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IS THERE A LINK BETWEEN FINANCIAL PERFORMANCE AND IMPACT PERFORMANCE? A QUALITATIVE CASE STUDY OF MUSTARD SEED MAZE, AN IMPACT VENTURE CAPITAL FUND

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Abstract

This thesis delves into the evolving landscape of impact investing. Drawing insights from the practices of impact venture capital fund Mustard Seed Maze, the study investigates the intricate relationship between financial and impact performance. While confronting prevalent myths about compromised returns in socially responsible investing, the research employs quantitative analyses to unravel the nuanced interplay of these dimensions. Despite severe data limitations, the findings suggest a harmonious pursuit of societal and financial objectives. The study advocates for transparent performance metrics and refined frameworks to enhance the credibility and efficacy of impact investing crucial for fostering positive change.

Keywords

Impact investing
Venture capital
Impact measurement
Financial performance
Impact performance

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1. Introduction

"We think we can take this beast called capitalism and help to direct it in a way that is productive" (McGlashan cited in Impact Alpha 2018). With these words, Bill McGlashan, founder of the impact private equity fund "The Rise Fund", articulates a vision that transcends the conventional boundaries of finance. This sentiment encapsulates the ethos of impact investing, a transformative approach that seeks to harness the power of financial markets to drive positive social and environmental change. While the practice of investing in projects or firms that offer solutions to societal challenges while generating a financial return dates back to the middle of the last century, this concept of "Impact Investing" only really started accelerating around 2010. Back then, the topic came to the attention of large investment banks such as J.P. Morgan and transnational organizations fostering the area's growth arose (Clarkin and Cangioni 2016; J.P. Morgan et al. 2010). According to the Global Impact Investing Network (GIIN), the expansion of the impact investment market is necessary to achieve global settled goals, such as the Sustainable Development Goals (SDGs) by 2030 and net zero emissions by 2050, as governments will not be able to raise required capital on their own (Hand et al 2022).

Although the consideration of social and environmental responsibility in investing has become more and more mainstream, many myths still surround the topic. In particular, a large proportion of investors assume that returns are lower when investing in companies that strive to optimise profit and social or environmental benefits at the same time (Morgan Stanley 2017). Meanwhile, existing empirical studies yield mixed results on the link between impact and financial performance. At the same time, they often concentrate on public markets and, therefore, exclude most of the impact investment universe which is primarily comprised of private assets. In addition, the discourse is largely characterised by comparisons between traditional funds and those that incorporate social or environmental responsibility in some way.

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Within the realm of impact investing, however, a pivotal inquiry lies in understanding the interconnectedness of financial and impact performance and identifying factors that influence the two dimensions, rather than solely looking at returns through the lens of traditional investing.

Accordingly, this paper aims to contribute to mitigating the lack of research in the field of impact investing by performing quantitative analyses on the example of an impact Venture Capital (VC) fund, Mustard Seed Maze. Given the restricted access to data in private markets (Tribush et al. 2021), the firm volunteered to collaborate with us on examining the link between financial and impact performance, through providing the data on which this study is based on. To understand the key concepts required for the subsequent analysis, this paper commences with an introduction to the field of impact investing. It then presents theoretical frameworks and empirical studies that previously worked towards determining the relationship between financial and impact performance in a broader sense. Based on this literature, as well as the data provided, several hypotheses are formulated and subsequently tested using various statistical methods. The results are critically evaluated and finally, impulses for further research are given.

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2. Literature Review

2.1 Basics of Impact Investing

Rather than examining the relationship between financial and impact performance across the whole investment universe, this paper aims to contribute to research in the field of impact investing. It can be considered a relatively new field as even though the underlying idea has historical roots in the 18th century, the term was only introduced by the Rockefeller Foundation in 2007 (Peralta 2018). In 2009, the non-profit organization GIIN was founded to promote the growth of the impact investing industry (GIIN 2009). In pursuit of this goal, the GIIN played a pivotal role in setting up definitions and parameters, introducing impact investments as an asset class with significant growth potential in a whitepaper in collaboration with the Rockefeller Foundation and J.P. Morgan in 2010 (J.P. Morgan et al. 2010).

While traditional investing focuses mainly on generating risk-adjusted financial returns (see e.g. Modigliani and Modigliani 1997 or Sharpe 1966), impact investing additionally seeks to achieve social or environmental benefits. It differs from philanthropy, which primarily finances projects and ventures with a clear emphasis on social and environmental value creation and no expectation of financial return. Impact investing combines traditional investing and philanthropic ideas, taking on a blended-value approach. It should be distinguished from Socially Responsible Investment (SRI), which aims to mitigate harm through negative screening rather than to actively promote positive change (J.P. Morgan et al. 2010). A more detailed classification of investment approaches on a spectrum between traditional investing and philanthropy is illustrated in *Figure 1*.

	Traditional Investing	Social responsible Investing	Impact Investing	Venture Philanthropy	Traditional Philanthropy
Objective	Profit maximisation as main objective	Earning financial returns through ESG integration or negative screening	Targeting social and environmental objectives along with a financial return	Main objective is to achieve a higher social return, alongside a financial return	Main objective is maximizing impact without expecting financial returns
Main Asset Classes	• All asset classes, primarily public debt and equity	• same asset classes as traditional investing with an ESG focus	• Private equity • Private debt • Real assets	• Private equity • Foundation	• Cash • Cash equivalents

Figure 1: Different Investment Approaches (Agrawal and Hockerts 2021)

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The total assets under management (AUM) in the realm of impact investing were estimated by the GIIN at USD 1.164 trillion in 2022, managed by more than 3,349 organizations (Hand et al. 2022). When comparing this number to the GIIN's previous estimate of USD 502 billion in 2019 (Mudaliar and Dithrich 2019), it becomes evident that the industry has displayed a significant compound annual growth rate (CAGR) of more than 26%. This upward trajectory is expected to persist, particularly due to a progressively favourable regulatory environment for the industry, exemplified by the introduction of the EU Taxonomy, making positive and negative impacts across companies more transparent[1]. As financial markets factor in heightened policy risk for detrimental businesses in the traditional investment sphere, responsible investments become more appealing (Uzsoki 2020; European Commission n.d.). Additionally, the gigantic wealth transfer in the coming years will lead to millennials gaining economic power, being twice as likely to invest in companies with social impact[2] as the overall investor population (Morgan Stanley 2017; Kelly 2023).

Still, fragmentation, an immature infrastructure, and a lack of research and available market data, notably in the field of private equity, pose a major obstacle to the advancement of the market (GIIN 2018; Case 2017). In comparison to SRI, which predominantly involves public equity (Agrawal and Hockerts 2021), impact investing predominantly unfolds on private markets (see *Figure 2*), due to the maturity and scale of investment targets. These often encompass socially responsible start-ups in their growth phase that encounter funding

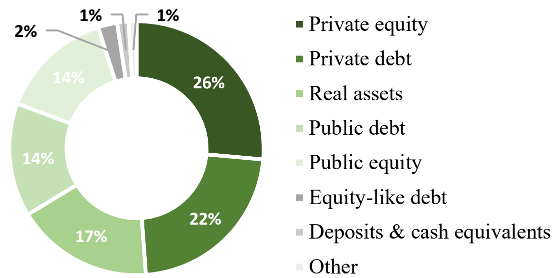

Figure 2: Allocations to impact across asset classes 2023 (Hand et al. 2013, 8)

[1] So far, the EU taxonomy only applies for environmental concerns. An extension to social objectives is already being planned (Platform on Sustainable Finance 2022).
[2] The term "social impact" in this paper always also refers to environmental impact and is used universally for better readability.

challenges that conventional finance has proven insufficient to address (Owen et al. 2018; Clark et al. 2018). This explains why novel types of financing have emerged within the sector, exemplified by Social Impact Bonds (SIBs), where financial return is attained only if pre-defined social outcomes are achieved (Bugg-Levine et al. 2012). Furthermore, this underscores the significance of VC within impact investing. As the EPVA (2021) highlights, the transformation towards a fair and green society depends on additionality, i.e., accepting bold risks to achieve a contribution through breakthrough solutions that without an investment would not have been realized. Due to their high-risk investment strategies, which will be further elaborated in 2.3, VC investors can mitigate the aforementioned funding gaps in social entrepreneurship, and in turn, foster social innovations (Pandit and Tamhane 2018). Similarly, the European Central Bank (2022) emphasises the central role VC can potentially play in decarbonising economies. After all, if these companies establish themselves in the market, this will also facilitate a more socially responsible asset allocation by more risk-averse investors, such as commercial banks or retail investors.

2.2 Impact Performance Measurement

To assess progress towards the objective of creating societal value, it is imperative to measure impact. Impact can manifest in different aspects of a company, such as the employment of individuals from underrepresented groups in the company's operations or the creation of impact through its products, like plant-based meat substitutes to promote sustainability in the food industry, for instance. Therefore, measuring impact performance can be a complex and potentially subjective process, often accompanied by higher costs, as to date, there is no binding standard for it (Brown cited in Knowledge at Wharton 2022). 84% of impact investors, hence, deem the current level of "sophistication of impact measurement and management" a challenge (Hand et al. 2020). When it comes to reporting the impact of companies within a fund's portfolio, frameworks and tools have been developed to facilitate this process. According to the GIIN, most impact investors measure and manage the impact of portfolio companies with the SDGs (73%), IRIS+ ("Impact Reporting and Investment Standard") (36%), and the Impact Management Project (32%) (CFA Institute Asia-Pacific Research Exchange n.d.). The SDGs are recognised as a global norm, ensuring consistent communication and a degree of comparability. However, while the SDGs provide clear targets, the implementation and assessment of progress against these targets can vary in different contexts and sectors (Mook 2019, 82-83).

The IRIS+ framework is a system developed by the GIIN in 2008. It offers essential metrics, standardized data categories, and templates to facilitate the utilisation of comparable impact data (GIIN n.d. a). The Impact Management Project (IMP) was established in 2016 as a forum to build consensus on interpreting and managing performance on environmental and social issues. In concert with insights from more than a thousand industry stakeholders, the IMP determined that gaining comprehension of impact performance entails gathering data across five dimensions (Impact Management Project n.d.). These five dimensions, "WHAT", "HOW MUCH", "WHO", "CONTRIBUTION" and "RISK", are used to measure and understand the impact of a company's actions. "WHAT" defines the type of outcome, "HOW MUCH" quantifies the extent of the change and its duration, and "WHO" identifies the stakeholders affected and their previous state. "CONTRIBUTION" assesses whether a company's or investor's actions have led to results that go beyond what could have occurred naturally, while "RISK" quantifies the probability of deviations from the expected results and the associated risks for people and the environment if expectations are not met (Impact Management n.d.) (Bouri et al. n.d.). The IMP's Investment Classification Guide introduces the ABC framework, enabling investors to align their investments with their intentions: "Act to avoid harm", "Benefit stakeholders", or "Contribute to solutions". "A" includes investments that integrate

Environmental Social Governance (ESG) factors to mitigate or minimise some of their adverse effects. "B" goes further, requiring investors to not only avoid harm but also consider positive impacts. "C" builds on this by emphasising that investments must result in a significant positive impact on underserved populations or the environment (Impact Management 2020).

In 2019, another methodology called the Impact Multiple of Money (IMM) was introduced by Bridgespan and The Rise Fund to measure the societal value creation per dollar of investment. The concept is partially grounded in the aforementioned IMP frameworks, yet it advances beyond by translating the dimensions into monetary value based on "anchor studies" (Addy et al. 2019).

2.3 Financial Performance Measurement

In impact investing, impact management coexists with the control of financial performance. At the company level, financial performance generally encompasses metrics like profitability and growth. For early-stage ventures with heterogeneous business models, however, these metrics are often not directly comparable, as revenue streams might not exist yet or fluctuate strongly (Ferrati 2021). When it comes to evaluating investment fund performance, relevant metrics can vary depending on the asset class, level of analysis, and the type of investor involved (Dossi and Patelli 2010, 500-504). According to modern portfolio theory (MPT), investors strive to achieve competitive returns while effectively managing risk through diversification, so relevant performance indicators such as the Sharpe Ratio, set the return of a portfolio in relation to its variability (Markowitz 1952; Sharpe 1994).

