The Performance of ESG-Oriented Private Equity Funds: A Quantitative Analysis

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THE PERFORMANCE OF ESG-ORIENTED PRIVATE EQUITY FUNDS: A QUANTITATIVE ANALYSIS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

ATE	Average Treatment Effect
ATET	Average Treatment Effect on the Treated
AUD	Australian Dollar
AUM	Assets Under Management
CFO	Chief Financial Officer
DPI	Distributions to Paid-in Capital
ESG	Environmental, Social and Governance
EU	European Union
EUR	Euro
GBP	Pound Sterling
GP	General Partner
IPO	Initial Public Offering
IRR	Internal Rate of Returns
IT	Information Technology
JPY	Japanese Yen
LBO	Leveraged Buyout
LP	Limited Partner
MN	Million
NAV	Net Asset Value
NN	Nearest Neighbour
NPV	Net Present Value
OLS	Ordinary Least Squares
PEI	Private Equity International

PME	Public Market Equivalent
PRI	Principles for Responsible Investment
PSM	Propensity Score Matching
RVPI	Residual Value to Paid-in Capital
SDGs	Sustainable Development Goals
SRI	Socially Responsible Investing
TVPI	Total Value to Paid-in Capital
UN	United Nations
USD	US-Dollar
VC	Venture Capital

1. INTRODUCTION

The urgency of sustainable development and the consideration of environmental, social and governance (ESG) factors are gaining increasing attention in the investment industry. In 2018, the ESG assets under management (AUM) amounted to 30.6 trillion USD, and are expected to further increase to 53 trillion USD by 2025, which would represent more than one-third of the expected total AUM (Bloomberg Intelligence, 2021). This development is encouraged by the creation of a growing number of standards and regulations, and by the expectations of investors and other stakeholders.

This evolution can also be observed in the private equity industry. Due to their characteristics, private equity funds are particularly well suited for ESG-oriented investments and impact investing strategies. For the most part, fund managers use ESG factors in the risk management process or as a value creation tool. Additionally, the fund manager can directly influence the company and its management of ESG issues. However, beyond the fact that private equity offers enormous potential to address ESG issues, the question of how ESG orientation affects the financial performance of private equity funds inevitably arises. Because even though institutional investors increasingly consider non-financial factors in their investment decisions, they still expect a return on their investments.

Finance research has only recently begun to address the thematic of ESG factor integration in the private equity industry. Therefore, there are only few studies that analyse the performance implications of an ESG factor integration. The question of whether the ESG orientation of private equity funds can lead to a better performance cannot yet be answered. That's why the aim of this master thesis is to make a performance comparison between ESG-oriented private equity funds, and private equity funds that are not considering these non-financial factors.

In a first step, Ordinary Least Squares (OLS) regression analyses are performed, with the ESG orientation being one of the explanatory variables. However, as it is likely that these results are biased, propensity score matching (PSM) is then applied to estimate the average effect of an ESG factor integration. These analyses are all carried out for two different performance measures, namely for the Total Value to Paid-in Capital (TVPI) multiple and the Net Internal Rate of Return (IRR).

The first part considers the existing literature to ensure that the readers have the necessary background knowledge. To this end, the terms ESG and ESG investing are first defined. Then the role of corporations in this context is described. Afterwards, it is explained how sustainability is integrated into the investment industry, what drives this development and what concerns exist. Then, the focus is placed on the private equity industry. It is briefly explained what private equity is and why this asset class is particularly suitable for an ESG orientation. Further, it will be briefly described which approaches exist to implement ESG factors into the investment processes of private equity funds, which motives are behind this implementation and how it is practically carried out. Thereafter, the research of different authors is considered in order to understand which fund characteristics have an impact on the performance of private equity funds. Finally, the two performance measures used in the analyses are explained.

The second part focuses on answering the question of whether ESG-oriented private equity funds can achieve better performance than private equity funds that do not take ESG factors into account. First, the data collection and processing is presented. Then, the sample is described using the descriptive statistics of the different variables. Thereby, the fund characteristics, which have been identified as performance drivers in the first part, are used as control variables in the analyses. Afterwards, the methodologies used to answer the research question are presented. In a first step, the simple and multiple OLS regression models are explained and applied to the sample under consideration. However, as these models have limitations, a second methodology is introduced, namely PSM. An explanation on how PSM helps to estimate average treatment effects will be given, with the ESG orientation being the treatment, followed by a short introduction of the different variants (ATE, ATET, oversampling). Following the explanations of the methods, the results are analysed. First, the OLS regression results are described and interpreted for the TVPI and the Net IRR. Thereby, the impacts of the different fund characteristics on the performance are also discussed. Afterwards, the results of eight different PSMs are presented and compared. Finally, the results of the OLS regression analyses and the PSMs are compared and conclusions are drawn.

2. LITERATURE REVIEW

2.1 The Definition of ESG

2.1.1 A Factor-Based Definition of ESG

The abbreviation ESG comprises three aspects, namely the "environmental" aspect, the "social" aspect and the "governance" aspect (Zaccone & Pedrini, 2020).

The main focus of the "environmental" aspect is the protection of the natural environment with its resources (Zaccone & Pedrini, 2020). It addresses among other things topics such as climate change, air and water pollution, carbon emissions, biodiversity, deforestation, water scarcity, energy efficiency, waste management, minimizing the impact of products and packaging, ensuring a responsible environmental footprint, and preventing the mistreatment of animals (CFA Institute, 2015; Zaccone & Pedrini, 2020).

The "social" aspect is addressing the following topics: human rights, child labour, labour standards, community relation and development, data protection and privacy, education and health, protecting gender and diversity, protecting and promising equal opportunity, providing support in humanitarian crises, supporting employee safety, and promoting work-life balance, customer satisfaction (CFA Institute, 2015; Zaccone & Pedrini, 2020).

The underlying idea of the "governance" aspect is to ensure that the stakeholders comply with their rights and responsibilities, which includes board composition, committee structure, political contributions, lobbying, bribery and corruption, whistle-blower schemes, codes of conduct and fair compensation policies (CFA Institute, 2015; Zaccone & Pedrini, 2020).

2.1.2 Three Definitions of ESG in the Investment Context

The CFA Institute defines ESG Investing as follows: "ESG stands for Environmental, Social, and Governance. Investors are increasingly applying these non-financial factors as part of their analysis process to identify material risks and growth opportunities" (CFA Institute, 2021).

Remy Briand, managing director of the MSCI ESG Research department, states that "At MSCI, we define ESG Investing as the consideration of environmental, social and governance factors alongside financial factors in the investment decisions-making process" (Briand, 2021).

The authors Caplan, Griswold and Jarvis define ESG investing as follows "Environmental, social and governance (ESG) investing, which involves integrating ESG factors into fundamental investment analysis to the extent that they are material to investment performance" (Caplan et al., 2013, p. 1).

2.1.3 Distinction between SRI, ESG Investing and Impact Investing

According to the Corporate Finance Institute (CFI) "Socially responsible investment, or SRI, is a strategy that considers not only the financial returns from an investment but also its impact on environmental, ethical or social change" (Corporate Finance Institute, 2021a). It is largely based on screening and excluding certain companies and industries from investment based on ethical principles (Caplan et al., 2013). SRI is an investment philosophy, which aims to fulfil a certain mission and to express certain moral, ethical or religious values through investments (Caplan et al., 2013).

