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Private Equity as a Sustainable Investment Vehicle? – Three Essays along the PE Fund Structure

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Summary

This dissertation examines three research questions on the potential of private equity as a vehicle to finance sustainable impact. First, I[1] study the Chief Investment Officer's (CIO) role within the institutional investor organization. I find that university endowments led by a CIO with investor experience in the past invest higher shares of their asset allocation towards alternative investments and exhibit higher returns. CIOs with higher educational qualification or professional investment experience are less likely to be replaced by their investor organization and CIOs that were investors in prior roles are more likely to be a replacing CIO. These results show that the individual CIO profile and his or her individual orientation is relevant for investment decisions made by institutional investors. Second, I conduct a conjoint study to assess the investment preferences of LPs during the private equity fund selection process. After deriving conventional and sustainability-driven investment criteria through literature and expert interviews, I assess the investment decisions of different private equity investors. I find that sustainable investment criteria like a CO2 reduction target on the fund portfolio, the existence of a sustainability expert in the fund team, EU SFDR article compliance or a sustainability-related carry are relevant for the investment decision. There are differences in relative importance and gained utility across different investor groups. Finally, I examine the impact of private equity deals on the green innovation potential of their portfolio companies. I study the green patenting activity before and after the private equity deal by constructing a deal window with deal data and patent portfolios of the involved companies. I find an increase in green patent activity post the private equity transaction. Upon detailed analysis for the drivers of the effect, I find that the effect is mostly driven by deals that involve companies that generally exhibit high patent activity. Additionally, I find no correlation of deals conducted by private equity funds with an higher ESG orientation and their target company's green patenting activity. My results provide initial evidence that some characteristics of the private equity fund model and its governance are suitable to finance part of the ambition of the Paris Agreement.

[1] In this dissertation, I use the tem "I" in the introduction and conclusion. It does not necessarily always refer to me directly since the essays are partially based on joint work with my co-authors.

Zusammenfassung

Diese Dissertation untersucht drei Forschungsfragen zum Potential von Private Equity als Finanzierungsinstrument für die nachhaltige Transformation. Zuerst untersuche ich die Rolle des Chief Investment Officers (CIO) innerhalb der Organisation von institutionellen Investoren. Ich zeige auf, dass Universitätsstiftungen, die von CIOs mit früherer Investorenerfahrung geleitet werden, einen höheren Anteil ihrer Vermögensallokation in alternative Investments investieren und höhere Renditen erzielen. CIOs mit höherer Bildungsqualifikation oder beruflicher Investmenterfahrung werden seltener von ihrer Investorenorganisation ersetzt, und CIOs, die in früheren Positionen Investoren waren, werden wahrscheinlicher als ablösender CIO eingestellt. Diese Ergebnisse stellen heraus, dass das individuelle CIO-Profil und seine individuellen Präferenzen für Investitionsentscheidungen institutioneller Investoren relevant sind. Als zweites führe ich eine Conjoint-Studie durch, um die Investitionspräferenzen von Limited Partners (LPs) während des Auswahlprozesses von Private-Equity-Fonds zu bewerten. Nach Ableitung konventioneller und nachhaltigkeitsgetriebener Investitionskriterien durch bestehende Literatur und Experteninterviews untersuche ich die Investitionsentscheidungen verschiedener Private-Equity-Investoren. Ich komme zu dem Ergebnis, dass nachhaltige Investitionskriterien wie ein CO2-Reduktionsziel auf das Fondsportfolio, die Existenz eines Nachhaltigkeitsexperten im Fonds-Team, die Einhaltung von EU SFDR-Artikeln oder eine nachhaltigkeitsbezogene Gewinnbeteiligung für die Investitionsentscheidung relevant sind. Es gibt darüber hinaus Unterschiede in der relativen Wichtigkeit und dem erzielten Nutzen zwischen verschiedenen Investorengruppen. Abschließend untersuche ich den Einfluss von Private-Equity-Transaktionen auf die grüne Innovationsfähigkeit ihrer Portfolio-Unternehmen. Ich analysiere die grüne Patentaktivität vor und nach der Private-Equity-Transaktion, indem ich ein Transaktionsfenster mit Transaktionsdaten und Patentportfolios der beteiligten Unternehmen erstelle. Ich finde eine Zunahme der grünen Patentaktivität nach dem Private-Equity-Einstieg. Bei einer detaillierten Betrachtung der Treiber dieses Effekts komme ich zu dem Ergebnis, dass der Effekt hauptsächlich von Transaktionen getrieben wird, die Unternehmen involvieren, die im Allgemeinen eine hohe Patentaktivität aufweisen. Darüber hinaus finde ich keine Korrelation zwischen Transaktionen, die von Private-Equity-Fonds mit vermeintlicher ESG-Orientierung durchgeführt werden und der grünen Patentaktivität ihrer Zielunternehmen. Meine Ergebnisse liefern erste Nachweise, dass einige Charakteristika des Private-Equity-Fondmodells und seiner Governance-Mechanismen geeignet sind, einen Teil der Ambitionen des Pariser Abkommens zu finanzieren.

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1 Introduction

The academic conversation on sustainable investing, impact investing, socially responsible investment (SRI) or environmental, social and governance (ESG) investing has been growing since decades (Renneboog et al. 2008, 2011; Shepherd and Patzelt 2011; Eccles et al. 2014; Edmans 2023). The debate of the public on its purpose, mechanics and impact is rising since the Paris Agreement. Private capital has recognized the dramatically yet potentially financially promising situation, that sustainable investments are needed. As of March 31, 2023, there are 4841 investors managing $121 trillion[2] that have signed the Principles for Responsible Investment (PRI) supported by the United Nations (UN). Larry Fink, the CEO of BlackRock overseeing $8.6 trillion in asset under management (AUM), predicts a transformation of every company and every industry by the transition to a net zero world (BlackRock 2022). Undoubtful, there are substantial investments needed to reach the transition to a net zero world. According to *The Economist*, the clean energy investments must have tripled by 2023 to reach $4 trillion each year (Economist Impact 2021). While this number seems unimaginable large[3], the total net private wealth fell to $454 trillion last year (UBS 2023). On an optimistic note, the need for sustainable investment is "only" 1% of total net private wealth. But how can this transition be financed? What financing vehicles are suitable?

Jensen introduced a novel form of business organization in his paper "Eclipse of the Public Corporation" in 1989 (Jensen 1989, revised 1997). These new organizations resolve central weaknesses of large public corporation. They resolve the conflict between owners and managers over the control and use of corporate resources. The hypothesis is, that this novel

[2] AUM calculations are based on reporting data by UN PRI, the most recent data available stems from a publication in 2021, likely it is even more today

[3] The numerical value is equivalent to the cost of approximately ~32 million new Porsche 911 vehicles, hypothetically parked behind each other, encircle the Earth's equator 3.7 times

form of organization achieves vast improvements in operating efficiency, employee productivity, and shareholder value (Jensen 1989, revised 1997). This form of organization has been introduced by Jensen as an leveraged buyout (LBO) Association, has evolved over time and is today rather referred to as Private Equity firm or short Private Equity (PE) (Kaplan and Strömberg 2009). Some evidence suggest that PE could be a driver of innovation (Lerner et al. 2011), that private equity activity creates economic value on average or – in contrast – that they take advantage of tax breaks and private (superior) information while not creating operational value (Kaplan and Strömberg 2009).

In this dissertation, I examine three research questions related to the operationalization of private equity as a vehicle to contribute to the net zero transition aiming to elaborate on characteristics that could help to innovate the business model. The first study is related to the Chief Investment Officer's background, how it impacts the investment behavior and its tenure within the investment firm. The second study shifts the focus from the limited partner's (LP) perspective towards the private equity firm. I conducted a conjoint study to investigate the LP's investment preferences when investing into Private Equity funds. Precisely, I am investigating the preferences of LPs towards sustainability characteristics of PE funds. Finally, the third study analyzes the impact of PE deals on the green patenting behavior as a proxy for sustainable impact and sustainable innovation.

1.1 Theoretical background and previous evidence on sustainable investing

1.1.1 A short history of sustainable investing

The public perception of sustainable investment activities really developed with the Paris Agreement. But already prior to the Paris Agreement, there have been initial efforts in sustainable investing. The PRI was originally initiated in early 2005 by UN Secretary-General

Kofi Annan. He invited a group of 20 person from the world's largest institutional investors and a 70-person group of experts from the investment industry, intergovernmental organizations and the civil society to establish a process to develop the Principles for Responsible Investment (UN PRI 2022). Muhammad Yunus was recognized in 2006 with the 2006 Nobel Peace Prize for founding the Grameen Bank and its pioneering work of microcredit and microfinance (NobelPrize.org 2006). In the same year, the PRI was founded by 63 investors overseeing $6.5 trillion. It serves as a proponent of responsible investment to understand the implications of ESG factors and to support the global network of investor signatories to incorporate those factors into their investment and ownership decisions. It has now grown to a total of 4841 investors managing $121 trillion in assets (in 2021).

As mentioned above, a major shift in sustainable investing happened in line with The Paris Agreement. The Paris Agreement was adopted by 196 parties at the UN Climate Change Conference (COP21) in Paris in December 2015. The ambition is to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels" and pursue efforts "to limit the temperature increase to 1.5°C above pre-industrial levels" (United Nations 2015). Economic and social transformation is needed for the implementation of the Paris Agreement. It follows a five-year cycle of increasingly ambition climate actions, that are carried out by the participating countries. Countries have been submitting their individual national climate action plans since 2020 (UNFCCC 2015). How these ambitions are being implemented over time can be observed with the European Commission (EC). With approving the Paris Agreement and the Sustainable Development Goals (SDGs), the EC has initiated frameworks for a more sustainable financial market. An expert group has prepared a draft that was then published as the "Action Plan: Financing Sustainable Growth" (European Commission 2018). The PRI held an observing role in this effort. The main objective of this action plan is to "reorient capital flows towards sustainable investment in order to achieve sustainable and inclusive growth;

manage financial risks stemming from climate change, resource depletion, environmental degradation and social issues; and foster transparency and long-termism in financial and economic activity" (European Commission 2018). The Action Plan is designed to finance the European Green Deal and derived ten actions, that were later cast into European laws. Those actions with direct impact on the PE industry (but also wider financial industry) are the Sustainable Finance Disclosure Regulation (SFDR), the Taxonomy Regulation (TR) and the amendment of the Benchmarking Regulation. Further obligations for numerous companies as part of the aforementioned European Green Deal will be entailed by the upcoming adaption of the non-financial reporting directive: the Corporate Sustainability Reporting Directive (CSRD) (European Commission 4/21/2021, 6/18/2020, 11/27/2019). Governments have initiated efforts like the European Green Deal (European Commission 2019) and the Inflation Reduction Act (IRA) in the United States (The White House 2023). Both efforts aim to mobilize public as well as private capital to tackle climate-related challenges through financial incentives, regulation policies or reporting standards. Regulatory bodies are establishing such taxonomies for corporate activities to be labeled "sustainable" and ranking funds based on their integration of ESG incorporation (Edmans 2023). This is accompanied by a heated debate in renowned newspapers about whether sustainable investing can fulfill its promise to make a positive contribution on the environment and society (Power 2021; Rushe 2021). Nonetheless, private capital sees great potential in sustainable businesses. Latest since the CEO of BlackRock (being the largest asset manager in the world) famously stated in his 2022 letter to CEOs, that "the next 1000 unicorns won't be search engines or social media companies, they'll be sustainable, scalable innovators – startups that help the world decarbonize and make the energy transition affordable for all consumers" (BlackRock 2022). A key way for researches to contribute to the debate on the effectiveness of sustainable investing is by clarifying the mechanisms of how it creates impact (PRI 2022; Marti et al. 2023). I aim to contribute to this debate with this dissertation from a PE perspective. Therefore, I start by elaborating on the empirical evidence on sustainable investing in general as a basis for amy studies in the later part of this dissertation.

1.1.2 Empirical evidence on sustainable investing

There are numerous studies on sustainable investing. In this section I am focusing on and providing an overview of the mechanisms to create impact, the incentive to pursue sustainable investing stemming from financial return or willingness-to-pay and the assessment of such impact.

There are three strategies to create impact: 1) capital allocation, 2) shareholder engagement, and 3) field building (Kölbel et al. 2020; Marti et al. 2023). Capital allocation or portfolio screening can create direct impact on companies by subsidizing sustainable companies and incentivizing non-sustainable companies. Portfolio screening can also create indirect impact via other shareholders or indirect impact via the institutional context. By mobilizing enough capital, shareholders could maintain a high share price for a company, creating an anomaly violating widely shared expectations, that leads other shareholders to reconsider their investment practice. Similarly, the mere existence of green investing in a region could transform the institutional context in which companies operate and challenge their often unfavorable assumptions of ESG practices (Marti et al. 2023; Pástor et al. 2021).

Shareholder engagement can produce impact directly and indirectly as well. Shareholders become relevant for companies when they directly provide support in a company's operations through operational characteristics or their networks with other stakeholders and industries. They are able to influence companies when they address issues with a strong business case or of societal importance. Shareholders can indirectly shape other shareholders' perceived risk of companies by raising and addressing environmental and social concerns within a company. But shareholders could also engage with a company addressing such environmental and social concerns to exert pressure on peer companies to reconsider the norms of the industry in which they operate (Marti et al. 2023; Dimson et al. 2015; Kölbel et al. 2020).

Field building refers to shareholder impact mechanisms that include shifting other shareholders' evaluation of issues like stigmatization or demonstration, sharing expertise with other stakeholders, endorsement, benchmarking, establishing voluntarily standards and supporting regulatory changes (Kölbel et al. 2020; Marti et al. 2023). While there is anecdotal evidence on field building, most of its impact is unproven due to a lack of empirical studies indicating their effectiveness (Kölbel et al. 2020; Marti et al. 2023). The effect of shareholder engagement and capital allocation has been demonstrated empirically. Broccardo et al. and Berk and van Binsbergen have both evaluated the mechanisms of shareholder engagement and exit. By modeling a world where companies generate externalities and agents care about the impact of their decisions, Broccardo et al. show that shareholder engagement achieves the socially optimal outcome if the majority of investors are even slightly socially responsible. Conversely, the strategy of exit does not - unless all investors are significantly socially responsible (Broccardo et al. 2022). In a quantitative study, Berk and van Binsbergen find no detectable effect on the cost of capital when firms are included or excluded in an ESG index that would affect real investment decisions. They conclude "to have impact, instead of divesting, socially conscious investors should invest and exercise their rights of control to change corporate policy" (Berk and van Binsbergen 2022). This logic is economically strengthened by the empirical study of Hartzmark and Shue. Directing capital from brown firms to green firms may even be counterproductive. In line with basic corporate finance theory brown firms might face a choice between dark-brown investment projects (e.g., maintaining or expanding environmentally harmful operations) and light-brown investments (e.g., transitioning toward cleaner, sustainable practices). The shift to light-brown investments typically requires the departure from existing production methods. This likely involves investment in new capital with higher initial costs and delivers cash flows skewed towards later periods compared to the dark brown project. Short term cash flows are more attractive relative to long-run cash flows due to financial distress or an increase in the cost of capital. Hence, the increase in the cost of capital causes the dark-brown project to be perceived more attractive. This leads to a negative impact elasticity of brown firms. Green firms are likely operating in a business segment in which the firm cannot generate substantial environmental externalities regardless of their choice in investment projects (e.g., service providers with pure office operations). As such, green firms have an impact elasticity close to zero (Hartzmark and Shue 2023). While aforementioned studies argue that engagement is the optimal solution and are claiming that exit is not ideal, there are some studies providing a mechnism how portfolio allocation can work. They suggest the vigorous capital allocation of sustainable investors could indeed lead to impact. Sustainability preferences of investors can influence asset prices, as preference-neutral investors require a premium for balancing out the portfolio choices of investors sharing nonfinancial preferences (e.g., sustainability preferences) (Fama and French 2007; HEINKEL et al. 2001; Kölbel et al. 2020). If the decrease in the stock price of firms that do not adhere to the required sustainability preferences of the sustainable invest is significant, these companies will initiate efforts demanded by such sustainable investors. Managerial incentives are tied to the stock market value and therefore managers are sensitive to such shifts in the share price (Edmans et al. 2012; HEINKEL et al. 2001). Or sustainable investors can tie their capital allocation to concessionary terms. By essentially subsidizing and promoting sustainable companies, private capital can provide better financing conditions than what theses companies would obtain from preference-neutral investors (Chowdhry et al. 2019; Kölbel et al. 2020).

Academic research shows that investors have several mechanisms to create impact for society through companies, but as Milton Friedman stated in 1970: “the social responsibility of business is to increase profits” (Friedman 1970). This theory must and is certainly be considered in a much more nuanced way today, but the underlying idea that companies should deliver returns to their investors remains fundamental. Eccles et al. provide evidence that financial return and sustainability orientation high sustainability companies indeed are positively interconnected. High sustainability companies significantly outperform their counterparts in the long run with regards to stock market performance as well as accounting performance (Eccles et al. 2014). This theory is reflected in the perception of investors themselves. Surveyed investors believe climate risks have financial implications for their portfolio firms. They, but in particular ESG-oriented ones, consider risk management and engagement to be the preferred approach over divestment to address climate risks and that first climate risks have already materialized (Krueger et al. 2020). In a natural experiment of an induced shock by the (first) publishing of a sustainability rating of a leading financial research website, causal evidence suggest the same. Mutual fund investors collectively view sustainability as positive predicting future performance given that their market wide demand for funds varied as function of their sustainability ratings (Hartzmark and Sussman 2019). And empirical models provide causal evidence alike. Firms, that choose to become greener realized higher market value given that agents with strong ESG preferences (they gain utility not only from expected returns), balancing their portfolios towards green assets. At the same time, investment shifts from brown to green firms are resulting because the cost of capital goes up for brown and down for green firms (Pástor et al. 2021). However, stocks of firms with emissions earn higher returns indicating, that investors demand compensation for their exposure to carbon risk emissions (Bolton and Kacperczyk 2021).

There might be a disparity between actual and expected return. Carbon emissions could be considered as a systematic risk factor if regulations come into force and disrupt the business or industry. Financial markets could price carbon risk inefficiently and hence, the risk associated with carbon emissions is underprice. Or stocks of firms with high emissions are considered “sin stocks", being avoided and refused by ESG investors in a way that they exhibit higher stock returns (Bolton and Kacperczyk 2021). The model from Pastor at al. suggests that green assets do have lower expected returns than brown assets due to two reasons: investors gain utility through their green taste, and greener assets are a hedge against climate risks. The same authors conclude in a second study that green assets can have higher realized returns whenever agents' demands shift unanticipated into the green direction (Pástor et al. 2022): investor's demand for green assets increases and thereby rising the green asset prices or consumers' demand for green products can grow due to e.g., green regulations which in turn drives up green firms' profits and thereby their stock prices. Vice versa, investors' demand for brown assets or consumers' preference for green products alike can decrease, enhancing the performance of green stocks (Pástor et al. 2022). In recent years green assets in fact delivered high returns reflected in unexpectedly strong increases in environmental regulations and societal concerns. The outperformance is likely driven by unanticipated increase in environmental concerns as green stocks tend to outperform brown stocks whenever there is bad news about climate, because they tend to be more efficient with their input factors, and because of their superior corporate governance (Pástor et al. 2022; In et al. 2018; Garvey et al. 2018).

One of the previously mentioned assumptions is that investors are willing to pay for being green characteristics and may be willing to sacrifice returns by investors. Barber et al. do find such willingness-to-pay. They show that investors gain non-financial utility and sacrifice returns when investing into green funds (Barber et al. 2021). In an experimental setup with experienced private investors and high-net-worth impact investors, Heeb et al. confirm this finding showing a substantial willingness-to-pay for sustainable investments. Investors and impact investors alike are willing to pay for sustainable investment but are not paying significantly more for more impact, their willingness-to-pay is sensitive to relative but not absolute levels of impact (Heeb et al. 2023). Problematic could be a potential for green washing issues, indicated by a study on hedge funds. Hedge funds that endorse the PRI attract greater investor flows, accumulate more assets under management and harvest greater fee revenues, while at the same time underperforming (risk adjusted). This research indicates that certain hedge funds may embrace responsible investment practices solely to embrace investor preferences (Liang et al. 2022).

To address greenwashing challenges and to assess - absolute or relative - impact, purpose, or ESG performance reliable measures are needed. Numerous rating agencies provide ratings, but their ratings differ significantly. In their "Aggregate Confusion" paper, Berg et. al. show the rating divergence and attribute their difference to deviations in scope, measurement, and weight (Berg et al. 2022). In addition to efforts from private companies, there are academic efforts (Barby et al. 2021), public efforts (The Economist 2022) and regulatory efforts (European Commission 2019) alike, contributing to constructive conversation. An important effort towards standardization could be driven through the SFDR by the European Union.

1.1.3 Private equity as a suitable transformation vehicle?

One motivation for this dissertation is, that private equity could serve a suitable vehicle to support the transition towards net zero. Private equity does have specific characteristics, that could prove valuable given that investors pursue such investment strategies discussed in the previous section.

Financial, Governance, and Operational Engineering

Private equity firms solve one of the weakness of large public corporations: the conflict between the owners and managers over control and use of corporate resources and their free cash flow. Their operating model has developed around highly leveraged financial structures, performance-based compensation systems, considerable equity ownership by management and directors and creditors limiting cross-subsidizing of business units within the firm and the waste of their free cash flow (Jensen 1989, revised 1997). Private equity firms heavily incentivize the management in their portfolio companies to align the target system and solve such inefficiencies of large public corporations. They typically give the management stock options and ensure commitment by demanding meaningful investment by the management in the company. The illiquidity due to the private status of the company further reduces management incentive for short term performance manipulation (Jensen 1989, revised 1997; Kaplan 1989; Kaplan and Strömberg 2009). Private equity investors ensure active involvement into their portfolio companies. They control the boards, are more actively involved and ensure smaller boards than those of comparable public companies. Their operating partners are specialized in a particular industry and often help the portfolio companies (Cornelli and Karakas 2008; Kaplan and Strömberg 2009; Jenkinson et al. 2021). Today, private equity firms are actively pursuing operational value creation, that can be attributed to the excellence and incentives of the operating management and the industry and operating expertise of the private equity firm (Puche et al. 2015; Kaplan and Strömberg 2009). Their approach on changing financial, governance and operational mechanisms offers promising possibilities to facilitate impact ambitions, if desired.

Operating Performance

This operating expertise contributes to the operating performance. PE funds leverage industrial experts with operational experience during the due diligence process of a potential transaction, deploy them in on-going leadership roles and utilize their expertise in improvement projects of the portfolio company. PE funds typically refocus the operations of the portfolio company through e.g., identifying and selling non-core assets, increasing the focus on and investing in the highest margin and growth parts of the business. They also strive to improve their operational efficiencies through increased out-sourcing, re-negotiating supplier contracts, closing less efficient plants or similar (Jenkinson et al. 2021). Larger ownership by the management themselves and the monitoring and controlling functions of the PE funds in combination with the discipline of debt is leading to such better run firms and improves the operational performance (Metrick and Yasuda 2011). The empirical evidence of various studies on the operating performance of companies after a private equity deal is largely positive. The empirical evidence generally shows that private equity investment enhances entrepreneurship, innovative activity, and operating efficiency of the respective portfolio company (Cumming and Johan 2014; Lichtenberg and Siegel 1990; Lerner et al. 2011). Several different measures have been analyzed in the past and lead to similar conclusions. The results show an increase in the ratio of operating income to sales, an increase in the ratio of cash flow to sales, and a decrease in the ratio of capital expenditures to sales (Kaplan 1989; Smith 1990; Lichtenberg and Siegel 1990). While the empirical evidence consistently suggests operating improvements, it should be carefully interpreted as it might be subject to biases. Studies could potentially suffer from selection bias since performance data for private firms is hardly accessible (Kaplan and Strömberg 2009). But the interpretation and empirical tendency of this positive track-record in improving portfolio companies operationally indicates, that PE funds are capable of creating an operational impact, if desired.

Field Building

Private equity and venture capital (VC, as a particular type of PE) business models can work well in newly emerging markets supporting substantial growth and large scale. Their business model evolves around identifying strong business ideas in markets with great growth potential and enable portfolio companies to achieve growth for attractive financial returns (Metrick and Yasuda 2011; Kaplan et al. 2009). Several studies document this economic role of PEs and VCs in the innovation environment. PE and VC funding within a particular industry is positively associated with higher patenting rates and patents of PE-backed companies are generally more valuable than those filed by non-PE-backed companies (Lerner et al. 2011; Kortum and Lerner

2000). The strategic alliances and informal networks are more frequent and profound when portfolio companies share the same investor (Metrick and Yasuda 2011; LINDSEY 2008). Marti et al. discuss sharing expertise with other shareholders as on impact mechanism to facilitate field building (Marti et al. 2023). The Norwegian sovereign wealth fund conducts best-practice site visits to obtain exclusive insights and share the gained knowledge within the investor community. It has established such a mechanism to professionalize responsible investment practices in Norway (Vasudeva et al. 2018). With its business model and ability to serve in the center of knowledge networks, PE funds could shape the growth of impact, if desired.

1.2 Research Questions

While there is some evidence on the general impact of PE, there is only scarce evidence on the sustainable impact within the private equity context. Although there is considerable research on sustainable investing, partially presented in chapter 1.1, less is known about the investment behavior and its dynamic within the private equity environment. Notable exceptions of studies within the field of private equity are from Crifo et al. (2015), Barber et al. (2021), Bellon (2022), or Hendriske et al. (2022). Crifo et al. have conducted a framed field experiment with private equity investors to show that investors react more to bad ESG practice disclosures than to good ESG disclosures (Crifo et al. 2015). Barber et al. study venture capital funds to show that investors derive nonpecuniary utility from investing in impact investing funds. In their models they show a willingness-to-pay for "impact" by investors (Barber et al. 2021). In his paper[4], Bellon uses US wells run by 1,701 operators to study the pollution of private equity backed firms. He shows that PE-backed companies reduce pollution whenever the company faces high environmental enforcement or political risk – and increase pollution whenever the

[4] As of November 2023: working paper

environmental liability risk low. He finds and suggests that this is manly driven by PE governance (Bellon 2022). Last to mention is a paper[5] by Hendriske et al. that provides initial ESG transparency of 4150 private equity and debt firms given recent data availability in Preqin. They show that larger, listed, older, and more recently fundraising GPs and those headquartered in Europe are more transparent in providing ESG information. They further provide evidence that the GP's ESG transparency is significantly associated with the portfolio-level ESG characteristics and the GP's investor base (Hendrikse et al. 2022).

Given research activity on sustainable investing in the context of the wider investor's landscape, this thesis provides new evidence as in how it operationalizes within the Private Equity context. Based on a hand-collected sample of 418 CIOs in 336 university endowments and their hand-collected asset allocation, a conjoint study with 140 global LPs investing into private equity funds and a deal level dataset of 2665 unique private equity deals and their (green) patent activity, this thesis provides new evidence on private equity and sustainable investment. The first research question is related to the CIOs role and impact within an LPs organization. The second essays attempts to unveil the LP's investment preferences when choosing PE funds. The third research question examines the impact of private equity deals on the environmental innovation performance concerning green patent activity.

1.2.1 The CIO in university endowments

The LP investment behavior in PE or more general the investment decisions of institutional investors are difficult research objects due to the private nature and challenging data access. As such, university endowments in the United States are an interesting object of research since they are obligated to report specific financial information annually. Since their success through the "Yale Model" and Swensen's work on managing institutional investment portfolios

[5] As of November 2023: working paper

(Swensen 2009), university endowments have been investigated by literature. Lerner et al. have documented the drivers and trends of their high historic returns and investment decisions (Lerner et al. 2008). Their success and active portfolio management has then been debated in the literature by e.g. Brown et al. who find that actively managed endowment funds generate alpha (Brown et al. 2010). Barber and Wang challenge this view and find no evidence that manager selection, market timing or tactical asset allocation generate alpha for the average endowment (Barber and Wang 2013).

However, while focus lied on drivers of return and the relationship of asset allocation decisions and their return in the past, there is scarce evidence on the organizational setup and the contribution of the individual CIO in university endowments. With this thesis, I empirically try to explore the CIO’s individual characteristics and its impact on asset allocation and return to contribute to literature, that has brought up this gap before (Lerner et al. 2008).

We utilize a hand-collected sample of 336 university endowments and their asset allocation data and combine it with a hand-collected sample of 418 individual CIO profiles. With a total of 3320 endowment-year observations between 2004 and 2019, we begin our analysis in establishing a relationship of asset allocation and future returns, that confirms existing literature. In line with past research, we find that higher asset allocation towards alternatives is positively correlated with positive future returns. This study also finds, that more aggressive and actively managed endowment funds, that exhibit higher share in commitments, are obtaining higher returns as well. Next, we try to elaborate on the question on how the individual CIO and his or her individual characteristics correlate with his/her investment decisions. We show the relationship between individual characteristics of the CIO like being a former investor, having a financial license or holding an MBA and its impact on the asset allocation towards alternative investments and endowment return. We find that CIOs with historic investment experience tend to allocate a higher share of asset under management towards alternatives. Li et al. have found that certain hedge fund managers characteristics that signal higher educational qualification tend to have higher returns, more inflows and take fewer risk (Li et al. 2011). The question arises, whether university endowments recognize and acknowledge higher qualification levels as well. Therefore, we lastly investigate the event of a CIO replacement. We observe the CIO's attempt to actively influence the portfolio around the replacement event through activity in commitments and cash holdings. We find consistent evidence of a decrease in likelihood of a CIO replacement when the CIO exhibits personal characteristics that signal professionalism. We also find evidence that the probability of being an incoming CIO increases when he or she was a financial investor in the past. These findings indicate that the individual education and experience matters both in terms of active engagement with the investments decisions and asset allocation made as well as the university endowment recognizing the qualification of the CIO. With regards to sustainable investment decisions, this results could imply, that the individual awareness and orientation of the CIO matters for investment decisions in favor of the net zero transition.

1.2.2 LPs' investment preferences of sustainability criteria

Several studies suggest to actively engage to create the most sustainable impact within firms (Broccardo et al. 2022; Kölbel et al. 2020; Berk and van Binsbergen 2022). Private equity funds do invest into portfolio companies and leverage their governance model of aligned incentives and active management within the invested company to create value in their target company. The question arises whether investors (LPs) are concerned with fund engagement aimed to create such sustainable value. Existing literature has elaborated on investment criteria of LPs in the past (Gompers and Lerner 1999; Loos and Schwetzler 2017; Da Rin and Phalippou 2017). Gompers and Lerner have shown that the performance of a fund and its reputation is positively affecting the fundraising of the subsequent fund using venture capital funds (Gompers and Lerner 1999). Loos and Schwetzler show that exits via a successful initial public offering have a positive effect on future fundraising. They also show that larger and industry-diversified PE firms raise larger funds and increase their likelihood in successful fundraising (Loos and Schwetzler 2017). And Da Rin and Phalippou find that LPs with large allocations to PE are performing the most intense due diligence on their fund selection (Da Rin and Phalippou 2017). In a framed field experiment, Heeb et al. have investigated the willingness-to-pay of 527 experienced private investors and 125 high-net-worth impact investors to assess their preference for sustainable investments. They find a substantial willingness-to-pay for sustainable investments (Heeb et al. 2023). However, to the best of our knowledge, there is no study yet that investigates the sustainable investment preference of dedicated private equity investors. This imposes the question on investment criteria of LPs and their preferences towards sustainable investment criteria in PE funds.

Block et al has used a conjoint analysis to asses the investment criteria of different private equity investors into their targets (Block et al. 2019). We have conducted a conjoint analysis assessing 8,400 observations from 2,100 decisions made by 140 different LPs that invest into private equity funds. Firstly, we derive investment criteria and in particular sustainable investment criteria through a literature analysis and expert interviews. We then conducted this experimental study with 140 limited partner to provide relative importance and differences in investor type's preference. In the study, qualified investors had to choose between three fictional funds (or not to invest at all) for a simulated follow-on investment with fund managers they were familiar with. We leverage a hierarchical Bayes approach as well as multinominal logit model to analyse the data. We find that rather traditional investment criteria like the management fee and the performance of the previous fund are still significantly more important than our proposed sustainability criteria. Together, the two traditional investment criteria account for ~60% of relative importance in our setup. Our results also suggest, that funds with EU SFDR article compliance, funds with an incentivization system incorporating a sustainability carry, funds with a CO_2 reduction target and funds with a sustainability expert in the fund team have a significant, positive impact on the investor's investment decision. Further, we try to understand whether there is a particular taste difference for certain sustainable investment characteristics as introduced by Fama and French (Fama and French 2007). In a more granular consideration of our results, we find that having a CO_2 reduction target on the fund's portfolio is more important for insurance companies than for family offices and it is also more important for self-committed ESG signatories. Our study implies, that there is an existing investor preference for sustainability criteria within the LP community of private equity funds and that their sustainability preference might be heterogenous based on their type. In line with study findings from other investor contexts (Heeb et al. 2023; Hartzmark and Sussman 2019; Kölbel et al. 2020), it is a promising finding that LPs could incentivize the PE business model to finance the transition towards net zero.

1.2.3 Private equity impact on green innovation

The actual impact of private equity investments on long-term sustainability performance of their portfolio companies still remains unclear. While the prevailing literature on the impact of private equity backed leveraged buyouts (or deals in general) on firms has primarily focused on firms' financial performance and evolving corporate governance landscape, there is only a limited amount of research on PE's potential impact on the innovation output of targets (Cumming et al. 2007; Kaplan and Strömberg 2009). Ughetto, Lerner et al. and Amess et al. have conducted studies to investigate the innovation impact of PE funds in their portfolio companies. Ughetto has analysed 681 firms that underwent a buyout, out of which 200 firms were granted a European patent in the considered time window. Ughetto shows that different investor types, pursuing different investment objectives affect the patent activity of the respective portfolio firm (Ughetto 2010). Lerner et al. analyze the long-term investment effects of 472 LBO transactions. They find that LBO firm patents are more cited, show no shifts in their orientation and become more focused in important areas of the companies' innovation portfolios (Lerner et al. 2011). Using a sample of 407 leveraged buyout deals in the UK, Amess et al. find that LBOs have a positive and causal effect on patent stock as well (Amess et al. 2016). But none of these innovation consideration focusses on the sustainable impact or environmental innovation. Building up on aforementioned studies, we analyze the impact of 2665 unique private equity deals on the green patent activity of the respective portfolio company. We extend the research on patent activity in private equity deals by focusing on green patents as a proxy for environmental knowledge innovation. We leverage research on green patenting from related research areas like research policy (Fabrizi et al. 2018), intergovernmental research on measuring environmental innovation by the OECD (Organization for Economic Co-operation and Development) (Haščič and Migotto 2015) and innovation literature on green patenting (Cohen et al. 2020). In doing so, we introduce green patenting as an innovation outcome within the private equity literature and shed light into the sustainable impact of private equity funds on their portfolio firms. In the paper, we start by deriving the reasoning for green patent activity as an indicator of environmental innovation. We then hand-match Preqin deal-level data with patent information from the Orbis Intellectual Property database creating a five-year pre and post deal event study around each deal. Using descriptive statistics, OLS regression models, and Poisson likelihood regression models, we obtain three key findings: portfolio firms in our sample exhibit significantly positive green patent activity post the private equity deal. Upon deeper consideration, we find that this effect is driven by a subset of highly patent-active companies. Lastly, we find no evidence suggesting a correlation between the ESG signaling of private equity firms and a surge in green patent activity. The indication of our results are in line with the patent-related findings of Lerner et al. (Lerner et al. 2011) and extend them towards green patent activity. Our findings also allow the interpretation, that private equity deals are positively correlated with increased green patent activity post deals. While it might not be a comprehensive assessment for sustainable innovation, it serves as a promising indicator whether a PE fund actively drives or participates in the needed transition towards net zero – while at the same time raising the question whether this is truly the main reason.