VC portfolios are inherently riskier than the in the MPT assumed market portfolio and diversification is treated differently because investments in start-ups tend to be illiquid and focused on a limited number of companies. Moreover, capturing risk-adjusted rates of return for VC funds can be difficult as they are usually privately held limited partnerships (Brophy and Guthner n.d.). Therefore, evaluating the financial performance of VCs requires a particular approach, using a unique set of metrics. Several key indicators are used for this purpose, including the Internal Rate of Return (IRR), Residual Value to Paid-in Capital (RVPI), Distribution to Paid-in Capital (DPI), Total Value to Paid-in (TVPI), and Multiple on Invested Capital (MOIC). In assessing financial performance within our case study, emphasis is placed on the metrics of TVPI, IRR, and MOIC. Thus, only these key performance indicators (KPIs) are explained in more detail.

IRR calculates the annual return rate that an investment or fund is expected to generate, and the metric usually follows a J-curve pattern, decreasing at the beginning of the fund due to initial cash outflows and increasing toward the end of the investment cycle due to cash inflows subsequent to exits (Kelleher and MacCormack 2005). TVPI measures both, the realised and unrealised value of investments relative to the total contributions, i.e., the paid-in capital. According to a study conducted by the investment firm Cambridge Associates, which analysed the TVPI of US VC funds spanning from 1981 to 2015, the median TVPI stands at approximately 1.77x, with the top quartile showing values exceeding 2.54x and the lower quartile having values below 1.4x (Thurston 2016). The metric is particularly useful for comparing funds at a later stage. MOIC indicates the realised and unrealised value of the fund's investments in portfolio companies relative to the amount invested. When comparing ratios for measuring financial performance, IRR considers the time value of money, unlike the multiples TVPI and MOIC. This means the latter neither considers the timeframe over which the value appreciation was achieved nor the cost of the committed but not yet invested capital (Carta 2023).

When gauging the financial performance of impact VC against traditional VC funds, it is essential to note that there can be variances in factors like fund size and investment lifecycle, which can have a significant influence on the performance indicators. For instance, traditional

VC funds tend to be larger than impact VC funds according to Barber et al. (2021, 167). Specifically, their study showed that the mean fund size for traditional VC funds is $204.6 million, while impact VC funds have a mean size of $129.6 million.

2.4 Relation between Return and Impact

While in conventional investing models, the relationship between risk and return is well-defined and widely acknowledged, reciprocal effects when factoring in social impact are much less evident, due to the difficulty in measurability of impact described earlier. To evaluate the link between financial and social impact performance, it will first be elaborated on what possible relationships theory suggests. Afterward, this paper presents some empirical evidence on these concepts to understand the context of the analysis and create the foundation for the interpretation of the findings.

2.4.1 Negative Correlation

A common reason to anticipate a negative relationship between financial and social impact performance is that the consideration of social responsibility might raise the cost of portfolio companies as argued by conventional finance literature. The presence of more than one overarching goal, traditionally profit maximisation, may lead to inefficient decision-making, and inadequate governance structures and would contradict the fiduciary duty to optimise shareholder value (see e.g. Friedman 1970; Jensen 2002).

On a fund level, MPT suggests that the limited amount of assets that are eligible for impact investors constrains the possibility for diversification and therefore, increases the risk and may shift the expected return away from the efficiency frontier, where the trade-off between risk and return is perfected (Barnett and Salomon 2006).

Moreover, as impact investment targets are often rather small, deal sizes are also comparatively small in value and can make the cost of due diligence seem unreasonable. These costs may be relatively higher than for traditional investment targets, as the scope is extended for impact factors and can also increase for companies in remote areas, i.e., emerging markets. Notably, for investors who are capable of investing larger amounts, this may impose significant opportunity costs (J.P. Morgan et al. 2010).

2.4.2 Positive Correlation

There is equally literature that suggests socially responsible behavior can be a source of competitive advantage for investees and therefore, have a positive impact on financial performance. This rationale is reflected in stakeholder theory, arguing that benefits from activities respecting all stakeholders, i.e. also society, offset the costs (Freeman 1984). On the revenue side, in a market with traditionally less sustainable companies, Corporate Social Responsibility (CSR) initiatives can help to better market products. Furthermore, there are so-called lock-step business models, where an increased impact is directly related to higher revenue (Gianoncelli and Boiardi 2018). Advantages can also emerge on the cost side, as socially responsible firms are more likely to acquire and keep high-quality employees, for example (Gross 2014).

For funds, MPT can meanwhile also be interpreted in a way that supports a positive relationship. It can be argued that the pool of assets to choose for diversification might be smaller, yet, comprising investment targets of "higher quality" (Barnett and Salomon 2006).

2.4.3 Empirical Evidence on Performance

Existing empirical findings on the relationship between impact and financial performance are conflicting. Moreover, even though there is a variety of studies to be found, many of them typically focus on the area of SRI. There is a lack of research in the field of impact investing, especially in impact VC. This chapter summarises the results of relevant studies to point out the gaps in current research.

First of all, return expectations of impact investors should be examined as they can serve as a crucial starting point for assessing the alignment of financial and impact objectives and their achievement. Particularly, according to a survey by Morgan Stanley (2017), the majority of investors (53%) in general assume a trade-off between social impact and financial return. J.P. Morgan et al. (2010) point out that there can be a difference between return expectations for impact private equity investments in developed markets and emerging markets when comparing them to benchmark indices of realised returns in the respective areas. In an investor survey, they discovered that while investors typically anticipate a lower return for impact VC in developed markets, expected IRRs in emerging markets on average lie above traditional VC performance.[3] Considering all impact investing instruments, including debt and real assets, there seems to be acceptance for a trade-off between impact and returns, on average.

In the same report, they show an analysis of the International Finance Corporation portfolio demonstrating that their impact VC fund has outperformed their traditional VC returns in emerging markets between 1986 and 2006. However, it is essential to acknowledge that their definition of impact considers investments addressing "the bottom of the pyramid"[4] in a broad sense and therefore, the analysed portfolio also includes oil and gas companies, for example.

Barber et al. (2021) conducted a case study, in the form of a global analysis of the financial performance of 4,500 traditional VC funds and 159 impact VC funds. Their results show that traditional funds consistently outperformed impact funds. Conventional funds exhibited an average internal rate of return (IRR) of 11.6%, whereas impact funds demonstrated an average

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[3] In this context, it is worth mentioning that investigated companies invested more than one-fourth of their funds in microfinance, one of the most developed areas in impact investing, offering comparatively high return potential (Pandit and Tamhane 2018).

[4] The World Resources Institute has defined the BoP as people earning less than USD 3000 per annum per capita (World Resources Institute 2007).

IRR of 3.7%. The outperformance of traditional VCs persisted even when factors such as fund size and vintage year were used as control variables. Slight performance variation can be explained by fund geography and industry. In comparison to traditional funds, impact funds are more likely to direct their investments to developing regions such as Africa, Latin America, and emerging Europe. In addition, impact funds tend to specialise in the energy sector or diversified sectors, while traditional VC funds tend to focus on the IT, healthcare, or media and communications industries (Barber et al. 2021, 167-171).

As this essentially encompasses the entirety of published empirical evidence within the field of impact VC, the literature review is expanded to include studies on asset classes other than impact private equity, to possibly identify overarching relationships between the variables of interest. Including debt, investors in private impact markets generally seem to meet or even exceed their anticipated outcomes. According to an impact investor survey, 68% of respondents reported financial performance aligning with their expectations, with an additional 20% indicating performance surpassing their projections. On the impact side, 78% of impact investors state in-line performance and 21% indicate outperformance (Hand et al. 2020). While the judgment of these figures hinges on the individual investor expectations, this suggests harmony in achieving financial and impact objectives at the same time.

The most comprehensive benchmarking analysis for private investment funds was performed by the GIIN together with Cambridge Associates in 2015. It was revealed that for most regions and vintage year categories, conventional funds outperformed impact funds in terms of TVPI and IRR. Still, impact funds initiated between 1998 and 2004, thus predominantly those with realised returns, have demonstrated performance superior to the comparative funds with identical vintage periods. In addition, they discovered that a lower percentage of impact funds report IRRs that significantly diverge from expected returns (GIIN and Cambridge Associates 2015).

Broadening the scope to include public vehicles, Morgan Stanley (2019) conducted a study on more than 10,000 mutual SRI funds to assess whether sustainable[5] funds exhibited inferior financial performance in comparison to traditional ones. No significant differences in returns were found but a 20% lower downward deviation was discovered for sustainable funds.

These two studies may indicate a lower market risk for more socially responsible funds and could support the hypothesis of a sounder asset pool by Barnett and Salomon (2006) mentioned in 2.4.2. Barnett and Salomon (2006) themselves discover a curvilinear relationship between social screening intensity and the financial performance of mutual funds, i.e. that return initially declines with a higher number of screens only to rebound as a maximum of social screening criteria is reached.

After all, these mixed findings, often due to diverging methodologies and impact definitions, emphasise the difficulties in identifying the link between impact and financial performance.

[5] Their definition of "sustainable" involves funds classified as "ESG Focus" by Morningstar. This comprises funds with multiple ESG screens, including those with only negative screening but also ESG-integrating ones.

3. Methodology

3.1 Research Approach

Unlike SRIs which are a lot broader in scope and mostly comprise publicly traded assets, in the field of impact investments the limited accessibility of data for private markets constrains the methods to answer the research question. Other studies have approached the topic by using Preqin, a data provider for alternative assets, to access VC data and then manually filtering for impact funds, to compare them to the financial performance of non-impact funds (see e.g. Mocci 2018, Dahl 2022). This, however, systematically excludes numerous impact VC funds due to a lack of reporting requirements to external stakeholders, resulting in an incomplete database. Moreover, previous quantitative analyses have focused strongly on benchmarking the impact of VC funds against traditional funds and then determining whether their financial performance is inferior or superior. In the course of this, impact is often treated as a binary criterion for funds. This means on the one hand that in the absence of a standardised label, the distinction between impact and non-impact might be biased. On the other hand, it provides only limited insights into the nuanced relationship between financial and impact performance. While existing empirical evidence can help traditional investors decide whether to invest in an impact VC fund, for impact investors and backed companies, it might be more interesting to investigate the intricate dynamics between the two dimensions. Without an exhaustive central database and given the disadvantages and open questions after reviewing existing methods, a quantitative analysis in the context of an individual case study on a particular impact VC fund, Mustard Seed Maze by Maze Impact, has been chosen as a reasonable mean to mitigate the existing gap in research on impact VC. The limitation to one fund allows for an in-depth understanding of the mechanisms between impact and financial performance within a portfolio. As mentioned above, aggregating impact at the fund level can be difficult due to the heterogeneity of investees. We will, thus, examine financial gain and impact creation on a company level and look for implications on the fund level.

Nevertheless, case studies come with shortfalls, which will be further elaborated in the context of the overall limitations of the findings in Chapter 5. Generally, it should be noted that the analysis conducted should identify patterns and provide practical insights for impact investors and fund managers. It is not intended to derive universally applicable statements, which is typically not the goal for case study research due to empirical analyses being based on non-random sampling (Brown 2008).

3.2 The MAZE Case

Maze Impact is an impact investment firm that offers financial and non-financial tools to ventures dedicated to achieving positive environmental and social outcomes. These tools include VC, impact advisory, growth programs, outcome-based commissioning, and platforms, the former being the focus of this paper. Maze Impact provides support to founders through the startup acceleration program, Maze X, and the impact fund, MSM.

The Maze X package includes EUR 100,000 funding in the form of a simple agreement for future equity (SAFE) to accelerate product development, hire staff, and increase sales, as well as three months of customised support that includes workshops and access to an extensive network of experts. Many startups that are part of the Maze X program later received additional investment tickets from the MSM fund.

