Do Investors Pay for Impact? An Empirical Analysis of Valuations in Private Equity and Venture Capital

Thomas David Bauck

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Title: Do Investors Pay for Impact? An Empirical Analysis of Valuations in Private Equity and Venture Capital

Author: Thomas David Bauck

Abstract:

In a capital market that is increasingly shaped by concerns around sustainability, impact investing promises to deliver measurable social or environmental benefits alongside a financial return. But do investors in private equity and venture capital actually pay for impact, or is it just a branding tool? This study provides the first large-scale, valuation-based evidence that investors are willing to pay a premium for impact in private markets. Using a unique dataset of 160 'impact' deals matched to a control group of 3,500+ private transactions, I employ propensity score matching and doubly robust regression to isolate the 'impact premium'. Results reveal that impact firms are valued 90–99% higher than comparable non-impact firms, even after controlling for industry, geography, and deal characteristics. This premium is higher for social impact over environmental impact, larger in emerging markets than developed markets and disappears in cross-border deals, suggesting that investor preferences are highly context-dependent. The results challenge the view that impact is a non-financial phenomenon and show that, in practice, social and environmental value is priced into private equity. For fund managers, institutional investors and policymakers, this work offers granular insights and guidance into impact investing in private markets.

Keywords: Impact Investing, Private Equity, Venture Capital, Impact Premium, Sustainability, Social Impact, Environmental Impact, Willingness to Pay (WTP), Propensity Score Matching, Emerging Markets.

Título: Os Investidores Pagam pelo Impacto? Uma Análise Empírica das Avaliações em Capital Privado e Capital de Risco

Autor: Thomas David Bauck

Resumo:

Num mercado de capitais cada vez mais moldado por preocupações com a sustentabilidade, o impact investing promete gerar benefícios sociais ou ambientais mensuráveis, juntamente com um retorno financeiro. Mas será que os investidores em private equity e venture capital pagam realmente pelo impacto, ou trata-se apenas de uma ferramenta de marketing? Este estudo fornece a primeira evidência em larga escala, baseada em avaliações, de que os investidores estão dispostos a pagar um prémio pelo impacto nos mercados privados. Utilizando um conjunto de dados único de 160 negócios de "impacto" emparelhados com um grupo de controlo de mais de 3.500 transacções privadas, recorro a propensity score matching e a doubly robust regression para isolar o "prémio de impacto". Os resultados revelam que as empresas de impacto são avaliadas entre 90% e 99% acima de empresas comparáveis sem impacto, mesmo após o controlo por indústria, geografia e características do negócio. Este prémio é mais elevado para o impacto social do que para o impacto ambiental, é maior nos mercados emergentes do que nos mercados desenvolvidos e desaparece em negócios transfronteiriços, o que sugere que as preferências dos investidores são altamente dependentes do contexto. Os resultados desafiam a visão de que o impacto é um fenómeno não financeiro e demonstram que, na prática, o valor social e ambiental é refletido nos preços do private equity. Para os fund managers, institutional investors e decisores políticos, este trabalho oferece uma análise detalhada e orientações sobre o impact investing nos mercados privados.

Palavras-chave: Impact Investing, Private Equity, Venture Capital, Prémio de Impacto, Sustentabilidade, Impacto Social, Impacto Ambiental, Disposição para Pagar (WTP), Propensity Score Matching, Mercados Emergentes.

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List of Abbreviations Used

CI	Confidence Interval
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortisation
EM	Emerging Market
ESG	Environmental, Social, and Governance
EV	Enterprise Value
GIIN	Global Impact Investing Network
HMOs	Health Maintenance Organizations
ICMA	International Capital Market Association
IPO	Initial Public Offering
IRR	Internal Rate of Return
M&A	Mergers and Acquisitions
MSCI	Morgan Stanley Capital International
PSM	Propensity Score Matching
SaaS	Software as a Service
SRI	Socially Responsible Investing
UNPRI	United Nations Principles for Responsible Investment
USD	United States Dollar
WTP	Willingness to P

1. Introduction

In the last years, sustainable finance has developed from a niche market to an established investment theme or asset class. Within sustainable finance, impact investing, which seeks to generate measurable and additional social or environmental benefits alongside financial returns (Global Impact Investing Network, 2019), has experienced particularly strong growth since the 2008 financial crisis, thereby attracting high-profile players such as BlackRock and Bain Capital (Trelstad, 2016, p. 3). As of March 2024, the UN Principles for Sustainable Investing Initiative counts 5,345 signatories with a combined US$128.4 trillion in assets under management (UN Principles for Responsible Investment, 2024), of which approximately 1% is impact investing (Kölbel et al., 2020, p. 555). This marks a substantial increase from US$86 trillion in 2019. Although the rise of sustainable finance has experienced a recent backlash, a growing number of investors appear to be embracing impact investing as a legitimate investment approach or asset class (Agrawal & Hockerts, 2021, pp. 1-2). However, this development raises questions concerning the legitimacy of the sector's 'impact' claim. Is it something that investors actually value or merely a marketing tool? If it is not purely marketing, is it possible to determine how much investors are willing to pay for impact and what exactly they are willing to pay for? Such questions are highly significant when considering the future potential of impact investing as a core element of sustainable finance. Specifically, I will ask the following research question:

Are investors in private equity and venture capital willing to pay a premium for impact?

There are several areas where a closer examination of impact investing can help to provide a strategic framework for stakeholders. Firstly, research can determine if there is a measurable 'impact' premium in valuations. Secondly, by analysing valuation patterns, this research can reveal the value investors place on different impact themes, geographies and firm/deal characteristics. Thirdly, the findings may offer practical insights and guidance for impact funds, mission-driven companies, development finance institutions and the broader asset management industry. This thesis aims to provide evidence on the existence of an 'impact' premium and where it exists.

Impact investing is a complex construct with various different definitions given in the relevant literature. There is, however, scientific consensus that impact investing must fulfil four requirements: It must first intend to cause social/environmental impact. Secondly, this impact must be measurable. Thirdly, the investment must provide additionality and finally, there must be a financial return at or below market rates (Barber et al., 2021, p. 2; Brest & Born, 2013, pp. 23-24).

To date, there have been no publications focusing on the analysis of investors' willingness to pay (WTP) for impact in private markets using valuations. Existing studies approach the question only indirectly or in limited context. Barber et al. (2021) use fund-level data to infer investors' WTP from financial return data, thereby neglecting the lower risk of 'impact' assets from increased resilience during negative shocks. Heeb et al. (2022), by contrast, run a framed field experiment to measure investors' WTP for a sustainable investment but do so in a hypothetical, non-market setting rather than using observed valuation data. Overall, the literature lacks empirical studies that analyse actual investor behaviour in pricing impact, particularly in the context of private equity and venture capital. My research seeks to fill this gap by providing a valuation-based analysis of investor preferences for impact in real-world private market transactions.

I utilise a unique dataset of a fund-of-funds investing thematically in impact in private equity and venture capital markets. By employing propensity score matching and using doubly robust regressions, I compare fund mangers' entry valuations in private equity and venture capital deals within this impact portfolio to a set of private market transactions from the PitchBook database. Thereby, I isolate if investors in private markets are willing to pay a premium for impact and how substantial that premium is, measured in using valuation multiples such as EV/Sales. Furthermore, I analyse how investors' willingness to pay for impact varies according to firm and deal-specific characteristics, offering a deeper understanding of what drives perceived value in impact investing.

My results show that investors are willing to pay a premium of 90 – 99% for impact firms over non-impact firms. The magnitude, direction and significance of these results hold even when controlling for size, geography, time, industry and deal characteristics. My research also shows that investors value impact in emerging markets more than in developed markets and place a higher value on social impact than on environmental impact. Notably, the effect does not persist within the sub-sample of cross-border deals.

Some limitations apply to my analysis. Firstly, I cannot test for omitted variable bias. However, Rosenbaum bounds show that the results are robust to moderate levels of unobserved confounding. Secondly, the classification of 'impact' relies on the subjective application of criteria potentially affecting sample selection and comparability. Lastly, the sample of impact firms is drawn from a single investor, thus hampering external validity. Although I show that the private equity and venture capital funds in the sample do not deviate significantly from industry averages, the results could be affected by unobservable selection bias.

This thesis is structured as follows. Section 2 gives a comprehensive overview of existing research in this field. Section 3 explains the methodology employed before going into detail on the available data in Section 4. Section 5 discusses and critically appraises the results before I conclude in Section 6.

2. Literature Review

2.1. Definition of Impact Investing

The notion of 'doing good' through investing is nothing new and already the Quakers in 17th century England engaged in values-based investment decisions. However, the concept has become more fragmented and complex over time (Bugg-Levine & Emerson, 2011). In the 1970s, the socially and responsible investing (SRI) movement emerged in response to Apartheid in South Africa and pioneered divestment and ethical screening (Bugg-Levine & Emerson, 2011). In 2000, the 'Blended Value Framework' argued that all investments deliver non-financial returns in addition to financial returns (Bugg-Levine & Emerson, 2011). In 2007, the term 'impact investing' itself was coined by the Rockefeller Foundation to bring together a range of sustainable investment approaches, such as microfinance, community investing, and clean-tech venture capital, that aim to achieve both social or environmental benefits as well as financial returns (Agrawal & Hockerts, 2021; Bugg-Levine & Emerson, 2011; Trelstad, 2016).

More recently, several different definitions of impact investing have emerged. The Global Impact Investing Network (GIIN), a globally recognised organisation promoting the impact investing industry, defines impact investing as "investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return" (Global Impact Investing Network, 2019). Hence, to qualify as 'impact', an investment must provide intentional and measurable social or environmental return and a financial return that can range from below-market to market-rate levels (Global Impact Investing Network, 2019). Brest and Born (2013) build on this definition by distinguishing between enterprise impact (the change a firm generates through its products and services), investment impact (the extent to which the investor's capital causes a change that would not have occurred otherwise) and non-monetary impact (advisory support or reputational effects that stem from investor involvement). Further, impact must provide additionality, meaning that the social or environmental impact must be attributable to the investment (Brest & Born, 2013, pp. 23-24; Heeb et al., 2022, p. 1738).

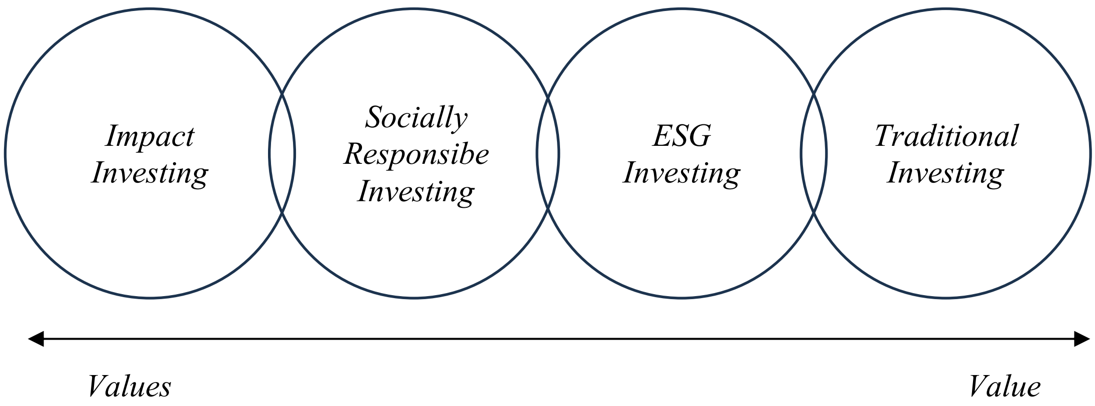
In contrast, Agrawal and Hockerts (2021, p. 6) develop a different framework by identifying characteristics of impact investors in practice using an ex-post conceptual approach:

1. Capital allocation to solve social/environmental problems
2. Dual pursuit of financial and social/environmental returns
3. Ex-ante commitment to impact
4. Use of measurable impact metrics
5. Active engagement with the investee
6. Targeting underserved markets or populations

This broader descriptive view includes not only characteristics of impact investors, such as those laid out in the framework developed by Brest and Born (2013), but also the mechanisms through which impact can be achieved.

