Impact Investing: analysing the potential trade-off between social impact and financial returns – evidence from private equity and venture capital funds

Fie Kragh Dahl

Dissertation written under the supervision of Eva Schliephake

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Abstract (English)

In this thesis, I study the financial performance of **153** impact labelled funds (ILF) with vintage years between **2000–2017** relative to **4,734** traditional funds. I show that no significant trade-off exists between ILFs and traditional funds when controlling for the vintage year, fund size and the fund's core industry. However, ILFs show a **3.37%** lower return (IRR) when only controlling for vintage year, fund size, and the fund's domicile region. ILFs have a higher exposure to the "Energy & Utilities" and "Raw Materials & Natural Resources" industries, which see a significant underperformance of **6.22%** and **11.96%,** respectively, compared to funds with diversified industry exposure. Furthermore, the analysis shows that larger funds underperform smaller funds by **1.05%–1.28%** and that no significant difference in financial performance exists between North American and European funds. Nonetheless, both are outperformed by funds domiciled elsewhere by **2.7%.** Moreover, the fund's vintage year is significant in explaining fund performance, with later years (2015–2017) outperforming earlier vintage years (2000–2002) by **20.25%–21.04%.** Lastly, I show that ILFs with a higher Impact Score (ImS) outperform ILFs with lower ImS by **5.84%**. I further show that this is not due to increased risk exposure to Environmental, Social, and Governmental (ESG) factors.

Abstract (Portuguese)

Nesta tese, estudo o desempenho financeiro de **153** fundos rotulados de impacto (ILF), que têm o ano de colheita entre **2000-2017** e comparo-lhos com **4,734** fundos tradicionais. O estudo apresenta que não existe um compromisso significativo entre os ILFs e os fundos tradicionais enquanto controlo o ano de colheita, o tamanho do fundo e a indústria principal do fundo. As ILFs mostram **3.37%** menos rentabilidade (IRR) quando apenas controlo o ano de colheita, o tamanho do fundo, e a região de domicílio do fundo. As ILF têm uma exposição maior nas indústrias de "energia e serviços públicos" e "matérias-primas e recursos naturais", que apresentam um desempenho significativamente inferior de **6.22%** e **11.96%**, em comparação com os fundos diversificados em várias indústrias. A análise mostra que os fundos maiores registaram um desempenho negativo de **1.05%-1.28%** aos fundos menores. Além disso, não existe uma diferença significativa no desempenho financeiro entre os fundos norte-americanos e europeus. Apesar disso, ambos são superados em **2.7%** pelos fundos domiciliados noutros locais. Além disso, o ano de colheita do fundo é significativo para explicar o desempenho dos fundos; os fundos dos anos posteriores (2015-2017) superarem em **20.25%-21.04%** o desempenho dos fundos com os anos de colheita anteriores (2000-2002). Por último, mostro que as ILFs com um índice de impacto (ImS) maior superam em **5.84%** o desempenho das ILFs com um ImS menor. Apresento ainda que este fato não deve ser ligado a uma exposição maior aos riscos de factores ambientais, sociais e governamentais (ESG).

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List of Abbreviations

Assets Under Management	AUM
Compounded Annual Growth Rate	CAGR
Environmental, Social, Governmental	ESG
Global Impact Investing Network	GIIN
Impact Labelled Funds	ILF
Impact Management Project	IMP
Impact Reporting and Investment Standards	IRIS+
Impact Score	ImS
Private Equity	PE
Principles of Responsible Investing	PRI
Social Impact Bond	SIB
Socially Responsible Investing	SRI
Sustainable Development Goal	SDG
Internal Rate of Return	IRR
Value Multiple	VM
Venture Capital	VC
Willingness to Pay	WTP

1 Introduction

Impact investing is defined by the Global Impact Investing Network (GIIN) as "investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return" (GIIN, 2022b). The term impact investing was first used in 2007, but the underlying idea dates to the 18th century. Impact investing has undergone much development since and is currently viewed as a fast-growing investment approach that breaches the gap between traditional investing for-profit and traditional philanthropy donations for social impact. As a subsection of sustainable investing, impact investing focuses solely on investments where a financial return and a social impact are possible simultaneously, making it a highly focused investment approach. It is distinguished from other investment strategies such as socially responsible investing (SRI) and Environmental, Social, and Governmental (ESG) screened investing, which focuses on minimising the negative impact on people and society by fundamentally concentrating on social and/ or environmental impact (hereafter referred to as social impact) instead. Furthermore, impact investing is uniquely positioned on the investment spectrum by having a dual objective as per the definition above.

Though impact investing is a growing field that continues to attract new investors and is predicted to reach $2 trillion in assets under management by 2025, very little research exists. By the end of 2019, only a handful of quantitative studies have been conducted, and most analysis is only exploratory. Most discussion focuses on whether impact investors obtain a competitive market rate risk-adjusted return or if a trade-off must be made to have a social impact. Moreover, the impact investing field faces several challenges due to the lack of reliable data available, transparency of financial and impact performance, as well as a reliable benchmark and standardised reporting practices.

This thesis studies whether a trade-off within impact investing exists and, if so, what factors affect it. This is done by analysing **153** impact labelled venture capital (VC) and private equity (PE) funds with vintage years between **2000-2017**. These impact funds have been manually screened to ensure a distinct dual objective. All funds have their performance data available in the Preqin performance database. The analysis is done through a series of regression models, analysing the IRR (%) and the Value Multiple (VM) of impact funds compared to a benchmark of **4,734** funds with the same vintage year span. Each model isolates different fund characteristics to identify whether impact funds see a lower financial performance or not. The analysis further explores if a higher impact potential or a higher ESG risk exposure influences the performance of funds.

2 Backgrounds and Literature Review

This section explores the existing research into impact investing and attempts to define and distinguish impact investing from other aspects of sustainable finance such as ESG investing, socially responsible investing (SRI), social impact bonds (SIB), and Venture Philanthropy. Furthermore, this section explores the arguments for and against an existing trade-off within impact investing and outlines the space in which research is lacking.

2.1 Impact Investing History

The term "Impact investing" was first used in an official capacity in 2007 by the Rockefeller Foundation at a meeting in Italy with a small group of impact investing pioneers. However, the broader idea behind impact investing dates to the 18th century, when the Methodist Church pursued an investment strategy that avoided investing in any ventures related to gambling, alcohol, and tobacco, which was not in line with their beliefs. This is one of the earliest accounts of SRI, a field that continues to grow (Agrawal & Hockerts, 2021; GIIN, 2018; The Impact Investor, 2022; Clark, Emerson, & Thornley, 2014). According to the GIIN (2020), the estimated assets under management (AUM) within impact investing was USD 715 billion in 2019. Furthermore, ForexToStocks (2021), the GIIN (2019), Vanguard Research (2018), and the GIIN (2016) all show that impact investing has grown from $25.4 billion in 2013, resulting in a compounded annual growth rate (CAGR) of 27% between 2013 and 2019 with great potential for further growth. The GIIN (2016) further predicts that impact investments could surpass $2 trillion by 2025 (Roundy, Holzhauer, & Dai, 2017).

The growth within the impact investing industry is led by the increasing focus on sustainability and responsible investing and the increasing importance of millennial investors. Millennials place significantly higher importance on the social impact generated from their investments than older generations. This, combined with the growing transfer of wealth to millennials, currently helps drive the expansion of the impact investing field (Snider, 2018; Uzsoki, 2020; Clark, Emerson, & Thornley, 2014). Supporting the increased visibility and promotion of these practices are several important players. First, the B-Lab is a non-profit network best known for its B Corporation Certification. The certificate is awarded to companies with a high level of social practices, transparency, and that ensures customers, investors, and other stakeholders, that they keep to the highest standards and can be trusted regarding their sustainability objectives (Clark, Emerson, & Thornley, 2014; B-Lab, 2022a; B-Lab, 2022b).

Furthermore, the Principles for Responsible Investing (PRI) was created with support from the United Nations in 2006. The PRI aims to improve ESG standards and increase transparency through improved reporting practices. This is achieved through 6 principles to ensure an overall improvement of a sustainable investment approach (PRI, 2022b). The PRI continues to grow from 63 signatories in 2006 to nearly 4000 signatories in 2021 (PRI, 2022a). Furthermore, the PRI help drive policy changes within the investment industry. Uzsoki (2020) shows the increasing number of sustainable financing and ESG related policies and regulations due to the increased focus on sustainability in recent years. The number of regulations adopted in the first 15 days of 2019 exceeded the total amount of regulations adopted in 2013, and this growth is expected to accelerate. The increasing number of regulations in this field further increases the policy risk exposure of "traditional" investors, thus causing more investors to engage in impact investing.