MSM is a EUR 45 million fund, with EUR 27.5 million already deployed. The fund was launched in 2019, with an investment horizon of up to twelve years[6], and consists to date of 36 companies invested in. It specialises in pre-seed and seed stage investments with initial volumes between EUR 100,000 and EUR 1 million (Maze Impact n.d.). The portfolio consists of ten

[6] Initially, the fund is set up for a duration of 10 years, with the possibility of extending its lifespan for one or two additional years if deemed necessary.

pre-seed, 22 seed, and four Series A companies. The smallest investment ticket in one company is EUR 40,000, while the largest amounts to EUR 1,250,000, with the average of the sum of tickets per company amounting to EUR 430,000. MSM is working with a lock-step model on a fund and company level. They actively seek opportunities to support rapidly expanding companies, focusing on business models that have an inherent synergy between impact and profits. On the fund level, remuneration is linked to impact as managers only receive a performance fee if a minimum threshold for the impact performance of the entire portfolio is reached. All the backed companies are located in Europe, most of them in Portugal, Germany, and the UK. Maze classifies impact according to their Venture Capital Impact Matrix. This matrix combines the five dimensions of the IMP framework with the classifications of the ABC framework, with Maze prioritising "B"- and "C"-classified investments as their pipeline is centered on achieving positive outcomes through scaling (see *Figure 3*) (Miguel 2023). Most investees prioritize SDGs 3 – "Good health and well-being" and 12 – "Responsible consumption and production" (both at 23%), followed by SDG 4 – "Quality education" (19%), and 8 – "Decent work and economic growth" (15%). This implies that MSM predominantly supports companies aiming for a social impact rather than an environmental one. Hence, they align with the predominant focus of most impact investors on fostering social impact, according to a study by the European Venture Philanthropy Association (EVPA 2022).

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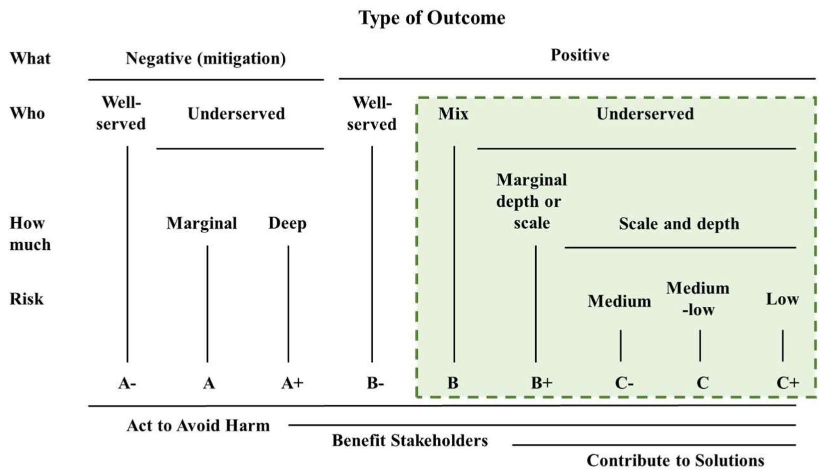

Figure 3: Venture Capital Impact Matrix (MAZE Impact Report 8 years)

3.3 Data Collection

For this analysis, two datasets sourced from Maze's internal records were delivered, one covering the financial performance of each investment ticket and one covering the social impact of each portfolio company (see *Appendix IV*). The financial observations most importantly include the variables "Company", "Stage", "Amount (€)", "Date", "Last Valuation (€)", "MOIC", and "Time since 1st investment (months)". The dataset covers the period since the initiation of the fund and was truncated from 30 August 2023. After consultation with the fund's management, we consider it reasonable to assume that all valuations relate to this date.

The data set for impact contains the variables "Company", "SDG", "Angle", "Impact Metric", "KPI Measurement" and several columns with target and actual values for the first four years after the investments. However, for most companies, the first reporting year taken into account was 2022. Since 10 investments have only been made recently before the cutoff date, and thus no impact was reported until then, they will be scoped out of the analysis, resulting in a sample of 26 companies.

To account for potentially confounding factors, the data was extended by additional information on the portfolio companies, such as geographical location, sector, company size, and year of foundation, collected manually via websites and LinkedIn.

3.4 Variable Description

3.4.1 Dependent Variables

Financial Performance

As discussed in Chapter 2.3, several metrics can be used to evaluate the financial performance of VC funds. Due to the MSM fund's short lifetime and the limited availability of historical financial data, common metrics like IRR and TVPI have proven challenging to apply. Additionally, the usefulness of the TVPI depends on benchmark data for comparison, which is not obtainable for the MSM fund. TVPI may be less informative for young funds in the early stages of the J-curve, due to initial investment costs and management fees. These costs must be recouped before significant valuation increases can be achieved, usually through profitable exits via IPOs or acquisitions (Lehman 2023).

Given these limitations and the objective of assessing performance at the company level, MOIC was chosen as the metric for expressing financial performance. The MOIC as illustrated in equation (1) quantifies the appreciation or depreciation in the value of the initial investment and therefore, provides a comparable basis between heterogenous early-stage ventures, which often do not yet report revenue or similar performance indicators.

$$(1)\ MOIC = \frac{Current\ valuation\ of\ Investment}{Initial\ amount\ of\ Investment}$$

Considering that Maze may have engaged in more than one of the companies' financing rounds, we have computed the Weighted average MOIC (2) for each company to take into account the value development in relation to the respective ticket size.

$$(2)\ Weighted\ average\ MOIC = \frac{Ticket_1 * MOIC_1 + \cdots + Ticket_n * MOIC_n}{Total\ amount\ of\ n\ initial\ Investments}$$

Group Part

In light of the last valuation date for all the companies, the reference date for Weighted average MOIC is 30.08.2023.

Impact Performance

To measure each company's impact, Maze has defined an impact metric for the business model of each company. Every impact metric follows the lock-step model, i.e. an increase in the metric should lead to an increase in revenue. For example, one startup has developed a rental marketplace to optimize product life cycles. This company's product targets “SDG 12 - Sustainable Consumption and Production” and is measured by the impact metric “incremental number of product utilization”. Prior to any capital commitment, for each company and metric, Maze formulates annual targets that are proposed to the five main investors who constitute the fund’s advisory board. Upon their agreement, the investees are obliged to regularly report the performance on the metric. Based on this, Maze computes the Impact Multiple for each portfolio company, representing the ratio between the targets set at the time of investment and the impact performance at the time of calculation (3). If a company has more than one quantifiable positive outcome, the Impact Multiple is calculated for each one and then weighted according to significance. As indicated above, General Partners (GPs) at Maze receive carried interest if not only the MOIC but also the Impact Multiple across the portfolio, weighted according to the invested amount, reaches a certain threshold. Above 60% impact achievement, the carry follows a linear scale.

$$(3)\ Impact\ Multiple = \frac{Impact\ performance\ at\ calculation\ date}{Targets\ set\ at\ investment\ date}$$

The Impact Multiple serves as the second key variable for our analysis. Though it does not display absolute impact, we suppose that an Impact Multiple of around 1 reflects effective impact value creation. Considering Maze's focus on "B"- and "C"-classified companies according to the IMP standard, we postulate that all investees are committed to societal or environmental value creation. We also assume that the target metrics determinative of the Impact Multiple are not set arbitrarily as they undergo an evaluation process by GPs, preventing the deflation of expectations to facilitate carry payments.

The calculation date for every company in our sample is 31.12.2022 since the impact is only comprehensively reported at year-end. In the impact data set provided, there were four companies whose impact reports were excluded from the carry benchmark in 2022 by Maze. We opted to include them in our analyses, considering that the initial investments in these companies transpired over 18 months prior, providing sufficient time for an evaluation of their impact metrics, considering their type of product or service and maturity stage.

3.4.2 Control Variables

Control variables improve the internal validity of an analysis by minimising the impact of confounding and other extraneous variables (Hünermund and Louw 2022). Thus, a correlative or causal relationship can be established between the dependent and independent variables. To account for factors that can have a considerable impact on MOIC, other than impact performance, the companies' founding year, size, sector, and region have been added to the data set manually. The founding year should serve for the determination of the firm's age, which can have a significant impact on valuations as younger companies may still be in the development phase and have not yet reached their full performance potential (Lorderer and Waelchli 2010). Moreover, the characteristics of a sector, such as market growth, profitability, and degree of product differentiation, affect venture capitalists in their valuation (Miloud et al. 2012). Therefore, we have classified the sample companies' activities into sector groups, comprising "Agriculture", "E-commerce", "Education", "Financial Services", "Food and

Catering", "Healthcare Services", "Resources" and "Technology". Additionally, the companies are divided into three different groups for size ("<10", "10-50", ">50") and six different groups for the geographical region ("BeNeLux", "France", "Germany", "Portugal", "Scandinavia", "UK"). The size of a company represents factors such as stability, resource availability, and growth stage. Furthermore, it can affect their capacity to generate positive social impact and can also be correlated with risk, as smaller firms may be more susceptible to market fluctuations (Perez-Quiros and Timmermann 2000). Like the studies presented in section 2.4.3, we recognise the region as a control variable to account for factors like regional economic variations and regulatory frameworks (Miloud et al. 2012).

3.5. Hypotheses

Based on the described data we will test several hypotheses to identify the link between financial and impact performance but also potentially uncover some other patterns that can serve as a basis for further research.

Considering that Maze follows the principle of investing in companies with a lock-step model, we hypothesise the following correlation between impact and financial performance:

H1a: A higher Impact Multiple comes with a higher Weighted average MOIC.

To acknowledge the possibility, that the interaction can also work in the other direction, we suggest to additionally test:

H1b: A higher Weighted average MOIC comes with a higher Impact Multiple.

To scrutinise these potential interaction effects, we hypothesise that companies that have raised various financing rounds have the potential to generate more impact:

H2: Companies that have completed several rounds of financing show a higher Impact Multiple.

Group Part

To test the robustness of the findings, we additionally look at this relation from the angle of the Venture Capital Impact Matrix, adapted by Maze. Capital from the MSM shall be dedicated to companies that can be classified under the category “B – Benefit Stakeholders” or “C – Contribute to Solutions”. Classification “B” can be viewed as a precursor to Classification “C”, where companies classified as “B” have the long-term objective of attaining financial performance and a positive impact on stakeholders. In contrast, “C”-classified companies prioritise achieving a substantial positive impact as their primary goal (Impact Frontiers n.d. a). We assume that this strategic focus increases the potential for impact creation and therefore examine:

H3a: Investments classified as “C” show a higher Impact Multiple than those classified as “B”.

Building on our assumption of a positive correlation between financial performance and impact performance in H1, we hypothesise the following:

H3b: Investments classified as “C” show a higher Weighted average MOIC than those classified as “B”.

Lastly, we found that the data set provides the unique opportunity to uncover further patterns relevant to impact investment decision-making, such as the difference in performance of companies dedicated to social topics in comparison to those that address environmental ones. According to GIIN, for a growing proportion of impact investors, investing in climate change mitigation or adaptation is a strategy that can be applied across many sectors. For this reason, GIIN states that nowadays, most impact investors direct their capital toward environmental solutions (Hand et al. 2023; GIIN n.d. b). Investigating the rationale behind this trend, we lastly hypothesise:

Group Part

H4a: Companies classified as working towards an environmental SDG achieve a higher Weighted average MOIC than those working towards a social SDG.

H4b: Companies classified as working towards an environmental SDG achieve a higher Impact Multiple than those working towards a social SDG.

Group Part

4. Analysis

4.1 Exploratory Data Analysis and Descriptive Statistics

Before the hypotheses are tested with statistical methods, the sample data will be explored to better understand the distribution of different variables and discover initial properties that might impact the analysis that follows.

MOIC and Impact Multiple

Looking at the Weighted average MOIC of the sample, most companies display performance between 1 and 1.5, with three companies in the sample having a value of zero due to bankruptcies and one company achieving a comparatively high MOIC (see *Figure 4*). For Impact Multiple, many companies reach a performance between zero and one, which is in line with expectations considering the Impact Multiple represents a ratio of target achievement (see *Figure 5*). However, several companies have outperformed their targets and therefore, have a multiple greater than one.