1.3 Contribution and implications

Although several white papers recently published articles and views on value creation through sustainability in private markets, there is scarce academic literature on this topic (Andrews et al. 2022; Fordham 2023; Seemann et al. 2023). Overall, this dissertation contributes to a better understanding of sustainable investing in the private equity context. The three essays of this dissertation contribute to multiple strands of the literature along the private equity investment cycle and have implications for academia and practitioners alike. In this dissertation, I provide three unique datasets to elaborate on different characteristics of the private equity business model and their contribution towards sustainable investing. Figure 1 provides an overview of the general structure of private equity funds and contributions by this dissertation. I obtain a datasets on 418 CIO profiles and asset allocation of 336 LPs, conduct a conjoint a conjoint analysis of 140 LPs on their investment preferences and investigate 2665 unique deal events and their corresponding green patent portfolio.

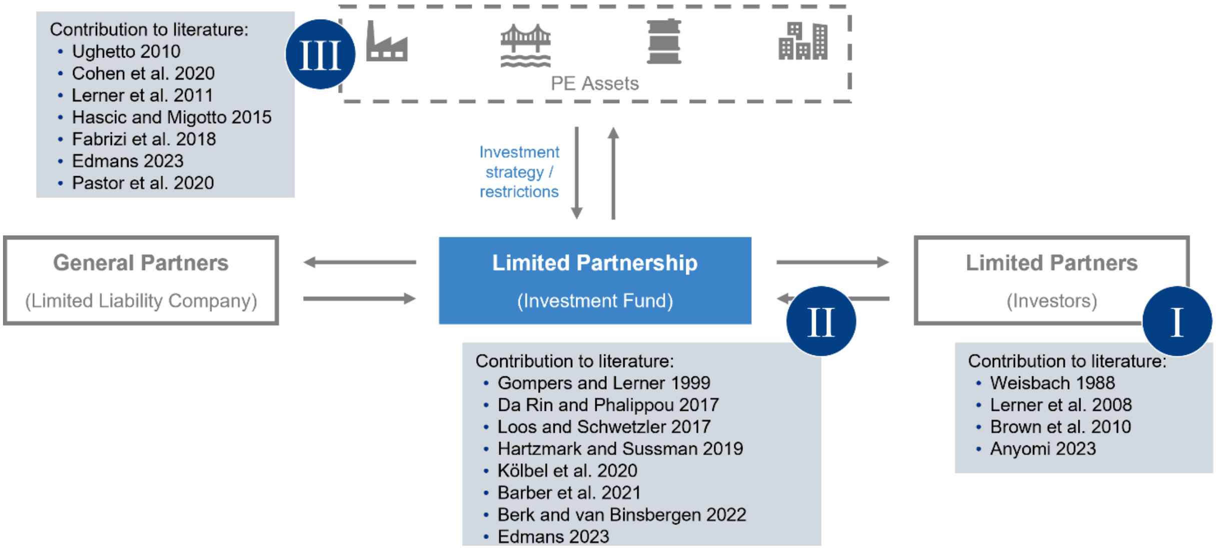

Figure 1: Limited partnership as a standard structure

This figure shows the standard structure of private equity funds. It provides the organizational relationship of the limited partners, the general partners and the PE assets. The graph is based on illustrations from Schefczyk, Cumming and Johan (Schefczyk 2006; Cumming and Johan 2014).

I: In the first essay, I provide empirical evidence that characteristics of the CIO profile affect the asset allocation in university endowments and that higher qualification levels are associated with a decreased likelihood of being replaced and an increased likelihood of being an incoming CIO. CIOs allocate higher shares of assets under management towards alternative investments when they have been former investors. By pursuing such active portfolio management these CIOs exhibit higher returns as well. CIOs with higher qualification levels (MBA, former investor, or financial license) are also less likely to be replaced by their university endowments. Overall, my results provide evidence that the individual plays an important role within an LP organization and influences the asset allocation.

I contribute to the literature on the organizational and operating setup of university endowments and limited partners (e.g., (Brown et al. 2010; Lerner et al. 2008) by studying the specific role of individual CIO profiles in such organizations. Furthermore, I contribute to the growing literature on the role of individual CIOs, their retention and the impact of the individual on investment behavior (Anyomi 2023). By studying their impact on asset allocation, correlation on return and the specific replacement event, I adapt approaches from the literature of corporate governance. Therefore, I also add to the literature investigating CEO turnovers initially introduced by Weisbach (Weisbach 1988) and extend this research to the setting of institutional investors.

II: In the second essay, I analyze the investment preferences of limited partners when investing into private equity funds. I conduct an experimental conjoint analysis to exploit their preferences for conventional fund characteristics as well as sustainability-related fund characteristics. There is substantial relative importance on fund characteristics that support sustainability efforts of private equity funds, yet the traditional investment criteria like past performance and management fee are of highest importance. In our setup investors' decision was significantly correlated with the existence of a CO2 reduction target on the fund portfolio and an sustainability expert in the fund team. Interestingly, while EU SFDR article compliance is important for LPs, there is slight confusion about the value add of article 9 as opposed to article 8 funds. Similarly, LPs gain a higher utility from a conditional carry based on sustainability targets, but only if the share is not too large. Our findings also suggest differences of preferences by LP type: in our setup insurance companies exhibit significantly higher importance from CO2 reduction targets on the fund's portfolio than family offices.

Most importantly, I add to the literature on investment criteria of investors when considering private equity funds (Da Rin and Phalippou 2017; Gompers and Lerner 1999; Loos and Schwetzler 2017). As a potentially crucial investment criteria in the future, our study provides experimental empirical evidence on the relevance of sustainability criteria in the investment decision of LPs. The study therefore contributes also to recent literature elaborating on investors' preference for sustainability efforts and their willingness-to-pay for such activities (Barber et al. 2021; Hartzmark and Sussman 2019). I also attempt to find initial evidence for investors seeking shareholder engagement to operationalize (and monetize) on the transition to net zero (Berk and van Binsbergen 2022; Edmans 2023; Kölbel et al. 2020).

III: In the third essay, I document the impact of 2665 unique private equity deals on the green innovation activity of the corresponding portfolio companies. The absolute and relative green patent count is significantly larger post the private equity deal. We also find that the ratio of green patents to overall patent count increases. We find that this effect is strongly driven by deals that involve companies that are very patent active. The effect with this sub-sample is even stronger which leads us to the assumption, that private equity funds seek to exploit the patent activity as a value driver as opposed to systematically seeking sustainable impact. This hypothesis is supported by the fact, that we find no evidence that ESG signaling of any kind is correlated to green patenting activity post deal.

With this study, I contribute to the innovation literature of private equity deals (Ughetto 2010; Cohen et al. 2020; Lerner et al. 2011) but add the perspective of environmentally-oriented innovation. I introduce the literature on green patenting (Haščič and Migotto 2015; Fabrizi et al. 2018; Cohen et al. 2020) in the private equity context and thereby add to the private equity literature two-folded: I introduce green patenting as an objective measure for environmentally-oriented impact and as an additional value driver for private equity investors (Edmans 2023). Therefore, this study also provides implications for practitioners in that case that green patenting could serve as a value driver to monetize on future cash flow stemming from "green assets" (Pástor et al. 2022). In the following chapters, each research project and corresponding essay is presented.

2 Does the Individual Matter? – CIOs, their Influence on Asset Allocation, and their Profiles in University Endowments

Abstract

Educational institutions in the US hold billions of dollars in endowment funds and the "endowment model" of building diversified portfolios has been adapted by many institutional investors, despite limited knowledge about the individuals role within the organization. Analyzing data from 336 university endowments and 418 individual Chief Investment Officer (CIO) profiles between 2004 and 2019, we evaluate portfolio asset allocation and CIO profiles. This paper first confirms findings on the historic endowment model, showing that higher allocations to alternatives correspond with positive future returns. Then, our analysis of CIO profiles and asset allocation provides evidence that CIOs with previous experience as an investor have a higher tendency to allocate capital towards alternative investments. We observe short-term activities of CIOs around the CIO replacement event and find significant evidence that CIOs with an MBA, a financial license, or investor experience in the past are less likely to be replaced. Similarly, we find evidence that professional experience as an investor significantly increases the likelihood of being an incoming CIO in a CIO replacement event.

Keywords: University Endowment, CIO replacement, CIO profile, Limited Partner

2.1 Introduction

Educational institutions, especially in the US, hold billions of dollars in endowment funds. As of February 2023, the top six educational endowments (Harvard University, University of Texas, Yale University, Stanford University, Princeton University, and Massachusetts Institute of Technology) managed a total of $230 billion and all educational endowments in the United States and Canada (included in the NACUBO study) combined managed $807 billion (NACUBO 2023a, 2023b). With this asset under management, they serve as an important and relevant investor in various asset classes. Yet, our understanding of how these institutions operate and how key stakeholders within the organization impact the investment decision remains limited. Main studies in the past focussed on the drivers of returns and the relationship between asset allocation decisions and performance in multiple asset classes (Lerner et al. 2008; Brown et al. 2010). Lerner et al. have provided evidence that drivers of high returns in university endowments are the size of the endowment, the quality of student body and the use of alternative investments. In particular, they conclude that endowments with the best performance allocate aggressively towards alternative investments like hedge funds, private equity and commodities (Lerner et al. 2008). Brown et al. extend that research in studying the relationship between asset allocation decisions and performance in multiple asset class portfolios. They find that actively managed funds exhibit significantly larger alphas compared to passively managed funds. They derive that the average endowment manager pursues a much more aggressive investment strategy than what appears to be the case for managers of mutual funds or pension funds. Conclusively they suggest, that more actively managed funds generate alphas and perform better than those for more passive endowments (Brown et al. 2010).

This study investigates the portfolio allocation, its relation to return and the contribution of the individual chief investment officer (CIO) on asset allocation. It tabs into the organizational setup of university endowments focusing on the individual CIOs. We analyze a sample of 336 university endowments and 418 individual CIO profiles with a total of 3320 endowment-year observation between 2004 and 2019 using university endowment-level financial information in combination with individual characteristics of CIOs. We assess the portfolio allocation especially towards alternatives and the effect on performance, the educational and professional backgrounds of CIO and its impact on portfolio allocation and investigate the CIO replacement event.

We begin our analysis by establishing a relationship of asset allocation and future returns. Our study confirms historic findings of the endowment model, that higher exposure towards alternatives has a positive impact on future returns. More aggressive and actively managed endowments with over-proportional commitments (in relation to their asset under management) tend to exhibit higher returns as well. Next, we establish the relationship with portfolio allocation towards alternative investments and the individual CIO's profile. CIOs that have been historic investors have a significantly higher tendency towards a higher share in alternatives to asset under management. Finally, we investigate the event of a CIO replacement. We observe activity in commitments and cash holdings around the CIO replacement year, both portfolio allocation decisions that are influenceable in the short term for an individual. We run linear probability models and find some evidence, that lower returns in the years prior to the replacement event are increasing the probability of CIO replacements. More strikingly, we find consistent evidence of decreased likelihood of CIO replacements whenever the CIO signals professionalism as in being a holder of an MBA, a financial license and/or having had investment experience in the past. Similarly, the probability of being an incoming CIO in a replacement event is higher, whenever the profile has had investor experience in the past. Descriptive results also suggest, that better performing endowments have a higher share of former investors as CIOs and that university endowments with larger assets under management have better access to high profile CIOs.

This research contributes to the literature on the organizational setup of university endowments and extends research on asset allocation by the consideration of the individual CIO as one of the key stakeholder. The paper taps into the proposed research gaps raised by Lerner et al. pointing towards the organizational setup of university endowments and its relation to their returns as well as the viability of the strategies pursued by endowments (stemming from the 90s and 00s) going forward (Lerner et al. 2008). Our paper contributes in replicating their findings with more recent data and extending it towards the CIO profile. It tries to elaborate further on the suggested differences in investor sophistication by assessing the CIOs together with the endowment's portfolio decisions (Lerner et al. 2007). Much literature has focused on the behavior of the endowment organization in general and how they generate alpha (Barber and Wang 2013; Brown et al. 2014; Brown et al. 2010), but not on the individual within the organization. However, recent literature has started to shed light on the incentive and compensation for performance within public pension funds to examine the relation between the individual CIO and the investment performance (Lu et al. 2022; Anyomi 2023). Some research has also been conducted on educational background of individual managers for other institutional investors (Chaudhuri et al. 2020), but (to the best of our knowledge) this study is the first one elaborating on the CIO profile within university endowments.

2.1.1 The endowment model and CIOs

In 2000, David Swensen published his book "Pioneering Portfolio Management" in its original version. Swensen was Chief Investment Officer at Yale during that time and is widely acknowledged for establishing the "endowment model" of investing with his book on Yale's investment approach to institutional investments (Swensen 2009; Dimmock et al. 2023). Endowments in the US and Canada today hold a substantial amount of ~$800 billion in assets under management and have become an increasingly important source of financing for universities itself, especially for student financial aid, academic programs and research as well as campus operations (NACUBO 2023a; Brown et al. 2014). Most of the historic endowment growth is stemming from positive investment returns generated and driven by the continuous shift of endowment investments from fixed income to equities in the 1970s and 1980s, subsequently followed by a shift towards alternative assets like hedge funds, private equity and venture capital in the 1990s and 2000s (Lerner et al. 2008; Brown et al. 2014). Following this model approach, a majority of sophisticated long-term investors like pension funds and family offices hold substantial shares of their portfolios in illiquid alternative assets (Dimmock et al. 2023). In 2022 university endowments allocated ~30% of their portfolios towards private equity and venture capital and had more than half of their portfolios allocated towards illiquid alternatives (NACUBO 2023a). This investment strategy of high allocations towards illiquid assets has been established under the term "endowment model" and was widely adopted by numerous types of institutional investors. The underlying hypothesis suggests to long-term investors that they should hold high allocations of alternative assets to earn illiquidity premiums and exploit the inefficiencies of illiquid markets (Dimmock et al. 2023).

Given this relevancy of the endowment model within the modern portfolio theory, it has been subject of various studies in the past. Lerner, Schoar, and Wang presented a study documenting the trends in university endowment returns and investments in the US and show that they have overall performed well growing ~7% annually. Using descriptive statistics, they show that the sector has been dominated in size and performance by the endowments of elite universities like Ivy League schools. They suggest an increasing skewness of endowment size, where the rich universities are getting richer and show that the underlying drivers of these high returns is related to the size of endowment, the quality of the student body, and the use of alternative investments (Lerner et al. 2008). Brown, Garlappi, and Tiu use university endowment funds by accessing a detailed panel of actual reported portfolio weights to study the relationship between asset allocation decisions and the performance in multiple asset class portfolios (Brown et al. 2010). They analyzed the strategic and tactical asset allocation, as well as security selection abilities of endowment managers and conclude that the risk-adjusted performance of the average endowment is negligible, but that actively managed funds generated larger alphas than passive ones (Brown et al. 2010). Barber and Wang have analyzed the returns of US university endowments using style attribution models to conclude that elite institutions perform better than public stock and bond benchmarks due to their large exposure towards alternative investments (Barber and Wang 2013). Thereby, they have confirmed the finding of Lerner, Schoar, and Wongsunwai, who have previously analyzed the returns within the private equity asset class and have identified that educational endowments enjoy the highest rates of return (Lerner et al. 2007). Brown et al. have therefore concluded, that actively managed funds generate alpha since endowment managers are over-weighting asset classes in which they have superior skills (Brown et al. 2010). However, Barber and Wang found no evidence that manager selection or tactical asset allocation generates alpha (Barber and Wang 2013). Generalizing the endowment perspective and considering the importance of asset allocation more broadly, Ibbotson finds, that most of a typical fund's return variation comes from market movements. According to Ibbotson the return drivers are threefold: 1) the return from the overall market movement, 2) the incremental return from the asset allocation policy of the respective fund, and 3) the active return (alpha) from timing, selection, and fees (Ibbotson 2010). Given the established importance of selection, management of funds and skills mentioned in previous studies, the individual person could play a crucial role in the (non-financial) decision making of university endowments. A recent study investigates the CIO compensation and incentive at public pension plans to elaborate on its relevance for the retention and attraction of talented executives to remain competitive. Anyomi finds that CIOs who are paid in the top quartile outperform their peers and that higher CIO compensation is positively correlated with investment efficiency (Anyomi 2023). Li, Zhang, and Zharo have considered manager characteristics such as SAT scores, years worked, years worked in the investment fund and manager's age to conclude, that higher education and experience levels are leading to better performances of hedge funds (Li et al. 2011). In a similar study, Chaudhuri et al. have analyzed the performance of investment products managed by firms in which PhDs play a major role. They find superior performance of investment products of those managed by PhDs than those managed by otherwise similar firms. They further find, that the performance is related to the PhD's field of study given that economics or finance PhDs outperform their peers (Chaudhuri et al. 2020). In prior studies on the contrary, Berk and Green indicate that the impact of individual managers on mutual fund performance is likely to be small due to the established investment process and team-oriented approach to portfolio management (Berk and Green 2004). Overall this raises the research questions to be explored within this paper: Do endowment managers have superior skills? Does qualification or past experience help them to develop such skill?

2.1.2 CIO and CEO replacement

In this paper, we extend the research from a pure asset allocation perspective to an investigation of the event of the CIO replacements in university endowments. While there is scarce literature on CIO replacements in university endowments, research has been conducted on CEO retention and replacements as well as CIOs at other investor types.

A popular study object of CEO replacements lies in the merger and acquisition process and its impact on the performance of the target firm. In this context, the CEO retention can have one main benefit, which could have relevance within the context of institutional investors as well: an integral part of a company's distinctive history, culture and capabilities is formed by their managers. Retaining managers therefore supports knowledge creation, retention within the company, and transfer of knowledge between key stakeholders of different institutions

(Devine et al. 2016; Barney 1991; Campagnolo and Vincenti 2022). Executives with tenure have unique knowledge of the company which is usually interlinked with multiple operational capabilities within the institutional environment (Devine et al. 2016; Campagnolo and Vincenti 2022). The CEO in particular is the central stakeholder within the organization overseeing and controlling the company, its vision, the organization and – most importantly within the context of financial markets and alternative investments (Hochberg et al. 2007) – the major relationships with external and internal stakeholders (Campagnolo and Vincenti 2022). Devine et al. analyzed the manager retention in acquisition and their institutional influence and their findings suggest the importance of managerial retention, especially involving "underdeveloped institutional context" (Devine et al. 2016). However, their results also suggest, that retaining managers within the context of an acquisition has disadvantages to the post-acquisition performance (Devine et al. 2016).

A replacement is usually associated with a relation of negative firm's performance and has been part of several studies in the literature (Coughlan and Schmidt 1985; Kang and Shivdasani 1995; LEHN and ZHAO 2006). Lehn and Zhao show, in the aforementioned acquisition context, that the probability for manager replacements is increasing as a result of value-reducing acquisitions compared to managers making value-enhancing acquisitions (LEHN and ZHAO 2006). Concluding higher CEO turnover as a result of poor institutional performance. Amongst the most famous CEO turnover papers is a study conducted by Weisbach in 1988 (Weisbach 1988). Weisbach predicted CEO resignations using stock returns and earning changes as a proxy for previous (poor) performance within the organization (Weisbach 1988). Later, Weisbach and Hermalin emphasized that perspective with their model on board effectiveness and independence (Hermalin and Weisbach 1998). Their consistent findings confirm CEO turnover has a negative relationship with performance and that this relation is stronger when boards overseeing the CEO are more independent. Boards also tend to become less independent over the course of the CEO’s career and suggests that management turnover is rather related to earnings than to stock returns (Hermalin and Weisbach 1998). Nguyen finds that CEOs of the same networks do not get fired easily after bad performance and they are more likely to find a good job later (Nguyen 2012). Amongst the first studies within the fund literature is a study from Khorana (Khorana 1996). Khorana investigates the relationship of performance of open-end mutual fund managers and their replacement. His results indicate the presence of an inverse probability of management change and past fund performance suggesting a similar pattern of CEO and CIO replacements within the fund industry (Khorana 1996). Five years later he documented “improvements in post-replacement performances relative to the past performance of the fund” and suggests that replacing overperforming managers leads to a deterioration in post replacement performance (Khorana 2001). Adams, Mansi, and Nishikawa examine the fund manager turnover in mutual funds for private and public ownerships and find that public sponsors, or perhaps more generalized: sponsors of public interest (like endowments), are more sensitive to prior fund performance when making replacement decisions. They additionally experience smaller post-turnover performance improvements (Adams et al. 2013). Wang and Ko have investigated the implications of fund manager turnover in China looking at internal relocation, switch to outside mutual funds, switch to hedge funds and dropouts from the fund industry. Their findings show, that among those for types, only dropouts from the industry show significantly negative pre-placement and positive post-placement excess returns. They further find that replacements of skilled managers result in worse post-placement performances and vice versa. In addition an experienced incoming manger is more likely to obtain better post-replacement performance than a takeover by an inexperienced manager (Wang and Ko 2017). These findings point to an interest around the experience and skills of CIOs, how it relates to the endowment performance and which profiles are desirable for then endowment organization in general. A recent study by Lu, Mullally and Ray has examined the relationship of public pension plan CIO compensation and its investment performance. Their findings suggest, that higher paid CIOs outperform their counterparts given their hiring and retention of better educated CIOs through higher compensation. Interestingly, the increase in performance is largely driven by an increased and superior investment into private equity and real estate (Lu et al. 2022).

2.2 Empirical strategy

2.2.1 Methodology

For our regression analysis we rely on two types of regression models. In the first part of our analysis we leverage the Stata package "reghdfe" that runs linear and instrumental-variable regressions with various levels of fixed effects (Correia 2016). We use a fixed-effects model to account for fixed factors at the year level and entity level, that do not change over time (Wooldridge 2008). We use this particular model to investigate linear and instrumental-variable regressions with many levels of fixed effects. In the second part of our analysis we also run panel regressions to tab into patterns that drive the CIO replacement event. We leverage the stata package "xtreg" to fit regression models to our panel data. We have an unbalanced data set and use the between regression estimator again with year fixed effects to analyze the relation of certain university endowment performance measures, CIO characteristics and the CIO replacement probability.

2.2.2 Data description

Our sample consists of U.S. university endowments' holdings and returns between 2004 and 2019 as well as corresponding personal information about senior staff members[6] in the

[6] Usually the CIO, partially (typically due to size) no dedicated CIO available. Then we aimed for the most senior investment staff member with that role (e.g., CFO, investment manager, …)

respective years. It is hand-collected from audited annual financial statements published on their websites, the Internet Archive and LinkedIn. Previous studies (Lerner et al. 2008; Brown et al. 2010; Goetzmann and Oster 2014) used National Association of College and University Business Officers (NACUBO) survey data to investigate asset allocation and returns of university endowments. However, existing sources do not include information on commitments, detailed asset allocation and, more importantly, the personal information of senior staff members such as the chief investment officer and alike which are needed for our empirical analysis. For sample construction, we hand-collect financial and non-financial data from the aforementioned sources to first identify endowments and their financial information and then secondly their CIO's profiles. An overview of the sample construction process can be found in Table 1.

Table 1: Sample construction process

Step	Description	N	University endowments
Panel A	General data collection and preparation		
1	We hand-collect U.S. University endowments' holdings and returns between 2004 and 2019	3320	336
2	We merge the sample data with hand-collected data from their university's financial statement information between 2004 and 2019	3284	242
3	We research the university endowment's chief investment officer (or equivalent) and hand-collect personal data	2505	225
Panel B:	Personal data on the CIO		
4	We research all historic CIOs and hand-collect personal data on their educational and professional background	418	225
5	We identify all CIO changes within our sample period	237	225

Note: This table provides an overview of the data collection logic. The data collection effort followed five steps and can be split into two perspectives: first, we hand-collected data on the university endowment's financial information (balance sheet and financial statements) and second, we researched each individual endowment and its CIO during the sample period. Through this logic we created panel-data set based on university endowment-years, the respective financial information and the corresponding CIO in the given year including all his/her personal information/characteristics.

We start by collecting balance sheet information of U.S. university endowments that include the university endowments' holdings and returns between the years 2004 and 2019. We similarly collect financial statement information of the U.S. universities, with which the endowments are associated and merge the information with the endowments' holdings and returns. Table 2 provides the summary statistics of the data regarding the university endowments within our sample. For all resulting university endowments' we have researched and hand-collected personal information on the endowments' chief investment officer or equivalent person being responsible for investment decision. We collected the information based on the universities' recent website and the web archive as well as LinkedIn and only searches of newspaper articles to shed light into the proposed research gap of organizational economics and recruiting professionals of such institutions by Lerner et al. (Lerner et al. 2008).

Table 2: Summary statistics asset information of university endowment

Summary statistics

Variable	N	Mean	SD	P25%	Median	P75%
commitments	2469	369.06	1079.93	16.37	61.89	207.75
holding cash	2505	88.77	142.42	6.16	25.25	88.82
holding alternatives	2501	433.60	1278.60	22.49	84.41	278.00
holding hedge fund	1980	452.93	1126.67	35.96	122.26	309.40
holding equity	2499	922.19	2101.39	121.21	292.91	713.16
dollar return	2495	139.59	602.92	3.73	29.16	100.72
asset under management (aum)	2505	2627.03	6831.73	299.76	782.78	1901.36

Note: All values are provided in $M.
The table provides an overview and summary statistics of university-year observations and the relevant financial data. A description of all variables can be found in Appendix A. Variables of interest are checked for outliers and are winsorized at the 1% and 99%-level.

We followed approaches of similar recent studies (Gompers et al. 2023) in collecting a variety of individual information about the CIOs and have displayed the main variables used in our further analysis in Table 3.

Table 3: Summary statistics of CIO profiles

Variable	N	Mean	SD	P25%	Median	P75%
Highest degree: bachelor	2364	0.18	0.39	0.00	0.00	0.00
Highest degree: master	2364	0.61	0.49	0.00	1.00	1.00
Highest degree: phd	2364	0.20	0.40	0.00	0.00	0.00
mba	2459	0.44	0.50	0.00	0.00	1.00
financial_license	2459	0.27	0.45	0.00	0.00	1.00
former_investor	2459	0.49	0.50	0.00	0.00	1.00
Investment years (prior to endowment)	1211	13.42	9.31	6.00	10.00	19.00

The table provides the year observation of CIO profiles and their corresponding educational and professional information.

Our main dependent variable of interest is the endowment return. We normalize the return of each endowment-year observation by asset under management of the given year. In the following we are referring to this relative value as *endow_return* and have considered lead variables for the endowment return in the following year as *endow_return_lead1* and *endow_return_lead2* respectively. In a similar approach, we have normalized asset allocation variables by asset under management for our analysis as well. A detailed explanation of all variables of interest can be found in Appendix A.

2.3 Empirical results

We start by confirming prior research (Lerner et al. 2008) in establishing a relationship of the asset allocation and the endowment's return in chapter 4.1. In chapter 4.2 we show how qualification and educational background has an impact on the respective asset allocation and in chapter 4.3, we look into the impact of qualification levels during replacements.

2.3.1 Asset allocation and return

Prior literature finds, that much of endowment performance is driven through allocation decisions between asset classes with different risk and return patterns (Lerner et al. 2008). We therefore start with several regression analyses in Table 4. We use the asset allocation to explain the endowment return of the following year (endow_ret_lead1) and the year after the following year (endow_ret_lead2) in a linear model with multi-level fixed effects (Correia 2016). We control for asset under management, private universities, and ivy league universities in models (1) – (5) while using robust standard errors and year fixed effects. The magnitude of the coefficients of commitments (commit2aum), alternatives (alt2aum) and real estate (real2aum) suggest that the asset allocation decision with a tendency towards alternative investments increases the endowment return. All of these coefficients are positive and significant for the year following the asset allocation decision and the year after the following. Hence, with our sample and analysis we confirm findings from Lerner et al (Lerner et al. 2008). We did also control for entity and year fixed effects at the same time, but given the size of n in our sample, we assume little variance within an entity is causing the significance to disappear. We therefore trace back the effect of the share in alternatives and share in real estate on future return to be related to the cross-university heterogeneity. We can therefore conclude and interpret the coefficients as follows: given a respective year, a university endowment with a larger share in alternatives (or real estate) tends to have a higher return in the subsequent years than a university endowment with a lower share. We cannot conclude the same in a within university endowment entity consideration. Accordingly, we run a descriptive analysis and plot the asset allocation over time in Figure 2.

Table 4: Regression table of asset allocation and return

Model	(1)	(2)	(3)	(4)	(5)
Dep. Variable	**endow_return_lead1**	**endow_return_lead1**	**endow_return_lead1**	**endow_return_lead2**	**endow_return_lead2**
commit2aum	0.0440***	0.0405***	0.0374**	0.0379***	0.0325**
	(0.0146)	(0.0146)	(0.0147)	(0.0147)	(0.0145)
cash2aum	-0.000905	0.000250	0.00640	0.0126	0.0200
	(0.0174)	(0.0174)	(0.0173)	(0.0187)	(0.0186)
equity2aum	0.0165**	0.0177**	0.0167**	0.0144*	0.0141*
	(0.00795)	(0.00808)	(0.00804)	(0.00775)	(0.00790)
bond2aum	0.00732	0.00698	0.0130	0.000266	0.00652
	(0.00851)	(0.00855)	(0.00886)	(0.00838)	(0.00871)
alt2aum	0.0365***	0.0370***	0.0382***	0.0329***	0.0346***
	(0.0114)	(0.0114)	(0.0115)	(0.0119)	(0.0119)
real2aum	0.0522***	0.0505***	0.0489***	0.0530***	0.0504***
	(0.0152)	(0.0155)	(0.0154)	(0.0166)	(0.0168)
loc2aum	-0.0374	-0.0365	-0.0508*	-0.0378	-0.0519*
	(0.0254)	(0.0255)	(0.0260)	(0.0274)	(0.0281)
aum		0.000142	3.63e-05		-3.07e-05
private			0.00569***		0.00613***
ivy			0.00710*		0.00730**
Year FE	yes	yes	yes	yes	yes
Constant	0.0316***	0.0310***	0.0266***	0.0329***	0.0277***
	(0.00555)	(0.00558)	(0.00591)	(0.00543)	(0.00584)
Observations	2,150	2,150	2,150	1,945	1,945
R-squared	0.824	0.824	0.825	0.821	0.822

Note: The table provides coefficients from linear regressions. e*ndow_return_lead1* and *endow_return_lead2* are the dependent variable and refer to the return in one year and two years respectively. The independent variables are each ratios to the overall asset under management and include the commitments, cash holdings, equity holdings, bond holdings, real estate holdings and line of credits. All models are year-fixed effect regressions. While models (1) and (4) are run with all variables of interest, model (2) also controls for asset under management (aum). Models (3) and (5) control for asset under management, private school and ivy league school. p*rivate* is a dummy variable set to one for private schools and zero otherwise. i*vy* is a dummy variable set to one for ivy league schools and zero otherwise. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

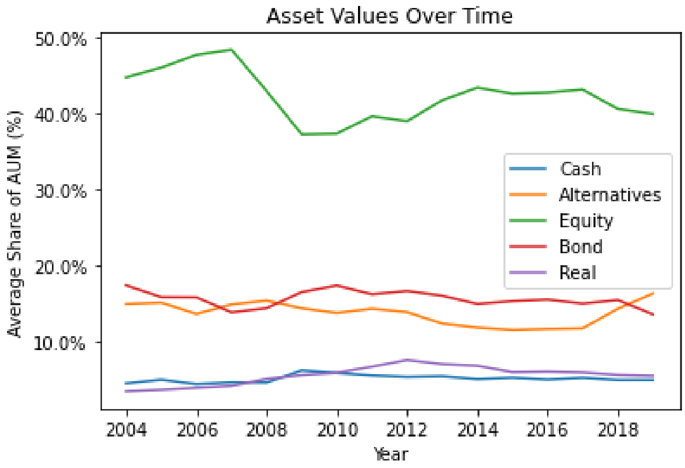

Figure 2: Asset allocation over time

This figure provides an overview of the individual asset class holdings over time. It depicts the mean of the respective asset class allocation as a share of the asset under management for all endowments. The x-axis shows the years of the observed time period. The y-axis indicates the share of overall aum of the respective asset class: the blue line shows the cash holdings, the orange line shows the alternative holdings, the green line shows the equity holdings, the red line shows the bond holdings and the purple line shows the real estate holdings.

Figure 2 provides the share in respective asset class over time. We observe little variance in the share of alternatives. This fairly stable tendency of ~15% share in alternatives over the entire observation period strengthens our hypothesis of little variance within entities themselves. We do observe a decrease in share of equities during and after the financial crisis (2007-2009). There seem to be other drivers for the exposure to certain asset classes other than pure effects of time. In their final conclusion and call for further contributions, Lerner et al. raise the question on the organization setup of endowment offices and the relation to returns (Lerner et al. 2008). We aim to tap into this research gap to elaborate on the organization of endowment offices and how it contributes to their performance. Therefore, we further take a look into the asset allocation drivers, relevant distinct characteristics of the endowment and its relation to the CIO.

2.3.2 Asset allocation and educational & professional background

We continue our analysis with a simple descriptive mean comparison of different panels of the university endowments and CIO characteristics in Table 5. Panel A splits the sample in ivy league university endowments and non-ivy league university endowments, panel B splits the sample in endowments led by CIOs with an investor background and those without, panel C in those led by CIOs with an MBA and those led by CIOs without an MBA and panel D splits it in those led by CIOs with a financial license and those without. The simple mean comparison already points to several interesting observations. Unsurprisingly, ivy league endowments have higher AUM considering that this group includes some of the most relevant and largest university in the US. They have, on average, a 3.7pp higher asset allocation exposure towards alternative assets and have 7.7pp higher commitments. They also seem to have exhibited 2pp higher returns within our observed time period. All these observations are statistically significant when running a t-test and an interpretation seems economically logical: ivy league schools have large aum intuitively given their size and are early adopters of the "Yale Endowment Model" (Swensen 2009) in which their focus on alternative investments in their portfolio management to obtain greater returns.

Further we can observe differences in those endowments led by allegedly higher qualified CIOs (former investors, MBA holder or financial license holder) and those with lower qualification: the simple mean comparison reveals that endowments led by former investors have a 3pp higher exposure towards alternative assets and 3pp higher commitments, both significant when running t-tests. We also observe that larger university endowments in terms of managed assets (AUM) are led by CIOs that are former investors, have an MBA and/or have a financial license. In other words, t-tests unveil that those with allegedly higher qualifications have significantly larger AUMs. This implies two thoughts: one hypothesis that university endowments with larger AUMs employ or are able to recruit higher qualified CIOs and that in our further analysis and robustness checks, we need to control for AUM.