While the definitions of impact investing vary, Starks (2023, pp. 1839-1841) offers conceptual clarity by framing impact investment in contrast to other forms of sustainable finance, drawing a distinction between values-driven and value-driven approaches:

Figure 1 – Sustainable Finance: Value vs. Values Approach



Source: Illustration by Starks (2023, p. 1840).

Traditional investing is value-based and refers to strategies focused solely on maximizing financial returns without any consideration of environmental, social or governance (ESG) factors or taking ethical aspects into account in investment decision-making. ESG investing has a stronger focus on values and integrates environmental, social, and governance factors into financial analysis and investment decisions to enhance risk-adjusted returns and protect long-term value. Socially Responsible Investing (SRI) refers to investment strategies that apply ethical or moral screens to specifically avoid or include companies based on social, religious or environmental criteria, typically through the means of negative/exclusionary screening (Starks, 2023, p. 1840).

Distinguishing impact investment from other forms of sustainable finance is essential when analysing the effects of impact investment itself. Although the presented literature deals with the delimitations and definition of impact, it lacks a clear definitional separation from other forms of sustainable finance strategies. With the aim of developing a clearer definition of impact, I five categories from Starks (2023), Kölbel et al. (2020), Heeb et al. (2022), Brest and Born (2013), Global Impact Investing Network (2019), Agrawal and Hockerts (2021) and Clarkin and L. Cangioni (2016) that distinguish impact investing from other forms of sustainable finance displayed in Figure 2.

Figure 2 – Impact Investing Within Sustainable Finance

	Sustainability Objective	Return Expectation	ESG Use	Outcome Measurement	Investor Role
Traditional	*None*	*Market-rate*	*None*	*None*	*Often Passive*
ESG	*Risk-focused*	*Market-rate*	*Risk-focused*	*Limited*	*Passive-moderate*
SRI	*Ethical*	*Mixed*	*Ethical screening*	*Often missing*	*Limited Engagement*
Impact	*Additionality*	*Mixed*	*Not primarily used*	*Required*	*Often active*

Source: Own synthesis of definitions of impact investing by Starks (2023), Kölbel et al. (2020), Heeb et al. (2022), Brest and Born (2013), Global Impact Investing Network (2019), Agrawal and Hockerts (2021) and Clarkin and L. Cangioni (2016).

The above five categories help distinguish impact investing from traditional, ESG and SRI approaches.

This framework does not only provide a structure for the conceptual foundation of this thesis but also serves as a means for the analysis of related literature. Different forms of sustainable finance are prevalent to a greater or lesser extent in different asset classes. While ESG integration and SRI are prevalent in public equity markets, impact investing tends to be concentrated in private markets. For this thesis, I utilise the definition of impact as defined by Heeb et al. (2022, p. 1738), Brest and Born (2013, pp. 23-24) and Global Impact Investing Network (2019), whereby an investment must fulfil the criteria of intentionality, measurability, additionality and an up-to-market-rate return expectation.

2.2. Does Impact Investing have an impact?

The existing literature examining the potential and the success of impact investing in achieving both financial and social/environmental returns is not conclusive. While there is a wide range of literature looking at the effect of ESG ratings on prices in public equity markets and the difference between conventional and green bond pricing in debt markets, the subject of impact investing in private equity is largely unexplored despite studies suggesting that private equity could be an area where impact investing can achieve the highest returns, both from a financial and a social/environmental point of view.

The literature on the real-world effects of impact investing can be broadly divided into two strands. The first strand conceptualises how investors might generate social or environmental outcomes through various mechanisms. The second one empirically investigates the effectiveness of these mechanisms in practice. A widely cited framework by Kölbel et al. (2020, p. 556) identifies three primary channels through which investors may exert influence: *shareholder engagement, capital allocation* and *indirect mechanisms* such as stigmatisation. *Shareholder engagement* refers to the engagement of investors with companies to influence their environmental and social practices through dialogue, voting or proposals. *Capital allocation* describes the practice of directing capital towards firms with strong social/environmental practices or withdrawing it from firms with poor social/environmental practices. *Indirect mechanisms* refers to concepts where investors exert influence on companies by providing expertise, reputational benefits or by shaping industry norms (e.g. stigmatisation, benchmarking) (Kölbel et al., 2020, p. 557). The investor influences are then assessed based on their potential for additionality in order to determine the extent to which an investor's actions can lead to outcomes that would not have occurred otherwise. An example of this is given by Brest and Born (2013, p. 24) who argue that capital allocation only achieves additionality when directed at assets that are genuinely constrained by limited access to capital. Both the above-mentioned studies also highlight the potential power of indirect mechanisms, such as reputational pressure or public scrutiny. However, they add a note of caution that these effects are difficult to quantify and isolate, thus identifying and emphasising a need for more robust causal identification strategies.

Shareholder engagement has received the most attention from academia and hence, provides most evidence on the effectiveness of different mechanisms in achieving real-world impact. Kölbel et al. (2020, p. 560) find strong evidence that shareholder engagement positively affects ESG ratings. However, the likelihood of success and the scale of impact diminish when firms face high compliance costs. Complementary findings by Dimson et al. (2015, p. 326), Dyck et al. (2019, pp. 694-695), and Barko et al. (2017, pp. 2-3) show that shareholder engagement is most effective when it is carried out by experienced investors, particularly those with substantial influence through ownership stakes.

Empirical evidence that capital allocation is a driver of real-world impact is sparse. Kölbel et al. (2020, p. 563) study the effect of capital flows on corporate ESG behaviour and find a positive relationship, however, this effect is limited in scale.

Finally, while indirect mechanisms like stigmatisation are often discussed as potentially powerful levers, they are underexplored in their effectiveness in achieving real-world impact. That highlights a critical gap in the literature on how impact is achieved in practice. This thesis looks at impact through the lens of capital allocation as a means for achieving impact, as the funds in the control dataset are mainly distributed to small and medium-sized enterprises which may otherwise not have the necessary capital to achieve their intended or desired impact.

2.3. Valuation in Impact Investing

A core component of the definition of impact investing is that investors earn a financial return alongside a social/environmental return. These financial returns must be positive and can be as high as market-rate returns. If investors are willing to forgo financial returns to achieve a social/environmental impact as suggested by its definition, this difference in returns between traditional and impact investing makes it possible to analyse the size of concessions made by investors for the impact achieved. This difference in return or value placed on an asset could be an indication of how investors value impact. Evidence on this relationship in private markets is limited. Studies analysing other asset classes are far greater in number and serve as a reference point for expectations on private markets.

Debt markets provide the clearest evidence on the existence of a willingness of investors to accept lower valuations for a social/environmental outcome. When looking at green bonds, defined as “any type of bond instrument where the proceeds will be exclusively applied to finance or refinance, in part or in full, new and/or existing eligible Green Projects” (International Capital Market Association (ICMA), 2022), several studies find a significant difference in pricing. This “difference in yields between a green bond and a synthetic conventional bond with similar characteristics” is called a ‘greenium’ (Zerbib, 2019, p. 231). This yield is generally lower and stems from green bonds being valued at a premium (Zerbib, 2019, p. 231). Typical green project categories include renewable energy, energy efficiency, pollution prevention, clean transportation, sustainable water management and climate change adaptation. Although not all green bonds satisfy the conditions of impact investing, due to their high degree of standardisation, they provide the most evidence on the valuation implications of investors’ preferences.

Baker et al. (2018, p. 118), Zerbib (2019, p. 231) and Nanayakkara and Colombage (2019, p. 139) all find significant greeniums from 2 to 6 basis points covering green corporate, municipal, supra-national and sub-sovereign bonds. This is consistent across geographies, however, Nanayakkara and Colombage (2019, p. 139) find that the effect is stronger in Europe and Asia.

Further, in their analysis of private and institutional bonds, Bachelet et al. (2019, p. 390) find that the existence of a greenium is contingent on third-party certification. This confirms studies like those of Heeb et al. (2022, p. 1765) showing that investors place value on the existence of social/environmental returns but have a low sensitivity towards the scale of these returns. Partridge and Medda (2020, p. 6) find that the greenium even holds for some sustainability-linked bonds. This shows that for bonds across geographies and for different types of bonds, investors value the impact that is achievable through the bond and are, hence, willing to forgo some financial return for it. Moreover, MacAskill et al. (2021, p. 23) find that the size of the impact premium varies by impact theme. Green bonds consistently receive a higher pricing benefit over traditional bonds than sustainability-linked bonds. This suggests that investors are not only willing to pay for impact as a single theme but that they also differentiate between environmental and social objectives and link the size of the premium to the scale of the expected impact.

Although these studies analyse bond markets, they offer strong justification for disaggregating impact themes in this thesis. If investors’ preferences for impact differ by impact theme within debt markets, it is worth exploring in private equity and venture capital. Particularly in the context of a hedonic pricing model, where the perception of value is relevant for the formation of a firm’s price, the perceived value of a firm’s impact can be expected to be found in equity markets, if it already exists in debt markets. Hence, despite structural differences between debt and private equity markets, these studies are robust as a reference point for the difference in valuations that investors are willing to pay for positive social/environmental outcomes.

The literature on public equity markets reveals significant differences between sustainable and traditional investments, though the effects vary by geography and most studies analyse other forms of sustainable finance.

Riedl and Smeets (2017, p. 2519) find that SRI mutual funds underperform traditional mutual funds by 5.17 percentage points annually. This is primarily driven by higher fees, suggesting that investors are willing to pay a premium for values-aligned investing. Renneboog et al. (2008, p. 1738) additionally show that this lower return mainly exists in Europe and Asia, indicating that investor preferences vary by geography.

While these studies focus on ESG integration and screening, Heeb et al. (2022, p. 1743) actually analyse impact investing an show that retail investors consistently select funds labelled as 'impact' despite their higher costs. This shows that investors have a positive willingness to pay for impact by forgoing returns for the perceived social/environmental value of an investment. Research by El Ghoul et al. (2011, pp. 4-5, 16) and Pástor et al. (2022, pp. 4-5) further support this. They find that firms with higher ESG scores benefit from a lower cost of capital, implying potentially higher valuations linked to sustainability. Although these studies do not directly examine private equity, they provide a strong indication that investors factor non-financial outcomes into their decisions, offering a basis for expecting similar trade-offs in private markets.

Evidence on private markets is limited due to a lack of data availability and a high degree of fragmentation.

One area of impact investing that is typically organised in private markets is microfinance. Despite its popularity and prevalence in impact investing, microfinance is underexplored with regard to the value that investors place on its outcome. In their meta-analysis, Heeb et al. (2022, p. 1764) argue that there is some return trade-off for the impact that can be achieved through microfinance, indicating again that investors are willing to value impact. However, data quality is poor and returns vary widely by region and target group. Returns even vary by ownership model with strategies such as group lending showing a better performance. Agrawal and Hockerts (2021, p. 1) and Ashta and Hudon (2012, pp. 332, 335) point to the high valuation of the first IPO of a microfinance institution (Compartamos Banco) to argue in favour of the added value investors place on this sector. However, no studies look at non-pecuniary sources of value in relation to microfinance.

Regarding private equity and venture capital markets, there is only one study addressing the value that investors place on impact.

Barber et al. (2021, pp. 3, 25, 34) look at the returns of 4,695 private equity funds with vintages from 1995 to 2014. By defining 159 funds as impact funds, they find that the return that investors earn annually is 4.7 percentage points lower for impact funds than for conventional funds, even after controlling for vintage, geography, sector and size. They find a willingness to pay (WTP) of investors for social/environmental returns of 2.5 to 3.7 percentage points expected internal rate of return (IRR).

However, by only analysing returns, Barber et al. (2021) do not account for the lower risk associated with impact investing. Lins et al. (2017, p. 1799) show that during the financial crisis of 2008, companies with higher ESG scores exhibited lower idiosyncratic risk. Similarly, Lu et al. (2023) and Rehman and Vo (2020) find that ESG investments acted as ‘safe havens’ during the COVID-19 pandemic due to lower variance. By focusing on returns, Barber et al. (2021) also fail to acknowledge the risk-return trade-off that could be causing lower returns.