On the other hand, ESG investing focuses on the consideration of ESG factors in investment decisions, which should have a positive impact on investment performance (Zambotti & Heeren, 2020). The ESG factors are used to manage risks and/or to create value. There exists also the possibility to address ESG issues, however, the investors' engagement is limited (Caplan et al., 2013; Zambotti & Heeren, 2020).

Impact investing is not just about investing or not investing in certain companies. It describes a form of investment with a high degree of engagement. The investors not only provide capital to a company, but influence the company, its activities and its structures, according to the institutional values (Caplan et al., 2013). The goal is to have a positive environmental and/or social impact and to provide investors at the same time with a financial return, even if this rate of return is lower than market rate (Caplan et al., 2013; Zambotti & Heeren, 2020).

2.2 The Role of Corporations in the ESG Context

Following the definition of ESG factors, it is not surprising that companies are at the heart of ESG discussions. The three ESG aspects represent necessities and requirements, which should be considered and addressed by the corporations. Different stakeholders are increasingly putting pressure on companies to address these issues and to adapt their business models and activities accordingly (Zaccone & Pedrini, 2020). These stakeholders include for instance consumers, employees, governments and investors (Zaccone & Pedrini, 2020).

In general, consumers are becoming more aware of the recent ESG issues and their consequences. Therefore, they expect companies to behave more ethically and to do business in a more environmentally conscious way (Pedrini & Ferri, 2014, cited by Zaccone & Pedrini, 2020). Additional pressure comes from the workforce, which puts more emphasis on a good work-life balance (Di Fabio, 2017). Moreover, job applications are not only determined by remuneration anymore, but also by factors such as a healthy work environment, the mission and values of the company, and the impact that their work will have on society and the environment (Di Fabio, 2017). In addition, governments enact laws, regulations and other policies that help to address ESG issues and that govern corporate behaviour (Guo et al., 2018, cited by Zaccone & Pedrini, 2020). Finally, shareholders are also becoming increasingly aware of these ESG issues and are recognising the important role that companies play in achieving a better common good (Zaccone & Pedrini, 2020; Bugg-Levine & Emerson, 2011).

But what about the impacts of the consideration of ESG factors on the performance of corporations? There is evidence that the consideration of ESG factors could lead to the satisfaction of stakeholders' needs, to better operating performance, and consequently even to a competitive advantage (Kotsantonis et al., 2016). For example higher employee satisfaction can be reflected in a more motivated and productive work environment and at the same time it can attract a new talented workforce (Kotsantonis et al., 2016). Furthermore, a good supplier relationship can also have a positive impact on productivity (Kotsantonis et al., 2016). And in relation to customers, considering ESG factors can help to satisfy their changing needs and thus enhance their loyalty (Kotsantonis et al., 2016).

Additionally, ESG factors include, as mentioned above, the efficient use of resources such as water and electricity, the reduction of waste,… which can lead to cost savings (Caplan et al., 2013; Kotsantonis et al., 2016). Cost savings are in turn appreciated by shareholders and show that the company has an efficient resource management and that no invested capital is wasted (Kotsantonis et al., 2016).

Incorporating ESG factors from an early stage can also help companies to prepare themselves for future regulations and to create thereby a competitive advantage (United Nations Global Compact et al., 2005). In addition, the company's brand value can be improved and corporate scandals can be avoided (Kotsantonis et al., 2016).

The increase in the operational productivity, the cost savings, and the management of ESG related risks are all positively related to the shareholder value (United Nations Global Compact et al., 2005).

However, it is important to address the ESG factors that are material to the company (Kotsantonis et al., 2016). This means that if a company addresses ESG factors that have nothing to do with its core business or the industry in which it operates, this may not have a positive impact on value creation. On the contrary, if immaterial ESG factors are considered, this can even lead to poorer performance (Kotsantonis et al., 2016).

There is also a strong consensus in the literature that companies that incorporate ESG factors into their activities and business model have a lower cost of capital (debt and equity) (Fulton et al., 2013; Caplan et al., 2013; Kotsantonis et al., 2016). Moreover, it seems that there is a positive correlation between the ESG rating of a company and its long-term financial performance, which is reflected in both the market valuations and the accounting measures (Fulton et al., 2013; Caplan et al., 2013; Kotsantonis et al., 2016). However, one question that cannot be easily answered is, how long is long-term? Thereby, the time span depends, among other things, on the risks identified by the ESG analysis and on the measures that can be taken to eliminate these risks (Fulton et al., 2013; Caplan et al., 2013).

However, in order to reach higher market valuations, it is important that the companies are transparent with regard to their ESG efforts. The Global Reporting Initiative (GRI) standards give corporations guidance in assessing and reporting their ESG impacts (Brown et al., 2009, cited by Zaccone & Pedrini, 2020; Kotsantonis et al., 2016). Moreover, the Sustainability Accounting Standards Board (SASB) designs industry-specific sustainability accounting standards that help companies to disclose sustainability-related data (Caplan et al., 2013; Kotsantonis et al., 2016). This also plays a major role in the increasing integration of ESG factors into analysis processes and investment decisions. (Kotsantonis et al., 2016).

2.3 The Sustainable Investment Industry

2.3.1 Sustainable Investment Strategies

There exist different strategies to integrate sustainability factors. These strategies differ largely in the extent to which the factors are taken into account in the investment processes and how illiquid the strategies are consequently.

Negative Screening, also called Value-based Screening, requires the lowest degree of engagement, as it consists in only excluding some companies, industries or geographical areas from investments, based on moral values (CFA Institute, 2015). Thereby, the attractiveness in terms of financial performance does not play a role (CFA Institute, 2015). Examples are the gambling, the alcohol and the tobacco industry (CFA Institute, 2015).

Another screening strategy is the Norms-based Screening, whereby the exclusion of some companies as potential investment targets is based on norms (CFA Institute, 2015). Examples of such standards could be human rights, labour standards, etc. (CFA Institute, 2015).

The Best-in-Class selection strategy chooses those companies which have the best ESG performance compared to its peers (CFA Institute, 2015; Zambotti & Heeren, 2020). Thereby, the level of ESG performance can be considered or the change in the ESG performance (CFA Institute, 2015). It is also possible to base the weighting of the portfolio companies on their ESG performance (Zambotti & Heeren, 2020). The engagement for this type of strategy is already a little bit higher, as the ESG performance needs to be assessed for each (potential) target firm (CFA Institute, 2015).

In the ESG Integration strategy, the focus is on assessing the investment opportunities additionally with regard to the ESG factors (CFA Institute, 2015). This means evaluating the associated risks and value creation opportunities, and then deciding accordingly whether to invest or not (CFA Institute, 2015).

Furthermore, there are Thematic Investment strategies that focus on sustainability or ESG factors. This means that only specific investment areas are selected that are closely related to sustainability or ESG factors (Zambotti & Heeren, 2020). Examples of such investment areas could be renewable energy, agriculture, education, etc. (CFA Institute, 2015).

In an Active Ownership strategy, the investor uses his ownership and voting rights to monitor and, if necessary, influence the company with regard to potential ESG issues (CFA Institute, 2015). Instead of simply selling his shares, he tries to achieve a positive influence with the means at his disposal (CFA Institute, 2015). However, the engagement potential is limited (CFA Institute, 2015).