Table 5: Asset allocation by university endowment characteristics

Variable									
Panel A: Ivy	**0**			**1**			**t-test**		
	N	**mean**	**p50**	**N**	**mean**	**p50**	**mean(1) - mean(0)**	**t-ratio**	**p-value**

commit2aum	2411	0.096	0.084	94	0.173	0.168	0.0774	10.9855	0.0000
cash2aum	2411	0.052	0.035	94	0.044	0.041	-0.0087	-1.5743	0.1156
alt2aum	2411	0.134	0.109	94	0.171	0.149	0.0376	3.4267	0.0006
endow_ret	2146	0.050	0.055	89	0.070	0.079	0.0198	2.3034	0.0213
AUM [$M]	2411	2,034	723	94	17,834	8,038	15799.50	24.4858	0.0000
Panel B: Former Investor	**0**			**1**			**t-test**		
	N	**mean**	**p50**	**N**	**mean**	**p50**	**mean(1) - mean(0)**	**t-ratio**	**p-value**
commit2aum	1294	0.083	0.066	1211	0.115	0.106	0.0328	12.3329	0.0000
cash2aum	1294	0.053	0.033	1211	0.051	0.036	-0.0020	-0.9414	0.3466
alt2aum	1294	0.120	0.093	1211	0.152	0.132	0.0320	7.7273	0.0000
endow_ret	1113	0.049	0.057	1122	0.054	0.056	0.0047	1.3982	0.1622
AUM [$M]	1294	781	399	1211	4,599	1,615	3817.85	14.5538	0.0000
Panel C: MBA	**0**			**1**			**t-test**		
	N	**mean**	**p50**	**N**	**mean**	**p50**	**mean(1) - mean(0)**	**t-Ratio**	**p-value**
commit2aum	1433	0.097	0.082	1072	0.101	0.092	0.0045	1.6239	0.1045
cash2aum	1433	0.049	0.032	1072	0.056	0.040	0.0065	3.0526	0.0023
alt2aum	1433	0.137	0.106	1072	0.133	0.116	-0.0032	-0.7460	0.4557
endow_ret	1268	0.051	0.055	967	0.052	0.057	0.0010	0.2819	0.7781
AUM [$M]	1433	2,290	745	1072	3,078	812	787.72	2.8594	0.0043
Panel D: Financial License	**0**			**1**			**t-test**		
	N	**mean**	**p50**	**N**	**mean**	**p50**	**mean(1) - mean(0)**	**t-Ratio**	**p-value**
commit2aum	1831	0.093	0.081	674	0.115	0.104	0.0222	7.2550	0.0000
cash2aum	1831	0.051	0.034	674	0.056	0.037	0.0049	2.0625	0.0393
alt2aum	1831	0.134	0.108	674	0.138	0.116	0.0043	0.9082	0.3639
endow_ret	1626	0.052	0.058	609	0.050	0.050	-0.0013	-0.3419	0.7324
AUM [$M]	1831	2,129	606	674	3,980	1,236	1851.07	6.0567	0.0000

This table presents mean and median values of chosen asset allocation shares and financial information for various panels. Commitments, cash holdings and alternative holdings are provided as a share of total aum, the endowment return is provided as a relative figure with regards to the aum and the absolute aum is provided as well. Panel A splits the sample in endowments from ivy league schools and non-ivy league schools, panel B splits the sample in endowments led by former investors and non-investors, panel C splits the sample in endowments led by CIOs with an MBA and without and panel D splits the sample in endowments led by CIOs holding a financial license and those who do not. The right part of the table provides a simple mean comparison and the results of a t-test.

With this implication of qualification of the CIO on alternative asset allocation, we further investigate these initial findings in regression models in Table 6. We investigate the impact of aforementioned individual background characteristics such as educational qualification (highest degree, MBA and financial license) and previous experience in the investment industry on the asset allocation towards alternative investments. In Table 7, we continue with an analysis of having prior investor experience, having an MBA, and having a financial license (e.g., CFA) on the endowment return in the subsequent year. Appendix A provides detailed description of all variables used.

We observe significant coefficients of *investor_experience* consistently for all models in Table 6. The interpretation of the coefficient ranging from 0.0309 to 0.0380 implies a 3-4pp higher asset allocation towards alternatives when the CIO leading the university endowment has previous investor experience. These results were implied already in the mean comparison in Table 5 and are robust for our models that additionally control for private universities, ivy league universities, AUM and year-fixed effects. The results are statistically significant and economically relevant. We observe similar coefficients for the categorical variable of highest degree [Bachelor, Master, PhD]. There is significant positive correlation of having a master's-degree as opposed to having a bachelor's degree and the exposure towards alternative investments (0.0157 and 0.0305). We observe negative correlation of having a MBA and the exposure towards alternative assets, but the coefficient is not significant in model (1) when only the MBA dummy is included in the model and only becomes significant when other personal characteristics are added to the regression (model (5) & (6)). The coefficient is consistently negative, which indicates some evidence, that having an CIO leading the endowment with an MBA, correlates with less exposure towards alternatives. All models are year fixed effects regressions and controlling for additional university characteristics like asset under management, private universities, and ivy-league universities.

Table 6: Regression analysis of CIO background on alternative asset allocation

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	**alternatives/ aum**	**alternatives/ aum**	**alternatives/ aum**	**alternatives/ aum**	**alternatives/ aum**	**alternatives/ aum**
mba	-0.00403				-0.00865**	-0.0191***
	(0.00413)				(0.00412)	(0.00531)
former_investor		0.0309***			0.0334***	0.0380***
		(0.00428)			(0.00443)	(0.00483)
financial_license			0.000817		-0.00665	-0.00368
			(0.00444)		(0.00452)	(0.00450)
Reference: Bachelor						
highest degree: Master				0.0157***		0.0305***
				(0.00503)		(0.00644)
highest degree: PhD				0.00799		0.0263***
				(0.00700)		(0.00760)
private	0.0100**	0.0121***	0.00982**	0.00697	0.0129***	0.00996**

ivy	0.0129	0.00420	0.0121	0.00765	0.00603	-0.000628
aum_scaled	0.00132***	0.000781***	0.00130***	0.00142***	0.000793***	0.000899***
Constant	0.126***	0.109***	0.124***	0.116***	0.113***	0.0926***
Year FE	yes	yes	yes	yes	yes	yes
Observations	2,448	2,448	2,448	2,307	2,448	2,307
R-squared	0.034	0.054	0.034	0.038	0.056	0.069

Note: The table provides coefficients from linear regressions. The share of alternative assets to asset under management is the dependent variable in all models (1) – (6). mba, former_investor and financial_license and the highest degree are the dependent variable. mba is a dummy variable set to one when the CIO has an MBA degree, and zero otherwise. former_investor is a dummy variable set to one whenever the CIO has been active in an investment role in the past, and zero otherwise. financial_license is a dummy variable set to one when the CIO is a holder of a financial license (e.g., CPA, CFA), and zero otherwise. highest degree is a categorical variable indicating the highest degree that the respective CIO obtained: bachelor's degree is set as the reference, a master's degree and a PhD are the alternative categories. All models are year-fixed effect regressions and controlled for size by the variable aum (asset under management, scaled by 1 billion US-dollars) as well as the two dummy variables private (being a private school) and ivy (being an ivy league school). T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

We continue the analysis in investigating the effect of the same characteristics of the respective CIO on the endowment return in Table 7. We use the endowment in the subsequent year (endowment return lead 1), given the delay of investment decisions and their materialization of it. We do observe similar correlations: there is significant correlation of endowment's led by former investors and the return. The coefficients are positive and significant at the 5% level for all models indicating ~0.39pp increase in average return when CIOs with investor experience are leading the endowment. We also observe positive coefficients for higher degrees: PhDs and master's degrees have significant and positive coefficients in relation to the reference bachelor's degree. This implies that CIOs with higher educational levels, as in master's degree and PhD, correlate with ~0.5pp higher returns of the endowment. Again, all models are year fixed effects regressions and controlling for additional university characteristics like asset under management, private universities, and ivy-league universities.

Table 7: Regression analysis of CIO background on endowment return

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	**endowment return lead 1**	**endowment return lead 1**	**endowment return lead 1**	**endowment return lead 1**	**endowment return lead 1**	**endowment return lead 1**
mba	0.000961				0.000393	-0.00202
	(0.00146)				(0.00146)	(0.00174)
former_investor		0.00326**			0.00380**	0.00394**
		(0.00152)			(0.00152)	(0.00159)
financial_license			-0.00218		-0.00305*	-0.00242
			(0.00177)		(0.00176)	(0.00179)
Reference: Bachelor						
highest degree: Master				0.00477**		0.00590**
				(0.00203)		(0.00239)
highest degree: PhD				0.00416*		0.00536**

				(0.00241)		(0.00254)
private	0.00646***	0.00673***	0.00658***	0.00593***	0.00685***	0.00632***
ivy	0.00881**	0.00818**	0.00927**	0.00769**	0.00834**	0.00716*
aum_scaled	0.000190	0.000134	0.000207	0.000191	0.000145	0.000148
Year FE	yes	yes	yes	yes	yes	yes
Observations	2,183	2,183	2,183	2,048	2,183	2,048
R-squared	0.820	0.821	0.820	0.820	0.821	0.821

Note: The table provides coefficients from linear regressions. The endowment return is the dependent variable in all models (1) – (6). mba, former_investor and financial_license and the highest degree are the independent variable. mba is a dummy variable set to one when the CIO has an MBA degree, and zero otherwise. former_investor is a dummy variable set to one whenever the CIO has been active in an investment role in the past, and zero otherwise. financial_license is a dummy variable set to one when the CIO is a holder of a financial license (e.g., CPA, CFA), and zero otherwise. highest degree is a categorical variable indicating the highest degree that the respective CIO obtained: bachelor's degree is set as the reference, a master's degree and a PhD are the alternative categories. All models are year-fixed effect regressions and controlled for size by the variable aum (asset under management, scaled by 1 billion US-dollars) as well as the two dummy variables private (being a private school) and ivy (being an ivy league school). T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

The findings from Table 4 confirming existing evidence (Lerner et al. 2008) and our robust findings from Table 5, Table 6 and Table 7 suggest that a) the return of university endowments is dependent on the asset allocation especially with a positive and significant relationship of alternatives to endowment return and b) that the exposure to asset holdings and the economic success (return) is dependent on the educational and professional background of the CIO. The results suggest that former investors have a higher tendency to allocate capital towards alternative investments and tend to have a higher share in commitments in general. Since the endowment model in literature advocates exactly aforementioned tendency to hold high allocations of alternative assets to earn illiquidity premiums and exploit inefficiencies found in these illiquid markets (Dimmock et al. 2023), the question is raised whether certain CIO profiles are expected to have higher skills and are hence of higher interest for the university endowment. Specifically, are university endowments expecting certain CIO profiles to have better skill to actively manage funds and generate larger alphas (Brown et al. 2010)? To further investigate this presumption, we examine the CIO profiles around the event of replacements in the following section.

2.3.3 CIO replacement

In light of the findings from section 3.1 and 3.2, we have drawn the interim conclusion that there is statistically significant and economically relevant correlation of the asset allocation and the return of an university endowment. Especially the exposure towards alternative assets is significantly and positively correlated to return. In addition, certain CIO profiles seem to play a role since certain CIO characteristics correlate with higher alternatives exposure and subsequent higher returns. The question remains whether university endowments recognize these implications and whether therefore the likelihood of replacement is affected by these circumstances. Figure 3 shows the CIOs' characteristics over time. It provides for the university endowments the share of CIOs with previous investor experience in panel A, the share of CIOs with an MBA degree in panel B, the share of CIOs with a financial license in panel C and the share of the highest degree of the respective CIO over time in panel D. We observe stable trends in CIOs with an MBA (~40%) and those with a financial license (~75%), an increase of CIOs with investor experience from ~40% to ~55% and a slight increase of CIOs with a bachelor's degree as their highest degree, in turn accompanied by a slight reduction of CIOs with a master's degree or PhD as their highest degree.

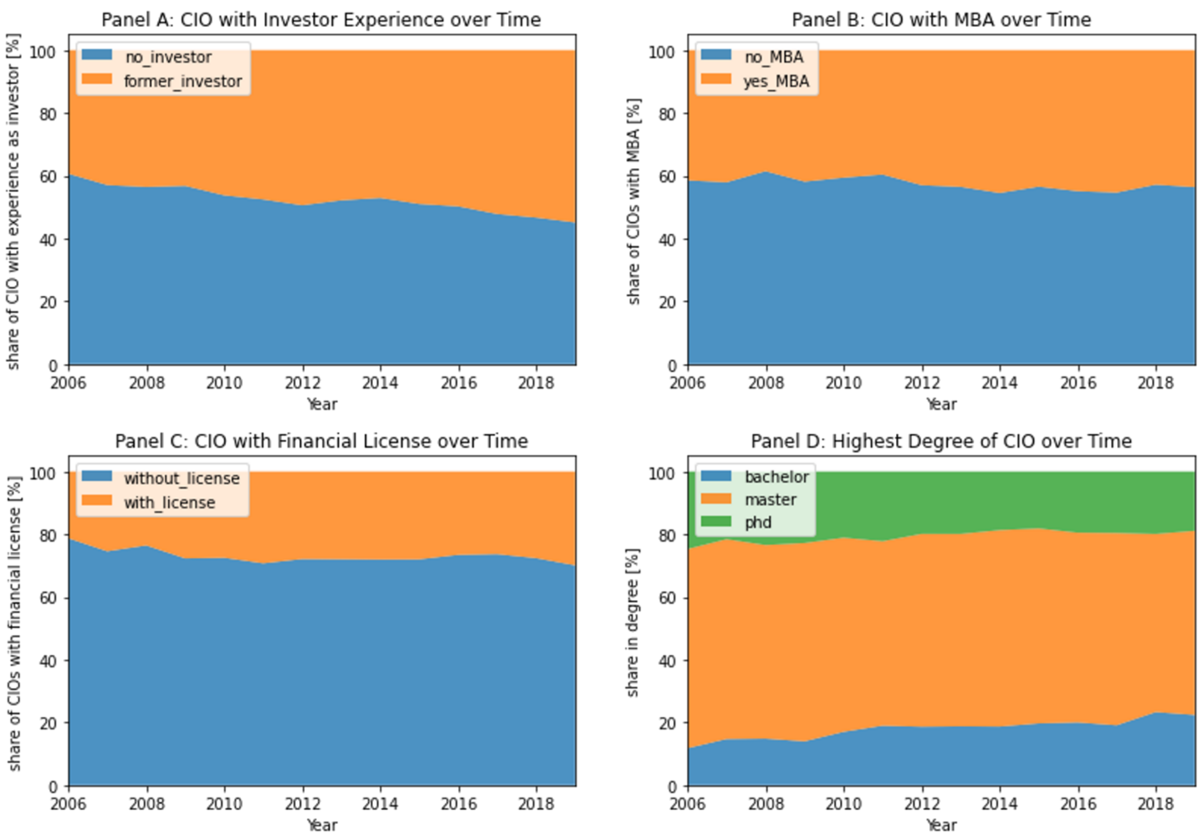

Figure 3: CIO characteristics over time

This figure depicts the CIO profile characteristics over time in four panels: Panel A shows the share in former investors over time, panel B shows the share of CIO profiles with and without an MBA degree over time, panel C shows the share of CIO profiles holding a financial license (e.g., CFA) and those profiles not holding such a financial license and panel D shows the share of highest degree for all CIO profiles. The x-axis represents the year within the observation period. The y-axis shows the share for each respective panel. In panel A, B and C, the blue shading indicates that the share for which the professional or educational background mentioned is not present. In panel D the blue shading provides the share for profiles with a bachelor's degree as their highest degree, the orange shading shows the share in respective master's degree and the green shading shows the share in CIO profiles with PhD as their highest degree.

We enhance this observation by a comparison of the CIOs' characteristics in the beginning of our observation period prior to 2008 and those characteristics towards the end of the observation period past 2016 in Table 8. We indeed see an increase by 10pp of the share in CIOs with prior investor experience, statistically significant when performing a t-test. We also see an increase in CIO profiles with an MBA (by 2pp) and of CIO profiles with a financial license by 5.7pp, of which the latter shows weak statistical significance in a t-test. These three positive developments towards a higher qualification level imply an increasing professionalization within the investment office of university endowments over time, at least with regards to their CIO's profile.

Table 8: Comparison of "Earlier" vs. "Later" CIO Profiles

Variable							
"Earlier" vs. "Later" CIO Profiles	**< 2008**		**> 2016**		**t-test**		
	N	**Mean**	**N**	**Mean**	**mean(1) - mean(0)**	**t-ratio**	**p-value**
mba	320	0.4156	619	0.4394	0.0238	0.6972	0.4858
financial license	320	0.2219	619	0.2795	0.0576	1.9095	0.0565
former investor	320	0.4344	619	0.5347	0.1004	2.9254	0.0035
Highest degree: Bachelor	282	0.1312	606	0.2162	0.0850	3.0215	0.0026
Highest degree: Master	282	0.6631	606	0.5891	-0.0740	-2.1105	0.0351
Highest degree: PhD	282	0.2057	606	0.1947	-0.0110	-0.3808	0.7034

This table provides a mean comparison of CIO profiles in the earlier period and later period of our overall observation period. The characteristics of the CIO profile are shown in the left part and the mean refers to the share in e.g., mba degree holder. On the right simple mean comparison are presented and the results of a corresponding t-test is provided. CIO profile characteristics of interest shown are MBA degree, holder of a financial license, CIOs that have been former investors, and their highest degree as in bachelor's degree, master's degree and PhD.

With these observed trends over time we proceed to examine the replacement event with a graphical analysis of the CIO replacements over time in. Figure 4 depicts the share of CIO replacements of the sample within each year. The development shows slightly cyclical replacements with an observable spike 2-3 years after the financial crisis in 2011. We assume that there is no event in a particular year that is driving CIO replacements in an unusual way and are controlling for year-fixed effects later on as well (see Appendix B).

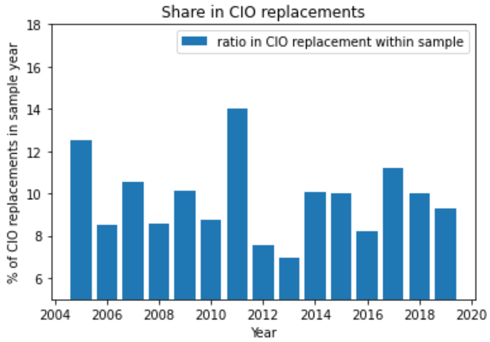

Figure 4: Share in CIO replacements of sample per year

The figure shows the share of CIOs that are replaced within our sample for each given year. The value is provided in relative terms given that we have an unbalanced sample and the number of universities observed varies across years.

While a majority of time-series total return variation is driven by market movement, some of it is driven by asset allocation and active management (Ibbotson 2010). The question arises whether CIOs make an active effort around the replacement event. Asset allocation in asset classes like private equity funds or real estate are of long-term consideration (Cumming et al. 2007). They are not necessarily immediately noticeable in the asset holdings as their monetarization from commitment, to investment, to return might take several years. Commitments and cash holdings can be influenced in the short term. Figure 5 displays the commitments (in panel A) and cash holdings (in panel B) over time relative to the CIO replacement event. The replacement line is constructed by the mean of all endowments replacing their CIO with normalized years, and the respective reference line includes the mean of all other university endowment that have not been involved in a CIO replacement within a window of a year prior and one year after the considered replacement in the given (normalized) year.

We observe a (fairly) stable level of commitments and cash to AUM of university endowments that are not replacing their CIOs. During times of regular operations, without any replacement (expected or recently occurred), there is no observable fluctuation in these investment holdings. Conversely, the lines referring to the group of universities that are replacing the CIO exhibit more fluctuation. In panel A, we observe the commitments prior to a replacement slightly below the level (or on a similar level) of the reference group and then strongly increasing after the CIO replacement. It allows for the assumption, that newly introduced CIOs want to actively engage with the portfolio they are inheriting and increase their commitments. The cash holdings exhibit two interesting observations: 2-3 years prior to the replacement event, there is a higher level of cash holdings compared to the reference group, that then decreases towards the replacement event and ~2 years after the replacement there is a stronger increase in cash holdings again (by ~1.5pp). Literature associating larger cash holdings with higher risk could explain the two observations (Bigelli and Sánchez-Vidal 2012; Acharya et al. 2012): first, CIOs that are replaced seem to have ~15% higher cash holdings, potentially stemming from an investment backlog and a pursuit of actively influencing the portfolio prior to the CIO's termination. And second, the new incoming CIO seems to be interested in building up cash reserves, investment flexibility and autonomy again.

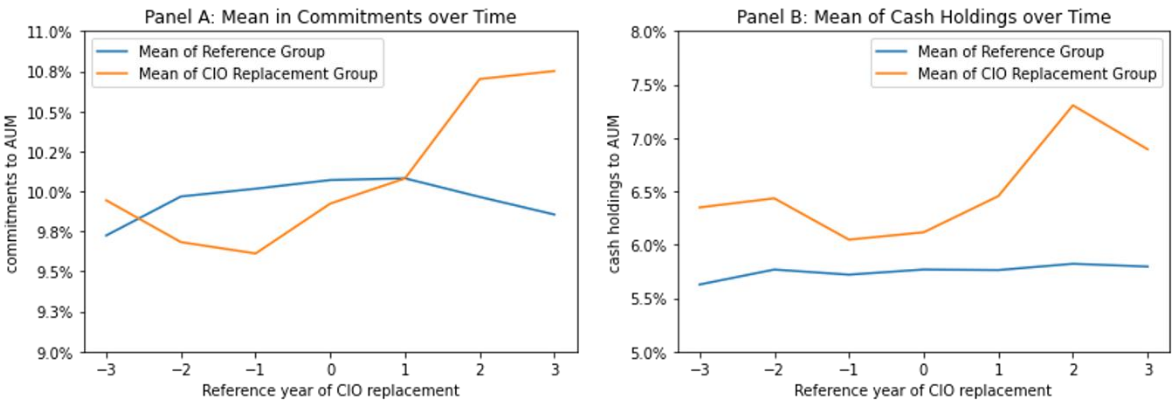

Figure 5: Commitments and cash holdings over time relative to CIO replacement

The figure shows the development of mean commitments to asset under management and mean cash holdings to asset under management and spreads around the CIO replacement event. The figure shows the time window of three years prior and past the CIO replacement and shows two lines: the mean of those university endowments in which a CIO replacement occurred (orange) and a reference mean of all university endowments that have not been involved with a CIO replacement event within a time period one year prior and year past the respective event. All observations and reference groups are normalized to the deal year.

These observation of short-term investment activities are relevant for two reasons: they indicate active decisions and contribution of the individual (CIO) towards the investment decisions and they indicate the university endowment's expectation to initiate change in investment decisions through a replacement. Both reflected in the two panels, illustrating particular dynamics around the replacement event.

In an attempt to better understand the differences of the replaced and replacing CIO's profile, Table 9 provides an overview of the CIO characteristics and average returns. The "Replaced" column refers to the last full year of the replaced CIO and the "Replacing" column refers to the first year in charge with the replacing CIO. Consistent with our hypothesis, the share of CIOs with investor experience (former investors) increases by 16.76pp from a 40% share in replaced CIOs to 57% in the replacing CIOs. The results of the t-test showed a significant difference between the replaced CIO profiles and replacing CIO profiles ($t = 3.3498$, $p < 0.01$). Similarly, yet not statistically significant using a t-test, the share of CIO profiles with an MBA increases by ~4pp and those with a financial license increases by ~5pp. The consideration of the endowment return is most vivid when considering "endowment return lag1" of the replaced CIO profile with "endowment return" of the replacing CIO. "endowment return lag 1" in this sense refers to the year prior to the last full year in which the replaced CIO was in charge and the "endowment return" of the replacing year is the first year in which the replacing CIO is in charge. The mean return in this consideration increases from 3.4% to 5.2%. An underperformance in realized returns could potentially be a driver to have the CIO replaced.

Table 9: Comparison of Replaced vs. Replacing CIO Profiles

Variable Replaced vs. Replacing CIO	Replaced		Replacing		t-test		
	N	Mean	N	Mean	mean(1) - mean(0)	t-ratio	p-value
endowment return	172	0.0526	203	0.0523	-0.0003	-0.0309	0.9753
endowment return lag 1	156	0.0340					
mba	187	0.3797	204	0.4167	0.0370	0.7447	0.4569
financial license	187	0.1979	204	0.2500	0.0521	1.2324	0.2185
former investor	187	0.4011	204	0.5686	0.1676	3.3498	0.0009
Highest degree: Bachelor	177	0.1299	202	0.1782	0.0483	1.2927	0.1969
Highest degree: Master	177	0.5763	202	0.5545	-0.0218	-0.4263	0.6701
Highest degree: PhD	177	0.2938	202	0.2673	-0.0265	-0.5713	0.5681

This table provides a mean comparison of CIO profiles that are replaced with those CIO profiles that are replacing for our observation period. The characteristics of the CIO profile are shown in the left part and the mean refer to the share in e.g., mba degree holder. The upper part shows the endowment return and the endowment return in the year before (lagged by one year), both relative values in relation to overall aum. *Replaced* refers to the last full year in which the CIO was in charge that is then replaced and shows the average CIO profile of the CIO that is replaced. *Replacing* refers to the year in which the replacement is conducted and hence shows the average CIO profile of the replacing, the incoming CIO. On the right simple mean comparison are presented and the results of a corresponding t-test is provided. CIO profile characteristics of interest shown are MBA degree, holder of a financial license, CIOs that have been former investors, and their highest degree as in bachelor's degree, master's degree and PhD.

This leads us to ask how educational characteristics of CIOs impact the replacement and what drivers of a replacement are. To predict which CIO characteristics have an influence on the replacement event, we estimate a linear probability regression model using our university endowment-year observations following recent studies (Cohn et al. 2022b). These probability panel regressions on the CIO replacement event can be found in Table 10 and Table 11. In Table 10, we ran several models to first investigate, which variables drive CIO replacements individually (models 1-4) and then control for additional endowment and individual characteristics (models 5-11). The dependent variable *prior_replacement,* is an indicator variable equal to one if an endowment is replacing the CIO in the following year, and zero otherwise. The models include university fixed effects, model 10 and 11 also include year fixed effects respectively. We begin with basic specification in the first five models (1) – (4) with endowment return as well as educational and professional characteristics of the CIO as explanatory variables. If university endowments are motivated by (short-term) performance and consider high-skilled CIOs as (more) sophisticated investors, then we expect negative coefficients to show, that the likelihood of a replacement event decreases. Indeed, we observe significant coefficients for the endowment return in the previous year, the previous investor experience, the MBA degree and financial license holder in models (1) – (4). By the direction of the coefficient (-0.197) in model (1), the result implies that higher endowment returns in the previous years are inversely correlated with the probability of a replacement event. In other words, lower returns in the previous year are associated with a higher tendency for a CIO replacement in the following year. The results from model (2) – (4) allow for similar interpretation: highly qualified CIOs with former investor experience, an MBA or a financial license have a lower inclination to be replaced. Their coefficients of -0.262, -0.0875 and -0.137 (model (2) – (4)) are all negatively correlated with the *prior_replacement* variable and statistically significant at the 1%-level. The coefficients for former investor experience and financial license holder are still significant and negative when controlling for asset under management (size), private universities, individual characteristics like highest degree and gender, investment environment (S&P 500) as well as year-fixed effects and university-fixed effects in models (5) – (11). The coefficient for an MBA remains negative throughout all models, but is significant only in model (3) (-0.0875) and model (9) (-0.0546). Hence, the experience of former investors and having a financial license are CIO characteristics, that are statistically significant and economically relevant for the replacement event. There are strong indications, that the same holds true for an MBA degree, but the statistical significance is less profound.

The significance of the coefficient of the endowment return of the previous year's return remains at the 1%-level in models (7) – (9) but disappears when adding year-fixed effects in models (10) & (11). However, the negative orientation of the coefficient remains, which strengthens the economic view, that lower returns increase the probability of a CIO replacement. In line with our assumptions from the mean consideration of Table 9, we conclude that CIOs with higher qualification and experience levels in the form of previous investor experience, financial license and to an extent an MBA degree are less likely to be replaced.

The dependent variable *cio_replacement* in Table 11, is an indicator variable for the first year of the replacing CIO. It is equal to one if in this year the endowment has replaced the CIO with a new CIO, and zero otherwise. The CIO characteristics of the replacing ("new") CIO are therfore displayed when this variable is set to 1. We run six different models and include the main variable of interest: *former_investor*, *mba* and *financial_license*. In addition we add the variable *inv_years* to further test on the relevance of years served as an investor. While we observed that highly qualified CIOs are less likely to be replaced, we find in the models in Table 11 that most relevant for the replacing CIO profile seems to be the former investor experience. The coefficient for being a former investor is positive and statistically significant for all models

(0.0622, 0.122, 0.134 and 0.790). We also test for overall years in investor occupation (inv_*years*), which also obtains significantly positive results in model (3) (0.0066) and model (5) (0.00720). Our results imply, that not only having some sort of investor experience is correlated with being a replacing CIO during a replacement event, but also the years of investor experience are positively and statistically significantly correlated with being a replacing CIO profile. The coefficients of an MBA degree and a financial license are not consistent and not statistically significant to an extent that would allow for robust interpretations. We do control for commitments, cash holdings and alternative holdings in the models in Table 10 and Table 11 to isolate the effect of the CIO profile given the movements we observed in Figure 5 around the replacement event.

In addition to these two types of regression models (Table 10 and Table 11), we ran a logistic regression of year-dummies on CIO replacement to investigate whether a particular year is driving the replacement and observe no significant coefficient indicating no significant effect of a particular year on the CIO replacement event (see Appendix B).

Table 10: Panel regression on year prior to CIO replacement

Dependent Variable						**prior_replacement**					
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
endow_ret_lag1	-0.197**				-0.202**		-0.225***	-0.228***	-0.238***	-0.0661	-0.0661
	(0.0816)				(0.0816)		(0.0827)	(0.0827)	(0.0848)	(0.230)	(0.230)
former_investor		-0.262***			-0.177***			-0.177***	-0.170***	-0.169***	-0.169***
		(0.0276)			(0.0383)			(0.0384)	(0.0389)	(0.0405)	(0.0405)
mba			-0.0875***		-0.0448			-0.0454	-0.0546*	-0.0441	-0.0441
			(0.0248)		(0.0299)			(0.0299)	(0.0303)	(0.0356)	(0.0356)
financial_license				-0.137***	-0.0717*			-0.0708*	-0.0713*	-0.0677*	-0.0677*
				(0.0315)	(0.0383)			(0.0383)	(0.0383)	(0.0407)	(0.0407)
gender					0.0257			0.0310	0.0277	0.0390	0.0390
					(0.0319)			(0.0322)	(0.0323)	(0.0344)	(0.0344)
Reference: Bachelor's degree											
Highest degree: Master										-0.0125	-0.0125
Highest degree: PhD										-0.0370	-0.0370
commit2aum_lag1						-0.236	-0.332**	-0.325**	-0.320*	-0.351**	-0.351**
						(0.147)	(0.165)	(0.165)	(0.173)	(0.179)	(0.179)
cash2aum_lag1						-0.176	-0.252	-0.0960	-0.0388	-0.0298	-0.0298
						(0.199)	(0.226)	(0.225)	(0.230)	(0.231)	(0.231)
alt2aum_lag1						0.108	0.172	0.0590	0.0746	0.0881	0.0881
						(0.0979)	(0.115)	(0.116)	(0.118)	(0.120)	(0.120)
aum_scaled					0.00247			0.00213	0.00206	0.00293	0.00293
private									0.0138	0.0354	0.0354
return_sp500											-0.000407
Uni.-fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	no	no	no	no	no	no	no	no	no	yes	yes
R-squared	0.004	0.009	0.026	0.002	0.008	0.042	0.006	0.029	0.029	0.032	0.032
Number of unameid	217	217	204	213	208	217	208	204	203	201	201

Note: The table provides coefficients from linear panel regressions. *prior_replacement* is the dependent variable and a dummy variable equal to one for the last full year before the replacement and zero otherwise. mba, former_investor and financial_license and the highest degree are the independent variable. mba is a dummy variable set to one when the CIO has an MBA degree, and zero otherwise. former_investor is a dummy variable set to one whenever the CIO has been active in an investment role in the past, and zero otherwise. financial_license is a dummy variable set to one when the CIO is a holder of a financial license (e.g., CPA, CFA), and zero otherwise. *gender* is a dummy control variable equal to one for male and zero for female CIOs. highest degree is a categorical variable indicating the highest degree that the respective CIO obtained: bachelor's degree is set as the reference, master's and a PhD. Models (6) – (11) control for commitments in the previous year, cash holdings in the previous year and alternatives allocation in the previous year. All models are university-fixed effect regressions, models (10) and (11) are also year-fixed effect regressions and some models control for size (asset under management, scaled by factor 1 billion US-dollars) as well as the two dummy variables private (being a private school) and ivy (being an ivy league school). T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

Table 11: Panel regression on CIO replacement year

Dependent Variable			cio_replacement			
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
endow_ret_lag2					-0.0179	-0.0668
					(0.311)	(0.238)
endow_ret_lag1			0.00478	-0.0748		
			(0.306)	(0.226)		
inv_years			0.00659***		0.00720***	
			(0.00252)		(0.00273)	
former_investor	0.0622**	0.122***		0.134***		0.0790*
	(0.0261)	(0.0288)		(0.0381)		(0.0436)
mba	-0.0188	-0.0125	0.0711	0.00782	0.112**	0.0311
	(0.0224)	(0.0228)	(0.0524)	(0.0325)	(0.0564)	(0.0364)
financial_license	-0.00523	0.0118	-0.0615	0.00738	-0.0817	0.00166
	(0.0288)	(0.0295)	(0.0515)	(0.0373)	(0.0540)	(0.0400)
gender_y		0.00787				
		(0.0245)				
Reference: Bachelor's degree						
Highest degree: Master			-0.110	-0.0464	-0.140*	-0.0786
Highest degree: PhD			-0.0632	-0.00304	-0.0921	-0.0764
commit2aum_lag1			0.203	-0.120	0.0668	-0.171
			(0.240)	(0.168)	(0.260)	(0.191)
cash2aum_lag1			-0.248	-0.296	-0.370	-0.412*
			(0.332)	(0.215)	(0.356)	(0.236)
alt2aum_lag1			0.233	0.124	0.384**	0.225*
			(0.149)	(0.111)	(0.164)	(0.129)
aum scaled		-0.00190	-0.00179	-0.00414	0.00322	0.00114
private		-0.108	-0.431	-0.121	-0.420	-0.131
return_sp500			-0.0126**	-0.00402	-0.00800***	-0.00277
Uni.-fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	no	no	yes	yes	yes	yes
R-squared	0.003	0.009	0.043	0.019	0.053	0.018
Number of unameid	225	221	122	206	119	203

Note: The table provides coefficients from linear panel regressions. *cio_replacement* is the dependent variable and a dummy variable equal to one for the year of the replacement and zero otherwise. *mba*, *former_investor*, *inv_years* and *financial_license* and the highest degree are the independent variable. mba is a dummy variable set to one when the CIO has an MBA degree, and zero otherwise. *former_investor* is a dummy variable set to one whenever the CIO has been active in an investment role in the past, and zero otherwise. *inv_years* is a variable expressing the count in years occupied as an investor prior to the university role. *financial_license* is a dummy variable set to one when the CIO is a holder of a financial license (e.g., CPA, CFA), and zero otherwise. *gender* is a dummy control variable equal to one for male and zero for female CIOs. highest degree is a categorical variable indicating the highest degree that the respective CIO obtained: bachelor's degree is set as the reference, master's and a PhD. All models are university-fixed effect regressions, models (3) – (6) are also year-fixed effect regressions and control for commitments in the previous year, cash holdings in the previous year and alternatives allocation in the previous year. Some models control for size (asset under management, scaled by factor 1 billion US-dollars) as well as the two dummy variables private (being a private school) and ivy (being an ivy league school). T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

In essence, we can conclude, that the CIO's past experience like being an investor, having an MBA or holding a financial license does have an impact on the asset allocation and the exposure towards alternative assets. Our results also imply a relation with the subsequent return within the university endowment and the CIO's characteristic of being a former investor. Endowment's seem to retain CIOs of assumingly higher qualification (expressed by former investor, MBA and financial license) and are more likely to higher CIOs with professional experience in the investment industry. There seems to be a desire to recruit or retain such individuals who signal expertise to the endowment organization (Connelly et al. 2011). To investigate this assumed ambition, we illustrated two types of plots in Figure 6. We have only included years in which the number of observations exceeded n = 100 per year. The upper plots show the upper and lower quartile university endowments by averaged return over the sample period. The lower plots show the upper and lower quartile of university endowments with regards to the average size (asset under management) over the sample period. Panel A in the left plots show the share of CIOs that have had investor experience in the past, the middle plots in panel B provide the share of CIOs being financial license holder, and panel C in the right plots show the share of CIOs with an MBA. The better performing university endowments seem to have a higher share of MBA holders and CIOs with prior investor experience. Similarly, the largest university endowments have a higher share in more professional CIO profiles as well: the gap is most pronounced considering the share in previous investors. While ~80% of the largest quartile university endowments have a CIO with prior investment experience, only ~10-40% of smallest quartile have CIOs with prior investment experience. A similar tendency is observable for financial license holder and partially for the share of MBA within the sample period. Interestingly, this observed professionalism gap is closing towards more recent year (see the graph of former investors in panel A and the respective share for both size and return distinction). The trend of a further professionalization in the role of the CIO offices is continuing. After decades and adaption of the “Yale-Model” across (larger) university endowments (Barber and Wang 2013; Swensen 2009), we observe indication for the professionalization in CIO profiles in replacement events and CIO’s impact on alternative asset allocation and successive return. This indication of CIO professionalization might be further exploited by more endowments as indicated in the development graphs of Figure 6.

