# An Analysis of The Characteristics of the Top Private Equity Firms in the United States That Determine ESG Practices.*

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This paper aims to improve upon the work done and data collected in the ESG in the Top 100 US Private Equity Firms paper, where they analysed different determinants of private equity firm's ESG practices. This is done by fixing certain data inaccuracies, using a different methology to calculate a firm's ESG scores, and considering different variables of interest. The findings reveal that internal rate of return (IRR) and the total number of funds have an impact on ESG score, whereas the number of employees, the fund's size, and the average size of each fund have negligible impact. This research contributes to the understanding the ESG practices of the top private equity firms in the United States.

## 1 Introduction

The corporate landscape is rapidly evolving, with a notable shift towards greater responsibility and transparency, spurred by the rise of Environmental, Social, and Governance (ESG) considerations. Whilst ESG has gained traction in publicly traded companies, there is a significant gap in understanding the ESG practices of private equity (PE) firms, despite their immense global impact. This gap is particularly surprising given the influential role PE firms play in the economy and their potential impact on ESG. This paper aims to address this gap by investigating the determinants and practices of ESG within PE firms.

This paper aims to reproduce the ESG in Top 100 US Private Equity Firms paper, and uses the dataset that were constructed by its authors (Markarian, Rakotobe, and Semionov 2023). That paper focuses on the top 100 PE firms based in the United States, conducting a thorough analysis of their ESG practices through content analysis of their websites. This paper aims

*Code and data are available at: https://github.com/Krishiv-J/ESG-in-Private-Equity to build upon their work by firstly amending the data collected for certain variables, such as number of employees. Secondly, this paper calculates new metrics, such as average fund size. Thirdly, a new methodology is used to calculate a firm's ESG score. Lastly, the paper focuses on different predictor variables. The reasons for each modification is detailed in the paper.

Understanding the ESG practices of PE firms is crucial for promoting transparency, accountability, and sustainable business practices in the global economy. By uncovering the current state of ESG engagement within PE firms and identifying factors that influence these practices, this study contributes to the broader discourse on corporate responsibility and fills a significant gap in the literature.

This paper is structured as follows. In Section 2, the source of the data, the methodology of data collection and cleaning, and the changes made to the data set is detailed. Section 3 discusses the choice and construction of our negative model. Section 4 presents the model's results. Section 5 further discusses the results, comparing it to the original paper, and discusses the limitations of the paper

The estimand for this paper is the effect of various firm-specific factors (Total Number of Funds, Fund Size, IRR, Staff Count, and Average Fund Size) on a private equity firm's ESG scores.

# 2 Data

## 2.1 Source, Collection, and Measurement

All data analysis was done through R (R Core Team 2023) with the help of the following packages: `tidyverse` (Wickham et al. 2019), `here` (Müller 2020), `ggplot2` (Wickham 2016), `knitr` (Xie 2014), `rstanarm` (Goodrich et al. 2022), `dplyr` (Wickham et al. 2023), `gridExtra` (Auguie 2017), and `janitor` (Firke 2023).

The raw data set used for this paper is obtained from the "ESG in the Top 100 US Private Equity Firms" paper (Markarian, Rakotobe, and Semionov 2023), which was published in July 2023. The data was collected for the year 2022. This dataset was created by the authors to capture the complex landscape of ESG commitments within private equity firms. Additionally, data was collected from LinkedIn to replace the staff data collected in the original dataset. This is further detailed below. The dataset combines both primary and secondary sources to gather firm-specific variables. The final dataset's sources include Preqin and LinkedIn, with additional insights derived from an analysis of each firm's individual website to assess ESG commitments.

The authors selected the top 100 U.S.-based private equity firms for the year 2022. This selection was guided by the rankings from Private Equity International, a renowned organisation that publishes an annual global ranking of PE firms. The rankings are based on fundraising amounts in millions of dollars over the preceding five years, providing a reliable measure of each firm's market presence and activity. The choice of U.S. firms was deliberate, as they wield significant global influence and impact. Furthermore, limiting the study to U.S. firms helped eliminate potential variations that may arise from country-specific factors, given that the top non-U.S. firms were spread across various countries with diverse regulatory environments. Whilst this subset represents only a fraction of the total number of private equity firms, it accounted for over 25% of the total committed capital and employed more than 26% of the industry's workforce in 2022.