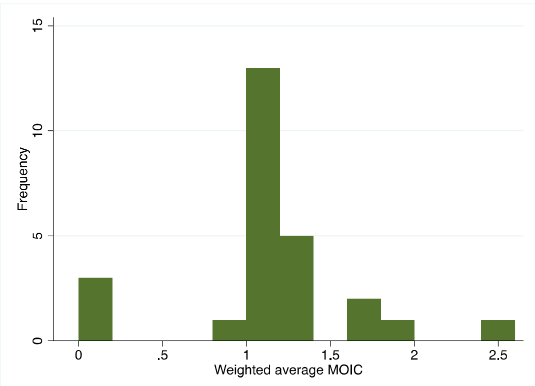

Figure 4: Histogram of Weighted average MOIC

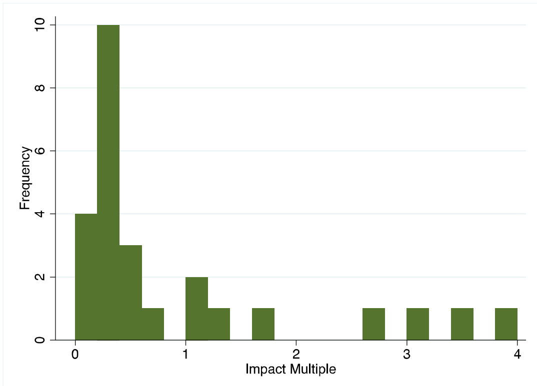

Figure 5: Histogram of Impact Multiple

Table 1 presents the descriptive statistics for both key variables. In our sample of 26 observations, the Weighted average MOIC has a mean of 1.11 and a median of 1.04. The spread of Weighted average MOIC extends from a minimum of 0.00 to a maximum of 2.59. The Impact Multiple exhibits a mean of 0.91 with a median of 0.37. The range of Impact Multiple spans from a minimum of 0.00 to a maximum of 3.97.

Group Part

Table 1
Descriptive statistics of the included variables.

	N	Mean	Median	Min	Max
Weighted average MOIC	26	1.11	1.04	0.00	2.59
Impact multiple	26	0.91	0.37	0.00	3.97

Relations between dependent and independent variables

As highlighted in section 3.2, Maze classifies its companies in "B" and "C" based on their Venture Capital Impact Matrix. *Figure 6* provides an overview of the distribution within these classifications and displays the number of companies that pursue either social or environmental objectives.

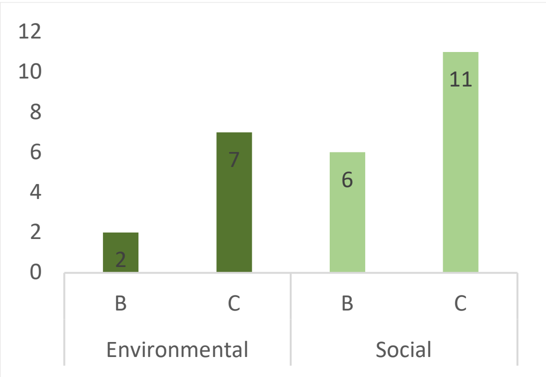

Figure 6: Distribution of classifications

When comparing the Impact Multiple between "B"- and "C"-classified companies, it becomes clear that "C"-classified companies attain a slightly higher median than their "B"-classified counterparts (see *Figure 7*). Conversely, when comparing the Weighted average MOIC between "B"- and "C"-classified companies, it is found that "B"-classified companies achieve a higher median than "C"-classified companies (see *Figure 8*).

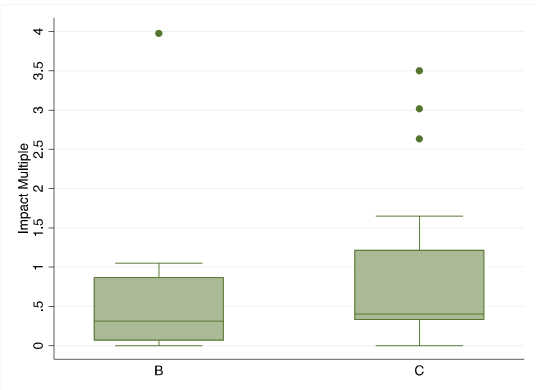

Figure 7: Boxplot Classification and Impact Multiple

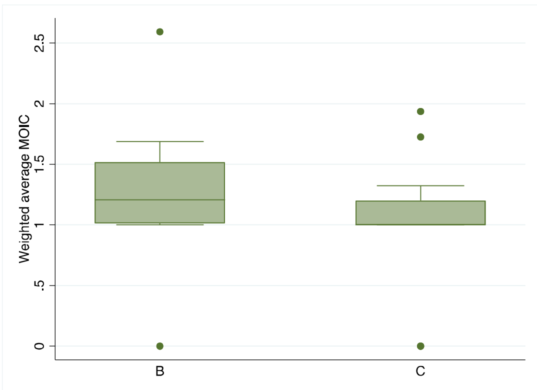

Figure 8: Boxplot Classification and Weighted average MOIC

Group Part

The portfolio companies received between one and four investment tickets, averaging 1.9 tickets per company. When analysing the Impact Multiple in relation to the number of investment tickets, an increasing trend in the median is observed as the number of tickets allocated to a company increases (see *Figure 9*). Similarly, when inspecting the relationship between the Weighted average MOIC in the same context, a similar median trend can be observed, with an exception in the group with four investment tickets (see *Figure 10*).

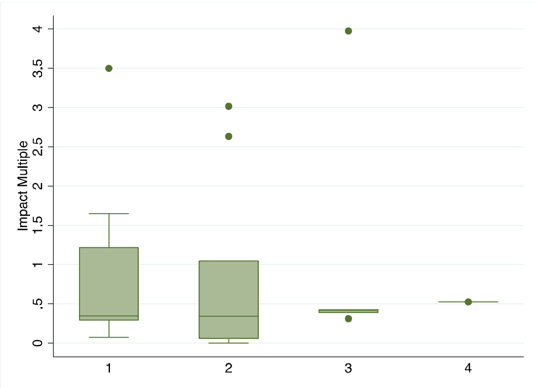

Figure 9: Boxplot Number of Investment Tickets and Impact Multiple

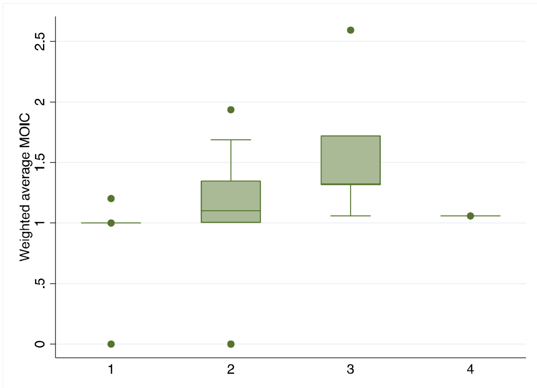

Figure 10: Boxplot Number of Investment tickets and Weighted Average MOIC

In *Figure 6*, we have already examined the distribution of portfolio companies in terms of social and environmental goals. Having a look at *Figure 12*, it is evident that in the case of the Weighted average MOIC, the median for companies with an environmental angle is noticeably higher than that for companies with a social focus but there are high outliers in the latter group. The median of the Impact Multiple is only slightly higher for companies with an environmental approach (see *Figure 11*).

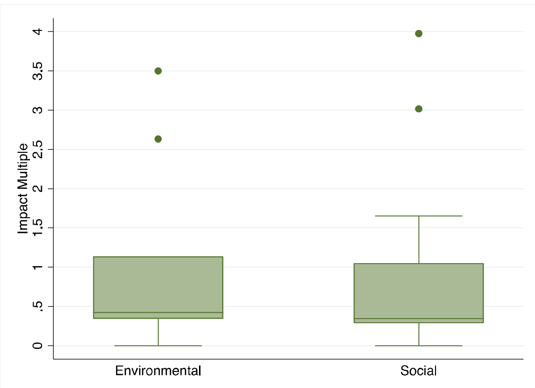

Figure 11: Boxplot Goals and Impact Multiple

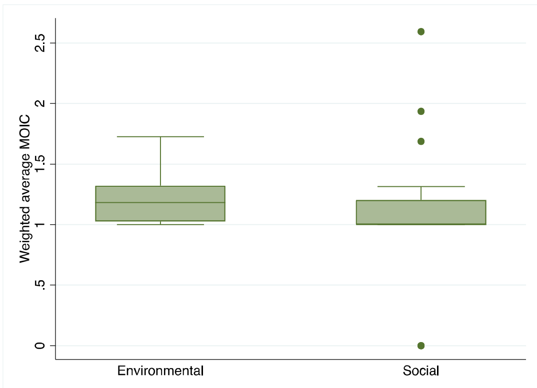

Figure 12: Boxplot Goals and Weighted average MOIC

Group Part

Table 2 presents the descriptive statistics for companies addressing various SDGs with social and environmental goals. Among companies with a social angle, those addressing SDG 16 – "Peace, justice, and strong institutions" exhibit the highest mean Weighted average MOIC at 1.80, along with the highest mean Impact Multiple of 1.99. Among companies focusing on environmental objectives, the company concentrating on SDG 11 – "Sustainable cities and communities" has the highest mean Impact Multiple at 3.50, while conversely, it performs the least favorably financially, with a mean Weighted average MOIC of 1.00.

Table 2
Descriptive statistics of the Weighted average MOIC and Impact Multiple, categorized by SDGs.

Social				Environmental			
SDG	N	Mean Weighted average MOIC	Mean Impact Multiple	SDG	N	Mean Weighted average MOIC	Mean Impact Multiple
SDG 3	6	0.72	0.82	SDG 9	1	1.73	0.43
SDG 4	5	1.07	0.84	SDG 11	1	1.00	3.50
SDG 8	4	1.16	0.32	SDG 12	6	1.16	0.81
SDG 16	4	1.80	1.99	SDG 13	1	1.32	0.34
Total	17	1.05	0.85	Total	9	1.22	1.02

Relations between dependent variables and control variables

As mentioned in 3.4.3, we have determined several control variables based on literature and data availability to improve the informative value of the models that follow in the regression analysis. We have observed the Weighted average MOIC in relation to the four variables with the help of box plots that can be seen in *Appendix I A)*. Although there were some notable differences in the medians of the categories in some cases, it has been found in the course of running regressions on models including different controls, only Sector helped to improve the estimations. Accordingly, further chapters will only consider the Sector control variable for H1a. In *Table 3*, the statistical characteristics of the Weighted average MOIC by sectors are compared. The sector with the highest Weighted average MOIC is "Food and Catering" (1.94), while the lowest value was recorded in the sector “Education” (1.09). The median is highest in the sector “Food and Catering” (1.94) and lowest in sectors “Agriculture”, “Education” and “Health Services” (all 1.00). The positive extreme is caused by the only company in the "Food and Catering" sector.

Table 3
Descriptive statistics of the Weighted average MOIC, categorized by sectors.

	Weighted average MOIC by Sector				
	N	Mean	Median	Min	Max
Agriculture	1	1	1	1.00	1.00
E-Commerce	2	1.12	1.12	1.06	1.18
Education	4	1.09	1	1.00	1.35
Financial Services	4	1.10	1.04	1.00	1.32
Food and Catering	1	1.94	1.94	1.94	1.94
Health Services	7	0.80	1	0.00	1.32
Resources	1	1.73	1.73	1.73	1.73
Technology	6	1.27	1.16	0.00	2.59
Total	26	1.11	1.04	0.00	2.59

Similarly, in preparation for the tests for H1b, we explored the relation of the Impact Multiple in connection to potential control variables, respective box plots can be seen in *Appendix I B)*. It has been found that the variable Region has the most remarkable influence on Impact Multiple. *Table 4* depicts the Impact Multiple by Region. Companies from the region BeNeLux exhibit the highest mean and median Impact Multiple (2.60). The lowest mean Impact Multiple was observed in Scandinavia while the lowest median was observed in the UK, due to two companies reporting an impact of zero.

Table 4
Descriptive statistics of the Impact Multiple, categorized by regions.

	Impact Multiple by Region				
	N	Mean	Median	Min	Max
BeNeLux	2	2.60	2.60	1.20	3.98
France	3	1.62	1.14	0.70	3.02
Germany	6	1.10	0.40	0.31	3.50
Portugal	8	0.45	0.36	0.22	1.05
Scandinavia	2	0.18	0.18	0.05	0.31
UK	5	0.60	0.07	0.00	2.63
Total	26	0.91	0.37	0.00	3.98

4.2 Hypothesis Testing

The following section will analyse the hypotheses based on variables that have the potential to influence the financial and impact performance of companies in our sample. To ensure the practicability of the statistical analyses, the properties of the sample were scrutinised first. According to the central limit theorem, a sum of numerous independent, identically distributed random variables with finite variance tends to follow an approximately normal distribution. Either a sample size of $n \geq 30$ must be given, as the central limit theorem suggests that the distribution of sample means approximates normality in such cases, or for $n < 30$, it must be secured that the sample is normally distributed (Mascha and Vetter 2018, 693). As shown in *Figure 4,* MOIC approximately follows a normal distribution.