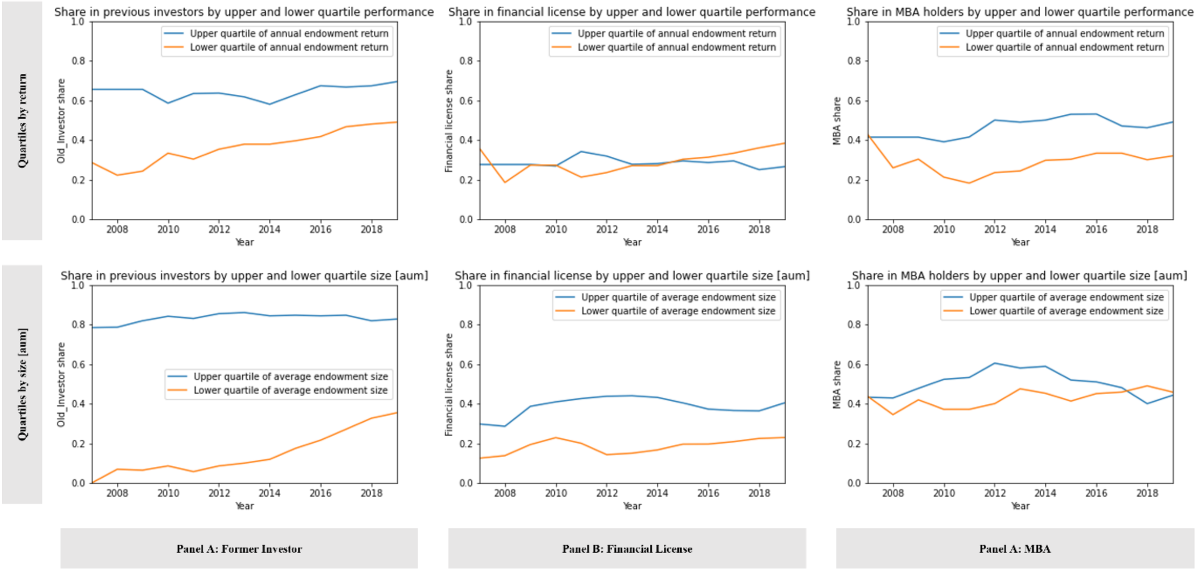

Figure 6: Development of CIO's educational/professional experience over time

The graphs show the development of a qualification/experience share in CIO profiles over time. The upper three graphs distinguish between the upper quartile (blue) and lower quartile (orange) of university endowment CIOs based on the average annual endowment return within the sample period. The lower three graphs distinguish between the upper quartile (blue) and lower quartile (orange) of university endowment CIOs with regards to the average endowment size over the sample period measured by asset under management. The left two graphs (panel A) provide the share in CIOs that have been investors in their previous roles over time. Panel B in the middle two graphs provide the share of CIOs that are holder of a financial license (e.g., CFA, CPA) over time. The right two graphs of panel C provide the share of CIOs that are MBA holder over time. We included only year observations in which the n of university endowment observations is larger than 100.

2.4 Conclusion

This paper investigates the organizational setup of the CIO office at university endowments and their corresponding asset allocation. Using financial data from US university endowments, our evidence suggests that the profile, past education and past experience of a CIO influences the way how assets are allocated within a university endowments, especially their exposure towards alternative asset classes. After establishing and confirming the historic academic evidence of "the endowment model", we widen our research towards the contribution and impact of the individual CIO on asset allocation and return. CIOs with previous investment experience have a higher tendency to allocate capital towards alternative asset classes. Our findings validate the research on "the endowment model", stating that larger shares in alternatives generally correspond with larger returns and add that such endowments led by CIOs with former investor experience not only allocate more share of their investments towards alternative assets but also exhibit higher returns for the endowment.

We then further provide evidence that CIOs of higher qualification as in being an MBA holder, a financial license holder and/or a previous investor are less likely to be replaced in the event of a CIO replacement. CIOs that have had investment experience in the past are even more likely to be hired during a CIO replacement event. While we do not find immediate evidence, that assumingly higher qualified CIO profiles lead to higher returns in general, we do find some evidence that certain profiles are more prone to certain asset classes and former investors as CIOs correlate with greater returns. Our results suggest that the educational and professional background is not equal to superior skill in the investment decision perse. However, it signals superior skill in that sense, that university endowments are more patient with and less likely to replace CIOs of higher qualification. Our descriptive findings further suggest, that successful university endowments have a higher share of more professional CIOs and that larger university endowments seem to have a better access to higher qualified CIOs.

Overall, our analysis of university endowment and their CIOs highlights important relations within the qualification of CIOs, its signaling effect on the endowment organization and the investment decision and asset allocation. The individual CIO does have, statistically significant and economically relevant, an impact on the asset allocation and thereby the return in the investigated investment organization.

3 Cutting through the ESG Nonsense: Relevance of Sustainability Criteria in Limited Partners' Investment Decision

Abstract

The investment industry widely discusses the need to report and improve Environmental, Social and Governmental (ESG) criteria to investors, especially in private equity (PE). Regulatory incentive and pressure are rising by initiatives like the Inflation Reduction Act (IRA) in the US or the EU's Sustainable Finance Disclosure Regulation (SFDR). However, the relevance of the criteria in the ultimate investment decision of investing in PE funds remains to be discovered. Using conjoint analysis based on a sample of 140 global limited partners, we investigate how conventional and sustainability investment criteria of a PE fund drive their investment decision. Our research suggests that EU SFDR article compliance, a CO2 reduction target on the portfolio and a conditional sustainability carry are essential attributes in the LPs investment decision. Further, we explore how the preferences vary across regions and across different LP types and we find that LPs, when self-committed ESG signatories have a higher tendency towards sustainability criteria.

Keywords: Private equity, ESG, Conjoint analysis, Investment criteria

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3.1 Introduction

Fundraising dropped in 2022 in the private equity (PE) industry both in capital raised (by ~$60B) and counts of funds closed (by ~150 funds) (Bain & Company 2023). PE firms need to adapt to new market environment with ~15% less capital investments in H1 2022 by PE firms in Europe compared to the same period in 2021 (Invest Europe 2022). At the same time the momentum slows after years of constant increase in allocations to private equity, more limited partners (LPs) signal to invest less in the next 12 months (7% to 21% increase) (PEI 2023). Several drivers include high inflation, rising interest rates, the record amount of dry powder and recession in core markets (PEI 2023). In addition, according to the perspectives of PEI, only 5% of LPs rate the GP’s ESG performance as ‘excellent’ (PEI 2023). In response to both, to become more attractive and competitive in fundraising as well as driving ESG initiatives, private equity funds are exploring novel fund models like impact funds or funds with ESG criteria. With this research, we aim to shed light into the “ESG-nonsense” (famously tweeted by Elon Musk) and elaborate on very concrete investment criteria to operationalize ESG approaches in private equity funds. While the study was conducted in Munich, Europe, we have a sufficient respondent rate from North America and globally as well. Our motivation stems from several strands of the literature (Broccardo et al. 2022; Kölbel et al. 2020; Berk and van Binsbergen 2022). Broccardo et al. show, that if the majority of investors are even slightly socially responsible, voice achieves the socially optimal outcome while in contrast, exits do not unless all investors are significantly socially responsible (Broccardo et al. 2022). Kölbel et al. suggest, that investors seeking impact should pursue shareholder engagement throughout their portfolio and allocate capital to sustainable companies that are struggling with growth restrictions through external financing conditions. At the same time, companies with the absence of specific ESG practices that can be adopted at reasonable costs should be screened out (Kölbel et al. 2020). Similarly, Berk and van Binsbergen claim that socially conscious investors should invest and exercise their rights of control to change corporate police to have impact instead of divesting (Berk and van Binsbergen 2022). Hence, this research paper is elaborating on how private equity funds can serve as such a vehicle and operationalize relevant sustainability criteria according to their LPs preferences.

We conduct a conjoint analysis to obtain 8,400 observations from 2,100 decisions made by 140 LPs. We will first elaborate on the theoretical background of private equity value creation, the limited partner and general partner relationship, and sustainability in finance theory. The intention is to raise awareness why and how private equity could serve as a vehicle to enable sustainable financing. Based on this foundation, sustainability attributes are derived that are then used in the conjoint study. The study's methodology is described in chapter 3 including a discussion of the data and sample, descriptive statistics, the experimental design and the variables used. The last part focuses on the analysis and results (chapter 4) and a discussion and limitation part in chapter 5. Thereby, this paper is contributing to the private equity literature in two ways. First, it is extending the conjoint study methodology into the private equity research field. To the best of our knowledge, there has been no limited partner study conducted using conjoint to investigate the decision behavior of limited partners when investing into private equity funds. Similar studies in this research field have considered the investment decision into target companies (Block et al. 2019), but we are the first ones to study the limited partner's perspective into fund selection. Secondly, we extend existing literature of investment criteria in private equity (Da Rin and Phalippou 2017; Loos and Schwetzler 2017; Gompers and Lerner 1999). We elaborate on the rising importance of sustainability investment criteria and how they could operationalize in the future. We find, that complying with EU SFDR article compliance, incentivizing with a sustainability carry, having a CO2 reduction target and having a sustainability expert in the fund team can have an effect on limited partner's investment decision. We also find, that having a CO2 reduction target on the fund is more important for insurance companies than for family offices, it is also more important for self-committed ESG signatories, and that American limited partners attribute higher importance to a sustainable carry incentive LPs while being less prone for a higher share of conditional sustainability carry than European LPs.

3.2 Theoretical background

In order to understand the mechanism behind sustainability operationalization within private equity, we first establish an understanding of value generation through private equity companies as well as the relationship of LPs and GPs. Subchapter 2.3 elaborates on ESG and sustainability theoretical background within the finance context. All of these subchapters serve as a basis for derivation of the relevant attributes in subchapter 2.4, that we will use in our further study.

3.2.1 PE value generation

In the current market environment, the PE industry could be well-equipped to cope with the rising need for a sustainable transformation of the entire asset class. While critics argue that private equity firms take advantage of tax breaks and superior information and do not create operational value, proponents of leveraged buyouts argue in favor of operational value creation (Jensen 1989, revised 1997; Kaplan and Strömberg 2009; Puche et al. 2015). According to the views of those supporting PE's value creation, the private equity industry applies financial, governance, and operational engineering to their portfolio companies, thereby improving their operations while contributing to economic value generation (Kaplan and Strömberg 2009).

First, according to Jensen (Jensen 1989, revised 1997), PE can improve the operational efficiency of firms by closely monitoring and steering a portfolio company's management. PE firms reduce potential conflict between owners and managers concerning corporate resources by incentivizing the top management. In most cases, management teams are strongly incentivized through equity shares and stock options and sometimes even required to make a meaningful investment in the company (Jensen 1989, revised 1997; Kaplan 1989).

Second, the literature says that the leverage component is a distinct characteristic in private equity driving how to invest. Borrowing money being strictly done in connection with the transaction in leveraged buyouts is restricting the free cash flow for the managers due to interest and principal payments. According to Jensen, companies only operate efficiently and create shareholder value when free cash flow is distributed to shareholders (or creditors) rather than retained (Bernstein et al. 2017; Jensen 1989, revised 1997).

Third, private equity firms change how they control their portfolio companies' boards and are more actively involved. Through closely steered governance, they operate smaller boards that meet and align more frequently than public peers (Kaplan and Strömberg 2009; Cornelli and Karakas 2008; Gertner and Kaplan 1996).

These allegedly superior characteristics of PE-backed firms could have a real tangible impact on the operational performance of companies. Supporting this assumption, Kaplan and Strömberg suggest that the empirical evidence on the operating performance of companies after an LBO is mainly positive. Driving this, operational performance improves due to increases in operating incomes, decreases in capital expenditures, and increases in net cash flows (Kaplan and Strömberg 2009; Kaplan 1989). Amongst other studies, Lichtenberg and Siegel find that total factor productivity increases above industry mean and unique plant productivities increase after a buyout (Lichtenberg and Siegel 1990). In addition, Lerner, Sorensen, and Strömberg suggest that LBO firms tend to become more innovation-focused: Patents are more cited, there is no shift in fundamental research orientation or sacrifices in long-term growth for short-term performances (Lerner et al. 2011).

Following the results of Berk and van Binsbergen and assuming that "to have an impact, instead of divesting, investors should invest and exercise their rights of control to change corporate policy" (Berk and van Binsbergen 2022), private equity could be a suitable vehicle to drive financial, governance and operational changes towards more sustainable companies.

3.2.2 LP/GP relationship

Yet, the PE market is characterized by high information asymmetry (Balboa and Martí 2005). Even though academics argue that agency costs between fund managers (GPs) and investors (LPs) are reduced compared to public cooperations, it is still existing (Jensen 1989, revised 1997; Kaplan 1989). The agency relationship is orchestrated by a management contract that specifies the compensation of the GPs, the GP's investment in the fund, and a range of other investment parameters like investment scope. These contracts are highly important given that investing in private equity involves long-term financial commitments of typically up to 13 years. LPs can hardly impact the governance mechanisms outside the management contract once the fund is closed. The management contract also outlines the formalities between the relationship of compensation and ownership with the fund performance (Robinson and Sensoy 2013; Cumming and Johan 2014). In order to assess the quality of a private equity fund, LPs must understand GP behavior and performance. Given the characteristics of high information asymmetries and that LPs vary in their sophistication, performance, and investment objectives, the overall performance and success of LPs is heterogeneous (Lerner et al. 2007).

Compared to other significant literature streams in PE dealing with macroeconomic importance, the performance of the industry or the selection process by fund managers themselves, the research about the dedicated investment criteria of LPs prior to a commitment to a PE fund is relatively scarce (Loos and Schwetzler 2017; Da Rin and Phalippou 2017; Gompers and Lerner 1999). Despite its importance, some authors point out the need for known systematic evidence on how institutional investors select private equity funds (Goyal et al. 2021).

There are two approaches in literature to circumscribe and explore investment criteria of limited partners: studies looking into drivers of fundraising and a strand of literature examining LP investment criteria in their genuine sense.

In their study and based on existing literature, Gompers and Lerner (1999) find that track record and fund performance are essential determinants for private equity firms to raise a next fund. They find that historical performance is a good indicator of the ability to raise a follow-on fund. While their study focusses on venture capital fundraising, this is equally plausible in the PE environment as a similar effect was also shown for capital flows into mutual funds (Gompers and Lerner 1999; Grinblatt et al. 1995). Kaplan and Schoar reaffirm this finding and add that GPs with higher performance are more likely to raise considerable following funds (Kaplan and Schoar 2005). In this context, IPOs are usually considered a very profitable means to exit an investment. Loos and Schwetzler confirm and complement this finding by ascertain that a higher share of IPO exits increases the fundraising likelihood and volume (Loos and Schwetzler 2017). Since there are sometimes no or limited references about past returns in private equity funds (e.g., developing private equity markets, first time funds), the reputation of such fund managers is also used as a signal to overcome information symmetries in this principal-agent constellation. Balboa and Marti find that additional factors influence a GP's reputation: the total investment volume, the ratio of investments per investment manager, or the membership of the national private equity association (Balboa and Martí 2005).

The strand of literature examining LP investment criteria in their actual sense, is typically referred to as "GP selection", "manager selection," or "investment criteria" by authors. Generally, the management team and improvement of operation performance are the main criterion limited partners are looking for in the selection of GPs (Kaplan and Strömberg 2009).

But also the compensation is closely tied to the GP selection (Mathonet and Meyer 2007). Da Rin and Phalippou studied LP investment criteria through a comprehensive and global survey with 249 complete responses from 30 countries. Their results for fund selection criteria suggest that, smaller LPs give a significantly higher score to the importance of commitments by other LPs, smaller LPs also give more importance to advisor and gatekeeper opinion of the GP, past performance (IRR or multiple) with the highest importance as selection criteria, and that larger LPs give a significantly higher score to the importance of fund-size and the valuation of unrealized investments (Da Rin and Phalippou 2017). Ultimately, contracts (limited partnership agreements) between the GPs and LPs address various agency issues. They are designed to best align their interest through a profit-sharing agreement (carried interest), closed-end fund structure, limited reinvestments, and explicit negative covenants preventing GPs from diverting from their strategic investment alignment or excessive risk (Metrick and Yasuda 2011).

3.2.3 Sustainable entrepreneurship, sustainable investing and investor's perspective

There has been numerous research in and an increasing number of literature reviews on sustainable entrepreneurship and ESG investing in the past with the topic being "perhaps the most prominent topic of our time" for at least two decades now (Anand et al. 2021; Shepherd and Patzelt 2011). Shepherd and Patzelt define „Sustainable Entrepreneurship" quite broadly as being "focused on the preservation of nature, life support, and community in the pursuit of perceived opportunities to bring into existence future products, processes, and services for gain, where gain is broadly construed to include economic and non-economic gains to individuals, the economy, and society." (Shepherd and Patzelt 2011). In line with this broad definition, sustainable investing is an investment approach considering environmental, social and governance (ESG) objectives beyond the financial criteria (Pástor et al. 2021).

The question arises which implication this has on investors. As capital market players invest more capital into sustainable and socially responsible endeavors, it is crucial to understand whether such investments reflect investors' preferences within the market. Hartzmark and Sussman have presented causal evidence of market-wide investors valuing sustainability. Their results suggest that sustainability positively predicts future performance (Hartzmark and Sussman 2019). High sustainability companies, as in corporations that voluntarily adopted sustainability policies, might outperform their low sustainability companies, that have adopted almost no sustainability policies. Their outperformance refers to their long-term stock market and accounting performance and differs among sectors. It is stronger in industries with individual consumers as their customers are more sensitive to the company's public perception as opposed to a business-to-business setup, given the stronger competition based on brand and reputation (Eccles et al. 2014). Green assets can generally outperform their brown peers with good performance of the ESG factors and thereby capture customers potentially shifting in customers' tastes for green products and investors' appetite for green holdings (Pástor et al. 2021). However, this trend seems to become increasingly present within the business-to-business relationships as well. Investors are increasingly affected by this trend and seemingly have a substantial willingness-to-pay for sustainable investments. They do not pay significantly more for more impact, suggesting that this willingness-to-pay stems primarily from an emotional as opposed to a calculative valuation of impact (Heeb et al. 2023).

In addition, the question may be raised whether sustainable investing is also beneficial for investors with regard to their main interest: financial returns of green assets. Investors demand compensation for their exposure to carbon emission risks. Literature finds that stocks of firms with higher total carbon dioxide emissions earn higher returns. Some institutional investors have implemented exclusionary screening based on direct emission intensity, but only in specific industries (Bolton and Kacperczyk 2021). Bolton and Kacperczyk suggest three hypotheses for this carbon emission pricing. Firstly, carbon emissions could be perceived as a systematic risk factor if regulatory interventions are introduced. Secondly, financial markets are failing to price carbon risk efficiently, underpricing carbon emissions. Many investors may need to fully integrate the risk associated with carbon since they tend to focus on projected cash flows based on their local perspective, thereby disregarding information about global warming and the related risks. Third, stocks of companies with high emissions are similar to other "sin stocks" that ESG investors avoid to such a degree that the rejected firms often offer higher returns on their stocks (Bolton and Kacperczyk 2021). But ex-post analysis shows that impact driven investors are willing to accept lower financial return in exchange for non-pecuniary benefits (Barber et al. 2021). Kölbel et al. identified two mechanisms driving how capital allocation of sustainable investors might be influenced: by creating incentives to improve ESG practices and affecting the growth opportunity (Kölbel et al. 2020). They even suggest that investors pool their shareholder rights with like-minded investors to increase their influence and outsource the engagement mandate to specialized firms. This implicitly suggests a financial vehicle like in private equity: investors can pool their shareholder rights with like-minded investors in a fund, with the fund having the mandate to engage in a way that is specialized on sustainability if done in the "right" way.

Like-minded investors can stem from various aggregations of investors. One of such aggregation is the commitment to ESG initiatives such as becoming a UN PRI signatory (PRI 2022), the science based targets initiative (SBTi) or alike. Participating in such thematic initiatives is an approach for companies to signal (a change in) their business conduct (Zerbini 2017). Those firms may be motivated to do so to positively affect their legitimacy (Weaver et al. 1999). However, the signatory and commitment to such initiatives principles is voluntary and the resulting actions vague. First studies show, that after committing to such initiatives, signatories integrate environmental, social, and governance criteria in their business activities significantly more than matched non-signatories from the financial sector (Bauckloh et al. 2021). Types of investment firms also differ in their public perception. Institutional investors are more exposed to public scrutiny concerning the environmental and social impact of their investments. Socially responsible investing has therefore gained momentum within institutional investors like pension funds (Cox et al. 2008; Boermans and Galema 2019). With fundraising being different across countries, the implication of regional differences across limited partners is apparent as well. Government policies, level of sophistication, differences in disclosure and reputation might differ across countries (Jeng and Wells 2000). In brief summary, considerations such as regional differences, investor type differences (e.g., institutional vs. family firms), or different tendencies towards ESG commitments could have implications of investment preferences of limited partners.

3.2.4 Attribute relevance

We proceeded in two activities to better understand which factors drive the willingness to invest in private equity funds and which are valued by the investors (limited partners). We derived a list of possible investment criteria from prior research (e.g., (Kaplan and Strömberg 2009; Lerner et al. 2011; Metrick and Yasuda 2011) and conducted expert interviews with limited partners of various types (e.g., fund-of-funds, pension funds, family offices). The following subsection will elaborate on the investment characteristics, that we will further look in to: performance of previous funds, CO2 reduction target on portfolio, sustainability experts, EU article compliance, management fee, and carry at risk.

3.2.4.1 Performance of previous funds

The likelihood of raising a follow-on fund as well as the size of the follow-on fund is dependent on the current or past performance (Chung et al. 2012). The reason is, that a previous fund's performance and track record heavily influence capital flows to the fund (Kaplan and

Schoar 2005). In fact, both the performance of an existing fund and performance of concluded funds are relevant for fundraising and reported from GPs. The fundraising impact is greatest when accompanied by exits, an even stronger effect for low reputation GPs (Barber and Yasuda 2017). Since exit events like IPOs or successful deals positively affect fundraising in private equity, it serves as one of the utmost important investment criteria and is therefore considered in our further study as a conventional investment criteria (Kaplan and Schoar 2005; Loos and Schwetzler 2017).

3.2.4.2 CO2 Reduction Target on Portfolio, Sustainability Expert, EU article compliance

Outside investors can only observe hard information such as realized returns or fund characteristics, whereas current investors can learn about skills (Hochberg et al. 2014). Unlike stock markets or debtholders, PE investors (GPs) are actively involved in providing their portfolio companies with bundles of value-added services. This can include direct benefits such as coaching activities or access to networks, as well as indirect benefits through certification effects to third parties like customers, skilled workers or alliance partners (Block et al. 2019). The implementation of sustainability criteria within the fund and portfolio companies can be such a value-add. During fundraising booms, the compensation even rises with performance-insensitive components and shifts to additional value-added services beyond the pure performance consideration (Robinson and Sensoy 2013).

To operationalize sustainability or ESG activities within a fund and its corresponding portfolio companies, funds could dedicate a sustainability expert towards that main activity. Since private equity board members seem most active in complex or challenging situations (Cornelli and Karakas 2008), setting up a dedicated sustainability role within a fund could foster active engagement. By 2022, 18% of GPs already disclose dedicated ESG investment staff on Preqin to enable impact-related fund offerings and ESG-related engagement processes with investee companies (Hendrikse et al. 2022). In-house sustainability experts build trust, as funds with in-house SRI (socially responsible investing) expertise attract higher money flows per month and, although only significant for European SRI funds, there is some evidence that leveraging in-house SRI research teams increases the risk-adjusted return by 3% per annum (Renneboog et al. 2011). Especially smaller LPs could "outsource" this sustainability expert role, since smaller LPs give a significantly higher score to the importance of the GP providing an 'advisor and gatekeeper opinion' and believing that their (ESG) due diligence is limited (Da Rin and Phalippou 2017). Hence, in line with our conclusion from the expert interviews, we consider having a "sustainability expert as part of the fund team" as one important investment criteria for LPs to include in our study.

Following the literature, that fund investors treat sustainability positively and allocate more money to funds with higher sustainability ratings (Hartzmark and Sussman 2019). LPs need to reach their private equity target quota (Goyal et al. 2021), which seems to be expanded towards ESG and sustainability quotas as well. A study amongst 582 institutional investors reports that the greatest barrier to ESG integration is the lack of high-quality data about the performance of companies on their material ESG factors and how it is used. The absence of common standards for measuring ESG performance is reported as the main concern (Eccles et al. 2017). The question arises about such ratings in the PE environment. Derived from the UN SDGs (United Nations Sustainable Development Goals) and the Paris Agreement, the SFDR (Sustainable Finance Disclosure Regulation) is set to come to full effect in 2023. This regulatory framework requires all companies in scope to publish information about their policies on the integration of sustainability risk in their investment decision-making process. Based on the intended fund, there is a classification of being an article 6 fund, article 8 fund, or article 9 fund. While an article 6 fund has pre-contractual disclosure obligations in common with all funds relating to the integration of 'sustainability risks', an article 8 fund has different approaches like promoting environmental or social considerations in a manner to qualify their investment policy or demonstrating their classification by applying climate concerns. An article 9 fund has a 'sustainable investment' as its objective, meaning an investment in an economic activity that contributes to an environmental objective or an investment in an economic activity that contributes to a social objective. Both article 8 and 9 funds require detailed disclosures in pre-contractual documentation, on the firm website and in periodic disclosures (Invest Europe July 2022). The topic is top of mind with limited partners during our interviews as well and therefore we include the "EU SFDR article compliance" to our study of investment criteria.

Another specific way of operationalizing sustainability implementation in funds is the investments' impact of carbon emissions savings which has been studied manifoldly in the past. Heeb et al. choose this measure because it is widely discussed in financial press, investors understand the topic and they are familiar with the metric. Emissions are clearly defined and measurable and there are even markets for CO_2 emissions savings with transparent prices for CO_2 emissions (Heeb et al. 2023). While the impact agenda of funds include the reduction of greenhouse gas emissions (Barber et al. 2021), the aforementioned study from Pástor et al. indicates that green assets obtain negative alphas due to their stocks' ability to hedge climate risk (Pástor et al. 2021). While the same study also discusses, that green assets can outperform brown ones during good performance of ESG factors, the question remains whether limited partners actually value and demand a "CO_2 reduction target on the portfolio". We therefore also include this fund characteristic in our study.

3.2.4.3 Management Fee and Carry at Risk (sustainability related)

The management fee and carried interest is a substantial part of the limited partnership agreement and typically expressed as fee in percentage of committed capital at first and then switches to a different basis like invested capital when the fund is maturing. The fee is usually ranging from 1.5%-2.5% of committed capital, while 2.0% is the general market standard. On top of the management fee, there is a profit sharing agreement, the carried interest, compensating the GP with 20% of the profit share when a prior defined return threshold (hurdle rate) is reached (Robinson and Sensoy 2013). Funds in more high-tech oriented industries are more likely to have higher performances fees to incentivize the fund managers and align their interests with that of the limited partners (given the agency problem and information asymmetries) (Cumming and Johan 2014). The question arises how prone limited partners are if funds are incentivizing their own sustainability performance and link their sustainability efforts to monetary incentives. Observations in current fundraising activities and during our interviews with both limited partners and general partners have underlined this consideration: first funds are fundraising with a conditional carry based on certain sustainability targets and both LPs and GPs are generally positively disposed towards such consideration. Hence, we are including the "traditional" management fee as well as a "sustainability-related carry at risk" in our study.

In summary, we consider the aforementioned six characteristics in our conjoint study. Two attributes are rather derived from the conventional fund selection criteria (management fee and past performance), while four are derived rather from the sustainable finance literature and put into private equity perspective (EU article compliance, CO2 reduction target, sustainability expert in fund team, sustainability carry). This setting should shed light into two perspectives: which sustainability criteria are more desired by LPs to operationalize sustainability in private equity funds and how do they perform with regards to importance to conventional investment criteria. Our study thereby contributes to two main literature strands in finance research: the investment criteria within the private equity industry as well as sustainable finance literature with a narrowed focus of private equity.

3.3 Method

We conduct an experimental conjoint analysis to exploit the decision-making behavior of limited partners as in investors choosing to invest into private equity funds. Conjoint analysis is generally a technique where respondents make decisions based on profiles. The various characteristics of each profile are called attributes. The technique aims to understand the decision-making process by decomposing its underlying structure into the attributes' significance in the judgement process and their relative importance of each attribute in this decision-making process (Shepherd and Zacharakis 1999). In our study, we are using a choice-based conjoint analysis that leverages the basic ideas and designs of metric conjoint analysis and asks the respondent to choose an option from several competing products. The participant is presented with hypothetical products and must make a simulated decision (Cohen 1997). Choice-based conjoint analysis overcomes several issues faced in traditional metric conjoint. Firstly, the research tasks closely imitate what people do in the real world, leading to more valid and reliable results. Respondents make real choices from a set of competing products instead of providing rankings or ratings like in metric conjoint analysis (Gustafsson et al. 2007). This results in a more immediate and concrete situation with a close simulation of actual investment decisions rather than abstract rating (Orme 2019). Secondly, traditional metric conjoint analysis generates values for each attribute of a product and thereby explains the respondents' preferences. The preference results must be translated by a simulator to predict choices. Given the various possibilities of simulator rules, various answers can be obtained for the same problem. In a choice-based setting, the preferences and utilities are derived by real choices of the respondents. The respondent will also evaluate few product profiles, whereas in a conjoint-based setting, the respondent will make few choices. But considering that each choice situation contains multiple different alternatives, the overall number of profiles the respondent is exposed to is much greater. Further, running an analysis for each respondent assumes that we have measured the importance of each respondent's preferences with certainty (Gustafsson et al. 2007). Conjoint analysis provides a more accurate representation of the actual decision behavior than post hoc approaches like questionnaires and interviews and has been used in the context of investment decisions in the past (Shepherd and Zacharakis 1999; Block et al. 2019).

Conjoint studies enjoy great popularity in entrepreneurship research, particularly in the venture capital research area (Franke et al. 2006; Theinert et al. 2017; Shepherd and Zacharakis 1999; Hill 2017; Hsu et al. 2014; Ademi et al. 2022). Yet, despite calls for broader use, there are very few studies, that have been leveraged the methodology within the private equity industry and private equity research area. To our knowledge, as of 2023, there are two published studies within the private equity research area by Block et al. and Dawson (Dawson 2011; Block et al. 2019). Block et al. are investigating the investment criteria of 749 private equity investors considering the differences amongst different private equity investors like family offices, business angels, VC funds, growth equity funds and leveraged buyout funds (Block et al. 2019). Dawson examined the decision making criteria employed by private equity investors while selecting family firms using an Italian sample of 35 PE firms (Dawson 2011).

Our study incorporates two major advances: on the methodological and academic-content-related side. Choice-based tasks are more realistic for the participants simulating an actual decision but contain less information per unit of respondent effort as e.g., rating-based conjoint studies. We leverage a hierarchical Bayesian approach to estimate part-worth values for the utility function estimates (Orme 2000; Baier and Brusch 2009; Moore 2004; Wuebker et al. 2015). Secondly, we are applying this methodology to a research area where conjoint studies have not been used: we are assessing the investment criteria of limited partners investing into private equity funds. In addition, we are exploring their inclination towards sustainability fund characteristics that are discussed and partially already deployed within the private equity industry.

3.3.1 Data and sample

We identified investors and investment professionals through the database Preqin, which is one of the most comprehensive databases in entrepreneurial finance and private equity and is regularly used for research in the field of PE investments (Barber and Yasuda 2017; Harris et al. 2014). Preqin collects a wide array of public data from public sources like public filings and reports combined with direct requests to LPs and GPs that voluntarily contribute their information (Brown et al. 2015). One main advantage of Preqin for our study is that it reports information on investors' individuals as well as their contact details in addition to information on the investment entity.

Given our research focus on limited partners in PE, we first started by filtering Preqin by investor type, selecting all investment entities ("Firm Type") that are involved in private equity fund investments (e.g., PE fund of funds, pension funds, insurance companies, …). Secondly, we considered only investment individuals from those entities with a complete profile including their email address and LinkedIn URL. This ensured that we could reach out to them later and that we were able to verify their initial profile fit through LinkedIn research. Additionally, we only considered investment individuals that had a job title indicating an influencing role in an investment decision, such as *Chief Investment Officer, VP of Investments, Investment Director, Investment Manager* and alike. This approach led to the identification of 8,031 relevant investment professionals, which we invited via email to participate in our research survey. We have sent the initial survey mail and two reminder within four months and collected 140 complete and qualified responses (response rate ~ 2%, given various returned error mails of inactive email addresses).

