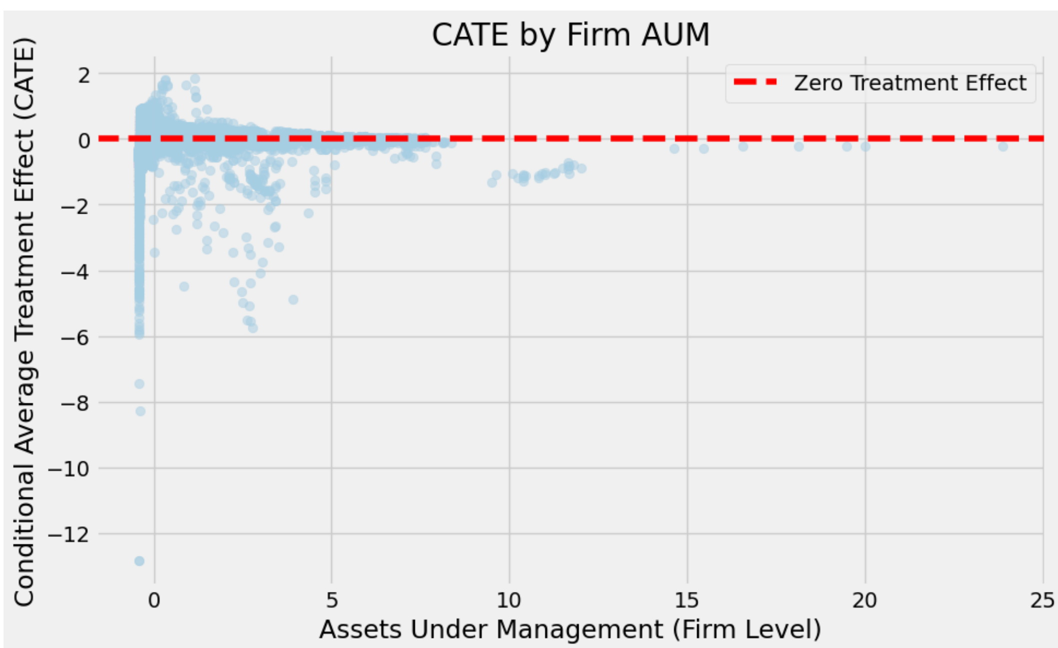

Figure 5: CATE by Firm AUM

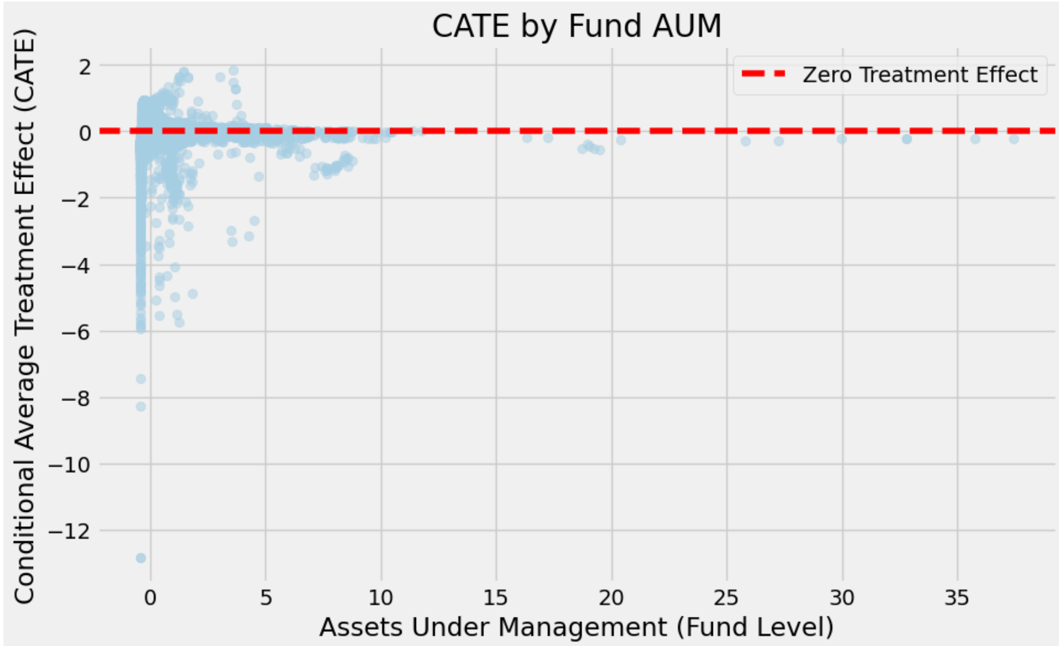

Figure 6: CATE by Fund AUM

The figures indicate that the impact of fund closures varies across different levels of AUM at both the firm and fund levels. To quantify these relationships, I conduct separate Ordinary Least Squares (OLS) regressions of CATE on Firm AUM and Fund AUM.
For Firm AUM, I find a small but statistically significant positive relationship (coefficient = 0.0158, $p < 0.001$). This suggests that larger firms tend to experience slightly more positive (or less negative) effects from fund closures. However, the R-squared value is very low (0.001), indicating that firm size alone explains very little of the variation in treatment effects.
For Fund AUM, I again find a small positive relationship (coefficient = 0.0398, $p < 0.001$), with a slightly higher R-squared (0.005). This implies that larger individual funds within a firm are associated with more positive treatment effects, although the explanatory power remains low.

Interaction Effects

To assess how fund characteristics can moderate the impact of closures, I conduct an additional OLS regression that includes the interaction terms between the treament indicator and the key fund characteristics. In the table below the results are displayed: Table 6.
Key findings from the interaction effects analysis are:

1. The coefficient for TREATED is negative (-0.1244) but not statistically significant ($p = 0.105$).
2.Firm Scope has a significant negative effect on performance (coefficient = -0.0159, $p < 0.001$), while the interaction term TREATED × Firm Scope shows a positive coefficient (0.0326, $p < 0.001$). This suggests that although having more funds generally decreases performance, it may mitigate the negative impact of fund closures.
3. The interaction terms between TREATED and AUM (both firm and fund level) are not statistically significant, indicating that the effect of fund closures is not systematically influenced by size.

Table 6: OLS Regression with Interaction Effects

Variable	Coefficient	P-value
Intercept	0.0975	<0.001
TREATED	-0.1244	0.105
Firm AUM	8.772e-12	<0.001
Fund AUM	-2.924e-11	<0.001
Firm Scope	-0.0159	<0.001
TREATED * Firm AUM	-3.454e-11	0.205
TREATED * Fund AUM	4.326e-11	0.670
TREATED * Firm Scope	0.0326	<0.001

Treatment Effect by Firm Size