To ensure the sample captured firms primarily dedicated to private equity, the authors excluded investment banks like Goldman Sachs or Blackrock, despite their presence in the Private Equity International rankings. These institutions were excluded due to their diversified operational structure, which includes private equity as a tertiary segment rather than a primary focus.

The selection criteria also took into account the primary investment strategies of the firms. While private equity firms typically engage in strategies such as buyouts, growth equity, and venture capital, some may have alternative approaches like management buy-ins, impact investing, or infrastructure investing. To maintain consistency and focus, the authors excluded firms that did not prioritise private equity as their primary investment strategy.

In cases where a firm was excluded or did not meet the predetermined criteria, the authors substituted it with the subsequent firm from the 2022 Private Equity International rankings. This approach ensured that the sample size reached the intended count of 100 while maintaining the integrity of the data. As such, the sample stops at the private equity firm ranking 116.

For the data collection process, the authors hand-collected the data to ensure its accuracy. The authors primarily relied on content analysis of the firms' websites. This method has a long-standing history in analysing company-related information. The websites provided a rich source of information, including financial reports, dedicated ESG microsites, documents, informational videos, interviews, and management letters. This extensive review aimed to capture all firm-level ESG-related information.

To ensure the data's reliability and validity, the authors adopted a coding system that aimed to distinguish between genuine involvement in ESG practices and mere lip service. While documents and presentations with substantial ESG-related content were included, boilerplate language lacking supporting material was excluded.

The majority of data on the specific characteristics of the private equity firms, such as size, staff count, investment strategy, total number of funds, and more, were extracted from Preqin.

## 2.2 Modifications made

### 2.2.1 Variables

The original dataset had 117 columns (1 column for the name of the firm, and 116 for various data points for each of the 100 firms). In analysing the determinants of ESG activities, the authors considered a range of PE firm-level variables. The authors organised the ESG information from the firms' websites into distinct content categories to capture various aspects of their practices. Initially, the results were classified into four main groups: Environmental (E), Social (S), Governance (G), and an "Other" category, which encompasses ESG aspects that do not fit neatly into the environmental, social, or governance classifications. Each of these primary categories was further divided into two sub-categories. The first sub-category contributes to the respective E, S, G, or "Other" score, while the second focuses on ESG frameworks, signatories, certifications, or sponsorships. The authors also created a "weighted" ESG-Score. Finally, the authors also assessed the private equity firms' explicit commitments to ESG frameworks beyond the ESG score. This involved evaluating whether the firms align with specific ESG frameworks, participate in related initiatives, hold ESG certifications, and engage in ESG sponsorships. In doing so, the paper aimed to determine if the firm was engaging in greenwashing, which is the deceptive practice of exaggerating or falsely claiming environmentally friendly initiatives (Bank, n.d.). Given the focus of this paper, any variable used for the analysis of the firm's greenwashing was excluded.

#### 2.2.1.1 Staff Count

It was observed that the count for the number of employees was significantly inaccurate. For instance, Sequoia Capital was reported having only 19 employees. Thus, to fix the dataset, data from the LinkedIn pages of each firm was used. For each company on LinkedIn, there is a section that includes the number of people that are currently employed by the firm. LinkedIn reported Sequoia as having 824 employees, a significant difference from the 19 employees previously reported. The implication of using this methodology is discussed further below. Energy & Minerals Group's LinkedIn's page could not be found, thus, the original number reported was used.

#### 2.2.1.2 Internal Rate of Return

The Internal Rate of Return (IRR) was gathered from the Preqin. Whilst Preqin provided comprehensive data for most of the utilised variables, there were some gaps that were filled in manually. Specifically, there were 22 missing observations for IRR.