Following the official acceptance of the term impact investing, the Global Impact Investing Network, also known as the GIIN, was set up in 2009 to further the expansion of impact investing. The GIIN currently has 220 asset managers and 110 asset owners as members worldwide as of April 2022 (GIIN, 2022a). The GIIN is also one of the leading providers of research within impact investing and has developed a framework for measuring impact created called "COMPASS", which it hopes can contribute to the much-lacking industry standard worldwide (GIIN, 2021a). A significant challenge facing the continued growth of the impact investing industry is the lack of widely adopted reporting and measurement standards (Snider, 2018; GIIN, 2018; Lamy, Leijonhufvud, & O'Donohoe, 2021; GIIN, 2020; Freeman, 2020; Schoenmaker & Schramade, 2019). To this extent, the GIIN has also created the Impact Reporting and Investment Standards (IRIS+), becoming one of the leading industry reporting tools used by impact investors (GIIN, 2022c; CNote, 2020). Though other frameworks such as the Impact Management Project (IMP) and the Global Impact Investing Rating System (GIIRS) developed by the B-Lab also attempt to consolidate and provide a solution to the lacking impact reporting standard and overall impact transparency (Impact Management Project, 2022; StartingUpGood, 2018; Corecentra, 2021).

Lastly, 2015 saw two important agreements adopted by many countries worldwide. First, the Paris agreement was signed in 2015, aiming to limit the global warming temperature increase to a maximum of 2.0°C in this century, even aiming at 1.5°C (United Nations, 2022). Another important event was the adoption of the United Nations 17 Sustainable Development Goals (SDG). These 17 goals aim at improving human lives by eradicating hunger, improving the

lives of women and children, and promoting peace and justice for all by 2030 (UNDP, 2022). Both agreements help further the focus on the sustainable finance field and are part of a paradigm shift from a pure profit maximising objective to a dual objective within investing (The Impact Investor, 2022; SEI, 2019).

This shifting focus and changing perceptions of traditional investments allow the impact investing field to gain traction and continue its growth. The increased focus on sustainability worldwide continues to drive growth in the area. However, to fully understand the field and understand its advantages and disadvantages, the first step is to understand what exactly impact investing is. The following section outlines the development of the impact investing definition and distinguishes it from other relevant terms in the sustainable finance field.

2.2 Impact Investing Defined

Throughout the years, many varying definitions of impact investing have existed. To clearly define impact investing as of 2022, the first step is to distinguish it from other terms related to sustainable financing. First, it is necessary to understand the scope of sustainable investing and SRI. These terms are considered umbrella terms covering several investment strategies such as ESG integration, active ownership, portfolio screening (positive and negative screening), impact investing, social impact bonds (SIB), and venture philanthropy (Vanguard Research, 2018; Agrawal & Hockerts, 2021). It is also essential to distinguish between investing *with* impact and *for* impact to further understand the differences between the abovementioned strategies (EVPA, 2018).

Responsible investing goes further than traditional for-profit investing by including negative ESG screening. This strategy avoids certain practices and thereby limits the harm done by investors but remains strictly a profit maximising strategy and is thus on the furthest end of the spectrum of investing *with* impact (Wilson, 2014; Sonen Capital, 2022; Agrawal & Hockerts, 2021; EVPA, 2018). This is the practice seen by the Methodist Church as seen in section 2.1.

Sustainable investing, however, includes several ESG strategies ranging from positive screening to ESG integration. These differ significantly from impact investing in that they focus on various degrees of incorporating ESG factors into investing decisions. These strategies limit a negative impact by including specific criteria in the investment decision. However, this is still investing *with* impact and thus maintains an objective of profit maximisation rather than impact maximisation (Agrawal & Hockerts, 2021; Wilson, 2014; Uzsoki, 2020).

Often, SRI is used interchangeably for impact investing though several factors distinguish the two. An important factor is the level of engagement between the investor and the investee. Agrawal & Hockerts (2021) argue that the level of engagement in impact investing is higher than SRI due to the nature of impact investing. As impact investors actively pursue a dual objective with both financial returns and a social impact, the engagement with the investee is higher to ensure that social impact is, in fact, pursued. J.P. Morgan (2010) further argues that SRI focuses more on publicly traded assets, focusing on minimising a negative impact as opposed to impact investing that mainly focuses on private equity and debt to maximise the positive social impact and is thus still considered investing *with* impact and not *for* impact. Furthermore, SRI sees larger average deal sizes compared to impact investors' smaller average deal sizes (Agrawal & Hockerts, 2021; Roundy, Holzhauer, & Dai, 2017; GIIN & Cambridge Associates, 2015).

Another important distinction to consider is between venture philanthropy and impact investing. These two are in many ways similar but have one distinguishing factor, namely, that venture philanthropists focus more on the social impact than the financial returns, i.e., investing *for* impact instead of *with* impact. Here, the objective is to do as much good, and if a financial gain is made, this is a positive outcome, but it is not always required. Investors are also willing to take on a higher risk to achieve this social impact (Agrawal & Hockerts, 2021; Roundy, Holzhauer, & Dai, 2017; EVPA, 2018).

Lastly, the distinction between SIBs and impact investing must be considered. SIBs and impact investing share several characteristics, such as the average deal sizes and the level of investor engagement. However, here the distinction lies in the structure of the SIB. These follow a "payments based on results" approach, and investors in SIBs only see a financial return when the social impact objectives are reached and thus not guaranteed (Agrawal & Hockerts, 2021; CFI Education, 2022). Investing in SIBs is, therefore, a strategy that invests *for* impact.

There is a shift in how investments are viewed. The gap in the spectrum of investments ranging from pure "traditional" profit maximising investments to pure social impact maximising philanthropy, is narrowing as the impact investing field increases (Tewari, Singh, Wadhwa, & Tandon, 2021). Figure 1 shows the investment spectrum and the main objective pursued in each category. It is only in more recent years that the category impact investing has become a category by itself with solid distinctions from the other fields. As previously discussed, traditional investors are becoming more aware of sustainable and social investments.

Moreover, original philanthropists and charitable donors are shifting their focus. Tekula & Shah (2016) argues that the desire of individuals and organisations engaged in charitable donations or philanthropy is shifting to include higher accountability as to the impact their donations have. This increased desire to measure and record the actual social impact created further drives the growth of impact investing. Therefore, impact investing attracts players from "both sides" of the spectrum of investments for profit (*with* impact) and investing *for* impact.

Figure 1: Investment spectrum model based on Sonen Capital's (2022) impact measurement model.

Agrawal & Hockerts (2021) reports that the definition of impact investing has undergone a development from a broader definition in the early 2000s to a more sophisticated and focused definition we see by the GIIN today. Before 2012, the general definition of impact investing was focused on the social mission of potential investment targets, paying less attention to the financial performance of such enterprises. This definition was developed between 2012 and 2016 to include more nuances of the field. Here, the focus was on enterprises with a social mission and a strategy to achieve this social mission. The aspect of a financial return was added with some degree of uncertainty depending on the fund mandate. It was not until after 2016 that the definition developed to include a clear statement of expected financial returns as well as measurable social impact. Going forward, the definition for what is considered an impact investing fund follows the GIINs current definition:

"Impact investments are investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return." (GIIN, 2022b)

From the distinctions and definitions laid out above, the main defining feature of impact investing is the clearly stated dual objective of pursuing both financial gains and social impact at the same time. Additionally, impact investing has four key characteristics (Schoenmaker & Schramade, 2019; Roundy, Holzhauer, & Dai, 2017; UNDP, 2016):

1) **Intentionality:** the investment must have a social impact objective
2) **Investment with return expectations:** the objective must also be to create positive financial returns
3) **Range of return expectations and asset classes:** depending on investor type and asset class preferences, the return on impact investments can vary
4) **Impact measurement:** Investors are committed to reporting social impact performance

These four characteristics should all be considered when studying impact funds.

2.3 Current Impact Investing Landscape

Having clearly defined impact investing, this section analyses the current impact investing landscape. As previously mentioned, impact investing is a growing field with $715 billion in AUM in 2019 (GIIN, 2020). Even though the field is growing, much research is still lacking within the field (Roundy, Holzhauer, & Dai, 2017). Agrawal & Hockerts (2021) published a literature review of all existing research on impact investing from 2005 to 2017 (except for one study from 2018). This review included 85 works, but only 3 were quantitative studies. This lack of quantitative studies is mainly due to a lack of data available and a lack of a common framework and definition, as laid out in the previous section (Schoenmaker & Schramade, 2019; GIIN, 2020).