For linear regressions, we have reviewed the distribution of residuals, as it can be seen in *Appendix II A)*. Additionally, we tested for multicollinearity and heteroscedasticity (see *Appendix II B)* and *C)*). To judge the significance of effects observed in the analyses, the level $\alpha = 0.10$ will be used. The decision to employ a 10% significance level, deviating from the standard of $\alpha = 0.05$, is rooted in the exploratory character of this study, rather than the aim to draw absolute conclusions. Furthermore, with a small sample size, the power of hypotheses tests may be limited, so a higher significance level may help to reduce the likelihood of Type II errors (Riffenburgh 2012).

Group Part

Hypothesis 1a and 1b

As the first hypotheses address the relationship between two continuous variables, linear regressions were applied for testing. For better robustness when testing H1a, we estimate three models. First, we assume a linear relationship without control variables (4), then with, fixing the effects of the sector (5), and lastly, we test an exponential relationship (6).

$$(4)\ Weighted\ average\ MOIC_i = \beta_0 + \sum_1^j \beta_{i,j}\ Impact\ Multiple_{i,j} + \varepsilon_i$$

$$(5)\ Weighted\ average\ MOIC_i = \beta_0 + \sum_1^j \beta_{i,j}\ Impact\ Multiple_{i,j} + Sector\ Control\ Variable + \varepsilon_i$$

The results of the first model can be found in *Table 5*. The regression produced a coefficient of 0.17 for the Impact Multiple and a respective p-value of 0.09, falling just below the applied significance level and therefore, indicating a moderately statistically significant positive correlation between Weighted average MOIC and Impact Multiple. This relation is illustrated in *Figure 13*.

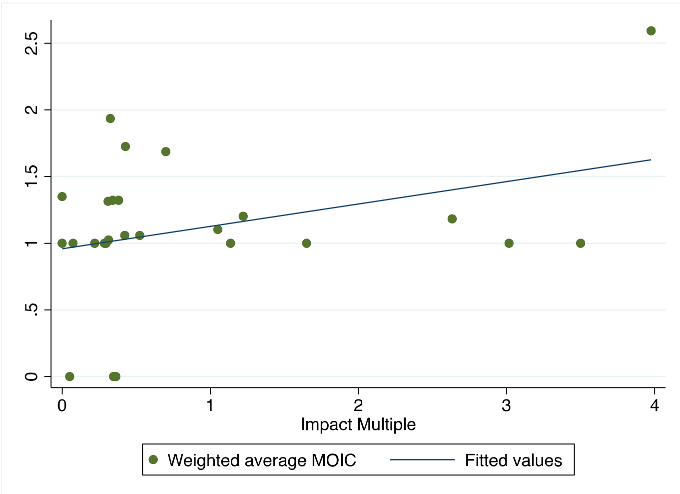

Figure 13: Linear regression of Weighted average MOIC on Impact Multiple

Table 5
Linear regression without control variables

Weighted average MOIC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig.
Impact Multiple	0.168	0.094	1.78	0.088	-0.027	0.363	*
Constant	0.959	0.135	7.13	0.000	0.681	1.236	***
R-squared			0.117	F-test		3.170	
Adjusted R-squared			0.080	Prob > F		0.088	

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

On the other hand, the R^2 achieved was only 0.12 (Adjusted R^2 = 0.08), suggesting that only a fraction of the variance in Weighted average MOIC can be explained with impact performance and equation (4) cannot be regarded as an appropriate model to estimate Weighted average MOIC in relation to impact. When controlling for the factor Sector in the second model (see *Table 6*), the influence of Impact Multiple on Weighted average MOIC slightly increased to $\beta_{IM} = 0.19$. This effect was, again, only moderately significant (p-value = 0.07). R^2 and Adjusted R^2 were improved and confirmed (5) as the model with more explanatory power (R^2 = 0.38, Adjusted R^2 = 0.09). When adding additional control variables to the model, its explanatory power, depicted in Adjusted R^2 only decreased, so Sector was determined as the only suitable predictor in combination with Impact Multiple.

Table 6
Linear regression with control variable (Sector)

Weighted average MOIC	Coef.	St.Err.	t-value	p-value	[95% conf.	Interval]	Sig.
Impact Multiple	0.193	0.101	1.91	0.073	-0.020	0.407	*
Agriculture	0	(omitted)					
E-Commerce	0.045	0.647	0.07	0.945	-1.319	1.410	
Education	0.147	0.590	0.25	0.806	-1.098	1.393	
Financial Services	0.251	0.595	0.42	0.679	-1.004	1.505	
Food and Catering	1.093	0.750	1.46	0.163	-0.490	2.675	
Health Services	-0.123	0.565	-0.22	0.830	-1.315	1.069	
Resources	0.863	0.749	1.15	0.265	-0.717	2.443	
Technology	0.211	0.570	0.37	0.716	-0.992	1.414	
Constant	0.780	0.540	1.45	0.166	-0.358	1.919	
R-squared			0.380	F-test		1.300	
Adjusted R-squared			0.088	Prob > F		0.307	

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

Considering the skewness of the Impact Multiple (see *Figure 5*), we estimated another model in which the independent variable was log-transformed (6). This led to the dropping of two observations whose Impact Multiple equaled zero and a new sample size of 24 companies.

Group Part

$$(6)\ Weighted\ average\ MOIC_i$$
$$= \beta_0 + \sum_1^j \beta_{i,j} \log\,(Impact\ Multiple)_{i,j} + Sector\ Control$$

The results (see *Table 7*) indicate that for every 10% increase in Impact Multiple, the Weighted average MOIC increases by 0.01 (0.252*log(1.1)). This effect is significant under the conventional significance level of $\alpha = 0.05$ (p-value = 0.03) and the model considerably improved to a R^2 of 0.48 and Adjusted R^2 of 0.20. Under the chosen significance level, we can reject the null hypothesis for all the performed regressions and accept H1a, while with the third model (6), H0 can also be rejected at a significance level of 0.05.

Table 7
Regression with control variable (Sector) and log(Impact Multiple)

Weighted average MOIC	Coef.	St.Err.	t-value	p-value	[95% Conf.	Interval]	Sig.
Log (Impact Multiple)	0.252	0.102	2.47	0.026	0.035	0.470	**
Agriculture	-1.251	0.737	-1.70	0.110	-2.822	0.319	
E-Commerce	-1.112	0.640	-1.74	0.103	-2.475	0.252	
Education	-0.966	0.593	-1.63	0.125	-2.229	0.297	
Financial Services	-0.857	0.574	-1.49	0.156	-2.080	0.367	
Food and Catering	0	(omitted)					
Health Services	-1.289	0.552	-2.33	0.034	-2.466	-0.112	
Resources	-0.279	0.726	-0.38	0.706	-1.827	1.269	
Technology	-0.806	0.567	-1.42	0.176	-2.015	0.403	
Constant	2.219	0.526	4.22	0.001	1.098	3.340	***
R-squared			0.477	F-test		1.710	
Adjusted R-squared			0.197	Prob > F		0.177	

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

Subsequently, dependent and independent variable should be interchanged to investigate the direction of potential causality. In our sample, however, it should be noted that the measurement of the MOIC took place after the last measurement of the impact performance, so that no logical connections can be drawn from a regression at this time. Based on the previous analyses, we propose to examine model (7) and (8) during regressions with a new data set including the Impact Multiples for 2023 as soon as they have been reported.

Group Part

$$(7)\ \log(Impact\ Multiple)_{i,j} = \beta_0 + \sum_1^j \beta_{i,j}\ MOIC_{i,j} + \varepsilon_i$$

$$(8)\ \log(Impact\ Multiple)_{i,j} = \beta_0 + \sum_1^j \beta_{i,j}\ MOIC_{i,j} + Region\ Control\ Variable + \varepsilon_i$$

Afterwards, the statistical properties of the models should be compared again, including varying control variables, to decide on the best-fitting model for the link between financial and impact performance.

Hypothesis 2

For H2, we employed an ANOVA (analysis of variance) to assess whether companies that have raised several financing rounds with Maze exhibit a higher Impact Multiple. ANOVA is suitable for examining whether the mean values of distinct groups differ statistically significantly. In contrast to a t-test, the ANOVA can also be used to compare more than two groups. Before performing the test, we ensured the homogeneity of variances between the groups (*Appendix II D)*). Moreover, considering the reference date of the Impact Multiple, three investment tickets were scoped out as they were issued after 31.12.2022.

The ANOVA did not produce any significant results, showing no difference between the four group means (number of ticket size from one to four) (see *Table 8*). The low R^2 indicates that almost none of the variance in the Impact Multiple can be explained by the number of tickets. The ANOVA yielded a p-value of almost one, far from any significance level. Thus, it is not possible to reject the null hypothesis and we find no evidence that companies that raised several rounds of financing perform better on the impact level.

Group Part

Table 8
ANOVA using log(Impact Multiple)

Source	Partial SS	df	MS	F	Prob > F
Model	0.064	3	0.022	0.02	0.997
Number of tickets	0.064	3	0.022	0.02	0.997
Residual	28.556	20	1.428		
Total	28.556	23	1.244		
R-squared		0.002	Adjusted R-squared		-0.147

Hypothesis 3a and 3b

To evaluate the potential differences between two different groups and therefore, the relationship between a discrete and a categorical variable, performing a t-test is a common method. Central assumption for the t-test is the normal distribution of the discrete variable. In *Figure 4 and 5*, the distribution of the two discrete variables, Weighted average MOIC and Impact Multiple are depicted. The histograms suggest that while the mean of Weighted average MOIC of companies under category "C" and the one of those under category "B" can be compared via t-testing for H3b (10), the non-normal distribution of Impact Multiple requires a different approach for H3a (9). Hence, for the latter, a Wilcoxon-Mann-Whitney-test was performed.

$$(9)\ mean_{ImpactMultiple}(B) - mean_{ImpactMultiple}(C) < 0$$

$$(10)\ mean_{MOIC}(B) - mean_{MOIC}(C) < 0$$

The results show a comparable mean of Impact Multiple of the two reviewed groups (p-value = 0.28). Thus, the classification in "B" and "C" does not exert a significant influence on this metric. For Weighted average MOIC, companies under category "B", in fact, attained a 0.21 higher mean than those under category "C". Yet, this difference was not statistically significant either (p-value = 0.19), see *Table 9*. Hence, in both cases, we cannot reject the null hypotheses and we do not find evidence for equations (9) and (10) holding true.

Group Part

Table 9
T – Test Company Classification

Group	Observations	Mean	Std. err.	Std. dev.	[95% conf.	Intervall]
B	8	1.25	0.26	0.73	0.65	1.87
C	18	1.04	0.11	0.46	0.81	1.28
Combined	26	1.11	0.11	0.55	0.89	1.33
Difference		0.21	0.24		-0.27	0.70

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr (T < t) = 0.814	Pr (|T| > |t|) = 0.371	Pr (T > t) = 0.186

Hypothesis 4a and 4b

H4 aimed to compare the impact as well as the financial performance of firms with a primarily social objective to those with a primarily environmental one which again was approached with a Wilcoxon-Mann-Whiney-test (11) and a t-test (12), respectively.

$$(11)\ mean_{ImpactMultiple}(Environmental) - mean_{ImpactMultiple}(Social) > 0$$

$$(12)\ mean_{MOIC}(Environmental) - mean_{MOIC}(Social) > 0$$

The findings reveal a lack of statistical significance in the disparities of Impact Multiple (12) between the two analyzed groups (p-value = 0.48). This implies that the impact angles, Social and Environmental, exhibit similarity in their Impact Multiples, indicating that they do not significantly influence this metric.

When it comes to MOIC, environmentally focused companies, on average, show a 0.17 higher value than socially prioritised ones. This effect was not statistically significant (p-value = 0.24), but neither was the converse hypothesis of social companies performing better. After all, there is insufficient evidence to reject the null hypothesis, i.e. we cannot infer that companies classified as working towards environmental SDGs achieve better valuations (see *Table 10*).