To address these gaps, the authors sourced the missing data from Bloomberg, bringing the total IRR observations to 96 out of the 100 firms in the sample. However, once again, it was observed that the data obtained from Bloomberg was significantly inaccurate. For instance, PSG's IRR was taken from Bloomberg since Preqin did not have data. It was reported to be

78.8%. However, a presentation from PSG reported their 2022 gross IRR as 56%, and their net IRR as 44% (PSG 2023). Thus, despite the lower number of observations, Preqin's data was used given its higher accuracy.

#### 2.2.1.3 Variables removed from regression

Moreover, a number of variables that were used in the original paper as predictor variables in their regression were removed:

- `Public`: A dummy variable indicating whether the private equity firm is publicly traded.
- `IRR (All)`: The overall Internal Rate of Return (IRR) of the private equity firm, from either of Preqin and Bloomberg
- `Buyout`: A dummy variable indicating whether the private equity firm specialises in buyout investments.
- `VC or Growth Capital`: A dummy variable indicating whether the private equity firm is a Venture Capital firm or specialised in Growth Capital.
- `Avg.Vintage`: The average vintage year of the funds within the private equity firm.
- `EastCoast`: A dummy variable indicating whether the private equity firm is located on the East Coast.
- `WestCoast`: A dummy variable indicating whether the private equity firm is located on the West Coast.
- `OtherUSLocation`: A dummy variable indicating whether the private equity firm is in another US Location, other than the East Coast or West Coast.
- `Total Number of Funds`: The total number of funds within the private equity firm.

### 2.2.2 Methodology

The authors' methodology for calculating the ESG-Score involves aggregating scores from four distinct categories: Environmental (E-Score), Social (S-Score), Governance (G-Score), and Other-Score. For each score, various data points collected for related to each specific subcategory, such as environmental initiatives for the E-Score, social considerations for the S-Score, and governance practices for the G-Score, are averaged. The Other-Score captures miscellaneous ESG-related factors like award recognition and dedicated ESG funds. For each category, a score of 1 indicates optimal performance in that aspect of ESG, while a score of 0 suggests a lack of effort or data. The scores are then added to produce an overall ESG-Score that ranges from 0 to 4. A score of 0 signifies a complete absence of ESG practices, whereas a score of 4 represents exemplary ESG commitment.

In this paper, the approach to calculating the ESG-Score diverges from the original methodology by opting for a summing method rather than averaging across the categories. This decision was driven by the desire to give equal weight to each component, ensuring that a firm's commitment across different ESG aspects is considered equally important. By summing the scores, the methodology emphasises the cumulative presence and effort towards ESG across all categories. This approach rectifies the potential imbalance that could arise when averaging, where fewer factors in one category could have the same weight as a larger number in another, leading to a more balanced and comprehensive assessment of a firm's ESG practices. In total, 19 columns are added to calculate the ESG Score. A value of 0 indicates that the firm does not engage in any form of ESG, whilst a score of 19 indicates optimal ESG practices. Section A.1 is a list of every variable that was used in the calculation of the ESG Score.

Furthermore, in their methodology, the authors adopted a weighted approach for calculating the ESG score, termed the Weighted ESG-Score. This method aggregates the scores of each E, S, G, and "Other" factors, with the E-Score and Other-Score, both heavy in environmental factors, given twice the weight of the S-Score and G-Score. Their rationale for this weighting is rooted in the heightened interest in environmental issues compared to other aspects of ESG. However, in this study, the Weighted ESG-Score was omitted for several reasons. First, there's the potential for bias in weighting; assigning environmental factors double the weight could skew the scoring system. Without a universally agreed-upon weighting scheme, scores may become subjective, compromising interpretability and comparability. Second, by excluding the weighted approach, the study adopts a more holistic perspective on ESG, treating each factor equally. This ensures that no single ESG component is prioritised over the others.