We conducted a web-based conjoint analysis with those individuals that take active private equity investment decisions. We invited participants from different limited partner types, regions, LP sizes, and personal characteristics to answer our anonymous survey. This approach compares to other academic limited partner surveys, to obtain LP characteristics that could explain heterogeneity in their investment decisions (Da Rin and Phalippou 2017).

3.3.2 Descriptive statistics

In the survey, participants were asked to complete a survey that included questions regarding their investment firm they work for as well as their own personal characteristics. The following sub-section summarizes the sample and their unique features of each investment individual.

Our sample consists of overall 140 participants, that have responded, are qualified and have completed the entire survey (N=140). Most respondents were male (76.4%) and had an educational background in business/economics (87.9%). Table 12 presents the participants that have completed our survey as well as a selection of their general individual characteristics.

Table 12: Respondents' characteristics

Variable	Definition	Absolute Number	Percentage
Gender	Male	107	76.4%
	Female	33	23.6%
Age	<25 years	1	0.7%
	25 - 34 years	34	24.3%
	35 - 44 years	43	30.7%
	45 - 54 years	45	32.1%
	55 - 64 years	16	11.4%
	>65 years	1	0.7%
Role	Partner or CxO	31	22.1%
	Director or principal	38	27.1%
	Investment manager	51	36.4%
	Investment analyst	11	7.9%
	Other	9	6.4%
Investor experience	<2 years	5	3.6%
	2-4 years	11	7.9%
	5-10 years	41	29.3%
	11-20 years	40	28.6%
	>20 years	43	30.7%
Educational background	Business/economics	123	87.9%
	Natural science	8	5.7%
	Engineering	14	10.0%

	Other	24	17.1%

Note: multiple answers possible in "Educational background"
The table shows the characteristics of the investment individual who participated in the study. The sample consists of a total of 140 participants that have responded to and completed the survey.

Each participant in our conjoint study was asked to fill out a questionnaire regarding their personal and their investment firm's characteristics. The following subsection provides a descriptive overview of the sample and describes specific characteristics of each investor. Table 13 provides a definition of each variable and descriptive statistics for the entire sample. The average respondent is male, between 35 and 44 years old, has 11 to 20 years of investment experience and has been 5 to 10 years with the current investment firm. The majority of the investment respondents have a background in business/economics. Most of the investment firms, in which the respondents are employed, are located and conducting their business from Europe (60%, including continental Europe and Scandinavia), around one fourth of the participants work at investment firms conducting their business from North America (26%) and 14% are distributed across the UK and the rest of the world. The average represented investment firm has between $1,001M to $5,000M in asset under management towards PE (incl. VC), is an ESG signatory to a generally known association (e.g., UN PRI, SBTi, iCI, Net Zero Alliance, …), and has no specific ESG incentivization in place for their investments. The investor types include fund of funds (26%), pension funds (corporate and public, 23%), family offices (single and multi-family offices, 18%), insurance companies (9%) and other investor types (finance company, bank, external CIO, sovereign wealth fund, …).

Table 13: Descriptive statistics and definition of the variables

Panel A: Respondents' descriptive statistics

Variable	Mean	S.D.	Min.	Max.	Description
Age	3.31	1.01	**1**	**6**	Participant's age (categorical: 1 = <25 years, 2 = 25 - 34 years, 3 = 35 - 44 years, 4 = 45 - 54 years, 5 = 55 - 64 years, 6 = >65 years
Gender	1.24	0.43	**1**	**2**	Participant's gender (categorical: 1 = male, 2 = female, 3 = other)
Investor experience	4.75	1.09	**2**	**6**	Participant's years of experience as an investor (categorical: 1 = None, 2 = <2 years, 3 = 2-4 years, 4 = 5-10 years, 5 = 11-20 years, 6 = >20 years)
Role	2.49	1.12	**1**	**5**	Participant's current role within investment firm (categorical: 1 = Partner or CxO, 2 = Director or principal, 3 = Investment manager, 4 = Investment analyst, 5 = Other)

Tenure with investment firm	2.93	1.05	**1**	**5**	Participant's tenure with current investment firm (categorical: 1 = <2 years, 2 = 2-4 years, 3 = 5-10 years, 4 = 11-20 years, 5 = >20 years)
Educational background: Law	0.06	0.23	**0**	**1**	Participant has an educational background in law (dummy: 1 = yes, 0 = No)
Educational background: Business/economics	0.88	0.33	**0**	**1**	Participant has an educational background in business/economics (dummy: 1 = yes, 0 = No)
Educational background: Natural science	0.06	0.23	**0**	**1**	Participant has an educational background in natural science (dummy: 1 = yes, 0 = No)
Educational background: Engineering	0.10	0.30	**0**	**1**	Participant has an educational background in engineering (dummy: 1 = yes, 0 = No)
Educational background: Other	0.11	0.32	**0**	**1**	Participant has an educational background in other (dummy: 1 = yes, 0 = No)

Panel B: investment firms' descriptive statistics

Variable	**Mean**	**S.D.**	**Min.**	**Max.**	**Description**
Region: North America	0.28	0.45	0	1	Investment firm is located in North America to conduct their investment decisions (dummy: 1 = Yes, 0 = No)
Region: Europe (excl. UK)	0.58	0.50	0	1	Investment firm is located in Europe (continental and Scandinavia) to conduct their investment decisions (dummy: 1 = Yes, 0 = No)
Region: United Kingdom	0.05	0.22	0	1	Investment firm is located in United Kingdom to conduct their investment decisions (dummy: 1 = Yes, 0 = No)
Region: Rest of World	0.09	0.29	0	1	Investment firm is located in the Rest of the World to conduct their investment decisions (dummy: 1 = Yes, 0 = No)
Asset under Management (AuM)	4.56	1.37	1	6	Investment firm's asset under management (asset under management and unfunded commitment) towards PE (PE & VC) in $M (categorical: 1 = <$25M, 2 = $26M - $100M, 3 = $101M - $500M, 4 = $501M - $1,000M, 5 = $1,001M - $5,000M, 6 = >$5,000M)
ESG signatory	0.54	0.50	0	1	Investment firm is signatory to a ESG-association (e.g., UN PRI, SBTi, iCI, Net Zero Alliance...) (dummy: 1 = Yes, 0 = No)
ESG incentivized	0.37	0.48	0	1	Investment firm is incentivized to invest along ESG criteria (dummy: 1 = Yes, 0 = No)
Investor type: Pension fund	0.23	0.42	0	1	Investor category of investment firm can be best described as pension fund
Investor type: Endowment	0.06	0.23	0	1	Investor category of investment firm can be best described as endowment
Investor type: Insurance company	0.09	0.29	0	1	Investor category of investment firm can be best described as insurance company
Investor type: Finance company/Bank	0.07	0.26	0	1	Investor category of investment firm can be best described as Finance company/bank
Investor type: Family office	0.18	0.38	0	1	Investor category of investment firm can be best described as family office or multi-family office
Investor type: Fund of funds	0.26	0.44	0	1	Investor category of investment firm can be best described as fund of funds
Investor type: Sovereign wealth fund	0.04	0.20	0	1	Investor category of investment firm can be best described as sovereign wealth fund
Investor type: Other	0.06	0.25	0	0	Investor category of investment firm can be best described as an other category

Note: This table provides an overview and summary statistics of the respondents and the investment firms. Panel A shows descriptive statistics on the indidvidual respondent and panel B shows descriptive statistics on their respective investment firm.

3.3.3 Experimental design of the conjoint analysis

As the main part of our study, we are conducting an experimental conjoint analysis to investigate the real-time decision making by limited partners while investing into private equity funds. Conjoint analysis are individual analysis methods to investigate the decision behavior for a specific person. The considered decision objects, in the case of this studies: funds, are characterized by specific features and are considered jointly (Backhaus et al. 2016). This approach allows for a more accurate representation of the actual decision behavior by capturing the decision process and decomposing it into their underlying structure (Shepherd and Zacharakis 1999). The traditional view that full-profile CBC is limited to six attributes or fewer has been successfully challenged in past literature (Orme 2010). But, given our initial test runs and recent recommendation from literature, we follow the traditional recommendation of having no more than 6 attributes with no more than 3 attribute levels (Backhaus et al. 2021). When deriving the attributes and their level based on literature above as well as expert interviews, there are seven recommendations, that were formally considered: attributes have to be relevant for preferences, attributes have to be manipulatable for the researcher, chosen attributes have to be independent and their attribute levels have to be realizable, individual attribute levels must have a compensatory relationship to each other, considered attributes and their levels cannot be exclusion criteria and the quantity of attributes and their levels have to be limited (Backhaus et al. 2021).

In summary, the main part of this study is a choice-based conjoint analysis conducted using objects (here: funds), that consist of several attributes (here: fund criteria) which are evaluated by respondents (here: limited partner). The participants are asked to make a deterministic investment decision between several hypothetical funds that differ only in specification of fund attributes displayed. To avoid conflicts with all generic screening criteria of LPs, the presented funds were said to match the participants' geographical, industrial and investment size preferences. The investment criteria have been derived from a literature review of prior research and 11 expert interviews of limited partners and general partners, that have been conducted to identify most relevant criteria for realization of sustainability implementation. We decided for a full-profile choice-based conjoint (CBC) in which all fund attributes are presented simultaneously since limited partners assess potential funds holistically. Since respondents would be exposed to too many decision tasks if combinations between all possible variations of attributes levels were presented, the CBC is used in combination with a reduced conjoint design. An asymmetric experimental design results due to an unequal number of attribute levels across attributes. Therefore, a CBC balanced overlap approach has been chosen because it is suitable to test for main effects, interactions and prohibitions. It has also been frequently used in previous studies (Chrzan and Orme 2000; Block et al. 2019).

Three possible order effects in a choice-based conjoint have to be considered: 1) choice set order within the set of choice sets, 2) profile order within choice sets and 3) attribute order, within profiles. (Chrzan 1994). To mitigate the effect of choice task order, we developed 300 unique experimental designs (questionnaire versions) where the order of choice task was randomly determined. To circumvent the effect of the order of option in a presented choice task, we randomized the level order so that the three options within the 300 different experimental designs are randomly ordered. And thirdly, to avoid the attribute order effect within one choice task, the presented order to the participant was randomized as well. But it is kept stable for each individual participant for better usability. In addition, the participants are randomly assigned to one of the 300 experimental designs. We have also included a “none” option for three main reasons: it makes the choice task more realistic because a “none” option is usually available, it makes the experience for the participant more pleasant when not being forced to select an unacceptable alternative, and it improves the quality of data by letting participants screen themselves out (Johnson and Orme 2003). A pre-test was conducted with seven researchers, general partners and limited partners that are familiar with the industry and have been conducted research within the field and methodology. The pre-test was used to confirm the validity of the attributes, their levels, the complexity of the decision as well as the number of the choice tasks. We included two fixed tasks to check the test-retest reliability of the participants’ choices in the study. By using the utility estimates from the 13 random choice tasks to predict the two fixed choice tasks, our model leads to an accuracy of ~70% correctly predicted choices.

3.3.4 Variables and measures

In our conjoint study, the dependent variable is the actual response decision made by the limited partner (choice in fund options). Hypothetical private equity funds were presented to the limited partners with differentiating fund characteristics, or attributes, with different attribute levels. Those different attributes and their categorical levels are the independent variables (Shepherd and Zacharakis 1999). To identify a list of typical screening criteria by limited partners, we proceeded in the aforementioned two steps: first we derived a list of possible criteria from prior research (Kaplan 1989; Jensen 1989, revised 1997; Lerner et al. 2011; Metrick and Yasuda 2011) and secondly, we conducted 11 expert interviews with limited partners of different investor types to identify the most relevant criteria within a transformation towards more sustainable investing. The interviews were transcribed and coded to derive the attributes as a basis for our conjoint analysis. Based on this procedure, we derived this list of fund attributes and attribute levels: 1) EU SFDR Article Compliance, 2) CO2 Reduction Target on Portfolio, 3) Sustainability-Expert as Part of Fund Team, 4) Carry at Risk (Sustainability-related), as well as rather conventional investment criteria as a reference to thoroughly researched criteria: 5) Performance of Previous Fund, and 6) Management Fee. In addition, Table 14 provides a detailed overview and description of our operationalization of the investment criteria. It also shows our operationalization approach with the different attribute level: for example, the attribute EU SFDR article compliance comprises the attribute levels “article 6 fund”, “article 8 fund”, and “article 9 fund”. All descriptions provided in Table 14 were also shown to the participants before being exposed to the investment decision of our conjoint study.

The respondents have been asked to make the decision based on a follow-on investment into a private equity funds. We chose that approach to provide the respondent with a selection of a new fund, but familiar investment setting. LPs obtain private information about GPs, their skills, and thereby asymmetric information only when invested in the previous fund (Hochberg et al. 2014). With this setting we can maximize the respondent's preference to only the mentioned characteristic differences assuming, that all other characteristics are equal for the presented funds. Appendix D provides an explanatory example of one of 15 random choice task through which participants had to navigate.

Table 14: Definition of attributes and attribute levels

Attribute (fund characteristic)	Description	Attribute level (options) operationalization
EU SFDR Article Compliance	▪ Fund has precontractual disclosure obligations of the EU's SFDR ▪ The fund's ESG/impact reporting requirements differ according to fund declaration	1=Article 6 fund 2=Article 8 fund 3=Article 9 fund
CO2 Reduction Target on Portfolio	▪ Fund has a CO2 reduction target on its entire portfolio ▪ Target can be an annual reduction target (e.g., each year 5%), a target reduction from entry to exit or similar	1=Non-existent 2= Existent
Sustainability-Expert as Part of Fund Team	▪ A Sustainability/ESG-expert is part of the fund team ▪ This can include senior advisors for ESG-topics, dedicated ESG officer, or similar	1=Non-existent 2= Existent
Carry at Risk (Sustainability-related)	▪ The fund's conditional carry is linked to sustainability targets ▪ There is a share of the carry, that is at risk as a component of the LP agreement	1=0% carry at risk 2=25% carry at risk 3=50% carry at risk
Performance of Previous Fund	▪ Relative performance of the previous fund generation ▪ Performance could refer to e.g., target Multiples and IRR of your expectations	1=Slighly above expectations 2=Slighly below expectations
Management Fee	▪ The regular management fee dependent on the committed capital ▪ The fee structure follows a standard scheme and is payable per year	1.5% 2.0% 2.5%

Note: This table provides an overview of all attributes and attribute levels of the used fund characteristics.

3.4 Analysis and results

This conjoint study uses Bayesian statistic to estimate the individual coefficients and part-worth utilities for all respondents. Their part-worth utilities are then used to draw conclusions about their heterogeneity in preferences (Baier and Brusch 2009). The hierarchical bayes model is called "hierarchical" due to its two levels of consideration. It is balancing between estimating parameters that fit an aggregated level ("upper level model"), and estimating parameters that fit the "lower level model" or each respondent's data. If a respondent provides lots of data and is consistent, then very little information is borrowed from the population parameter (relatively low "Bayesian shrinkage"). If a respondent has little data and is inconsistent, lots of information is borrowed from the population parameters (high "Bayesian shrinkage"). Initially, crude estimates of the individuals' parameters (betas or part-worths) are estimated for each participant as a starting point. New estimates are continuously updated in an iterative process and the model estimates individual betas, the mean and covariances of the distribution of betas in each iteration. After numerous iterations, this process converges towards correct estimates for each parameter (Orme 2000). Typically, 10,000 or more iterations are used until the estimates converge. After the convergence, one uses the next several thousands of iterations for the further analysis. A major advantage of this methodology is, that it can recover heterogeneity and estimate individual-level part-worth values, even when individual-level least squares estimators do not exist due to a fractional factorial design. This is especially useful in those fractional factorial designs, in which an application of standard OLS may lead to less precise coefficient estimates or, in choice-based conjoint studies, where less information are generated per respondent than by other methods (Lenk et al. 1996). Bayesian estimation, like classical frequentist procedures, can basically be utilized for any statistical model. However, Bayesian analysis provides a distinct advantage for discrete choice experiments since it can cope with major limitations of classical procedures such as maximization requirement of functions (e.g., logit or probit models) (Train 2009). Several studies comparing different methods have shown, that using hierarchical Bayes within a conjoint context is outperforming frequentist-based estimations and predicting holdout profiles (Lenk et al. 1996; Andrews et al. 2002; Moore et al. 1998; Moore 2004).

3.4.1 Conjoint results and relative importance of attributes

Our results are based on the responses of 140 limited partners, that are investing into private equity, performing 2,100 choice tasks resulting in 8,400 observations. The main results of our conjoint experiment are reported in Table 15 and Table 16. A detailed description of all variables used in the analysis can be found in Appendix C. An analysis of the relative importance of the six investigated attributes shows, in line with previous studies (Barber and Yasuda 2017; Chung et al. 2012), that rather traditional private equity investment criteria are of highest importance for limited partners. The performance of the previous fund (29.57%) and the management fee (27.12%) account for more than 55% of the perceived relative importance in our study (Table 16). However, most of the attribute levels related to the operationalization of sustainability characteristics within a fund are significant (see Table 15). The attributes have a relative importance of 15.41% (carry at risk sustainability-related), 11.80% (EU SFDR article compliance), 8.32% (CO_2 reduction target on portfolio) and 7.78% (sustainability-expert in fund team) (see Table 16). The results in Table 15 further disclose the average effect of a particular attribute level on the investment decision. On the left side of the Table 15, we are reporting effects-coded raw utilities (Orme 2019) resulting from the part-worth's from the hierarchical Bayes estimates derived from an individual consideration of each of the 140 participants. The average part-worth utility measures the influence of a change of the respective attribute level on the investment decision. Positive values imply an increase in the individual's utility and thereby implying a higher desirability while negative values indicate the opposite. It is important to note that the absolute value of an attribute does not allow for conclusions in relative importance of the respective attribute. Part-worth utilities are interval data that are zero-centered and scaled based on an arbitrary additive constant within each attribute. Hence, it is not feasible to draw direct conclusions from a comparison of utility values across attributes (Wuebker et al. 2015). Instead, the change in the overall utility must be considered if an attribute level changes. Thus the range of the part-worth values is decisive for its importance (Backhaus et al. 2016). Noticeable is the attribute preferences for the attribute levels. The utility for attributes related to the CO2 reduction target on the portfolio, the performance of previous fund, sustainability expert in the fund team, and management fee all follow an obvious and intuitive order: an existence of a sustainability criteria yields higher part-worth estimates and lower management fees also offer the higher part-worth utilities. Interestingly, limited partners value a 25% carry at risk related to sustainability targets with the highest part-worth utility while having negative part-worth utilities resulting from both: no carry-commitment in the fund and a 50%-carry at risk related to sustainability targets. Similarly, the coefficient for EU article SFDR compliance is of similar magnitude indicating no additional improvement and suggesting even slightly less utility stemming from article 9 vs. article 8 funds.

Table 15: Results of the hierarchical Bayes (HB) and multinomial logistic regression of the decision in the fund selection

	Hierarchical Bayes model				Multinomial logistic regression	
	Coefficient	**Standard deviation**	**95% Interval of posterior distribution**		**Coeefficient**	**Standard error**
CO2 reduction target on portfolio						
co2red_nonexist	-0.5752	0.0947	-0.5794	-0.5711	-0.2824***	0.0344
co2red_exist	0.5752	0.0947	0.5711	0.5794	0.2824***	0.0344
Performance of previous fund						
performance_below	-2.4230	0.1992	-2.4317	-2.4142	-0.942***	0.0393
performance_above	2.4230	0.1992	2.4142	2.4317	0.942***	0.0393
EU SFDR article compliance						
article6fund	-0.7226	0.1579	-0.7295	-0.7157	-0.2533***	0.0497
article8fund	0.3745	0.1222	0.3691	0.3799	0.1381**	0.0470
article9fund	0.3481	0.1341	0.3422	0.3540	0.1152**	0.0479
Carry at risk (sustainability related)						
carryatrisk0	-0.2635	0.1742	-0.2711	-0.2559	-0.0095	0.0478

carryatrisk25	0.4724	0.1128	0.4674	0.4773	0.1189**	0.0479
carryatrisk50	-0.2089	0.1646	-0.2161	-0.2017	-0.1094*	0.0486
Sustainability expert in fund team						
sustain_exp_nonexist	-0.5062	0.0952	-0.5104	-0.5020	-0.2009***	0.0340
sustain_exp_exist	0.5062	0.0952	0.5020	0.5104	0.2009***	0.0340
Management fee						
mgmtfee15	1.6952	0.1594	1.6882	1.7022	0.754***	0.0480
mgmtfee20	0.7025	0.1166	0.6974	0.7077	0.2492***	0.0476
mgmtfee25	-2.3978	0.1990	-2.4065	-2.3891	-1.0032***	0.0586
Number of observations	7280				7280	
RLH value	0.661					
Log-likelihood					-1905.07	

Note: This table provides coefficients of Hierarchical Bayes and multinomial logistic regression of the fund characteristics on the decision of LPs. Within each attribute, the effects sum to zero. That is because one level for each attribute is omitted in doing the estimation, afterwards a value for the missing level that is equal to the negative of the sum of the others is added. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

When performing Wilcoxon signed-rank tests and comparing the relative importance of each attribute in descending order, we see significance within each paired order except for a direct comparison of the sustainability-related carry at risk with the EU SFDR article compliance. All of the other attributes in our sample have significantly more influence in the individual's choices than the next attribute with lower average importance e.g., the EU article compliance is significantly more important than the CO2 reduction target on the portfolio. There is no significant difference in relative importance of the EU SFDR article compliance and the sustainability-related carry at risk. But both attributes are significantly more (relatively) important than the CO2 reduction target on the portfolio but less (relatively) important than the management fee. The results of the Wilcoxon signed-rank test can also be found in Table 16.

Table 16: Average relative importance values of attributes based on hierarchical Bayes model

Average Importances	Average Importances	Standard Deviation	z-value Wilcoxon signed-rank test
Performance of Previous Fund	29.57%	13.70	2.026**
Management Fee	27.12%	11.33	6.573***
Carry at Risk (Sustainability related)	15.41%	10.72	2.369**
EU SFDR Article Compliance	11.80%	7.26	5.729***
CO2 Reduction Target on Portfolio	8.32%	6.37	0.426
Sustainability-Expert in Fund Team	7.78%	5.88	-
Total	100.00%		

Note: This table shows the order of relative importance and coefficients of Wilcoxon signed-rank test. The relative importance values for each attribute are calculated based on the difference between the highest and lowest part-worth utility within each attribute and scaling this value to 100% across all attributes (Orme 2019). Wilcoxon signed-rank test are performed with attribute next in order of importance, e.g., Performance of Previous Fund vs. Management Fee in first line. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

3.4.2 Differences across limited partner characteristics

After having established the relative importance and relevance of sustainability characteristics in LP's fund decision (in our setup), we want to further understand the drivers across limited partners. Table 17 provides a summary of differences across limited partner characteristics. There are two types of models run using OLS multiple regressions: the upper part of Table 17 – panel A – shows the model results of formula (1). The dependent variable is the relative importance of the attribute and the independent variables are the investors characteristics: LP type, LP region, LP's asset under management and ESG signatory:

$$(1)\ relative\ importance_i = \beta_0 + \beta_1 typeinsurance + \beta_2 typepublicpension + \dots + \beta_9\, regioncontinentaleurope + \ \dots + \beta_{13} aum1 + \beta_{17}\, esgdummy + u$$

Panel B, in the bottom part of Table 17 runs the base model indicated in formula (2). It uses the HB raw utility of the respective attribute level of each respondent while the same fund characteristics are the independent variables:

$$(2)\ HB\ utilities_i = \beta_0 + \beta_1 typeinsurance + \beta_2 typepublicpension + \dots + \beta_9\, regioncontinentaleurope + \ \dots + \beta_{13} aum1 + \beta_{17}\, esgdummy + u$$

We checked for heteroscedasticity and used robust standard errors in all regressions, that are provided in parentheses. Significance levels at the 10%, 5% and 1% level are indicated accordingly. This detailed consideration obtains four observations worth mentioning.

Firstly, family offices attribute significantly less importance towards a CO2 reduction target on the fund portfolio than insurance firms. Positive coefficients with public and corporate pension funds, endowments, fund of funds and banks/finance companies indicated that they tend to attribute more importance towards a CO2 reduction target as well. The values of utility coefficients for the levels of a CO2 target reduction confirm the intuitive interpretation: all of the aforementioned LP types seem to draw greater value from an existing CO2 reduction target (with positive coefficients of 0.191, 0.123 …) while considering lower utility coefficients when it is not existing (-0.191, -0.123).

Secondly, following the results from Bauckloh et al. (Bauckloh et al. 2021), LPs that are ESG signatories like UN PRI or SBTi (Science Based Target initiative) allocate significantly more importance (2.505) towards the criteria of a CO2 reduction target on the fund portfolio while considering the management fee (-7.177) as significantly less important of a characteristic. Interestingly, those signatories gain a greater utility from higher management fees (0.316) and inversely (even statistical significant -0.311) less utility from lower management fees. In line with our findings, Heeb et al. (Heeb et al. 2023) show in a framed field experiment, that investors have a substantial willingness-to-pay for sustainable investments, while not actually paying more. The utility of an existing CO2 reduction target is also significantly higher (0.399) than for non-ESG signatories. In line with this tendency towards sustainability, LPs that are ESG signatories gain significantly more utility from EU SFDR article 8 (0.175) and article 9 (0.464) funds and less utility from conventional article 6 funds (-0.680) than non-signatories. However, they also gain significantly more utility from a positive performance of the previous fund (0.544), indicating a strong preference of past performance as a necessity for sustainability characteristics.

Thirdly, Scandinavian LPs consider the EU article compliance and the sustainability-related carry at risk significantly less important than North American LPs (and, yet not significant, LPs from Continental Europe). In doing so, LPs from Scandinavia seem to see less value stemming from article 9 funds (see lower part of Table 17) than North American LPs. Scandinavian LPs also consider the utility of a 25% share of carry at risk significantly higher, than LPs from North

America. However, they consider the criteria of a sustainability expert as significantly more important compared to North American LPs.

Since performance-based compensation is a major mechanism in the LP-GP relationship, we fourthly consider the conditional carry related to sustainability ambitions. North American LPs seem to attribute a higher importance to the characteristic of a sustainability-related conditional carry than LPs from Continental Europe (-4.022) and Scandinavia (-6.554). Interestingly, LPs from Continental Europe seem to gain utility from having a 25% or 50% share in conditional carry compared to LPs from North America. LPs from North America therefore seem to consider this criteria as more important for the decision, while gaining relatively more value from having no carry at risk for sustainability efforts. Family firms do also consider the importance of a carry at risk for sustainability purposes slightly less than the other LP types of our study. Or in other words, institutional LP types such as insurance companies, pension funds, banks/finance companies as well as endowments, fund of funds and sovereign wealth funds consider a sustainability-related carry at risk of higher importance (indicated by positive coefficients) while gaining more utility from a 25%-carry at risk than family offices.

Table 17: Differences across limited partner characteristics

Dependent variable: Panel A	*Reference: Family offices*	Insurance company	Public pension fund	Corporate pension fund	Endow-ment	Fund of funds	Bank/ Finance company	Sovereign wealth fund	Other	*Reference: North America*	Conti-nental Europe	Scandi-navia	United Kingdom	Rest of world	*Reference: AUM <$100M*	AUM $101M - $500M	AUM $501M - $1,000M	AUM $1,001M - $5,000M	AUM > $5,000M	ESG signatory	Constant	Obser-vations	R-squared
Relative importance of attribute...																							
1) CO2 Reduct. Target on Portfolio		4.451*	3.576	1.357	1.859	0.408	1.531	-3.939	3.370		-0.0388	3.588	1.083	2.023		1.148	-0.122	-1.336	0.169	2.505*	5.297***	140	0.159
		(2.464)	(2.516)	(1.908)	(2.878)	(1.822)	(2.405)	(2.496)	(2.592)		(1.128)	(3.410)	(2.513)	(2.144)		(2.007)	(1.806)	(1.868)	(2.094)	(1.298)	(1.805)		
2) EU SFDR Article Compliance		5.140*	-1.490	0.657	-2.734	-1.976	0.618	-2.434	-2.744		0.207	-4.673*	3.087	5.490**		3.733*	1.653	-0.00860	0.534	2.081	9.687***	140	0.179
		(2.975)	(2.949)	(2.896)	(3.402)	(2.500)	(3.042)	(3.946)	(2.687)		(1.569)	(2.669)	(2.171)	(2.375)		(2.215)	(2.274)	(2.446)	(2.810)	(1.689)	(2.000)		
3) Carry at Risk (Sustain. related)		1.430	0.489	3.976	2.926	4.118	7.924	4.562	1.884		-4.022	-6.554*	1.480	-5.952*		-4.928	-3.267	-7.910	-8.267	-1.868	22.78***	140	0.112
		(3.660)	(3.917)	(4.026)	(5.001)	(3.298)	(4.804)	(6.803)	(4.317)		(2.514)	(3.521)	(6.537)	(3.231)		(5.237)	(4.840)	(5.240)	(5.098)	(2.055)	(4.323)		
4) Sustain.-Expert in Fund Team		-1.249	1.085	1.232	0.268	-1.851	-0.450	-5.122**	2.041		1.237	4.627*	2.820	1.431		-1.591	0.634	-1.420	-1.027	0.486	7.677***	140	0.120
		(2.568)	(2.266)	(2.100)	(2.410)	(1.831)	(2.608)	(2.197)	(2.649)		(1.287)	(2.467)	(2.492)	(1.618)		(2.319)	(2.462)	(2.430)	(2.574)	(1.222)	(2.735)		
5) Management Fee		-1.514	0.433	-1.041	-6.623	-2.904	-3.119	5.268	1.192		0.687	6.913	-2.996	1.147		-0.0161	-1.727	7.249*	4.793	-7.177***	28.18***	140	0.164
		(5.009)	(4.542)	(4.239)	(5.538)	(3.885)	(4.617)	(5.333)	(4.850)		(2.476)	(4.703)	(4.440)	(3.869)		(4.776)	(4.103)	(4.326)	(4.677)	(2.149)	(3.676)		
6) Performance of Previous Fund		-8.258	-4.094	-6.180	4.304	2.206	-6.504	1.665	-5.744		1.930	-3.901	-5.474	-4.139		1.654	2.829	3.425	3.798	3.972	26.38***	140	0.135
		(5.016)	(5.294)	(5.378)	(5.350)	(3.850)	(5.158)	(7.875)	(4.927)		(3.207)	(5.442)	(6.104)	(4.434)		(5.330)	(5.686)	(5.790)	(5.799)	(2.920)	(5.547)		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: Panel B	*Reference: Family office*	Insurance company	Public pension fund	Corporate pension fund	Endow-ment	Fund of funds	Bank/ Finance company	Sovereign wealth fund	Other	*Reference: North America*	Conti-nental Europe	Scandi-navia	United Kingdom	Rest of world	*Reference: AUM <$100M*	AUM $101M - $500M	AUM $501M - $1,000M	AUM $1,001M - $5,000M	AUM > $5,000M	ESG signatory	Constant	Obser-vations	R-squared
HB raw utiltiy																							
CO2 Reduct. Target on Portfolio																							
1) Non-existent		-0.191	-0.123	-0.0579	-0.202	0.000911	0.0477	0.253	0.0887		-0.111	-0.0477	-0.221	-0.0742		-0.207	-0.0924	0.0206	-0.0601	-0.339***	-0.221	140	0.183
		(0.191)	(0.171)	(0.168)	(0.201)	(0.150)	(0.205)	(0.174)	(0.215)		(0.0926)	(0.212)	(0.192)	(0.170)		(0.186)	(0.178)	(0.185)	(0.196)	(0.104)	(0.169)		
2) Existent		0.191	0.123	0.0579	0.202	-0.000911	-0.0477	-0.253	-0.0887		0.111	0.0477	0.221	0.0742		0.207	0.0924	-0.0206	0.0601	0.339***	0.221	140	0.183
		(0.191)	(0.171)	(0.168)	(0.201)	(0.150)	(0.205)	(0.174)	(0.215)		(0.0926)	(0.212)	(0.192)	(0.170)		(0.186)	(0.178)	(0.185)	(0.196)	(0.104)	(0.169)		
EU SFDR Article Compliance																							
3) Article 6 fund		-0.434	0.313	0.260	-0.0910	0.127	0.137	0.110	0.247		-0.304	0.400	-0.409	-0.441		-0.615*	-0.672**	-0.238	-0.429	-0.640***	0.137	140	0.247
		(0.339)	(0.307)	(0.347)	(0.376)	(0.305)	(0.356)	(0.357)	(0.350)		(0.197)	(0.289)	(0.359)	(0.313)		(0.328)	(0.326)	(0.356)	(0.349)	(0.200)	(0.338)		
4) Article 8 fund		0.343*	0.0397	0.228	0.253	0.290**	0.359**	0.121	0.116		0.0865	0.0236	0.202*	0.0368		0.132	0.122	-0.0382	-0.0322	0.175*	0.00896	140	0.182
		(0.175)	(0.142)	(0.181)	(0.154)	(0.125)	(0.177)	(0.182)	(0.188)		(0.100)	(0.136)	(0.116)	(0.159)		(0.164)	(0.154)	(0.171)	(0.163)	(0.0922)	(0.151)		
5) Article 9 fund		0.0910	-0.353	-0.488	-0.162	-0.418	-0.496	-0.231	-0.363		0.217	-0.424	0.207	0.404		0.483*	0.550**	0.276	0.461*	0.464***	-0.146	140	0.164
		(0.271)	(0.313)	(0.328)	(0.326)	(0.259)	(0.362)	(0.333)	(0.286)		(0.176)	(0.266)	(0.363)	(0.284)		(0.261)	(0.264)	(0.270)	(0.277)	(0.173)	(0.244)		
Carry at Risk (Sustain. related)																							
6) 0% carry at risk		0.195	-0.280	-0.602	0.0529	-0.367	0.340	0.263	0.149		-0.274	-0.257	0.271	0.396		0.468	0.382	0.571	0.433	-0.389	-0.244	140	0.097
		(0.489)	(0.490)	(0.498)	(0.657)	(0.488)	(0.622)	(0.678)	(0.625)		(0.353)	(0.454)	(0.812)	(0.398)		(0.625)	(0.565)	(0.528)	(0.523)	(0.294)	(0.522)		
7) 25% carry at risk		0.0762	0.111	0.296*	0.193	0.262*	0.0920	0.000568	0.0277		0.0888	0.303*	-0.0183	-0.170		-0.368**	-0.255	-0.283	-0.254	0.0190	0.531***	140	0.163
		(0.156)	(0.140)	(0.158)	(0.221)	(0.145)	(0.163)	(0.151)	(0.156)		(0.0868)	(0.166)	(0.168)	(0.117)		(0.175)	(0.172)	(0.179)	(0.175)	(0.0866)	(0.136)		
8) 50% carry at risk		-0.271	0.169	0.305	-0.246	0.105	-0.432	-0.264	-0.177		0.185	-0.0467	-0.253	-0.226		-0.0993	-0.128	-0.287	-0.178	0.370	-0.287	140	0.065
		(0.409)	(0.410)	(0.443)	(0.616)	(0.398)	(0.580)	(0.612)	(0.571)		(0.309)	(0.448)	(0.702)	(0.357)		(0.515)	(0.493)	(0.438)	(0.429)	(0.251)	(0.464)		
Sustain.-Expert in Fund Team																							
9) Non-existent		0.226	0.148	0.00635	-0.0102	0.240	0.224	0.460**	0.100		-0.0656	-0.271	-0.275	-0.0509		-0.122	-0.253	-0.128	-0.0848	-0.149	-0.381*	140	0.092
		(0.224)	(0.205)	(0.202)	(0.212)	(0.191)	(0.277)	(0.203)	(0.270)		(0.122)	(0.212)	(0.191)	(0.139)		(0.212)	(0.238)	(0.219)	(0.237)	(0.114)	(0.211)		
10) Existent		-0.226	-0.148	-0.00635	0.0102	-0.240	-0.224	-0.460**	-0.100		0.0656	0.271	0.275	0.0509		0.122	0.253	0.128	0.0848	0.149	0.381*	140	0.092
		(0.224)	(0.205)	(0.202)	(0.212)	(0.191)	(0.277)	(0.203)	(0.270)		(0.122)	(0.212)	(0.191)	(0.139)		(0.212)	(0.238)	(0.219)	(0.237)	(0.114)	(0.211)		
Management Fee																							
11) 1.50%		-0.529	-0.216	-0.273	-0.558	-0.381	-0.439	0.528	-0.118		0.111	0.0633	-0.103	-0.324		0.163	-0.0512	0.585**	0.430	-0.311*	1.769***	140	0.127
		(0.346)	(0.319)	(0.308)	(0.408)	(0.293)	(0.355)	(0.393)	(0.375)		(0.177)	(0.397)	(0.361)	(0.306)		(0.313)	(0.300)	(0.280)	(0.317)	(0.169)	(0.277)		
12) 2.00%		-0.193	-0.0156	-0.0245	0.221	0.124	0.106	-0.0768	0.167		0.132	0.335*	-0.00644	0.117		-0.0584	0.0322	0.0976	0.0212	-0.00463	0.539***	140	0.078
		(0.176)	(0.201)	(0.182)	(0.196)	(0.158)	(0.211)	(0.264)	(0.167)		(0.109)	(0.200)	(0.233)	(0.181)		(0.224)	(0.228)	(0.228)	(0.230)	(0.103)	(0.192)		
13) 2.50%		0.722*	0.232	0.297	0.338	0.257	0.332	-0.451	-0.0488		-0.243	-0.398	0.110	0.207		-0.104	0.0190	-0.682*	-0.451	0.316	-2.308***	140	0.106
		(0.399)	(0.384)	(0.359)	(0.519)	(0.340)	(0.462)	(0.478)	(0.462)		(0.213)	(0.438)	(0.504)	(0.345)		(0.404)	(0.372)	(0.379)	(0.418)	(0.191)	(0.339)		
Performance of Previous Fund																							
14) Slightly below expectations		1.151**	0.560	0.643	-0.238	-0.231	0.580	-0.237	0.500		-0.145	0.463	0.366	0.762*		-0.137	-0.201	-0.216	-0.257	-0.544*	-2.215***	140	0.180
		(0.499)	(0.500)	(0.530)	(0.569)	(0.402)	(0.563)	(0.755)	(0.534)		(0.312)	(0.526)	(0.606)	(0.409)		(0.526)	(0.560)	(0.556)	(0.564)	(0.286)	(0.546)		
15) Slightly above expectations		-1.151**	-0.560	-0.643	0.238	0.231	-0.580	0.237	-0.500		0.145	-0.463	-0.366	-0.762*		0.137	0.201	0.216	0.257	0.544*	2.215***	140	0.180
		(0.499)	(0.500)	(0.530)	(0.569)	(0.402)	(0.563)	(0.755)	(0.534)		(0.312)	(0.526)	(0.606)	(0.409)		(0.526)	(0.560)	(0.556)	(0.564)	(0.286)	(0.546)		
16) None (no fund chosen)		-0.808	-1.781*	-1.799	0.790	-1.810*	-2.773**	-1.833	-0.382		0.449	-0.879	1.978*	-0.625		0.858	1.789*	0.621	2.175*	0.0977	0.223	140	0.184
		(1.400)	(0.990)	(1.181)	(1.614)	(0.984)	(1.184)	(1.536)	(1.478)		(0.714)	(1.033)	(1.072)	(1.136)		(1.228)	(1.050)	(1.148)	(1.244)	(0.651)	(0.956)		

