Title	Exploring impacts of impact investments
Sub Title	
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Publisher	慶應義塾大学大学院経営管理研究科
Publication year	2024
Jtitle	
JaLC DOI	
Abstract	
Notes	修士学位論文. 2024年度経営学 第4251号
Genre	Thesis or Dissertation
URL	https://koara.lib.keio.ac.jp/xoonips/modules/xoonips/detail.php?koara_id=KO40003001-00002024-4251

慶應義塾大学大学院経営管理研究科修士課程

学位論文（　　2024　年度）

論文題名

Exploring impacts of impact investments

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（論文題名）

Exploring impacts of impact investments

（内容の要旨）

The rising popularity of environmental, social, and governance (ESG), socially responsible investments (SRI), and impact investments has created a complex landscape for investors seeking to understand the distinctions and similarities among these investment approaches and their associated public disclosures. While extensive research has been conducted on ESG and general SRI topics, particularly in comparison to conventional investments, the body of literature on impact investing remains limited. Researchers in this field are employing both qualitative and quantitative methodologies to explore the potential of impact investments.

A significant challenge in impact investing is the insufficient disclosure of information and the lack of universally accessible datasets. This is primarily due to the predominance of private equity and venture capital firms as impact investors, which, as non-public entities, are not subject to the same disclosure requirements as public companies. Consequently, investors face difficulties in comprehending the financial and non-financial (social impact) benefits of impact investments.

This study investigates the semantic similarity between impact fund investment theses and UN Sustainable Development Goals (SDGs) using BERT-based text mining techniques. Analyzing data from 152 impact fund managers, the research explores relationships between fund characteristics, Assets Under Management (AUM), target returns, and SDG alignment.

Key findings include ① No statistically significant correlation between AUM size and target returns, challenging assumptions about larger funds' risk aversion. ② BERT semantic analysis revealed varying degrees of alignment between investment theses and SDGs, with some goals (e.g., "No Poverty" and "Industry Innovation and Infrastructure") showing closer alignment than others. ③Cluster analysis identified six distinct groups of impact funds with statistically significant differences in return target preferences ($p = 0.045$), suggesting shared risk appetites and investment strategies within clusters. ④ Only three impact fund managers explicitly focused their investment theses on specific SDG goals, highlighting a gap between general SDG consideration and targeted goal alignment. ⑤ The study observed a concentration on four prominent SDGs: Decent Work and Economic Growth (SDG 8), Climate Action (SDG 13), No Poverty (SDG 1), and Reduced Inequalities (SDG 10). ⑥ Over 70% of impact fund managers target market-rate or above-market-rate returns, challenging the notion that impact investing necessarily entails financial sacrifice.

The findings of this study contribute to the growing body of knowledge on impact investing and offer practical implications for investors, investees, fund managers, and policymakers in the field of sustainable finance. By enhancing transparency and understanding of impact investment strategies, this research aims to facilitate more informed decision-making and promote the growth of impactful and sustainable investment practices.

Contents

1 Introduction

1.1 What is impact investing?

The term "impact investing" has initially been coined by the Rockefeller foundation in 2007 with other philanthropists and investors, entrepreneurs together where they decided to entitle the investments as "impact" investment that provide measurable social impact alongside with financial returns as impact investors.

Later, Rockefeller foundation has established Global Impact Investing Network (GIIN) (GIIN Impact Investing Guide, 2023), a network of sophisticated investors and professionals that promote the infrastructure, research, and education around impact investing (Foroughi, 2022).

Impact investments are investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return. Figure 1 is illustrated by the GSG National Advisory Committee to describe the impact of impact investing.

As illustrated in Figure 1, impact investment is relatively similar to conventional investments when it comes to considering financial return and risk, but completely different when it comes to evaluating the impact they bring on a specific investment. Therefore, in this research, it is vital to explore and observe the impact and return of the impact fund through the content of the non-financial text of the impact funds.

One of the important data set providers under GIIN is Phonex Capital. Positions impact investments between ESG integration and impact only philonthropical investments on Figure 2. Within impact funds, it is divided impact investments into two groups, financial-first and impact-first driven.

Furthermore, impact investments can be made in both emerging and developed markets and target a range of returns from the below market rate to the market rate, depending on investor‘s strategic goals. The growing impact investing market provides capital to address the world's most pressing challenges' in sectors such as sustainable agriculture, renewable energy, conservation, microfinance and affordable and accessible basic services, including housing, healthcare and education.

According to the book "The power of impact investing: Putting Markets to Work for Profit and global good" published by authors, Judith Rodin, Margot Brandenburg, the past form of impact investing is microfinance. For more than three decades, providing small loans to the world‘s poorest people has proved a noble contribution in decreasing the amount of poverty.

Microfinance as an old form of impact investing has been very popular in Bangladesh and Latin America in the 1970‘s and 80‘s. In 2006, Muhammed Yunus has been awarded with the Nobel Peace Prize for the greatest impact and contribution he has achieved with small loans to group of people from villages into self-

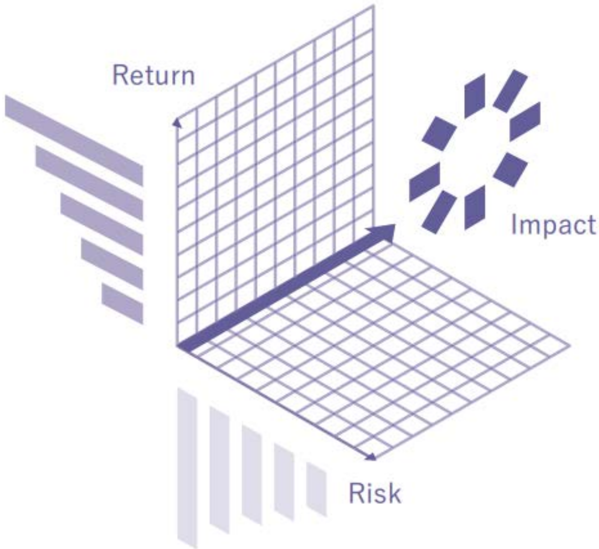

Figure 1: Position Paper on Expanding Impact Investing 2019 (Source:GSG-NAB Japan)

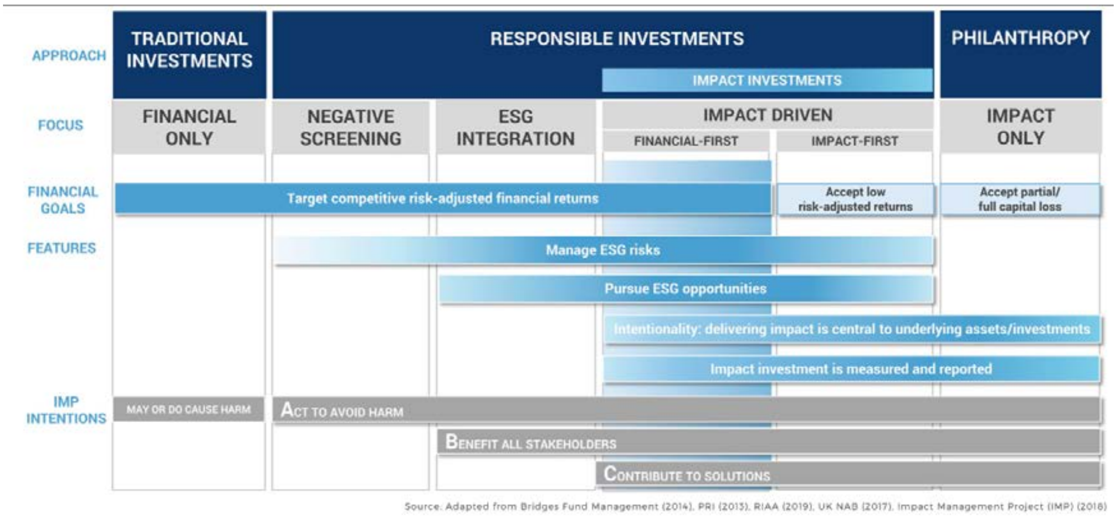

Figure 2: Adapted from Bridges Fund Management (2014), PRI (2013), RIAA (2019), UK NAB (2017), Impact Management Project (IMP) (2018) (Source: Impact Fund Universe Report by Phonix Capital 2024)

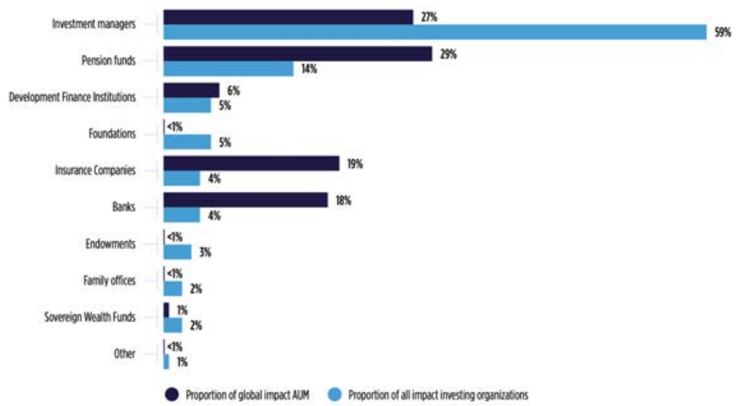

Figure 3: Global impact investing network (Source: GIIN impact survey 2024)

supporting network of millions of borrowers.

1.2 Ecosystem and players of impact investing, and their expected roles

So far, impact investing has been practiced by individuals and institutions, both in the public and private sectors. Those investors can be investment fund managers, foundations, endowments, pension funds, insurance companies, NPO's, family offices and religious organizations. Refer to Appendix 1 to see the systematic model of impact investing participants and to understand who investors and investees are. According to a recent survey conducted by GIIN on Figure 3, a major proportion of the global market size by organization type and AUM is that of investment managers and pension funds, insurance companies.

Based on the report, provided by GIIN in 2024, it is estimated that 3,907 organizations currently manage 1.571 trillion USD in impact investing assets under management (AUM) worldwide (Herold et al., 2024). From this data, it is obvious that impact investing has become very popular recently. Moreover, more than 71% of investors are investment managers, followed by foundations. The private equity and public equity remain to be two-digit numbered allocations among other asset classes.By geographic allocations, USA Canada and Europe hold equally 34 percent and other regions have only one digit allocation of investment funds (Sunderji et al., 2023).

Therefore, it is necessary to include the fund data sets from both American continent and EU regions as well, respectively[1].

Moreover, based on the statistics provided by the Pitchbook report on Figure

[1]https://impactdatabase.eu/

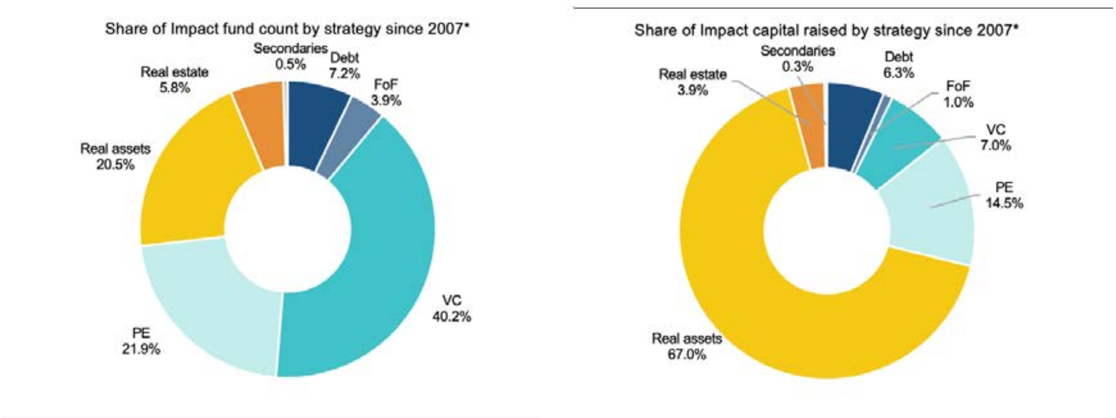

Figure 4: Share of impact fund count and capital raised by strategy since 2007 (Source:Impact Fund Universe Report by Phonix Capital 2024)

4, one of the important data set distributors of impact investors, private equities and venture capitalists cover more than half of capital raised and fund count of impact investing.

Despite the fact the that impact investing has been popular and widely invested by institutions and funds, there is lack of the recognition and understanding of the impact funds in SRI investments (Uo et al., 2020).

Impact reports are more complicated and time-consuming and require financial resources to prepare. Impact report, you need to interview investors, conduct surveys and collect the data from all stakeholders of the impact investing including investors, investees and other beneficiaries and it also takes the time to integrate those information. To ease the collection of those processes mentioned above and increase the efficiency of the impact fund investment thesis, it is vital to utilize text mining tools that can effectively optimize the data interpretation and its integration with SDG goals.

However, there is no single study that has analyzed the texts and content written within Impact Fund using NPL tools such as BERT.

In case of ESG related investments, most of the companies are public companies. Therefore, their reports can be accessed through the integrated and Sustainability reports publicly available. However, some of the PE impact fund investors and venture capitalists do not release these reports.

2 Purpose, Aims and Motivation

This research concentrates on empirical fact-finding through the examination of impact fund samples and an exploratory analysis of the outcomes of impact investments, taking into account previous studies and the aforementioned issues. The scope of the study encompasses a detailed description of the investment theses employed by impact funds, as well as an attempt to conduct text analysis to quantify the semantic relationship between these investment theses and the United Nations Sustainable Development Goals (SDGs).

The ultimate goal of this study is to observe the characteristics of impact funds and help investors understand impact funds and their focus areas based on the SDG goals by using text mining analysis.

In the meantime, the study will help impact fund managers position their funds by writing more concrete investment thesis and aiming at specific impact investment areas by focusing semantic similarities with SDG goals.

To achieve this goal, this thesis explores the characteristics of impact investments and proposes a quantitative methodology to understand the relationships, specifically semantic similarities between investment thesis of the impact funds and SDG goals by using statistics and natural language processing (NLP) tools.

It is important that investors in impact funds understand what impact-driven investment funds aim to achieve. Several research studies aimed to analyze financial return and risk related to impact funds, but very few studies attempted to analyze the impact quality of impact funds.

Therefore, this research aims to fill the gap by analyzing the investment thesis of non-financial disclosure of investment fund and semantic similarities with SDG goals. Furthermore, this thesis aims at exploring relationship between impact fund size and its target investment rate.

This solution facilitates both impact fund investors and impact investors to tackle with their non-financial disclosures and to specify their focus area of investment and set more specific investment thesis.

2.1 Originality and Contributions

Thesis attempts to contribute to the "impact-driven" or "impact-first" investments and observe their "impact" through non-financial disclosure literature by utilizing text mining techniques to evaluate semantic similarities between investment thesis of impact funds and SDG goals definition provided by United Nations.

As a novelty of the study, this research contributes into three main ways:

Pioneering Quantitative Analysis on the impact investments: At the best of our knowledge, this study is the first to apply a quantitative methodology to evaluate non-financial disclosures in impact investing based on the reviews of the literature conducted to date, utilizing NLP techniques.

Figure 5: Research focus on impact return and impact risk

SDG-Based Framework: The research proposes quantifying impact by measuring the semantic distance between investment theses and the United Nations SDG goals, employing BERT (Bidirectional Encoder Representations from Transformers). This approach aligns with the fundamental purpose of impact investing and builds upon recent study, which is published by Islam and Rahman (2023). BERT calculates and vectorizes semantic similarities between investment theses and SDG goals, providing a robust and nuanced evaluation of impact. This methodology offers a groundbreaking approach to objectively assess the alignment of impact funds with global sustainability objectives, contributing significantly to the field of impact investing research.

Empirical findings: We have found that the investment thesis of most impact funds misaligns with their target SDGs, while a few alignments have been observed. It can be argued that some of the impact investment objectives have been biased due to the impact dimension of the advertised fund. Furthermore, regardless of the trends of SRI investment in climate change and environmental issues, we have found that the majority of impact funds focus on social SDGs rather than environmental SDGs, which differs from the findings of Islam and Rahman (2023).

In Figure 5, it is illustrated which area of impact fund this research attempts to explore and contribute. Since several research studies have been carried out on the financial return and risk that impact funds tackle, but very few papers have been published on the impact side of impact investments, this research contributes to the understanding of those impacts that exists on impact fund.

This thesis can be utilized by SRI investors, specifically, impact fund investors and fund managers to identify their target invesment areas and its relativeness to worldwidely recognized SDG goals and set more specific investment thesis and differentiate the their fund position than other funds available in the SRI market.

2.2 Datasets

Since most of the types of impact fund investments are private debts,private equities, and venture capitalists, it is difficult to access complete integrated data sets of impact funds and are not available publicly.

However, ImpactAssets IA50 is the first publicly available data set of impact funds since 2010. This data set covers more than 150 impact funds and fund managers, it is statistically sufficient and also enables to observe entire characteristics of the impact fund data. Furthermore, a large data set was collected by the Harvard Business School Impact Investment Database of the Impact Investments Project in 2019, which contributed highly to the Impact Investments data set ‘, but it is not publicly available and only accessible by a recognized group of SRI investments researchers. This data includes a comprehensive database of 445 impact investors and 14,165 portfolio companies (Zochowski, 2020) [2].

[2]Moreover, during author‘s exchange period at the University of Chicago, he was able to participate in seminars organized by a Rustandy Center for Social Innovation of Booth School of Business (BSB). During impact investing seminars, author could delve into impact investing topics and could learn Impact Finance Research Consortium (IFR) launched by 3 outstanding business schools in US, by Social Impact Collaboratary of Harvard Business School, Rustandy center of Social Sector Innovation and later in 2014, ESG initiative of Wharton Business School. This impact fund data set includes 300 impact funds and only 180 impact funds‘ names are publicly released on the their website (https://impactfinanceresearchconsortium.org/)

3 Literature Review

3.1 Introduction to Impact Investing Literature

The field of impact investing has undergone substantial evolution since its emergence in the early 2000s. A comprehensive review of literature spanning from 2005 to 2017 reveals the field's transformation from practitioner-led initiatives to a more structured academic discipline (Agrawal and Hockerts, 2021). This body of knowledge encompasses 57 journal articles, 18 reports, 6 book chapters, 3 working papers, and several books, demonstrating the growing academic interest in this investment approach. The literature's progression from conceptual frameworks to empirical analyses reflects the maturation of impact investing as a distinct field within financial research.

Theoretical frameworks and financial performance: Recent developments in theoretical frameworks have provided robust foundations for understanding the financial implications of impact investing. Lo and Zhang made significant contributions by developing a quantitative framework that employs Treynor-Black portfolios to evaluate the financial consequences of impact investing strategies (Lo and Zhang, 2023). Their research establishes conditions under which impact investing can enhance, diminish, or maintain portfolio performance relative to traditional investment approaches. This framework has proven particularly valuable in analyzing various impact investment categories, including biotech venture philanthropy and environmental, social, and governance (ESG) investments.

Empirical research has provided substantial evidence regarding return expectations in impact investing. A comprehensive study by Barber et al., analyzing over 24,000 investments across 4,659 venture capital funds, revealed that investors demonstrate a willingness to accept lower financial returns in exchange for social impact (Barber et al., 2021). Their findings indicate a reduction in expected internal rates of return ranging from 2.5 to 3.7 percentage points for impact funds compared to traditional venture capital investments. This research also uncovered significant variations in preferences across different investor categories and geographical regions, with European and developing market investors showing higher willingness to pay for impact.

Market structure and investment patterns: Research into the organizational structure of impact investment firms has revealed distinct patterns that differentiate them from traditional investment entities. Cojoianu et al.'s analysis of 8,903 firms worldwide demonstrated that impact investment organizations tend to be younger but larger in terms of employee count compared to their conventional counterparts (Cojoianu et al., 2022). These organizations exhibit a pronounced focus on sectors with positive environmental or social externalities, such as agriculture, forestry, clean technology, and education. Additionally, their research highlighted a higher prevalence of government ownership among impact investors, particularly in European markets. Characteristics of the Impact investing firms are summarized in Table 1.