However, in their analysis, Barber et al. (2021, p. 26) distinguish the WTP between investor type and find that development finance institutions, foundations, public pension funds and UNPRI signatories have a higher WTP for impact and that these effects are also larger for European investors that for investors in the US. In line with evidence on the scalability of capital allocation to achieve impact being higher for underserved markets (Kölbel et al., 2020, p. 564), emerging markets are overrepresented in their sample of impact funds. It can, therefore, be expected that because the fund-of-funds, whose data serves as a baseline for the treatment sample in this study is a signatory of the UNPRI, there is a positive WTP for impact here too.

By analysing valuations instead of returns directly, I am able to better capture investors’ WTP for impact. Further, I am able to distinguish what exactly investors are willing to pay for by performing my analysis on the company-level rather than using fund-level data.

2.4. Valuation in Private Equity and Venture Capital

This thesis focuses on the value placed on impact by analysing valuation multiples of entry valuations, in particular EV/Sales multiples. In order to be able to interpret these values meaningfully, it is necessary to understand how firm valuation in private equity and venture capital is usually done and in what way it takes non-financial investor preferences into account.

Standard valuation methodologies in private equity and venture capital focus on enterprise value or equity value as a share of a financial performance metric such as revenue, EBITDA, EBIT or net income. Rosenbaum and Pearl (2021, pp. 2-3) present a structured approach widely adopted in practice, highlighting three primary methods for determining firm value: Comparable Companies Analysis, Precedent Transactions Analysis, and Discounted Cash Flow Analysis. These models typically utilise metrics like EV/EBITDA, P/E, and EV/Sales**.** EV/Sales is especially relevant in venture capital or growth-focused deals due to profits often not being positive, resulting in negative multiples.

Due to the venture capital funds in the treatment dataset investing in early-stage or growth companies, the use of EV/Sales as the valuation metric in this thesis aligns with industry practice for deals where earnings are not yet stable or meaningful.

While these traditional valuation models provide a robust benchmark, they assume that investors merely value firms based on financial risk and return. However, in the context of sustainable finance an in particular in impact investing, this assumption is challenged. Investors may derive non-pecuniary utility from backing firms with social or environmental missions, leading to systematically higher valuations even when financial performance is comparable.

Many factors determine firm valuation. Deal characteristics are expected to have a significant effect on valuations. In their analysis of EV/Sales multiples in private equity, Hammer et al. (2021, p. 706) find a significant 25-37% higher valuation for cross-border deals. Further, there is no expectation for a difference in valuations between emerging and developed markets. Despite large differences and a higher level of risk, Cole et al. (2024, p. 1) show that when looking at risk-adjusted returns for private equity funds in emerging markets, they are comparable to those in developed markets. The implication for valuations in private equity deals is unclear, as there are no studies directly addressing this question.

This thesis contributes to the literature by using deal-level valuation data to directly measure whether investors pay a premium for impact**.** The underlying assumption is a hedonic pricing model, where the market price is a function of an assets' observable characteristics (Rosen, 1974). Here, the investor places value in non-pecuniary characteristics such as expected social/environmental outcomes. By comparing EV/Sales multiples between impact and non-impact firms and controlling for firm, industry, and deal characteristics, I test whether valuations reflect more than just expected cash flows, looking specifically at whether they incorporate investors' preferences for impact**.**

A consistent valuation premium shows that impact is actually being priced into deals, suggesting that some investors are willing to pay more upfront to achieve expected social or environmental objectives. Thus, valuation serves as a revealed preference mechanism for non-financial value, providing a new lens for understanding the way investors value firms in private markets.

3. Methodology

3.1. Identification Strategy

For the analysis, I implement a quasi-experimental setup by classifying firms as 'impact' or 'non-impact'. Whether a firm qualifies as 'impact' determines the treatment, with every other company representing the control group.

For my analysis I utilise a revealed preference theory approach as developed by Samuelson (1948), as the price that is paid for an impact firm over a non-impact firm reveals the value that an investor places on impact.

More concretely, I use a hedonic pricing model as defined by Rosen (1974), where the price of a company is determined by its observable characteristics:

$$\boldsymbol{P_i = f(z_{i1}, z_{i2}, \dots, z_{ik})} \tag{1}$$

where

- $\boldsymbol{P_i}$ is the price of a good $\boldsymbol{i}$;
- $\boldsymbol{z_{ij}}$ is the $\boldsymbol{j}$-th attribute of good $\boldsymbol{i}$.

The underlying assumption is that the price reflects all observable characteristics, enabling the marginal value of each characteristic to be inferred based on its contribution to the overall valuation. From this relationship it is then possible to infer the Willingness to Pay (WTP) from the first partial derivative:

$$\boldsymbol{WTP} = \frac{\partial \mathrm{P}}{\partial \mathrm{z_k}} \tag{2}$$

The WTP for impact is the target outcome that specifies whether investors value impact based on their revealed preferences. This framework assumes competitive pricing and complete information. However, private equity transactions are subject to negotiation, limited disclosure, and market frictions. These features introduce potential deviations from equilibrium pricing, which may limit the precision of WTP estimation.

3.2. Propensity Score Matching

I use propensity score matching (PSM) to reduce confounding bias from observable variables and to approximate the conditions of a randomised experiment, given that firms are not randomly assigned to impact status. Caliendo and Kopeinig (2008, p. 32) show that PSM is particularly effective in estimating causal treatment effects. Further, it helps overcome a large imbalance in sample size between firms that are classified as 'impact' and those that are not. By reducing the control sample size, I reduce noise in the data through the PSM.

In the first step of the PSM, I estimate the probability that a firm is an 'impact' firm based on observable characteristics. This is done using a probit model, which assumes the latent propensity to be treated follows a standard normal distribution:

$$\boldsymbol{P(Impact_i = 1) = \Phi(\beta_0 + \beta_1 Year_i + \beta_2 IND_i + \beta_3 EM_i + \beta_4 Size_i)} \qquad (3)$$

where

- $\boldsymbol{\Phi(\;)}$ is the cumulative distribution function of the standard normal distribution;
- $\boldsymbol{Impact_i}$ is a dummy variable for if firm $\boldsymbol{i}$ is sorted into 'impact' (1) or not (0);
- $\boldsymbol{Year_i}$ represents the year in which the transaction for firm $\boldsymbol{i}$ took place;
- $\boldsymbol{IND_i}$ is a dummy variable for if firm $\boldsymbol{i}$ is in an impact-likely industry (1) or not (0);
- $\boldsymbol{EM_i}$ is a dummy variable for if firm $\boldsymbol{i}$ is in an emerging market (1) or not (0);
- $\boldsymbol{Size_i}$ represents the enterprise value of firm $\boldsymbol{i}$ at the date of the transaction;
- $\boldsymbol{\epsilon_i}$ represents the error term.

3.3. Matching Implementation

Caliendo and Kopeinig (2008, pp. 38-39) show that explanatory variables used in PSM must affect both treatment and outcome variables, must not be impacted by the treatment and that over-parametrisation renders worse results. While PSM effectively balances observable covariates, it does not control for unobservable confounding factors. This means that if unmeasured firm attributes affect both the likelihood of being labelled 'impact' and firm valuation, the estimated treatment effect may be biased.

The propensity score approach relies on the assumption of unconfoundedness. It requires that all covariates influencing both the assignment into the treatment group and the outcome variable are observed. While this assumption cannot be tested directly, I argue that it is plausible given the amount and quality of the covariates included and their grounding in empirical findings from the sustainable finance literature. Furthermore, Rosenbaum bounds indicate that the estimated treatment effects are robust to moderate levels of unobserved confounding, suggesting that the results are not sensitive to potential hidden bias[1].

Barber et al. (2021, p. 12) show that companies in emerging markets have a higher representation in impact funds compared to traditional private equity funds. Hence, I include a dummy variable for emerging markets. Further, Lerner et al. (2016, p. 9) point to the fact that valuations have historically been lower in emerging markets compared with developed markets.

A dummy for impact-likely industries is included, as "impact funds are more likely to be energy or diversified funds, and less likely to be IT, health care, or media and communication funds than traditional" funds (Barber et al., 2021, p. 12). The classification of an industry as 'impact-likely' follows the framework developed by Pástor et al. (2022, p. 10). In their analysis, they assign scores to MSCI industries based on the impact an industry has on the environment. I match industries as classified by PitchBook with industries as defined by MSCI and include industries with a positive environmental impact as impact-likely industries[2].

Barber et al. (2021, p. 12) also show that private equity valuations vary across industry and highlight cross-border transactions as being overrepresented in impact funds, compared with traditional funds. Axelson et al. (2013, pp. 2224-2226) show that a firm's capital structure is determined not only by firm characteristics, but also by deal-specific characteristics. In cross-border settings, access to debt and risk assessments may differ significantly, leading to different pricing dynamics. However, a variable capturing cross-border transaction status is excluded from the omitted score estimation due to a lack of significance[3].

I include size, proxied through firms' enterprise value at deal date, as an explanatory variable, since Balasubramanian et al. (2021, p. 11) find that firm size is a key factor in a firm's ability to implement positive environmental and social practices and hence, a firms' impact. Further, Hirdinis (2019, p. 184) shows that firm size has a statistically and economically significant negative effect on valuation (Firm-to-Book-Value).

[1] The full results on Rosenbaum bounds are displayed in the appendix.
[2] The full list of industries that are classified as impact-likely and their corresponding matches from the MSCI industries listed in the appendix.
[3] The PSM estimation results with inclusion of a cross-border dummy variable are reported in the appendix.

PSM estimators differ based on how they define the 'neighbourhood' of comparable observations and how weights are assigned to those matches. Each method involves trade-offs between bias and variance, and the appropriate choice depends on the data structure and balance between treated and control units.

I utilise nearest-neighbour propensity score matching with replacement at the ratios 1:1, 1:5 and 1:10. Caliendo and Kopeinig (2008, p. 42) show that nearest-neighbour matching is preferred when there is a significant difference in the explanatory variables between the treatment and control group. In the data available, there is a significant difference in EV/Sales and industry variables, which is why propensity score matching with replacement is employed. In that way, treatment firms are matched to their closest possible counterparts and the issue of a match depending on the order of matching is avoided. To address the potentially increased variance from matching with replacement, robust standard errors are applied.

3.4. Treatment Effect Estimation

To estimate the Average Treatment Effect on the Treated (ATET), I implement a doubly robust approach. Bang and Robins (2005, pp. 962-964); Rubin (2005, p. 329); Stuart (2010, p. 15) and Shipman et al. (2017, pp. 217-218) show that regression adjustment on a matched sample effectively reduces biases and yields more precise estimators. After performing propensity score matching, I estimate a regression-adjusted treatment effect by regressing the outcome variable on the matched sample, including similar covariates used in the matching procedure:

$$\log\left(\frac{EV}{Sales}\right)_i = \beta_0 + \beta_1 Impact_i + \beta_3 IND_i + \beta_4 EM_i + \beta_5 CB_i + \epsilon_i \tag{4}$$

where:

- $\log\left(\frac{EV}{Sales}\right)_i$ represents the log Enterprise Value over Sales ratio of firm i;
- $Impact_i$ represents the treatment (control) indicator if a firm is 'impact' (1) or not (0);
- IND_i and EM_i represent covariates used in PSM;
- CB_i represents a dummy variable for if a deal is cross-border (1) or not (0);
- ϵ_i represents the error term.

Due to the use of log-transformed valuation multiples, the resulting ATET and WTP for impact, $\boldsymbol{\beta_1}$, can be transformed for interpretability of the resulting coefficient using the following formula:

$$\boldsymbol{Impact\ Premium\ in}\ \% = \mathbf{exp}(\boldsymbol{\beta_1}) - \mathbf{1} \tag{5}$$

This combination of matching and regression adjustment improves precision and ensures consistency of the ATET estimate under the double robust property: the estimator is consistent if either the treatment assignment model or the outcome model is correctly specified (but not necessarily both).