Note: The table provides coefficients from linear regressions. In the six models of panel A (model 1 – 6), the relative importance of each attribute is the dependent variable (*CO2 Reduction Target on Portfolio, EU SFDR Article Compliance, Carry at Risk (Sustainability-related), Sustainability Expert in Fund Team, Management Fee* and *Performance of Previous Fund*). In the 16 models of panel B (model 1 – 16), the HB raw utility of each attribute level is the dependen variable. Panel A therefore allows for interpretations concerning the relative importance of the fund characteristic on the decision of the investor while panel B allows for interpretations of the utiltiy gains for each attribute level. The independent variables are the categorical variable of the different investor type (*familiy office, insurance company, public pension fund, corporate pension fund, endowment, fund of fund, bank/finance company, sovereign wealth fund* and *other),* the categorical variable of the primary region of the investor (*North America, Continental Europe, Scandinavia, United Kingdom* and *Rest of World),* the categorical variable of the AUM of the investor *(<$100M, $101M - $500M, $501-$1,000M, $1,001-$5,000M* and *>$5,001M)* and the dummy variable *ESG signatory* that takes the value 1, when the investor signed an ESG-commitment and 0 otherwise. Given the categorical nature of the variables investor type, investor region and AUM, one category serves as the reference category to avoid collinearity issues. The reference categories are *Family Office, North America* and *AUM <$100M* respectively. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

3.5 Conclusion

3.5.1 Discussion

Although investment criteria of limited partners into private equity funds have been implicitly or explicitly discussed in previous academic literature (Gompers and Lerner 1999; Da Rin and Phalippou 2017; Loos and Schwetzler 2017), and although sustainable investing is a recently extremely popular topic in research (Eccles et al. 2017; Eccles et al. 2014; Kölbel et al. 2020; Pástor et al. 2021), relatively little is known about limited partners' consideration for sustainability criteria in the private equity context. We address this research gap by analyzing which sustainability investment criteria are relevant for limited partners and elaborate on differences in preferences amongst different investor types. We do so in first deriving relevant sustainability fund characteristics from literature (Kaplan and Schoar 2005; Robinson and Sensoy 2013; Hartzmark and Sussman 2019; Hendrikse et al. 2022; Da Rin and Phalippou 2017) and then conducting a choice-based conjoint analysis to simulate a similar situation of investment decisions during the fund selection process of LPs (Hill 2017). In spite of large interest in sustainable finance and investment decision of limited partners in private equity, this study is among the first and largest to assess the investment criteria of limited partners. We investigate the general relevance, compare the importance of frequently discussed sustainable investment criteria and discuss different predilection of limited partners. We compared the decision behavior of 140 limited partners conjointly in 8400 investment decisions. We find that having a CO2 reduction target on the portfolio, complying with the EU SFDR article regulation, having a sustainability-related carry at risk and having a sustainability expert in the fund team are, in our setting, significantly influencing the investment decision of limited partners. In line with prior research, traditional investment criteria like the management fee and the performance of the previous fund are also significantly influencing the investment decision of limited partners. Second, we find that limited partners attribute greater relative importance to traditional fund characteristics like previous performance and management fee and less to sustainability characteristics. But the relative importance of sustainability criteria still seems to be driving the fund selection (e.g., having a sustainability-driven carry at risk and EU SFDR article compliance together are almost equally important like the previous fund's performance). Third, we find differences in different types of LPs: limited partners that are self-committed through signing ESG affiliations are attributing higher importance to a CO2 reduction target on the portfolio, while being less sensitive to the management fee. Institutional investors like insurance companies have a higher tendency to value a CO2 reduction target than family offices and North American limited partners are more sensitive towards a conditional sustainability carry than European limited partners.

3.5.2 Limitations and future research

Limitations of this study stem from the research setting and the methodology used to address the individual preferences based on hypothetical investment decision. This limitations come from a two-folded consideration: a priori researchers cannot derive the most critical attributes and levels affecting the respondent's decision making process, especially in a research area like limited partner investment criteria where theory testing has been scarce (Lohrke et al. 2010; Da Rin and Phalippou 2017). Our study focuses, to our best intentions, on several (sustainability) characteristics and thereby cannot provide a comprehensive decision scenario for the participant. Results like relative importance need to be carefully interpreted, given their contextual values. Further, research in experimental economics deals with the challenge of incentivization of participants. While we have tried to incentivize participants with an overview of the results and an invitation to a LP networking event, a lack in true (dis)incentives to motivate behavior can result in a reduced cognitive effort that is needed to reveal true judgements, resulting in unreliable data (Smith and Walker 1993). The study conducted in a hypothetical context lacks actual consequences and the accordance with “true” preference structures of participants can be questioned (Lohrke et al. 2010). But this study broadens the academic view beyond descriptive information to predict the investment preferences of limited partners by real trade-off decisions (Orme 2010).

The methodology itself offers various opportunities for further application within the private equity research field, has it yet only been leveraged in very few studies (Orme 2010; Dawson 2011; Block et al. 2019). Since the data foundation for sustainable financing around ESG is developing, research based on actual data will take some time. Initiatives like the ESG data convergence initiative are aiming to setup standardized data (EDCI 2023), that can be leveraged for academic research in the upcoming years to improve the setup and LP characteristics even more.

4 Patent to the Future? – Private Equity Impact on Green Innovation

Abstract

We assemble a deal level dataset of 2665 unique private equity (PE) deals to analyze the environmental innovation impact of private equity deals on their portfolio companies. We analyze quantitative patent and green patent information in relation with deal level data using OLS models and Poisson likelihood models. PE deals are positively correlated with green patent activity post deal. The positive correlation is most profound for a sub-sample of highly patent-active companies that are involved in the deal. However, ESG signaling of the investors is not related to green patent activity. Our findings support the view of positive long-term innovation impact of private equity deals as it confirms existing literature while introducing an additional variable for consideration: green patent activity. But it also raises a question as to why there is no correlation of PE firm's ESG commitments to green patent activity and rather suggesting that PE firms promote responsible investment to serve investor preferences.

Keywords: Private equity, patent activity, green patent, sustainable impact

4.1 Introduction

Achieving the goals of the Paris Agreement will require substantial investment in climate mitigation technologies. A study published in the Economist states that the global energy transition investments need to increase to ~130 Trillion US-dollar by 2050 to reach the 1.5°C scenario, equal to ~4.4 Trillion US-dollar each year (Economist Impact 2021). The private sector needs to play a key role in this net-zero transition and has been actively addressed by regulatory institutions like the European Union already (D'Arcangelo et al. 2023; European Commission 2019). With a record of 3.7 trillion US-dollar in dry powder by the end of 2022, the private equity (PE) industry would be financially well set up to contribute substantially to the net-zero transition (Bain & Company 2023). The global publication and media company *Private Equity International (PEI)* sets the tone for the wider private equity industry and dedicated an entire edition to "Responsible Investment". The narrative sounds promising: "Private markets are well placed to support […] companies required to mitigate climate change", "Investors double down on ESG", "Investing with impact - Private equity's active ownership model means firms are uniquely positioned" and "Innovative technology and business models mean the opportunity set around climate risk is expanding" indicate the industry's self-perception (PEI 2022). Recent research has focused on the investor's nonpecuniary utility through impact investing (Barber et al. 2021), their value through sustainability (Hartzmark and Sussman 2019), the investor's willingness to pay for sustainable investments (Heeb et al. 2023; Barber et al. 2021) or the path of investors like pension funds to decarbonize their portfolios (Boermans and Galema 2019). Yet none of them have focused on private equity funds or their operating model, even though the mechanisms of active shareholder engagement has been empirically derived as successful approach (Berk and van Binsbergen 2022; Marti et al. 2023). Therefore, this paper attempts to elaborate on the sustainable impact of private equity deals. Following approaches of Lerner et al., Amess et al.

and Ughetto, we assess our deal sample's innovation impact by patent activity (Lerner et al. 2011; Amess et al. 2016; Ughetto 2010). We extent their assessment of innovation in the private equity context by focusing our research on green patents as a proxy of "environmental" knowledge following research from other academic research fields (Fabrizi et al. 2018; Ghisetti and Quatraro 2017). First we provide an overview on our theoretic consideration of the patent activity within the private equity environment and on green patents as an environmental innovation proxy. We then describe our empirical strategy and how we have hand-matched Preqin deal-level data with patent data from Orbis Intellectual Property database to create an event study setup with a time window of five years prior and post deal. We then use descriptive statistics, OLS regression models and Poisson likelihood regression models to obtain three findings: we find that in our sample private equity deals are significantly positively correlated with an increase in green patent activity. In an attempt to deeper understand the drivers of the increase in patent activity post deal, we then find that the effect is stemming from a sub-sample of highly patent-active companies. Thirdly, we find no indication that ESG signaling of the private equity firms is correlated to an (over proportional) increase in such green patent activity.

Our study contributes to the existing literature in several ways. First, it responds to research questions raised recently by McGrath and Nerkar who are pointing out the research potential to assess the long-term investment outcome of buyout firm's patent activity (McGrath and Nerkar 2023). The paper addresses the question whether PE creates impact or whether the debate on impact is merely a green washing issue implied by a study by Liang et al.. Their study shows that hedge funds endorsing the United Nations Principles for Responsible Investment (UN PRI) underperform other hedge funds but attract greater investor flows, accumulate more assets and ultimately earn greater fee revenues (Liang et al. 2022). This paper does not provide a final answer, but suggestes that PE deals actually do create impact, but it is not driven by presumingly sustainability commitments expressed through self-signatories with the UN PRI or disclosure of ESG metrics publicly (ESG score). Instead it seems to rather stem from a pure value consideration: the green patent activity signals innovation and business in attractive markets in the future (policy, consumer demand or alike) and hence contribute to recent conversations of Edmans (Edmans 2023). Our paper contributes in elaborating on a pre and post deal consideration and the relative impact within PE-group on green patent activity. It does not allow for any conclusions whether PE-backed companies are enforcing green innovation better than public peers. Green patent activity is an objective and reliable measure of environmental innovation and as such has been chosen for this study. But there are many more relevant dimensions, and it is not a holistic measure for impact.

4.1.1 Theoretical considerations

ESG ratings are widely used by institutional investors for risk management and engagement purposes (Krueger et al. 2020). However, in academic conversations about measuring ESG or impact investing, there is one major agreement: that there is strong disagreement on sophisticated ESG or impact measurements. Berg et al. have shown in their paper "Aggregate Confusion: The Divergence of ESG Ratings" how ESG ratings differ in their methodologies and as such result in different ratings (Berg et al. 2022). They decompose the divergence into the drivers scope, weight, and measurement and conclude that the ESG divergence is "not merely a matter of varying definitions but a fundamental disagreement about the underlying data" (Berg et al. 2022). In 2018, Eccles and Stroehle have already argued, that there are two different clusters of organizations measuring ESG: data providers with a value-driven and data vendors with a values-oriented approach. While the former focusses mostly on quantitative and performance-based metrics, the latter is including more qualitative and policy-related information (Eccles and Stroehle 2018).

Dumrose et al. foment hope in demonstrating a positive relation between the EU Taxonomy and ESG ratings of major data provider to show a path towards more standardized ESG measures. They suggest, that an harmonization of measurement through a reflection of the EU Taxonomy could result in an convergence of the (E part of) ESG scores (Dumrose et al. 2022). The EU Taxonomy was introduced within the framework of the European Green Deal. The European Green Deal aims to transform Europe into the world's first climate neutral continent by 2050. In order to finance the path to net zero emissions "massive public investment and increased efforts to direct private capital towards climate and environmental action" are required (European Commission 2019). Therefore, the EU is strongly incentivizing and mobilizing private investments, e.g. through carbon pricing or programs such as Horizon Europe (European Commission 2019). These aforementioned developments are rising the need for two efforts with regards to potential measures: firstly, to find and leverage a more standardized measure for (sustainable) impact or innovation and secondly, a quantitative measure to serve our rising challenge in finding ways to finance the path to net zero emissions. Edmans is tapping into this complex academic field by suggesting further implications for ESG research in his opinionated paper "The end of ESG" (Edmans 2023). He states that investors are often very number driven, including their ESG approaches. But especially the qualitative aspects are prone to be mispriced by the market and hence are tied to the long-term return (Edmans 2023). Using the quality of innovation based on the payoffs from past R&D expenditures, Cohen et al. are showing, that this quality-based measure significantly predicts stock returns in the future while the sole focus on quantity of R&D expenses does not (Cohen et al. 2013). Edmans concludes a research direction in which academics shall use numerical data, but pay attention to "quality rather than just quantity" (Edmans 2023). Calibrating the ESG view through a long-term value perspective and considering it as one of many value drivers, leads to implications for further research. This long-term value perspective shifts the conversation towards studying issues because they create value, regardless of fitting into an ESG category or not. Instead, it elaborates on the investor's support to drive success long term and the pricing of intangible assets by the market. These mechanisms have been leveraged in the past already: most drivers of long-term value – especially intellectual property like patents, but also customer attrition, or net promoter scores – are reported by companies and thoroughly analyzed by stakeholders and investors. The conversation usually extends from a pure quantitative reflection to an understanding of the reasoning (Edmans 2023).

While patents have been used within the context of private equity research frequently in the past (Lerner et al. 2011; Amess et al. 2016), green patents have not - despite its potential to contribute to aforementioned discussion suggested by Edman. Green patents add this qualitative categorization to a purely focused patent consideration and have been used in different studies in the recent past (Cohen et al. 2020; Hoang et al. 2020; Fabrizi et al. 2018). Hence, we will first elaborate on the importance and relevance of patents in general and then further discuss the potential for evaluating green patent activity.

Patents are of economic relevance for the individual company and as such are relevant for the long term value perspective for the investor. Based on a survey of >9000 European inventors, Giuri et al. derive six uses of patents within a company (Giuri et al. 2007): 1) *Internal Use*: the patent can be leveraged internally for both commercial or industrial use, whether in a production process or as an integral part of a product; 2) *Licensing*: the applicant does not utilize the patent internally, but instead licenses it out to another party; 3) *Cross-Licensing*: the patent is licensed to another party in exchange for another invention; 4) *Licensing and Use:* the patent is licensed to a third party and utilized internally within the applicant's organization at the same time; 5) *Blocking Patent*: the patent is not in use at all (neither internally nor for licensing) and solely used to for blocking competitors; 6) *Sleeping Patents*: the patents are not utilized in any of the uses described above, but it may still be advantageous and an asset protecting a completely different technical approach in the future. At the same time, investors have to rely on signals of economic value that they perceive as more genuine (Cohen and Dean 2005). Signals are observable firm characteristics which are directly controllable by the firm at the time of an equity issue such as the possibility of the entrepreneur developing valuable products that are the property of the firm in the future (DOWNES and HEINKEL 1982). Firms with suitable timing in signaling, with adequate frequency in signaling and the overall ability to strategically signal their value are able to reassure their investors and thus attract future resources more easily (Janney and Folta 2003).

As such, patents are fulfilling the criteria for being a strong signal and have been used within the private equity context in the past. Ughetto has used panel data setting to test whether deal characteristics of the deal of private equity firms affected the acquired companies' innovation effort. As measured by the number of patents granted, the innovation activity of 681 companies was investigated concluding that various drivers like type of investor, risk propensity, expected return and investment policies are affecting the innovation activity (Ughetto 2010). Lerner et al. investigate 472 LBO transactions to investigate the long-run activity of LBO funds. Their results suggest, that LBO firm patents are more cited, are more concentrated in important areas of the companies' innovation portfolios and that they show no shifts in fundamental nature of the research (Lerner et al. 2011). Amess et al. have used a sample of 407 UK deals to suggest that LBOs have a positive causal effect on patent stock and quality-adjusted patent stock. They show, that the increase in innovation activity is in particular concentrated among private-to-private transactions with a 14% increase in quality-adjusted patent stock (Amess et al. 2016). Investigating the potential of patents as signals for the IPO market, Useche has analyzed the patent applications of 476 companies before their respective IPO and has found significant and robust positive correlations of the patent application activity and IPO performance. The signaling power significantly differs between US and European companies due to its scarcity and difficulty to obtain a signal (Useche 2014). However, using patents as an innovation driver has advantages and disadvantages over alternative measures (like R&D expenditures). Patents are a good innovation output indicator, thereby a good indicator of new technology and also account for the effectiveness of the innovation activity (Acs et al. 2002; Amess et al. 2016). Patent data follows objective standards and is retrieved from independent administrative databases, the indicator does not rely on self-reporting measures of new products, processes and KPIs. It is therefore not only widely available, but it also measures intermediate output, is quantitative and can be disaggregated into specific technological fields (Haščič and Migotto 2015). In addition, securing patents is a costly endeavor and a granted patent requires a level of uniqueness which reduces the risk of counting innovation of little relevance (Amess et al. 2016). Several studies have also shown, that patent applications seem to be highly correlated with other common indicators of innovative performance (Griliches 1990; Hagedoorn and Cloodt 2003). Hagedoorn and Cloodt's findings suggest that the statistical overlap between innovation indicators is that strong, that future research can focus on either measure as a proxy for innovation performance of companies (Hagedoorn and Cloodt 2003). It is problematic though, that not every invention is leading to a patent per default, the exact degree of its originality is hardly expressible and firms may make use of different strategies of formal IP rights protection for their innovation (Hall and Ziedonis 2001; Haščič and Migotto 2015; Basalla 1988). It is also expected that there is evident divergence within the value of individual patented innovations, they vary in quality (Amess et al. 2016). Despite these challenges, there is very recent research demand suggested by McGrath and Nerkat to use buyout firm's patent activity to assess long-term investment outcomes, especially elaborating on the evaluation of type and level of innovation outcomes (McGrath and Nerkar 2023).

4.1.2 Green patents and green codes

While the aforementioned papers are investigating solely the effect of PE firms on financial constraints and the funding of innovation (Amess et al. 2016; Lerner et al. 2011), this paper is additionally also concerned with the funding of green innovation. As introduced in the previous section, we would like to discuss the potential of evaluating such specific green patent activity in this section. In Edmans' paper "The end of ESG", the author is pointing the ESG research towards more granular research and directed to a more focused research towards for example that "E" component (Edmans 2023). Institutional investors show efforts for ESG integration into their investment decisions, but their major barrier for ESG integration is the lack of standards in both ESG data and how to properly use it (Eccles et al. 2017). Lanjouw and Mody were amongst the first to introduce patent data to study green or environmental innovation. They use the share of environmental patents in all patents as a trend in environmental innovation and diffusion (Lanjouw and Mody 1996). Their environmental innovation focused on pollution abatement innovation and new technologies lowering the production of pollution and was extracted using the international patent classification (IPC) codes based on a keyword consideration (Lanjouw and Mody 1996). Since then, this approach has been used as a good proxy for green innovation and further refined. Most development within this approach has focused on better classifying patents in environmental (related) technologies (Ghisetti and Quatraro 2017). The recent derivations of green patents are typically going back to an effort by the OECD in 2015 where Hascic and Migotto conclude, that patent data is best suited in order to identify specifically "environmental" sound innovation. They argue, that patent classification systems are "technological by nature […] and allow for a rich characterization of relevant technology […] at a fine level of detail" (p. 17) (Haščič and Migotto 2015). They provide a detailed explanation of an OECD's algorithm called ENV-TECH, that identifies patents based on their technological classification that relate to environmental pollution, water scarcity, and climate mitigation. This approach is based on the International Patent Classification (IPC) system, that has been developed at the World Intellectual Property Organization. The hierarchical classification system comprises more than 70,000 technological groups and subgroups in which inventions are classified (Haščič and Migotto 2015). Prior to the OECD, in 2010 the World Intellectual Property Organization (WIPO) in collaboration with the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC) published a first "IPC Green Inventory" list which collects IPC codes related to Environmental Sound Technologies. In 2012, the European Patent Office (EPO) developed a new classification scheme (Y02/Y04S tagging scheme) to detect climate change mitigation technologies (Favot et al. 2023). To identify a comprehensive set of green patents, a combination of the ENV-TECH (developed by OECD) and the IPC Green Inventory list is best used (Favot et al. 2023).

There are several reasons, why the signaling of green patents could be of relevance for private equity investors. The production of green patents could be considered as a proxy of new "environmental" knowledge. The production of green patents is impacted by market-based regulation policies and participation in green European research networks with universities and public research centers (Fabrizi et al. 2018). Both could be seen as signals for the investor. While the latter could be interpreted as an indicator for competitive activities in innovative networks and a strong development position, the former could be reflected as a market opportunity due to regulatory change. Given the patent activity in a market environment with regulatory pressure, there is an indication of dynamics in the market that could be favorable for a firm and corresponding investor. Both could be positive signs for promising future cash flows, that are favorable for PE investments.

A private equity investor could also seek investments into companies with an increased activity of green patents to invest in line with ESG or sustainability commitments such as the

UN PRI. Investors could seek an active involvement in companies with green patent activity to exploit exposure to impact investors that have a higher willingness to sacrifice returns for a mission objective (Barber et al. 2021). Conversely, Cohen et al. found, that the majority of green patenting is not driven by these impact funds or ESG firms, but instead by firms that are typically excluded from ESG funds investment scope (Cohen et al. 2020).

In order to direct private capital towards climate and environmental actions as demanded by the EU in their European Green Deal (European Commission 2019), the private equity business model could be an effective vehicle contributing to this transformation. In literature, there have been three mechanisms identified of how sustainable investing can positively impact environment and society (Marti et al. 2023): portfolio screening, shareholder engagement and field building. There seems to be growing consensus, that voice (as in shareholder engagement) achieves better outcomes over exit (as in screening out of portfolio companies), companies should invest and exercise their rights of control to change corporate structures (Broccardo et al. 2022; Berk and van Binsbergen 2022). The traditional operating model of private equity and leveraged buyouts with its aligned incentives, orientation towards value creation and focus on effectiveness could be well suited for both portfolio screening and shareholder engagement (Jensen 1989, revised 1997; Kaplan and Strömberg 2009). Field building is a mechanism suitable for operationalization by the private equity industry as well. Venture capital (VC) is one particular form of private equity investing, with a business model that works best in newly emerging markets that can support fast growth (at large scale) (Metrick and Yasuda 2011). While the term “PE” refers to both, the transition from “traditional VC” to often interchangeably used term of “leveraged buyouts” for a more narrow definition of private equity is seamless and its motivation for growth in emerging market remains (Metrick and Yasuda 2011; Kaplan and Strömberg 2009). Recent research provides some initial indication, that PE governance can drive sustainable change. The results of Bellon’s study on PE ownership and liability risks, suggests that PE ownership does reduce pollution but only, when “the target company faces high environmental enforcement or political risk” (Bellon 2022). His results suggest that PE governance mainly drives the result.

In light of the academic consensus on the problem of what is the “best” ESG measurement, we acknowledge the fact, that there is (yet) not such measure (Berg et al. 2022; Edmans 2023). Measures diverge in their results, measurement, and interpretation and as such might be considered in the individual context. However, we consider green patents as an objective measure, independent indicator of technological development and intermediate output that is of quantitative nature and accessible – even though it might also not be the perfect measure. Under the assumption, that the private equity industry could serve as a suitable vehicle to contribute towards the sustainable transformation, we have chosen the green patent activity as a proxy to elaborate on its impact within this paper.

4.2 Empirical strategy

4.2.1 Methodology

Having established a justification on why we consider the (green) patent activity as a measure for private equity impact on environmentally sound efforts, we derive an empirical setup to elaborate on the impact of private equity deals on portfolio company’s green patent activity. We run two different types of regressions to obtain robust results. Firstly, we estimate the following fixed-effects panel regression model:

$$patent_{i,t} = \alpha_i + \tau_{j,t} + \gamma \cdot post_t + \delta \cdot groupdummy_i + \beta \cdot post_t \cdot groupdummy_i + \varepsilon_{i,t}$$

$patent_{i,t}$ is the dependent variable and refers to the patent count (or normalized patent count) of company *i* in year *t*. α_i and $\tau_{j,t}$ are company and deal-year fixed effects, respectively. $post_t$ is a dummy equal to one in and after the year of the respective deal. $groupdummy_i$ is a dummy equal to one if the firm is in the considered group (e.g., country dummy, industry dummy) and zero if not. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered by deal. Secondly, we estimate a fixed-effects Poisson pseudo likelihood regression model estimating $log(E[y|x]) = x\beta$. A potential option would have been to leverage a log-linear regression to account for only positive count values that are rather approximately exponentially distributed (density distribution is skewed positive, see log density plots in Appendix F). But, while estimating linear regression models of the log of 1 plus the outcome produces estimates lacking meaningful interpretation and suffering from inherent biases, simple fixed-effects Poisson models produce consistent and reasonably efficient estimates (Cohn et al. 2022a). The key difference between the Poisson and log-linear regression models is that Poisson regression estimates $log(E[y|x]) = x\beta$ while log-linear regression estimates $E[log(y)|x]) = x\beta$. Our setup follows an event study logic in which multiple time periods and variation in treatment timing are normalized for the deal year, typically used in a Difference-in-Difference setting (Callaway and Sant'Anna 2021; Goodman-Bacon 2021). In our setting, we are only investigating outcome regressions on a pre and post deal consideration.

4.2.2 Data description

The sample we use for our event study analysis contains data from mainly private firms (some public firms that went private during the observation period) on private equity deals, the involved funds and GPs as well as the respective portfolio companies. It is based on data from Preqin and Bureau van Dijk's Orbis database, that has been used for the academic purpose regularly in the recent past (Braun et al. 2023; Böni and Roon 2023; Jenkinson et al. 2021; Harris et al. 2014). An overview of the sample construction can be found in Table 18.

Table 18: Sample generation process

Step	Description	N patents	Deals	Unique portfolio companies
Panel A: General data preparation				

1	We start with all completed buyout deals included in Preqin ("Deal Status: Completed")		99871	79804
2	We hand match the unique portfolio companies to the Orbis database to obtain BvD-IDs and additional information		79020	62368
3	We filter for "US" and, to cover a wide range of Western European countries, for Germany, France, Italy, UK, Norway, Sweden, Denmark, Finland, Netherlands, Belgium, Spain, Switzerland, Austria, Luxembourg, Portugal		64713	50988
4	We hand collect the individual patent stock of each respective portfolio company available in Orbis through BvD-IDs	3316714	14947	10757
5	We categorize each individual patent based on IPC classification and reorganize the patent stock into a panel dataset by company and year	3316714	14947	10757
Panel B: Sample construction				
6	We filter the patent stock for only "Granted" and "Expired" patents (to only consider granted patents or those, that have been granted in the past) and merge the information with the deal level data to create basis for event study dataset	2208789	14419	9698
7	We filter the dataset for deal events in years 2000-2017 and drop duplicates of the same portfolio company and the same deal year under the assumption that those deal events refer to the same overall deal (e.g., several transactions)	1574591	8749	6625
8	We create an event window dataset with five years prior and post deal and exclude all deals in which none of the five years post deal show any granted (or expired) patent (assuming that the patent registration is then filed under a new entity)	560655	4262	3313
9	Considering a delay in the patent filing process and hence assuming a better data quality, we drop all deals with deal date > 2014 in the sample.	480259	3326	2665
10	We consider only the first deal of each unique portfolio company to avoid potential overlaps of the effect (e.g., second deal falls into the deal window of the first deal)	480259	2665	2665

Note: This table provides an overview of the data collection logic. The data collection effort followed 10 steps and can be split into two steps: first, we hand-collected data on the PE deals, the involved portfolio companies and their patent stock and second, we setup our final sample. The final sample was constructed under economically logical assumptions to setup a event-study deal window in line with good academic practice.

We start with all completed buyout deals available in Preqin of our extract from 2022. We hand-match the portfolio companies involved to the Orbis database to be able to retrieve additional information. In order to cover the majority of European and US deals we filter our deals for the US, Germany, France, Italy, UK, Norway, Sweden, Denmark, Finland, Netherlands, Belgium, Spain, Switzerland, Austria, Luxembourg and Portugal. For the companies involved in these deals of relevance, we then manually obtain the full available patent stock from Orbis' Intellectual Property database. These patent information amongst others include the publication ID, the publication date, the IPC classification and the publishing status. We label each individual patent based on its IPC classification in line with the suggestions of Favot et al. as green following the IPC Green Inventory (WIPO), the ENV-TECH (developed by OECD) and a combination of both classifications (Favot et al. 2023). The patent stock is then organized into a panel dataset by counts per year for each respective company.

To derive the final sample, we then filter the patent stock for "granted" and "expired" patents to only consider patents that are or have been granted in the past. After merging the patent stock with the deal level data, we only consider deals in the years from 2000-2017 to ensure patent stock data five years prior and past the deal event. Additionally, we drop all duplicate deals within the same year involving the same company under the assumption that those deal events refer to the same overall deal. This includes several minority transactions involving the same portfolio company in the overall deal process or simply funds processing the same transaction during different months. The event study dataset is finally created by setting up an event window dataset with five years prior and post the buyout deal and merging the patent stock information with the deal level dataset. We clean the dataset and drop all deals in which we do not observe any patent activity in all five years after the deal event year assuming, that the patent registration is filed under a new entity after deal (e.g., buyout company is integrated into a different holding). The overview of the annual patent stock and share in green patents per company can be found in Appendix G. Given the strong decrease in average patents/company in the later years, we assume the patent stock for the more recent deals to be less comprehensive, than the patent stock for deals in the further past. Patent filing routes at e.g., the EPO (European Patent Office) can take up to ~3 years. To ensure, that these patents are potentially included in our deal sample, we only include deals until (and including) 2014 to consider our five year event study window and account for application periods of up to three years in the patent stock (van Zeebroeck and van Pottelsberghe de Potterie 2011). Information on the annual patent stock and deals considered can be found in Table 19.