Finally, there exists also the Impact Investing strategy. As mentioned above, this is about having a positive social and/or environmental influence on the portfolio companies, while still achieving financial performance. Thereby, the rate of return should exceed the risk-adjusted market rate (CFA Institute, 2015). Moreover, it is necessary to measure and disclose the impacts reached through this strategy (CFA Institute, 2015).

2.3.2 Existing Framework Fostering Sustainable Investments

The beginnings of responsible investing go back to the 20th century, when responsible investing began under the form of the SRI philosophy with a negative screening strategy (Caplan et al., 2013). In 1921, the first mutual fund applied negative screening by deciding not to invest in the tobacco, alcohol and gambling industry (Caplan et al., 2013).

In July 2000, the United Nations (UN) Global Compact was founded, which is nowadays the largest corporate sustainability initiative. It established 10 principles concerning Human Rights, Labour, Environment and Anti-Corruption. These principles should encourage and guide companies to align their strategies and interests with their responsibilities to people and the planet (United Nations Global Compact, 2021a). The UN Global Compact is applied by 13,832 companies from around the world (United Nations Global Compact, 2021c). Moreover, the UN Global Compact is active in the field of sustainable finance. It aims to ensure that investments are made in a way that contributes to the realisation of the Sustainable Development Goals (SDGs). Therefore, they established a Chief Financial Officer (CFO) taskforce for the SDGs and four additional principles that should help CFOs to incorporate sustainable development in their investment policies (United Nations Global Compact, 2021b).

In 2005, the "Who cares wins" conference report has been published, which aims to integrate ESG factors into capital markets (Zambotti & Heeren, 2020). One of the main subjects was also to address the issues which are encountered throughout the integration of ESG factors into research, analysis and investment processes (United Nations Global Compact et al., 2005).

Afterwards, in 2006, the UN published a set of practical standards that should encourage investors to incorporate ESG factors that are material to investment performance into their investment decisions and to pursue active ownership (Caplan et al., 2013).

This set of practice standards is called Principles for Responsible Investment (PRI). Once the UNPRI have been signed, the signatories are required to follow these standards (Caplan et al., 2013; Kotsantonis et al., 2016). When the UNPRI were launched, 4 trillion USD of AUM were invested according to these practical standards (Caplan et al., 2013). Most signatories of the UNPRI were asset management firms, with some of them already being private equity firms (Caplan et al., 2013). At the End of March 2020, the AUM reached an amount of 103.4 trillion USD, and the signatories base comprised 2,701 investors and 337 service providers (United Nations Environment Programme Finance Initiative & United Nations Global Compact, 2021). Thereby, it can also be observed that the 98% (99% in 2018) of the investor signatories are incorporating ESG factors in their listed equity investments, and 94% (87% in 2018) of investor signatories are also incorporating ESG factors in their private market investments (United Nations Environment Programme Finance Initiative & United Nations Global Compact, 2021).

In 2009, the private equity industry took its first official step towards ESG orientation when the US Private Equity Council issued guidelines to help address ESG issues (Schell, 2020, cited by Zaccone & Pedrini, 2020). Subsequently, from 2010 to 2012, it can be observed that in the alternative investment industry, assets managed under consideration of ESG factors have increased by 250 per cent, reaching a value of 132 billion US dollars (United States SIF Foundation, 2012, cited by Caplan et al., 2013).

In 2014, the European Union (EU) issued a directive on non-financial reporting (Kotsantonis et al., 2016). “The directive requires large public- interest entities with more than 500 employees to disclose in their management report information about company policies, risks, and outcomes regarding environmental matters, social and employee aspects, respect for human rights, anticorruption and bribery issues, and diversity in their board of directors” (Kotsantonis et al., 2016, p. 14).

Moreover, in 2018, the EU launched the EU Sustainable Finance Action Plan, which focuses on redirecting investments towards a more sustainable economy, integrating sustainability into risk management processes and reporting on sustainability factors and risks (Zambotti & Heeren, 2020). An important element of the action plan is the EU Taxonomy. It became effective in July 2020 and consists of a list of economic activities that are classified as environmentally sustainable (Zambotti & Heeren, 2020). The EU Taxonomy provides different actors with a unique classification system. This should help companies to better identify which activities are sustainable, protect investors from investing in firms that are greenwashing, and support policymakers in the design of future regulations (European Commission, 2020).

2.3.3 Developments in the Sustainable Investment Industry

Most investors are becoming increasingly aware of the need to address ESG issues and recognise the role they can play in this context. Therefore, they are attempting to incorporate sustainability aspects into their investment decisions and strategies, by analysing the target companies with regard to ESG factors, and by considering the characteristics of their industries and geographies (Kirkland, 2020, cited by Zaccone & Pedrini, 2020; Caplan et al., 2013).

As already mentioned above, SRI and negative screening were the first applied responsible investment approaches. However, they became increasingly mainstream and are already reaching maturity on the public markets (Crifo & Forget, 2013). Therefore, ESG integration strategies and active ownership strategies have been increasingly applied by investors for some years now (Kotsantonis et al., 2016).

A comparison between the continents shows that Europe has clearly the most developed sustainable investment industry (Kotsantonis et al., 2016). Worldwide, the development of ESG products is growing, but Europe is far ahead, contributing 76% of the sustainable offerings and 81% of the sustainable assets (Zambotti & Heeren, 2020). Moreover, the number of European sustainable funds is increasing, with 72 new funds in the first quarter of 2020 (Zambotti & Heeren, 2020).

The big concerns about the consideration of ESG are that these investment approaches cannot generate sufficiently high rate of returns (Fulton et al., 2013; Kotsantonis et al., 2016; Lagerkvist et al., 2020). SRI funds that use negative screening have difficulties to outperform conventional funds. Their returns are often lower than the market averages (Kotsantonis et al., 2016). This is, among other things, due to the fact that they cannot fully exploit the potential offered by companies already successfully addressing ESG issues (Fulton et al., 2013; Kotsantonis et al., 2016). Therefore, ESG factor integration should no longer be seen as a separate approach, but should be integrated in every due diligence and investment process (Fulton et al., 2013; Kotsantonis et al., 2016; United Nations Global Compact et al., 2005). This is consistent with Bugg-Levine and Emerson's (2011) point of view. They are against the outdated idea that charity is responsible for solving environmental and social problems and that investments are only there to generate returns (Bugg-Levine & Emerson, 2011).

On the contrary, Bugg-Levine and Emerson believe that value creation can consist of an economic, a social and an environmental component, which do not need to be separated from each other (2011).

Furthermore, ESG orientation is nowadays representing an opportunity for the development of a competitive advantage for certain funds, as not all fund managers are integrating ESG factors in their conventional investment process yet (Caplan et al., 2013).

However, due to the abundance of ESG factors, there is the need to identify those ESG factors that are material to financial performance and to include these factors especially in the investment analyses (Kotsantonis et al., 2016; Caplan et al., 2013).