Characteristic	**Impact Investing Firms**
Size	Larger in employee numbers
Age	Younger
Focus	Industries with positive externalities
Ownership	More likely government-owned, especially in Europe
Geographical Preference	Higher propensity in developing countries and European nations

Table 1: Characteristics of Impact Investing Firms

Investment behavior and performance patterns: The investment behavior of impact funds demonstrates distinctive characteristics that reflect their dual mandate of financial returns and social impact. Cole et al.'s examination of 275 impact investors and their 6,064 portfolio companies revealed that approximately 12% of impact investors operate as "additional" investors, focusing on companies that might not attract traditional venture capital (Cole et al., 2022). Their research documented longer investment holding periods and different risk-return profiles compared to conventional investments, particularly in underserved markets and regions.

Governance and legal frameworks: The legal architecture of impact investing presents unique challenges in balancing financial and social objectives. Geczy et al.'s analysis of 207 legal documents from 53 impact investment funds revealed sophisticated approaches to integrating social impact goals within traditional financial frameworks (Geczy et al., 2021). Their research demonstrated that while funds predominantly maintain conventional financial incentive structures, they implement specific impact-related contractual terms and governance mechanisms to ensure the achievement of social objectives alongside financial returns.

The development of standardized frameworks for impact measurement and reporting remains a significant challenge in the field. Research by Poe identified several critical barriers to standardization, including legislative constraints, regulatory complexity, and difficulties in impact definition and verification (Poe, 2023). These challenges highlight the need for balanced approaches that can accommodate the diverse nature of impact investments while maintaining sufficient standardization for effective comparison and evaluation.

Impact measurement and management: The complexity of impact measurement is evidenced in O'Flynn and Barnett's comprehensive review, which established five fundamental criteria for effective impact assessment: impact magnitude, differential impact, causality establishment, aggregation capability, and accountability mechanisms (Barnett, 2017). Their research highlighted the absence of a single methodology that adequately addresses all these criteria, suggesting the need for complementary approaches in impact evaluation.

Taticchi and Andreoli's research, based on extensive stakeholder engagement, identified several operational challenges in impact measurement, including data quality issues, stakeholder alignment difficulties, and the risk of impact washing (Paolo Taticchi and Andreoli Chiara, 2022). These findings emphasize the importance of developing robust measurement frameworks that balance standardization with contextual flexibility.

Theoretical models and investment approaches: Roth's theoretical framework provides valuable insights into the mechanisms through which impact investing creates value (Roth, 2019). The model demonstrates how organizational sustainability drives impact investing outcomes and explains the relationship between market competition and investment effectiveness. These theoretical insights contribute to understanding the conditions under which impact investing can achieve optimal social and financial returns.

Research by Reeder et al. (Reeder et al., 2014) established a taxonomy of impact investors based on their measurement approaches, identifying systematic, contextual, and evidence-based investors. This classification provides a framework for understanding the diverse strategies employed in impact investing and their implications for measurement and evaluation practices.

3.2 Research gap and current study position

A recent systematic review conducted by Islam (2022) has examined impact investing in the social sector. The study analyzed 114 peer-reviewed articles from Scopus and Web of Science databases, using carefully selected keywords through multiple itiration.

The research identified four main areas of focus in impact investing: decision-making processes,impact evaluation methods, behavioral aspects and ecosystem dynamics.

The authors conclude that further research into these key areas could significantly advance both the theory and practice of impact investing. This comprehensive review provides a solid foundation for understanding the current state of impact investing in the social sector and highlights potential avenues for future research (Islam, 2022).

Impact investing is identified as a prominent vehicle for achieving SDGs by follow-up research, published by the Islam and Rahman. The study explores both direct and indirect linkages between impact investing deals and SDGs and analysis of 292 deals provides insights into how impact investing aligns with global sustainability objectives (International Finance Corporation, 2019, Islam and Rahman, 2023).

European Securities and Markets Authority underlines that The Sustainable Development Goals (SDGs) of the United Nations have emerged as one of the most prominent sustainability frameworks for conveying the concept of "impact" creation. This popularity can be attributed to the comprehensive nature of the SDGs, which encompass a wide range of environmental, social, and governance (ESG) topics, including climate action and sustainable urban development.

The multifaceted nature of the SDGs makes them particularly appealing to issuers seeking to communicate their impact claims to investors. By aligning their initiatives with specific SDGs, organizations can demonstrate their commitment to addressing global challenges and creating positive societal impact. However, this alignment can also lead to confusion regarding the true impact dimension of advertised products, as the broad scope of the SDGs may obscure the specific nature and extent of an organization's contributions.

Despite their widespread adoption, the voluntary nature of sustainability frameworks like the SDGs presents significant challenges in terms of disclosure quality and comparability. The lack of standardized reporting requirements and verification mechanisms can result in inconsistent and potentially misleading impact claims. This variability in reporting practices underscores the need for more robust and standardized approaches to measuring and communicating the creation of "impact", particularly in the context of ESG investment and sustainable finance (Sara Balitzky and Natacha Mosson, 2024).

Based on the literature reviews conducted, this thesis aims to address the following main research question:

How can the "impact" of impact investment be observed, measured, or evaluated?

The existing literature reveals a significant gap in standardized methodologies for assessing and evaluating the impacts of impact investment. To address this deficiency, this study proposes a quantitative approach to explore the "impacts" of impact investing by analyzing semantic similarities in investment theses. This methodology builds upon previous studies and rationalities to provide a novel perspective on impact measurement.

In the context of impact investments' potential to contribute to the Sustainable Development Goals (SDGs), the availability and distribution of investment opportunities across various SDGs are crucial factors. This research posits that realizing the full potential of impact investing in advancing the SDGs depends on the presence of a diverse and abundant array of impact investment funds aligned with these global objectives.

To further understand this topic, the following secondary research questions have been explored: How accurately does SDG-based semantic analysis reflect the actual impact objectives of investment funds; what is the distribution of semantic similarities across 17 SDGs; what is the association between impact focus areas and targeted returns?

These research questions are interconnected and aim to provide a comprehensive understanding of impact investment evaluation. The first question examines the validity of using SDG-based semantic analysis as a proxy for assessing impact objectives. The second question explores the landscape of impact investments across the SDGs, potentially revealing areas of concentration or neglect. Finally, the third question explores the relationship between impact focus and financial returns, addressing the ongoing debate about the potential trade-offs between social and financial performance in impact investing.

This study aims to address the aforementioned research questions through a rigorous analytical approach. While acknowledging the complexity of the subject matter, we will endeavor to provide substantive insights into these inquiries, recognizing that complete resolution may not be feasible within the scope of this research.

By addressing these questions, this thesis seeks to contribute to the development of more robust methodologies for evaluating impact investments and to provide insights into the current state of the impact investing landscape in relation to the SDGs. This research has the potential to inform both impact fund managers, investors, investees and practitioners in their efforts to maximize the positive impact of investments while achieving financial sustainability.

By elucidating the relationship between semantic similarities of investment thesis of impact investment funds availability and SDG progress, this research aims to contribute to a more comprehensive understanding of the impact investing landscape and its impact creation disclosures. Furthermore, it will offer valuable guid-

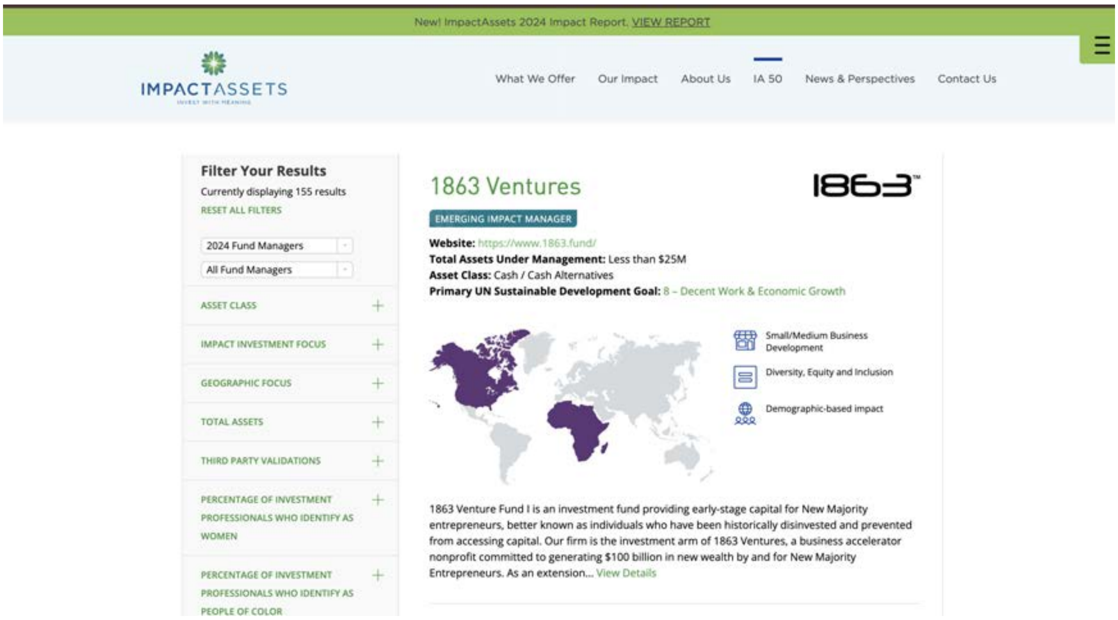

Figure 6: Impact Assets IA50 database

ance and a novel methodology for fund managers, investors, investees and other stakeholders in their efforts to leverage impact investing as a tool for sustainable development in the field of the finance.

This research specifically investigates the relationships between fund characteristics such as geographic distribution of funds and fund size (assets under management), asset classes, categories, target returns, and clustering of investment thesis, contributing to a deeper understanding of the characteristics and performance patterns of impact funds. This analysis builds upon the existing theoretical and empirical work while providing new insights into the relationship between investment strategy articulation and fund performance metrics.

Moreover, this study seeks to solve the issue of disclosure quality and communicating impact creation in the field of impact investing by observing impact funds data.

4 Method

4.1 Sample selection and Data Collection

In this thesis, we have used the data set of more than 150 impact fund managers provided by the first publicly available data set provider ImpactAssets 50 database since 2010. The data set in the website looks like on Figure 6.

It is stated on the website as follows:

"The IA 50 is not an index or investable platform and does not constitute an offering or recommend specific products. It is not a replacement for due diligence. It is an information resource to begin research on the impact investing sector."

This study focuses on the comprehensive analysis of impact investment funds, utilizing data primarily sourced from the Impact Assets IA 50 website. The research aims to provide a thorough examination of the impact investment landscape, with a particular emphasis on fund characteristics, performance metrics, and investment strategies.

The sample data categorize the impact fund managers in Impact Assets IA50 in the appendix (Figure 18 and 19).

Data collection was conducted using Octoparse, an AI-powered web scraping tool. This method allowed for the efficient extraction of detailed information from 150 impact fund URLs, accessed through the "View Details" links of the listed companies. The scraping process was run in four separate iterations, each taking data from 40 URLs simultaneously, to ensure a complete and robust data set. [3]

While the study initially aimed to incorporate multiple data sources, the Impact Assets IA 50 website emerged as the primary and most comprehensive resource available. Other potential data sets in the impact investment field were considered but ultimately excluded due to various constraints, which are elaborated upon in the study's delimitation subsection.

It is important to note that this research is conducted for academic purposes only. The compiled information does not represent an index or investable platform, nor does it offer specific investment products. The study's objective is to provide a scholarly analysis of the impact investment sector, contributing to the broader understanding of this growing field in finance and social responsibility.

The collected data encompasses a wide range of information about each impact fund, including but not limited to the appendix (Figure 28 and 29):

- Fund size and structure
- Geographic focus
- Impact investment focus areas, thesis and impact sectors
- Investment criteria and strategies
- Performance metrics (if it is available)
- Social and environmental impact measurements

[3] https://www.octoparse.com/

- Fund size and structure

This comprehensive dataset allows for a multifaceted analysis of the impact investment landscape, offering insights into trends, challenges, and opportunities within the sector.

By leveraging AI-powered data collection methods and focusing on a authoritative source in the impact investment field, this study aims to contribute valuable insights to the academic literature on impact of impact investing. The findings may inform future research, policy discussions, and practical applications in the rapidly evolving domain of socially responsible and impact-oriented finance.

After scraping, this thesis covers data on 152 impact fund managers with separate fund names, firm headquarters, total number of investors % of capital from top 3 investors, investment overview, investment thesis, company differentiator, impact investment example, total AUM, asset class, verification by a Third-Party and whether their impact is tracked or not, business focus areas, firm overview, target SDG goals of the UN principles, target financial returns relative to benchmark in 2024.

4.2 What is the distribution of impact investing funds over various characteristics (through Python)?

The two bar charts on Figure 7 and Figure 8, present the distribution of asset classes and investment categories in what appears to be an investment portfolio sample.

The figure 7 reveals that venture capital - early stage (pre-seed/seed, accelerator) leads with about 34 counts, followed by private debt - financial inclusion (microfinance, SME finance) at roughly 20 counts. The distribution then shows a gradual decline across various categories including venture çapital late stage, private equity growth stage, private debt categories, real estate related categories.

The figure 8 shows that private equity is the dominant asset class with approximately 70 counts, followed by private debt - absolute return/notes with around 27 counts, and private debt - absolute return/notes at about 25 counts. The remaining asset classes show significantly lower frequencies, with most having counts below 5.

The data suggest a portfolio that is heavily weighted toward private equity investments and early-stage venture capital, with significant exposure to private debt instruments, particularly in financial inclusion sectors. The diverse but uneven distribution indicates a specialized investment strategy focusing on private market opportunities.

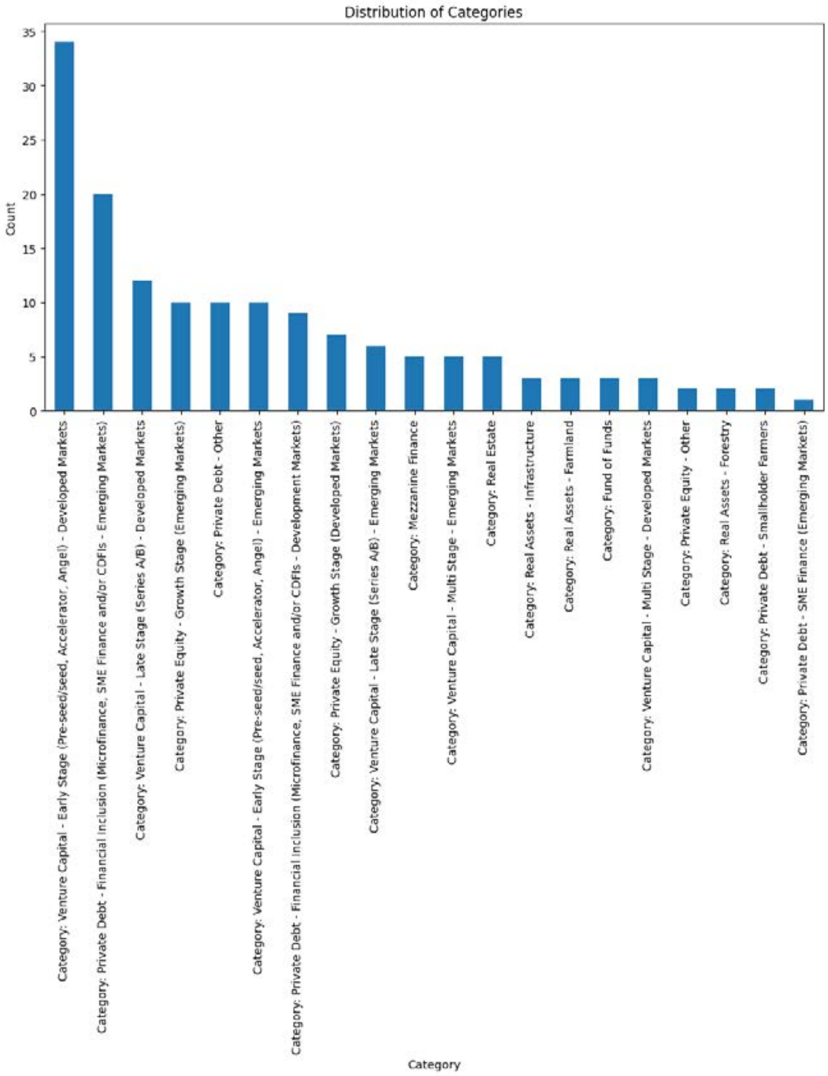

Figure 7: Number of funds over categories

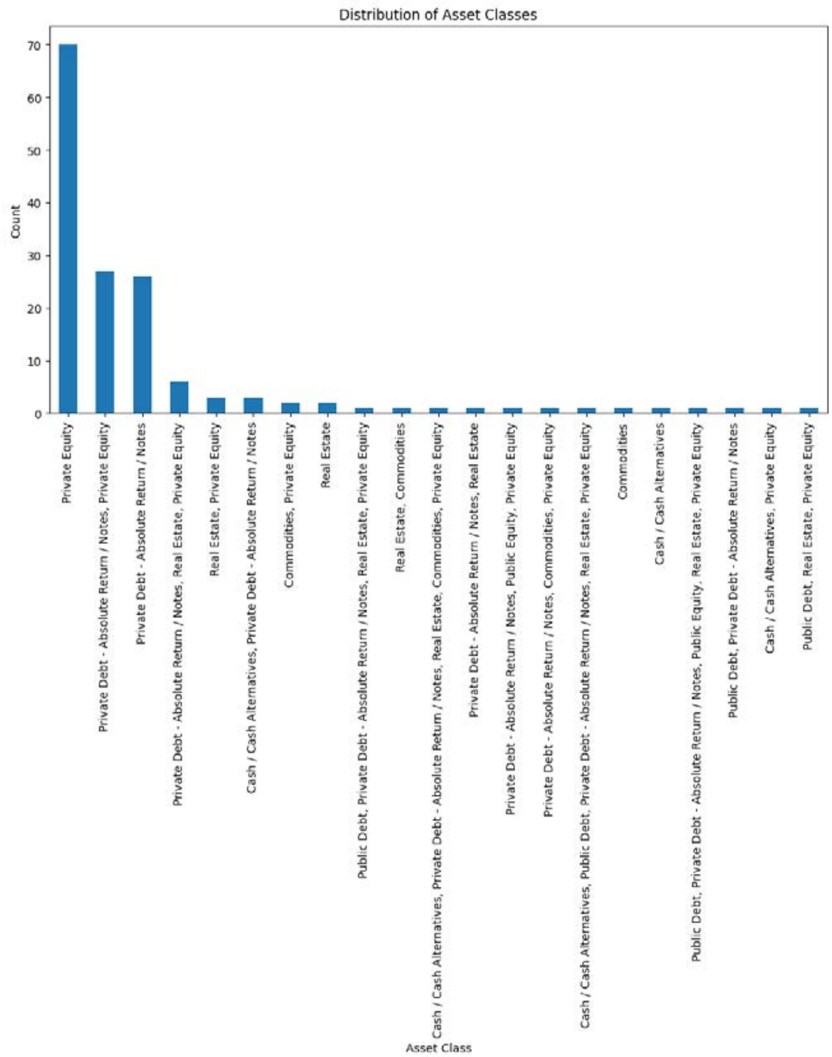

Figure 8: Number of funds over asset classes

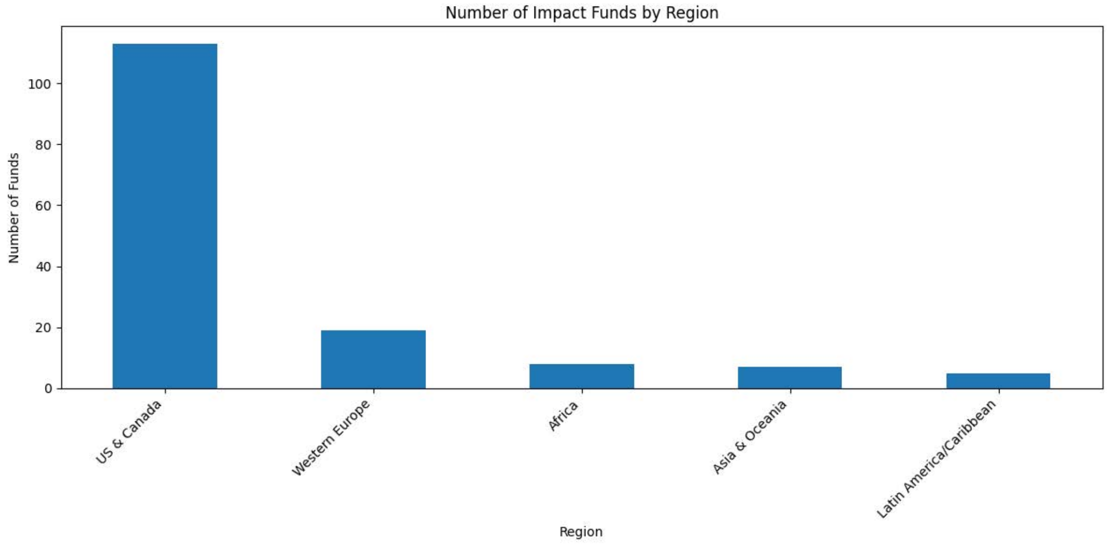

Figure 9: Distributions of impact funds across regions

Furthermore, based on the structured data, impact funds sample is distributed by regions and is illustrated in Figure 9. The bar chart illustrates the distribution of impact funds across five global regions, measured in millions of USD.