As demonstrated in the PSM section above, all included covariates have theoretical and empirical justification for inclusion: each is documented in prior literature as predictive of both impact status and private equity valuation. Therefore, the requirement for correct model specification is satisfied to the highest degree possible given the available data. This strengthens the credibility of the estimated treatment effect and supports the interpretation of the treatment coefficient as the ATET. Resulting estimators represent the willingness to pay for the corresponding observable characteristic of a company. The coefficient for Impact represents the willingness to pay for impact.

3.5. Robustness Checks

To test the robustness of the results and to account for unobserved heterogeneity across time, industries, and firm sizes, I additionally include fixed effects specifications. In line with methodological guidance from Angrist and Pischke (2009, pp. 165-182), I include fixed effects for year, industry, and firm size to control for heterogeneity. These fixed effects absorb systematic differences in valuation trends over time and across sectors, improving the internal validity of the estimated treatment effect.

Further, I rerun the estimation for sample selection to test for robustness of the model specification. For this, I separate firms into environmental and social-focused firms, to capture any inconsistencies in my model specification and to analyse if investors' value of impact changes according to its cause. I also check for differences between emerging and developed markets, domestic and cross-border deals, as well as, re-running the estimation for other valuation multiples. I utilise MSCI's classification of emerging markets[4] (MSCI Inc., 2025).

[4] The full list of countries classified as 'emerging' can be found in the appendix.

While the propensity score matching and doubly robust regressions effectively control for observable confounding, the risk of unobserved bias remains. To address this, I implement Rosenbaum bounds (Rosenbaum, 2002), which estimate how strongly an unobserved covariate would have to influence selection into treatment (i.e., classification as 'impact') to undermine the observed treatment effect.

4. Data

4.1. Treatment Sample: Fund-of-Funds Portfolio Data

For my analysis, I utilise two sources of cross-sectional data. Firstly, a unique and exclusive source of data available from an evergreen structured fund-of-funds investing thematically into impact private equity and venture capital funds. Since 2011 the fund-of-funds has invested in 20 different private equity and venture capital funds. From quarterly fund reports I obtain data on individual target investments including name, date of acquisition, enterprise value at entry, latest fiscal year reported sales, EBITDA, EBIT and Net Income, measures of achieved impact, company description, industry and HQ location. Further, I collect data on the acquirer (the private equity and venture capital funds) regarding the HQ location. Based on an individual assessment of each target investment I exclude companies that do not meet the characteristics of an 'impact' company.

I define key characteristics of impact investing as in line with Kölbel et al. (2020, pp. 555-557), Brest and Born (2013, pp. 23-24) and Global Impact Investing Network (2019):

- Intentionality
- Measurability
- Additionality
- Return expectation

A company must meet all requirements to pass as an 'impact' company. The company must pursue a social/environmental return with intent. This return must be measurable and provide additionality. Beyond this, the company must aim to provide financial returns at or below a market rate.

The return expectation is satisfied by companies being private equity or venture capital backed with these funds ensuring financial return expectations. Intentionality is derived from the mission statements of each company. Measurability is assessed through analysis of impact reports provided by fund managers, which report impact metrics for portfolio companies that manage to achieve these social/environmental returns. Additionality is the most difficult to capture. To assess additionality, I review publicly available information on each company, including mission statements, investor reports, and website content. I look for qualitative indicators that the company or its investors play a causal role in delivering impact, for example, by operating in underserved markets, introducing previously unavailable products, or deploying catalytic capital. Companies lacking evidence of such causal contribution were excluded from the final impact sample.

After screening, I am left with a sample of 160 'impact' companies, excluding 6.9% of the original sample of 171 companies. Examples of exclusion are an organic food manufacturer selling in a saturated market or a software as a service (SaaS) provider that provides communication solutions for teams. While these businesses provide value to customers, they do not achieve a social or environmental outcome that would also not have been possible without their existence.

Based on an individual assessment of each company, I assign each company to a macro-industry and a mid-industry as defined by PitchBook. Further, each company is assigned to contribute mainly to either social or environmental goals based on impact metrics reported by fund managers.

4.2. Control Sample: PitchBook M&A Data

Secondly, I utilise data retrieved from PitchBook on all completed M&A transactions for the same period starting 2011. PitchBook is a widely used commercial database providing detailed data on private capital markets, including venture capital, private equity, and M&A transactions. Variables retrieved on the target include name, location, stock price on announcement day, business description, macro industry, mid-industry and enterprise value at deal date. Variables retrieved on the acquiror include name, location, type (financial sponsor involvement or not), macro industry, mid-industry and a short business description. Further, I gather data on deal valuation multiples including enterprise value (EV) over sales, EV over EBITDA, EV over EBIT and EV over net income.

4.3. Sample Comparability

The question this thesis is trying to answer is, if firms that are classified as 'impact' are valued differently at entry compared to non-impact firms. For the analysis to be credible, the treatment group (impact companies) and control group (non-impact companies) must be comparable in terms of their observable characteristics that influence valuation.

At a first level, the variables being compared must represent the same underlying values. For the valuation measure, PitchBook reports EV at investment with the latest reported fiscal year sales, EBITDA, EBIT or net income. I retrieve the same data from fund managers' reports to construct the valuation multiples.

Further, to achieve comparability, I apply a series of sample restrictions and matching techniques to the PitchBook dataset to align it with the characteristics of the impact firm dataset.

First, I restrict the PitchBook dataset to only those transactions involving financial sponsors (i.e., private equity, venture capital, or growth equity investors). This is necessary because all impact firms in the treatment group are private equity or venture capital-backed and including strategic acquisitions or corporate M&A would introduce structural differences in valuation logic.

Second, I exclude deals where the target company is publicly listed at the time of acquisition unless the transaction involves a financial sponsor (e.g., take-private buyouts). This avoids bias from public-to-public M&A transactions.

Third, I apply a keyword exclusion filter to the company descriptions in the PitchBook dataset to remove deals that are plausibly impact-oriented, based on terms defined as impact-related terms by Agrawal and Hockerts (2021, Appendix A, Table A1) such as "sustainable", "affordable", "inclusive", "renewable", "clean energy" and other impact-related terms[5]. This way, it is possible to exclude the vast majority of potential impact firms from the control dataset. However, it also introduces attrition due to false positives being excluded too.

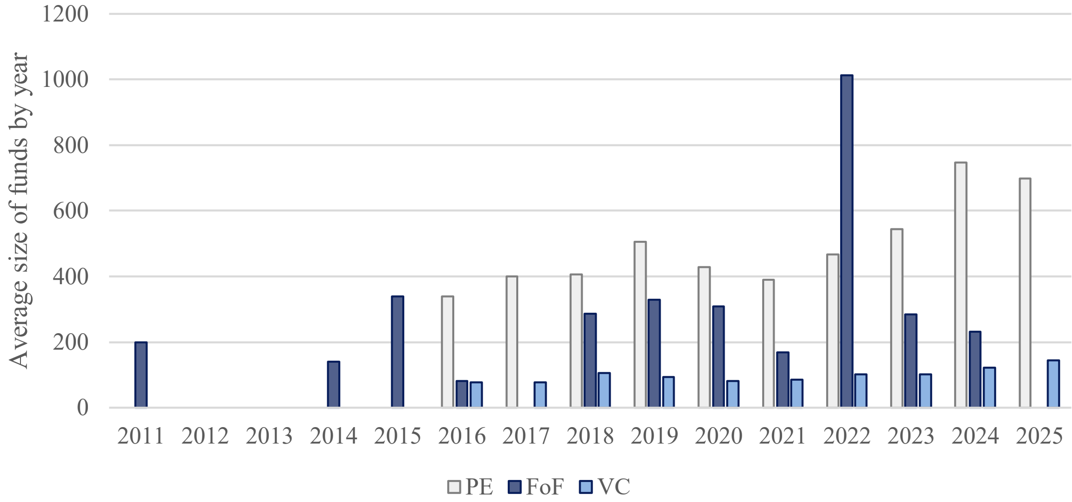
Finally, I exclude deals with the same acquiror in the control group as in the treatment group to ensure that there is no overlap.

4.4. External Validity and Representativeness

To assess the external validity of the impact-focused fund sample used in this study, I benchmark the fund sizes of private equity and venture capital funds backed by the fund-of-funds in my dataset against the broader private capital market.

[5] The full list of impact-related terms used for exclusion of impact-likely deals from PitchBook dataset is listed in the appendix.

Figure 3 – Comparison of Treatment Funds to Benchmark



Source: Own illustration using data from PitchBook and fund-of-funds database.

Figure 3 plots average fund sizes by vintage year for three groups: private equity funds, venture capital funds, and the fund-of-funds' selected portfolio funds representing the control group in my dataset. Benchmark data are retrieved from PitchBook and include all private equity and venture capital funds launched between 2011 and 2025, excluding restructuring funds, which are not present in the treatment sample. The following observations support the credibility of my dataset as representative of the broader private equity/venture capital market.

Firstly, across most vintage years, the funds selected by the fund-of-funds fall between the average sizes of private equity and venture capital funds. While venture capital funds are consistently smaller than private equity funds, the treatment funds track closely to both benchmarks, sometimes aligning more with venture capital, sometimes with private equity. This shows that the fund-of-funds does not systematically invest in outlier funds (e.g., only first-time micro funds or mega-buyout funds), but rather in funds of comparable size to the industry norm.

This supports the claim that observed valuation patterns in the underlying portfolio companies are not simply an artifact of investing in atypically small or large funds, which could otherwise confound the interpretation of an 'impact premium'.

Finally, there is no consistent bias in terms of timing. The fund-of-funds invested regularly across vintages. As the fund-of-funds strives for diversification across vintages, it invested during the full period from 2011 to 2025. The 2022 spike reflects a large fund in that year. Nevertheless, the broader pattern shows steady deployment that mirrors trends in the private equity/venture capital fundraising environment. This helps mitigate concerns that the treatment sample is concentrated in boom or bust years, which could skew entry valuations.

4.5. Data Limitations

Several limitations should be acknowledged that may affect the interpretation of the results.

The impact dataset is drawn from a single fund-of-funds. Since this fund-of-funds follows a unique investment strategy and geographic focus, there is a potential bias due to certain types of funds, geographies, sizes or sectors being over-represented. Hence, the results might deal with generalisability issues, as they do not represent the boarder impact investing landscape.

Further, the individual screening of the treatment dataset for firms to meet the definition of impact investing leaves room for subjectivity, hampering the generalisability of the findings. Although screening follows the definitional consensus of impact investing within the sustainable finance literature and screening was implemented with due care, the existence of a potential selection bias into the treatment group cannot be negated.

The financial data for impact firms is sourced exclusively from fund manager reports, as there is no publicly available or third-party-verified data for these privately held portfolio companies. While these reports are prepared by professional fund managers and typically follow consistent internal standards, they may vary in terms of calculation methodologies.

The PitchBook dataset may suffer from selection bias if deals are more likely to be reported for larger, more visible companies or those backed by well-known sponsors. Smaller or unsuccessful deals may be underrepresented, which could bias valuation multiples. Further, PitchBook partly relies on reporting by fund managers and an unobservable reason for self-selection could bias the sample. The analysis is limited to data availability in PitchBook. Not all deals report EV/Sales multiples and hence, observations without value are excluded inducing a potential selection bias.

Although a keyword-based filter was used to exclude potentially impact-oriented firms from the PitchBook control group, this method is imperfect. Some firms with implicit or unstated impact goals may remain in the sample, which would bias results toward zero by making the control group more similar to the treatment group.