One of the main obstacles to the growth of the impact investing sector is the notion that there is a trade-off between having a social impact and having a financial return, as argued by Snider (2018), and shown in the study by Barber, Morse, & Yasuda (2021) discussed below. There are very few confirmatory studies regarding this, so it is challenging to posture whether this is true or not (Agrawal & Hockerts, 2021). One of the most recent quantitative studies is by Barber, Morse, & Yasuda (2021), who looks at the willingness to pay (WTP) for impact on various investor types. They found that *"impact funds reliably underperform traditional VC"* and that the WTP for impact is 2.5% – 3.7%. However, the magnitude of the WTP depends on the investor type, as they also found that North American investors have a lower WTP for impact than European investors. This finding aligns with the GIIN's (2021b) suggestion that North American Investors focus more on financial performance than social impact compared to European investors. Barber, Morse, & Yasuda (2021) further found that their sample of 159 impact labelled funds (ILF) performed 7.9% (mean) and 1% (median) lover than traditional funds when analysing the IRR (%). This is one of the few quantitative studies that attempt to show the trade-off in impact investing using an empirical approach (GIIN, 2021b; Agrawal & Hockerts, 2021).

This argument for a trade-off existing between impact funds and traditional funds stems back from the shareholder theory by Friedman (1970), which states that a company's social responsibility should be to maximise its profits. Furthermore, Smith (2002) argues that maximising profit is the company's fiduciary duty to its shareholders. Moreover, a study on investor perception of sustainable investments shows that more than half of investors (53%) believe that sustainable investments see a trade-off from traditional investments (Morgan Stanley, 2019; Morgan Stanley, 2017; Snider, 2018). One of the main reasons for this is the lack of reliable data within the impact investing field. Schoenmaker & Schramade (2019) argue that one of the main challenges in impact investing is that companies are not accustomed to reporting on social impact as there is no set industry-wide standard yet, as seen in section 2.1.

When it comes to an industry standard, the GIIN, in collaboration with Cambridge Associates, set up an impact investing benchmark for PE and VC funds in 2015, originally comprised of 68 funds (GIIN & Cambridge Associates, 2015; Roundy, Holzhauer, & Dai, 2017). As of March 31st, 2021, 102 ILFs were included in the benchmark (Cambridge Associates, 2021). This is the first consistent attempt at creating an overall industry benchmark that can be used to provide valuable insights into the performance of ILFs. Furthermore, it incentivises investors to engage in impact investing as the performance expectations become more evident and the overall transparency in the industry improves.

The idea of having to forgo profits to have a social impact has changed throughout the past years (Snider, 2018). The argument against a trade-off is rooted in the growing evidence that businesses can produce financial returns and create a social impact by aligning their business model with their impact model, i.e., operating in "lockstep" (Gianoncelli & Boiardi, 2018). This is further where the investment strategy moves from investing *with* impact to investing *for* impact, as described earlier.

Morgan Stanley (2019) studied over 10,000 mutual funds to determine whether the sustainable funds experienced lower financial performance compared to traditional mutual funds and found no existing trade-offs. Moreover, Schoenmaker & Schramade (2019) argues that impact investing has a high probability of generating at least market-rate financial returns due to the alignment with the SDGs, which are increasingly gaining traction with investors. This alignment should help drive the impact investments' value propositions and thereby achieve an advantage compared to non-SDG aligned investments (Sener, 2021). Furthermore, the GIIN & Cambridge Associates (2015) found that ILFs with vintage years between 1998 and 2004

outperformed equivalent traditional funds with the same vintage years. Yet, they also find that ILFs with vintage years between 2005 and 2010 have underperformed traditional funds.

However, it is still not clear whether a trade-off exists. Much debate is done on this topic, and depending on the definition of impact investing applied, different results emerge. As only a few quantitative studies attempt to answer this question, and most are exploratory papers, the continued uncertainty is one of the obstacles to growing the impact investing field. This thesis attempts to fill in some of the gaps by focusing on providing an empirical contribution and providing an answer to whether a trade-off exists within impact investing.

3 Data

3.1 Database and Data Screening

3.1.1 Preqin Database

The data used for fund performance and characteristics come from the Preqin Database using the Performance Analyst data set. The first step of the data selection process is to define the scope of the search. To best determine the accuracy of the performance of impact investors vs traditional investors, the data is restricted to only include "Private Equity Funds". This category consists of PE and VC fund which include general ventures, balanced, buyout, fund of funds, growth and more, but most funds are either general ventures or growth.

The Preqin database has performance data on 9,952 PE and VC funds as of April 1st, 2022, and an advanced search is, therefore, necessary to find potential impact funds. The search was set up using various keywords related to social finance and impact investing, such as "Impact Investing", "Impact Fund", "SRI", etc. A complete list is found in Appendix 1. To further optimise the search, the vintage year was restricted to 1990-2021, yielding a total of 430 funds. These funds make up the main part of the potential impact fund list.

Furthermore, Giant Leap's open impact investing VC fund database was used to find additional impact investing funds. Giant Leap provides a list of 497 ILFs, and these were cross-referenced with the funds available in the Preqin performance database. This provided 176 additional funds for the potential impact fund list (Giant Leap Fund, 2021).

Moreover, ImpactYield provides a list of 216 impact funds that are cross-referenced with the list of 9,952 funds and the existing potential impact fund list. This resulted in an additional 23 funds being added to the potential impact fund list (ImpactYield, 2022).

Lastly, other funds were added to the potential impact fund list by searching third-party resources for mentions of impact funds. These third-party sources include Impact50's impact fund list, SustainFi's top 75 global impact funds list, GIIN members, B Corp members, and general web searches (SustainFi, 2021; ImpactAssets, 2022; Paris Impact Investing, 2018; GIIN, 2022a).

Once all resources were pooled together, the final potential impact fund list consisted of 649 funds. An extensive screening process is set up to determine which of these funds can be labelled as impact funds in alignment with the criteria previously set up for such funds. The screening process is explained in detail in the next section.

The benchmark used for this analysis is also retrieved to finalise the data collection. The benchmark is set up from the original sample size of 9,952 funds. After removing the ILFs, the sample is further restricted to vintage years between 1990 and 2021 to match the potential impact fund list. The benchmark funds are further restricted to reflect specific key ILF characteristics. This process is also described in detail in section 3.1.3. However, it is essential to note that the restriction of the benchmark introduces a potential self-selection bias to the dataset (GIIN, 2021b). To see if the restriction of the benchmark influences the results, the "original" benchmark and the restricted benchmark are used initially in Model 1. This is described further in sections 3.1.3 and 4.3.

3.1.2 Designation of Impact Fund Label

The designation of the impact fund label is done through an elaborate screening process. The first step of the screening process is to check for any predefined impact label. The Preqin database already has some funds with an impact label assigned according to their impact fund screening process (Preqin, 2022a). These funds were automatically labelled as impact funds due to the extensive screening process already completed by the Preqin database.

If the funds did not have the impact fund label, the next screening level was the fund description. This short description was checked for any mention of a clear dual objective, mentioning either a social impact objective or other descriptions stating a clear objective to also "do good". If such an objective was clearly stated, the fund was also labelled as an impact fund.

Most funds on the potential impact fund list did not have an impact label nor a fund description stating a true dual objective. In this case, further research was conducted for each fund to determine whether it could be labelled as an impact fund or not. The further research consisted of checking the fund website, the website of the fund manager, as well as any stated

memberships or signatories of impact associations like the GIIN, PRI, and the European Venture Philanthropy Association (EVPA). The websites were checked for any mention of a clear dual objective for social impact mainly by checking the "about us", "investment strategy", "our mission", and "our philosophy" pages. Furthermore, if any sustainability reports were available, these were included in the screening process. If any doubt remained about the fund's clear objectives, the fund was taken off the impact fund list. The main importance here was distinguishing between actual impact funds and funds that are "just" ESG or PRI aligned.

Throughout the screening process, each fund was checked for the dual objective. If there were multiple funds from the same asset manager, the VC and PE company would be assessed first to determine the overall business objectives. Then the funds would be checked individually for a dual objective to determine if all could be labelled as impact funds or not. If the VC or PE company was purely impact investing, all funds were labelled as impact. On the contrary, if the VC or PE company were not purely impact investing, each fund would be individually assessed. Only funds that clearly stated a dual objective were labelled as an impact fund.

Once the ILFs were identified, the impact assessment and ESG risk assessment scores were retrieved manually from Preqin. The impact assessment score was assigned on a portfolio company level and designated between four possible categories: "unknown/ unlikely", "possible", "likely", and "very likely". A numerical score of 0 to 3 was assigned to each category, and an overall weighted impact score (ImS) was calculated for the overall fund portfolio. A score of 3 represents a portfolio with a high probability of creating social impact. In contrast, a portfolio with an ImS of 0 has an unlikely or unknown probability of creating social impact.

For the ESG risk assessment score, the same process was applied. Here the four categories were "low", "moderate", "high", and "very high". The Preqin database assigns these scores based on a company level assessment where a combination of firm-specific ESG risk, industry risk, and geographical risk is used to determine the individual firm-specific ESG risk. Again, the numerical scores of 0 to 3 were assigned for each portfolio company, and the overall weighted ESG risk score was calculated for the portfolio. Here, a score of 0 implies a low overall ESG risk exposure, whereas an overall score of 3 implies a very high ESG risk exposure. It is, therefore, more attractive to have a lower ESG risk assessment score for the overall portfolio.