This distribution indicates a significant concentration of impact funds in North America followed by the Europe, while regions like Asia, Oceania, and Latin America receive considerably less. The bar chart visually emphasizes these disparities through distinct bar heights and colors, making regional differences clear.

The bar chart on Figure 10 shows the distribution of impact funds based on their operational age. The majority of funds (70) have been operating for 10 years or more, followed by funds with 5-9 years of operation (36), and those with less than 3 years (32). The smallest group consists of funds operating for 3-4 years (12). This distribution suggests a mature market dominated by established funds, while also showing continued growth through newer entrants.

The bar chart on Figure 11 shows the distribution of impact funds based on their total assets under management (AUM). The majority of funds (55) manage assets between $100-499M, followed by funds with less than $25M (40). Large funds with $1B or more in assets represent 18 funds. The middle segments show a fairly even distribution, with $25-49M having 15 funds, $50-99M with 13 funds, and $500-999M with 12 funds. This distribution indicates a market predominantly composed of mid-sized and smaller funds, with a select group of large-scale players managing significant assets.

This boxplot on Figure 12 shows the distribution of Assets Under Management (AUM) across different operational age groups of financial institutions. Here are

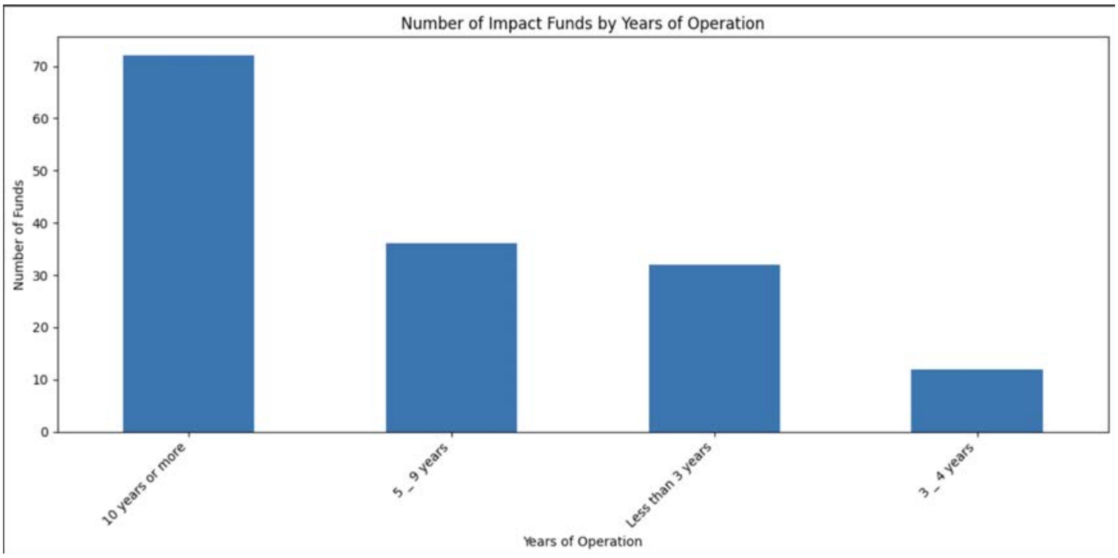

Figure 10: Years of operation

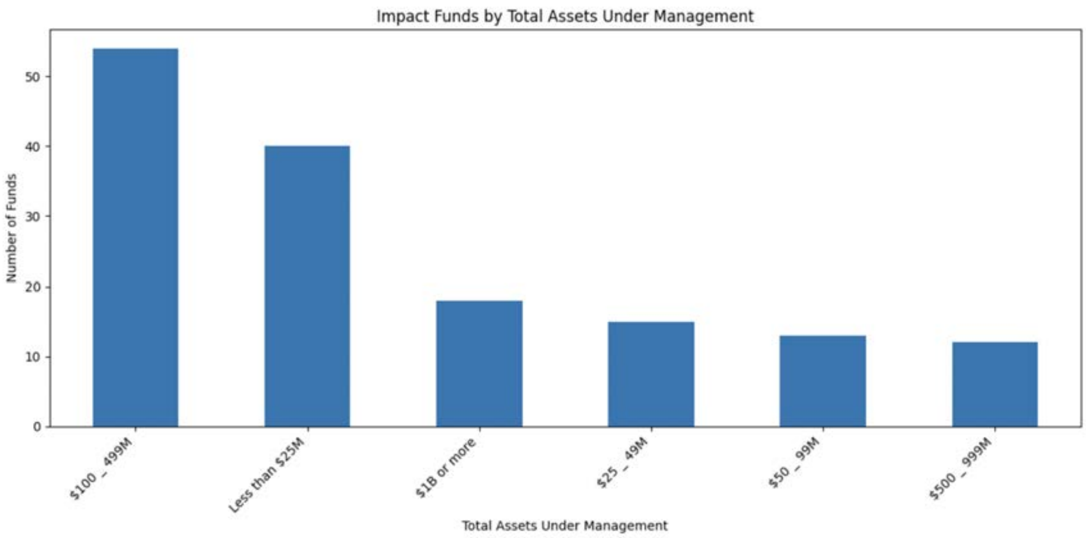

Figure 11: Impact funds across AUM categories

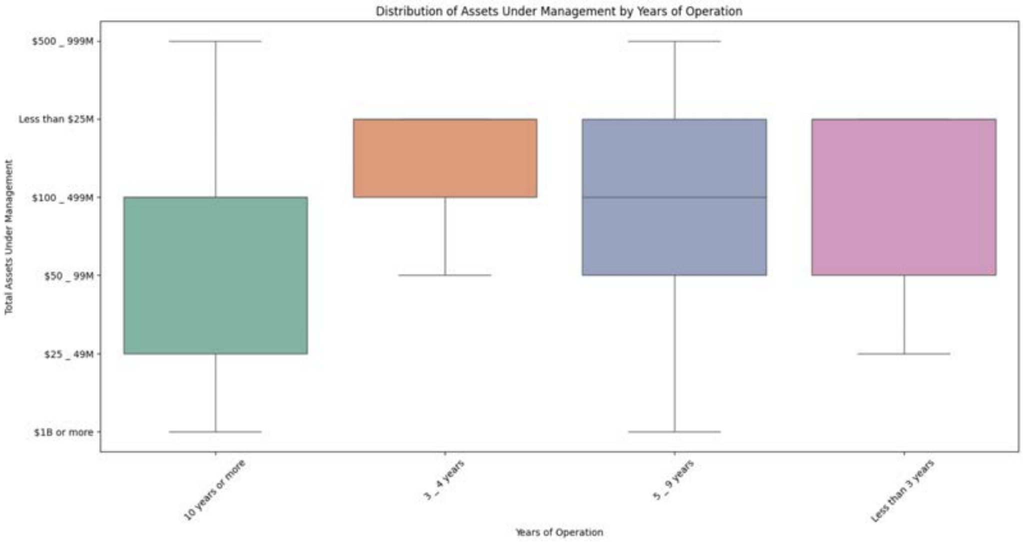

Figure 12: Distribution of the AUM size across the years of operation

the key takeaways:

The most established firms (10+ years) show the widest range of AUM, from $1B or more to $25-49M, indicating high variability in asset sizes among mature institutions.

Mid-range firms (3-9 years) demonstrate more concentrated asset distributions, typically between $50-99M and Less than $25M, suggesting more consistent business sizes in this segment.

Especially, newer firms (less than 3 years) maintain competitive asset ranges similar to their more experienced counterparts, with their median AUM comparable to other groups.

The visualization reveals that operational age isn't necessarily a predictor of AUM size, as institutions across all age groups show significant overlap in their asset ranges.

The boxplot on Figure 13 displays the distribution of Total AUM across various investment categories. Here are the key highlights: Real estate shows the broadest distribution, ranging from less than $25M to $1B or more while infrastructure and Forestry categories maintain substantial asset bases, typically above $100M.

Growth Stage investments in emerging Markets demonstrate wide asset ranges, whereas early stage investments generally show smaller asset concentrations, while late stage investments display moderate to high asset ranges.

Financial Inclusion in emerging Markets shows significant variation whereas SME finance and smallholder farmers categories tend toward lower asset ranges

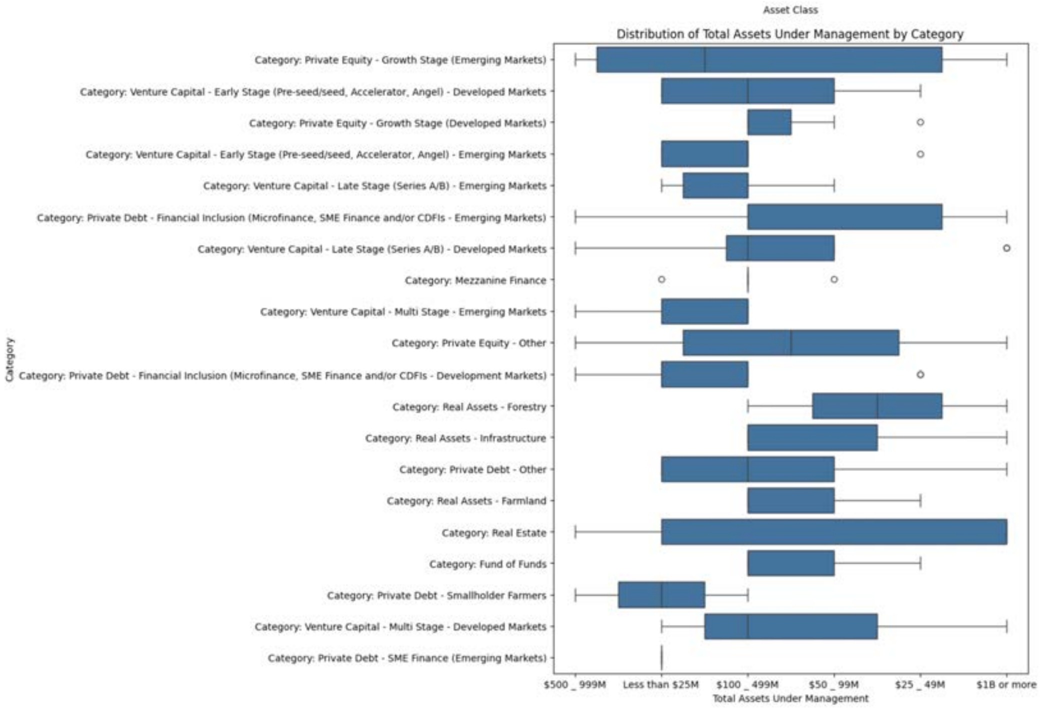

Figure 13: Investment categories over AUM size

while mezzanine finance shows limited distribution with notable outliers.

The visualization reveals considerable variation in asset sizes across investment categories, with Real Estate and Emerging Markets generally showing the widest distributions, while Early Stage and Smallholder Farmer investments tend to have more concentrated, lower ranges.

Later, the regional distribution is observed by categories and asset classes. These comparisons are illustrated in Figures 14 and 15.

The heatmaps present a comprehensive view of the distribution of investments between regions, with two distinct perspectives: asset classes and investment categories.

In figure 14, real estate and infrastructure have also a concentration in the US and Canada with 4 investments and 33 investments with the early stage venture capital (pre-seed / seed, accelerator, angel) in developed markets. Furthermore, infrastructure investments are also concentrated in the US, Canada (4 investments) and limited real estate activity in other regions.

Private debt categories have strong financial inclusion focus in the US and Canada regions(9 investments in developments markets). SME finance also heavily concentrated in the US and Canada (10 investments). Furthermore, private debt

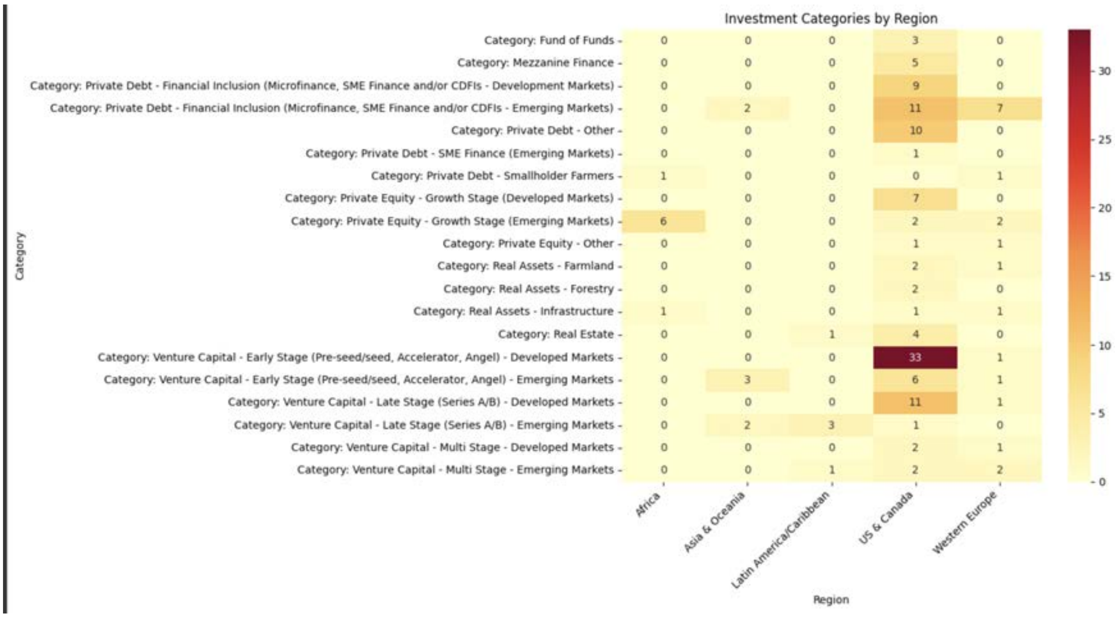

Figure 14: Categories over regions

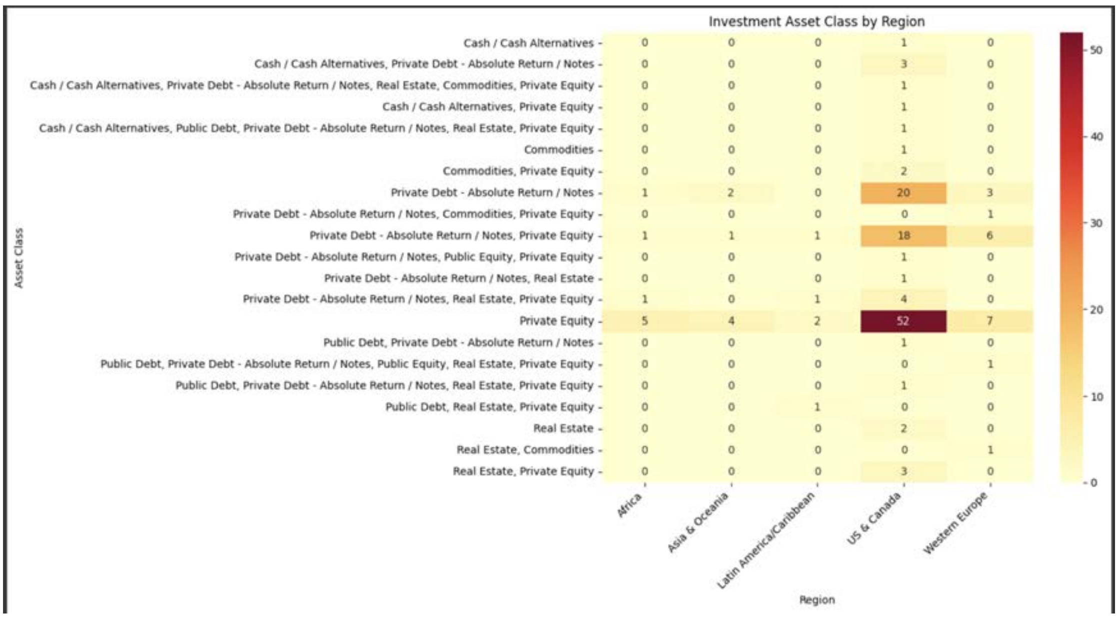

Figure 15: Asset classes over regions

and other categories show a significant presence in the region(7 investments).

Early stage venture capital investments concentrated in the US and Canada regions (11 investments in Developed Markets) multi-stage investments unevenly distributed across western Europe and the US, Canada regions. Moreover, late-stage venture capital investments showing a balanced distribution in developed regions.

From regional point of view, the US and Canada dominate in private debt and private equity. However, Western Europe shows a balanced distribution across venture capital stages, Africa focuses on growth stage private equity in emerging markets and Asia, and Oceania maintains a modest but strategic presence across categories.

In Figure 15, the distribution of the asset class is illustrated. Private equity demonstrates the dominant presence with the highest concentration in the US, Canada with 52 investments, moderate activity in Western Europe (7 investments) and Africa (5 investments), and notable presence in Asia and Oceania (4 investments).

Private debt instruments show significant activity for private debt, the absolute return / notes have 20 investments in the US, Canada, combined private debt instruments show strong presence in regions and a notable concentration of 18 investments in the US, Canada for private debt with private equity combinations.

This distribution reveals clear regional specializations and investment preferences, reflecting different market maturities and stages of economic development in global regions.

Furthermore, when we have carried out the distribution analysis of funds across categories and asset classes on Figure 16, the most significant concentration appears in the venture capital in the early stage (pre-seed/seed, accelerator, angel) in developed markets category with 27 funds in the private equity asset class, representing the highest single concentration in the dataset.

Financial inclusion in emerging markets shows substantial activity with 11 funds in private debt - absolute return / notes, 5 funds in private debt - absolute return/notes, private equity.

Two notable secondary concentrations in the private equity growth stage (emerging markets) with 7 funds in the asset class of the private equity and the early stage of venture capital (emerging markets) with 7 funds in private equity.

The distribution shows clear specialization patterns private equity assets are exclusively concentrated in their corresponding asset class. Private Equity investments categories predominantly appear in the private equity asset class. Financial inclusion demonstrates the most diverse asset class allocation.