There is also often the concern that the integration of ESG factors into the valuation models violates the fiduciary duty (Kotsantonis et al., 2016; Caplan et al., 2013). It states that “[...] fiduciaries under their duty of loyalty to protect the financial interest of their beneficiaries, must consider traditional economic factors in their valuation models […]” (Kotsantonis et al., 2016, p.15). However, Kotsantonis et al. (2016) argue that even if the ESG factors are not belonging to the traditional economic factors, they can nowadays still be material to the financial performance and therefore it is in some cases necessary to include them. Therefore, policymakers are also working on a more adequate interpretation of the fiduciary duty (Kotsantonis et al., 2016). Moreover, it is sometimes assumed that the consideration of ESG factors is a failure of the "prudent investor", as it limits the resources that can be used for diversification (Kotsantonis et al., 2016).

Concerning the disclosure of ESG data, it is observable that since 2011, an increasing number of companies are reporting ESG data and that the quality of the data is also increasing (Kotsantonis et al., 2016). However, according to Kotsantonis et al. (2016), this is also necessary, because new initiatives, standards and regulatory requirements make it almost impossible to ignore ESG integration and related reporting. Moreover, investors are demanding more and better ESG information to carry out their due diligence and investment process (Kotsantonis et al., 2016). Kotsantonis et al. point out that stock exchanges are playing an important role in this context, because they can demand, as additional listing requirement, that the companies report on ESG factors (2016). Additionally, data providers such as MSCI and Bloomberg are increasingly making ESG data available (Kotsantonis et al., 2016). Based on data from stock exchanges and other data providers, better ESG rankings can then be produced, which creates additional transparency and provides investors with the necessary information (Kotsantonis et al., 2016).

2.3.4 Challenges with Regard to an ESG Orientation

The challenges already start at the company level. It is necessary that companies provide more non-financial data on the problems they have with ESG factors and the efforts they undertake to address these issues. It would also be very helpful if the different companies, at least those of the same industry, would have the same ESG reporting approach in order to make the results comparable and to ensure good quality (Caplan et al., 2013; Zaccone & Pedrini, 2020).

The availability of company-related ESG data would make it easier for both investors and asset managers to integrate ESG factors into their investment processes. Many investors do not have sufficient expertise to carry out detailed analyses with regard to ESG aspects. Moreover, not all investors have access to ESG experts who can advise them on this subject matter. At the fund level, the situation is somewhat better, as asset managers have more expertise and other analytical tools at their disposal. However, also at the fund level, there is a lack of experts who could facilitate the integration of ESG factors into due diligence and strategies (Zaccone & Pedrini, 2020). Moreover, there exist no standard methods to measure the impacts of the investments (Zaccone & Pedrini, 2020). One possible solution could be to offer training and seminars that address ESG factors and their integration into investment processes and strategies, as well as the corresponding reporting (Kotsantonis et al., 2016).

It would also be very helpful if further efforts could be made to help companies, investors and asset managers to identify the ESG factors that are material to their performance (Kotsantonis et al., 2016).

It is also observable, that the environmental aspect receives the most attention from funds (Lagerkvist et al., 2020; Zaccone & Pedrini, 2020). However, the social aspect and the governance aspect are just as important. Therefore, it should be ensured that the factors belonging to these two ESG aspects are also taken into account in the future.

The sustainable development can be fostered by a good fiscal, legal and regulatory framework, as this encourages entrepreneurship and innovation and improves competitiveness (Precup, 2019). Therefore, an important challenge will be to put in place additional governance measures and incentive systems to encourage an advanced integration of ESG factors into companies but also into the investment and decision making processes (Kotsantonis et al., 2016).

2.4 The Sustainable Private Equity Industry

2.4.1 Definition of Private Equity

Private equity is part of the private capital asset category, which in turn belongs to the alternative investment industry. Therefore, only institutional investors are allowed to invest in private equity funds. Moreover, such funds are not publicly traded. Assets worth 4.5 trillion USD are managed by private equity firms, thereby making up the largest part of the private capital category in terms of AUM (Lambert, 2020).

A private equity fund is generally structured as a Limited Liability Company, which represents a partnership (Lambert, 2020). The investors, also called limited partners (LP), commit to invest a certain amount into the fund, and therefore their liability is limited to this amount (Lambert, 2020). The committed amount does not necessarily need to be invested directly in its entirety. The fund manager, also called fund sponsor or general partner (GP), identifies the target companies (private or delisted firms) and manages the day-to-day operations of the fund (Lambert, 2020; Crifo & Forget, 2013).

The LPs have generally a passive role, as they only need to provide the capital if capital calls are made (Lambert, 2020). The GP, conversely, is responsible for the different due diligence processes, the investment decisions, and for the management of the portfolio companies. The compensation of the GP is based on management fees (1% - 3%) and performance fees (± 20%) (Lambert, 2020). In some cases, the LPs can, however, also intervene in the management and give advice, which is in line with the concept of value-add investors (Precup, 2019).

There exist different forms of private equity funds, which differ in terms of their strategies. It can mainly be distinguished between LBO funds, venture capital (VC) funds, funds following growth strategies, funds following turnaround strategies, private equity secondaries and fund of funds (Lambert, 2020).

According to Lambert (2020), private equity funds have a limited lifetime which ranges generally from 7 to 10 years. During this period, the investors are locked into the fund. The year in which the first investment is made represents the vintage year. In the following years (± 5 years), the GP invests in other target companies and manages them according to the fund's strategy and risk-return profile (Lambert, 2020). The aim is to increase their value, which can for example be done by "[…] organically expanding a business, completing a series of acquisitions in the same industry, and improving an underperforming business" (Zaccone &

Pedrini, 2020, p.3). In the following years, the exit strategies are established, the portfolio companies are sold again and the proceeds are distributed to the investors (Lambert, 2020). If there are no more portfolio companies in the fund, the fund is considered as liquidated. The investors' returns depend on the value increase of the portfolio companies, i.e. the difference between the selling price and the acquisition price (Lambert, 2020; Zaccone & Pedrini, 2020).

2.4.2 Integration of ESG Factors

A sustainable investment approach is also gaining importance in the private equity industry and is therefore progressively combined with traditional strategies. Negative screening strategies were used in the target company selection process, but concerns arose whether this approach is really effective (Zaccone & Pedrini, 2020). As a result, private equity firms are increasingly adopting extended approaches, such as ESG investing and impact investing (Zaccone & Pedrini, 2020).

One of the characteristics of private equity funds is that they have a long investment horizon and that they are therefore very illiquid. As already mentioned, the integration of ESG factors in companies represents a high potential, however, it usually only pays off in the long run. Therefore, private equity investments are very suitable to capture this long-term potential (Caplan et al., 2013). In addition, the consideration of ESG factors is becoming increasingly important for these longer-term investment strategies (United Nations Global Compact et al., 2005). Moreover, ESG-oriented private equity funds can contribute to the consideration of ESG factors by non-listed companies (Crifo & Forget, 2013). This is because the fund manager has the possibility to take an active role in the management of the target companies. It allows fund managers, and potentially also investors, to make use of their expertise and to implement ESG factors (Crifo & Forget, 2013, Precup, 2019).

For private equity funds, the ESG orientation can range from a simple consideration of ESG factors in the conventional investment processes to targeted ESG private equity funds taking the form of impact investing funds (Caplan et al., 2013; Crifo & Forget, 2013). So basically, ESG orientation is not an all or nothing approach, but fund managers can decide to what extend they take ESG factors into account and if they consider these factors during the portfolio construction phase and/or during the monitoring phase (Caplan et al., 2013). Furthermore, the ESG factors can be assessed per portfolio company or on the level of the entire investment portfolio in order to evaluate the aggregated exposure (Caplan et al., 2013).