Only **195** funds are labelled as actual impact funds from the potential impact fund list. All ILFs have vintage years between 2000 and 2021, and the lower boundary is, therefore, restricted to

2000. To ensure that the performance data truly reflect the ILFs performance, the ILF sample is restricted further to have vintage years between 2000-2017. The GIIN & Cambridge Associates (2015) argue that it takes about five years for funds to see sufficient performance data, which is mainly due to the limited exists experienced during the first years of a fund's lifespan. This vintage year range is also imposed on the benchmark funds. The ILF sample thus consists of **153** funds, with **104** having the IRR (%) and **139** with Value Multiple (VM) data.

3.1.3 Benchmark selection

As discussed above, the benchmark is restricted from the original **9,952** funds to reflect the characteristics of the ILFs. The first restriction is imposed by removing three asset class categories: infrastructure, natural resources, and multi, leaving just VC and PE funds. As the ILFs strictly focus on these two asset classes, the restriction ensures that the benchmark performance is not biased to other asset class performance standards. The above vintage year restriction of 2000-2017 is also applied to the benchmark.

The benchmark is further restricted by removing any buyout funds. This is mainly due to the highly skewed fund size that buyout funds cause. Furthermore, buyout funds account for 28.73% of traditional funds but only 4.10% of ILFs. As one of the main fund characteristics of a buyout fund is its size, it is evident that this large gap influences the overall analysis. By removing the buyout funds from the sample, the mean fund size of traditional (ILF) decreased from $687.85M ($175.81M) to $342.16M ($122.27M). This is a decrease of 50.26% (30.45%) respectively. Introducing this restriction may cause a selection bias in the model due to the increased subjectivity in fund selection (GIIN, 2021b). However, as Model 1 will explore, no significant influence on the performance of ILFs is experienced by removing these. Restricting this is, therefore, a trade-off between possible bias in the model and optimised benchmark representation of the ILFs.

The last adjustment to the benchmark is removing seven categories for the core industries[1]. These are removed to simplify the model that tests the influence of the core industry on performance, as only a few funds (15) are assigned to these categories, and none of them are ILFs. These restrictions leave the final benchmark with **4,734** funds.

[1] The categories removed are "Energy & Utilities - Raw Materials & Natural Resources", "Consumer Discretionary - Energy & Utilities", "Consumer Discretionary - Information Technology", "Consumer Discretionary - Raw Materials & Natural Resources", "Healthcare - Telecoms & Media", "Financial & Insurance Services – Healthcare", and "Real Estate".

3.1.4 Data Limitations

It is essential to mention the limitations of the data available for this thesis and the analysis. The main limitation to consider is the restricted access to data as the focus is on VC and PE, data is not publicly available (Barber, Morse, & Yasuda, 2021; Roundy, Holzhauer, & Dai, 2017; Schoenmaker & Schramade, 2019; Snider, 2018). Through access to the Preqin database, a decent number of impact funds have been identified. However, most impact funds found on lists provided by third-party resources were not available in the Preqin performance database and have, therefore, been left off the final impact fund list. This is connected to the survivor's bias, another critical bias that should be considered. As private data is not readily available, it is important to realise that funds are not obliged to disclose fund performance data other than to their investors (Hochberg, Ljungqvist, & Lu, 2007). This is important to consider when analysing the findings as there is a high probability of only the stronger performers disclosing their performance and thereby causing the results to be right-skewed (GIIN & Cambridge Associates, 2015; GIIN, 2021b; Higson & Stucke, 2012).

Additionally, it is important to note the possible selection bias in the manual screening process of the potential impact funds as well as in restricting the benchmark mentioned above. As discussed, impact investing has many different definitions that constantly change in character. Many funds found through the later steps in the screening process are subject to a higher subjective selection bias. Ideally, this process would be repeated by a third party to check that the ILFs, in fact, are impact funds. This bias further gives rise to a potential type I error in the data by allowing false positives in the ILF dataset. This could be the case with funds that use "impact washing" to seem more impact focused. Impact washing is possible due to the lack of standards within the impact investing industry, as discussed above (GIIN, 2020; GIIN, 2018; Schoenmaker & Schramade, 2019). However, this is unlikely to occur in this analysis due to the rigorous screening process. A more likely error is the type II of a false negative, i.e., an actual impact fund labelled as a traditional fund.

Furthermore, it is important to realise the relatively young dataset of the ILFs. Measuring the actual performance of VC and PE funds is difficult in the first years of the fund's existence as most deals are still active and no exits have been realised (McCallum & Viviers, 2020). As previously discussed, the GIIN & Cambridge Associates (2015) argue that funds younger than approximately five years should not have their performance considered as they do not have a sufficient track record. They further argue that generally, it takes 8-9 years before funds see a reliable position in the percentile ranking and, therefore, the percentile ranking is left out.

Lastly, due to the constraint of data availability and the scope of this study, it is critical to note the potential omitted variable bias. This analysis controls for four main fund characteristics as including more would lower the viability of the study due to an insufficient degree of freedom. It is, therefore, likely that the performance of funds can be explained by certain variables not included in this thesis, such as other characteristics or even external factors.

3.2 Variable Description

3.2.1 Dependent Variable – Financial Performance

This paper tests two different dependent variables using several different models. These variables are the IRR (%) and the VM. The most accurate and objective representation of fund performance is the IRR as it is a time-weighted return that includes both the distributed cash, the current value of unrealised investments as well as the current capital invested and is, therefore, the primary dependent variable used (Preqin, 2022b).

The value multiple is also used as more funds have this data available, and it gives an insight into funds that may not have realised any returns yet. The VM shows the magnitude of investors realised and potential returns and is calculated by adding the distributed capital to the residual value of the portfolio, as seen below. Therefore, a VM of 2 means that the investor has or is expected to receive two times their capital paid in (Preqin, 2022b).

$$VM = \frac{Distribution\ (\%) + Residual\ Value\ (\%)}{100}$$

It is important to note that the VM is exposed to a higher subjectivity due to different fund characteristics such as the fund's target investor. This is important as it causes a potential omitted variable bias in the model as it does not account for investor type. This is out of the scope of this analysis due to a lack of data available and the amount of time it would take to retrieve manually. However, Barber, Morse, & Yasuda (2021) analysed this factor and found interesting and significant results for different investor types. Further research may provide additional key insights into the impact investing fund performance drivers.

3.2.2 Independent Variables – Impact Measurements

To determine the performance of ILFs compared to traditional funds, the independent variable is the Impact Dummy variable. This variable takes the value 1 for ILFs and 0 for traditional funds. This variable will isolate the mean difference between the ILFs and the traditional funds. If a significant coefficient is found, this will imply a difference in fund performance between ILFs and traditional funds.

3.2.3 Control Variables

To determine whether ILFs see a trade-off between financial and social returns, multiple control variables are applied to the sample. The first control variable is the vintage year. This is controlled to isolate any economic trends such as the economic downturn in 2009 and cyclicality that might influence the performance as suggested by Higson & Stucke (2012) and The World Bank (2022). Furthermore, this also helps control for heterogeneity in the exit timing and the consequential market conditions of these (Hochberg, Ljungqvist, & Lu, 2007). The vintage years are grouped into six groups of 3 years each (2000-2002 to 2015-2017). Each group is assigned a dummy variable leaving out the first group to avoid any multicollinearity in the model. This group (2000-2002) becomes the base for measuring this variable.

The next control variable is the fund size. This ensures that the returns are not dependent on the fund size. Kaplan & Schoar (2005) and Higson & Stucke (2012) found that the fund size is significant in explaining a fund's performance as performance improves as the fund size grows. This is, however, at a decreasing rate, suggesting a decreasing return to scale. Though most ILFs tend to be smaller than traditional funds, as shown in section 3.1.3, this is an important variable to control for. The fund size is controlled by including the log(size) variable to ensure that the fund performance is not due to the difference in average fund size between ILFs and traditional funds.

Another variable to control for is the fund geography. As described in section 2.3, Barber, Morse, & Yasuda (2021) found that the WTP of North American investors is lower than European Investors. Three categories are set up for the fund geography to test if this is the case. These are North American, European, and the rest of the world, with Europe being used as the base group. This variable is determined by where the fund is domiciled and not the focus geography of the funds.

Lastly, the main industry focus is isolated to control any industry-related performance. It is evident from the descriptive statistics (see next section) that the different core industries have varying average returns for both ILFs and traditional funds. To control for this, 12 different industries are identified after removing the seven core industries not representing any ILFs[2]. Again, each group is assigned a dummy variable with the "diversified" industry left out to avoid

[2] The 12 industries represented are "Diversified", "Business Services", "Consumer Discretionary", "Energy & Utilities", "Financial & Insurance Services", "Healthcare", "Healthcare, Information Technology", "Industrials", "Information Technology", "Information Technology, Telecoms & Media", "Raw Materials & Natural Resources", and "Telecoms & Media".

multicollinearity. This is the base reference for the fund industry as it is the category with the highest fund allocation (58.11%) across all funds.