4.6. Variable Transformations and Distribution Normalisation

I apply winsorisation at the 2.5th and 97.5th percentiles due to extreme skewness in the EV/Sales variable and in order to limit the influence of outliers on the regressions. The raw

EV/Sales distribution is heavily right-skewed, with a mean of 509, a standard deviation of over 15,000 and a maximum value exceeding 844,000. The 99th percentile is 1,754, and the kurtosis exceeds 2,700, indicating a highly leptokurtic distribution with extreme outliers. After winsorising, the distribution becomes markedly more stable. The mean drops to 20.76, the standard deviation falls to 64.94, and the maximum value is reduced to 372.88. Skewness and kurtosis are substantially reduced to 4.60 and 23.94, respectively.

These changes confirm that the winsorisation process effectively compresses the extreme right tail while retaining all observations in the sample.

To further normalise the distribution, I take the natural logarithm of EV/Sales after winsorisation. Comparing the log-transformed to the raw EV/Sales raio, the log-transformed variable has improved statistical properties. The maximum value drops from 13.65 to 5.92, skewness is reduced from 2.25 to 1.40, and kurtosis decreases from 10.74 to 4.73[6]. These transformations lead to a more normalised distribution and reduce the influence of outliers on regression results. At the same time, they preserve the structure and economic interpretability of the data.

4.7. Summary Statistics and Sample Overview

Table 1 provides an overview of key variables utilised in the analysis.

The dataset includes 3,677 private equity and venture capital-backed firms, of which 160 (4.4%) are classified as ‘impact’ firms. While the treatment group is smaller, it remains sufficiently sized to support credible econometric analysis. Across both raw and log-transformed measures, impact firms show a significantly higher EV/Sales ratios.

The difference between the treatment and control group on the log_EV/Sales ratio is economically and statistically significant. Log-transformed EV/Sales multiples are on average 0.73 points (107%) higher than for the control group. Despite the higher valuation multiples, firms in the treatment group are smaller in size. The mean enterprise value at entry is €457m for impact firms vs. €880m for control firms. Although this difference is not significant, it suggests that investors expect proportionally greater growth or returns from impact firms.

[6] The distribution of the log_EV/Sales ratio before and after winsorisation can be found in the appendix.

Table 1 - Summary Statistics

		Treatment				Treatment - Control	
	Obs.	Obs.	Mean	Median	SD	Coeff.	p-value
Impact	3,677	160	1	1	0	1	
log_EVSalesRatio	3,677	160	2.36	2.20	1.36	0.73	0.00
EVSalesRatio	3,677	160	32.56	8.01	75.4	12.44	0.02
log_EnterpriseValue	3,677	160	4.59	4.22	1.75	0.21	0.19
EnterpriseValue	3,677	160	457	67	1,053	-423	0.26
EVNetIncRatio	2,065	15	128	41	203	-336	0.84
IND	3,677	160	0.36	0.00	0.48	0.20	0.00
EM	3,677	160	0.09	0.00	0.29	-0.33	0.00
CB	3,677	160	0.41	0.00	0.49	0.05	0.17
Year	3,677	160	2018.8	2019.0	2.55	1.76	0.00

Notes: Unit of observation: company. Data on characteristics of companies analysed in the paper. Treatment refers to those were assigned to represent 'impact' companies. Control represents companies that were not assigned to represent 'impact' companies. Values for log_EVSalesRatio, EVSalesRatio, Enterprise Value and log_EnterpriseValue represent winsorised (2.5%) values.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset.

Table 2 - Treatment and Control Samples: Main Countries

	Treatment		Control	
Rank	Country	Share of Sample	Country	Share of Sample
1	USA	27.50%	South Korea	13.36%
2	France	8.13%	China (Mainland)	12.82%
3	UK	8.13%	India	8.76%
4	Italy	7.50%	Japan	8.64%
5	Canada	6.88%	USA	7.90%
6	Sweden	6.88%	Italy	7.05%
7	Germany	5.63%	France	6.68%
8	India	5.63%	UK	5.86%
9	Switzerland	2.50%	Spain	4.61%
10	Norway	1.88%	Sweden	2.62%

Notes: List of top 10 countries represented in the control and treatment dataset respectively. Treatment refers to those were assigned to represent 'impact' companies. Control represents companies that were not assigned to represent 'impact' companies.

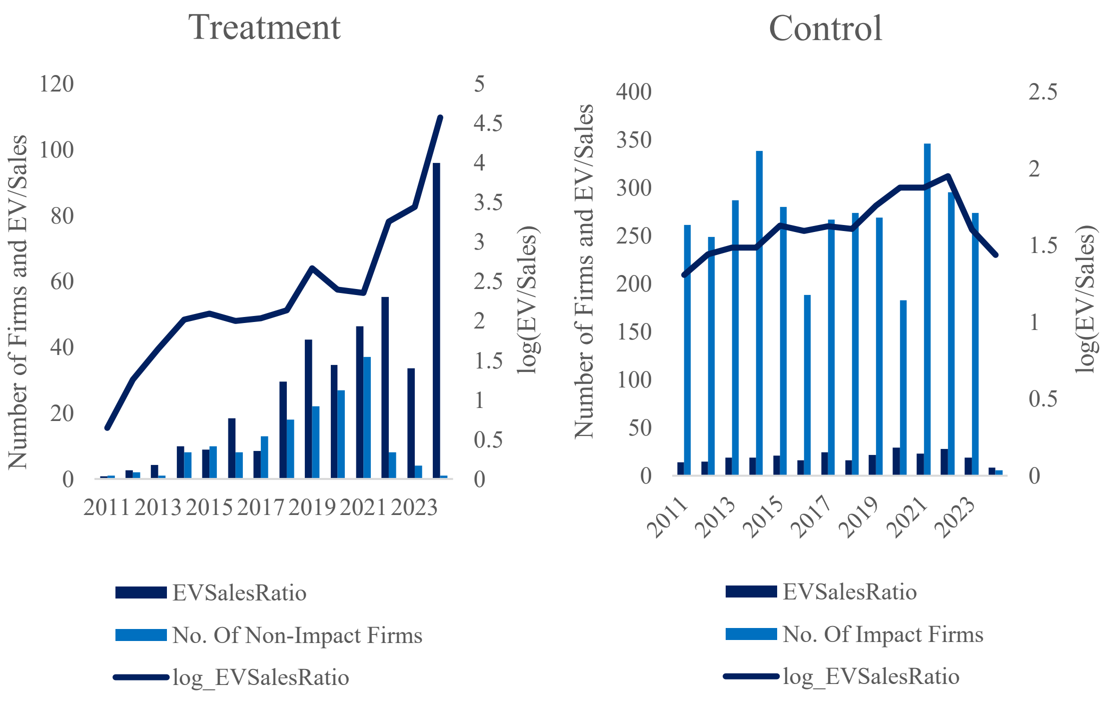
Source: Own illustration using data from PitchBook and fund-of-funds database.

The majority of impact firms are headquartered in developed markets (91%), whereas for the control dataset, only 57% are based in developed markets. Table 2 provides an indication of differences between treatment and control group regarding the location of deals. There is a large difference between the two datasets in terms of geography. While the treatment group is largely concentrated in Europe and North America, the control dataset is tilted towards Asia. This highlights the need for PSM.

Further, Impact firms are slightly more likely to involve cross-border investments (41% vs. 36%), though this difference is not statistically significant. This is in line with expectations of a cross-border deal variable being able to predict impact.

Lastly, Impact investments tend to be more recent. A close look at the distribution of deals across years and corresponding enterprise values and valuations show that the divergence between impact and non-impact firms has become increasingly pronounced over time, particularly since 2017. Figure 4 shows the average log-transformed EV/Sales multiple by year against the raw EV/Sales multipe and the number of deals in that year. Due to the single source of the treatment dataset, there is a large increase in the number of deals, whereas this is more balanced for the control group. There is also a large increase in valuation multiples in time that is not reflected in the control dataset to the same extent.

Figure 4 - Control vs. Treatment Group



Source: Own illustration using data from PitchBook and fund-of-funds database.

This pattern aligns with the broader surge in interest in impact investing post-2015 but may also partially reflect the increasing activity of the fund-of-funds from which the impact sample is drawn. As the fund ramped up its investment program and committed capital to a growing number of underlying funds, deal volume in the treatment group accelerated, potentially introducing a time-related skew in valuation dynamics. While this could reflect an increasing 'impact premium' over time in private markets, this figure shows the importance of controlling for time effects.

4.8. Thematic and Contextual Heterogeneity

The goal of the analysis is not only to identify if investors are willing to pay a premium for impact, but also to dissect this premium into value placed on environmental or social returns. Table 3 shows summary statistics for each subsection of the treatment sample[7].

Table 3 - Treatment Group by Thematic Focus

	Environmental	Social
log_EVSalesRatio	2.338	2.412
EVSalesRatio	33.215	31.460
log_EnterpriseValue	4.446	4.913
EnterpriseValue	405.3	502
IND	0.486	0.082
EM	0.035	0.224
CB	0.423	0.388
Year	2018.747	2018.959
Obs.	111	49

Notes: Reported values represent the mean of each variable separated into two thematic investing focuses that investors might place value on. Number of observations differ for EVNetIncRatio due to a lower level of reporting on Net Income from fund managers and lower data availability on this valuation ratio from PitchBook.

Source: Own calculations using data from a fund of fund's portfolio data.

Firms in the sample differ by sustainability theme. Social targets are the larger companies and there are more deals in emerging markets than for environmental firms. The value placed on these themes seems to be higher for social focused targets, as their log_EVSalesRatios are

[7] A table on summary statistics for sustainability themes including climate can be found in the appendix.

higher than those for environmental focused targets. This could indicate that investors place a higher value on social returns than on environmental returns.

Further analysis of differences across the treatment group in Table 4 shows that firm and deal characteristics vary meaningfully between emerging and developed markets, as well as between domestic and cross-border transactions.

For the treatment sample, impact firms in emerging markets are larger in size than in developed markets. This could be due to investors choosing more mature firms due to the already higher uncertainty in emerging markets. It could also simply be a result of the small sample size of impact firms in emerging markets. The emerging market impact firms also on average have higher EV/Sales multiples. This could mean that investors assign greater value to their potential for scalable impact or their ability to serve underserved populations. Notably, the investments in emerging markets are more recent than those in developed markets. This could be a result of many causes, e.g. potentially reflecting a more recent strategic shift toward emerging market impact or the maturation of such markets as investable opportunities. Further, the higher valuation multiples for emerging market deals could result from a combination of perceived additionality, market expansion potential, and investor optimism around frontier impact themes. However, due to the small sample size, these means are subject to individual high-valuation outliers and values must be interpreted with caution.

The treatment sample, split into sub-samples based on cross-border deals and domestic deals, shows key differences between the deal-characteristics. Companies in cross-border deals are larger than in domestic deals and there is a tilt towards cross-border deals in time. This could mean that cross-border deals involve more mature firms.

For companies in a domestic deal setting, valuations are higher than for cross-border settings. This could suggest a higher value that investors place on firms that are embedded within local contexts. Potentially, this could be due to stronger traction, reduced execution risk or a closer alignment with local policy incentives. Furthermore, impact firms in cross-border deals are less likely to fall under ‘impact focus industries’. This could mean that firms in cross-border deals are more commercially driven. However, since the variable for impact-focused industries is a dummy that includes impact-likely industries, there is potentially a lot of noise. These structural differences reinforce that it is important to control for these effects when trying to isolate the impact premium.

Table 4 - Treatment Group by Deal Characteristics

	Emerging (1)	Developed (2)	Domestic (3)	Cross-border (4)
log_EVSalesRatio	2.785	2.314	2.504	2.151
EVSalesRatio	52.619	30.588	35.971	27.928
log_EnterpriseValue	5.458	4.498	4.419	4.829
EnterpriseValue	705.814	408.416	348.551	561.269
EVNetIncRatio	7.832	146.502	162.550	58.936
IND	0.067	0.393	0.415	0.288
EM	1.000	0.000	0.128	0.045
CB	0.200	0.434	0.000	1.000
Year	2019.867	2018.703	2018.606	2019.106
Obs.	15	145	94	66

Notes: Summary statistics for impact firms, split by geography (emerging vs. developed) and deal structure (domestic vs. cross-border). EV/Sales and Enterprise Value are reported in both raw and log-transformed form. IND, EM and INT are binary indicators for impact-likely industry, emerging market and cross-border deal, respectively. Year refers to the acquisition year. Monetary values are in millions of euros.