Crifo and Forget (2013) explain that the motives behind an ESG orientation of private equity funds are rather of a strategic nature. It represents an alternative way to manage risks, to create value and additionally it can represent a differentiation strategy (Crifo & Forget, 2013).

Under current conditions, it is becoming progressively more important to manage risks related to ESG issues. Investors are increasingly concerned about environmental and social problems, and therefore have a growing interest in contributing to solve these problems (Bugg-Levine & Emerson, 2011). Moreover, other stakeholders, such as the media, and regulators are also putting more and more pressure on private equity funds to take ESG factors into account (Crifo & Forget, 2013). Therefore, for most of the fund managers, the consideration of ESG factors is a way to mitigate risk. They are aware that ignoring these ESG issues not only risks to dissatisfy stakeholders, but that ignoring them when making investment decisions can also have a negative impact on the value of the investments (Zaccone & Pedrini, 2020). This is because some of these ESG factors are material to the investment performance and therefore it is really important to identify and focus on them (Caplan et al., 2013). A simple example: If the target company gets involved in scandals, then it becomes difficult to exit the investment with a profit (Zaccone & Pedrini, 2020).

However, the authors Kotsantonis et al. (2016) argue in their article that it is not sufficient to use ESG factors only as a risk management tool. It is necessary to develop new technologies and innovations that address ESG issues and at the same time improve operational efficiency and performance (Kotsantonis et al., 2016).

The highest level of engagement is needed for impact investing. Thereby, private equity offers the opportunity to invest directly in carefully selected companies and to actively intervene in their management in order to achieve a positive impact. Consequently, addressing ESG issues is the main objective, but at the same time, investors hope that this strategy will pay off in the long run so that they can achieve a return (Bugg-Levine & Emerson, 2011). Examples are so-called green private equity funds that aim to foster the sustainable and environmentally friendly development of the economy (Crifo & Forget, 2013).

The people surveyed for Zaccone and Pedrini (2020) have indicated that they consider ESG factors mostly during the pre-deal due diligence. Furthermore, ESG factors are also taken into account during the value creation due diligence in order to assess which role an ESG orientation can play for the fund's value creation (Zaccone & Pedrini, 2020). The respondents have specified that they focus on two main criteria when integrating ESG factors in the due diligence: first the business model and second the industry maturity with regard to ESG. Zaccone and Pedrini explain that in order to gather related information, the respondents mostly use checklists, focusing on the business activities, on the management of related risk and on the company's compliance with ESG-related laws and standards (2020). These checklists help them to establish and compare the ESG profiles of potential targets (Zaccone & Pedrini, 2020).

External advisors are also sometimes consulted. However, this is mostly the case when the fund managers see an opportunity to create value by considering ESG factors, for example through business opportunities or innovations (Zaccone & Pedrini, 2020).

Although, an ESG orientation is increasingly becoming a necessity, and the characteristics of private equity funds favour the consideration of ESG factors, the question remains whether the time horizon is long enough to exhaust the potential of an ESG orientation and whether the ambition for a positive impact does not come at the expense of returns. How is the performance of ESG-oriented private equity funds compared to other Non-ESG-oriented private equity funds?

2.5 The Performance of Private Equity Funds

2.5.1 Performance Drivers

The return of private equity funds depends on the ability to select the right investment targets, to impact the portfolio companies positively and to sell them at a profit. However, there are also other factors that can impact the private equity fund's performance. A number of authors have already studied the performance of private equity funds and have carried out research on potential performance drivers.

Kaplan and Schoar (2005) have examined the performance of private equity funds. The focus of their analysis lies among other things on return characteristics and on the persistence of fund performance (Kaplan & Schoar, 2005).

According to Kaplan and Schoar (2005), private equity funds are characterised by a wide heterogeneity in returns from one fund to another. This is because GPs have different skills and qualities. Kaplan and Schoar argue that the top GPs' expertise helps them to select the right investment targets but also gives them access to better investment opportunities.

Moreover, they might be able to negotiate better terms with the target companies (Kaplan & Schoar, 2005). Consequently, their skills help to achieve higher returns (Kaplan & Schoar, 2005). This means that for funds of the same GP a substantially constant performance can be observed. Therefore, according to Kaplan and Schoar, the track record can be used as a reliable source of information for the estimation of future funds' performance. The authors examine if this persistence is driven by an overlap of investments or by an overlap of time periods, but conclude that neither is the case (Kaplan & Schoar, 2005). Kaplan and Schoar also group the funds according to their industry focus and their investment stage focus, in order to investigate whether the persistence in private equity fund performance is due to risk differences, but again this is not the case. Moreover, the authors argue that the sequence number of a private equity fund impacts the performance (Kaplan & Schoar, 2005). Thereby, the sequence number indicates if the fund is a first, second, third time etc. fund, and provides information on how many funds have already been set up prior to the fund under review. In the authors' opinion, higher sequence number funds achieve a better performance than first-time funds, which is due to the learning effect and the growing experience of the GP (Kaplan & Schoar, 2005).

When considering different points in time, private equity fund returns have also a wide dispersion. As Kaplan and Schoar's (2005) analysis shows, the prevailing market conditions have a strong impact on the returns. On the one hand, private equity funds that are raised in boom times are likely to have lower returns (Kaplan & Schoar, 2005). Kaplan and Schoar explain that this is due to the fact that during a boom period the market-adjusted returns are high, which leads to more fund entries and as a consequence the market-adjusted returns decrease. But on the other hand, it gets easier to raise capital when the overall market conditions are good (Kaplan & Schoar, 2005).

Furthermore, Kaplan and Schoar (2005) find evidence that there is a concave relationship between fund size and fund performance. This means that larger private equity funds tend to outperform smaller ones. However, the marginal returns are decreasing the larger the funds get. That is why top-performing funds grow proportionally slower than poorer-performing funds (Kaplan & Schoar, 2005). Possible explanations for this concavity are that the number of attractive investment opportunities are limited or because it is difficult to hire an additional partner who has the same skills and expertise in order to maintain the performance (Kaplan & Schoar, 2005).

Besides, Kaplan and Schoar's (2005) study results imply that on average VC funds perform better than buyout funds, and that the persistence in performance can be observed especially for VC funds.

From 1988 to 2001, VC funds have had a good performance with a Public Market Equivalent (PME) higher than 1, relative to the S&P 500 (Kaplan & Schoar, 2005). But during that same period, buyout funds almost never reached a PME higher than 1 (Kaplan & Schoar, 2005). Moreover, Kaplan and Schoar explain that well-established VC funds are nearly unaffected by the number of new VC funds entering the market, and only the new VC funds' returns are getting lower. However, for buyout funds the returns are diluted, regardless of whether they are well-established or new (Kaplan & Schoar, 2005).

Moreover, the life stage of the investment target can also have an impact on the performance, as the different stages imply different levels of risks and therefore higher return volatilities (Cochrane, 2005, cited by Kaplan & Schoar, 2005).