I further investigate the role of firm size by categorizing firms into 'Small' and 'Large' based on the median AUM and comparing the average CATE for each group (Table 7).

Table 7: Mean CATE by Firm Size

Firm Size	Mean CATE	Standard Deviation
Small	-0.0405	0.545
Large	-0.0406	0.545

The results show minimal difference in the average treatment effect between smaller and larger firms, suggesting that firm size does not primarily drive the heterogeneity in treatment effects.

Comparison of Treated and Untreated Groups

Comparing the mean CATE for treated and untreated groups reveals only a small difference:

- Mean CATE for Untreated: -0.0405
- Mean CATE for Treated: -0.0432

This indicates, on average, the funds that experienced closures (treated) had slightly more negative expected treatment effects, but the difference is minimal.

Descriptive Statistics by Treatment Status

In order to better understand the differences between treated and untreated funds, I compare their characteristics:
This comparisons shows clearly that treated funds usually belong to larger, older, and firms with more funds. This suggests that treated firms are not randomly distributed across my sample.

Table 8: Mean Characteristics by Treatment Status

Characteristic	Untreated	Treated
Firm AUM (mean)	1.66 B	4.47 B
Fund AUM (mean)	667 M	767 M
Firm Scope (mean)	2.26	11.98
Firm Age (mean)	70.15	118.91
Fund Age (mean)	58.84	88.96

Overall, the extended analysis that I provide sheds light on the significant heterogeneity in the impact of fund closures, which is not fully explained by simple linear relationships with fund characteristics. The causal machine learning approach captures complex interactions between firm size, scope, and age when determining the effects of fund closures.

4.4 Comparison with Original Study

4.4.1 Comparison And Implications

The results of my study in cannot be directly compared to the results in the original study as the sample is very different, however as this is an exploratory replication study I will put them side by side however they are neither meant to validate nor challenge their findings:

- Direction of Effect: I found a marginally positive significant coefficient in column 1 for the impacts of fund closures on remaining fund performance, in comparison to the significant negative effects reported in the original study.
- Relatedness Impact: I did not find evidence supporting the original study's conclusion that closures of more closely related funds lead to higher refocusing costs.