## 2.3 Data Cleaning

After converting the dataset from its original Stata file type to csv, a column for the Average Fund Size variable was added. This was calculated as the Fund Size divided by the Number of Funds. This was done as larger fund sizes might indicate more resources available for ESG initiatives, potentially correlating with a stronger ESG commitment. The data for the number of employees was also added to the table. All the unneeded columns, including the ones mentioned before, and other unneeded ones, such as the year the PE firm was established were removed. Furthermore, there were repetitive columns, columns with no description throughout the paper, and any columns that were used to calculate other columns that were removed. For instance, three individual columns indicating the presence of a DEI policy, a Chief Diversity Officer, and a DEI committee were removed during the data cleaning process. These columns became redundant as their information was already consolidated into a single DEI column. The DEI column effectively captures the combined presence of these components, making the individual columns unnecessary. Next, the ESG score was calculated using the methodology detailed above. After doing so, all the columns used in its calculation were also deleted since they were not needed anymore.

For our regression, the following variables are included:

- `Total Number of Funds`: The total number of funds within the private equity firm.
- `Fund Size`: The accumulated capital commitments across all of the private equity firm's individual funds, measured in millions of USD.

- `IRR`: The overall Internal Rate of Return (IRR) of the private equity firm, which is a percent ranging from 0 to 100.
- `Staff`: The number of employees working for the private equity firm.
- `Average Fund Size`: The average size the funds within the private equity firm, measured in millions of USD.

A snippet of the first 10 firms is seen in Table 1. Moreover, Figure 1, Figure 2, Figure 3 demonstrate the correlations between each firm characteristic, and their ESG Score.

Table 1: First 10 Private Equity Firms in the cleaned dataset

| Firm | No. of Funds | Fund Size | IRR | Staff | Average Fund Size | ESG Score |
|---|---|---|---|---|---|---|
| Searchlight Capital Partners | 3 | 6203.0 | 1.32 | 143 | 2067.67 | 0 |
| Vista Equity Partners | 32 | 52167.8 | 11.23 | 856 | 1630.24 | 9 |
| K1 Investment Management | 7 | 7460.0 | 4.21 | 165 | 1065.71 | 0 |
| ACON Investments | 8 | 3514.8 | 7.40 | 78 | 439.35 | 1 |
| Thomas H Lee Partners | 7 | 8283.1 | NA | 180 | 1183.30 | 1 |
| One Equity Partners | 6 | 7471.9 | NA | 97 | 1245.32 | 2 |
| Veritas Capital | 5 | 14204.0 | 2.31 | 143 | 2840.80 | 0 |
| Roark Capital Group | 9 | 13314.9 | 13.43 | 227 | 1479.43 | 4 |
| KPS Capital Partners | 3 | 10897.5 | 7.24 | 122 | 3632.50 | 0 |
| Lindsay Goldberg | 3 | 11629.2 | 14.36 | 90 | 3876.40 | 1 |