Source: Own calculations using data from a fund of fund's portfolio data.

Overall, these sub-samples show that even within the treatment group, impact investing is not a simple homogeneous asset class. Rather, the value that investors place on a firm is shaped by deal-characteristics as well as, the thematic focus (social, environmental). This serves as an important argument for heterogeneity analyses on the impact premium across these dimensions.

5. Results

5.1. Propensity Score Matching

Table 5 reports results from the propensity score estimation using a probit model.

The results show that all included explanatory variables yielded significant statistical power to predict the impact status of a company. Later deals are more likely to be classified as impact, reflecting the difference from more entries into firms by the funds as the fund-of-funds grows resulting in more impact valuations at later dates.

The definition of the impact-likely industries can be seen to have been significant. Firms operating in impact-focused industries are significantly more likely to be labelled as impact.

This is consistent with prior literature that finds impact funds concentrate in sectors such as healthcare, energy, and infrastructure (Barber et al., 2021, p. 12).

As a result of the large tilt towards developed markets in the treatment dataset, a dummy for if a company is based in an emerging market is negative. This result is surprising given evidence from Barber et al. (2021, p. 12) and Kölbel et al. (2020, p. 564), which highlights that impact investors often overweight emerging markets due to higher additionality and catalytic capital potential.

The size of a company has a miniscule effect on whether a firm is classified as impact or not, however, the sign is negative, showing that smaller firms are more likely to be 'impact'.

Table 5 - Propensity Score Estimation (Probit)

	Coefficient
Year	0.078***
	(0.012)
IND	0.527***
	(0.089)
EM	−0.910***
	(0.109)
Size	-0.00007*
	(0.0004)
_cons	−2.183***
Obs.	3,677
Pseudo R2	0.129

Notes: Probit regression estimating the probability that a firm is classified as an impact firm based on pre-treatment characteristics. Variables include year, a dummy for impact-focused industries, emerging market status and Enterprise Value at deal date cantered to 2010. Standard errors are in parentheses. The results inform the propensity score matching procedure used to balance treated and control groups on observable characteristics.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset.

Cross-border deal status is omitted from the propensity score estimation probit model due to a lack of significance and to achieve a better model performance. This is given, when non-significant variables are excluded better model performance when non-significant variables are excluded (Caliendo & Kopeinig, 2008, p. 41).

Overall, the model identifies several statistically significant and theoretically motivated predictors of impact status. These covariates form the basis for the subsequent matching procedure and help strengthen the validity of the causal inference strategy.

I use 1:5 nearest-neighbour propensity score matching with replacement as the baseline specification, as it offers a strong trade-off between covariate balance and statistical power.

Table 6 reports covariate balance diagnostics for the 1:5 nearest-neighbour propensity score matching procedure. Matching using 1:5 achieves a significant reduction in bias. Bias is reduced by over 95% for the EM and Year variables, and by over 84% for IND. After matching, there are no significant differences between the treatment and the control group, as indicated by the p-values. Results are robust to alternative specifications using 1:1 and 1:10 matching ratios, which show similar balance metrics.

Table 6 - 1:5 Matching Success

		Treated Mean	Control Mean	% Bias	% Bias Reduction	p-value
Year	Unmatched	8.813	7.053	54.5	–	0.000
	Matched	8.813	8.866	−1.7	96.9	0.858
IND	Unmatched	0.363	0.159	47.6	–	0.000
	Matched	0.363	0.394	−7.3	84.6	0.566
EM	Unmatched	0.094	0.428	−82.2	–	0.000
	Matched	0.094	0.110	−4.0	95.1	0.632
Size	Unmatched	436.3	582.8	-13.9	–	0.125
	Matched	436.3	482.1	-4.3	68.8	0.660

Notes: Covariate balance diagnostics for 1:5 nearest-neighbour propensity score matching with replacement. The table reports means for treated and control groups before and after matching, standardised bias, percentage bias reduction, and post-matching p-values. Matching substantially reduces bias across all covariates, indicating successful balancing. Negative bias reduction indicates an increase in imbalance.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset.

Among the three matching ratios tested (1:1, 1:5, and 1:10), I choose the 1:5 matching results as a base case due to its optimal trade-off between covariate balance and sample size. Although the 1:1 matching achieves a slightly lower bias between treatment and control groups on some covariates, it also substantially reduces sample size and hence, statistical power. On the other hand, 1:10 matching retains more observations but results in a marginally worse covariate balance[8].

[8] Detailed diagnostics for the 1:1 and 1:10 matchings are reported in the appendix.

Overall, the 1:5 matching procedure offers high-quality covariate balance while preserving a sufficiently large and representative matched sample for robust estimation.

5.2. Main Findings

The central question of this thesis is whether investors in private markets are willing to pay a premium for impact and if so, how large that premium is once observable deal characteristics are accounted for.

Table 7 - Main Findings

	1:1 (1)	1:5 (2)	1:10 (3)
Impact	0.640***	0.689***	0.684***
	(0.165)	(0.126)	(0.120)
IND	-0.095	-0.058	-0.050
	(0.169)	(0.108)	(0.090)
EM	0.082	-0.098	-0.005
	(0.244)	(0.129)	(0.103)
CB	0.190	0.316***	0.357***
	(0.166)	(0.104)	(0.083)
Constant	1.667***	1.569***	1.546***
Obs.	292	699	1,083
R2	0.055	0.058	0.049

Notes: Regression results estimating the impact premium using matched samples with 1:1, 1:5, and 1:10 nearest-neighbour propensity score matching. The dependent variable is the log EV/Sales ratio. All models include the same covariates used in the matching procedure, except for the deal year. Standard errors are robust and reported in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.

Table 7 presents the main regression results using matched samples based on 1:1, 1:5, and 1:10 nearest-neighbour propensity score matching. All three models for each sample include similar covariates to those used in the matching model and are estimated using robust standard errors.

For all three matching methods, the coefficient for the impact dummy is statistically significant at the 1% level. They are also all economically meaningful. For the base case, a firm that is classified as 'impact' has a log_EV/Sales valuation multiple that is 0.689 higher than for non-impact firms, which corresponds to a 99.2% higher valuation based on EV/Sales multiples.

This directly answers the question posed in this thesis. Investors, based on the sample analysed, are willing to pay a higher price for a company because it is an impact firm. The size of this premium is significant, as investors are almost willing to pay twice as much for a firm because it is impact.

Importantly, these results are robust. The estimated premium is similar under alternative matching ratios. This consistency in magnitude and significance reinforces the internal validity of the finding. Given the doubly robust estimation strategy, combining propensity score matching with regression adjustment, the treatment effect is likely to be consistent even if one of the models (treatment or outcome) is mis specified.

The results also show that for the 1:5 and 1:10 samples, cross-border transactions are priced higher. This could be due to larger deal sizes, the ability for global scalability or perhaps due to jurisdictional arbitrage priced into the valuation expectation.

By contrast, neither the EM nor the IND dummy variables are statistically significant in any matching sample. This is not in line with expectations of these variables' significance. Emerging markets are often a key target for impact investors, because firms in emerging markets are able to achieve higher additionality and the capital invested in emerging markets often has catalytic potential (Barber et al., 2021, p. 12; Kölbel et al., 2020, p. 564). The absence of a premium for emerging markets shows that either, the effect is captured by the cross-border characteristic, or that, although there is a large market for impact investors in emering markets, this does not translate into higher valuations. Similarly, the lack of an industry effect implies that investors do not systematically value specific impact-prone sectors (e.g., health, energy, infrastructure) over others once impact status is accounted for. It is the impact attribute itself that investors place value on.

Further, since the value is placed on impact itself, investors do not value impact-likely industry as an attribute and hence, there is no significant valutiaon effect for the impact-likely dummy. These results are in line with the theoretical models of non-pecuniary utility in investment decisions (Pástor et al., 2022, pp. 3-5, 25; Rosen, 1974) where impact is considered a priced characteristic for certain investors.

To test for the validity of these findings, I run Rosenbaum bounds. Results show that the estimated impact premium remains robust up to a Γ (gamma) of 1.4, meaning an unmeasured confounder would need to increase the odds of treatment assignment by at least 40% to render the results statistically insignificant. At $\Gamma = 1.6$, the significance of the treatment effect disappears, indicating moderate sensitivity[9]. This suggests that while the main findings are not immune to hidden bias, they are reasonably robust to small-to-moderate unobservable heterogeneity.

Taken together, these findings provide strong evidence of a sizable, consistent, and statistically significant impact premium in private market valuations, supporting the view that capital markets are increasingly pricing social and environmental value, not just financial fundamentals, into firm valuations.

5.3. Robustness Checks

To assess the robustness of the estimated impact premium, Table 8 introduces fixed effects regressions using the 1:5 matched sample.

The reported models control for unobserved heterogeneity across time (Year), firm enterprise value at deal date (Size), and industry (TargetMacroIndustry). Across all models, the coefficient on the Impact variable remains positive, highly significant, and economically meaningful, ranging from 0.648 to 0.715 log points. The corresponding valuation premium that investors are willing to pay is approximately 91% to 104% for impact firms relative over non-impact firms.

Column 1 shows results when including fixed effects for the deal year, thereby, accounting for macro trends influencing valuations. Column 2-5 show results when including fixed effects for size and industry. This enables isolation of the effect of impact within comparable firm and sector cohorts. For size fixed effects, the sample is split into quintiles according to the firm's enterprise values. When controlling for both firm size and industry, results show the highest valuation premium for impact firms. Hence, the effect does not seem to be explained by systematic differences in firm or sector characteristics.

However, the inclusion of fixed effects is subject to data limitations. Some industry-size or year-sector combinations include sparse observations. More granular models with more combinations of fixed effects are not feasible due to these data limitations. Despite this, the consistency of the impact coefficient across all specifications reinforces the robustness of the main result. Even when accounting for variations in macro trends or comparable firm and sector characteristics, impact firms are valued at a significant premium in private markets relative to non-impact firms.

[9] The full reporting of Rosenbaum bounds can be found in the appendix.

Table 8 - 1:5 with Fixed Effects

	Year	Size	TargetMacroIndustry	Year + Size	BigFirm + TargetMacroIndustry
	(1)	(2)	(3)	(4)	(5)
Impact	0.648***	0.715***	0.697***	0.664***	0.712***
	(0.122)	(0.118)	(0.120)	(0.118)	(0.117)
IND	0.001	0.007	-	0.083	-
	(0.113)	(0.109)	-	(0.111)	-
EM	-0.204	-0.183	-0.081	-0.284*	-0.171
	(0.156)	(0.147)	(0.149)	(0.152)	(0.146)
CB	0.271***	0.176*	0.285***	0.125	0.164
	(0.104)	(0.102)	(0.102)	(0.117)	(0.102)
Constant	1.594***	1.614***	1.561***	1.637***	1.621***
Obs.	699	699	698	699	698
R2	0.088	0.112	0.115	0.144	0.157

Notes: Regression results using the 1:5 matched sample with various fixed effects to control for unobserved heterogeneity across time, firm size, and industry. All models estimate the log EV/Sales ratio. Fixed effects specifications are introduced incrementally across columns. The impact premium remains positive and significant across all models, confirming robustness to time-invariant contextual factors. Standard errors are reported in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.

To further test the robustness of the impact premium, Table 9 presents results using alternative valuation metrics: EV/Net Income, EV/EBITDA, and EV/EBIT. These results are compared to the EV/Sales multiple for the same sub-sample for which there is data available on each of the other valuation multiples.

The coefficient on the Impact dummy is no longer significant for any of the model specifications, regardless of the valuation multiple analysed.

Reported results are based on 1:5 matching. Sample sizes are in parts too small to capture a significant valuation premium. Despite this, these results point to the fact that the impact premium might not be robust to different valuation multiple specifications. This is amplified by the fact that some coefficients for impact are negative and others are positive. There is no clear pattern in the results. Investors perhaps focus more on revenue potential when valuing impact firms, rather than using earnings-based multiples.