Kaplan and Schoar (2005) compare the returns of private equity funds to the returns of the S&P 500. Thereby it turns out that the gross-of-fees returns lie above the returns of the S&P 500, and that net-of-fees this overperformance disappears (Kaplan & Schoar, 2005). These observations show that the fees can play an important role in private equity performance, as the excess returns achieved through the fund managers are eaten up by the fees they charge (Kaplan & Schoar, 2005).

Another relevant paper addressing the performance of private equity funds is the one of Phalippou and Gottschalg (2009), which is also often referred to by other authors. They suggest that fund characteristics, such as the fund size, the fund sequence, the track record of previously raised funds, the regional focus, the fee structure and as well as the exit success impact the fund performance (Phalippou & Gottschalg, 2009).

According to their research, larger funds tend to perform better than smaller funds, suggesting that the fund performance correlates positively to the fund size (Phalippou & Gottschalg, 2009).

Moreover, Phalippou and Gottschalg (2009) argue that private equity funds with a higher sequence number seem to perform better than first-time funds, which can be explained by a learning effect. In private equity a lot of skills are required, which develop over time and with experience. The better the GPs' abilities get, the better the decisions they make and the better the returns that they can achieve (Phalippou & Gottschalg, 2009).

Additionally, in Phalippou and Gottschalg's (2009) opinion, the track record of previously raised funds is a good indicator of future funds' performance, which is in line with Kaplan and Schoar's (2005) findings. Phalippou and Gottschalg even suggest that if past performance data is available, it becomes the unique explanatory variable of future performance.

Furthermore, US-focused private equity funds seem to perform better than private equity funds with an EU focus, suggesting that the region focus has an impact on the performance (Phalippou & Gottschalg, 2009).

The fee structure should also be considered. Phalippou and Gottschalg (2009) highlight that gross-of-fees, most private equity funds have a very good performance with positive alphas, relative to the S&P 500. However, net-of-fees this overperformance tends to disappear, with returns that are on average 3% below those of the S&P 500 (Phalippou & Gottschalg, 2009). This is in line with the observations of Kaplan and Schoar (2005). According to Phalippou and Gottschalg, one point to consider is, on what basis the management fees are calculated. For example, whether they are calculated on the committed capital over the entire period or whether they are calculated on the committed capital during the investment period and then on the invested capital or on the Net Asset Value (NAV) (Phalippou & Gottschalg, 2009). Additionally, a change in the percentage of management fees has a direct impact on the alpha (Phalippou & Gottschalg, 2009). Phalippou and Gottschalg explain that performance fees, potential hurdle rates and catch-up provisions play an important role in the fee structure as well.

Finally, the authors also argue that there is a significant positive relation between exit success and fund performance, and that Initial Public Offerings (IPO) and M&As are often the most successful exit mechanisms (Phalippou & Gottschalg, 2009).

In their article "Private equity: Changing perceptions and new realities", Ghai et al. (2014) also deal with the performance of private equity funds. Ghai et al. state that private equities outperform public equities on a risk-adjusted basis. They believe that the returns are better in 2014 than in the mid-2000s, when private equity performance drifted towards the performance of the public markets (Ghai et al., 2014).

In Ghai et al.'s (2014) opinion, a fund's track record is no reliable indicator of future performance anymore and the observed persistence in performance of the early 2000s is vanishing. Ghai et al. argue that a deeper dive into the performance-drivers and managers' skills is needed.

The LPs should enhance their due diligence process in order to identify the GPs' capabilities and strengths, which have driven the past performance, and to evaluate if they are still present and sufficient to maintain the outperformance in the subsequent funds (Ghai et al., 2014). Additionally, the investors should consider which strategies are applied and if the fund manager has a specialisation in a specific sector or region (Ghai et al., 2014).

However, regarding the fund size as a potential performance driver, Ghai et al. (2014) differ in their interpretation in comparison to Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009). They argue that GPs are searching for larger deals and that they consequently try to increase their fund's size, but that no meaningful correlation between fund size/deal size and fund performance can be found (Ghai et al., 2014).

Lastly, the authors suggest that by substituting management fees by performance fees, the profit pool, shared by LPs and GP, would increase and consequently improve the fund's performance (Ghai et al., 2014).

In chapter 7 of the book "Private Equity Investments - Drivers and Performance Implications of Investment Cycles", Sommer (2013) takes a closer look at the performance of private equity funds. Sommer agrees with Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009) that private equity does generally not outperform public markets, even after having controlled for the differences in risk. Moreover, evidence can be found that the performance can vary from one country to another (Sommer, 2013), but also across time (Cochrane, 2006, cited by Sommer, 2013).

Sommer's (2013) research findings show that if the market is close to a peak, GPs' investment activity increases considerably, and private equity firms are also more likely to launch funds. This tendency is further reinforced by the herding effect (Sommer, 2013). Nevertheless, Sommer states that there is a negative correlation between fund performance (IRR) and both increased investment activity and the higher number of fund launches. This highlights the fact that the cycles are also impacting the returns of the fund (Sommer, 2013).

In his paper “Challenges to scaling sustainable private equity markets in emerging Europe”, Precup (2019) also addresses some aspects of the performance of private equity funds.

According to his analysis, for the vintage years 1990-1994 and 2000-2004, Net IRRs of more than 10% have been reached in European countries (European Venture Capital Association, 2013, cited by Precup, 2019). Precup suggests that private equity investments provide higher returns than other listed asset classes.

A sample consisting of VC funds and leveraged buyout (LBO) funds, for example, achieves annual returns that are on average at least 3% higher than those of the S&P 500 (Harris et al., 2014, cited by Precup, 2019). A possible explanation could be that private equity investments earn an illiquidity premium of 3.5% to 4% because of the long investment horizon (Patrick, 2008, cited by Precup, 2019).

Precup (2019) believes that one of the most important success factors is obviously the selection and monitoring of the investment targets. However, in his opinion, the management teams of the target companies play also an important role in achieving a good performance for the fund, not just the fund managers (Precup, 2019). Good managerial skills are crucial for increasing the investment value of the company, as they are needed for the elaboration and further development of the business plan and corresponding strategies and the implementation of corporate restructuring (Precup, 2019). Precup claims that it is therefore important to align the interest of the fund with those of the management team and to create a relationship based on trust.

In addition, Precup (2019) points out the importance of good exit strategies for fund performance, which is in line with the findings of Phalippou and Gottschalg (2009).

A developed and dynamic stock market, for example, can facilitate the exit from a VC investment through an IPO, which positively impacts the returns of the investment (Black & Gilson, 1998, cited by Precup, 2019).

In summary, it can be concluded that the authors' opinions are divided on whether private equities outperform public equities or not. This can be explained, for instance, by the fact that some authors refer to data for Europe and other authors focus on the United States and that the time periods that have been studied are not the same for all authors. There may also be inconsistencies in the way returns are calculated, as explained by Ghai et al. (2014).

Nonetheless, there is broad consensus among the authors that private equity performance is characterised by a large dispersion of returns, but at the same time also by a persistence in returns for funds of the same GP. Of the articles mentioned above, only Ghai et al. belief that this persistence is disappearing.

Based on the analyses of these authors, it can be assumed that the fund size, the fund sequence, the fund manager's skills, the timing (market conditions and business cycle), the strategy, the regional focus, the fee structure and the exit strategy influence the performance of private equity funds. In addition, Precup (2019) also points out the importance of the management team of the investment target. But what about the impact of an ESG orientation on funds' performance. These findings will support our analysis aimed at evaluating the effects of an ESG orientation on performance.