4.4.2 Implications of Causal Machine Learning Findings

My CausalForestDML analysis provides several important insights that extend beyond traditional econometric approaches:

- **Non-linear Relationships**: I have found that for this research linear models are inadequate in comprehending the intricate dynamics of refocusing, due to the presence of non-linear patterns.
- **Feature Importance**: The identification of Firm AUM, Fund AUM, and Firm Scope as key determinants of refocusing effects gives guidance for both researchers and practitioners. These factors should be given particular attention in future studies and in managerial decision-making processes.
- **Robustness to Confounding**: The double machine learning component of my approach provides added confidence in my results by mitigating potential biases from high-dimensional confounding.

4.4.3 Comparison Table

Table 9: Comparison of Regression Results

	Original Study			Replication Study		
	(1)	(2)	(3)	(1)	(2)	(3)
TREATED	-0.32***	-0.14***	-0.08***	0.2605*	0.0571	0.211
	(0.02)	(0.02)	(0.03)	(0.071)	(0.825)	(0.534)
Relatedness × TREATED			-0.11**			-0.586
			(0.05)			(0.617)
Fund FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	489,037	489,037	489,037	94,311	94,311	94,311
R-squared	0.04	0.13	0.13	0.044	0.0761	0.0763

P-values in parentheses underneath the coefficients

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

Model specifications are as follows:

Model (1): $Y_{it} = \alpha + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$

Model (2): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$

Model (3): $Y_{it} = \alpha + \lambda_i + TREATED_{it}\beta_{cc} + Relatedness_i \times TREATED_{it}\beta_{cc} + T_t + X_{it}\beta_c + \epsilon_{it}$

5 Discussion

5.1 Summary of Findings

In the exploration of the methods and ideas in the research by de Figueiredo, Feldman, and Rawley (2019) on refocusing costs in hedge funds, I have uncovered several insights. The findings cannot be directly compared given the significantly differing samples and robustness of data-work. But we can explore the results nonetheless.

The first hypothesis suggests that refocusing in a multi-business firm imposes refocusing costs on that company. My baseline regression revealed potential gains in contrary to costs. However, it is important to note that these positive results were not robust once fixed fund effects were included.

The second hypothesis stated that refocusing costs would be larger when a business closely related to its sister divisions is removed. The results that followed from the analysis on my sample were not in line with this conclusion.

My exploration of causal machine learning, revealed significant heterogeneity in treatment effects. Which suggested that fund characteristics would impact the effects of fund closures on the performance of the remaining funds. The causal forest model I identified Firm Scope Firm AUM and Fund AUM as the most important factors in determining the effects of fund closures.

5.2 Dataset Considerations

An important aspect of my study that needs to be considered is the nature of my dataset compared to that used in the original study. Both my study and the original work by de Figueiredo et al. (2019) use datasets that should, in principle, cover a major part of the hedge fund universe for the same time period. My data comes from The Hedge Fund Data Engine managed by Aurum Research Limited, while the original study used data from Lipper TASS. The differences occurring in results between the original study and the replication might caused by the differing datasets due to the following factors:

- Sample Characteristics: My sample is smaller than the original study's sample, both in terms of the number of funds and firms included, which may affect the statistical power of my analysis. For instance, my dataset contains 1,728 funds and 804 firms, whereas the original study analyzed 7,201 funds and 3,141 firms. A smaller sample size may limit my ability to detect statistically significant effects. According to Randolph B. Cohen and Pastor (1992), smaller samples reduce the power of statistical tests, increasing the risk of Type II errors (failing to detect an existing effect).

- Size of the funds and firms: The funds and firms in my sample are larger on average than those in the original study. For example, the average Assets Under Management (AUM) for funds in my sample is \$668 million, compared to \$215 million in the original study. Similarly, the mean Firm AUM in my sample is \$1.7 billion, while it was \$591 million in the original study (see Table 2). Larger entities may have greater resources and diversification to better manage the stress of the financial crisis and potential refocusing costs. As the literature shows, larger firms may be better positioned to absorb shocks due to economies of scale and scope (Amihud and Mendelson, 1986; Acharya and Pedersen, 2012). Additionally, larger hedge funds may employ more sophisticated risk management practices, which could mitigate the negative impact of fund closures (Getmansky et al., 2004).

- Firm Scope: On average, firms in my sample manage fewer funds—2.37 funds per firm—compared to 6.0 in the original study. This results in fewer treated funds, as fewer firms meet the criteria of having a sister fund nearby during the financial crisis. Specifically, only 1.18% of my fund-month observations are treated, compared to 4% in the original study. The smaller number of treated observations may affect the estimation of treatment effects due to lower statistical power (Gelman and Hill, 2006). Moreover, firms with fewer funds could experience different dynamics when a fund closes, potentially altering the impact on the remaining funds.

5.3 Theoretical Implications

The causal machine learning approach underlines the awareness needed towards heterogeneity in strategic management theory. Future theoretical work should attempt to incorporate this complexity, allowing us to better understand how and why the impacts of strategic decisions might differ across firms.