3.3 Descriptive Statistics

The final sample is made up of **153** ILFs and **4,734** benchmark funds. Table 1 Panel A shows a complete overlook of the descriptive statistics for ILFs and traditional funds. The first thing to notice is that the vintage year mean (median) of ILFs is 2010.10 (2011), which is similar to traditional funds with 2009.17 (2009) respectively. This shows that the ILF sample is slightly younger than the benchmark funds. This is also evident in Figure 2 and Figure 3, which show the vintage year distribution of ILFs and traditional funds, respectively. This is not surprising as the impact field is relatively young and still sees an increasing number of new impact funds as more traditional fund managers transition into the impact fund universe.

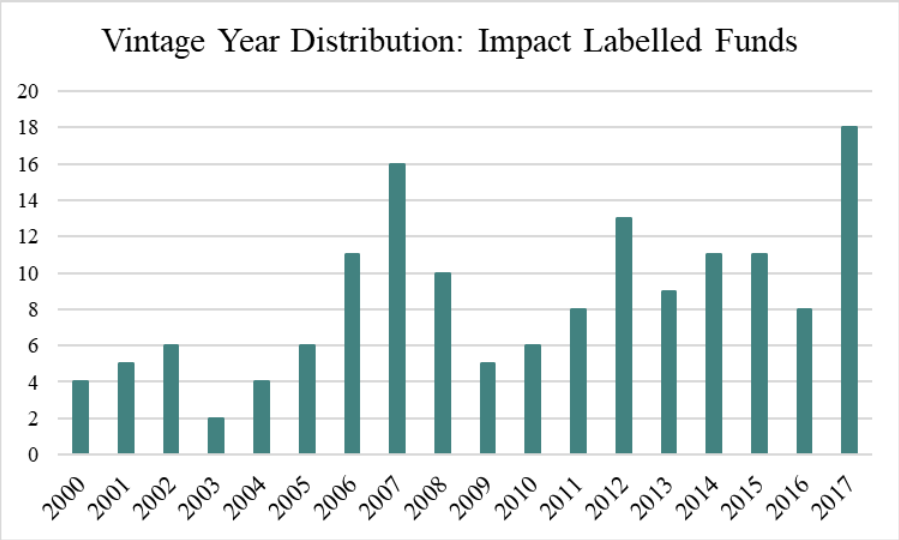

Figure 2: The vintage year distribution of impact labelled funds between 2000-2017.

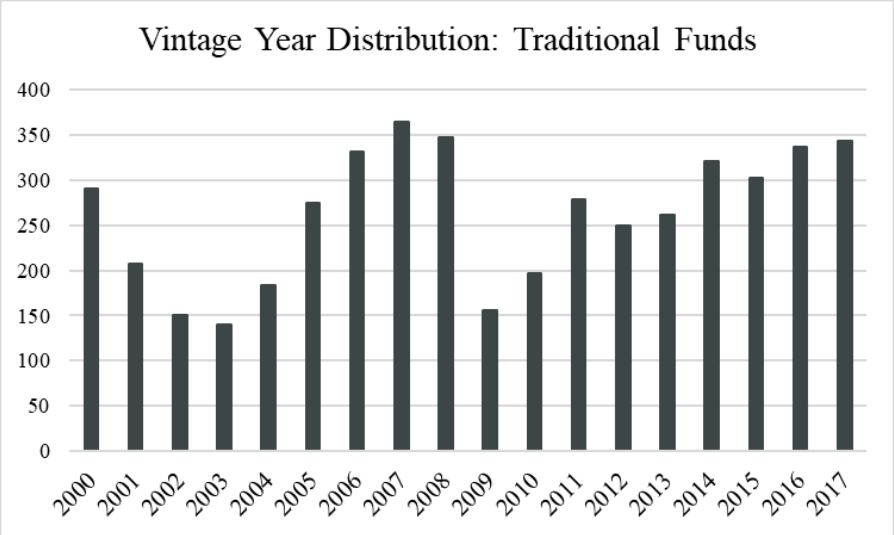

Figure 3: The vintage year distribution of traditional funds between 2000-2017.

Another important characteristic is the difference in mean (median) fund size of ILFs and traditional funds. These are $122.27M ($69.30M) and $342.69M ($150.00M) respectively. ILF are significantly smaller on average than traditional funds. This is partly due to the relatively untested field of impact investing as well as the higher focus on very young target companies of impact funds. However, recent years have seen several larger impact funds close with a final fund size above $1B, though most are domiciled in North America. In January 2022, Summa Equity announced the largest European impact fund to date, with a closing size of nearly $2.5B (Summa Equity, 2022). Furthermore, the original ILF list includes five ILFs larger than $1B ($1.3B - $2.2B), all with vintage years after 2017. This interesting trend should be considered for further studies as more time passes and reliable performance data becomes available.

Table 1: Descriptive Statistics

	Impact funds				**Traditional funds**			
Panel A: Descriptive Statistics	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
Vintage year	153	2010.1	2011	4.94	4,734	2009.17	2009	5.2
Fund size ($ million)	145	122.27	69.3	147.05	4,490	342.69	150	741.5
IRR (%)	104	16.47	10.37	33.36	3,810	15.18	12.93	19.98
Value Multiple (VM)	139	1.61	1.27	1.54	4,432	1.84	1.56	1.96
Panel B: Domicile Region		Mean IRR (%)	Mean VM			Mean IRR (%)	Mean VM	
Europe	38	33.08	1.61		1,093	14.28	1.62	
North America	83	14.4	1.76		2,811	14.37	1.83	
Rest of the World (RoW)	32	10.43	1.27		825	19.23	2.19	
Panel C: Industry Focus		Mean IRR (%)	Mean VM			Mean IRR (%)	Mean VM	
Diversified	72	16.89	1.37		2756	15.23	1.76	
Business Services	6	13.29	2.01		33	16.50	1.76	
Consumer Discretionary	6	27.49	2.98		91	20.05	2.27	
Energy & Utilities	16	-2.80	0.76		136	8.81	1.27	
Financial & Insurance Services	11	13.83	1.74		29	14.51	1.53	
Healthcare	7	19.87	2.17		463	15.84	1.72	
Healthcare, Information Technology	2	NA	0.53		137	9.28	1.58	
Industrials	1	NA	0.25		43	8.99	1.51	
Information Technology	18	22.77	3.23		764	18.53	2.40	
Raw Materials & Natural Resources	5	2.77	1.02		35	5.75	1.24	
Telecoms & Media	1	15.73	1.97		87	14.18	1.97	
Information Technology, Telecoms & Media	3	32.00	1.78		145	10.29	1.61	

Looking at the fund performance, this analysis looks at two performance metrics. The IRR is the most accurate measure, as previously discussed. The mean (median) IRR of ILFs across all vintage years is 16.47% (10.37%). On the other hand, the mean (median) for traditional funds is 15.18% (12.93%). From the mean fund performance, it is suggested that the ILSs outperform traditional funds. However, looking at the median fund performance, this is no longer the case. Alternatively, the VM shows a different picture of ILFs relative to traditional funds. Here the VM mean (median for ILFs and traditional funds are 1.61 (1.27) and 1.84 (1.56), respectively. This indicates a better performance of the traditional funds relative to ILFs.

Panel B in Table 1 gives an overview of the mean IRR and VM of ILFs and traditional funds across the three domicile regions. Here it is interesting to note the seeming outperformance of European ILFs, where the mean IRR is 33.08%. This again would suggest that ILFs outperform traditional funds. However, keeping in mind the skewness of the ILFs IRR, it is likely due to this and not an actual outperformance. This will be further analysed in Model 3 and Model 4.

Panel C in Table 1 shows an overview of the core industry in which the ILFs and traditional funds operate. For the ILFs, the mean IRR varies significantly across industries. From "Energy & Utilities" with -2.80% to "IT, Telecoms & Media" with 32.00%. This variation is also present for traditional funds though at a smaller scale, with "Raw Materials & Natural Resources" showing a mean IRR of 5.75% compared to "Consumer Discretionary" with 20.05%.

Another important distinction between the ILFs and the traditional funds is the differences in core industry focus. The distribution for ILFs and traditional funds is further shown in Figure 4 and Figure 5, respectively. Most industries see a similar distribution between ILFs and traditional funds. However, the main difference is that ILFs are more exposed to the "Financial & Insurance Services", "Raw Materials & Natural Resources", and the "Energy & Utilities" industries. This is not surprising as one of the main drivers of impact investing is the increased focus on sustainability and the UN's SDGs, as discussed in section 2.1.