There is a notable bias toward developed markets in early stage investments,

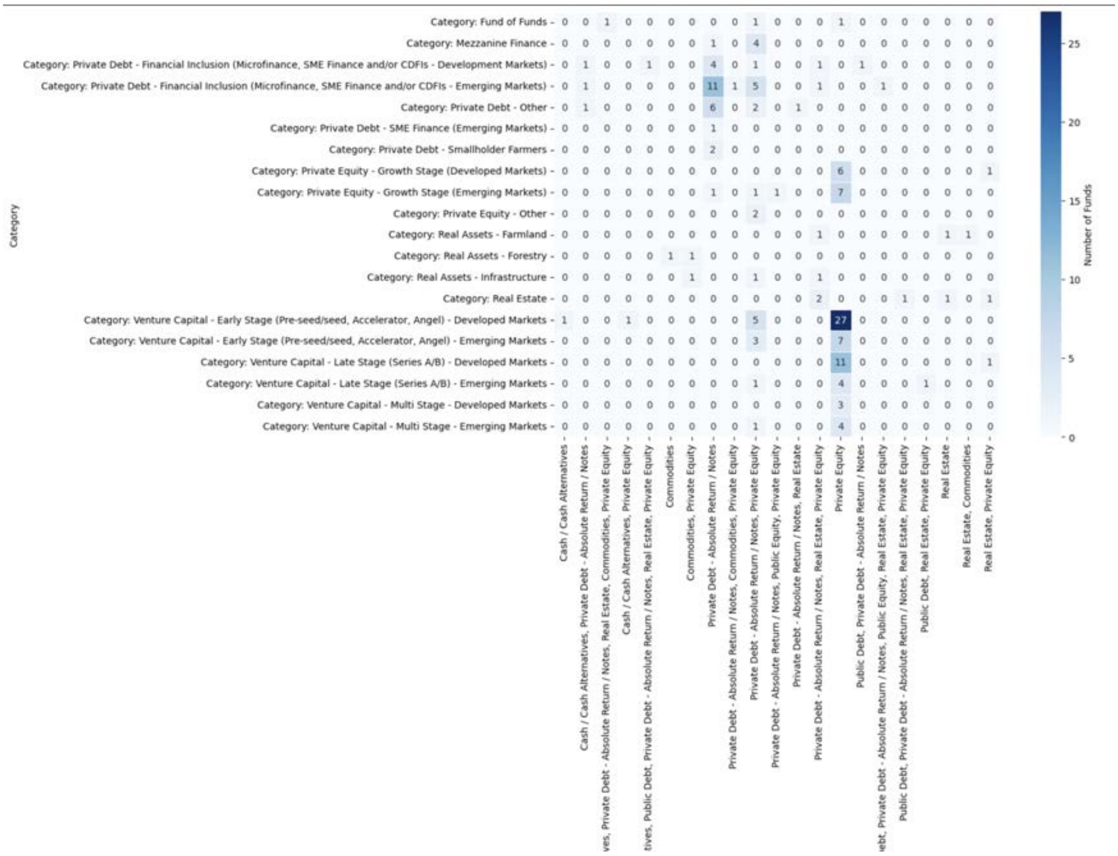

Figure 16: Association between assets classes and investment categories

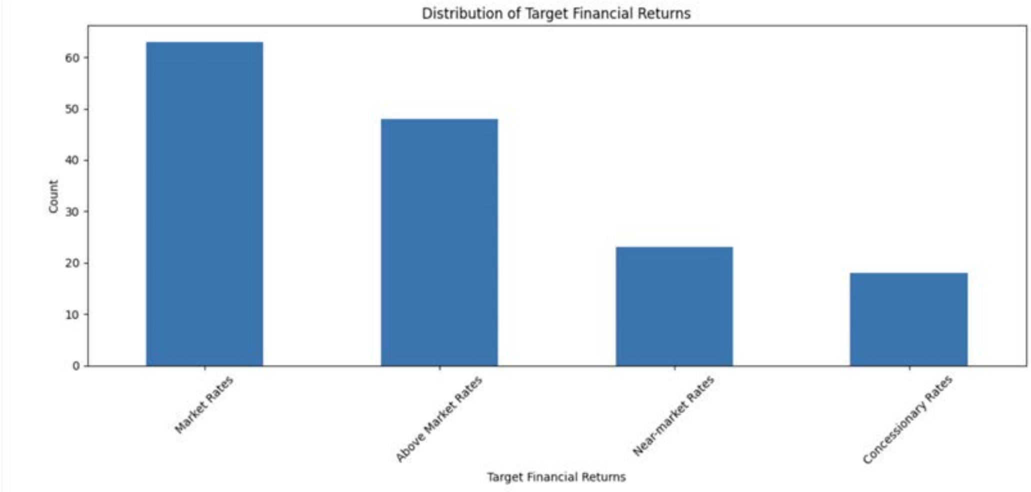

Figure 17: Distribution of the fund counts across rates

emerging markets in financial inclusion and domestic markets in private equity investments.

The distribution pattern suggests a structured market segmentation where asset classes maintain strong alignment with their traditional investment categories, while financial inclusion demonstrates the highest cross-asset class diversification, and private equity maintains the strongest category-asset class correlation.

This analysis reveals a highly specialized investment landscape with clear preferences for certain asset-category combinations, suggesting established market structures and investment strategies.

The stacked bar chart in Figure 17 and Figure 18 illustrate the distribution of target financial returns relative to benchmark rates in five major geographical regions, revealing significant regional variations in financial performance metrics.

The distribution reveals a clear preference for market-rate returns, with a gradual decline in frequency as we move towards concessionary rates. This pattern suggests that while most investors seek standard market returns, there is still significant interest in above-market opportunities and some appetite for investments with lower financial returns, possibly balanced by other non-financial benefits.

The skewed distribution towards market and above-market rates indicates a predominantly return-focused investment landscape, though the presence of near-market and concessionary rates suggests some diversity in investment objectives and strategies.

The bar chart below displays the distribution of the target financial returns in four distinct categories in Figure 18.

The North American region demonstrates the highest overall count of financial

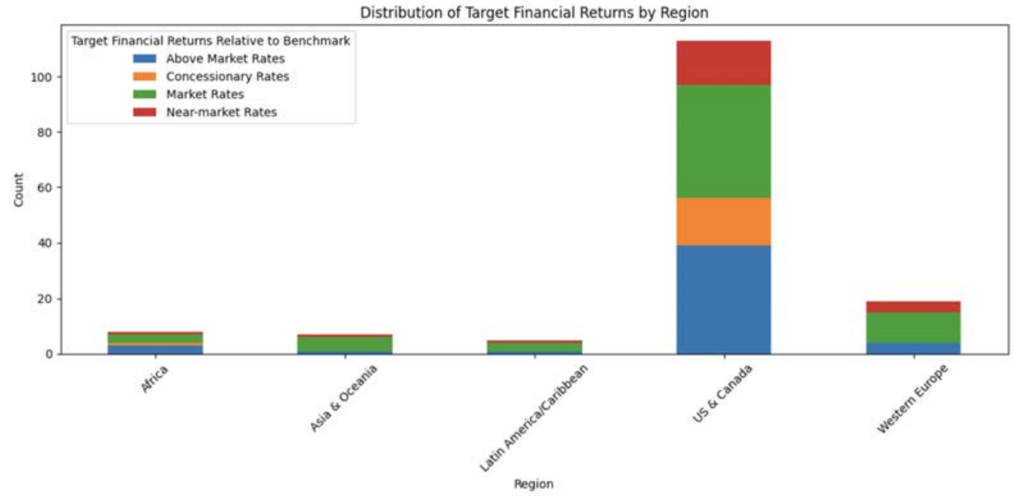

Figure 18: Target Financial Returns across regions

returns, with approximately 110 total cases distributed in four categories. The distribution shows a strong preference for above-market rates, followed by market rates, with smaller proportions of concessionary and near-market rates.

Western Europe exhibits a more moderate distribution pattern, with approximately 18 cases in total. The distribution maintains a relatively balanced mix across all four rate categories, although with a slight preference for market rates over other categories. The emerging market regions show distinct patterns. For example, Africa displays a modest but diverse distribution across all four rate categories, totaling approximately 8 cases. Asia and Oceania show a concentration in market rates, with approximately 7 cases. Lastly, Latin America/Caribbean demonstrates the smallest total count, with approximately 4 cases divided primarily between market and near-market rates.

The data reveal a clear hierarchical structure in rate preferences. For example, the above market rates are predominantly concentrated in the US and Canada, while the market rates are strong across all regions. However, concessionary rates are limited but have a notable presence in developed markets, while rear market rates have a relatively uniform distribution across regions.

The distribution pattern suggests a mature financial market in developed regions, particularly in North America, with a greater capacity for above-market returns. Emerging markets show more conservative return targets, possibly reflecting higher risk considerations and market development stages.

This distribution pattern has significant implications for global investment strategies and regional market development theories, particularly in understanding the relationship between market maturity and target return expectations.

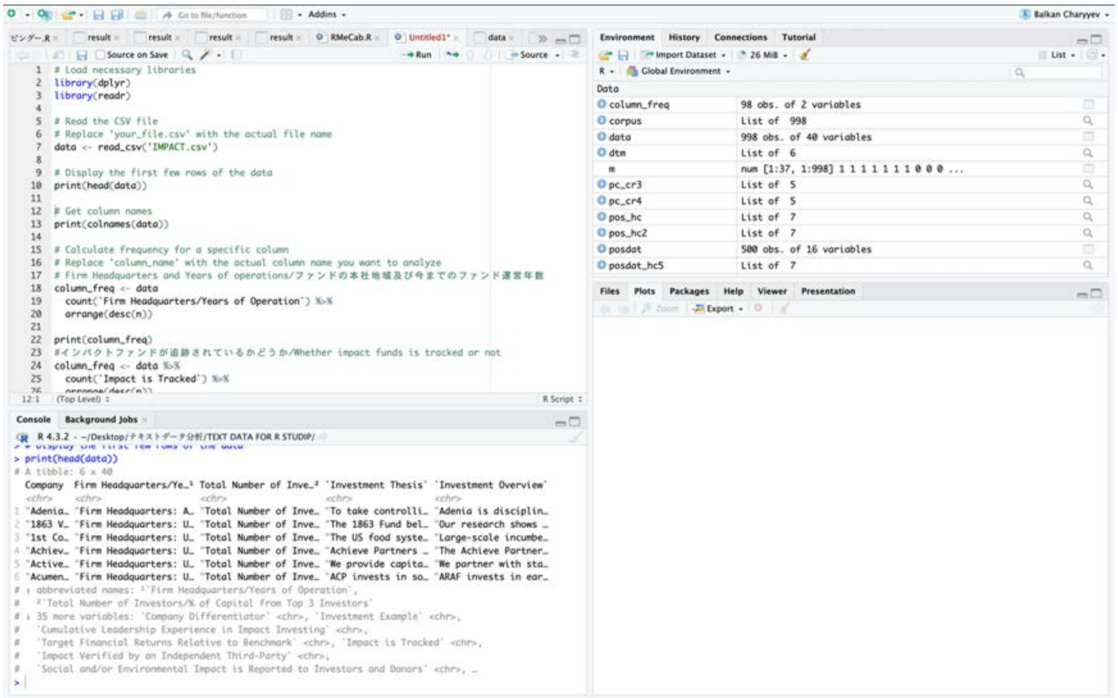

Figure 19: Data set on R studio

4.3 Observations on the R/RStudio and Python

We have uploaded the csv format file of the scraped list of impact fund managers, conducted some observations on investment focus area, category, investment financial returns relative to benchmark, primary target UN development goals of impact fund managers,and whether impact fund is verified by an independent Third-Party in R/RStudio as shown on Figure 19.

An observation of impact fund managers' investment focus reveals a notable concentration on four prominent Sustainable Development Goals (SDGs) set by the United Nations. The findings on Figure 20 and Figure 21 demonstrate a clear prioritization of specific SDGs among impact fund investors:

- *Decent Work and Economic Growth (SDG 8)* emerges as the most targeted goal, with 35 impact funds directing their investments toward this goal.
- *Climate Action (SDG 13)* ranks second in prominence, attracting the attention of 25 impact funds.
- *No Poverty (SDG 1)* is the third most focused goal, with 19 impact funds aiming to address this critical issues.

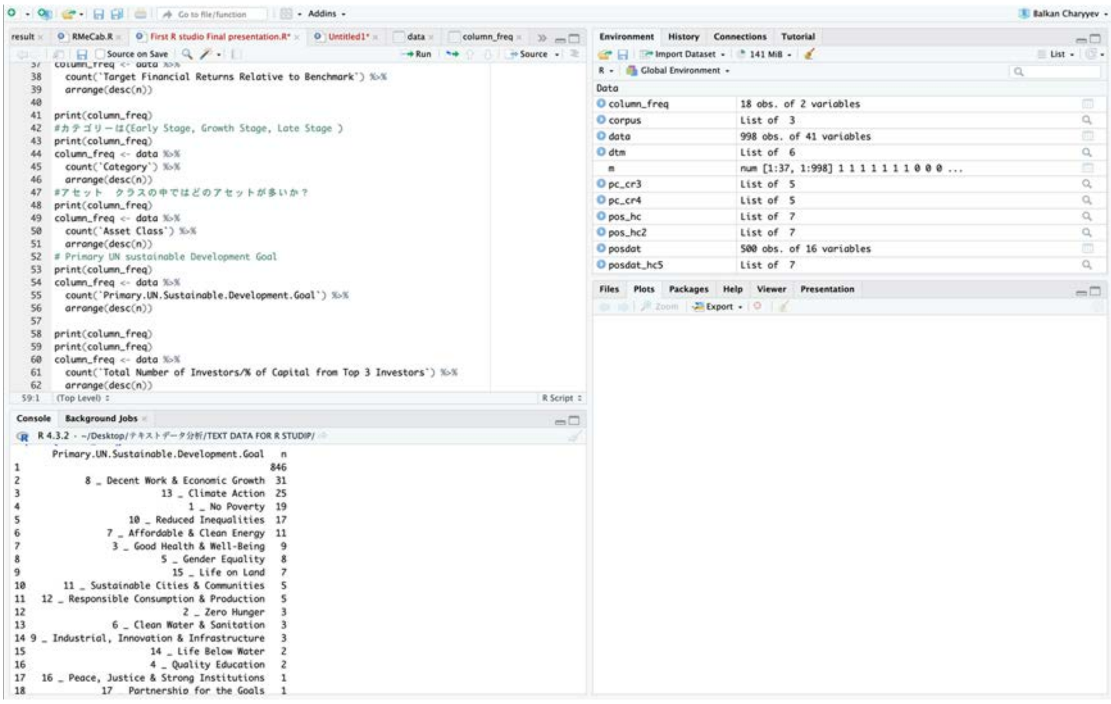

Figure 20: Top 4 UN SDG goals, targeted by Impact fund managers

- *Reduced Inequalities (SDG 10)* rounds out the top four, with 17 impact funds concentrating their efforts on this objective.

The distribution of focus among impact fund managers highlights the industry's current priorities in addressing global challenges. The emphasis on economic growth, climate action, poverty alleviation, and inequality reduction aligns with pressing global concerns and demonstrates the impact investing sector's commitment to driving positive change in these areas.

The concentration on these specific SDGs may reflect both the urgency of these issues and the perceived opportunities for measurable impact and financial returns in these domains. It's worth noting that this focus could also be influenced by factors such as investor preferences, market trends, and the availability of investable opportunities aligned with these goals.

The research sample provides valuable insights into the current landscape of impact investing and the SDGs that are receiving the most attention from fund managers. It underscores the importance of these particular goals in the impact investing ecosystem and may guide future investment strategies and policy decisions in the field.

An analysis of impact fund managers' investment preferences reveals a signifi-

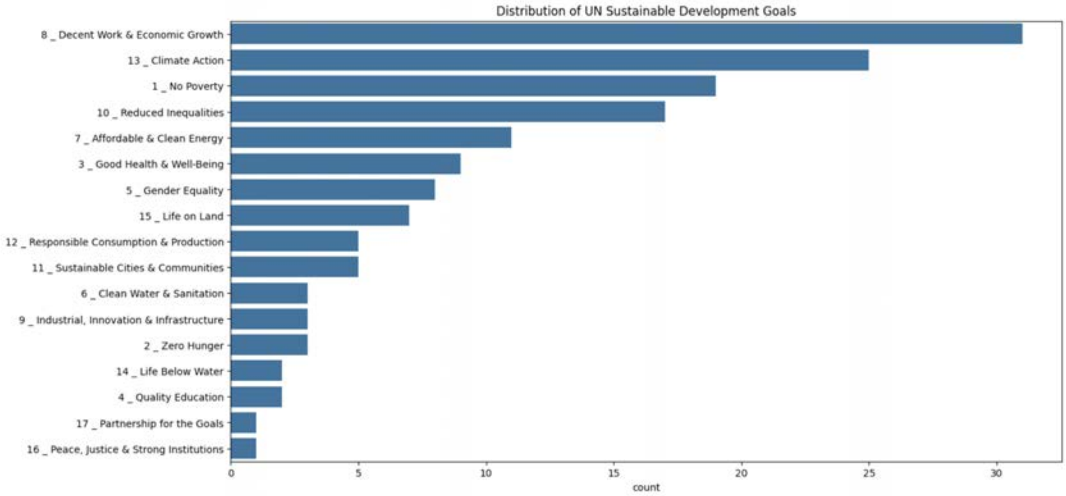

Figure 21: Impact funds count across UN SDG goals

cant inclination towards market-rate or above-market-rate projects. The findings show that over 70% of the impact fund managers are willing to invest in ventures that offer returns at or above market rates.

This trend aligns with the broader impact investment landscape, where the majority of investors seek competitive financial returns along with positive social and environmental outcomes. According to the Global Impact Investment Network , approximately 74 percent of impact investors target risk-adjusted market rate returns. This preference for market-competitive returns challenges the misconception that impact investing necessarily entails financial sacrifice (GIIN Impact Investing Guide, 2023).

Several factors contribute to this phenomenon:

- **Performance expectations:** Most impact investors report that their portfolios meet or exceed expectations for both financial returns and social/ environmental impact.
- **Diverse investor base:** The growing presence of institutional investors, including pension funds and insurance companies, in the impact investing space may be driving the demand for market-rate returns.
- **Maturation of the sector:** As the impact investing market expands and matures, there is increasing evidence that impact and financial performance can be positively correlated.

- **Investor satisfaction:** A high proportion (86%) of impact investors report satisfaction with their financial performance, indicating that market-rate returns are achievable in this sector.

This preference for market-rate returns among impact fund managers reflects a shift in the perception of impact investing. It suggests that these managers believe in the possibility of generating competitive financial returns while simultaneously creating positive social and environmental impact. This approach may help attract more mainstream capital to impact-focused projects, potentially scaling up the overall impact of the sector.

However, it is important to note that a minority of impact investors still intentionally target below-market returns, often aligning with specific strategic objectives or philanthropic goals. This diversity in return expectations highlights the range of approaches within the impact investing ecosystem.

The high proportion of impact fund managers targeting market-rate or above-market-rate projects underscores the evolving nature of impact investing. It suggests a growing confidence in the ability to achieve both financial and impact objectives without compromising either, potentially paving the way for increased capital allocation to impactful ventures in the future.

The study's findings reveal a significant disparity in third-party verification among impact fund managers on figure 24. Out of the total sample, only 22 fund managers were found to have undergone verification by an independent third party, while the remaining 130 lacked such external validation. This observation highlights a notable gap in the adoption of independent verification practices within the impact investment sector.

The low rate of third-party verification among impact fund managers raises important questions about transparency and accountability in the industry. This discrepancy may have implications for investor confidence and the overall credibility of impact claims made by fund managers. More research is needed to explore the reasons behind this low verification rate and its potential consequences for the impact investment ecosystem.

To understand and observe the text of the impact fund managers data, this research utilizes the KH-coder, quantitative text-mining applications and realized the following illustrations.

4.4 Observations on KH-coder

The visual analysis of the impact fund landscape reveals several major thematic clusters, each highlighting significant areas of focus for impact fund managers.