Group Part

Table 10

T – Test Company Goal

Group	Observations	Mean	Std. err.	Std. dev.	[95% conf.	Intervall]
Environmental	9	1.22	0.08	0.24	1.04	1.40
Social	17	1.05	0.16	0.66	0.71	1.39
Combined	26	1.11	0.11	0.55	0.89	1.33
Difference		0.17	0.23		-0.31	0.64

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr (T < t) = 0.76	Pr (|T| > |t|) = 0.47	Pr (T > t) = 0.24

Group Part

4.3 Discussion

Hypothesis 1

Regressing MOIC on Impact Multiple, we have discovered a statistically significant correlation and hence, we have found an indication of a positive relationship between financial and impact performance. However, at first, this does not provide any implications for causality or the direction of the influence that the variables might have on each other. While a better impact target achievement might come with a better weighted average MOIC, a better financial position, represented in the Weighted average MOIC can also result in facilitated impact creation. Therefore, we have formulated two sub-hypotheses, one with Weighted average MOIC as the dependent variable and one with Impact Multiple as the dependent variable. We estimated different models with changing dependencies and control variables to identify the most suitable link between impact and financial performance in the context of our data.

The best statistical results when testing the potential impact of Impact Performance on MOIC were achieved with model (6). In our sample, Impact Multiple and Sector classification explain almost half of the variation in Weighted average MOIC. Considering the scope of the effect, the regression implies that a 10% increase in Impact multiple comes with an increase in MOIC of 0.01. Though statistically significant, this can be considered a rather marginal effect.

Across sectors, Stata returns that Health Services performs statistically significantly worse than the reference sector, "Food & Catering". Yet, it should be pointed out that the automatically chosen reference sector is the one with the highest mean of Weighted average MOIC, only comprising one observation of 1.94. Sector differences displayed in *Table 7* are thus not conclusive. Nevertheless, since Health Services is most represented by companies in our sample, as the sample size grows, it should prospectively be further investigated if results keep pointing at an inferior financial performance. Particularly, in light of an initial study on impact investments in India by McKinsey (2018) that has suggested lagging financial performance in the areas of healthcare and education.

Subsequently, the direction of the correlation should be scrutinised. However, while MOIC has been recorded for all investees on 30 August 2023, impact performance data refer to performance as of year-end 2022. Generally, a time lag in the effect of one variable on the other seems plausible, for example, due to impact initiatives taking time to manifest in financial performance or companies' investments in initiatives enabled through a better financial position realise in outcomes with a delay. Still, this means that regressions on H1b can only be performed as soon as the impact performance data set is updated with values for the current year. When performing these regressions prospectively, it should be recognised that in a univariate linear regression, simply interchanging the dependent and independent variable yields the same statistical results. Thus, the usage of control variables will be decisive for the result. While Region seemed to explain a lot of the variance in the impact data in 2022 according to the EDA, this step should be repeated before. Potentially, model (8) needs to be adjusted accordingly. In case that no significant influence of MOIC on Impact Multiple is found, this could point to a causal relationship of impact on financial performance.

To summarise, our statistical findings supported H1a and were in line with our expectations as the lock-step model that Maze follows, directly links a greater impact performance with more revenue which in turn, should be reflected in MOIC. Nevertheless, we may not draw any conclusions at this point due to open questions with regards to direction of the interaction and, as will be further elaborated in section 4.5, significant limitations in the variables as well as the amount of data available to date. For prospective analyses on a more comprehensive data set, model (6) and (8) should be used to verify the robustness of the findings.

Hypothesis 2

With H2 we investigated whether companies that have gone through more financing rounds with Maze display higher Impact Multiples as this could confound the findings of H1. While in our sample, MOIC can be weighted according to the ticket sizes to reflect the financial performance of a company over time, the Impact Multiple is a performance snapshot at a specific moment. This means that companies that have undergone multiple financing rounds may hold a distinct advantage in their impact performance, potentially due to the cumulative effect of increased funding over time. After all, our analysis showed that this effect is non-existent in our data as the results were far from being significant.

Yet, the insignificance could be due to the size of the different groups, especially the group with four investment tickets, only consisting of one company. Although it is technically possible to perform an ANOVA with only one observation in a category, such a situation may limit the robustness of the test. In such cases, the ANOVA may have difficulties adequately capturing the variation between groups because there are no other observations to compare, which affects the sensitivity of the statistical model. *Figure 9* indicates that this might have influenced the results, as it shows that except for group four, the median of the Impact Multiple increases as the number of investment tickets increases. As the fund progresses towards its dissolution, it is plausible that more companies will receive at least a fourth investment ticket from Maze, potentially impacting the results. Future analyses should revisit this investigation and if a substantial positive correlation is identified, the number of tickets as a control variable in the regressions conducted for H1 should be considered.

Moreover, the relation of impact performance relative to investment rounds can have important implications for fund managers. In traditional investing, funding is only provided if it is believed to create financial value for the investors through growth perspectives (Le Sourd 2007). In impact investing, it would similarly be desirable to observe a higher Impact Multiple, through an increase in “HOW MUCH” impact is created, subsequent to new tickets issued. It is noteworthy, though, that investments might also serve for an improvement in the dimensions of “WHO” or “RISK”, but these effects are not recognised in the data.

Accordingly, this relation should also be monitored in context with the relation of MOIC to the number of investment tickets received. *Figure 10* displays that the MOIC medians increase as the number of ticket increases. Running an ANOVA on this relationship was not part of the central analysis in section 4 but revealed a positive correlation that was considerably more significant, yet still not enough to reject the null hypothesis (see *Appendix III C)*). In case it will be found that MOIC and the number of tickets correlate positively, just like MOIC and Impact Multiple, but Impact Multiple and the number of tickets do not, this can have implications for H1 that should be scrutinised.

Hypothesis 3

In H3a we hypothesised a stronger impact creation in the “C”-group as we assumed a stronger commitment to impact creation of those companies striving to achieve a quantifiable impact outcome for a population or environment that is presently underserved. During the statistical analysis, we found no evidence indicating that companies classified as “C” exhibit a higher Impact Multiple than those classified as “B”. Still, this does not mean that “C” companies are indeed equally or even less impactful than “B” ones. First of all, it should be emphasised that the Impact Multiple does not measure the absolute impact creation aimed for in a firm’s strategy that is concerned in the ABC framework but the actual achievement ratio of these targets, i.e. their internal performance in relation to their goals (LaFond 2020). Therefore, companies with relatively high impact targets due to their ambitious strategy might actually display a worse Impact Multiple than the ones that aim for outcomes to a smaller degree. This, in turn, raises the question of the suitability of the metric for comparing impact performances across firms with different business models and strategies.

Given that no direct link was identified between ABC-classification and Weighted average

MOIC, H3b cannot provide qualification of the positive correlation of impact and financial performance found in H1. In fact, looking at the results of the analysis, companies classified as "B" seemed to attain a higher Weighted average MOIC. This observation would align with the theory of negative correlation, suggesting a potential cannibalisation effect, where a heightened commitment to impact may come at the expense of financial performance, but the effect did not reach statistical significance and can, thus, not be interpreted reliably.

Furthermore, it is again important to highlight that the conclusiveness of the findings might also be constrained due to the properties of the sample. In *Figure 8* of Chapter 4.1, one "B"-classified company was identified as an outlier with a Weighted average MOIC of 2.59x which represents by far the highest Weighted average MOIC within the sample. The company received three investment tickets at different stages, with the first investment in the pre-seed stage showing the highest MOIC in the sample at 8.32x (the other two investment tickets with MOIC of 2.30x and 1.00x). Due to the small sample size, this outlier likely affects the appraisal of the results for the two classifications.

Repeating this analysis at a later stage can offer valuable insights for Maze. According to the Maze VC Impact Matrix, the aim is to transform "B"-classified companies into "C"-classified companies in the long term, so it should be ensured that these companies in practice also perform better from an impact as well as a financial perspective.

Hypothesis 4

While the first three hypotheses primarily concentrated on the connection between financial performance and impact outcomes, H4 sought to identify possible differences in the financial and impact performance of companies with a social angle compared to those with an environmental one. This exploration was motivated by the prevalent interest among impact investors in environmental topics, along with the higher mean Weighted average MOIC observed for environmentally focused companies, as detailed in Chapter 3.1.

When testing H4, we have observed that there is no statistically significant evidence that companies categorised as working towards an environmental SDG achieve a Weighted average MOIC or an Impact Multiple that differs from those working towards a social SDG. As with the other hypotheses, these results should again be treated with caution due to the outliers that potentially distort the results.

Generally, it should be recognised in this context that the measurability of impact differs between social and environmental activities. Scientific measures, such as carbon emissions, make environmental impact easier to quantify, utilising standardised units like kilograms of CO_2 emissions. In contrast, social metrics, such as employee satisfaction or the user base of a mental health app, can rely on subjective assessments or assumptions. Additionally, even though not directly applicable for early-stage ventures, increasingly stringent sustainability reporting requirements provide investors with a better understanding through greater transparency in the environmental domain compared to social impact areas (Bernow et al. 2019). Consequently, the increasing attractiveness of environmental impact investments may, over time, influence the valuation of companies in this sector. Given that over two-thirds of Maze's portfolio are currently comprised of entities striving for social impact, it is crucial to closely monitor this trend in the future.

4.4 Limitations

4.4.1 Limitations in data and methodology

As indicated before, some level of uncertainty persists with all conclusions owing to the limited sample size. Small sample sizes can lead to increased variance, resulting in unstable and unrepresentative estimates. In our sample, the Impact Multiple exhibits a variance of 1.31, indicating that individual values in the sample vary relatively widely. A sample size that is too small increases the likelihood of a type II error, which distorts the results and reduces the significance of the study (Faber and Fonseca 2014, 27-29). As explained during the discussion of H1 and H2, some groups were only represented by one or two observations that, in some cases, took on extreme values. These outliers can heavily influence the statistics, particularly on a small sample size. We have still decided not to winsorise or trim the data as in the field of VC, extreme values are usually decisive for the performance of a fund rather than spurious (De Treville et al. 2014).

In addition, the selected significance level of $\alpha = 0.10$ must be discussed, as according to Lehmann, a significance level of $\alpha = 0.10$ can only be considered marginally significant. A significance level of 0.1 contributes to an increased risk of type I errors as it accepts the probability of a false positive error. This can lead to an over-acceptance of results that may be due to chance, which affects the validity of our conclusions (Lehmann 2007). Nevertheless, since the results on the best-fitting model for H1 were significant under a 5% level and results on the other hypotheses were far from any significance, we do not consider this a problem for our conclusions.

Furthermore, the use of variables should be discussed. It can be questioned if MOIC and Impact Multiple can be seen as proper representations of financial and impact performance. From the company's management perspective, financial performance usually encompasses indicators such as revenue, profit, and cash flow. We would argue that for early-stage ventures, the MOIC of the company reflects the overall financial situation properly as actuals, e.g. revenues, might not exist yet but investors will consider all future performance factors in their valuation. Primarily, MOIC reflects how effectively the investee is translating the capital provided into growth perspectives. Especially for investors, MOIC might, therefore, be more indicative than looking at absolute numbers. Yet, this investor perspective can also distort the expressiveness of the variable as the MOIC can be high at a given point in time due to a successful exit strategy or favorable market conditions, but it does not ensure the sustainable financial health of the company itself.

The Impact Multiple is similarly arguable. Since it is a ratio determined through target setting by Maze in relation to an individually defined outcome for each investee, it is hardly comparable between companies and not directly transferrable to other funds. If individual impact targets change over time, this might further complicate comparability across companies as well as periods.

Moreover, we cannot rule out the potential endogeneity of the variables. On the one hand, the financial performance, represented by the MOIC, may be a factor in companies' impact performance target-setting. On the other hand, there might be unobserved factors that influence both, MOIC and Impact Multiple similarly, such as the market conditions or regulatory environment, for example. There are also several aspects influencing valuations as well as impact achievement that go beyond the control variables accounted for in our model, due to constraint data availability. The error terms might, hence, also comprise variables that correlate with the dependent variable.

Lastly, analysing the financial performance and impact of companies at a specific point in time only provides a snapshot that does not offer discernment of their long-term performance. For simplicity, we assume that all company valuations took place on 30 August 2023, and thus, the Weighted average MOIC always refers to this date. Factors such as seasonal or cyclical fluctuations, and geopolitical events are therefore not considered, which underlines the need to monitor performance over time. Time series data on MOIC would facilitate observing the evolvement of a company's impact in relation to the valuation at different points in time. After all, it needs to be recognised that the data, in the frequency it is currently collected, is not able to reflect any real-time changes in the dependent variable when the independent variable changes.