2.5.2 Performance Measures

In order to evaluate private equity fund performance, different measures exist. The most frequently used performance measure is the IRR (Phalippou, 2008).

The "IRR is defined as the discount rate which makes the Net Present Value (NPV) of a series of cash flows equal to zero" (Phalippou, 2008, p. 3). Thereby, the "Net Present Value (NPV) is the value of all future cash flows (positive and negative) over the entire life of an investment discounted to the present" (Corporate Finance Institute, 2021b). Consequently, this measure is based on the cash flows to the LPs.

However, in his article Phalippou (2008) shows that the rate of return earned by the investor corresponds only rarely to the IRR. This is partly due to the assumption that the cash distributions are directly reinvested at a rate equal to the IRR, which is quite unrealistic (Phalippou, 2008). On the one hand, if the IRR is lower than the actual reinvestment rate, then the effective rate of return is higher than the IRR (Phalippou, 2008). But on the other hand, if the IRR is higher than the reinvestment rate, then the IRR is exaggerated und lies above the effective rate of return (Phalippou, 2008).

Phalippou (2008) also explains that fund managers often distort IRRs by timing cash flows and trying to make distributions as early as possible to artificially increase the IRR. Moreover, the GPs group different funds together and use the average IRR as their track record, instead of the IRR of the aggregated cash flows, because the latter is generally lower (Phalippou, 2008).

Consequently, the IRR is no reliable performance measure for asset classes that have intermediary cash flows and are highly volatile, such as private equity (Phalippou, 2008).

An alternative measure of performance is the Total Value to Paid-in Capital (TVPI) multiple. This is a money multiple, which puts the total value, consisting of the sum of distributions and the NAV, in relation to the total capital invested, which corresponds to the sum of the capital calls (Lambert, 2020). It measures the return generated on the invested capital. The TVPI is formed by the sum of two more multiples, the Residual Value to Paid-in Capital (RVPI) and the Distributions to Paid-In Capital (DPI) (Higson & Stucke, 2012).

The RVPI relates the residual value of the fund to the total amount of capital called. Thereby, the residual value corresponds to the NAV of the fund's portfolio (Higson & Stucke, 2012). The DPI puts into relation the distributions to the investors and the capital invested by the investors. In the first four to five years, the RVPI is increasing as the GP makes several investments in different target companies (Higson & Stucke, 2012). From the fifth year onwards, the portfolio companies are sold and the distributions to the investors are carried out. At the end of the fund's lifetime, the RVPI is close to zero and the TVPI corresponds to the DPI (Higson & Stucke, 2012).

The advantage of this performance measure is that it is more difficult to manipulate (Lambert, 2020). The TVPI multiple is not dependent on when the distributions to the investors are made, because the time value of money is not taken into account (Higson & Stucke, 2012; Lambert, 2020). It is assumed that the reinvestment rate for the capital distributions is zero (Lambert, 2020).

Since the IRR and the TVPI are the most widely used absolute performance measures both in the literature and in practice, they are also used as performance measures in the following analysis. Even though the IRR is not a reliable performance measure due to the unrealistic reinvestment assumption and the possibility of manipulation, it is nevertheless included in order to compare the effects that an ESG integration has on both performance measures.

3 DATA

3.1 Data Collection

The data we use to carry out this performance comparison are obtained from Preqin Pro[1]. Preqin is an international company with 12 offices and 300 full-time researchers around the world (Preqin, 2021d). It offers access to the industry's most comprehensive private capital data sets (Preqin, 2021d). Preqin collects its data from around 6,000 individual GPs, from 60 global news sources, which are tracked daily, and from other public data sources (Preqin, 2021c).

On this platform, the data collection was oriented towards performance related data of private equity funds. An additional filter was added so that only liquidated private equity funds are part of this data set. This is essential for the comparability of the private equity funds' performance. A private equity fund that has not yet been liquidated, has not exited all its investments, and thus the performance measures are not only based on cash flows to LPs but also on subjective value estimations (Kaplan & Schoar, 2005).

The resulting data set (hereafter referred to as "performance data set") consists of 3,057 private equity funds[2], which are the observations in the analysis, and 159 variables (Preqin, 2021b). It should be kept in mind that private equity funds are part of the alternatives industry and that they are less regulated and have less disclosure requirements. That is why the availability of return data is limited.

3.2 Data Processing

The aim of this analysis is to determine how the consideration of ESG factors affects the performance of a private equity fund. Consequently, a distinction has to be made between ESG-oriented private equity funds and Non-ESG-oriented private equity funds. However, in the performance data set, it is not possible to filter for ESG-oriented funds. Therefore, more detailed information on the funds is needed.

[1] https://pro.preqin.com

[2] When the term "fund" is used hereafter without further specification, it always refers to "private equity funds", as the underlying data set consists only of private equity funds.

The "Search For Funds" section on Preqin Pro is used to collect the necessary data. Again, the same filters as for the performance data set are chosen, i.e., only private equity funds are included and all the funds need to have been liquidated. The resulting data set consists of 6,820 observations and it is called hereafter “fund data set” (Preqin, 2021a). Afterwards, the filter “ESG/Ethos: Private Equity” is applied to the fund data set, so that the resulting data set consists only of ESG-oriented funds (hereafter referred to as “ESG data set”). It comprises 2,225 observations (Preqin, 2021a).

In a next step, the Fund ID is used to check whether all funds from the performance data set are also contained in the fund data set. Since this is the case, it can then be checked which funds from the performance data set are also included in the ESG data set. This allows the identification of the ESG-oriented funds within the performance sample. The remaining funds are Non-ESG-oriented, as they are contained in the fund data set but not in the ESG data set.

To identify the ESG-oriented funds throughout the analysis, a variable called “ESG” is manually added. It is a binary variable, and takes the value “1” if the fund is ESG-oriented and the value “0” if it is not. Out of the 3,057 funds from the performance data set, 1,179 are ESG-oriented funds, representing almost 38.6%.

For further data processing, the software Stata[3], is used. The performance data set consists of 159 variables (see Appendix 1). The first step is to select the variables which are relevant for the performance comparison. Variables with less than 1,000 observations are excluded from the analysis, because they would reduce the size of the final sample too much. Moreover, there are some variables which are not relevant for the analysis, and which are thus excluded. Thereby, we refer to the literature review on the performance of private equity funds. As a result, we end up with 21 variables.

For clarity and identification purposes, two of the variables are renamed (see Appendix 1). Afterwards, it must be checked whether the formats of the variables are correctly recognised by Stata. Otherwise, the formats have to be adjusted manually. This was the case for the variables “CALLED”, “DPI”, “RVPI”, “TVPIX” and “NETIRR”.

In a next step, two new variables are created. The first variable is “TVPI_PERCENTAGE”. It is the sum of “DPI” and “RVPI”, which are both expressed in percentages. This variable,

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

calculated manually in Stata, will be compared subsequently with the variable “TVPIX”, provided by Preqin. The second variable is “FUNDSIZESQUARED”, and as the name already indicates it is the square of the variable “FUNDSIZEUSDMN”. This variable is created and included in the analysis to control for the concave relationship between fund size and fund performance.