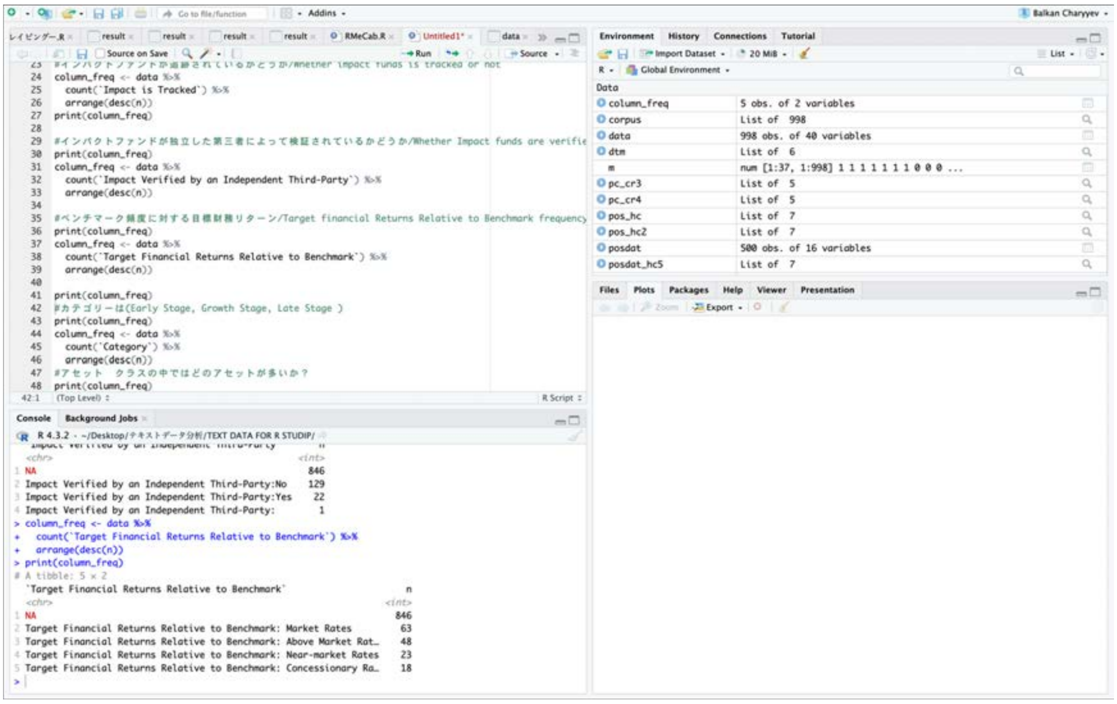

Figure 22: Target financial returns relative to benchmark

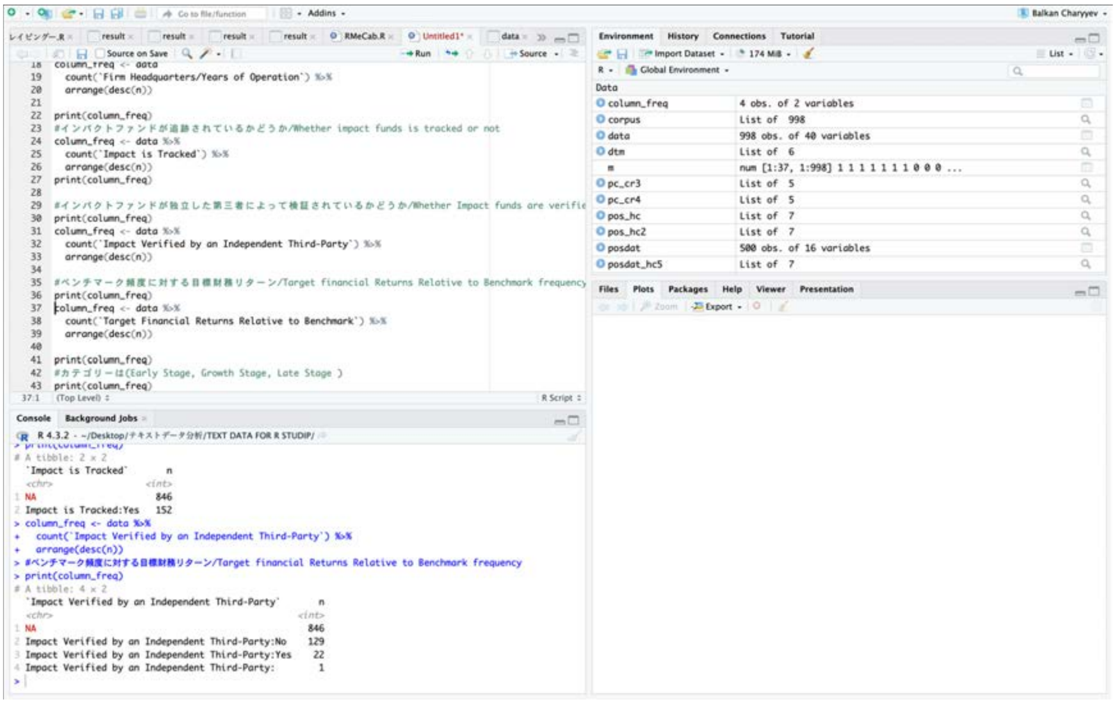

Figure 23: Impact is verified by an Independent Third-party

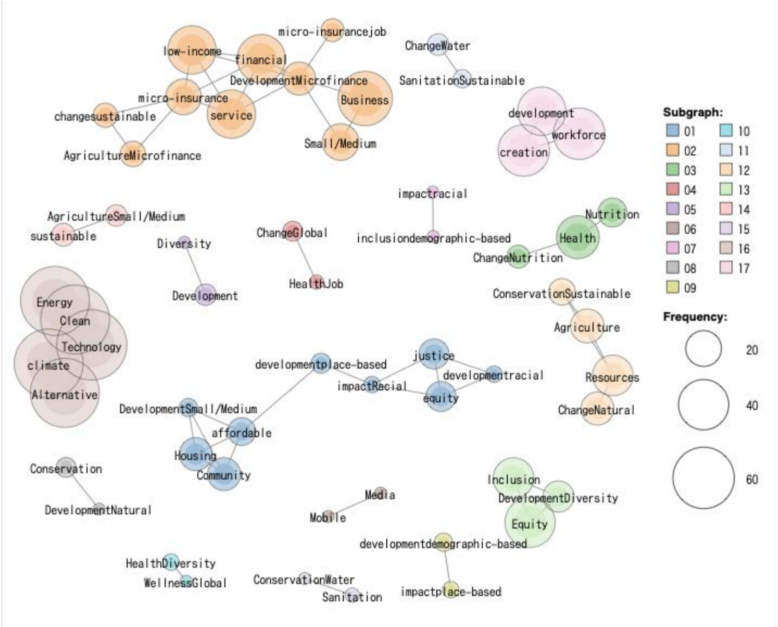

Figure 24: Investment focus areas

These clusters provide insights into the current priorities and trends within the impact investing sphere.

A prominent cluster of interconnected terms demonstrates a substantial emphasis on climate technology and renewable energy solutions:

- “Energy”
- “Clean”
- “Technology”
- “Climate”
- “Alternative”

This cluster indicates that a considerable portion of impact investments is directed towards addressing global climate challenges and promoting sustainable energy alternatives. The strong connection between “Conservation” and “Development Natural” emphasizes the importance of environmental conservation in impact fund portfolios, suggesting that fund managers are actively seeking investment opportunities that align with sustainable development practices while simultaneously preserving natural resources and ecosystems.

Another prominent cluster focuses on financial inclusion and microfinance:

- "Financial"
- "Low-income"
- "Microfinance"
- "Insurance"

This cluster indicates a substantial emphasis on providing accessible financial services to minorities and underserved populations. The strong connection between these terms and "Development Microfinance" highlights the importance of developing markets as a key thematic area for impact fund portfolios.

The health and well-being sector emerges as another significant focus area:

- "Health"
- "Nutrition"
- "Sustainable"

This cluster suggests that a considerable portion of impact investments is directed towards improving health outcomes and promoting sustainable wellness solutions. The connection between these health-related terms and broader development themes underscores the recognition of health as a fundamental component of overall societal progress.

A cluster centered around social justice and racial equity includes:

- "Justice"
- "Equity"
- "Development racial"

This cluster indicates that impact fund managers are directing investments towards addressing systemic inequalities and promoting more equitable outcomes for marginalized communities. The strong connection between these justice-related terms and "affordable housing" and "community" underscores the recognition of housing and community development as critical components of advancing social equity.

The analysis reveals several key insights about the impact investing landscape:

Thematic concentration: Significant clustering around key themes such as environmental sustainability, social finance, health and well-being, and justice and equity.

Integrated Approach: Multiple interconnections between social and environmental impact themes, indicating a holistic strategy that recognizes the interdependence of various sustainability challenges.

Targeted investments: Strong presence of place-based ("development geographic based") and demographic-based ("Small/Medium") targeting, implying tailored investments to specific regions and population segments.

Cross-Sector Sustainability Focus: Recurrence of sustainability-related terms across multiple domains (agricultural, financial, environmental), underscoring the pervasive nature of sustainability considerations in impact investing.

Alignment with Global Development Agendas: Themes and interconnections showing strong parallels with the United Nations Sustainable Development Goals (SDGs).

Emerging Priorities: Prominence of justice and equity themes, along with their connection to community development and affordable housing, reflecting an increasing recognition of the role of impact investing in addressing systemic inequalities and promoting inclusive growth.

Given these observations, conducting a semantic similarity analysis between the investment theses offered by impact fund managers and the UN SDGs would be a valuable exercise. This analysis would quantify alignment, identify gaps, enhance reporting, guide strategy development, and facilitate collaboration within the impact investing sector.

4.5 Semantic similarity measurements

This section employs the concept of cosine similarity to quantify the semantic similarity between investment theses of firms and the United Nations Sustainable Development Goals (UN SDGs). This approach, grounded in previous studies, offers a nuanced understanding of textual similarities beyond mere word matching. The rationale for using SDG goals as semantic measurements for impact fund companies' investment theses is rooted in the fundamental alignment between these goals and the objectives of impact investing.

Alignment of Impact Funds with SDGs Impact funds are inherently designed to achieve and realize SDG goals, often reporting their progress and alignment on their websites. Concurrently, each fund develops its own investment thesis, which serves as a clearly defined hypothesis about where and how capital can be deployed to address specific social or environmental issues. A well-defined thesis helps to crystallize thinking around a problem set and is particularly useful in aligning teams on common shared values and focus areas.

Investment Thesis and SDGs The investment thesis of an impact fund plays a crucial role in narrowing the search for investment opportunities, providing actionable insights to share with co-investors or sources of deal flow and guiding the deployment of capital towards specific social and environmental issues

Semantic Similarity Analysis By observing the semantic similarities between SDG goals and investment theses, we can gain valuable insights into how closely the deployed impact capital aligns with SDG objectives in addressing specific social and environmental issues. This analysis goes beyond surface-level comparisons, delving into the underlying meanings and intentions expressed in both the SDGs and the investment theses.

Validation of SDGs as Semantic Measurements The use of SDG goals as semantic measurements for impact fund investment theses is validated by several factors. Firstly, SDG goals provide a globally recognized, comprehensive framework for addressing social and environmental challenges. Secondly, both SDG goals and impact investment theses often use similar terminology and concepts, facilitating meaningful semantic comparisons.Thirdly, SDG goals and impact investment theses are both focused on achieving tangible, positive outcomes, making them conceptually aligned. Fourthly, both SDG goals and well-crafted investment theses consider the interconnected nature of social and environmental issues. Lastly, SDG goals offer specific, measurable targets that can be mapped to the objectives outlined in investment theses.

By employing cosine similarity to analyze the semantic relationship between SDGs and investment theses, we can quantitatively assess the degree to which impact funds are aligning their capital deployment strategies with globally recognized sustainability objectives. This approach provides a more nuanced and accurate representation of the alignment between impact investing strategies and sustainable development goals, offering valuable insights for investors, policymakers, and researchers in the field of impact finance.

4.6 Semantic Similarity and Cosine Similarity

Cosine similarity measures the cosine of the angle between two vectors in a multi-dimensional space. In the context of text analysis, these vectors represent the semantic content of documents. This method is particularly effective because it captures semantic relationships rather than exact word matches. It can also identify passages expressing similar concepts using different terminology. Cosine similarity is less sensitive to document length compared to other similarity measures.

The similarity score ranges from 0 to 1, where 0 indicates perfect similarity, and 1 indicates perfect dissimilarity. In practice, for text analysis, the scores typically range from 0 to 1 due to the non-negative nature of term frequencies. This score quantifies the degree of semantic difference between two passages. A higher modification score indicates greater divergence in meaning between the compared texts.

4.7 Vector Space Model (VSM)

The thesis utilizes the Vector Space Model, a well-established approach in information retrieval and text mining. In VSM, documents are represented as vectors in a high-dimensional Euclidean space. Each dimension corresponds to a unique term in the corpus. This model has also been applied by, for example, Lu (2021), who has examined quality of non-financial reporting practices.

The semantic similarities are determined using word embeddings, which are dense vector representations of words in a continuous vector space. These embeddings capture semantic relationships between words based on their usage contexts in large text corpora.

This approach allows for a robust comparison of investment theses with UN SDG goals, capturing semantic nuances that might be missed by simpler text matching techniques. By employing this methodology, the thesis aims to provide a more accurate assessment of how closely firms' investment strategies align with specific SDG objectives.

The VSM-based similarity score is defined as follows:

$$\mathrm{sim} = \cos(\theta) = \frac{\mathbf{A}}{\|\mathbf{A}\|} \cdot \frac{\mathbf{B}}{\|\mathbf{B}\|} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} \tag{1}$$

The formula to calculate cosine similarity between two d=768 dimension vectors A and B is

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{d} A_i B_i}{\sqrt{\sum_{i=1}^{d} A_i^2}\sqrt{\sum_{i=1}^{d} B_i^2}} \tag{2}$$

Where θ is the angle between A and B, $\|\mathbf{A}\|$ is the vector length of A and $\|\mathbf{B}\|$ is the vector length of B.

The cosine similarity is bounded by -1 and +1 with a higher score indicating ($\cos(\theta) = 1$), a value of 1 corresponds to perfect similarity (that is, the two vectors are aligned in the same direction), while - 1 indicates perfect dissimilarity (i.e., the two vectors are aligned in opposite directions). We define the measure of

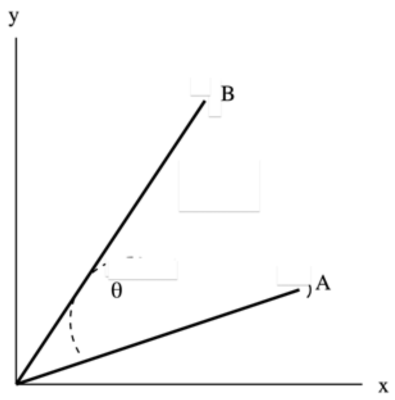

Figure 25: VSM-based two-dimensional space

corresponding dissimilarity score as $1 - \cos\theta$. From this definition, it follows that the cosine distance is zero if and only if the two vectors are positive scalar multiples of each other (i.e., they point in the same direction). It attains its maximum value of 2 if and only if the two vectors are negative scalar multiples of each other (i.e., they point in opposite directions). The formula of disimilarity score is shown as follows:

$$\boxed{\text{Disimilarity score} = 1 - \cos\theta} \tag{3}$$

An alternative approach, which has been taken by aforementioned Lu (2021) is to compute $1 - \cos\theta^2$ have also been tried, but we have not found significant differences in quality between $1 - \cos\theta$ and $1 - \cos\theta^2$.The random distribution of pairs of $1 - \cos\theta$ and $1 - \cos\theta^2$ is attached into Appendix as a figure 36. Based on the that boxplot, we have decided to continue with the standard approach $1 - \cos\theta$ as a disimilarity equation (3).

4.8 BERT vector analysis

This study employs the pre-trained BERT (Bidirectional Encoder Representations from Transformers) model from Huggingface to embed our corpus. BERT represents a significant advancement in natural language processing (Devlin et al.).

The BERT base model architecture comprises 12 transformer layers (blocks), 12 attention heads, 110 million parameters and a hidden size of 768 dimensions.

The model is trained on an extensive unlabeled text corpus, including Wikipedia and Book corpus, utilizing transformer architecture with an attention mechanism for learning word embeddings.

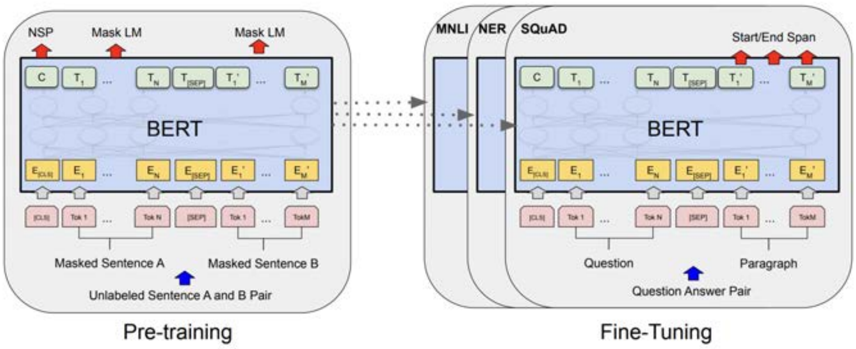

Figure 26: BERT training architecture (https://aclanthology.org/N19-1423.pdf)

BERT's pre-training process consists of two crucial steps masked Language Modeling (MLM) and next Sentence Prediction (NSP). The model represents text using three complementary embedding layers token embeddings, segment embeddings, position embeddings.

In our analysis, we utilized this pre-trained BERT model to generate 768-dimensional vectors and subsequently computed cosine similarity between pairs of non-zero vectors corresponding to specific documents. The resulting vector representations capture the semantic relationships between documents in a high-dimensional space, enabling precise similarity measurements between textual content.

The vector outputs, as demonstrated in our implementation, take the form of dense numerical arrays, each containing 768 dimensions that encode the semantic information of the input text. These vectors serve as the foundation for our similarity calculations and subsequent analysis.

Prior to generating vectors using BERT, this study implements a comprehensive text preprocessing pipeline to ensure optimal data quality and meaningful analysis. The preprocessing steps address several key considerations: 1. Stop Words and Punctuation Removal 2. To enhance the quality of semantic analysis, the following elements are removed from the corpus from stop words, punctuation marks, corporate names, numeric digits. Because these elements are generally considered semantically meaningless. Their modifications should not be interpreted as substantial changes. Changes in numeric values alone do not constitute meaningful semantic alterations.

After preprocessing, the cleaned corpus is processed through the BERT model, which generates 768-dimensional vectors representing the semantic content of each definition. These vectors capture the nuanced semantic relationships between texts while excluding noise from non-semantic elements.

Refer to Figure 23 on Appendix to observe matrix obtained after BERT vector analysis. For better understanding, the visualization matrix is illustrated on Figure 24 on Appendix.

5 Results and Discussion

5.1 Observation between AUM size and return

In this section, we examine the possible association between asset size (AUM) and the target financial return of impact fund managers, relative to their respective benchmarks, by building a contingency table using Chi-square statistics. The underlying hypothesis posits that impact investment funds with larger AUM sizes tend to exhibit more risk-averse behavior in their investment strategies.

The study's primary objective is to analyze whether the magnitude of AUM influences the target return set by impact fund managers. This target return is defined as the desired financial performance in relation to a specified benchmark. By exploring this relationship, the research seeks to shed light on the risk appetite and investment strategies employed by impact funds of varying sizes.

The rationale for this assumption comes from the assumption that larger impact funds, which manage more substantial asset pools, can adopt more conservative approaches to risk management. This conservative stance could potentially manifest in lower target returns relative to their benchmarks, as these funds prioritize capital preservation and steady growth over aggressive performance targets.

Through this analysis, the research aims to contribute to the growing body of knowledge surrounding impact investing, particularly in understanding the interplay between fund size, risk tolerance, and financial objectives within the impact investment landscape.

The chi-square test of independence was conducted to examine the relationship between AUM size and target financial returns relative to benchmarks. The analysis yielded the following key findings on Figure 14 where chi-square statistic is 15.88, p-value equals to 0.39 and degrees of freedom is 15.

The p-value of 0.39 is substantially higher than the conventional significance level of 0.05, indicating that there is no statistically significant relationship between AUM size and target financial returns. This suggests that the size of assets under management does not significantly influence the choice of target returns relative to benchmarks.