Table 9 - Alternative Valuation Multiples

	Net Income Sample		EBIT Sample		EBITDA Sample	
	EV/Sales (1)	EV/ Net Income (2)	EV/Sales (3)	EV / EBIT (4)	EV/Sales (5)	EV/EBITDA (6)
Impact	0.435	0.358	-0.188	0.066	-0.150	-0.077
	(0.285)	(0.428)	(0.165)	(0.341)	(0.149)	(0.244)
IND	0.096	0.353	0.432	1.306	-0.049	-0.274
	(0.221)	(0.394)	(0.414)	(0.829)	(0.130)	(0.191)
EM	0.051	0.069	-	-	0.556	0.282
	(0.259)	(0.376)	-	-	(0.427)	(0.567)
CB	0.291	-0.034	-0.070	-0.287	0.406***	0.251
	(0.263)	(0.317)	(0.200)	(0.344)	(0.116)	(0.179)
Constant	1.094***	3.387***	1.460***	3.340***	1.236***	2.864***
Obs.	90	90	108	108	218	218
R2	0.049	0.019	0.018	0.038	0.067	0.019

Notes: Regression results using alternative valuation multiples, EV/Net Income, EV/EBITDA, and EV/EBIT as dependent variables. All dependent variables are log-transformed. The analysis is based on the 1:5 matched sample. For comparability, results for the regression on EV/Sales are also reported using the sample of data available for the alternative valuation multiples. Robust standard errors are reported in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.

The lack of significance could also be a result of low earnings and net income values in the treatment sample. Not all fund managers report values for earnings metrics. This is mainly due to the face that a lot of firms are early-stage or growth-stage companies that do not yet have positive earnings to report. The results here could merely, be a result of a large variance in reported results.

However, since the results for EV/Sales multiples for the corresponding samples are also not significant, it cannot directly be inferred that the choice of valuation multiple is what is driving the results. Nevertheless, the lack of consistency between top-line valuation multiples and bottom-line metrics opens the door to questions of validity.

5.4. Contextual and Thematic Variation in the Valuation of Impact

5.4.1. Emerging vs. Developed Markets

Deal characteristics are shown to have a significant influence on firm valuations. Table 10 reports results on the impact premium in sub-samples by looking at emerging and developed markets individually. The impact premium is significantly larger in emerging markets than in developed markets. In emerging markets investors are willing to pay a 235% higher valuation for firms if they are classified as 'impact' compared to non-impact firms. For developed markets the premium is not of the same magnitude, however, investors are willing to pay a premium of 79% over non-impact firms.

Table 10 - Emerging vs. Developed

	Emerging (1)	Developed (2)
Impact	1.208***	0.580***
	(0.413)	(0.132)
IND	0.080	0.065
	(0.401)	(0.125)
INT	-0.056	0.247**
	(0.220)	(0.117)
Constant	1.583***	1.601***
Obs.	90	605
R2	0.150	0.039

Notes: Regression results estimating the impact premium separately for firms in emerging and developed markets using the 1:5 matched sample. The dependent variable is log EV/Sales. The impact premium is larger in emerging markets but estimated with less precision due to smaller sample size. Standard errors are robust.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data

These findings are in line with theoretical arguments and expectations based on the additionality that can be provided in emerging markets and the potential for catalytic capital. The role of the investor in emerging markets is greater due to undercapitalised and underserved markets (Brest & Born, 2013, pp. 23-24; Kölbel et al., 2020, p. 564). Further, it supports findings by Barber et al. (2021, p. 34) who find that development finance institutions and European investors have a higher willingness to pay for impact in emerging markets. A higher value placed on impact firms in emerging markets also support the theory of Cole et al. (2024, pp. 1, 24) who argue that a scarcity of capital in emerging markets creates a higher potential for impact and favourable entry valuations.

The lower valuation premium in developed markets could point to the fact that in developed markets there is a more mature impact ecosystem. Investors could have a preference for investing domestically with lower risks associated with this. The results could also simply point to a greater availability of impact capital in developed markets and impact itself being less distinctive due to this.

These results show that the valuation of impact is highly context-dependent. Investors' valuations are not only sensitive to the deal-characteristics but also the potential for impact.

5.4.2. Domestic vs. Cross-Border Deals

The results in Table 11 show the impact premium dissected by sub-samples for cross-border deals and domestic deals.

The impact premium is consistent in statistical and economical significance for domestic deals. Investors in a domestic deal setting are willing to pay 174% more for firms that are classified as 'impact' over non-impact firms. In contrast, in a cross-border deal setting, the impact premium does not persist. Although still positive, the coefficient for the impact premium is far smaller and no longer significant.

Column 3 paints a clearer picture by using an interaction term to capture the effect of firms that are classified as 'impact' in a cross-border setting. The results show that the interaction term is statistically significant and negative, almost fully offsetting the entire main effect of 'impact'. This confirms the finding that the impact premium that can be found in domestic deal settings does not exist in cross-border transactions. Hence, in a cross-border deal setting, in this sample investors are not willing to pay more for an impact firm over a non-impact firm.

These findings are in line with the concept of 'liability of foreignness' (Cumming & Dai, 2010, p. 2; Hammer et al., 2021, pp. 706-709). They state that in international settings, investors face informational disadvantages such as limited access to soft information and reduced negotiation power partially as a result of cultural unfamiliarity. In the context of impact investing in private markets, this 'liability of forgiveness' could translate into greater uncertainty regarding the impact that is promised. Issues might arise regarding the impact's authenticity and additionality.

Such informational disadvantages could explain a lack of investors' willingness to pay for this impact in cross-border settings.

Table 11 - Cross-Border vs. Domestic

	Domestic (1)	International (2)	Impact x Cross-Border (3)
Impact	1.011***	0.286	1.060***
	(0.157)	(0.194)	(0.158)
IND	0.005	0.180	-0.086
	(0.125)	(0.201)	(0.109)
EM	0.070	-0.196	-0.108
	(0.138)	(0.255)	(0.128)
CB			0.518***
			(0.118)
Imapct_x_CB			-0.891***
			(0.249)
Constant	1.483***	1.822***	1.493***
Obs.	428	281	699
R2	0.100	0.013	0.076

Notes: Regression results estimating the impact premium separately for domestic and cross-border deals (columns 1 and 2), and using an interaction term in the full sample (column 3). The dependent variable is log EV/Sales. The impact premium is significant for domestic deals but not for cross-border transactions; the interaction model confirms that the premium does not extend to international settings. Standard errors are robust and reported in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.

Moreover, Hammer et al. (2021, pp. 706-707) show that cross-border buyouts tend to be associated with higher pricing overall, but that foreign acquirers often overpay due to informational asymmetries. This would explain why the general premium for cross-border deals does not translate to impact firms. If foreign investors cannot confidently assess the impact component, they are unlikely to assign it added value.

These results show that investors value impact when the deal takes place in a familiar context, where verification and monitoring is stronger and information asymmetries are reduced. In a cross-border setting the perceived social/environmental return may be offset by the lack of security around its existence. This again shows how context-dependent the value that investors place on impact is.

5.4.3. Impact Premium by Sustainability Theme

Table 12 displays results on how the impact premium differs by thematic impact category.

The results show that investors in this sample value firms that pursue social impact higher than those that pursue environmental impact. Investors value firms pursuing social impact 142% higher than non-impact firms and firms pursuing environmental impact 81% higher.

Table 12 - Impact Themes

	Environmental (1)	Social (2)
Impact	0.592***	0.884***
	(0.149)	(0.224)
IND	0.032	-0.394*
	(0.129)	(0.202)
EM	0.318	-0.042
	(0.246)	(0.161)
CB	0.270**	0.217
	(0.133)	(0.155)
Constant	1.583***	1.540***
Obs.	504	247
R2	0.040	0.089

Notes: Regression results estimating the impact premium separately by thematic focus: environmental and social. The dependent variable is log EV/Sales. All models are based on the 1:5 matched sample. Results indicate significant variation in the size of the impact premium across themes, with the highest premium observed for social impact firms. Standard errors are robust.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.

These findings show that investors do not value all types of impact equally. The preference for social impact firms may reflect investor preferences for business models that directly address human welfare or underserved communities. This could be due to a higher degree of tangibility of outcomes or a higher degree of emotional involvement. The premium for environmental firms is lower than for the entire sample. This relatively modest valuation premium could be due to environmental firms being more fragmented in their goals. Metrics reporting on the success of environmental returns could be less standardised and hence, the perception of the expected outcome more diffuse.

A more granular analysis also looking at climate-themed firms, defined as any firm where the main reported metric targets CO2-emissions, shows that investors place a higher value on climate than on the general environmental firms. This supports the theory of return reporting tangibility as a driver of impact valuation, as CO2 emissions are fairly standardised in terms of their reporting.

This pattern aligns with evidence from bond markets. MacAskill et al. (2021, p. 23) find that green bonds tend to receive stronger pricing benefits than social or sustainability-linked bonds, indicating that investors differentiate by theme even within sustainable finance products. Additionally, the results showing differing values placed on different impact themes are in line with the underlying assumption of a hedonic pricing theory and recent research on impact motivation (Heeb et al., 2022, p. 1739).

Overall, these results show that there is significant heterogeneity in the impact premium. Hence, it is necessary to disaggregate the impact premium. Merely analysing the existence of an impact premium risks obscuring highly insightful variation in investors' preferences.

6. Conclusion

The aim of this thesis is to answer the question: Are investors in private equity and venture capital markets willing to pay a premium for impact, and if so, under what conditions and for which types of impact? I utilise a unique dataset of a fund-of-funds investing thematically in impact funds to provide first direct, valuation-based evidence of investors' willingness to pay for impact in private markets. I employ a hedonic pricing model to capture the value that investors place on impact by comparing impact deals to non-impact deals using propensity score matching and doubly robust regression.

The main finding is that investors do show a willingness to pay for impact and value impact firms significantly higher than non-impact firms. This impact premium ranges from 90 to 99% for companies classified as impact over non-impact companies. Results persist even after controlling for sector, geography, timing and firm characteristics. The impact premium persists over multiple econometric specifications, however, not for different valuation multiples. Results further show that investors value social firms over environmental firms and that the impact premium only hold in domestic deal settings. Overall, the results show that investors vary the value they place on impact by impact theme, deal characteristic and the perceived authenticity of impact.

The findings contribute to several strands of academic literature. First, this thesis fills a gap by empirically measuring investor behaviour in private markets, an area where data access is limited and prior research has largely relied on surveys or public market proxies. Second, it measures and quantifies the willingness to pay for impact. It is the first study measuring a normative preference and translating it into a concrete valuation effect using real-world transactions in private markets. Third, by employing causal inference methods, this thesis is able to show that the observed premium for impact is due to the selection into the impact group and not a result of firm, deal or macro characteristics. Fourth, it offers empirical support to asset pricing models incorporating non-pecuniary investor preferences and extends this logic to private markets. Lastly, the data and methods applied in this thesis serve as a foundation for future research on how sustainability considerations shape investor behaviour in private capital markets.

The broader implications of these findings span several stakeholder groups. For impact investors and fund managers, the study helps benchmark pricing and informs investment strategy. For development finance institutions and foundations, the results can guide subsidy allocation by indicating where commercial capital is already flowing. For mainstream private equity and venture capital firms, the findings offer insights into how impact positioning may affect entry valuations and exit opportunities. Institutional investors can better evaluate the trade-off between financial return and social impact when allocating capital to private impact funds. Policymakers and regulators can interpret the presence of an impact premium as a sign that markets partially internalise social value, but also as a diagnostic to identify where further regulation or standardisation may be needed. Impact measurement providers may take the results as validation that investors respond to credible impact signals. Finally, founders of impact-oriented startups may draw strategic insight from understanding where and how impact translates into higher valuations.