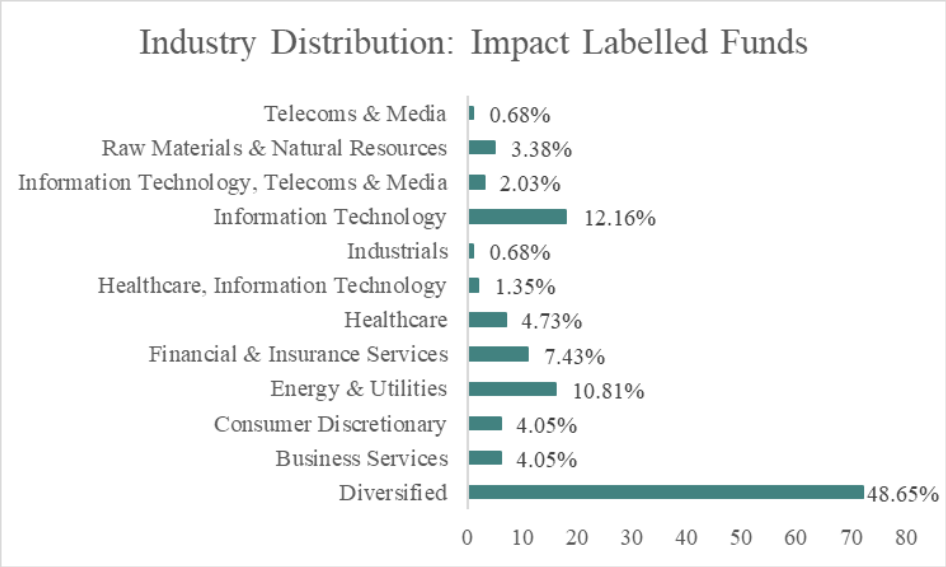

Figure 4: Industry distribution of impact labelled funds.

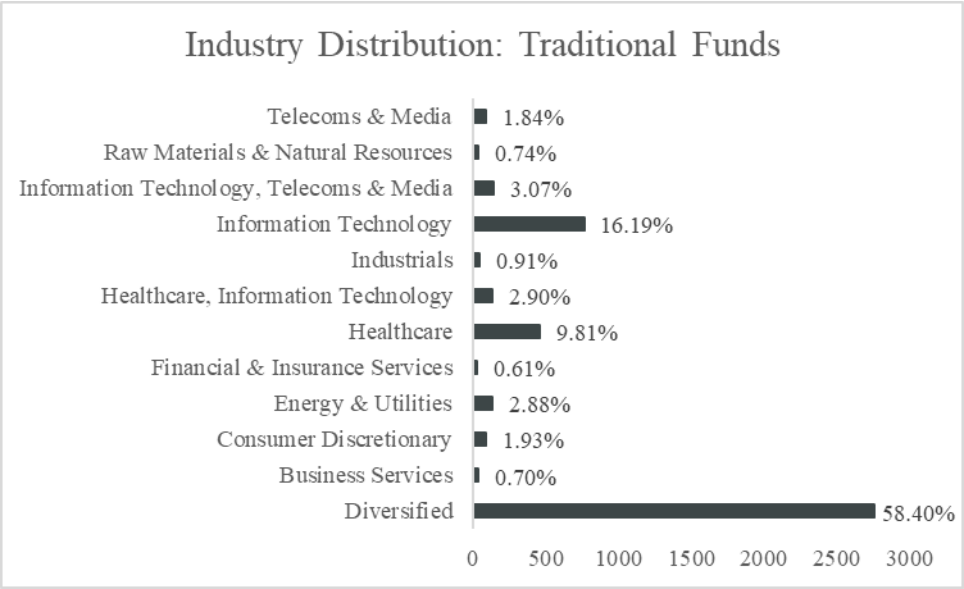

Figure 5: Industry distribution of traditional funds.

4 Hypothesis and Methodology

Section 2 laid out the current landscape of impact investing and clearly defined impact investing as of 2022. The section also identified the gaps in research regarding impact investing and gave an overview of the continued disagreement for and against a trade-off existing within impact investing. Section 3 provided an overview of the data selection process and the limitations of this study. This section goes through the methodology applied for further research on whether this trade-off exists or not. It outlines the main hypothesis of this thesis and any further research questions explored to determine whether a trade-off exists and what factors influence it.

4.1 Main Hypothesis

The main hypothesis lacking a definitive answer is whether a potential investor must forego financial profits to have a social impact. To test this, the main hypothesis is whether the return of ILFs is the same as traditional funds, and is set up as follows:

$$H0: Return_{\text{traditional}} = Return_{Impact}$$

$$H1: Return_{traditional} \neq Return_{impact}$$

To test this hypothesis, a set of regression models is developed to determine what factors (if any) influence a potential trade-off within impact investing compared to traditional investments. These are described in detail in section 4.3.

4.2 Further Research Questions

As discussed in section 3.1.2, the Preqin database has the impact assessment data available for most ILF. An overall ImS was calculated for each fund with the available data. To test if this ImS influences the overall fund performance, a secondary hypothesis is set up as follows:

$$H0: The\ Impact\ Score\ (ImS)\ drives\ the\ performance\ of\ an\ ILF$$

$$H1: The\ Impact\ Score(ImS)\ does\ not\ drive\ the\ performance\ of\ an\ ILF$$

Additionally, the ESG risk assessment score is included in the analysis to determine if the ImS indeed helps drive ILF's performance or if it is simply explained by a relationship between the ESG risk and the overall ImS.

4.3 Methodology

The methodology used to determine what factors, if any, have an impact on the trade-off between financial performance and social impact is a set of models designed to isolate the significant factors, if any, that influence whether there is a trade-off or not. This approach takes inspiration from the 2021 study by Barber, Morse, & Yasuda (2021) published in the Journal of Financial Economics. The first model is a univariate regression of the internal rate of return (IRR %) as the dependent variable on the dummy variable representing whether the fund is an ILF or a traditional fund. This dummy variable takes the value 1 corresponding to an ILF and 0 when referring to a traditional fund. The model is then repeated using the value multiple (VM) as the dependent variable. Both variations of Model 1 are shown below:

$$IRR_f = \alpha + \delta Impact + \varepsilon_f$$

$$VM_f = \alpha + \delta Impact + \varepsilon_f$$

The following models control for some key fund characteristics to further distinguish whether impact funds see a trade-off between impact and financial returns. These characteristics include the vintage year, fund size, geographical and industry focus. Model 2 includes the vintage year and fund size control variables and is set up with both dependent variables as follows:

$$IRR_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \varepsilon_f$$

$$VM_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \varepsilon_f$$

Model 3 is set up to test whether the findings made by Barber, Morse, & Yasuda (2021) and supported by the GIIN (2021b) regarding a lower WTP for impact for North American investors vs European investors hold. Therefore, dummy variables are set up for funds domiciled in North

America, Europe, and other countries. The European fund dummy is kept out of the model to avoid multicollinearity. Model 3 is seen below with both dependent variables.

$$IRR_f = \alpha + \delta Impact + \beta Vintage + \beta Region + \varepsilon_f$$
$$VM_f = \alpha + \delta Impact + \beta Vintage + \beta Region + \varepsilon_f$$

Model 4 combines Model 2 and 3 to control the fund size, geography, and vintage year. This is done knowing the limited data availability, and the results should, therefore, not be taken without considering this possible bias.

$$IRR_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \beta Region + \varepsilon_f$$
$$VM_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \beta Region + \varepsilon_f$$

Model 5 further explores the fund's focus industry to control industry-specific performance. Due to the lack of data availability, it is impossible to test all factors simultaneously. The model, therefore, leaves out the fund domicile region to allow for sufficient degrees of freedom.

$$IRR_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \beta Industry + \varepsilon_f$$
$$VM_f = \alpha + \delta Impact + \beta Vintage + \beta Log(size) + \beta Industry + \varepsilon_f$$

To further explore whether ILFs, experience an influence on their performance depending on their ImS or ESG risk score, a separate "Impact Model" is set up. This model focuses only on the ILF's data as the IS, and the ESG risk score have not been retrieved for the traditional funds. Therefore, the model is as follows:

$$IRR_{Impact} = \alpha + \beta ImS + \beta ESG + \varepsilon_{impact}$$
$$VM_{Impact} = \alpha + \beta ImS + \beta ESG + \varepsilon_{impact}$$

Another factor to consider is the relationship between the ImS and the ESG risk score. This ensures that a significant result, for example, the ImS is not a direct result of higher ESG risk exposure. Therefore, the correlation between the ImS and the ESG risk score is calculated.

5 Empirical Findings and Analysis

5.1 Benchmark Restriction Analysis

Before exploring the regression models, the appropriate benchmark must be selected. To do so, Model 1 is run using the IRR as the dependent variable using three different benchmarks. The "Original" benchmark consists of all traditional funds from 2000-2021 and includes all strategies and industries. The "Semi-Restricted" benchmark restricts the funds to the vintage

years 2000-2017 to allow a sufficient track record in measuring performance. Lastly, the "Restricted" benchmark restricts the strategy and the industry, as explained in 3.1.3. The regression results are seen in Table 2 below for all three benchmarks.