5.4 Practical Implications

For managers or other practitioners planning to refocus, my findings indicate approaching these decisions with caution. The benefits and costs associated with refocusing could depend significantly on firm-specific and fund-specific factors. There is no one-size-fits-all approach to making this decision. According to my findings, factors such as firm size, scope, and other firm and fund-specific characteristics play a major role in determining the outcomes of refocusing decisions. Managers are advised to carefully weigh these factors in their decision-making process.

This research demonstrates the value of advanced analytics in strategic decision making, applying the results from my causal machine learning approach to take informed decisions. By employing these techniques, firms could gain a more intricate understanding of how strategic decisions affect their organization.

6 Limitations and Future Research

6.1 Methodological Limitations

Although my research provides a number of valuable findings and methodological advances for the study, the study has many limitations that provide various avenues for future research. The absence of statistical significance from my fixed-effects models keeps us from drawing definitive conclusions about the refocusing costs in my sample. The difference in results between my OLS and fixed-effects models underscores the substantial influence of unobserved fund-specific characteristics, which are controlled for in the fixed-effects approach but not in OLS.

My measures, are in line with the original study, and although they are commonly used in hedge fund research they also carry some limitations. The Information Ratio may not be well suited for all risk types, especially tail risks relevant during financial crises, and can thus poorly estimate risk in non-normal distributions (Bacon, 2008). The binary TREATED variable does not capture the various types of refocusing possibilities, such as spinning off or selling, all of which might have different implications (Brauer, 2006). Then the Relatedness, calculated by the correlations of excess returns, may not capture all of the facets under which fund relationships exist (Brown and Goetzmann, 2003). These limitations should be taken into considerations when interpreting my results.

Although the novel approach based on causal machine learning creates new insights, the interpretability of models can be problematic due to it being a 'black box' approach. Besides these challenges, the data requirement of the causal approach and the risk of overfitting need to be considered as well.

6.2 Issues of Data and Generalizability

My smaller sample size and treatment group compared to that of the original study may reduce the statistical power of my analysis. Future research could benefit from larger samples to uncover relationships that are not immediately obvious in this study. Additionally, my findings are specific to the hedge fund industry during a particular period. The generalizability of my results to other industries or time frames still needs to be established. Replicating the causal methodology from this research using data from the Lipper TASS database, as in the original study, would be particularly valuable.

6.3 Future Research Directions

Any future research could investigate how refocusing costs evolve over time which could offer enhanced insights into the long-term consequences of scope reduction decisions. Finding alternative measures of relatedness, performance, or refocusing costs could also provide new perspectives on the scope reduction phenomenon in multi-business firms.

Future research should also investigate methods that account for latent confounding, such as the Cross-Moment algorithm proposed by Kivva et al. (2023). This approach could provide more robust estimates in our setting by estimating causal effects with latent confounders using a single proxy variable, while also relaxing the common trend assumption required by DiD estimators.

In conclusion, while my study advances the understanding of refocusing costs through novel methodological approaches, it also highlights the complexity of this phenomenon. The limitations identified here offer a roadmap for future research to add to my understanding of scope reduction in multi-business firms and its financial consequences.

7 Conclusion

This study set out to explore the work of de Figueiredo Jr et al. (2019), on the refocusing costs associated with hedge funds, using a different dataset, and incorporating machine learning techniques to account for causality. My findings suggested marginally significant benefits specific to my sample. While these are interesting results, we cannot directly compare these results to the results in the previous research as a significantly smaller untested sample was used, and the data work was not as robust.

My research has employed causal machine learning to find heterogeneity in these treatment effects, showing that firm size, fund size, and firm scope become important in determining the impact of refocusing. The findings indicate that the costs of refocusing are not uniform for all multi-business firms; rather, they depend on specific firm characteristics. These results provide further understanding into the hedge fund refocusing and the complexity associated with strategic decision-making in multi-business firms.

While my research reveals insights into these questions, there are a number of limitations with regard to the specific context of the hedge fund industry, as well as to the inherent challenges of many causal machine learning approaches. The current findings could thus be explored in other industries and at different points in time, further investigating the mechanisms driving the heterogeneous effects observed here.

Concluding, my study underlines the importance of replication and sophisticated analytical methods in management research; a deeper understanding is therefore gained of the scope reduction of hedge funds and the implications this has on performance. These findings add to the work of scholars studying corporate strategy, as well as professionals in the hedge fund industry, suggesting that the influence of refocusing decisions may be more diverse and context-bound than previously thought.

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