Group Part

4.4.2 Limitations in Transferability

When contextualising the study with other research, it becomes evident that direct transferability to other impact investment funds is not possible due to the special features of the fund analysed. Approximately 18% of impact investing organisations do not set targets for impact and therefore differ from Maze's definition of impact performance (Hand et al. 2023). The investment thesis of Maze has some peculiarities, too. Firstly, they focus on start-ups in early stages that have not yet realised their full impact potential. The link between impact and financial performance might differ in the initial phase of a firm's lifecycle. Like financial performance, impact performance is also subject to a changing risk profile as a company matures. Notably the execution risk, i.e. the possibility that activities do not result in desired outcomes (Impact Frontiers n.d. b), can be particularly high in the beginning. Thus, the interaction between the two multiples might differ for equity investments in more mature companies. Secondly, Maze specifically invests according to a lock-step model, which is not universally applicable. For investees with a different strategy, the link between impact and financial value creation might differ, too.

4.5 Further Research

Reperforming the foregone analysis in a few months has the potential to generate enhanced results due to the incorporation of additional data. Originally, the portfolio had 36 companies, but ten were excluded due to unavailable impact performance reports, and two more were excluded after the log-transformation of the Impact Multiple. Once impact performance data for the recently added companies is available, the sample will gain explanatory power, reaching a critical size for a random sample ($n \geq 30$). As the sample is expanded, encompassing additional groups and augmenting smaller subsets, analyses exploring differences between sectors or regions will become more insightful.

Furthermore, the relationship between impact and financial performance should be monitored over time to make sure there are no biases through effects specific to the point in time of the analysis. The data should therefore be expanded with time-series data points. As a result, further analyses should be performed in the form of panel regressions. The difficulty that remains is the acquisition of MOIC, which usually transpires at different points in time, not necessarily every year as it is the case for Impact Multiple.

To find out whether more capital deployment leads to better impact performance, it would be necessary to also observe the Impact Multiple per company over time in consideration of the number of tickets, once a longer track record is available.

In addition to reperforming the analyses when more data will be available, a similar analysis on more funds, also with different investments strategies, could help to validate the findings on Maze's investments. Specifically, it would be reasonable to examine a fund with a similar regional, target size, company age, and sector focus to check the robustness of findings. Ideally, these would be compared with a fund with a regional prioritisation on emerging markets to investigate diverging investor expectations in comparison to developed markets.

Finally, conceptualising a study using a variable capturing the actual impact creation rather than impact progress, for example, the IMM, would be recommendable. MOIC and IMM, both put the value creation in perspective to investment and are thus easier to compare, particularly across funds. While a universal application of the IMM for impact funds seems unlikely due to the complexity of calculations and the fact that some types of impact are simply not appraisable, a comprehensive quantitative analysis could help to discover more transferrable patterns. This would also facilitate comparisons between different classification systems, like the ABC framework and social/ environmental angle and it could be more transferrable funds for which such comprehensive calculations are out of scope.

Group Part

5. Conclusion

Since the determination of value for impact, as exemplified in the concept of IMM, is highly complex, judging the success of impact and financial performance to date is highly dependent on putting individual performance data into perspective. Annual investor surveys by the GIIN hence emphasise the impact and financial performance in relation to respective expectations, rather than comparing absolute performance metrics. As demonstrated in section 2.4.3, these financial performance expectations can be lower than in traditional investing. Yet, over the past years, it has been shown that most impact investors indeed achieve their performance targets in both dimensions. This is in line with our finding that there seems to be a positive correlation between financial and impact performance. Even though it is not a strong one, it suggests at least a harmony between both goals.

While due to data restrictions, our study could not deliver any definite conclusions on the link between financial and impact performance, it can serve as an impulse for looking at the relation from a different perspective than in previous studies. The question has often been whether return on social investment strategies really is inferior, as often assumed by the broader investor circle. However, for investors with a clear objective to create societal value, learning about the synergies between the social and financial dimension is more relevant for investment decision making than only comparing financial returns.

In the course of this, frameworks like the ABC-classification help to create a unified understanding of impact, and clustering investments into impact angles facilitates performance comparisons at least within those clusters. Still, labels that deliver quantified insights on the performance on both goals of impact investors, financial and societal value creation, should be established to improve transparency in the impact investing universe. Recent regulatory considerations by the European Commission, such as the broadening of the EU taxonomy and the implementation of an EU Ecolabel for funds, mark considerable progress in this direction.

Nevertheless, these efforts concentrate on environmental sustainability so far. Moreover, the EU Ecolabel is specifically tailored for retail financial products, once more emphasising public markets (European Securities Market Authority 2021). An expansion of efforts towards standardisation across the entire investment landscape will become evermore relevant in light of growing greenwashing concerns; to strengthen the trust of the mainstream investment market that will be essential for the sustainable establishment of the asset class (Furlow 2010).

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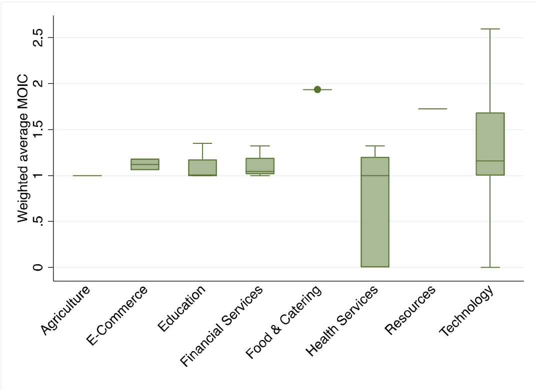
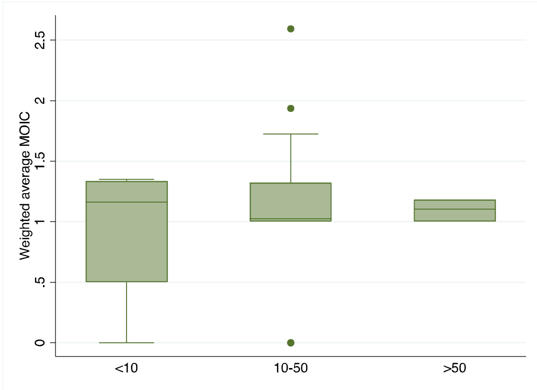
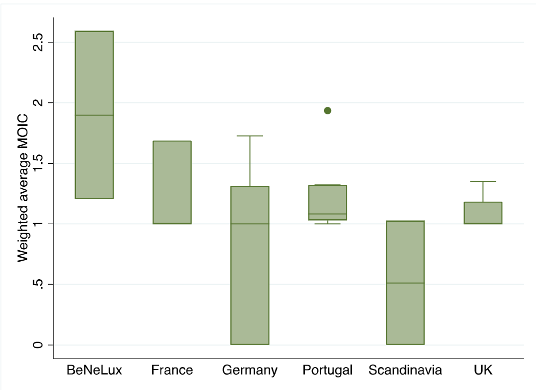
7. Appendices

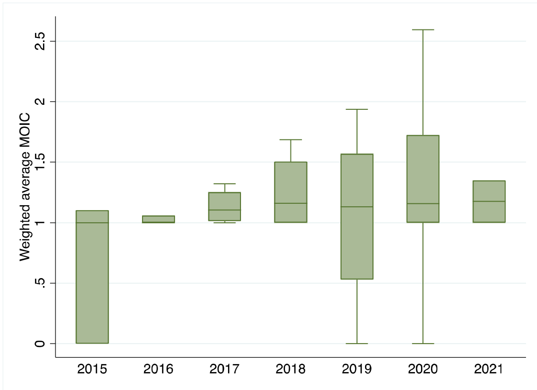
Appendix I: Boxplots control variables

A) MOIC

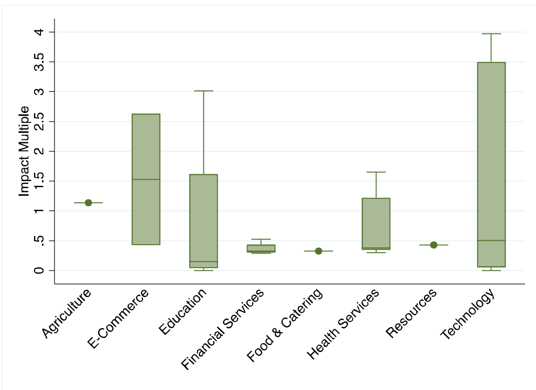


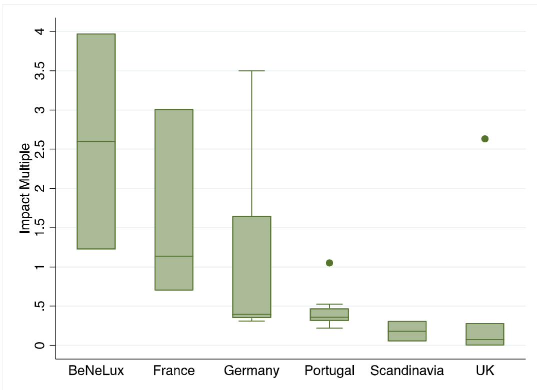


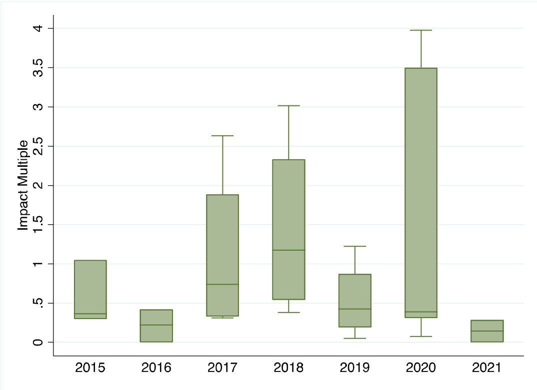


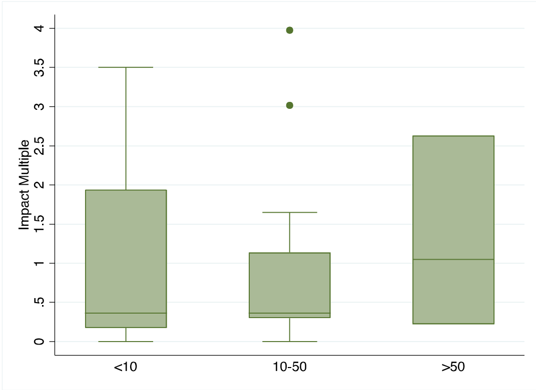


B) Impact Multiple



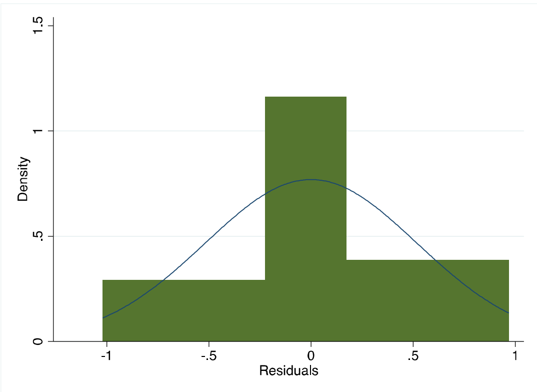






Appendix II: Assumptions for hypothesis testing (based on model (6))

A) Normality of residuals (Weighted average MOIC):




```
. swilk MOIC_res

                   Shapiro–Wilk W test for normal data
```

Variable	Obs	W	V	z	Prob>z
MOIC_res	**26**	**0.93640**	**1.819**	**1.226**	**0.11015**

B) Homoskedacity:

```
. hettest

Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of MOIC

H0: Constant variance

    chi2(1) =   0.12
Prob > chi2 = 0.7243
```

C) Multicollinearity:

```
. correlate MOIC log_IM DummySector* DummyRegion*
(obs=24)
```