Based on the contingency tables, several notable patterns emerge: funds in the $100-499M range show the highest frequency of targeting market rates (23 funds) and above market rates (16 funds) and smaller funds (less than $25 M)

```
Contingency Table:
Return          Target Financial Returns Relative to Benchmark: Above Market Rates  \
AUM
$100 _ 499M                                                    16
$1B or more                                                     3
$25 _ 49M                                                       6
$50 _ 99M                                                       6
$500 _ 999M                                                     6
Less than $25M                                                 11

Return          Target Financial Returns Relative to Benchmark: Concessionary Rates  \
AUM
$100 _ 499M                                                     8
$1B or more                                                     5
$25 _ 49M                                                       2
$50 _ 99M                                                       1
$500 _ 999M                                                     0
Less than $25M                                                  2

Return          Target Financial Returns Relative to Benchmark: Market Rates  \
AUM
$100 _ 499M                                                    23
$1B or more                                                     8
$25 _ 49M                                                       4
$50 _ 99M                                                       5
$500 _ 999M                                                     3
Less than $25M                                                 20

Return          Target Financial Returns Relative to Benchmark: Near-market Rates
AUM
$100 _ 499M                                                     7
$1B or more                                                     2
$25 _ 49M                                                       3
$50 _ 99M                                                       1
$500 _ 999M                                                     3
Less than $25M                                                  7

Chi-Square Test Results:
Chi-square statistic: 15.881551158181592
p-value: 0.3899672767852277
Degrees of freedom: 15

Expected frequencies:
[[17.05263158  6.39473684 22.38157895  8.17105263]
 [ 5.68421053  2.13157895  7.46052632  2.72368421]
 [ 4.73684211  1.77631579  6.21710526  2.26973684]
 [ 4.10526316  1.53947368  5.38815789  1.96710526]
 [ 3.78947368  1.42105263  4.97368421  1.81578947]
 [12.63157895  4.73684211 16.57894737  6.05263158]]
```

Figure 27: AUM size and Target Return Chi-square statistics

also demonstrate substantial representation across different return targets, with 20 funds targeting market rates. However, concessionary rates are less commonly targeted in all AUM sizes, with particularly low frequencies in the category $500 -999M.

The initial hypothesis suggesting that larger AUM sizes correlate with more risk-averse investment strategies (reflected in target returns) is not supported by statistical evidence. The data indicates that fund size does not systematically predict the target return strategy chosen by impact fund managers.

This finding challenges the conventional assumption that larger impact funds necessarily adopt more conservative return targets, suggesting that other impact factors may play more significant roles in determining target return strategies in impact investing. Therefore, it was necessary to analyze the BERT semantic similarity analysis.

5.2 BERT semantic similarity results

The results obtained are illustrated as box plots on Figure 15. In the vertical line, the distances generally range from about 0.10 to 0.45 which can indicate that most impact fund managers are closely aligned with SDG goals. In horizontal line, it represents the SDG goals and most SDG distances cluster between 0.15 and 0.35. Lower values indicate closer alignment with the SDG goals, while higher values suggest greater distance / less alignment.

Goals with higher distances demonstrate less alignment. Observation represents "Life on Land" and "Climate Action" shows relatively higher median distances, and "Gender Equality" also shows a higher median distance and more spread.

Goals with lower distances represent better alignment. "No Poverty" and "Industry Innovation and Infrastructure" show lower median distances, and "Clean Water and Sanitation" appears to have relatively better alignment.

However, some goals show high variability represented by larger boxes and more spread in dots. They are "Gender Equality", "Life Below Water" , "Climate Action" goals. The rest of the impact fund managers show more consistency which is represented by smaller boxes ("No Poverty", "Industry Innovation and Infrastructure").

There are also outliers and extremes. Several SDGs have notable outlier points (black dots) far above their boxes. These represent companies that are significantly underperforming in specific SDGs or have misaligned their investment thesis with their target SDG goals. The pattern of outliers is fairly consistent between goals, suggesting systematic challenges for certain companies. From distribution perspective, the most goals show relatively symmetric distributions. Some goals (such as

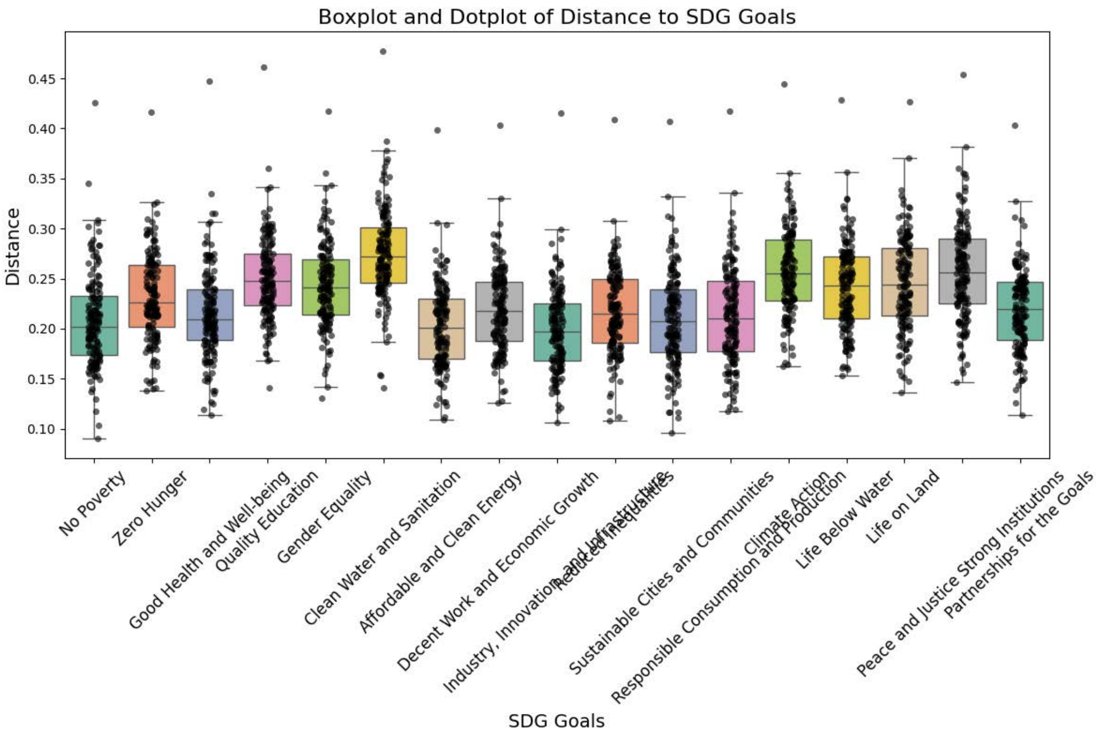

Figure 28: Distribution of the impact fund companies aligning with SDG goals

"Climate Action") show a slight positive skew, with more companies having larger distances.

Furthermore, we have conducted a clustering analysis with the closest neighbors of impact fund managers with alignments with the SDG goals. As a result I have built 6 clusters and visualized them in Figure 16.

5.3 Clusters and Target Financial Returns

This research also aims to investigate the potential correlation between impact fund clusters and the target returns set by impact fund managers. To this end, we conducted a hierarchical cluster analysis. We have adopted Ward‘s method as our clustering criterion and the Euclidean distance as our distance measure points. The underlying hypothesis posits that clusters closely aligned with Sustainable Development Goals (SDGs) may exhibit similar risk appetites.

The investigation seeks to examine whether impact funds grouped into specific clusters based on their alignment with SDG objectives demonstrate comparable target return profiles. This analysis is predicated on the assumption that funds operating within similar SDG-aligned sectors or themes may share analogous impact risk-return characteristics. By exploring this relationship, the study aims to shed light on potential patterns in risk appetite and return expectations across different impact investment categories.

The examining the interplay between impact objectives, as represented by SDG alignment, and financial return targets.

The contingency table reveals distinct patterns in six groups regarding target financial returns relative to benchmarks. A chi-square test yielded x = 25.38 with p value = 0.045, indicating a statistically significant relationship between groups and return targets.

Since the p-value (0.045) is less than the conventional significance level of 0.05, we can reject the null hypothesis of independence. This suggests that there is a statistically significant relationship between the clusters and returns. The contingency table shows the distribution of returns across different clusters.

Cluster 1 demonstrates strong preference for above-market rates (17) and market rates (12), suggesting an aggressive return strategy, whereas cluster 4 shows similar tendencies with 16 funds targeting above-market rates and 19 targeting market rates and cluster 6 exhibits the highest concentration in market rates (20) while maintaining moderate representation in concessionary rates (8). Furthermore, group 3 shows minimal activity across all categories, with only one fund targeting market rates, and group 5 maintains low frequencies across categories but shows equal preference for market and near-market rates (3 each).

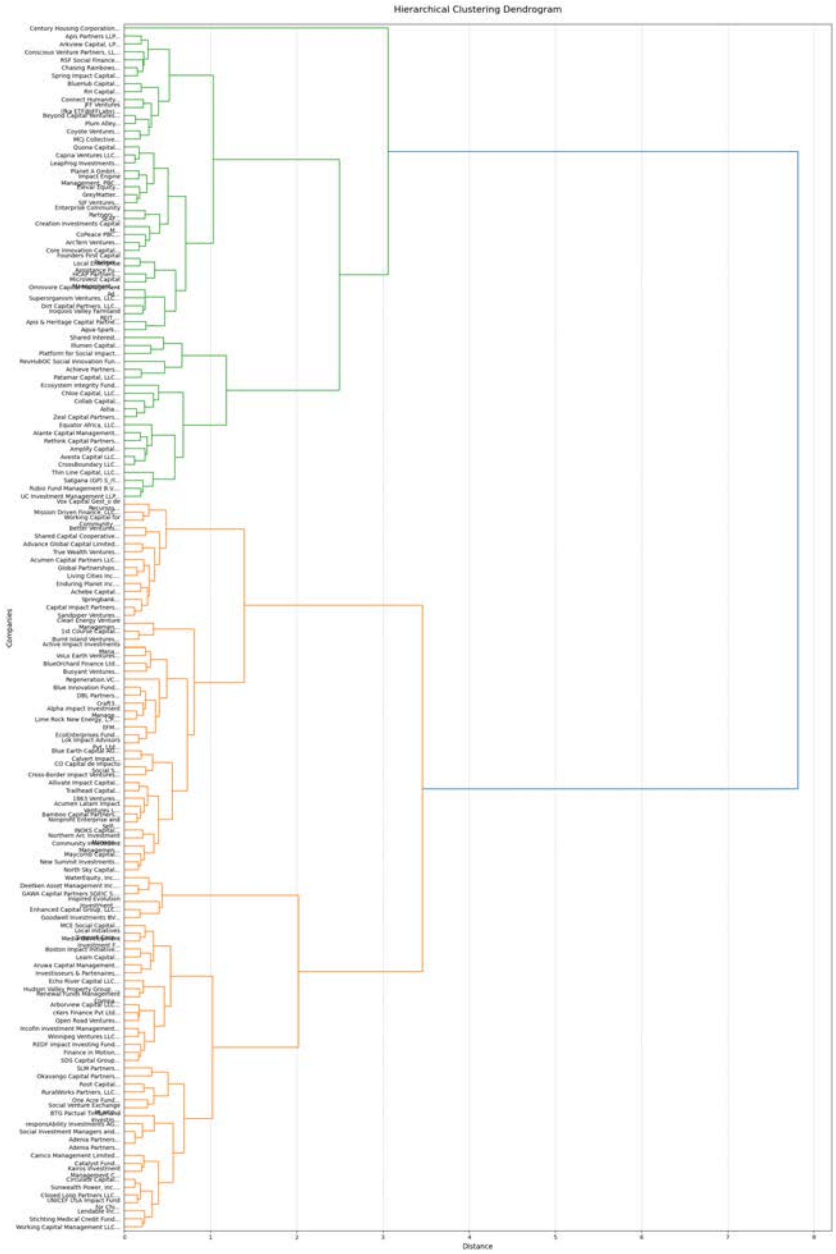

Figure 29: Hierarchical clustering dendrogram

The p-value of 0.045 falls below the conventional significance level of 0.05, suggesting that the clustering pattern is not random. This indicates significant differences in return target preferences between clusters, implying that funds within each cluster share similar investment strategies and risk appetites. These variations from expected frequencies contribute to the statistical significance of the relationship between clusters and return targets.

Furthermore, the hierarchical clustering algorithm in Figure 29 grouped the companies into 6 distinct clusters, revealing interesting patterns in the dataset.

- **Cluster 1:** Contains 38 companies, representing a significant group.
- **Cluster 2:** Comprises 21 companies, forming a moderate-sized group.
- **Cluster 3:** A unique cluster with only 1 company (Century Housing Corporation), suggesting it has distinctive characteristics.
- **Cluster 4:** The largest cluster with 47 companies, indicating a common set of features among these firms.
- **Cluster 5:** A smaller cluster of 6 companies, potentially representing a niche group.
- **Cluster 6:** Another substantial cluster with 39 companies.

This result indicates:

- **Dominant Clusters:** Clusters 1, 4, and 6 are the largest, suggesting three main categories or types of companies in the dataset.
- **Niche Groups:** Clusters 2 and 5 represent smaller groups, which might indicate specialized investment theses and unique business models or characteristics.
- **Outlier:** Cluster 3, suggests this company has unique features and investment thesis that set it apart from all others in the dataset.

Moreover, we do not have sufficient evidence to observe and validate the governance structure of impact investments. This question remains to be open and requires further analysis and investigation. It is out of the scope of this thesis and does not aim to answer governance structure of the impact investing. This is an important issue to discuss and carry out further analysis and observations.

However, research provided by Geczy et al. (2021) mentions that impact funds employ several key mechanisms to address potential conflicts between financial and

```
Contingency Table:
Cluster                                                             1   2  3   4  5   6
Return
Target Financial Returns Relative to Benchmark: Above Market Rates   17  10  0  16  0   5
Target Financial Returns Relative to Benchmark: Concessionary Rates   5   2  0   3  0   8
Target Financial Returns Relative to Benchmark: Market Rates         12   8  1  19  3  20
Target Financial Returns Relative to Benchmark: Near-market Rates     4   1  0   9  3   6

Chi-Square Test Results:
Chi-square statistic: 25.384363544037125
p-value: 0.0450136443040441
Degrees of freedom: 15

Expected frequencies:
[[12.         6.63157895  0.31578947 14.84210526  1.89473684 12.31578947]
 [ 4.5        2.48684211  0.11842105  5.56578947  0.71052632  4.61842105]
 [15.75       8.70394737  0.41447368 19.48026316  2.48684211 16.16447368]
 [ 5.75       3.17763158  0.15131579  7.11184211  0.90789474  5.90131579]]
```

Figure 30: Chi-square test statistics between clusters and return

social goals by underlining impact funds do not choose not to fix compensation to impact:

Firstly, most funds (70-80%) incorporate measurable impact metrics and due diligence processes into legal agreements, creating enforceable duties rather than just aspirational goals.

Secondly, over 90% of funds establish LP advisory committees with oversight on deal selection, due diligence, and conflicts of interest. This enables dynamic monitoring of both financial and impact objectives.

Thirdly, funds often use more flexible language for impact goals (e.g., "best efforts" clauses) compared to rigid financial terms, allowing adaptation to evolving impact opportunities.

Fourthly, market-rate seeking (MRS) funds tend to employ more rigid impact terms (e.g., veto rights, ESG standards) compared to non-market-rate seeking (NMRS) funds, potentially to mitigate stronger profit motivations.

Lastly, stronger impact terms in Limited Partners agreements correlate with more impact-focused portfolio company contracts, creating a governance cascade.

These mechanisms demonstrate how impact funds structurally adapt governance to balance financial returns with social/environmental objectives, moving beyond symbolic commitments to enforceable accountability.

6 Conclusion

6.1 Findings

This study aimed to investigate the semantic similarity of non-financial disclosures and the correlation between impact fund managers' characteristics and their Assets Under Management (AUM) size, returns, and clusters sharing similar Sustainable Development Goal (SDG) alignments. The research employed text-mining techniques to explore similarity scores and conducted analyses using various statistical tools.

Correlation Between AUM Size and Target Returns: Our analysis revealed no statistically significant correlation between AUM size and target returns relative to benchmarks. This finding challenges the conventional hypothesis that larger impact funds necessarily adopt more conservative return targets. Instead, it suggests that other factors may play more significant roles in determining target return strategies in impact investing.

BERT Semantic Similarity Analysis: The lack of correlation between AUM size and target returns necessitated a deeper analysis using BERT semantic similarity techniques. This approach allowed for a more nuanced understanding of the relationships between impact funds' characteristics and their investment strategies.

Cluster Analysis and Target Returns: In examining the relationship between the six identified clusters and target returns, we observed a p-value of 0.045, which falls below the conventional significance level of 0.05. This finding suggests that the clustering pattern is not random. Secondly, there are significant differences in return target preferences between clusters. Lastly, impact funds within each cluster likely share similar investment strategies and risk appetites.

These results indicate that impact funds with similar SDG goal alignments tend to share comparable risk appetites and investment strategies. This insight is crucial for investors, investees, and policy makers to understand the common impact return and impact risk strategies employed in impact investments.

Analysis of SDG-Focused Impact Funds: Upon examining the 17 closest matches of impact funds, as summarized in Figures 25, 26, and 27 of the appendix, we identified only three impact fund managers that specifically focus their investment theses on certain SDG goals.

This finding is particularly noteworthy, as it highlights that while SDG alignment is a consideration for many impact funds, only a select few explicitly structure their investment theses around specific SDG goals.

These findings provide valuable information for fund managers, investors, and investors in formulating future investment theses. The observed patterns in SDG alignment, risk appetite, and investment strategies can inform more targeted and effective impact investing approaches. Further research could explore the reasons behind the limited number of funds explicitly focusing on specific SDG goals and the potential benefits of such focused strategies in the impact investing landscape.

6.2 Similarities and Differences with Previous Studies and Novelty of the Research

Our findings demonstrate both convergence and divergence with existing literature while introducing methodological innovations. Below we structure these relationships through three thematic lenses:

Alignment with Existing Research on Fund Characteristics

The study corroborates three key observations from prior work:

- Impact funds' focus on industries with positive externalities aligns with Cojoianu et al. (2022)'s framework for ESG-conventional investment comparisons, though our narrower focus on pure impact funds (n=80 under 10 years old, Figs. 10 & 12) provides granular insights into younger portfolios.
- The absence of statistically significant relationships between AUM size and target returns mirrors Geczy et al. (2021)'s findings about impact fund compensation structures, further validated by Barber et al. (2021)'s thesis on return trade-offs for social impact.

Methodological Contributions This research advances impact investment analysis through

- BERT Semantic Similarity Techniques: First application in impact fund analysis, enabling sophisticated evaluation of non-financial disclosures through investment thesis text mining.
- Cluster Analysis: The identification of six statistically distinct fund groups ($p = 0.045$) reveals new patterns in risk appetites and investment strategies, providing quantitative rigor to portfolio categorization.

Metric	Current Study	Islam (2023)
SDG 8 Dominance	31 funds (31.6%)	70.2% collective share
SDG 13 Priority	25 funds	Climate action underrepresented
SDGs 1+10 Focus	36 funds combined	10% deal representation

Table 2: Comparison of SDG Investment Priorities

SDG Investment Dynamics: Continuity and Evolution Our SDG prioritization analysis shows:

This reflects both persistent trends of SDG 8's dominance by the article of UNCTAD (2023) and shifting priorities, particularly in climate action investments showing 25% growth since 2015. The divergence in SDG 1/10 allocations (+15% in developing countries 2022) suggests evolving geographical focus patterns.

Structural Innovations Two features distinguish our analytical framework:

- Integration of organizational structure characteristics with financial metrics (AUM size, target returns)
- Cluster-strategy correlation analysis revealing shared risk profiles within investment groupings

These advancements enable more nuanced performance benchmarking while maintaining alignment with established impact measurement paradigms.

Table 3: Critical Differences

Aspect	Previous Studies	Our Findings
Top Investment SDGs	2,3,4,8 (70.2%)	8,13,1,10 (84.6% of top 4)
Education Priority	SDG 4 as major focus	SDG 4 absent from top targets
Regional Distribution	Concentration in 2 regions	Implicit broader distribution
Environmental Focus	Limited climate action	Strong SDG 13 prioritization

- Our data shows a 150% increase in climate-focused funds compared to pre-2020 baselines, reflecting responses to the $2.2 trillion energy transition gap.