Nonetheless, several limitations apply. While the matching approach controls for observable covariates, unobservable confounding cannot be ruled out entirely. Although Rosenbaum bounds show that results are robust to moderate levels of hidden bias, causal claims should be interpreted with appropriate caution. Furthermore, the classification of firms as 'impact', while grounded in established frameworks, relies on subjective interpretation, particularly in the assessment of additionality. Finally, the impact dataset is derived from a single fund-of-funds investor, potentially limiting the external validity of the findings.

Future research should aim to replicate and extend this analysis using a more diverse set of investors and different valuation contexts. In particular, further work is needed to explore whether investors differentiate based on the scale of impact. Current research on this topic mainly focuses on single aspects of impact that can be measured. Studies should aim at creating frameworks to measure different strands of 'impact'. This would enable investors to more accurately price impact and would form the baseline for studies looking at investors' sensitivity to the scale and scope of impact.

Overall, this thesis shows that impact is not merely a marketing label, nor is it discounted by the market. Instead, it is a measurable and valued firm characteristic. As impact investing continues to mature, the ability to quantify and price impact credibly will become increasingly important for investors, fund managers, entrepreneurs, and regulators. By offering evidence that impact commands a premium in real-world transactions, this study contributes to a more grounded understanding of how social and environmental preferences are being priced in private markets.

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Appendix

Table A1 – Rosenbaum Bounds

Γ (Gamma)	sig+	sig−	t-hat+	t-hat−	95% CI+	95% CI−
1.000	0.115	0.115	−0.291	−0.291	−0.779	0.206
1.100	0.063	0.190	−0.344	−0.215	−0.856	0.302
1.200	0.033	0.280	−0.409	−0.121	−0.936	0.391
1.300	0.017	0.378	−0.495	−0.060	−1.031	0.450
1.400	0.009	0.475	−0.563	−0.011	−1.085	0.497
1.500	0.004	0.568	−0.616	0.030	−1.137	0.567
1.600	0.002	0.651	−0.684	0.093	−1.206	0.663
1.700	0.001	0.723	−0.730	0.142	−1.289	0.713
1.800	0.001	0.784	−0.778	0.202	−1.359	0.745
1.900	0.000	0.834	−0.810	0.255	−1.425	0.781
2.000	0.000	0.874	−0.856	0.302	−1.478	0.816

Notes: This table reports the results of a Rosenbaum bounds sensitivity analysis, which tests how strongly an unobserved confounder would need to influence treatment assignment (i.e., being classified as an impact firm) to nullify the observed treatment effect. Γ represents the assumed level of hidden bias; sig+ and sig− are upper and lower bound p-values; t-hat+ and t-hat− are Hodges–Lehmann bounds; and CI+ / CI− are the corresponding 95% confidence intervals. The results show that the impact premium remains robust up to $\Gamma = 1.4$, indicating moderate sensitivity to unobserved heterogeneity.

Source: Own calculations using matched sample of impact and non-impact firms.

Table A2 – List of 'Impact-Likely' Industries

Target Mid Industry	Corresponding MSCI Industry	MSCI Avg. g
Advertising & Marketing	Professional Services	0.85
Alternative Financial Investments	Diversified Financials	0.73
Asset Management	Asset Mgmt & Custody Banks	0.87
Banks	Banks	0.35
Biotechnology	Biotechnology	0.57
Broadcasting	Media & Entertainment	0.7
Brokerage	Investment Banking & Brokerage	0.39
Credit Institutions	Consumer Finance / Life & Health Insurance	0.84 / 0.76
Healthcare Equipment & Supplies	Health Care Equipment & Supplies	0.84
Healthcare Providers & Services (HMOs)	Health Care Providers & Services	0.83
Hospitals	Health Care Providers & Services	0.83
Insurance (some types)	Life & Health Insurance / Multi-Line	0.76 / 0.40
Internet Software & Services	Interactive Media & Services	0.74
Professional Services	Professional Services	0.85
Publishing	Media & Entertainment	0.7
Telecommunications Equipment	Telecommunications Services	0.84

Notes: The table contains industries as classified by PitchBook and used in the analysis as TargetMidIndustry matched to GICS industries that are expected to have a positive impact based on g-scores, where a positive g-score represents a positive impact on the environment

Source: Target Mid Industry classificaiton from PitchBook, MSCI Industry and Average g-score from Pástor et al. (2022)

Table A3 - Propensity Score Estimation with Firm Size (Probit)

	Coefficient	p-value	95% CI
Date	0.0002	0.000	[0.0002, 0.0003]
	(0.00003)		
IND	0.45	0.000	[0.352, 0.701]
	(0.089)		
EM	−0.836	0.000	[−1.140, −0.706]
	(0.111)		
CB	0.126	0.059	[−0.223, 0.099]
	(0.082)		
_cons	−6.045	0.000	[−7.527, −4.835]
Obs.	3,677		
Pseudo R2	0.128		

Notes: Probit regression estimating the probability that a firm is classified as an impact firm based on pre-treatment characteristics. Variables include deal date (Date), a dummy for impact-focused industries, emerging market status, and whether the deal is cross-border. Standard errors are in parentheses. The results inform the propensity score matching procedure used to balance treated and control groups on observable characteristics.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset.

Table A4 – List of Emerging Market Countries

Emerging Market Countries	
Brazil	Malaysia
Chile	Mexico
China	Peru
Colombia	Philippines
Czech Republic	Poland
Egypt	Qatar
Greece	Saudi Arabia
Hungary	South Africa
India	Taiwan
Indonesia	Thailand
Korea	Turkey
Kuwait	United Arab Emirates

Notes: This table lists the 24 countries currently classified as Emerging Markets by MSCI as of April 2025.

Source: MSCI Emerging Markets Index Factsheet (April 2025)

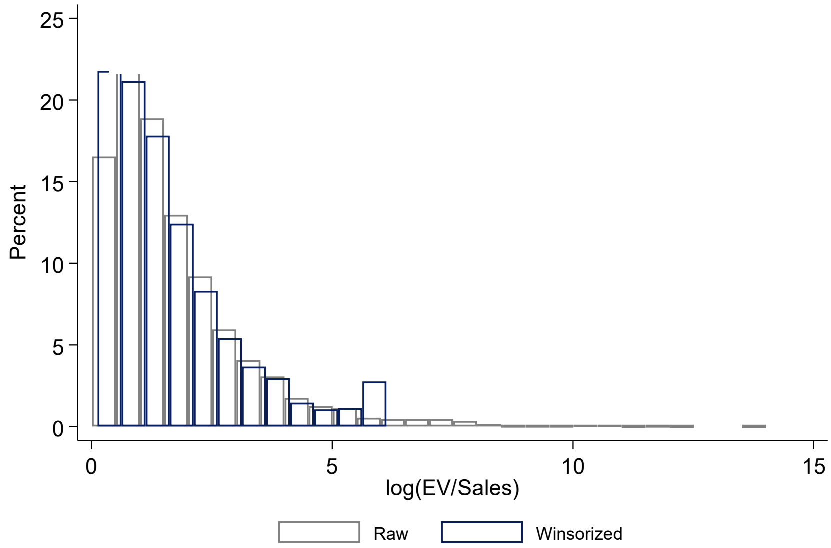
Table A5 – Impact-Related Terms

base of the pyramid	minority-owned
bottom of the pyramid	missing middle
clean air	mission driven
clean water	mission investing
community invest	mission related
disadvantaged	mission-driven
double bottom line	mission-related
dual bottom-line	poverty
environmental impact	S.R.I.
environmental objective	social finance
environmentally clean	social good
environmentally conscious	social impact
environmentally motivated	social objectives
environmentally sustainable	social responsible
ethical invest	socially conscious
ethical objectives	socially motivated
ethically conscious	socially responsible
ethically motivated	socially-motivated
ethically-conscious	SRI
ethically-motivated	sustainable agriculture
green energy	sustainable development
green focused	sustainable economic development
greenhouse	sustainable farming
impact investing	sustainable forestry
impoverished	sustainable investment
indigenous	sustainable property
invest ethical	sustainable water
investing ethical	tribe
low carbon	triple bottom line
low-carbon	triple bottom-line
lower-carbon	women owned
minority community	women-owned

Notes: The table reports impact-related terms used for exclusion of deals in the control sample.

Source: Agrawal and Hockerts (2021, Appendix A, Table A1).

Figure A1 – Raw vs. Winsorised Dataset



Source: Own illustration using data from PitchBook and fund-of-funds database.

Table A6 - Treatment Group by Thematic Focus

	Environmental (1)	Climate (2)	Social (3)
log_EVSalesRatio	2.255	2.453	2.412
EVSalesRatio	32.072	34.806	31.460
log_EnterpriseValue	4.464	4.417	4.913
EnterpriseValue	472	312	502
IND	0.500	0.467	0.082
EM	0.044	0.022	0.224
CB	0.424	0.422	0.388
Year	2018.879	2018.556	2018.959
Obs.	66	45	49

Notes: Reported values represent the mean of each variable separated into three thematic investing focuses that investors might place value on. Number of observations differ for EVNetIncRatio due to a lower level of reporting on Net Income from fund managers and lower data availability on this valuation ratio from PitchBook.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using data from a fund of fund's portfolio data.

Table A6 – 1:1 Matching Success

		Treated Mean	Control Mean	% Bias	% Bias Reduction	p-value
Year	Unmatched	8.813	7.053	54.5	–	0.000
	Matched	8.813	8.981	-5.2	90.4	0.577
IND	Unmatched	0.363	0.159	47.6	–	0.000
	Matched	0.363	0.406	-10.2	78.5	0.423
EM	Unmatched	0.094	0.428	-82.2	–	0.000
	Matched	0.094	0.113	−4.6	94.4	0.583
Size	Unmatched	436.3	582.8	-13.9	–	0.125
	Matched	436.3	485.4	-4.6	66.5	0.626

Notes: Covariate balance diagnostics for 1:1 nearest-neighbour propensity score matching with replacement. The table reports means for treated and control groups before and after matching, standardised bias, percentage bias reduction, and post-matching p-values. Matching substantially reduces bias across all covariates, indicating successful balancing. Negative bias reduction indicates an increase in imbalance.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset

Table A7 – 1:10 Matching Success

		Treated Mean	Control Mean	% Bias	% Bias Reduction	p-value
Year	Unmatched	8.813	7.053	54.5	–	0.000
	Matched	8.813	8.823	-0.3	99.4	0.974
IND	Unmatched	0.363	0.159	47.6	–	0.000
	Matched	0.363	0.397	-8.0	83.1	0.528
EM	Unmatched	0.094	0.428	-82.2	–	0.000
	Matched	0.094	0.117	−5.7	93.1	0.502
Size	Unmatched	436.3	582.8	-13.9	–	0.125
	Matched	436.3	478.1	-4	71.4	0.683

Notes: Covariate balance diagnostics for 1:10 nearest-neighbour propensity score matching with replacement. The table reports means for treated and control groups before and after matching, standardised bias, percentage bias reduction, and post-matching p-values. Matching substantially reduces bias across all covariates, indicating successful balancing. Negative bias reduction indicates an increase in imbalance.

Source: Own calculations using data from PitchBook deals and separate fund-of-funds dataset

Table A8 - Impact Themes with Climate

	Environmental (1)	Climate (2)	Social (3)
Impact	0.363*	0.557**	0.809***
	(0.202)	(0.223)	(0.206)
IND	0.153	0.029	0.122
	(0.161)	(0.189)	(0.197)
EM	0.229	-0.251	0.021
	(0.320)	(0.613)	(0.226)
CB	0.610***	0.407**	0.406**
	(0.168)	(0.203)	(0.166)
Constant	-3.591**	-6.213***	-2.743*
Obs.	316	226	252
R2	0.095	0.116	0.111

Notes: Regression results estimating the impact premium separately by thematic focus: environmental, climate, and social. The dependent variable is log EV/Sales. All models are based on the 1:5 matched sample. Results indicate significant variation in the size of the impact premium across themes, with the highest premium observed for social impact firms. Standard errors are robust.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Own calculations using PitchBook and fund-of-funds portfolio data.