	MOIC	log_IM	DummyS~1	DummyS~2	DummyS~3	DummyS~4	DummyS~5	DummyS~6	DummyS~7	DummyS~8	DummyR~1	DummyR~2	DummyR~3	DummyR~4	DummyR~5	DummyR~6
MOIC	1.0000															
log_IM	0.4022	1.0000														
DummySector1	-0.0392	0.1378	1.0000													
DummySector2	0.0082	0.1787	-0.0629	1.0000												
DummySector3	-0.0711	-0.1420	-0.0788	-0.1140	1.0000											
DummySector4	-0.0031	-0.1804	-0.0933	-0.1348	-0.1690	1.0000										
DummySector5	0.3087	-0.1010	-0.0435	-0.0629	-0.0788	-0.0933	1.0000									
DummySector6	-0.3451	0.0552	-0.1338	-0.1935	-0.2425	-0.2870	-0.1338	1.0000								
DummySector7	0.2306	-0.0489	-0.0435	-0.0629	-0.0788	-0.0933	-0.0435	-0.1338	1.0000							
DummySector8	0.1954	0.1037	-0.1070	-0.1547	-0.1939	-0.2294	-0.1070	-0.3292	-0.1070	1.0000						
DummyRegion1	0.4261	0.3821	-0.0629	-0.0909	-0.1140	-0.1348	-0.0629	0.1382	-0.0629	0.2165	1.0000					
DummyRegion2	0.0833	0.3065	0.5517	-0.1140	0.2381	-0.1690	-0.0788	-0.2425	-0.0788	0.1163	-0.1140	1.0000				
DummyRegion3	-0.2734	0.1076	-0.1204	-0.1741	-0.2182	-0.2582	-0.1204	0.2646	0.3612	0.1777	-0.1741	-0.2182	1.0000			
DummyRegion4	0.1508	-0.2103	-0.1474	0.1066	-0.0000	0.1581	0.2949	0.1296	-0.1474	-0.3627	-0.2132	-0.2673	-0.4082	1.0000		
DummyRegion5	-0.3188	-0.4064	-0.0629	-0.0909	-0.1140	0.2697	-0.0629	-0.1935	-0.0629	0.2165	-0.0909	-0.1140	-0.1741	-0.2132	1.0000	
DummyRegion6	-0.0300	-0.1274	-0.0788	0.3419	0.2381	0.1690	-0.0788	-0.2425	-0.0788	-0.1939	-0.1140	-0.1429	-0.2182	-0.2673	-0.1140	1.0000

```
. vif
```

Variable	VIF	1/VIF
DummySector6	9.38	0.106613
DummySector4	6.88	0.145262
DummySector8	6.74	0.148390
DummyRegion3	5.29	0.188884
DummyRegion2	4.75	0.210596
DummySector2	4.72	0.211781
DummyRegion4	4.63	0.216059
DummySector3	4.45	0.224799
DummyRegion1	3.48	0.287276
DummyRegion6	2.92	0.341912
DummySector7	2.78	0.359755
DummySector5	2.74	0.364518
log_IM	2.25	0.443836
Mean VIF	4.69	

D) ANOVA homogeneity of variance:

```
. robvar log_IM, by(Numberoftickets)
```

Number of tickets	Summary of log_IM Mean	Std. dev.	Freq.
1	-.61721233	1.2074329	9
2	-.61978262	1.2469547	9
3	-.49300808	1.0551293	5
4	-.64544338	0	1
Total	-.5934766	1.115503	24

```
W0  =  0.81985467   df(3, 20)     Pr > F = 0.49812923

W50 =  0.57346329   df(3, 20)     Pr > F = 0.63904319

W10 =  0.81985467   df(3, 20)     Pr > F = 0.49812923
```

Appendix III: Stata test results

A) Hypothesis 1

```
. reg MOIC ImpactMultiple

      Source |       SS           df       MS      Number of obs   =        26
-------------+----------------------------------   F(1, 24)        =      3.17
       Model |  .887645462         1  .887645462   Prob > F        =    0.0879
    Residual |  6.72876943        24  .280365393   R-squared       =    0.1165
-------------+----------------------------------   Adj R-squared   =    0.0797
       Total |   7.6164149        25  .304656596   Root MSE        =     .5295

------------------------------------------------------------------------------
        MOIC | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
ImpactMultiple |   .1678592   .0943382     1.78   0.088    -.0268453    .3625637
       _cons |   .9587302   .1345261     7.13   0.000      .681082    1.236378
------------------------------------------------------------------------------
```

```
. reg MOIC ImpactMultiple DummySector*
note: DummySector5 omitted because of collinearity.

      Source |       SS           df       MS      Number of obs   =        26
-------------+----------------------------------   F(8, 17)        =      1.30
       Model |  2.89171541         8  .361464427   Prob > F        =    0.3071
    Residual |  4.72469948        17  .277923499   R-squared       =    0.3797
-------------+----------------------------------   Adj R-squared   =    0.0877
       Total |   7.6164149        25  .304656596   Root MSE        =    .52718

------------------------------------------------------------------------------
        MOIC | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
ImpactMultiple |   .1932681   .1011486     1.91   0.073    -.0201368     .406673
 DummySector1 |  -1.092663    .750057    -1.46   0.163    -2.675145     .489819
 DummySector2 |   -1.04731   .6570196    -1.59   0.129      -2.4335    .3388803
 DummySector3 |  -.9452403   .5915948    -1.60   0.129    -2.193396    .3029157
 DummySector4 |  -.8420421   .5894245    -1.43   0.171    -2.085619    .4015348
 DummySector5 |          0  (omitted)
 DummySector6 |  -1.215598   .5652864    -2.15   0.046    -2.408248   -.0229479
 DummySector7 |  -.2298366   .7456232    -0.31   0.762    -1.802964    1.343291
 DummySector8 |  -.8820219   .5801433    -1.52   0.147    -2.106017    .3419736
        _cons |    1.87291   .5282114     3.55   0.002     .7584813    2.987339
------------------------------------------------------------------------------
```

```
. reg MOIC log_IM DummySector*
note: DummySector1 omitted because of collinearity.

      Source |       SS           df       MS      Number of obs   =        24
-------------+----------------------------------   F(8, 15)        =      1.71
       Model |  3.59620795         8  .449525994   Prob > F        =    0.1771
    Residual |    3.949805        15  .263320333   R-squared       =    0.4766
-------------+----------------------------------   Adj R-squared   =    0.1974
       Total |  7.54601295        23  .328087519   Root MSE        =    .51315

------------------------------------------------------------------------------
        MOIC | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      log_IM |   .2523168   .1019594     2.47   0.026     .0349955    .4696382
DummySector1 |          0  (omitted)
DummySector2 |   .1397428    .628521     0.22   0.827    -1.199918    1.479404
DummySector3 |   .2856508   .6036702     0.47   0.643    -1.001042    1.572343
DummySector4 |   .3948924   .5858295     0.67   0.511    -.8537737    1.643558
DummySector5 |   1.251437   .7368225     1.70   0.110    -.3190633    2.821937
DummySector6 |  -.0375664   .5523018    -0.07   0.947     -1.21477    1.139637
DummySector7 |   .9724445    .732516     1.33   0.204    -.5888764    2.533766
DummySector8 |   .4455146   .5644422     0.79   0.442    -.7575655    1.648595
       _cons |    .967596   .5133145     1.88   0.079     -.126508      2.0617
------------------------------------------------------------------------------
```

B) Hypothesis 2

```
. anova log_IM Numberoftickets
```

Number of obs = 24   R-squared = 0.0023
Root MSE = 1.1949   Adj R-squared = -0.1474

Source	Partial SS	df	MS	F	Prob>F
Model	.06446869	3	.02148956	0.02	0.9974
Numberoft~s	.06446869	3	.02148956	0.02	0.9974
Residual	28.555512	20	1.4277756		
Total	28.619981	23	1.244347		

```
. anova MOIC Numberoftickets
```

Number of obs = 26   R-squared = 0.2108
Root MSE = .522692   Adj R-squared = 0.1032

Source	Partial SS	df	MS	F	Prob>F
Model	1.6058513	3	.53528376	1.96	0.1496
Numberoft~s	1.6058513	3	.53528376	1.96	0.1496
Residual	6.0105636	22	.27320744		
Total	7.6164149	25	.3046566		

C) Hypothesis 3

```
. ranksum ImpactMultiple, by(CompanyClassification)
```

Two-sample Wilcoxon rank-sum (Mann–Whitney) test

CompanyCla~n	Obs	Rank sum	Expected
B	8	88.5	108
C	18	262.5	243
Combined	26	351	351

Unadjusted variance 324.00
Adjustment for ties -0.11

Adjusted variance 323.89

H0: Impact~e(Compan~n==B) = Impact~e(Compan~n==C)
z = -1.084
Prob > |z| = 0.2786
Exact prob = 0.2927

```
. ttest MOIC, by (CompanyClassification)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
B	8	1.259265	.2572804	.727699	.6508936	1.867637
C	18	1.044963	.1092942	.463696	.8143722	1.275553
Combined	26	1.110902	.1082477	.5519571	.8879617	1.333842
diff		.2143024	.235342		-.2714196	.7000244

diff = mean(B) - mean(C)   t = 0.9106
H0: diff = 0   Degrees of freedom = 24

Ha: diff < 0   Ha: diff != 0   Ha: diff > 0
Pr(T < t) = 0.8142   Pr(|T| > |t|) = 0.3716   Pr(T > t) = 0.1858

D) Hypothesis 4

```
. ranksum ImpactMultiple, by(Angle)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        Angle |      Obs    Rank sum    Expected
--------------+---------------------------------
  Environmenta |        9       134.5       121.5
        Social |       17       216.5       229.5
--------------+---------------------------------
      Combined |       26         351         351

Unadjusted variance      344.25
Adjustment for ties       -0.12
                      ----------
Adjusted variance        344.13

H0: Impact~e(Angle==Environmental) = Impact~e(Angle==Social)
             z =  0.701
Prob > |z| = 0.4834
Exact prob = 0.4978
```

```
. ttest MOIC, by(Angle)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. err.   Std. dev.   [95% conf. interval]
---------+--------------------------------------------------------------------
 Environm |       9    1.220878    .0795689    .2387067    1.037392    1.404365
   Social |      17    1.052679    .1603545    .6611584     .712743    1.392616
---------+--------------------------------------------------------------------
Combined |      26    1.110902    .1082477    .5519571    .8879617    1.333842
---------+--------------------------------------------------------------------
    diff |             .168199    .2296738               -.3058245    .6422226
------------------------------------------------------------------------------
    diff = mean(Environm) - mean(Social)                          t =   0.7323
H0: diff = 0                                     Degrees of freedom =       24

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.7645         Pr(|T| > |t|) = 0.4711          Pr(T > t) = 0.2355
```

Appendix IV: Data Sets

Financial Performance

	A	B	C	D	E	F	G	H	I	J	K	L
1	ID	Company	Stage	Amount (€)	Date	Last Valuation	MOIC	Label 1	Time since 1	Label 2	Label 3	Label 3
2	1	Company 1	Pre-seed	500 000,15 €	11/10/2019	[redacted]	[redacted]	1st ticket	50,1	ok	more12m	more18m
3	1	Company 1	Seed	263 158,00 €	03/02/2021	[redacted]	[redacted]	2nd ticket	34,3	ok	more12m	more18m
4	2	Company 2	Pre-seed	578 908,95 €	11/10/2019	[redacted]	[redacted]	1st ticket	50,1	ok	more12m	more18m
5	2	Company 2	Seed	780 000,00 €	03/03/2021	[redacted]	[redacted]	2nd ticket	33,4	cost	more12m	more18m
6	2	Company 2	Seed extension	250 000,00 €	30/06/2022	[redacted]	[redacted]	3rd ticket	17,5	cost	more12m	less18m
7	2	Company 2	Series A	1 250 000,00 €	08/12/2022	[redacted]	[redacted]	4th ticket	12,2	cost	more12m	less18m
8	3	Company 3	Seed	662 534,48 €	12/02/2020	[redacted]	[redacted]	1st ticket	46,0	zero	more12m	more18m
9	3	Company 3	Seed extension	50 000,00 €	21/06/2021	[redacted]	[redacted]	2nd ticket	29,8	zero	more12m	more18m

Impact Performance

	B	C	D	E	F	G	H	I	J	K	L	M	S	Y
4	ID	Company	SDG	Angle	Impact metric	KPI measurement	Mesured in	Weighting	2019	2020	2021	2022	Y1 of reporting	Y1
5	1	Company 1	SDG 8 - Decent Work and Economic Growth	Social	Independent restaurants	Point-in-time	Number of restaurants	100%	[redacted]				2022	4 750
6	2	Company 2	SDG 4 - Quality Education	Social	Job placements	Cumulative	Job placements	100%	[redacted]				2020	126
7	3	Company 3	SDG 8 - Decent Work and Economic Growth	Social	Number of satisfied employees	Cumulative	People	50%	[redacted]				2021	5 400
8	3	Company 3	SDG 8 - Decent Work and Economic Growth	Social	Number of retained new hires	Cumulative	People	50%	[redacted]				2021	648