- The emergence of SDG 10 (Reduced Inequalities) as a top-4 target contrasts with prior findings of its underrepresentation, suggesting increased ESG integration in financial strategies.
- While infrastructure (SDG 9) remains underrepresented (consistent with UNCTAD's reported 24% decline in African infrastructure investment), our findings show improved gender lens investing (SDG 5) through integrated approaches.

Our research validates three critical hypotheses from the prior literature. The "SDG dealflow gap" phenomenon first identified by Islam and Rahman (2023).UNCTAD (2023)'s observed investment migration from social infrastructure to energy transition and emerging "impact stacking" strategies combining SDGs (8-13-1-10).

The findings suggest a market maturation where investors combine financial returns with climate resilience and social equity objectives, though structural barriers persist in mobilizing the required $4.3 trillion annual SDG financing. Future research should investigate temporal investment patterns (2015-2025) and spatial distribution mechanisms to address regional imbalances.

6.3 Research Issues and Limitations

This analysis faces three principal constraints that shape its findings and generalizability: data availability challenges, methodological limitations, and scope constraints. Each category presents specific considerations for interpreting the results.

6.3.1 Data Availability Challenges

Private market opacity Impact investments predominantly occur in private debt, equity, and venture capital markets, where comprehensive disclosure requirements remain limited. This results in fragmented data sources requiring manual aggregation, inconsistent reporting standards across funds and lack of mandatory impact metric disclosure.

Dataset access limitations While notable resources exist, their accessibility varies:

- ImpactAssets IA50: Publicly available dataset covering 150+ funds since 2010
- Harvard Business School Database: Contains 445 investors and 14,165 companies (non-public)
- IFRC Collaboration: Includes 300 funds with 180 disclosed names (access restricted)

Methodological Limitations

- **Semantic analysis constraints**: BERT vectorization demonstrates reduced efficacy when processing lengthy documents with overlapping thematic content and nuanced contextual differences in impact terminology.

- **Similarity scoring**: Current approach employs single-score evaluation that may oversimplify multidimensional semantic relationships and neglect temporal evolution of impact themes.

- **Data exclusions**: Analysis omits firm overviews and competitive differentiators, impact fund reports (due to inconsistent disclosure) and qualitative investment rationale.

Sample homogeneity IA50 dataset exhibits geographic concentration in North America, sectoral focus on clean energy and microfinance and overrepresentation of growth-stage ventures.

Ecosystem coverage This thesis excluded entities such as institutional investors (pension funds, insurers), development finance institutions and emerging market-focused funds.

6.3.2 Longitudinal Analysis Challenges

This study includes limited historical data (most datasets initiated post-2010), evolving impact measurement frameworks and lack of standardized tracking metrics across reporting periods.

These constraints collectively necessitate cautious interpretation of findings while highlighting critical needs for enhanced industry transparency protocols, development of public-private data partnerships and standardized impact reporting frameworks.

The study's methodological rigor remains intact within these acknowledged boundaries, providing a foundation for future research with expanded data access and refined analytical techniques.

6.4 Future Work

In future research, we propose several recommendations to enhance the robustness and applicability of our findings:

We recommend expanding the sample collection to include a more diverse range of databases. This approach would allow for a comprehensive cross-sectional analysis, potentially revealing modifications implemented by impact fund managers based on various factors such as investment theses, investment overviews, and company differentiators.

To increase the sample size and enable more detailed analysis, we suggest broadening the scope to include insurance companies, financial institutions, pension funds, and endowments.

Furthermore, categorizing funds into private and public sectors could provide a more transparent understanding of each sector's behavior and investment strategies.

Although Brown's study (2010) considered the impact of text file length on similarity scores, the effects of length on vectors generated using BERT and their subsequent similarity scores remain unclear in our study. Consequently, we did not make any length adjustments in the semantic similarity scores. More research is needed on the impact of text file length on BERT modification scores.

Although our results suggest that semantically similar clusters of impact funds may adopt identical investment strategies, this finding warrants further exploration to establish a more definitive correlation.

To address the limitations outlined above, future research should focus diversifying data sources to capture a wider range of impact fund characteristics. We also recommend methodological approaches can be refined, particularly in relation to text length impacts on BERT-generated vectors. Expanding the sample size to encompass diverse financial entities and broadening the analytical scope across private and public sector funds represents a recommended strategic approach to enhance the comprehensiveness of impact investment research.

By addressing these aspects, future studies can significantly enhance the depth and breadth of insights into impact fund strategies and behaviors. This comprehensive approach will contribute to a more nuanced understanding of the impact investment landscape and its various stakeholders.

Acknowledgment

We express my profound gratitude to several distinguished professors who have been instrumental in my research journey and academic growth.

First and foremost, we extend my heartfelt thanks to Professor Hayashi Takaki for his invaluable support and guidance throughout this research process. His expertise in artificial intelligence and data analysis has been pivotal in enhancing my analytical skills. Professor Hayashi's patient instruction in the use of R Studio and Python has significantly expanded my capabilities, enabling me to tackle complex research challenges with confidence. His insightful feedback and unwavering encouragement have not only contributed to the successful completion of this research but have also fostered my growth as a researcher in the field of AI.

We are deeply indebted to Professor Saito Takuji for his expert guidance in the realms of investments and corporate finance. His profound knowledge and practical insights have greatly enriched my understanding of these crucial areas, providing a solid foundation for my research. Our sincere appreciation goes to Professor Takeda Fumiko for her invaluable contributions to my research methodology. Her expertise in quantitative methods and her groundbreaking research on hedge funds have been instrumental in shaping the analytical framework of this study.

We would also like to express my gratitude to Professor Ashizawa Michiko for her enlightening strategy classes and her extensive knowledge of venture capital and private equity investment strategies. Her teachings have provided me with a comprehensive understanding of the strategic aspects of investment, which has been crucial in contextualizing my research findings. The knowledge, techniques, and perspectives we have acquired under the mentorship of these distinguished professors will undoubtedly continue to shape my academic and professional endeavors in the years to come. Their collective wisdom and guidance have been instrumental in the successful completion of this research and have significantly contributed to my development as a scholar in the fields of artificial intelligence, finance, and investment strategies.

We are deeply grateful to the Japanese government's Ministry of Education, Culture, Sports, Science and Technology (MEXT) scholarship committee for their generous support, which has afforded me the invaluable opportunity to pursue my studies at Keio Business School in Japan. Their commitment to fostering international education has not only provided me with financial assistance but also with the essential resources and support needed to embark on this transformative academic journey. The MEXT scholarship has opened doors to world-class education, cultural immersion, and personal growth that would have otherwise been beyond my reach. This experience has profoundly shaped my academic and professional trajectory, and I am sincerely thankful for the trust and investment the MEXT committee has placed in my potential.

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A Appendix

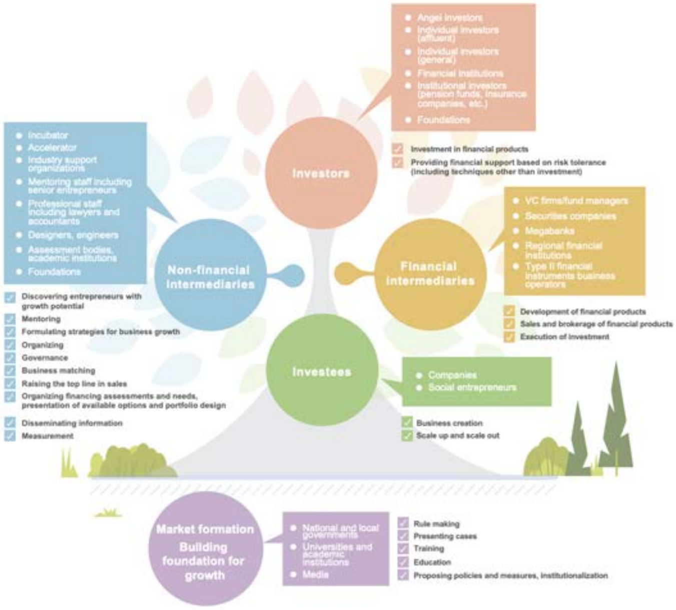

Figure 31: Ecosystem and players of impact investing, and image of their expected roles from Report of Proposal for the Expansion of Impact Investing 2019

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IA 50 2024 PROFILE

1863 Ventures

IA 50 2024 EMERGING IMPACT MANAGER

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Website: https://www.1863.fund/
Total Assets Under Management: Less than $25M
Asset Class: Cash / Cash Alternatives
Primary UN Sustainable Development Goal: 8 – Decent Work & Economic Growth

- Small/Medium Business Development
- Diversity, Equity and Inclusion
- Demographic-based impact

Firm Overview

Firm Overview

Category: Venture Capital - Early Stage (Pre-seed/seed, Accelerator, Angel) - Developed Markets

1863 Venture Fund I is an investment fund providing early-stage capital for New Majority entrepreneurs, better known as individuals who have been historically disinvested and prevented from accessing capital. Our firm is the investment arm of 1863 Ventures, a business accelerator nonprofit committed to generating $100 billion in new wealth by and for New Majority Entrepreneurs. As an extension of the non-profit 1863 Venture Fund I leverages Black, Brown, and women entrepreneurs through its business accelerator programming to provide risk-mitigated investments through revenue-based financing and equity capital. The success and impact derived from Fund I led to the District of Columbia selecting 1863 Ventures as its General Partner for the Inclusive Impact Equity Innovation Fund, which focuses on supporting historically marginalized founders in the nation's capital.

Firm Headquarters: US & Canada
Years of Operation: 3 – 4 years

Total Assets Under Management: Less than $25M

Total Number of Investors: Between 5 – 25
% of Capital from Top 3 Investors: 50% – 99%

Investment Thesis:
The 1863 Fund believes that by providing appropriately aligned capital to New Majority entrepreneurs, who have been historically excluded from accessing capital, we can support individual, enterprise, and community wealth creation while generating untapped growth for the economy.

Investment Overview:
Our research shows that it costs at least $250k more for an entrepreneur of color to start the same business

Investment Overview:
Our research shows that it costs at least $250k more for an entrepreneur of color to start the same business as their white peer. We know founders of color have a survival rate of at least 8.5 years. Even with this data, entrepreneurs of color receive less than 1% of VC funding and pay at least 1.5%+ more in debt servicing costs than their white peers. This lack of access to capital causes hardship to the economy as New Majority entrepreneurs contribute significantly to the economic vitality of their communities. The 1863 Venture Fund I believes that by providing appropriately aligned capital we can support individual, enterprise, and community wealth creation while generating untapped economic growth. To achieve this, the Fund leverages diverse investment instruments - from debt to equity to revenue-based financing - to expand access for New Majority entrepreneurs to a coherent and accessible investment continuum.

Company Differentiator:
1863 is unique in six ways: 1. We focus on execution and outcomes and not pitching and optics. 2. We are one of the only that offers rigorous finance and sales training. 3. We are one of only 12% of the programs in the country focused on growing and scaling businesses and not just startups 4. We are one of the few that is entirely run by experienced entrepreneurs. 5. We are sector agnostic and take all types of companies including tech, CPG, B2B, etc. 6. Our team is comprised 100% of members of the new majority.

Investment Example

Lingo was founded to eliminate barriers to entry for students underexposed to STEM opportunities. LINGO was created by a former NASA Rocket Scientist, Aisha Bowe, who we helped become a part of the Blue Origin trip to space in 2024. Our investment has helped the company expand its products into schools, Target, and corporations. Freeing Returns is an enterprise SaaS solution that leverages retail data from point-of-sale systems, receiving (inbound and outbound), and inventory management, including pricing and promotions, for loss prevention. Our investment in Barbara led to a follow-on investment from Serena Williams Ventures. Freeing Returns was named Minority Technology Firm of the Year by the Department of Commerce in 2022. Mentor Method is a mentor-matching platform designed to assist organizations in assigning the best mentors for their employees. Mentor Method was acquired by The Cru in 2022.

Leadership and Team

Cumulative Leadership Experience in Impact Investing: 20 – 29 years

Cumulative Impact Experience of Top Three Firm Leaders: 10 – 19 years

Melissa Bradley – General Partner More Info
Melissa L. Bradley serves as a General Partner of 1863 Venture Fund I and Inclusive Innovation Equity Impact Fund. She is a board member of Ureeka, a small business platform company she co-founded and sold, and Eat the Change. She is also a member of the Milken Institute DEI in Asset Management Initiative, Goldman Sachs' 1M Black Women Advisory Council, Launch with GS Advisory Council, and Fast Company Executive Board. Melissa is the former Co-Chair and current National Advisory Council for Innovation and Entrepreneurship member. Melissa is a Professor of Practice at the McDonough School of Business at Georgetown University. Over the last two years, she was commended with the Entrepreneurship Faculty Excellence Award, the Joseph F. LeMoine Award for

Percentage of Senior Management Team who identify as women:
50% or more

Percentage of Senior Management Team who identify as people of color:*
50% or more

*People of color include: Black, Latinx, Asian, Native American/Alaskan Native, Pacific Islander, Middle Easterm and multi-racial Americans

Financial Performance

Target Financial Returns Relative to Benchmark:
Near-market Rates

Actual Performance of Impact Products/Funds Relative to Target Financial Returns in the Past Three Years:
In line with initial target returns

Financial Reporting Frequency to Investors or Donors
Quarterly

Impact Performance

Percentage of Total Assets Under Management that are Impact Investments: 100%

Primary Impact Outcomes:
- Addressing racial inequities

Secondary Impact Outcomes:
- Increasing access to financial services

Value-added Services Offered:
- Access to markets
- Business and legal training
- Financial literacy training
- Education services

Investments systematically target companies where social and/or environmental impact is integral to the product/service being created:
During our sourcing and review process, we ask for and verify ownership and seek business plans for wealth

Impact Tracking and Monitoring

Impact is Tracked:
Yes

Impact Verified by an Independent Third-Party:
No

Social and/or Environmental Impact is Reported to Investors and Donors:
Yes – to the public

View Impact Report

Third Party Validations:
- GIIRS-rated fund
- B-Corp certified firm
- Participant in Global Reporting Initiative
- Signatory of the United Principles for Responsible Investing
- Member of Impact Capital Managers
- Impact Frontiers Cohort Participant
- Implement recommendations from Task Force on Climate Related-Financial Disclosure
- Net Zero Assets Managers Initiative

Figure 33: Impact fund sample: 1863 VENTURES (Part 2)

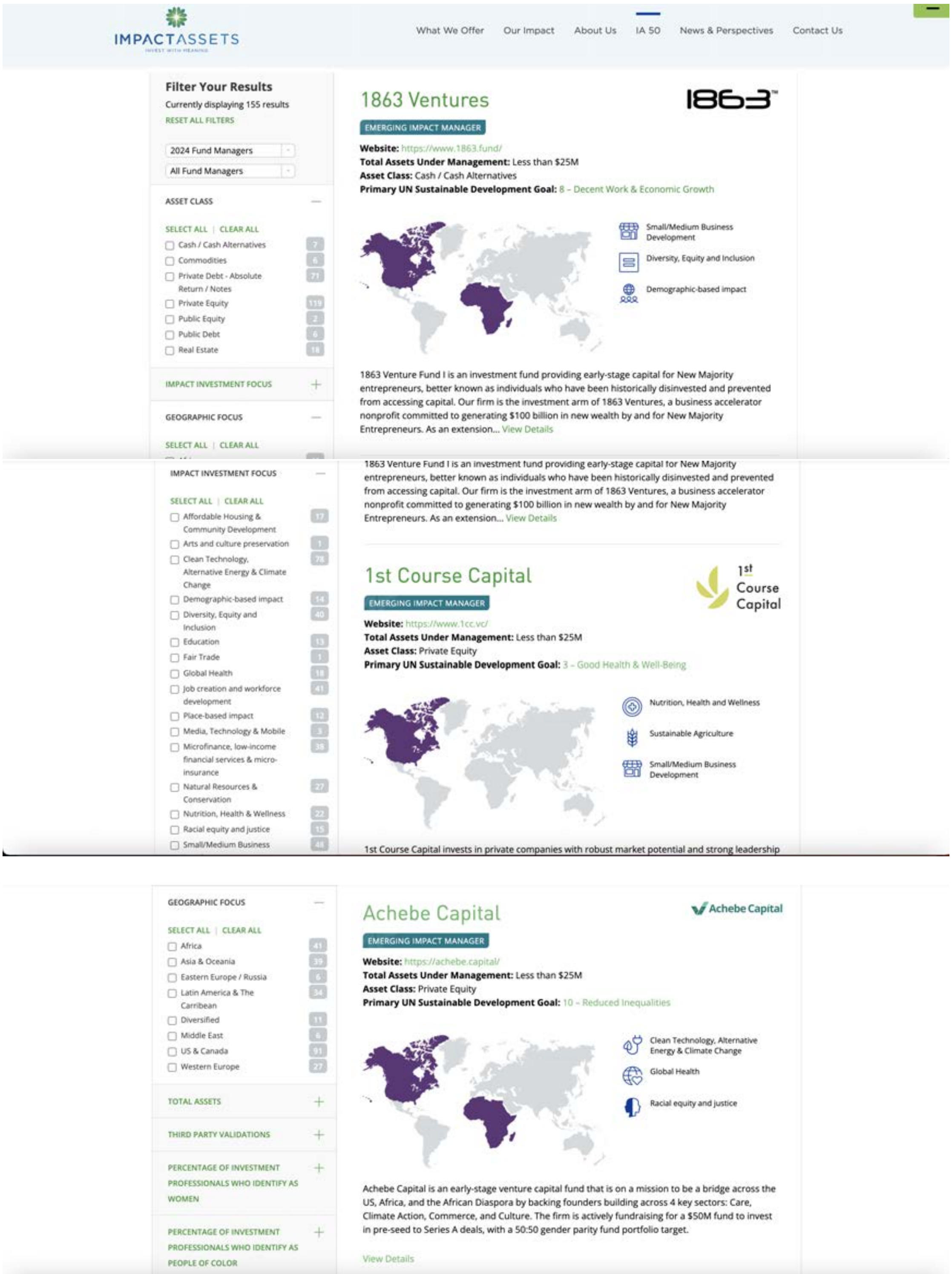

Figure 34: Impact fund Database IA50 categories (Part 1)

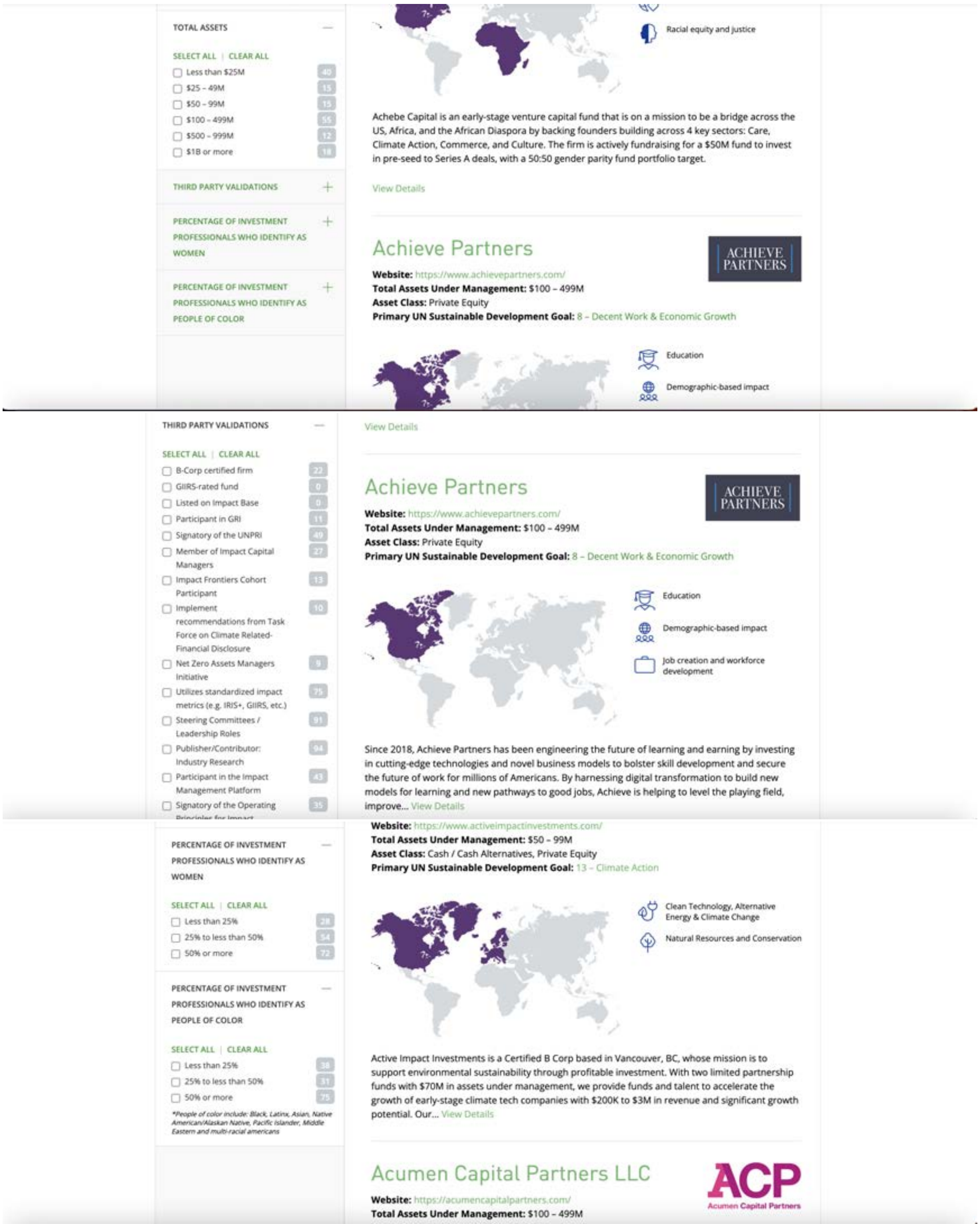

Figure 35: Impact fund Database IA50 categories (Part 2)