Table 2: Model 1 regression using the "Original", "Semi-Restricted", and the final "Restricted" benchmark and using the IRR as the dependent variable.

*The significance level is indicated by: *** p<0.01, ** p<0.05, * p<0.1*

Variables	Original	Semi-Restricted	Restricted
Impact	4.459*	0.463	1.286
	(2.498)	(2.280)	(2.032)
Constant	18.43***	16.10***	15.18***
	(0.348)	(0.317)	(0.331)
Observations	6,302	5,587	3,914
R-squared	0.001	0.000	0.000

As is evident from the two last regressions using the semi-restricted and the restricted benchmark, no significant results are seen for the ILF performance as the coefficient is not statistically significant. Therefore, it is not possible to reject the hypothesis that the return of ILF is equal to that of traditional funds. This further suggests that ILFs do not see a trade-off from traditional funds when no fund characteristics are controlled for. However, this model is the most reduced form. It does not offer any insights into what factors influence fund performance, and the factors driving the performance of ILF may differ from those driving the performance of traditional funds. The results only show that restricting the vintage years removes the significance of the impact dummy variable, thus suggesting an inflated IRR for ILFs with vintage years 2018-2021.

5.2 Main Hypothesis Analysis

Going forward, only the restricted benchmark is used in the regressions. The results from regression models 2 – 5 using the IRR and the VM as the dependent variable are seen in Table 3 and Table 4 respectively. Both tables can be found with the standard errors in Appendix 2 and Appendix 3, respectively.

The results from Model 2 show that all variables are significant in explaining fund performance. Most important is the Impact dummy, which is statistically significant at the 10% level. This indicates that ILFs show an underperformance of 3.37% compared to traditional funds when controlling for the vintage year and fund size. This would suggest that a trade-off exists between

traditional and ILFs, as earlier research suggests and as is still a commonly held assumption amongst investors. Furthermore, this finding is consistent with Model 4, which controls the fund's domicile region. Here the result shows an underperformance by ILFs of 3.38%. Only when removing the fund size (Model 3) or including the core industry control variable (Model 5) is the Impact variable not statistically significant.

Table 3: Regression results from models 2 – 5 using the IRR as the dependent variable.

*The significance level is indicated by: *** p<0.01, ** p<0.05, * p<0.1*

Variables	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Impact	**-3.367***	**-0.301**	**-3.377***	**-2.866**
Vintage Year				
2003 - 2005	2.635**	2.341*	2.526**	2.731**
2006 - 2008	3.302***	2.904***	3.157***	3.594***
2009 - 2011	10.38***	10.04***	10.22***	10.65***
2012 - 2014	14.22***	14.09***	14.06***	14.17***
2015 - 2017	21.04***	20.25***	20.74***	20.79***
Log(size)	-1.275**		-1.048**	-1.254**
Domecile Region				
North America		0.194	0.799	
Other		2.707***	2.780***	
Industry				
Business Services				1.296
Consumer Discretionary				1.845
Energy & Utilities				-6.220***
Financial & Insurance Services				-1.591
Healthcare				1.456
Healthcare, Information Technology				-3.531*
Industrials				-4.112
Information Technology				1.952**
Information Technology, Telecoms & Media				-2.013
Raw Materials & Natural Resources				-11.96***
Telecoms & Media				-0.642
Constant	8.713***	5.543***	7.393***	8.646***
Observations	3,732	3,909	3,727	3,720
R-squared	0.142	0.138	0.144	0.154

These findings are supported by the regressions using the VM as the dependent variable instead. Here models 2 – 5 all see significant results for the Impact dummy. The underperformance by ILFs range from 0.29 to 0.40 compared to traditional funds. The significance of the impact dummy disappears only when including the core industry in the analyses. However, as previously concluded, the VM is a less reliable measure of performance compared to the IRR and, therefore, only acts as a supporting factor rather than a conclusive one.

Table 4: Regression results from models 2 – 5 using the VM as the dependent variable.

*The significance level is indicated by: *** p<0.01, ** p<0.05, * p<0.1*

Variables	Model 2	Model 3	Model 4	Model 5
Impact	**-0.404****	**-0.290***	**-0.404****	**-0.290**
Vintage Year				
2003 - 2005	0.193*	0.185*	0.194*	0.237**
2006 - 2008	0.339***	0.301***	0.336***	0.385***
2009 - 2011	0.885***	0.854***	0.879***	0.924***
2012 - 2014	0.890***	0.860***	0.878***	0.889***
2015 - 2017	0.621***	0.543***	0.593***	0.588***
Log(size)	-0.233***		-0.220***	-0.195***
Domecile Region				
North America		0.219***	0.253***	
Other		0.492***	0.447***	
Industry				
Business Services				0.0499
Consumer Discretionary				0.421*
Energy & Utilities				-0.545***
Financial & Insurance Services				-0.0928
Healthcare				0.0120
Healthcare, Information Technology				-0.0332
Industrials				-0.246
Information Technology				0.615***
Information Technology, Telecoms & Media				-0.0162
Raw Materials & Natural Resources				-0.683**
Telecoms & Media				0.237
Constant	1.852***	1.160***	1.606***	1.668***
Observations	4,348	4,566	4,343	4,332
R-squared	0.031	0.033	0.037	0.049

The analysis also shows that the fund size plays a significant role in explaining fund performance. Only producing significant results when included in the model, it is evident that larger funds seem to underperform smaller funds across all models. The analysis shows increasing the fund size by 1% results in a decreased performance (measured by IRR) of 1.05% to 1.28%. This is in line with the ILFs seeing a significant underperformance when the fund size is controlled for as they tend to be smaller in size, as concluded in section 3.3.

It is also important to note the significance of controlling for the fund's vintage year. Each model includes this control variable, and the results are consistent across all models. It is evident that as the vintage year increases, so does the expected return. The mean IRR for funds with vintage years between 2015 – 2017 is consistently around 20-21% higher than the base group of vintage years 2000-2002. This contrasts with funds with vintage years 2003-2005, which only see a mean IRR of about 2.5% higher than the base group. This might be explained by the possible lacking track record of performance measurement and realisation for the later vintage

years. This would be the case for funds that have a longer lifespan than five years and may, therefore, not be fully liquidated yet and thus experience potential inflation of the expected residual value. However, this remains speculation without further research as no solid evidence is obtained from this analysis.

Another important finding is the result from including the fund's domicile region in models 3 and 4. In both models, only the "other" variable is statistically significant at the 1% level. No significant difference between the performance of European and North American funds exists, as suggested by the GIIN (2021b) in section 2.3. However, this result differs slightly when looking at models 3 and 4 using the VM. Here, both regions see a statistically significant difference between funds domiciled in Europe and North America and the rest of the world. This result suggests that European funds underperform other funds by 0.22 – 0.49. This is not surprising when looking at the descriptive statistics in section 3.3 that show the mean VM for both ILFs and traditional funds domiciled in North America is higher than the mean VM for European-based funds. Although this result is statistically significant, it is not possible to say if any difference in the WTP exists between the two groups. Furthermore, the performance seen by funds domiciled outside of Europe and North America could be explained by an increased risk profile due to higher exposure to emerging markets or possibly by the relatively higher valuation of emerging market assets, thus overstating the performance of funds located outside of Europe and North America (Kwok, 2017).

Lastly, the results from Model 5 suggest that the trade-off between ILF and traditional funds can be explained by controlling for the core industry of the funds. Here, the impact dummy is no longer statistically significant and thus provides no evidence of a trade-off between ILFs and traditional funds. The dummy variable controlling for the "Energy & Utilities" industry is most noticeably. As explained in section 3.3, the ILFs are more exposed to this industry than traditional funds. This is one of the only core industries with a significant coefficient (underperforming with 6.22% compared to the diversified funds); it might influence the overall ILF performance. Furthermore, ILFs have a slightly higher exposure to the "Raw Materials & Natural Resources" industry which also sees a significant underperformance of 11.96% compared to a diversified portfolio. The higher exposure to specific industries could suggest an increased risk exposure as the diversification benefits are removed and thus causing a higher exposure to the overall industry performance. This should be considered as the decrease in the diversification of ILFs would explain the underperformance when not controlled for. This is mainly due to increased social impact generation as some of the major impact investing themes

are into environmental impact through improved sustainable energy and increased resource efficiency (Barber, Morse, & Yasuda, 2021; UNDP, 2016).