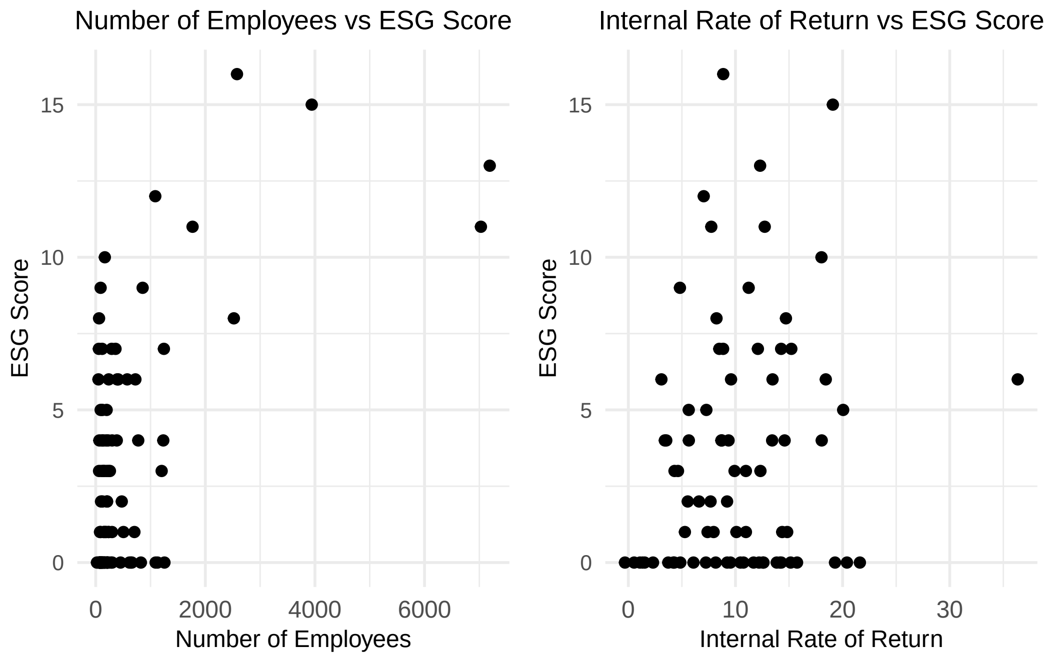


Figure 1: ESG Score by Staff Count and IRR

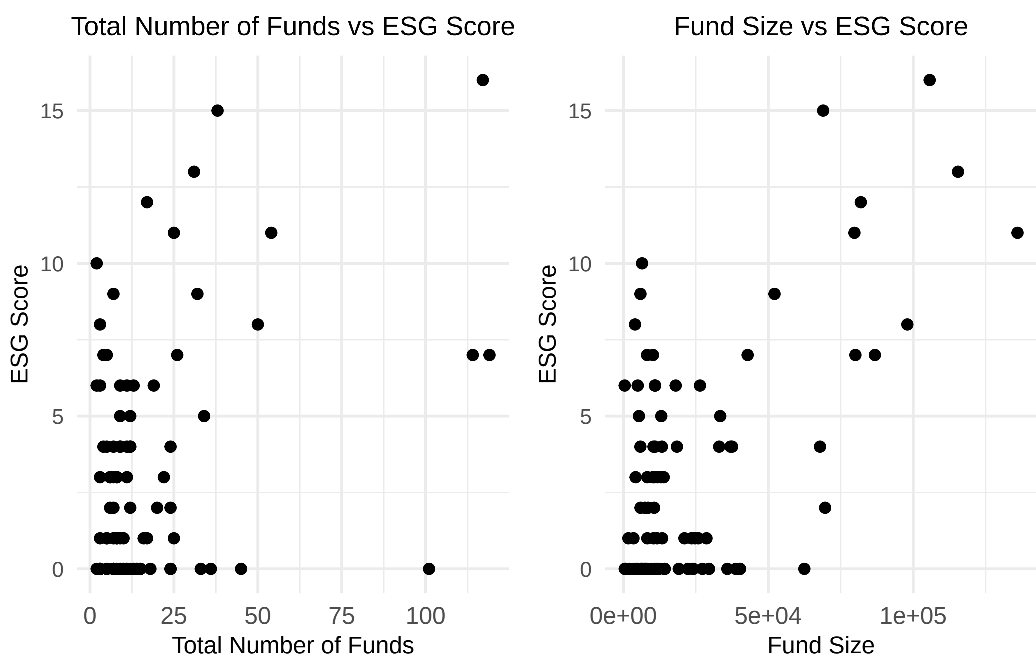


Figure 2: ESG Score by Number of Funds and Fund Size

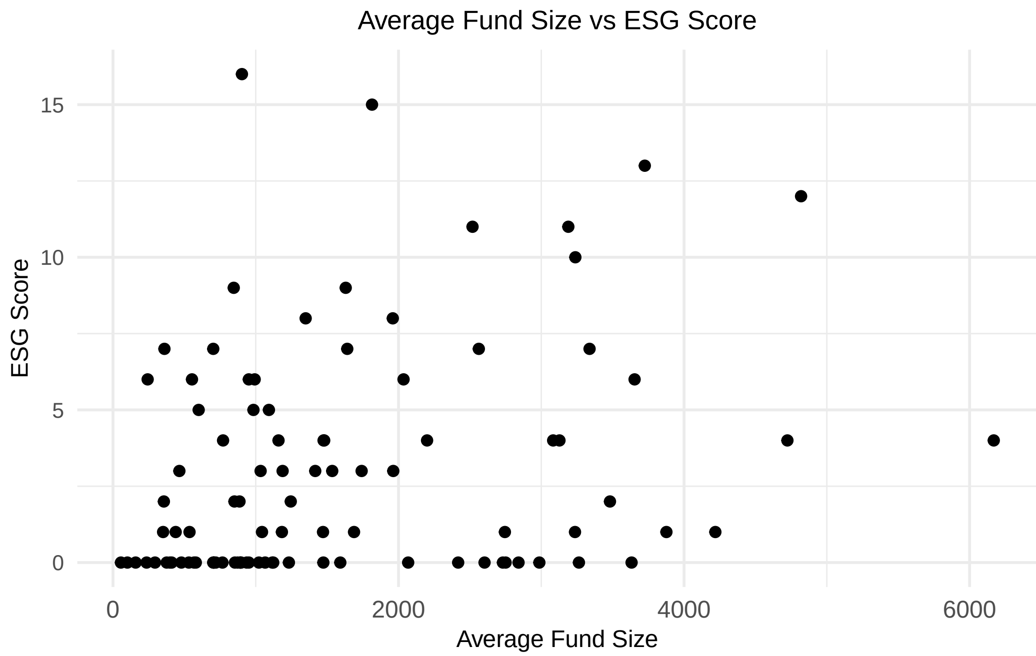


Figure 3: ESG Score by Average Fund Size

# 3 Model

## 3.1 Model set-up

$$
\begin{aligned}
ESG_i|\pi_i &\sim \text{Negative Binomial}(r, \pi_i) && (1)\\
(\pi_i) &= \beta_0 + \beta_1 \text{funds}_i + \beta_2 \text{fund\_size}_i + \beta_3 \text{IRR}_i + \beta_4 \text{staff}_i + \beta_5 \text{avg\_fund\_size}_i && (2)\\
\beta_0 &\sim \text{Normal}(0, 2.5) && (3)\\
\beta_1 &\sim \text{Normal}(0, 2.5) && (4)\\
\beta_2 &\sim \text{Normal}(0, 2.5) && (5)\\
\beta_3 &\sim \text{Normal}(0, 2.5) && (6)\\
\beta_4 &\sim \text{Normal}(0, 2.5) && (7)\\
\beta_5 &\sim \text{Normal}(0, 2.5) && (8)
\end{aligned}
$$

## 3.2 Model justification

Negative binomial regression offers a robust approach to analyzing count data, especially when the assumption of equal mean and variance, inherent to Poisson regression, is violated.

This regression model accommodates overdispersion, a common characteristic in count data where the variance exceeds the mean, providing a more flexible framework than the Poisson model. In this paper, the negative binomial regression is employed to examine the relationship between firm characteristics and their ESG scores. Given the potential for overdispersion in these counts, the negative binomial regression provides a suitable and robust approach to our analysis.

# 4 Results

Table 2: Model Summary of the firm's ESG Score by various firm characteristics

| Term | Estimate | Std. Error |
|---|---|---|
| Intercept | 0.692 | 0.864 |
| Total Number of Funds | 0.012 | 0.039 |
| Fund Size | 0.000 | 0.000 |
| IRR | 0.116 | 0.083 |
| Staff | 0.001 | 0.001 |
| Average Fund Size | 0.000 | 0.001 |

Table 2 presents the results of the negative binomial regression model examining the relationship between various firm characteristics and their ESG scores. The intercept of 0.692 serves as the baseline ESG score when all predictor variables are set to zero, though its practical interpretation is limited.

The coefficient for 'Total Number of Funds' is estimated at 0.0119 with a standard error of 0.0385. This suggests that for each additional fund a firm manages, there is an expected increase of 0.0119 in its ESG score, holding other variables constant. With a relatively high standard error compared to the coefficient, this suggests that the relationship between the number of funds and ESG score is uncertain. The low coefficient value indicates that for each additional fund, the expected increase in ESG score is quite small, and given the standard error, this effect may not be statistically significant.