Table 19: Annual deal and patent stock overview deals 2000-2014

Year	Qty companies	Qty deals	Patent count	Ave. Patents/company	Green patent count	Ave. green patents/company	Green patents/patent ratio
1995	140	0	1602	11.44	27	0.19	0.017
1996	248	0	3153	12.71	76	0.31	0.024
1997	355	0	4962	13.98	168	0.47	0.034
1998	479	0	6684	13.95	164	0.34	0.025
1999	627	0	9924	15.83	347	0.55	0.035

2000	819	140	13381	16.34	550	0.67	0.041
2001	1039	108	22055	21.23	1013	0.97	0.046
2002	1284	107	31622	24.63	897	0.70	0.028
2003	1472	124	35658	24.22	1106	0.75	0.031
2004	1594	148	28927	18.15	928	0.58	0.032
2005	1793	192	27241	15.19	906	0.51	0.033
2006	1865	220	25411	13.63	533	0.29	0.021
2007	1980	245	24288	12.27	637	0.32	0.026
2008	2061	188	23831	11.56	656	0.32	0.028
2009	2180	122	22702	10.41	590	0.27	0.026
2010	2033	200	21351	10.50	586	0.29	0.027
2011	1844	215	20956	11.36	557	0.30	0.027
2012	1625	224	18955	11.66	600	0.37	0.032
2013	1381	189	14178	10.27	392	0.28	0.028
2014	1193	243	11212	9.40	324	0.27	0.029
2015	1071	0	9630	8.99	183	0.17	0.019
2016	871	0	6647	7.63	145	0.17	0.022
2017	656	0	5050	7.70	88	0.13	0.017
2018	432	0	2354	5.45	62	0.14	0.026
2019	243	0	554	2.28	12	0.05	0.022

Note: deals considered within years 2000-2014 with patent activity five years prior and post deal year
The table provides an overview of the quantity of deals per year in our sample. The second column indicates the how many companies are considered for the given year due to the event study setup (+- 5 years around the deal). The further columns provide information on the total patent and green patent count of these companies, the average patent and green patent quantity per company as well as the share of green patents to overall patents for each year.

Our main dependent variable of interest is referring to the number of patents (patent count) and the number of green patents (green patent count). Given that the sample includes various companies with a large patent stock and other countries with a rather smaller patent stock, we also include a scaled patent variables and a ratio of green patents by overall patent count.

The scaled patent count is defined as the patent count divided by the maximum patent count in the observed deal window, whereby $x_{i,scaled}$ is referring to the scaled patent score for the considered year:

$$x_{i,scaled} = \left(\frac{x_i}{x_{Max,\, event\ window}}\right)$$

x_i refers to the absolute patent count in the considered year, $x_{Max,\, event\ window}$ is the maximum patent count in our considered event window (+- 5 years around deal year) respectively. Thereby, we normalize the patent count by the event window amplitude per deal. The values of the scaled patent value therefore provide a share of maximum patent activity (within the considered respective deal window). A scaled patent value of 1 indicates a patent activity of the given firm is equally high as during its year with the most granted patents within the deal window. The green patent ratio simply refers to the quantity of green patents as a share of overall patents within the given year for the respective firm.

Descriptive statistics of each four types of patent variable for all and green patents can be found in Table 20. The lower part of Table 20 shows the same variables but under the condition, that the company had >0 green patents within the event window period. We have a total of 2665 deals (and unique portfolio companies), with 11 deal-year observations (deal year +- 5 years) resulting in 29315 observations. We observe high variation in deals and their patent activity. For instance, the median in patent count is still at 0 patents, while the mean = 13.38. The 75th percentile is at 4 and still lower than the mean. The tendency of the skewness in (green) patent count and high standard deviations of these figures are comparable to those in other datasets covering similar deal window observations (see Amess et al. 2016, patent count: mean = 0.048 and SD = 1.817, whereas we only consider deals with a patent count >0). Other PE studies are not reporting their patent count numbers to that extent making a thorough comparison difficult (see (Amess et al. 2016; Lerner et al. 2011; Ughetto 2010)).

We are in addition reporting additional fund information, that we will use for interaction effects in our analysis. UN PRI deal is a dummy variable, that takes the value 1 whenever one of the involved investors self-committed and became a signatory of the UN Principles for Responsible Investment (UN PRI) prior to the deal. Given that this involves only 3% of deals in our sample, we also include the UN PRI investor variable. UN PRI investor is a dummy variable, that takes the value 1 whenever one of the involved investors became a signatory of the UN PRI during the observation time (until 2022). We also include Preqin's ESG transparency score. The ESG transparency score can take values between 0 to 100 and increases with every ESG metric the investment firm publicly reports.

Additionally, we include a sub-sample of the patent variables for all deals, that have had at least one green patent within the deal window. This sample involves 558 unique deals with 6138 deal-year observations. The overall patent activity is logically higher for this sample, but the overall tendency is similar: several deals (companies) with high patent activity are affecting the mean of patent count and green patent count.

Table 20: Summary statistics

Variable	N	Mean	SD	P5%	P25%	Median	P75%	P95%
Total sample:								
Patent count	29315	13.38	84.99	0.00	0.00	0.00	4.00	40.00
Scaled patent count	29315	0.25	0.35	0.00	0.00	0.00	0.44	1.00
Green patent count	29315	0.39	5.08	0.00	0.00	0.00	0.00	1.00
Scaled green patent count	29315	0.03	0.17	0.00	0.00	0.00	0.00	0.14
Green patent ratio	29315	0.02	0.10	0.00	0.00	0.00	0.00	0.01
additional variables								
UN PRI deal	29315	0.03	0.17	0.00	0.00	0.00	0.00	0.00
UN PRI investor	29315	0.26	0.44	0.00	0.00	0.00	1.00	1.00
ESG transparency score	19855	37.86	26.06	5.00	16.00	30.00	59.00	86.00
Fund size [million USD]	20339	1878.92	3417.82	57.33	216.76	525.00	1840.00	8000.00
if min 1 year with green patent count > 0								
Patent count	6138	49.07	179.39	0.00	0.00	4.00	21.00	231.00
Scaled patent count	6138	0.35	0.34	0.00	0.00	0.27	0.60	1.00
Green patent count	6138	1.88	10.98	0.00	0.00	0.00	1.00	7.00
Scaled green patent count	6138	0.17	0.33	0.00	0.00	0.00	0.10	1.00
Green patent ratio	6138	0.08	0.22	0.00	0.00	0.00	0.01	0.61

The table provides an overview and summary statistics of firm-year observations of the patent variables, additional PE fund variables and patent variables for a sub-sample of deals that obtained at least one green patent within the deal window. The table provides the quantity, mean, standard deviation, percentile and median information. A list of full variable description can be found in Appendix E.

Several deal characteristics are considered during our analysis. An overview of these can be found in Table 21. It also includes the share in our sample and within the corresponding Preqin universe (relevant for our sample period). We classify the deal type into four types, following the initial types from Preqin (i) Buyout, (ii) Growth Capital, (iii) Public to Private and consider all other types of deals within (iv) Other. (iv) Other includes deal types such as add-ons, merger, restructuring, or private investment in public equity (PIPE), for which we believe that the patent count might be not as representable due to less active shareholder engagement through minority investments by the investor. The largest category in our sample is buyout comprising almost two third of the sample, 11% of the sample driven by growth capital deals and public-to-private deals representing 6% of our sample. We pool countries to form two major regions: US and Europe. With 47% representation of US deals in our sample and 53% of deals in our sample from Europe, we have good representativeness for both regions. To avoid potential time biases, we divide our time period to check for representativeness in time balance: "early" deals prior to 2007 and "later" deals from 2007 onwards. The fraction in our sample of 39% deals within the first half of our considered time period is comparable to the 30% in the overall Preqin universe, yet slightly higher due to the fact, that we are only considering the first deal of a company. Lastly, we are considering UN PRI deals, whenever one of the investors involved in the deal has been a UN PRI signatory before 2022. The share in deals with a UN PRI investor in our sample is 27% and hence slightly higher than the share in the Preqin universe, but both groups are well presented.

Compared to the Preqin universe, we similarly have the largest percentage for buyout, while it is slightly overrepresented in our sample, a fairly even split within the regions, similar balance in the time period of the deals and a similar representation of UN PRI investors involved in deals. We can therefore conclude a good representation of the Preqin universe within our deal sample.

Table 21: Main deal characteristics and sample representativeness

Panel A: Deal type			
Deal type	Obs	Fraction in our sample	Fraction in Preqin universe
Buyout	1724	65%	54%
Growth Capital	287	11%	2%
Public To Private	152	6%	2%
Other	502	19%	42%
Panel B: Deal region			
Deal region	Obs	Fraction in our sample	Fraction in Preqin universe
US	1260	47%	60%
Europe	1405	53%	40%
Germany	379	14%	5%
France	218	8%	8%
UK	218	8%	12%
Other	590	22%	16%
Panel C: Time balance			
Time period	Obs	Fraction in our sample	Fraction in Preqin universe
First half of sample (< 2007)	1039	39%	30%
Second half of sample (>= 2007	1626	61%	70%
Panel D: UN PRI deal			
UN PRI deal	Obs	Fraction in our sample	
UN PRI investor	684	26%	21%
Non-UN PRI investor	1981	74%	79%

Note: Preqin universe considered for deals in sample period (2000-2014) and regional focus on US and selected European countries as defined in this paper. The table provides a comparison of our sample and the full sample from the database Preqin. Four panels are presented: Panel A is a sample by deal type, panel B presents the comparison by deal by deal region/country, panel C provides an overview of the time balance of the sample splitting it in first and second half of our observation period and panel D considers the sample by deals performed by investors that are UN PRI signatories and non-signatories. The columns show the observation in our sample as well as the respective fraction in our sample and the Preqin universe.

4.3 Empirical results

4.3.1 Patent activity after a private equity deal

In this section, we analyze whether a private equity deal is related to the patent activity within the portfolio company. We start with a graphical analysis of the patent activity normalized over time. Figure 7 depicts patent count and scaled patent count for the entire sample. As the deal sample consists of 2665 deals between 2000 and 2014, the development in (scaled) patent activity is shown relative to the year of the deal of each transaction in Figure 7.

We observe slightly contradictory trends: the absolute patent count per annum seems to decrease after a private equity deal, while the graph of the scaled patent count shows an increase post PE deal. The increase in scaled patent count is in line with the view indicated by Ughetto. Ughetto found some evidence that the average number of patents granted per firm increases (from an average value of 1.06-1.59), but suggests that this increase stems from different investor types, with different objectives, different risk preferences and different return expectations (Ughetto 2010). Bearing in mind the unbalanced patent distribution over the years (see Table 19 and Appendix G) and these slightly contradictory trends in the descriptive graphs, we are controlling every analysis we are running for year fixed effects.

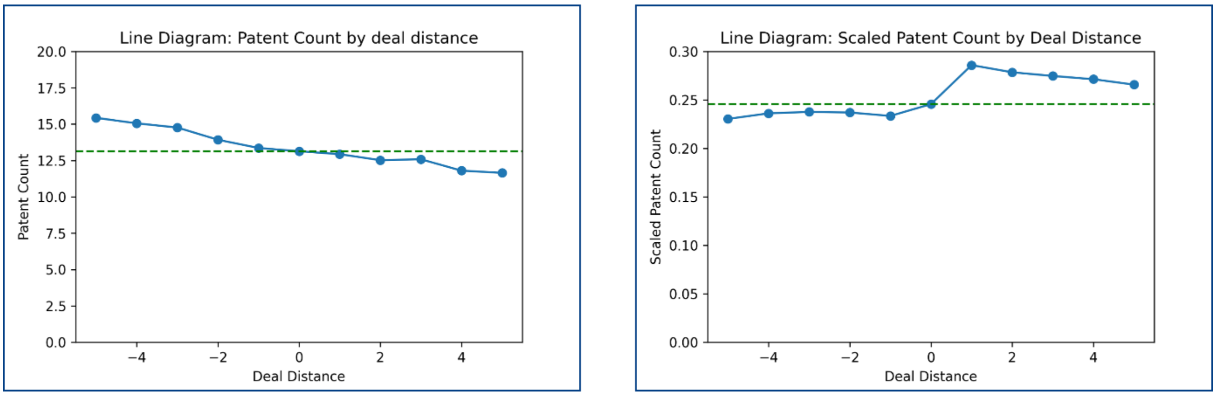


Figure 7: Patent activity over time

This figure depicts the development of the patent activity around the deal distance. All deals are presented with a relative deal window five years prior, and five years post the year in which the transaction took place. The left graph shows the mean of absolute patent count of all deals over time, the right graph shows the mean of scaled patent count of all deals over time. The dotted green line indicates the level of mean patent activity of the deal year.

The initial analysis in Table 22 uses the entire sample of 2665 firm deals and shows two types of regressions. We are running simple OLS regressions in model (1) and (3) and Poisson-Pseudo-Likelihood regressions in model (2) and (4) for both variables of. The table presents results where the dependent variable is patent count and scaled patent count of the respective observation year and *post* equals one in and after the deal takes place. A positive correlation in *post* suggests a positive trend in patent activity post deal. All specifications control for deal fixed effects and year (as mentioned above).

There are two main observations emerging from Table 22. First, the sign of the post deal coefficient for absolute patent activity is changing sign for the two different models reflecting the contradictory observation from Figure 7 (left). The second observation emerging from the table is that the coefficients for post-deal term are positive and statistically significant at the 1% level for the regressions on scaled patent count. This suggests a positive correlation and therefore a positive trend of scaled patent activity after a private equity deal. Both observations resonate with some existing patent literature in private equity in which there is indication, that patent activity is positively affected by private equity deals (Ughetto 2010; Amess et al. 2016), but it still remains unclear to which extent (Ughetto 2010; Lerner et al. 2011).

Table 22: OLS models and Poisson models of general patent count

General Patents				
	(1)	**(2)**	**(3)**	**(4)**
	linear	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**
Dependent variable	patent_count	patent_count	scaled_patent_count	scaled_patent_count
post	0.663	-0.00799	0.0438***	0.172***
	(0.817)	(0.0402)	(0.00779)	(0.0287)
year FE	yes	yes	yes	yes
deal FE	yes	yes	yes	yes
# of observations	29,285	29,285	29,285	29,285
# of unique deals	2,665	2,665	2,665	2,665
R-squared (within)	0.011		0.017	
Pseudo R-squared		0.90		0.08
Robust standard errors in parentheses	yes	yes	yes	yes

Note: The table provides coefficients from linear panel regressions in model (1) and (3) as well as Poisson pseudo-likelihood regressions in model (2) and (4). The absolute patent count (variable*: patent_count)* is the dependent variable in model (1) and (2). The scaled patent count (variable: *scaled_patent_count)* is the dependent variable in model (3) and (4). *post* is the independent variable and a dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. All models include year-fixed effects and deal-fixed effects. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. The within R-squared is reported for linear models and the Pseudo R-squared is reported for Poisson models. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

4.3.2 Green patent activity after a private equity deal

The novel insights of this paper are the perspectives on green patent activity around a private equity deal, which we analyze in this section. Figure 8 shows the development of green patent activity and the ratio of green patents to overall patents over time relative to the deal year. We observe a slightly positive trend for the green patent count post deal, a more profound positive trend post deal in scaled patent count and an increase from ~1.5% before the deal to ~2.5% in the green patent ratio post deal.

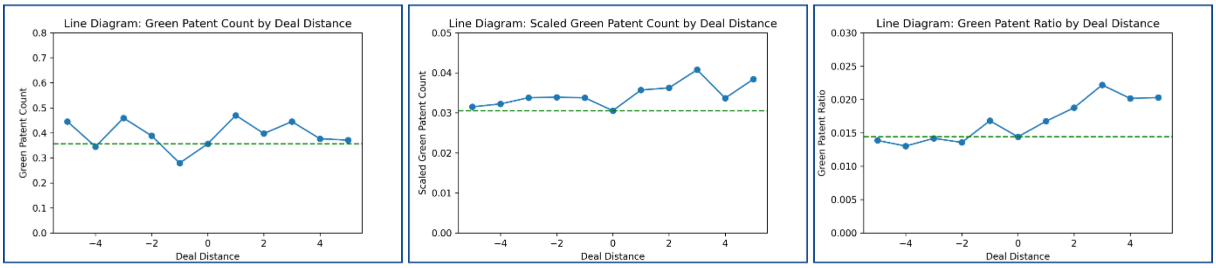


Figure 8: Green patent activity over time

This figure depicts the development of the green patent activity around the deal distance. All deals are presented with a relative deal window five years prior, and five years post the year in which the transaction took place. The left graph shows the mean of absolute green patent count of all deals over time, the graph in the middle shows the mean of scaled green patent count of all deals over time and the right graph shows the mean ratio of green patents to overall patents of all deals. The dotted green line indicates the mean level of patent activity of the deal year.

The corresponding analysis is presented in Table 23. In addition to the previous models, this table also includes the variable of the green patent ration to overall patent count in the given year. The main finding of this table is that in all models the coefficients for the post deal term are positive indicating a positive correlation of *post* and green patent activity. The interpretation suggests a positive correlation of the period after a private equity deal with green patent activity. The coefficient is significant at the 1% level for all Poisson models and significant at the 5% level for the linear model on green patent count as well. The coefficient of 0.211 in model (1) suggest, that the mean of green patent count increases by 0.211 after the deal. The interpretation of the Poisson coefficient is more cumbersome and not as easily applicable for our setup: for a one unit change in the predictor dummy, the difference in the logs of expected counts is expected to change by 0.518. Due to the non-negative and discrete characteristics of green patent count, linear regression potentially produce coefficient estimates that are inefficient, inconsistent and biased coefficient (Hausman et al. 1984). But, since both, the linear and the Poisson model's coefficient estimates for green patent count are significant and positive the view of a positive correlation of the post deal event on green patent activity becomes more robust. Similarly, the models predicting scaled variable of green patents obtain positive coefficients, that are strongly significant for the Poisson model (0.327) as well. And the coefficients of the post deal variable for the models for the ratio of green patents to overall patents are also positive and significant for the Poisson model (0.383). The observations become even more robust given the combination of different consideration in the dependent variable and application of two different model types (linear and Poisson) leading to the same orientation of results. All linear models are including year and deal level fixed effects and the Poisson models are all controlled for country of company, industry of company and type of PE deal since previous literature indicates effects of these variable (Cohen et al. 2020; Useche

2014; Lanjouw and Mody 1996; Ughetto 2010; D'Arcangelo et al. 2023). We follow the approach by Ewens and Rhodes-Kropf for the categorization of industries (EWENS and RHODES-KROPF 2015). When controlling for deal fixed effects, Poisson regression would drop all deals without any green patent activity and therefore resulting in an analysis of 558 firm deals, that have at least one granted patent within the deal window. Hence, we are taking a closer look into those companies, that have at least one green patent granted within the deal window, to elaborate further which characteristics are driving our analysis results.

Table 23: OLS models and Poisson models of green patent count and green patent ratio

Green Patents (for all deals)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	linear	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**
Dependent variable	green_patent_count	green_patent_count	green_scaled_patent_count	green_scaled_patent_count	green_patent_ratio	green_patent_ratio
post	0.211**	0.518***	0.00381	0.327***	0.00161	0.383***
	(0.103)	(0.140)	(0.00362)	(0.0656)	(0.00219)	(0.0851)
country		yes		yes		yes
industry		yes		yes		yes
deal type		yes		yes		yes
year FE	yes	yes	yes	yes	yes	yes
deal FE	yes		yes		yes	
# of observations	29,285	29,186	29,285	29,186	29,285	29,186
# of unique deals	2,665		2,665		2,665	
R-squared (within)	0.005		0.002		0.002	
Pseudo R-squared		0.18		0.02		0.04
Robust standard errors in parentheses	yes	yes	yes	yes	yes	yes

Note: The table provides coefficients from linear panel regressions in model (1), (3) and (5) as well as Poisson pseudo-likelihood regressions in model (2), (4) and (6). The absolute green patent count (variable*: green_patent_count)* is the dependent variable in model (1) and (2). The scaled green patent count (variable: *green_scaled_patent_count)* is the dependent variable in model (3) and (4). The ratio from green patents to overall patents per deal-year is the dependent variable in model (5) and (6). *post* is the independent variable and a dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. All models include year-fixed effects and all linear models include deal-fixed effects as well. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. The within R-squared is reported for linear models and the Pseudo R-squared is reported for Poisson models. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

We are not reporting descriptive plots by year since it would be the same pattern like in Figure 8, only with the plot shifted along the y-axis. The corresponding regression results in which only deals are considered, that have at least one green patent within the deal window, are reported in Table 24.

Table 24: OLS models and Poisson models of green patent count and green patent ratio for all deals with at least 1 green patent within the deal window

Green Patents if min 1 year with green patent count > 0						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	linear	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**
Dependent variable	green_patent_count	green_patent_count	green_scaled_patent_count	green_scaled_patent_count	green_patent_ratio	green_patent_ratio
post	0.992**	0.357***	0.0183	0.0984	0.00788	0.0903
	(0.478)	(0.124)	(0.0169)	(0.0944)	(0.0104)	(0.121)
year FE	yes	yes	yes	yes	yes	yes
deal FE	yes	yes	yes	yes	yes	yes
# of observations	6,138	6,138	6,138	6,138	6,138	6,138
# of unique deals	558	558	558	558	558	558
R-squared (within)	0.019		0.007		0.009	
Pseudo R-squared		0.75		0.06		0.19
Robust standard errors in parentheses	yes	yes	yes	yes	yes	yes

Note: The table provides coefficients from linear panel regressions in model (1), (3) and (5) as well as Poisson pseudo-likelihood regressions in model (2), (4) and (6). The sample includes only deals with at least one granted green patent within the deal window (+- 5 years around deal year). The absolute green patent count (variable*: green_patent_count)* is the dependent variable in model (1) and (2). The scaled green patent count (variable: *green_scaled_patent_count)* is the dependent variable in model (3) and (4). The ratio from green patents to overall patents per deal-year is the dependent variable in model (5) and (6). *post* is the independent variable and a dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. All models include year-fixed effects and deal-fixed effects. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. The within R-squared is reported for linear models and the Pseudo R-squared is reported for Poisson models. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

We firstly observe increased R-squared and pseudo R-squared when including deal fixed-effects in all models and only running the models for this constrained sample (≥1 green patent in deal window). Pseudo R-squared values only have a meaning when directly compared to another pseudo R-squared of the same type, on the same data and predicting the same outcome. The pseudo R-squared for the Poisson model for discrete green patent count has a value of 0.75 and thereby higher than the R-squared of 0.18 from the overall sample for green patents (Table 23). Therefore, the model in Table 24 predicts the outcome better explaining the variability in the dependent variable better. We again observe that all coefficients of the post deal dummy are positive, indicating a positive correlation. However, the effect seems to disappear for the scaled green patent count (models (3) and (4)) and the green patent ratio (models (5) and (6)), as none of these coefficients are statistically significant. The remaining coefficients of the linear model (1) and Poisson model of the discrete (and absolute) count of green patents are still significantly positive. This implies, that the absolute number of green patents is significantly higher post the private equity deal. The relative number of scaled green patent count, that controls and adjusts the increase (decrease) in green patent count by the maximum patent count of the respective deal, shows no significant correlation any longer. Neither do the coefficients for the green patent ratio which is the share in green patents to overall patents granted within the corresponding deal-year. Deal fixed effects provide robustness towards other factors, that might impact green patent activity like certain industries, that are prone for green innovation (Cohen et al. 2020). The view, that outliers are driving the result is becoming entrenched. In light of this ambiguity, we proceed to another, deeper level of analysis by splitting the sample into two groups to run the same analysis: one group of deals in which involved portfolio companies are very patent-active having >100 patents granted in at least one year and the other group that is less patent-active indicated by having no year with >100 patents within the deal window. The resulting sub-sample A exhibits a similar level of granted patents per million US-dollar revenue as the five companies with the most (absolute) US-patents filed per million US-dollar (Samsung, IBSM, TSMC, Huawei and Canon in 2021). The results of the regressions can be found in Table 25 and Table 26 respectively.

Table 25: OLS models and Poisson models of green patent count and green patent ratio for deals with >100 patents in at least one year of the deal window

Sub-sample A: Green Patents, if company > 100 patents at least one year

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	linear	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**	**linear**	**poisson pseudo-likelihood**
Dependent variable	green_patent_count	green_patent_count	green_scaled_patent_count	green_scaled_patent_count	green_patent_ratio	green_patent_ratio
post	4.351**	0.539***	0.103***	0.471***	0.00923***	0.427***
	(1.983)	(0.183)	(0.0365)	(0.169)	(0.00318)	(0.146)
year FE	yes	yes	yes	yes	yes	yes
deal FE	yes	yes	yes	yes	yes	yes
# of observations	1,221	956	1,221	956	1,221	956
# of unique deals	111	87	111	87	111	87
R-squared (within)	0.059		0.050		0.044	
Pseudo R-squared		0.82		0.08		0.19
Robust standard errors in parentheses	yes	yes	yes	yes	yes	yes

Note: The table provides coefficients from linear panel regressions in model (1), (3) and (5) as well as Poisson pseudo-likelihood regressions in model (2), (4) and (6). The sample includes only deals with high patent activity, that have at least one year with >100 patents within the deal window (+- 5 years around deal year). The absolute green patent count (variable*: green_patent_count)* is the dependent variable in model (1) and (2). The scaled green patent count (variable: *green_scaled_patent_count)* is the dependent variable in model (3) and (4). The ratio from green patents to overall patents per deal-year is the dependent variable in model (5) and (6). *post* is the independent variable and a dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. All models include year-fixed effects and deal-fixed effects. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. The within R-squared is reported for linear models and the Pseudo R-squared is reported for Poisson models. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively

The effect of the post deal coefficient on green patent count, scaled green patent count and the green patent ratio becomes pronounced and significant across all coefficients again for sub-sample A in Table 25. We observe strong effects and robust correlation for this group of 111 and 87 unique deals given the consistent positive coefficient and its magnitude. The initial regression results obtained a coefficient of 0.211 for the overall sample in the OLS model (1) in Table 23, whereas the same analysis with very patent-active companies obtains a coefficient of 4.351 (model (1) in Table 25). Both coefficients are statistically significant at the 5%, but they differ by the factor 20. The effect seems to be much more profound for companies that are already very actively pursuing patent innovation. The same pattern is observable for the normalized green patent counts in models (3) and (4) of both tables. The results of the OLS regression of the overall sample obtains a (non-significant) coefficient of 0.00381 whereas the coefficient of the patent-active sample is significant and taking a value of 0.103, again a magnitude of a factor >20. Hence, the existence of the correlation and increase in effect is observable for both absolute and relative patent activity. This finding suggests and fosters the view, that firms with much patent activity are driving the effect of the overall sample. Under this assumption, the effects should be at least weaker in the sample of deals with portfolio companies, that are less active in annual patenting. Indeed, we can observe assumed patterns in the coefficient of these regressions of sub-sample B in Table 26 further below. But there is another interesting observation within Table 25: the share of green patents of overall patent is significantly increasing post deal as indicated by positive and significant (at 1% level) coefficients of 0.00923 and 0.427 respectively. This observation could lead to initial insights as to why green patent activity is increasing post a private equity deal, regardless of whether it is a selection or treatment effect by the investor. Investors could consider green patent as promising long-term value driver to secure cash flows in the future, driven by future markets or regulations alike (Edmans 2023; Fabrizi et al. 2018).

Table 26: OLS models and Poisson models of green patent count and green patent ratio for deals with ≤100 patents in all years of the deal window

Sub-sample B: Green Patents, if company has < 100 patents each year

	(1) linear	**(2)** poisson pseudo-likelihood	**(3)** linear	**(4)** poisson pseudo-likelihood	**(5)** linear	**(6)** poisson pseudo-likelihood
Dependent variable	green_patent_count	green_patent_count	green_scaled_patent_count	green_scaled_patent_count	green_patent_ratio	green_patent_ratio
post	0.000357	-0.00167	-0.000892	-0.0187	0.00126	0.0680
	(0.0197)	(0.140)	(0.00341)	(0.114)	(0.00228)	(0.127)
year FE	yes	yes	yes	yes	yes	yes
deal FE	yes	yes	yes	yes	yes	yes
# of observations	28,053	5,170	28,053	5,170	28,053	5,170
# of unique deals	2,553	470	2,553	470	2,553	470
R-squared (within)	0.001		0.001		0.002	
Pseudo R-squared		0.39		0.05		0.17
Robust standard errors in parentheses	yes	yes	yes	yes	yes	yes

Note: The table provides coefficients from linear panel regressions in model (1), (3) and (5) as well as Poisson pseudo-likelihood regressions in model (2), (4) and (6). The sample includes only deals with low patent activity, that have no year with >100 patents within the deal window (+- 5 years around deal year). The absolute green patent count (variable*: green_patent_count)* is the dependent variable in model (1) and (2). The scaled green patent count (variable: *green_scaled_patent_count)* is the dependent variable in model (3) and (4). The ratio from green patents to overall patents per deal-year is the dependent variable in model (5) and (6). *post* is the independent variable and a dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. All models include year-fixed effects and deal-fixed effects. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. The within R-squared is reported for linear models and the Pseudo R-squared is reported for Poisson models. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively

Running the same analysis for deals in which companies had ≤100 patents granted in every year within the deal window, we observe much smaller coefficients again, that change signs across the different models and that are not showing statistical significance any longer. In strong contrast to the same analysis of patent-active portfolio companies, the coefficient of *post* on green patent activity of all run analysis are not only not significant anymore but also close to 0. In conclusion, our results imply two main interpretations: first, that portfolio companies become more active in green patenting after a private equity deal, but second, that this correlation is mainly driven by few deals with companies that are very active with patent activity in general. A simple explanation could lie in a certain exposure towards an industry with a tendency to develop green patents in general. Cohen et al. have found that specifically oil, gas and energy-producing firms are key innovators in the US-American patent landscape (Cohen et al. 2020). We have checked the sample for industry focus and find no indication for such exposure. There is no sign for a strong focus on a specific industry in the 111 companies with >100 patents. The most frequent industries represented in this sub sample are automotive, chemicals (both 10 times), consumer, software (both 9 times), industrial machinery, materials, and medical devices (all three 8 times). A full overview can be found in Appendix H.

We run an additional analysis to see, if deals of ESG-oriented investors have a different effect on the post deal activity in green patents. Private equity firms are significantly less transparent in ESG disclosures than public firms (Hendrikse et al. 2022), their sheer ambition on committing or providing such information could be considered as a positive signal towards ESG orientation. Hence, we include the interaction terms for investors, that are UN PRI signatories during the time of the deal, have signed during the observation period and their ESG transparency score. Table 27 provides the results of three different configurations of OLS and Poisson model configurations. Each configuration is referring to one of the aforementioned ESG-signals of the investors involved in the respective PE deal. We have run linear models and Poisson models on the absolute green patent count and scaled green patent count, which can be found in the columns of Table 27. Each section of the table then refers to one configuration considering one dimension in ESG orientation of the involved investor. We observe that there is no consistent tendency in the coefficients of the interaction terms of *post* with an ESG characteristic. We observe a significant negative coefficient for *post* with UN PRI deal (-0.287) and a weak significant negative coefficient for *post* with UN PRI investor indicating a potentially negative correlation of an PE deal performed by an UN PRI involved investor. This indication of no correlation of UN PRI deal, UN PRI investor or ESG transparency with a positive trend in green patent activity is in line with research of similar context. Cohen et al.

find that firms with lower ESG scores or those that are often excluded from ESG funds' investments are key innovators of green patents (Cohen et al. 2020). Gibson et al. have found that investors that signed the UN Principles for Responsible Investment have exhibited worse portfolio-level ESG scores, which points to potential green washing issues (Gibson Brandon et al. 2022). Our findings are therefore somewhat contradictory to findings from Bauckloh et al. who find ESG integration being substantially improved after becoming a UN PRI signatory, at least this seems to not be the case for commitments in the form of innovation as in green patents (Bauckloh et al. 2021). The positive effect of increased green patent activity following a private equity seems to not stem from the ESG orientation of the investor. At the same time, all of the deals in our sample took place before 2015 and prior to the Paris Agreement, which possibly raised awareness for sustainable impact in the investment industry (United Nations 2015).

Table 27: OLS models and Poisson models of green patent count for deals with >100 patents in at least one year of the deal window, for different ESG signals

Green Patents, if company > 100 patents at least one year				
	(1)	**(2)**	**(3)**	**(4)**
	linear	**poisson**	**linear**	**poisson**
Dependent variable	green_patent_count	green_patent_count	green_scaled_patent_count	green_scaled_patent_count
Panel A: UN PRI deal				
post	4.335**	0.541***	0.109***	0.494***
	(1.992)	(0.183)	(0.0365)	(0.171)
post x UN PRI deal	0.775	-0.459	-0.287**	-0.802
	(2.851)	(0.601)	(0.110)	(0.532)
# of observations	1,221	956	1,221	956
# of unique deals	111	87	111	87
Panel B: UN PRI investor				
post	4.848	0.557***	0.127***	0.580***
	(3.259)	(0.185)	(0.0399)	(0.182)
post x UN PRI investor	-1.277	-0.0722	-0.0622	-0.270*
	(4.250)	(0.164)	(0.0450)	(0.163)
# of observations	1,221	956	1,221	956
# of unique deals	111	87	111	87
Panel C: ESG Transparency				
post	1.211	0.0921	0.0951	0.467*
	(3.685)	(0.334)	(0.0703)	(0.279)
post x ESG Transparency	0.0577	0.00720*	-1.67e-05	-0.000973
	(0.0500)	(0.00398)	(0.000939)	(0.00329)
# of observations	847	659	847	659
# of unique deals	77	60	77	60

Note: The table provides coefficients from linear panel regressions in model (1) and (3) as well as Poisson pseudo-likelihood regressions in model (2) and (4). The sample includes only deals with high patent activity, that have at least one year with >100 patents within the deal window (+- 5 years around deal year). The table provides coefficients for three panels for which we ran the analysis: panel A considers deals for which the investor was or was not a UN PRI signatory during the deal, panel B considers deals for which the investor was or was not a UN PRI signatory within our observation period (until 2019), and panel C provides the coefficients for a consideration of investors with ESG transparency score. The absolute green patent count (variable*: green_patent_count)* is the dependent variable in model (1) and (2). The scaled green patent count (variable: *green_scaled_patent_count)* is the dependent variable in model (3) and (4). *Post, UN PRI deal, UN PRI investor,* and *ESG Transparency* are the independent variable. *post is a* dummy variable set to one in the year of the deal and afterwards and zero prior to the deal. *UN PRI deal* is a dummy variable set to one when the investor was a UN PRI signatory at the time of the deal, and zero otherwise. *UN PRI investor* is a dummy variable set to one when the investor became a UN PRI signatory within our period of observation (until 2019), and zero otherwise. *ESG Transparency* is a variable and a number value based on the information made available by the investor that is obtained through Preqin. All three variables are interacted with *post.* All models include year-fixed effects and deal-fixed effects. We report the number of deal-year observations as well as the number of unique deals considered in the regression model. All variables are explained in Appendix E. T-statistics based on Huber/White robust standard errors are presented in parentheses. ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

In summary, we are using two different models (OLS and Poisson) to assess our event study and check for robustness. Simple graphs over time in Figure 8 indicate a first positive trend of green patent activity in the post private equity deal period. This trend for absolute and relative increase in green patent activity is rigidified by the corresponding regression analyses in Table 23. It remains open which reasons are pursued by PE investors to either select promising portfolio companies or operationally drive actions that lead to higher green patent scores post deal. PE funds could hope to attract greater investor flows, accumulation of more assets and thereby harvesting of greater fee revenues by investing in line with investors (LP) preferences (Liang et al. 2022). PE investors could also simply strive for financial returns and expectations of future cash flows. A company’s positive engagements in environmental, social and governance concerns have led to positive abnormal returns (Dimson et al. 2015). Academic evidence has shown, that high sustainability companies have significantly outperformed their counterparts over the long-term in stock market and accounting performances (Eccles et al. 2014). And also experimental evidence suggests that sustainability is considered to positively predict future performance, even though an outperformance of high-sustainability funds over low-sustainability funds has not been found (Hartzmark and Sussman 2019). Thirdly, PE investors could expect higher cash flow expectations from improved risk management and adaptation potential on policy mitigation strategy. Generally, outcomes of engagements are more likely if the engaged firm faces reputational concerns and has a higher capacity to implement adaptation measures (as in green patents here) (Dimson et al. 2015; Bellon 2022). Portfolio companies with good patenting activity in mitigation technologies could benefit from lower cost of debt as climate-change mitigation policies become more dominant in the future (D'Arcangelo et al. 2023). At the same time, ESG signaling not being in line with innovation in green patenting could lead to greenwashing concerns that have been raised in the literature before (Gibson Brandon et al. 2022).