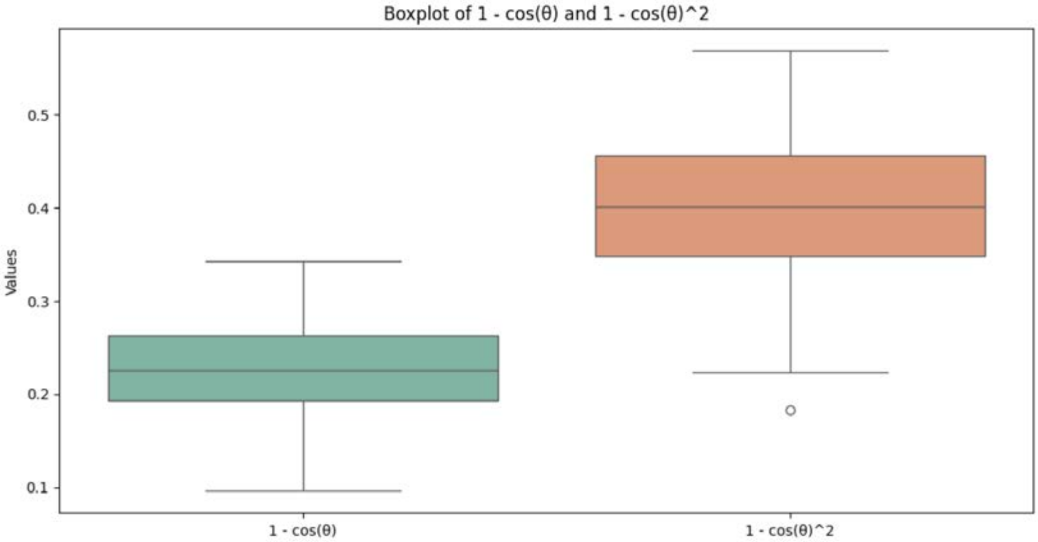

Figure 36: Random distribution of $1 - \cos\theta$ and $1 - \cos\theta^2$

	SDG 1.00	SDG 2.00	SDG 3.00	SDG 4.00	SDG 5.00	SDG 6.00	SDG 7.00	SDG 8.00	SDG 9.00	SDG 10.00	SDG 11.00	SDG 12.00	SDG 13.00	SDG 14.00	SDG 15.00	SDG 16.00	SDG 17.00
Company 1	0.18345642	0.18918443	0.19962609	0.22711092	0.2141434	0.24112487	0.16548765	0.16629332	0.15019667	0.17240429	0.16476256	0.15521991	0.20408428	0.18955839	0.19919115	0.19346195	0.14879262
Company 2	0.17567271	0.21929932	0.20877445	0.21649593	0.23149216	0.27529377	0.19307208	0.1981616	0.19220245	0.2000255	0.19936824	0.18235248	0.27353495	0.22226787	0.21995127	0.22917187	0.21140051
Company 3	0.16699445	0.19567817	0.16592205	0.19350421	0.25634915	0.28017908	0.18733048	0.2333821	0.20924914	0.24726349	0.2105968	0.18140072	0.2514634	0.21956348	0.2384609	0.26980448	0.24610293
Company 4	0.2887178	0.32454073	0.30491865	0.3395989	0.31073213	0.3782735	0.26848066	0.29254204	0.26733935	0.2901293	0.2916637	0.3008628	0.33963448	0.3198334	0.32935345	0.3541873	0.26183665
Company 5	0.20216984	0.22645402	0.20556837	0.26082218	0.27325606	0.2691896	0.1722238	0.2256344	0.18655002	0.2490269	0.20936215	0.19958115	0.24827832	0.2500553	0.24313956	0.26527655	0.22065341
Company 6	0.171071	0.24559873	0.21669137	0.24261403	0.23356557	0.27980554	0.20890146	0.21522093	0.20342451	0.19620359	0.2136975	0.220402	0.28886276	0.2753427	0.27530205	0.25107908	0.23645401
Company 7	0.19158733	0.22195089	0.17789888	0.22047913	0.24669093	0.27160567	0.18657094	0.22529632	0.16622245	0.19577092	0.18580127	0.19941127	0.24357373	0.24460298	0.24205464	0.24127805	0.20651007
Company 8	0.18345642	0.18918443	0.19962609	0.22711092	0.2141434	0.24112487	0.16548765	0.16629332	0.15019667	0.17240429	0.16476256	0.15521991	0.20408428	0.18955839	0.19919115	0.19346195	0.14879262
Company 9	0.17771	0.21391404	0.20641363	0.20433807	0.23965293	0.2819363	0.21774268	0.21432233	0.20614892	0.19955164	0.22822261	0.20179135	0.2612452	0.24583495	0.24327141	0.26302558	0.239856
Company 10	0.27708673	0.26624888	0.25304085	0.28400022	0.28998214	0.30435705	0.24541903	0.25349307	0.22540188	0.2593727	0.26122797	0.2521053	0.29448086	0.2844138	0.30234212	0.30462104	0.2632575
Company 11	0.18139344	0.21716815	0.19430947	0.22000253	0.24274719	0.26493853	0.20531178	0.22915727	0.1910553	0.20946515	0.19288105	0.1893335	0.25513577	0.22918993	0.21207088	0.24562156	0.22873366
Company 12	0.23151577	0.21396458	0.2060479	0.24608707	0.26197577	0.2709458	0.16990566	0.20910949	0.15832877	0.21022916	0.19414937	0.20038629	0.24410558	0.2259633	0.23517084	0.25907135	0.1959238
Company 13	0.24457234	0.26993704	0.25040734	0.27593762	0.2986529	0.32343507	0.22641623	0.25922602	0.24619293	0.26346922	0.25910592	0.26450866	0.28477478	0.27242976	0.2854519	0.31810904	0.24437302
Company 14	0.2295698	0.25539684	0.26804143	0.27351326	0.28452235	0.3462596	0.25113112	0.24675345	0.23634326	0.25448692	0.24604666	0.23175693	0.32094997	0.25464118	0.2532211	0.28369194	0.27246404
Company 15	0.21975672	0.2889036	0.25333697	0.30045223	0.24128997	0.29779893	0.24648929	0.26207316	0.25096607	0.24309695	0.25685704	0.24259925	0.2917812	0.2649014	0.29778093	0.2961797	0.2399028
Company 16	0.23974347	0.24215966	0.2731831	0.3050763	0.3005234	0.31663716	0.23180401	0.24309224	0.24204242	0.26759768	0.24144483	0.21585464	0.30394238	0.21559525	0.2608055	0.28981268	0.2511679
Company 17	0.18659401	0.20126027	0.18882942	0.24371755	0.22871572	0.2530957	0.1723485	0.20060807	0.17163509	0.18606198	0.16624677	0.1643632	0.22419238	0.20120943	0.206074	0.22504449	0.1724307
Company 18	0.26538122	0.25180614	0.27359807	0.3027194	0.29324317	0.32489955	0.2297312	0.25404316	0.22215778	0.24766284	0.26568234	0.2478581	0.2707215	0.25860256	0.27331382	0.2960496	0.23080617
Company 19	0.24223554	0.27564108	0.2752487	0.29642648	0.27283466	0.31671846	0.24079382	0.24680012	0.2324509	0.23364496	0.25883853	0.25157118	0.29510504	0.26714635	0.28375822	0.2885903	0.24035603
Company 20	0.15499043	0.18865043	0.1759175	0.19555843	0.17461598	0.25676268	0.17178214	0.17358464	0.18288624	0.17593801	0.17454684	0.1803655	0.24148512	0.20790589	0.20862597	0.21358925	0.19389737
Company 21	0.2808197	0.2971146	0.29278785	0.29404444	0.2704404	0.32266134	0.26411957	0.26989925	0.25686574	0.26280844	0.28698695	0.2922734	0.30956882	0.3090223	0.3246081	0.3294863	0.2712295
Company 22	0.2861293	0.2806067	0.27132297	0.3034808	0.30637765	0.3316418	0.23643947	0.2620753	0.22303915	0.25053352	0.26252878	0.26924902	0.3032747	0.28679204	0.29130292	0.3072462	0.24681377
Company 23	0.18409532	0.20528674	0.20010227	0.22597557	0.24298596	0.2613101	0.19077235	0.21257812	0.16385573	0.18372524	0.19294834	0.18580985	0.25360525	0.22860432	0.2277571	0.23045284	0.2080602
Company 24	0.20219475	0.25756925	0.1766445	0.23690796	0.23916727	0.26545084	0.21623051	0.23192132	0.19907308	0.24437821	0.21977288	0.22648352	0.26751626	0.27097708	0.26185274	0.2339977	0.23923647
Company 25	0.24776089	0.27882117	0.23847848	0.28463238	0.2324037	0.2946388	0.2254504	0.24156845	0.22160918	0.24887788	0.23823023	0.26959187	0.29406488	0.2960111	0.29274273	0.28971195	0.23336661
Company 26	0.18940079	0.22381866	0.18893325	0.26450372	0.22369516	0.2410239	0.1795494	0.21420401	0.17241037	0.18737924	0.16328764	0.19604588	0.23109931	0.23386782	0.2558099	0.23029381	0.17568266
Company 27	0.20715386	0.21497238	0.20289516	0.24351275	0.24077123	0.26321614	0.1609264	0.19364065	0.182158	0.20605326	0.19162798	0.204198	0.22744447	0.20487553	0.23664165	0.26668257	0.18515086
Company 28	0.20875287	0.27381676	0.23346925	0.24948645	0.22676432	0.2942676	0.25501746	0.2461406	0.23941535	0.22109973	0.23256099	0.25878948	0.31164795	0.277035	0.2946729	0.26837254	0.27044493
Company 29	0.18988532	0.251774	0.20622897	0.258919	0.22856998	0.27240634	0.19966912	0.20611781	0.21416986	0.23235983	0.19585085	0.21013379	0.24919719	0.2289244	0.23195207	0.2444042	0.19664365
Company 30	0.16616023	0.22109091	0.18871874	0.23136127	0.1967302	0.25337493	0.18704945	0.18368143	0.17883497	0.19433093	0.17265052	0.1875844	0.26386535	0.22640908	0.21464646	0.19749153	0.20428962
Company 31	0.20108753	0.18699086	0.21211088	0.28280735	0.23966318	0.2257213	0.16292763	0.19641316	0.16455233	0.19429237	0.14897352	0.15683192	0.21903801	0.18166202	0.17326081	0.20345211	0.16336429
Company 32	0.19869155	0.22832948	0.18633181	0.24961734	0.2478978	0.26174968	0.20129645	0.23292625	0.20277297	0.22215962	0.20581222	0.21259093	0.20729315	0.22614056	0.24245751	0.27246124	0.21323031
Company 33	0.16257834	0.21937406	0.16724735	0.1882903	0.24878871	0.26208568	0.18121612	0.22795796	0.23951894	0.24575329	0.20036459	0.18309951	0.23929256	0.21192783	0.23322219	0.28565687	0.24217904
Company 34	0.15678799	0.1780163	0.14799047	0.20909154	0.21261895	0.2143842	0.12403309	0.18531442	0.14845443	0.17604882	0.14016587	0.15716141	0.2000398	0.20281678	0.20045769	0.2263295	0.17225409
Company 35	0.18933326	0.23764348	0.20045263	0.24492353	0.20831907	0.24212211	0.19403815	0.21126765	0.17544794	0.20799732	0.19452488	0.21300125	0.22824007	0.2445541	0.2625832	0.24697232	0.18953621
Company 36	0.17079103	0.2394377	0.19599158	0.22850811	0.20956099	0.25981152	0.21759236	0.23046619	0.20819908	0.2142632	0.20812058	0.22092694	0.24915403	0.25583464	0.2592324	0.25866836	0.224706
Company 37	0.24690807	0.2638315	0.22805041	0.2719714	0.27866483	0.29378986	0.20883995	0.2471034	0.19166148	0.22384715	0.22237408	0.2508011	0.28227413	0.28981274	0.2870413	0.28524393	0.23135185
Company 38	0.16243613	0.18816149	0.1733079	0.24234807	0.19680393	0.21552444	0.14499539	0.16212302	0.14411455	0.18035924	0.14332086	0.16684556	0.19453162	0.19228941	0.18739444	0.21735919	0.15907621
Company 39	0.4258448	0.4162529	0.44735008	0.46155077	0.4173082	0.4771636	0.3987097	0.40272802	0.4149959	0.40850127	0.406896	0.4173969	0.44426298	0.42877066	0.42683417	0.45353568	0.40360606

Figure 37: Distance matrix of the companies which aligns with UN SDG goals

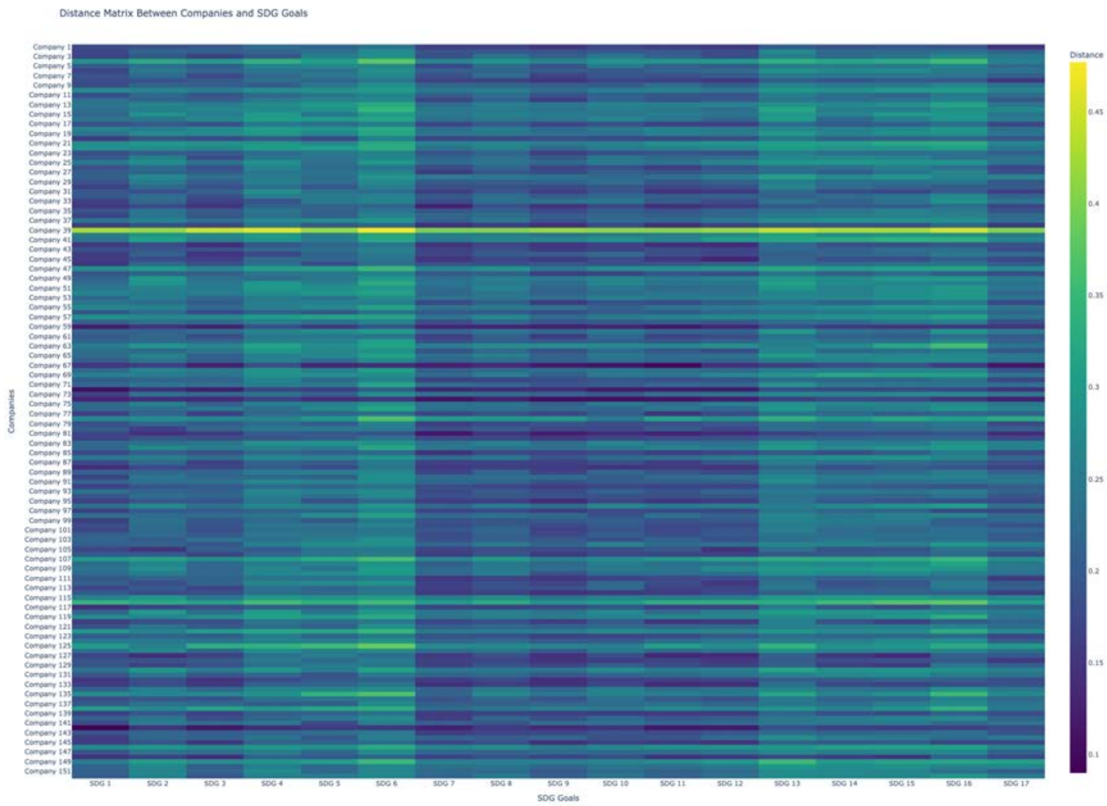

Figure 38: Distance matrix

SDG Number	SDG Goal Name	Closest Company	Company Statem	Distance Score	Company Name	Target SDG goals	Math ●-✗
SDG 1.00	No Poverty	Company 142	Lack of financing i	0.089858472	WaterEquity, Inc.	6 _ Clean Water & Sanitation	✗
SDG 2.00	Zero Hunger	Company 127	Using investment	0.138104558	SLM Partners	15 _ Life on Land	✗
SDG 3.00	Good Health and Well-being	Company 142	Lack of financing i	0.113744497	WaterEquity, Inc.	6 _ Clean Water & Sanitation	✗
SDG 4.00	Quality Education	Company 142	Lack of financing i	0.141125858	WaterEquity, Inc.	6 _ Clean Water & Sanitation	✗
SDG 5.00	Gender Equality	Company 67	Enhanced believes	0.130996227	Enhanced Capital Group, LLC	10 _ Reduced Inequalities	●
SDG 6.00	Clean Water and Sanitation	Company 67	Enhanced believes	0.140720427	Enhanced Capital Group, LLC	10 _ Reduced Inequalities	✗
SDG 7.00	Affordable and Clean Energy	Company 74	Our investments s	0.109192312	Goodwell Investments BV	10 _ Reduced Inequalities	✗
SDG 8.00	Decent Work and Economic Growth	Company 74	Our investments s	0.125973821	Goodwell Investments BV	10 _ Reduced Inequalities	✗
SDG 9.00	Industry, Innovation and Infrastructure	Company 74	Our investments s	0.105904579	Goodwell Investments BV	10 _ Reduced Inequalities	✗
SDG 10.00	Reduced Inequalities	Company 74	Our investments s	0.10761863	Goodwell Investments BV	10 _ Reduced Inequalities	●
SDG 11.00	Sustainable Cities and Communities	Company 67	Enhanced believes	0.096006513	Enhanced Capital Group, LLC	10 _ Reduced Inequalities	✗
SDG 12.00	Responsible Consumption and Production	Company 72	We believe that rea	0.117915809	GAWA Capital Partners SGEIC S.A.	1 _ No Poverty	✗
SDG 13.00	Climate Action	Company 67	Enhanced believes	0.162755728	Enhanced Capital Group, LLC	10 _ Reduced Inequalities	✗
SDG 14.00	Life Below Water	Company 127	Using investment	0.152596414	SLM Partners	15 _ Life on Land	✗
SDG 15.00	Life on Land	Company 127	Using investment	0.135953724	SLM Partners	15 _ Life on Land	●
SDG 16.00	Peace, Justice and Strong Institutions	Company 74	Our investments s	0.146714211	Goodwell Investments BV	10 _ Reduced Inequalities	✗
SDG 17.00	Partnerships for the Goals	Company 67	Enhanced believes	0.113322437	Enhanced Capital Group, LLC	10 _ Reduced Inequalities	✗

Figure 39: SDG alignments of the impact fund companies