'Fund Size' has an estimated coefficient of 0.0000350 with a standard error of 0.0000427. This relatively low coefficient suggests a negligible impact of fund size on ESG scores. The standard error is also relatively high, indicating uncertainty around this estimate.

'IRR' has an estimated coefficient of 0.116 with a standard error of 0.0830. This suggests that a 1 unit increase in IRR is associated with an expected increase of 0.116 in the ESG score. Whilst the coefficient suggests a positive relationship between IRR and ESG scores, the high standard error indicates a considerable amount of uncertainty around this estimate. Given the magnitude of the standard error, the relationship between IRR and ESG scores may not be robust.

For ‘Staff’, the estimated coefficient is 0.000914 with a standard error of 0.00109. The low coefficient suggests a minimal impact of staff count on ESG scores. Additionally, the standard error is relatively high compared to the coefficient, implying uncertainty in this relationship.

Lastly, ‘Average Fund Size’ has an estimated coefficient of 0.0000386 with a standard error of 0.000529. Similar to the ‘Fund Size’, the low coefficient and high standard error suggest that the impact of average fund size on ESG scores is negligible and uncertain.

In summary, whilst some variables like ‘Total Number of Funds’ and ‘IRR’ show positive associations with ESG scores, the low coefficient values coupled with high standard errors suggest these relationships are weak and potentially not statistically significant. On the other hand, ‘Fund Size’, ‘Staff’, and ‘Average Fund Size’ exhibit negligible. effects on the firm’s ESG score.

# 5 Discussion

## 5.1 Findings and Comparison

The results from the negative binomial regression model provide insights into the factors influencing ESG scores in private equity firms. The findings suggest that ‘Total Number of Funds’ and ‘IRR’ are positively associated with ESG scores, although with relatively modest coefficients and high standard errors. Conversely, ‘Fund Size’, ‘Staff’, and ‘Average Fund Size’ demonstrate negligible impact on ESG scores.

Comparing these results to (Markarian, Rakotobe, and Semionov 2023), there are several similarities and differences. In the original paper, neither ‘IRR (Preqin)’ nor ‘IRR (All)’ showed significant influence on ESG scores. In contrast, this paper’s results identify a positive relationship between IRR and ESG scores. This discrepancy suggests that firm performance, as measured by IRR, might indeed predict ESG activities. The original paper also considered the variables ‘Log Fund Size’ and ‘Staff Count’ as potential regressors, and found that neither variable had a statistically significant relation with a firm’s ESG Score. This paper did not apply a log to the fund size, and had replaced the data for staff (instead of using Preqin’s data, LinkedIn’s data was used). However, despite the aforementioned changes to the data,this paper also found that neither of these two variables had a significant relation with ESG scores.

## 5.2 Limitations

There are several limitations and weaknesses. The original dataset, crafted by the authors of the base paper, introduces potential biases due to the subjectivity involved in data collection, such as the use on website content analysis to determine a large number of the variables. Even with this paper’s efforts to mitigate subjectivity in this study, there are elements that retain a subjective component, particularly those collected by the original authors. This could influence the accuracy and reliability of the dataset used in our analysis. The study focuses exclusively on the top 100 U.S.-based private equity firms, which may not be representative of smaller or non-U.S. firms. This limited scope may introduce bias, potentially overlooking trends and practices in smaller or regional private equity firms that could differ from those in larger, more global firms. Additionally, the exclusion of certain types of firms, such as investment banks, might limit the external validity of the findings. For instance, discerning genuine ESG commitment from mere lip service can be challenging, potentially affecting the reliability of the ESG scores assigned to each firm. Moreover, the decision to opt for a summing method instead of averaging the ESG scores across categories may have implications on the interpretation of the ESG-Score. This methodological choice might not capture the nuances firms might have in their ESG practices. Furthermore, the exclusion of the Weighted ESG-Score, which was part of the original methodology, might overlook the importance of environmental factors, given the global emphasis on environmental sustainability. The regression results present associations rather than causality. Whilst the study identifies relationships between firm characteristics and ESG scores, it does not establish causative links. Also, using LinkedIn for gathering staff count introduces potential inaccuracies. Firstly, the data from LinkedIn was from 2024, whereas the rest of the metrics is from 2022. Moreover, the data from LinkedIn might not be up-to-date or fully reflective of the actual number of employees, given that not all employees maintain or update their LinkedIn profiles regularly. This could lead to an underestimation or overestimation of staff counts, affecting the analysis.