Due to these considerations, we have taken a more detailed approach in isolating the effect within our data. We ran the same analysis with deals of portfolio companies, that had at least one green patent within the deal window in Table 24. The effect is disappearing for the relative green patent count variable and the green patent ratio, but there is still significant correlation on absolute green patent activity post a PE deal. In an assessment of drivers for the observed effect, we discover that deals of generally higher patent activity seem to be predominantly responsible for the effect within our setup. We therefore consider two separate analysis in Table 25 and Table 26 distinguishing two sub-samples by patent-active (deals with >100 patents in at least one year of the deal window) and less patent-active involved portfolio companies. The regressions with both sub-samples confirm the assumptions, that the effect is driven by those deals in which very patent-active companies are involved. In every type of regression for this sub-sample (sub-sample A in Table 25) we observe significant coefficients indicating significant correlation of the deal event on the post-deal green patent activity. In an attempt to elaborate on additional drivers for this significant increase in green patenting after the deal, we run three sets of regressions to elaborate on potential ESG tendency of the involved investors. We run regressions including interaction terms for those deals that have been performed as an UN PRI signatory, those in which investors became UN PRI signatories within our observation time and including Preqin's ESG transparency score. We find no evidence, that these allegedly sustainable driven investors increase the green patenting activity post deal. Instead it seems to rather stem from a pure value consideration: the green patent activity signals innovation and business in attractive markets in the future (policy, consumer demand or alike)

4.4 Conclusion

Our study uses a novel dataset in the PE investment context to elaborate on the sustainability impact prior and post a PE deal. To the best of our knowledge, we provide the first empirical analysis on green patent activity within the private equity deal context. We leverage green patenting activity as quantitative and objective measure of "impact". Our approach could prove especially useful if we consider that these (PE) markets are characterized by strong information asymmetries and inconsistent – if any – reporting standards.

In this paper, we analyze a newly created dataset that we have obtained by combining Preqin deal information with hand collected patent information from Orbis. By categorizing each individual patent, we introduce the consideration of green patents within private equity research. We conduct traditional econometric analysis of the impact of the private equity deal using two types of regression for robustness. Our event study setting allows for a pre-post consideration, but does not include a comparison of different groups like in a classic Diff-in-Diff setup.

Overall, we attempt to elaborate on the question, whether PE funds truly create impact or not and whether their sustainable positioning is rather a green washing issue. We do so in analyzing the green patenting activity prior and post a private equity deal. While the results in this paper suggest, that there actually is a positive correlation on the post deal green patent activity, we observe this effect stemming from deals which involve companies with a higher tendency of patent activity in general. We find no evidence, that allegedly sustainable investors, labeled by UN PRI signatures or higher ESG transparency, are driving green patent activity post deal. Therefore, we propose that private equity investors rather consider green patents and green innovation as a long-term value driver anticipating positive future cash flow due to exploitation of future markets, successful policy adaptation or risk mitigation (Edmans 2023; D'Arcangelo et al. 2023).

This paper is not without its shortcomings. Our dataset is constructed under the assumption of patent activity after the deal event and hence potentially suffers from survivorship bias (Brown et al. 1992). We have mentioned the discussion of the validity of green patents as a proxy for an ESG or impact measure – while the objectivity is valid, the precision as a proxy for green innovation/green impact could be criticized (Cohen et al. 2013; Hoang et al. 2020; Fabrizi et al. 2018; Basalla 1988).

The findings of this paper do have implications on academics and practitioners. This paper contributes to green finance literature within the private markets. The adaptation of green patenting in the private equity context could be further applied to study in this phenomenon in more depth and address some of the limitations of our work. Further research could investigate the green patent activity of private equity backed companies against a (public) peer group. It could also be elaborated on the derivation of performance differences, whether it is a selection or a treatment effect. This kind of setup could contribute to the broader sense of green finance literature as well (Heeb et al. 2023; Barber et al. 2021; Eccles et al. 2014; Hartzmark and Sussman 2019). It could allow to study private equity deals with a sustainable impact investigating whether green deals financially outperform their peers and what investor's willingness-to-pay look like. For practitioners, this study has implications for their governance and monitoring activities. Limited partners and investors into private equity funds could consider the measure of green patent as one of many (green) value drivers and as an objective measure for green impact. Green patent activity could help to shed light into the ESG and green labeling labyrinth to prevent implicit or explicit green washing.

5 Conclusion

In the raising regulatory, competitive and ultimately existential pressure for an increased effort to pursue the Paris Agreement's path towards "net zero", considerable effort in the private sector and considerable research is being conducted. A major questions remains on how to finance the path to "net zero" and how to direct finance flows towards the sustainable transition. With the allegedly superior governance and simply the sheer amount of dry powder in the market, the private equity industry could serve as a suitable vehicle to contribute to this transition. Based on a sample of 336 university endowments and 418 individual CIO profiles, a conjoint study conducted with 140 LPs and a deal sample of 2665 unique private equity deals, this dissertation elaborates on three characteristics to provide initial evidence of its suitability. It is organized around three specific research questions that focus on specific aspects of the private equity fund structure. The first research question focusses on the role of the individual CIO within the LP's organization (here university endowments) and whether the individual matters in the investment decisions. The second research question seeks to explore the sustainable investment criteria of LPs when investing into private equity funds. The third research question attempts to assess the sustainable impact of private equity deals on the involved portfolio company.

5.1 Main results

5.1.1 The CIO in university endowments

Since Swensen's invention of *"The Yale Model"* and his pioneering work on successfully managing institutional investment portfolios (Swensen 2009), university endowments have regularly been a study object of the literature. Historic research has focused on performance drivers of the endowment model's success (Lerner et al. 2008), their approach to actively managing funds (Brown et al. 2010) or their behavior during financial shocks (Brown et al.

2014). Given the private nature of the private equity fund model, it is challenging to conduct research on the asset allocation of LPs in private equity. As such, while focus lied on drivers of return and asset allocation in the past, we empirically seek to provide answers to the organizational setup in university endowments by investigating the individual CIO profiles.

In the first essay of this dissertation, we exploit a hand-collected sample of 336 university endowments and their asset allocation data together with a hand-collected sample of 418 individual CIO profiles. We create a panel-data set of 3320 endowment-year observations between 2004 and 2019 with asset allocation and individual characteristics of the CIO profiles. We begin the analysis in replicating the findings of existing literature (Lerner et al. 2008) using our unique dataset. We establish the relationship of a correlation of higher allocation towards alternative investments with future endowment returns. We also find, that more aggressive and actively managed endowment funds, that exhibit higher share in commitments, are obtaining higher returns (Brown et al. 2010). We establish the relationship between individual CIO characteristics and asset allocation. CIOs with former experience as an investor exhibit a higher asset allocation towards alternative investments, that in turn correlates with higher returns as well. In an approach inspired by the turnover investigation of Weisbach (Weisbach 1988), we further investigate the CIO replacement event in the endowments. University endowment seem to recognize and acknowledge higher qualification levels as CIOs with an MBA, a financial license or former investor experience are less likely to be replaced. Equally, in a CIO replacement event, CIOs that have had former investor experience are more likely to be an incoming CIO. This is in line with findings from Li et al., who studied hedge fud managers' characteristics and their educational backgrounds (Li et al. 2011). Our findings indicate the importance of the individual in a limited partner organization. The individual educational background and professional background matters with regard to the investment decisions and asset allocation made as well as the organizational structure within the LP's organization. In light of the motivation of this dissertation to elaborate on the private equity business model concerning its contribution to the net zero transition, it allows for promising interpretation as well. In an LP's organizational setup, the individual CIO has an impact on the asset allocation. The individual education, sensitization for sustainable investments and individual incentivization could lead to investment decisions and asset allocation in favor of such impact creation.

5.1.2 LPs' investment preferences of sustainability criteria

In the second essay, I assess the investment criteria of LPs when investing into private equity funds. Existing private equity related literature has mostly focused on conventional investment criteria like past performance, a fund's reputation, or successful past exits in the past (Gompers and Lerner 1999; Loos and Schwetzler 2017; Da Rin and Phalippou 2017). Studies focusing on the mechanisms on how investors could create sustainable impact within firms suggest to invest into companies and actively engage (Broccardo et al. 2022; Kölbel et al. 2020; Berk and van Binsbergen 2022). As stakeholder increasingly recognize the importance of responsible investing and the aforementioned mechanism aptly describes the operational setup inherent to the private equity business model, the question arises whether LPs are concerned with fund engagement aiming to create such sustainable value. While existing research provides empirical evidence of investors for a willingness-to-pay for such sustainable investments (Heeb et al. 2023; Barber et al. 2021), our results shed light into investors' investment preferences thoroughly focused on private equity fund investments. We conduct a conjoint analysis with 140 individual limited partners, assessing 8,400 observations from 2,100 decisions made. First, we derive relevant investment criteria through a literature analysis and expert interviews with limited partners and private equity fund managers. We obtain two traditional investment criteria and four sustainability-related investment criteria to setup up an experimental conjoint analysis. The 140 limited partners had to make 15 random (fictional) investment decisions each between three funds or the option to not invest at all. We then leveraged a hierarchical bayes simulation approach and a multinominal logistic model approach to assess the data. We find that traditional investment criteria like the past performance of the previous fund and the management fee are of highest importance for the LPs accounting for ~60% of relative importance for the investment decisions within our setup (e.g., the six defined investment criteria). Further, we show, that the sustainability criteria are also significantly correlated with the investment decision of the LPs. A CO2 reduction target and a fund with a sustainability expert in the fund team have a significant and positive effect on the the investors' investment decision. We find that a conditional carry based on sustainability targets is significantly positively correlated with investment decision but only when the share in conditional carry is not too large. Similarly, EU SFDR article compliance with article 8 and article 9 funds exhibit significant, positive correlation with investment decisions, but the gained utility decreases from article 8 to article 9 funds. This is in line with anecdotal evidence from our expert interviews and several studies read, that there is confusion in the market on the regulatory implications related to article 8 and article 9 funds. Based on our results, we additionally found differences between different investor types. We find that insurance companies consider a CO2 reduction target significantly more important than family offices. The CO2 reduction target is also more important for self-committed ESG signatories as opposed to those who are not self-committed. In summary, our study implies, that there is existing investor preference for sustainability criteria within the LP community of private equity funds and that their sustainability preference is heterogenous based on their type. Our study suggest, that private equity funds who offer sustainability characteristics are considered more attractive, which is a promising finding in favor of supporting the transition towards net zero.

5.1.3 Private equity impact on green innovation

In the third essay, we assess the impact of private equity deals on the green patent activity of the portfolio company. Existing PE literature has primarily focused on firms' financial performance, evolving corporate governance landscape and only partly discussed the impact of PE deals on the innovation output of their target companies amount (Cumming et al. 2007; Kaplan and Strömberg 2009; Amess et al. 2016; Ughetto 2010). To the best of our knowledge, this study is the first leveraging green patents as an innovation proxy to assess the sustainable impact of private equity deals on the portfolio companies. We analyse the impact of 2665 unique private equity deals in an event study setup considering green patenting activity in an event window from five years before to five years after the PE deal. We hand-matched Preqin deal-level data with patent information from the Orbis Intellectual Property database creating the five-year pre and post deal event window. After identifying all green patents within each company's patent stock, we use descriptive statistics, OLS regression models, and Poisson likelihood regression models to obtain our three key findings. First, we find that portfolio firms in our sample exhibit significantly positive correlation of green patent activity after the private equity deal. Our results indicate this positive trend in absolute green patent count, relative green patent count as well as an increased green patent ratio of overall patents. Secondly, trying to better understand the driver of this effect, we find that this effect is mainly driven by a subset of highly patent-active companies. In assessing potential ESG orientation, we lastly find no evidence suggesting correlation between ESG signalling of the private equity funds and an increase in green patent activity. While the findings concerning the sole green patent activity are in line with findings of Lerner et al. (Lerner et al. 2011), they allow for rather controversial interpretation with regards to the green innovation capability. While the deal sample exhibits a positive trend in green patent activity post deal, the absent correlation between ESG commitments by the PE funds and actual green innovation performance rather points towards green washing controversies. Given that the first effect is driven by a smaller patent-active sample, it may suggest that (some) PE funds simply consider green patents as one of many value drivers to secure future cash flows (Edmans 2023). The latter effect rather indicates that PE funds endorse ESG commitments (like the UN PRI) in order to attract greater investor flows, accumulate more assets, and ultimately harvest greater fees (Liang et al. 2022). As a vehicle to support the net zero transition, this study finds that private equity deals can increase green innovation, but ESG signals of the PE funds might not be an unequivocal indicator for such.

5.2 Contribution and Implications

To conclude, the three essays of this dissertation address research questions on the private equity business model and its potential to serve as a vehicle towards supporting the net zero transition. The findings motivate several avenues for further research. The first essay shows that individual CIO characteristics impact the investment decision and asset allocation of the limited partner and are commended by the LP organization. There are several implications for further research upon this study: it would be interesting to further under the drivers of CIO replacements and the persistence of the organization vs. the individual CIO. It would also be interesting to shed light into incentivization system of the LP organization and its CIO to direct more funds towards sustainable investments. The second essay provides methodological as well as empirical implications for further research. The conjoint study poses an interesting methodology to further investigate investment behavior of both limited partners and private equity funds. A conjoint study offers the possibility to unveil novel data, that is generally scarce within private capital market research. It would be interesting to understand the relevant consideration during the fund selection. Our results indicating significant relevance of sustainability criteria within the fund selection of PE funds poses additional opportunity in understanding the sustainability appetite of PE investors. What is their willingness-to-pay for such additional nonpecuniary services? How do these efforts monetize with regards to the fund’s performance? The third essay shows, that PE deals are correlated with an increase in green patent activity, while we have not found correlation of ESG-driven investors and increased green patenting activity post deal. The study introduces a novel approach of leveraging green patent data within the PE research. It would be instructive to examine the drivers behind green patent activity in PE deals and further elaborate on our interpretation. The green patent activity could be used in a difference-in-difference setting to assess the sustainable impact of PE-backed companies versus public peer companies. Ultimately, this objective measure could be investigated as to how well it could be used to tie the ESG commitments of PE fund managers to actual sustainable impact – both in an academic sense, but also for practitioners.

Appendix

Appendix: The CIO in university endowments

Appendix A: Explanation of variables

Definition of Variables

General data	Description
commitments	Unfunded commitments of university endowment to make contributions in future periods, source: Notes to financial statements
holding cash	Level of cash (and short-term investments) holdings of university endowment, source: Notes to financial statements
holding alternatives	Level of holdings in alternatives like private equity, natural resources, source: Notes to financial statements
holding hedge fund	Level of holdings in hedge funds, source: Notes to financial statements
holding equity	Level of holdings in equity including domestic equity, foreign equity, global equity and emerging market equity, source: Notes to financial statements
dollar return	Return of endowment in absolute terms
endow_ret	Return of endowment in relative terms in relation to asset under management
aum	Total assets under management including all asset classes
Highest degree: bachelor	A dummy variable that takes the value 1 if the highest degree of the CIO is a bachelor's degree, and 0 otherwise
Highest degree: master	A dummy variable that takes the value 1 if the highest degree of the CIO is a master's degree, and 0 otherwise
Highest degree: phd	A dummy variable that takes the value 1 if the highest degree of the CIO is a PhD, and 0 otherwise
mba	A dummy variable that takes the value 1 if the CIO is a holder of an MBA, and 0 otherwise
financial_license	A dummy variable that takes the value 1 if the CIO is a holder of a financial license such as CFA, and 0 otherwise
former_investor	A dummy variable that takes the value 1 if the CIO has been active as an investor in the past, and 0 otherwise
inv_years	Number of years the CIO has been occupied as an investor in the past
Total working years	Total years the CIO has worked in the past (including endowment engagement and prior experience)
Analysis	**Description**
endow_ret	Relative endowment return in relation to asset under management
endow_ret_lead1	Relative endowment return in relation to asset under management in the following (leading) year
endow_ret_lag1	Relative endowment return in relation to asset under management in the previous (lagged) year
commit2aum	Commitments in relation to asset under management
cash2aum	Cash holdings in relation to asset under management
equity2aum	Equity holdings in relation to asset under management
bond2aum	Bond holdings in relation to asset under management
alt2aum	Alternatives holdings in relation to asset under management
real2aum	Real estate holdings in relation to asset under management
loc2aum	Line of credit in relation to asset under management
private	A dummy variable that takes the value 1 if the university of the endowment is a private university, and 0 otherwise
ivy	A dummy variable that takes the value 1 if the university of the endowment is an ivy league school, and 0 otherwise
gender	Indication of the gender of the CIO taking the value 1 if male and 0 if female
aum_scaled	Total assets under management including all asset classes scaled by the factor one billion
prior_replacement	Dummy variable indicating the year prior to the CIO replacement event, that takes the value 1 in the year prior to the CIO replacement event, and 0 otherwise
cio_replacement	Dummy variable indicating the year of the CIO replacement event, that takes the value 1 in the year of the CIO replacement, and 0 otherwise

This table provides a detailed description of the variables used in the first essay. The upper part provides description of the variables used for the general data, while the lower part explains the variables used in the analysis.

Appendix B: Year-dummy regression on CIO replacement event

Model	prior_replace
2005	-0.0366
	(0.0603)

2006	-0.0223
	(0.0566)
2007	-0.0508
	(0.0589)
2008	-0.0508
	(0.0579)
2009	-0.0659
	(0.0565)
2010	-0.0111
	(0.0582)
2011	-0.0786
	(0.0560)
2012	-0.0837
	(0.0564)
2013	-0.0570
	(0.0566)
2014	-0.0518
	(0.0571)
2015	-0.0722
	(0.0563)
2016	-0.0460
	(0.0574)
2017	-0.0585
	(0.0572)
2018	-0.0673
	(0.0562)
Constant	0.159***
	(0.0513)
Observations	2,280
Number of unameid	217
R-squared	0.005

Robust standard errors in parentheses

This table provides the coefficients of a linear regression on the dummy variable *prior_replacement* and using year dummies as the explanation variable. . ***, **, and * indicated significance at the 1%, 5% and 10%-levels respectively.

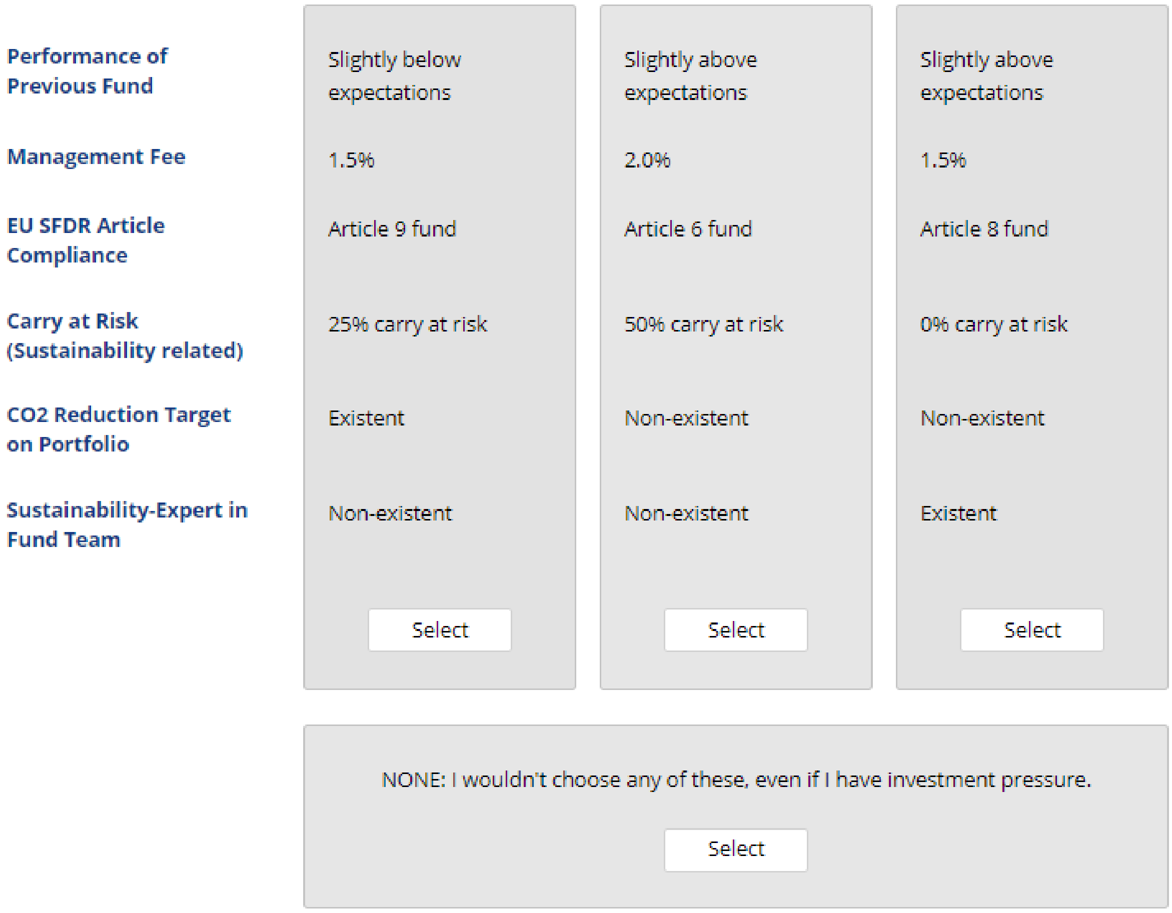
Appendix C: Description of variables

Descriptive data: personal level	Description
Age	A categorical variable indicating the participant’s age group: 1 = <25 years, 2 = 25 - 34 years, 3 = 35 - 44 years, 4 = 45 - 54 years, 5 = 55 - 64 years, 6 = >65 years
Gender	A categorical variable indicating the participant's gender, taking the value 1 if male, 2 if female, and 3 if other
Investor experience	A categorical variable for different groups indicating the participant’s years of experience as an investor: 1 = No experience, 2 = <2 years, 3 = 2-4 years, 4 = 5-10 years, 5 = 11-20 years, 6 = >20 years
Role	A categorical variable indicating the participant's current role within the investment firm: 1 = Partner or CxO, 2 = Director or principal, 3 = Investment manager, 4 = Investment analyst, 5 = Other
Tenure with investment firm	A categorical variable indicating the participant's tenure with the current investment firm: 1 = <2 years, 2 = 2-4 years, 3 = 5-10 years, 4 = 11-20 years, 5 = >20 years
Educational background: Law	A dummy variable indicating whether the participant has an educational background in law, that takes the value 1 if so, and 0 otherwise
Educational background: Business/economics	A dummy variable indicating whether the participant has an educational background in business/economics, that takes the value 1 if so, and 0 otherwise
Educational background: Natural science	A dummy variable indicating whether the participant has an educational background in natural science, that takes the value 1 if so, and 0 otherwise
Educational background: Engineering	A dummy variable indicating whether the participant has an educational background in engineering, that takes the value 1 if so, and 0 otherwise
Educational background: Other	A dummy variable indicating whether the participant has an educational background in other subject than the listed ones, it takes the value 1 if so, and 0 otherwise
Descriptive data: firm level	**Description**
Region: North America	A dummy variable taking the value 1 if the investment firm is primarily located in North America, and 0 otherwise
Region: Europe (excl. UK)	A dummy variable taking the value 1 if the investment firm is primarily located in Europe (excl. UK), and 0 otherwise
Region: United Kingdom	A dummy variable taking the value 1 if the investment firm is primarily located in the United Kingdom, and 0 otherwise
Region: Rest of World	A dummy variable taking the value 1 if the investment firm is primarily located in the Rest of the World, and 0 otherwise
Asset under Management (AuM)	A categorical variable indicating the asset under management (asset under management and unfunded commitment) towards PE (PE & VC) in $M of the participant’s investment firm: 1 = <$25M, 2 = $26M - $100M, 3 = $101M - $500M, 4 = $501M - $1,000M, 5 = $1,001M - $5,000M, 6 = >$5,000M
ESG signatory	A dummy variable indicating whether the investment firm is signatory to a ESG-association (e.g., UN PRI, SBTi, iCI, Net Zero Alliance...), that takes the value 1 if so, and 0 otherwise
ESG incentivized	A dummy variable indicating whether the investment firm is incentivized to invest along ESG criteria, that takes the value 1 if so, and 0 otherwise
Investor type: Pension fund	A dummy variable indicating whether the investor category of the investment firm can be best described as pension fund, that takes the value 1 if so, and 0 otherwise
Investor type: Endowment	A dummy variable indicating whether the investor category of the investment firm can be best described as endowment, that takes the value 1 if so, and 0 otherwise
Investor type: Insurance company	A dummy variable indicating whether the investor category of the investment firm can be best described as insurance company, that takes the value 1 if so, and 0 otherwise
Investor type: Finance company/Bank	A dummy variable indicating whether the investor category of the investment firm can be best described as Finance company/bank, that takes the value 1 if so, and 0 otherwise
Investor type: Family office	A dummy variable indicating whether the investor category of the investment firm can be best described as family office or multi-family office, that takes the value 1 if so, and 0 otherwise
Investor type: Fund of funds	A dummy variable indicating whether the investor category of the investment firm can be best described as fund of funds, that takes the value 1 if so, and 0 otherwise
Investor type: Sovereign wealth fund	A dummy variable indicating whether the investor category of the investment firm can be best described as sovereign wealth fund, that takes the value 1 if so, and 0 otherwise
Investor type: Other	A dummy variable indicating whether the investor category of the investment firm can be best described with an other category, that takes the value 1 if so, and 0 otherwise
Analysis: variables	**Description**
CO2 reduction target on portfolio	A categorical variable indicating whether the displayed fund has an existing CO2 reduction target (co2red_exist) or has not an existing reduction target (co2red_nonexist).
Performance of previous fund	A categorical variable indicating whether the performance of the previous fund was above the expectations (performance_above) of the participant or below his/her expectations (performance_below)

EU SFDR article compliance	A categorical variable indicating whether the displayed fund is a fund that is compliant with the EU SFDR article 6 (article6fund), compliant with the EU SFDR article 8 (article8fund), or compliant with the EU SFDR article 9 (article9fund).
Carry at risk (sustainability related)	A categorical variable indicating whether the displayed fund has no carry at risk (carryatrisk0), has 25% share of its carry at risk conditional on pre-defined sustainability targets (carryatrisk25), or has 50% share of its carry at risk conditional on pre-defined sustainability targets (carryatrisk50)
Sustainability expert in fund team	A categorical variable indicating whether the displayed fund has a sustainability expert within the fund team (sustain_exp_exist) or not (sustain_exp_nonexist)
Management fee	A categorical variable indicating the management fee of the displayed fund. Management fee categories include 1.5% management fee on the AUM (mgmtfee15), 2.0% management fee on the AUM (mgmtfee20) and 2.5% management fee on the AUM (mgmtfee25)

This table provides a detailed description of the variables used in the second essay. Many of the variables chosen are categorical variables to improve the participant's usability during the data entry process in the survey. The last level within each attribute is "omitted" to avoid linear dependency. However it is recoded and displayed as the negative sum of the other levels within the attribute (e.g., see Table 15).

Appendix D: Conjoint Task



This figure shows an explanatory task of a conjoint task, that investors had to choose from. Each task was randomly designed as described in the text. The participating investors had the option of choosing one of the three displayed funds or to not invest into a fund at all. Each participant was instructed to generally have investment pressure, to be familiar and generally satisfied with the fund manager and to consider this investment decision as a follow-on investment.

Appendix: Private equity impact on green patent activity

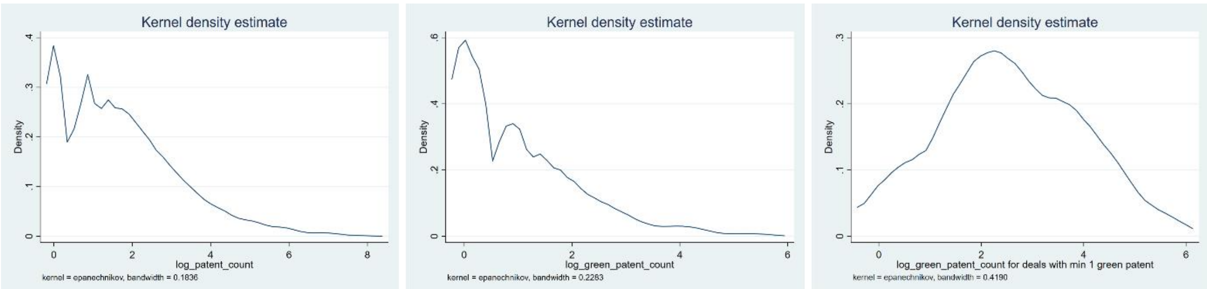
Appendix E: Description of variables

Definition of Variables

Analysis	Description
Patent count	The absolute count of granted (or meanwhile expired, as they were granted) patents for a particular company within a year
Scaled patent count	The relative count of granted (and expired) patents for a particular company within a year. The relative count is obtained by normalizing the absolute patent count by the maximum patent count within the deal window of the company.
Green patent count	The absolute count of granted (and expired) green patents for a particular company within a year. Green patents are classified based on their IPC class following the methodology by Hascici and Migotto and Favot et al. (Haščič and Migotto 2015; Favot et al. 2023)
Scaled green patent count	The relative count of granted (and expired) green patents for a particular company within a year. The relative count is obtained by normalizing the absolute green patent count by the maximum green patent count within the deal window of the company.
Green patent ratio	The ratio of green patents to overall patents for a particular company within a year.
UN PRI deal	Dummy variable indicating whether the PE deal was conducted by an investor that was a UN PRI signatory during the transaction. The variable is set to 1 for UN PRI deals and 0 otherwise.
UN PRI investor	Dummy variable indicating whether the PE deal was conducted by an investor that was a UN PRI signatory during our observation period (until 2019). The variable is set to 1 for deals performed by UN PRI investors and 0 otherwise.
ESG transparency	A measure for an indication on how many ESG measures are transparently reported by a PE fund manager. The numeric variable is provided ranging from 0 to 100
Fund size	The total fund size provided in million US-dollar
Deal type	The deal type of the private equity transaction as provided by Preqin: Buyout, Growth Capital, Public to Private and other. Other can include Add-on, Mergers, Private Investment in Public Equity, Recapitalization, Restructuring and Turnaround
Post	Dummy variable indicating the time period before or after the private equity deal. The value is set to 1 for the year of the private equity deal and afterwards, otherwise (and before the private equity deal) it is set to 0
country	A categorical variable with countries as categories: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, Netherlands, Norway, Portugal Spain, Sweden, Switzerland, United Kingdom and United States
Industry	A categorical variable with industries as categories following the approach of Ewens and Rhodes-Kropf (EWENS and RHODES-KROPF 2015): Software, Other Information Technology, Healthcare, Consumer/Retail, Energy and Utilities, Other

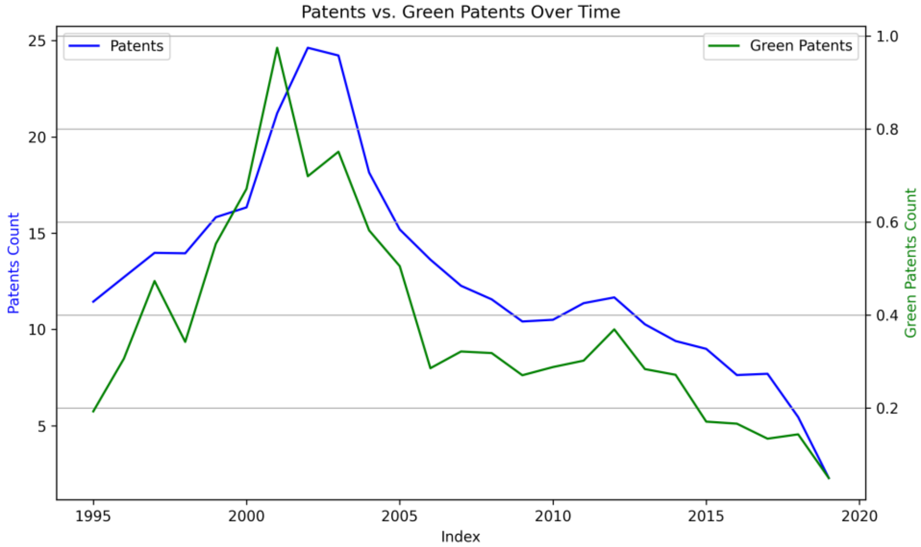
This table provides a description for all variables of the third essay.

Appendix F: Kernel density estimate for log patent count, log green patent count and log patent count for all deals with >0 green patents



This figure depicts the Kernel density distribution of the logarithmic patent count in the left graph, the middle graph depicts the Kernel density distribution of the logarithmic green patent count and the right graph depicts the Kernel density distribution of the logarithmic green patent count for all deals with at least one green patent.

Appendix G: Average patent count and green patent count per company over time



The figure shows the mean patent count and mean green patent count per company over time. The blue line shows the mean patent count over time and refers to the y-axis on the left side. The green line shows the mean green patent count over time and refers to the y-axis on the right side. The mean (green) patent count is provided for all considered deals over the entire observation period of the deal window. While deals analyzed took place within the years 2000-2014, the deal window spans from 1995 to 2019 (+- 5 years of the deal).

Appendix H: Industry distribution if company > 100 patents at least in one year

Industry	Freq.	Percent	Cum. [%]
Automobiles, Other Vehicles & Parts	10	9.01	9.01
Chemicals	10	9.01	18.02
Consumer Products	9	8.11	26.13
Software	9	8.11	34.23
Industrial Machinery	8	7.21	41.44
Materials	8	7.21	48.65
Medical Devices & Equipment	8	7.21	55.86
Telecoms	6	5.41	61.26
Packaging	5	4.5	65.77
Semiconductors	5	4.5	70.27
Biotechnology	4	3.6	73.87
Electronics	4	3.6	77.48
Hardware	3	2.7	80.18
Healthcare	3	2.7	82.88
Logistics & Distribution	3	2.7	85.59
Pharmaceuticals	3	2.7	88.29
Business Support Services	2	1.8	90.09
Power & Utilities	2	1.8	91.89
Aerospace	1	0.9	92.79
Energy Storage & Batteries	1	0.9	93.69
Food	1	0.9	94.59
IT Infrastructure	1	0.9	95.5
Information Services	1	0.9	96.4
Marketing/Advertising	1	0.9	97.3
Media	1	0.9	98.2
Rail Transport	1	0.9	99.1

Retail	1	0.9	100
Total	111	100	

This table provides a detailed overview of all industries considered within the sub-sample of all companies within the deal window that obtained more than 100 patents in at least one year of the deal window. It provides the frequency of the industry within the sub-sample, the share of it within the sub-sample and the its cumulative value.

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