The key findings from the analysis above are that no consistent trade-off between ILFs and traditional fund performance is found. By including control variables for the fund size, vintage year, and core industry, the significance of the impact dummy variable disappears. Furthermore, no evidence is found as to the difference in the performance of North American and European based funds. However, funds located in all other regions see a slightly higher performance of around 2.7%, which is statistically significant. Lastly, the difference in industry exposure between ILFs and traditional funds is a significant factor in determining if a trade-off exists or not. This is mainly due to the higher concentration of ILFs in the "Energy & Utilities" industry, which is not surprising as one of the main foci of impact investors is generating environmental impact.

As generating a social impact and generating financial returns is the foundation of impact investing with both working in "lockstep", it could be hypothesised that a higher impact potential also results in a better financial performance. This hypothesis is explored further in the next section.

5.3 Impact Score and ESG Risk Analysis

The further analysis looks at the possibility of the ImS driving the ILFs returns. To analyse this, the impact regression was tested using both the IRR and the VM as dependent variables. The results from the regressions are found in Table 5. The main finding is that the ImS is statistically significant when looking at the IRR as the dependent variable. This result suggests that ILFs with a higher relative impact potential also see higher financial returns. By increasing the ImS of a fund by 1 point, the performance of the fund increases by 5.84%. This supports the idea that impact investing is based on the dual objective of both financial returns and social impact works in lockstep. However, as this is a reduced regression, it is not possible to say if the performance is due to the higher ImS, an omitted variable, or simply due to an increased ESG risk exposure.

Further analysis into the potential omitted variables could be conducted with more data available. Though, this is out of the scope of this thesis. However, the relationship between ESG risk and the ImS can be further explored.

Table 5: Regression results from the Impact Model (IRR and VM as dependent variables).

*Standard errors are in parentheses, and the significance level is indicated by: *** p<0.01, ** p<0.05, * p<0.1*

Variables	Impact Model (IRR)	Impact Model (VM)
Impact Score	5.854**	-0.105
	(2.388)	(0.159)
ESG Risk Score	5.274	0.349
	(4.133)	(0.269)
Constant	-1.569	1.350***
	(6.831)	(0.454)
Observations	83	118
R-squared	0.092	0.019

To determine if the impact potential score is driven by increasing the ESG risk exposure, the correlation of the two variables was determined. The correlation coefficient of 0.0064 is not significant (p-value > 0.1) between the ImS and the ESG Risk score, indicating that no linear relationship exists between the two variables, thus further validating the results found from the model above. The correlation coefficients are seen in Table 6.

Table 6: Correlation between the ImS and ESG Risk Score.

	Impact Score	ESG Risk Score
Impact Score	1	
ESG Risk Score	0.0064	1
P-Value	0.942	

6 Conclusion

This thesis looks at the performance of ILFs relative to traditional PE and VC funds to determine if a trade-off exists between financial returns and social impact. This is done through a quantitative analysis that uses several control variables to isolate the potential factors influencing this trade-off. It is one of only a few quantitative studies that look at the performance of impact investing funds and contributes valuable knowledge to the continued growth of the impact investing field. Furthermore, the impact potential assessment and ESG risk assessment scores are analysed to determine if the magnitude of a potential social impact influences a fund's performance.

The thesis presents several key findings. First, no significant trade-off between ILFs and traditional funds exists when the vintage year, fund size, and the fund's industry is controlled for. This finding supports the increasing view that investors need not forgo financial returns to have a significant social impact and that the notion of "lockstep" is a reality. However, this finding changes when the core industry is left out of the model, giving rise to a significant financial underperformance by ILF of 3.37%. This finding is partly explained by the divergence in industry exposure between the ILFs and the traditional funds, as ILFs have a higher exposure to the "Energy & Utilities" industry, which underperforms by 6.22% compared to a diversified industry fund. Furthermore, the higher level of industry-specific ILFs implies higher industry-specific risk exposure, thus removing the benefits of diversification. This is due to the objective of maximising the social impact obtained, as seen in Model 5.

Secondly, no significant difference between North American and European funds exists, as suggested by (GIIN, 2021b). However, both regions are outperformed slightly by funds domiciled outside these two regions. However, it is not possible to determine if this is due to increased risk from higher exposure to emerging markets, overvaluation of emerging market assets or other factors due to the limitations and scope of this thesis.

Lastly, a significant result was obtained when looking at the impact score and ESG risk score. The findings suggest that an increase of 1 point in the impact score results in an increased performance of 5.85%. It is further shown that this result is not due to an increased ESG risk exposure as no linear relationship between the two variables is found. Nonetheless, more research should be conducted into other possible factors affecting this result though more data is needed.

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Appendix 1 List of fund search keywords

Double Bottom	Impact Investment	Social II
Environmental Fund	Impact Investor	Social Impact
Environmental Impact	Impact Investors	Social Impacts
Ethical Fund	Impact Invests	Social Implications
Impact Fund	Mission Driven	Social Responsible
Impact Initiative	Mission Investing	SRI
Impact Investing	Social Finance	

Appendix 2 Regression Results of Model 2 – 5 (IRR as Dependent Variable)

Variables	Model 2	Model 3	Model 4	Model 5
Impact	**-3.367***	**-0.301**	**-3.377***	**-2.866**
	(1.923)	(1.891)	(1.923)	(1.948)
Vintage Year				
2003 - 2005	2.635**	2.341*	2.526**	2.731**
	(1.206)	(1.210)	(1.206)	(1.198)
2006 - 2008	3.302***	2.904***	3.157***	3.594***
	(1.056)	(1.058)	(1.059)	(1.058)
2009 - 2011	10.38***	10.04***	10.22***	10.65***
	(1.172)	(1.170)	(1.176)	(1.174)
2012 - 2014	14.22***	14.09***	14.06***	14.17***
	(1.104)	(1.100)	(1.109)	(1.104)
2015 - 2017	21.04***	20.25***	20.74***	20.79***
	(1.077)	(1.070)	(1.084)	(1.076)
Log(size)	-1.275**		-1.048**	-1.254**
	(0.506)		(0.517)	(0.507)
Domecile Region				
North America		0.194	0.799	
		(0.773)	(0.777)	
Other		2.707***	2.780***	
		(0.996)	(0.998)	
Industry				
Business Services				1.296
				(3.303)
Consumer Discretionary				1.845
				(2.079)
Energy & Utilities				-6.220***
				(1.845)
Financial & Insurance Services				-1.591
				(3.243)
Healthcare				1.456
				(1.028)
Healthcare, Information Technology				-3.531*
				(1.832)
Industrials				-4.112
				(3.463)
Information Technology				1.952**
				(0.875)
Information Technology, Telecoms & Media				-2.013
				(1.818)
Raw Materials & Natural Resources				-11.96***
				(3.662)
Telecoms & Media				-0.642
				(2.160)
Constant	8.713***	5.543***	7.393***	8.646***
	(1.357)	(1.031)	(1.488)	(1.420)
Observations	3,732	3,909	3,727	3,720
R-squared	0.142	0.138	0.144	0.154

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 3 Regression Results of Model 2 – 5 (VM as Dependent Variable)

Variables	Model 2	Model 3	Model 4	Model 5
Impact	**-0.404****	**-0.290***	**-0.404****	**-0.290**
	(0.174)	(0.166)	(0.173)	(0.179)
Vintage Year				
2003 - 2005	0.193*	0.185*	0.194*	0.237**
	(0.115)	(0.111)	(0.115)	(0.115)
2006 - 2008	0.339***	0.301***	0.336***	0.385***
	(0.101)	(0.0978)	(0.101)	(0.102)
2009 - 2011	0.885***	0.854***	0.879***	0.924***
	(0.115)	(0.110)	(0.115)	(0.115)
2012 - 2014	0.890***	0.860***	0.878***	0.889***
	(0.107)	(0.103)	(0.107)	(0.108)
2015 - 2017	0.621***	0.543***	0.593***	0.588***
	(0.105)	(0.0997)	(0.105)	(0.105)
Log(size)	-0.233***		-0.220***	-0.195***
	(0.0493)		(0.0500)	(0.0494)
Domecile Region				
North America		0.219***	0.253***	
		(0.0692)	(0.0722)	
Other		0.492***	0.447***	
		(0.0906)	(0.0938)	
Industry				
Business Services				0.0499
				(0.320)
Consumer Discretionary				0.421*
				(0.218)
Energy & Utilities				-0.545***
				(0.175)
Financial & Insurance Services				-0.0928
				(0.314)
Healthcare				0.0120
				(0.102)
Healthcare, Information Technology				-0.0332
				(0.186)
Industrials				-0.246
				(0.332)
Information Technology				0.615***
				(0.0846)
Information Technology, Telecoms & Media				-0.0162
				(0.170)
Raw Materials & Natural Resources				-0.683**
				(0.328)
Telecoms & Media				0.237
				(0.219)
Constant	1.852***	1.160***	1.606***	1.668***
	(0.131)	(0.0932)	(0.141)	(0.136)
Observations	4,348	4,566	4,343	4,332
R-squared	0.031	0.033	0.037	0.049

Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1