## 5.3 Future Research

Whilst this study has examined several firm-specific variables like fund size, IRR, and staff count, there remain other potentially influential factors that could shape ESG practices. For instance, firm age, geographical location, and the presence of specific ESG committees or policies might provide additional insights into the determinants of ESG scores. Investigating these additional variables could offer a more comprehensive understanding of the factors driving ESG commitments in private equity firms and help identify new avenues for promoting and enhancing ESG practices. Moreover, expanding the analysis to include firms from different regions or countries could provide valuable insights into the global trends, practices, and challenges in ESG commitments. Furthermore, whilst quantitative analysis provides valuable insights into the trends, patterns, and relationships between variables, incorporating qualitative methods like interviews, case studies, or stakeholder engagement could offer a richer, more nuanced understanding of the motivations, challenges, strategies, and perceptions behind ESG practices. Understanding the perspectives and preferences of various stakeholders, including investors, employees, communities, and industry peers, could shed light on the human aspects, motivations, and dynamics influencing ESG commitments within private equity firms.

# A Appendix

## A.1 Variables used to calculate ESG

Each variable below is a binary variable, meaning a 1 indicates that firm possess it, and a 0 means it does that. Each variable was added to determine a firm's ESG Score:

- `HasESGonWebsite`: A dummy variable indicating whether the private equity firm has a ESG section on its website.
- `E_Portfoliocasestudies`: A dummy variable indicating whether the private equity firm has portfolio case studies related to environmental factors.
- `E_Media`: A dummy variable indicating whether the private equity firm's website has media related to environmental factors.
- `E_HasDocumentsorPages`: A dummy variable indicating whether the private equity firm has various website documents or pages related to environmental factors.
- `S_Portfoliocasestudies`: A dummy variable indicating whether the private equity firm has portfolio case studies specifically related to social factors.
- `S_Media`: A dummy variable indicating whether the private equity firm has media content related to social factors.
- `S_HasDocumentsorPages`: A dummy variable indicating whether the private equity firm has documents or dedicated pages on its website related to social factors.
- `S_HasDEI`: A dummy variable indicating whether the private equity firm has a Diversity, Equity, and Inclusion (DEI) policy or initiatives in place.
- `S_10PctWomenBoardExec`: A dummy variable indicating whether the private equity firm has at least 10% women representation in its board of directors or executive positions.
- `G_Portfoliocasestudies`: A dummy variable indicating whether the private equity firm has portfolio case studies specifically related to governance factors.
- `G_HasDocumentsorPages`: A dummy variable indicating whether the private equity firm has documents or dedicated pages on its website related to governance factors.
- `Other_ESGfund`: A dummy variable indicating whether the private equity firm has a dedicated fund specifically focused on ESG investments.
- `Other_ESGdocument`: A dummy variable indicating whether the private equity firm has documents on its website related to ESG components that do not fit in the other 3 categories.
- `Other_Portfoliocasestudies`: A dummy variable indicating whether the private equity firm has portfolio case studies that are related to ESG, but do not fall into the other 3 categories.
- `Other_ESGMedia`: A dummy variable indicating whether the private equity firm has media content related to ESG, but does not fall into the other 3 categories.
- `Other_ESGpolicy`: A dummy variable indicating whether the private equity firm has an official ESG policy outlining its commitment and approach to ESG factors.
- `Other_ESGreport`: A dummy variable indicating whether the private equity firm publishes regular reports specifically addressing its ESG performance and initiatives.

- `Other_ESGAwards`: A dummy variable indicating whether the private equity firm has received any awards or recognition for its ESG practices.
- `Other_HasESGHeadorCommittee`: A dummy variable indicating whether the private equity firm has an appointed individual or committee responsible for overseeing ESG matters within the organisation.

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