Moreover, dummy variables must be created for the string variables, in order to be able to include them in the analysis. Dummy variables are quantitative variables that represent qualitative variable categories. In total 55 dummy variables are created. They can either take the value “1” or “0”. A value of “1” means that the variable category applies to the observation, otherwise it takes the value “0”. For the variables “ASSETCLASS”, “FUNDSTRUCTURE”, “QUARTILE”, and “SINGLEDEALFUND”, dummy variables are created for each of the variable’s categories.

For the variables “STRATEGY”, “COREINDUSTRIES”, “HOMEREGION”, ”PRIMARYREGIONFOCUS”, and “FUNDCURRENCY”, individual dummy variables are created for the variable categories, which have a lot of observations. Sometimes, similar categories are also grouped together into one dummy variable, as for example “Early Stage”, “Early Stage: Seed”, and “Early Stage: Start-up”. The remaining categories, which apply only to a few observations are summarized together into one dummy variable. Thereby the threshold is 50 observations per category for most of the variables.

For the variable “FUNDMANAGER”, dummy variables are created based on the Private Equity International (PEI) 300 ranking of 2021 (Private Equity International, 2021a), which ranks GPs according to the capital they have raised from 2016 to 2021 (Private Equity International, 2021b). A first dummy variable is created for the top 10 fund managers, then additional dummy variables are created for the ranks 11 to 30, 31 to 60, 61 to 90, 91 to 160, 161 to 230, and 231 to 300. By making the rank ranges larger, it can be ensured that no dummy variable contains less than 75 observations. The remaining GPs, not included in the ranking, are distributed in alphabetical order over three more dummy variables.

It should be kept in mind that when the dummy variables are integrated into the analyses, for each main variable, one of the dummy variables is omitted by Stata. This omitted dummy variable is then considered as the reference category. This means that the other dummy variables/categories are always expressed relative to this reference category.

A final step is to select again all the variables, including the dummy variables, which are necessary for our further analysis and to delete all the observations that have blanks for one or more of these variables. Each observation should contain data for all the relevant variables. As a result, three dummy variables no longer have any observations and can therefore be deleted. There are no funds in the sample that are single-deal funds, that are structured as separate managed accounts or that use co-investment strategies. However, all funds engage in multiple deals and are structured as commingled funds. Therefore, these two dummy variables can also be dropped as there cannot be any performance differences due to the deal or fund structure.

3.3 Sample Description

The resulting sample used for the analysis consists of 1,918 observations and has 70 variables. From the 1,918 funds, 795 funds are ESG-oriented, representing 41.5%, as shown in Table 1. This means that in the resulting sample, the proportion of ESG funds is slightly higher than in the initial performance data set, where 38.6% of the funds consider ESG factors in their investment decisions.

ESG	Frequency	Percentage
0	1,123	58.55%
1	795	41.45%
Total	1,918	100%

Table 1: Breakdown between ESG-oriented and Non-ESG oriented funds

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

3.3.1 Variables

We can differ between three types of variables, namely the treatment variable, the dependant variables and the independent or control variables. The independent variables are included in the analysis, as they potentially have (i) an impact on fund performance and/or (ii) an impact on the decision to consider ESG factors or not. As mentioned above, we consider the literature review on private equity fund performance to select and categorise these variables.

Treatment Variable:

- **ESG:** The ESG orientation of a fund is the explanatory variable of interest. The objective is to determine the effect of an ESG orientation on the private equity funds' performance. In other words, do private equity funds with an ESG orientation (ESG = 1) outperform private equity funds without an ESG orientation (ESG = 0) or not. As was already mentioned, 41.5% of the funds within this sample are considering ESG factors in their investment decisions.

Dependent Variables:

- **TVPI:** The TVPI is used as a performance measure which is assumed to be impacted by independent variables such as fund characteristics. Our aim is to investigate how the ESG orientation of a fund affects the TVPI.
  A distinction can be made between "TVPIX", which is the multiple expressed in absolute terms and included in the data set, and the "TVPI_PERCENTAGE", which is expressed in percentages and calculated manually based on the data provided. Appendix 2 shows that, apart from the fact that they are expressed in different units, there are no differences observable between them both. Our further analysis will be based on the "TVPIX", which will be referred to as "TVPI".
  To illustrate the interpretation of the TVPI multiple more concretely, the currency USD is used as an example, since 1,442 of the 1,918 sample funds are denominated in USD. However, this interpretation can also be applied to any other currency.
  As all the funds in our sample have been liquidated, there is almost no unrealised value left in the funds. Thus, the RVPI is for 98% of the funds equal to 0, resulting in an average RVPI of 0.28% (see Appendix 2 and 3). For the remaining 2% of the funds, it is expected that the RVPI will tend to 0. Consequently, the TVPI is more or less equal to the DPI.

Appendix 2 presents the descriptive statistics and shows that the average TVPI lies at 2.10, which means that the total value achieved by the sample funds corresponds on average to 2.10 times the capital invested. The highest TVPI reached by one fund is equal to 32.42, indicating that for each USD invested, the fund manages to earn 32.42 USD.

If we consider the mean TVPI for ESG funds and Non-ESG funds in isolation, a first performance comparison can be made. For ESG funds, the average TVPI is 2.26 and for Non-ESG funds it is only 1.98 (see Appendix 4). This signifies that the ESG funds are able to earn on average 0.28 USD more per USD invested than Non-ESG funds. Based on the *t*-value of the one-sample *t*-test, it can be stated that the difference between both averages is significant at the 1% level. In conclusion, it can be stated that, according to the descriptive statistics of the TVPI, funds that take ESG factors into account perform better than funds that do not base their decisions on ESG factors.

- **Net IRR:** Similarly, the Net IRR is also used as a performance measure in the analysis and again the objective is to assess the impact of the consideration of ESG factors on this performance measure. As the name suggests, the Net IRR is already net of fees, which allows us to base our analysis on the pure returns that are remaining at the investor's disposal. This is favourable, as the fee structure often significantly reduces the performance of a private equity fund (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009).

  The average IRR net of fees is 18.37%. However, the dispersion of this performance measure is quite high. The minimum Net IRR is at -100%, which means that the investors have lost their entire investment, and the maximum Net IRR is at 514%, which means that they have earned more than five times their investments (see Appendix 2).

  By considering the average Net IRR of ESG-oriented funds and Non-ESG-oriented funds, the same conclusion can be drawn as for the TVPI. The Net IRR of ESG funds is on average 4.04 percentage points higher than for Non-ESG funds, and according to the one-sample *t*-test this difference is significant at the 5% level (see Appendix 4). Therefore, in terms of average Net IRR, ESG funds perform better than Non-ESG funds.

The analysis is conducted for both performance measures in order to enable a comparison of the effects that the ESG orientation has on the respective measures. This way, one can make sure that the effect is not linked to only one specific performance measure.

- **Quartile:** This variable classifies the funds into four quartiles depending on their performance. It is not integrated as a dependent variable in the analysis, but it could be interesting to see how the ESG funds are distributed across the different quartiles.
  Based on the descriptive statistics represented in Appendix 4, it can be observed that the first and second quartiles each contain 31% of the ESG funds, but only 25% of the Non-ESG funds. For the third and fourth quartiles, on the other hand, there are relatively more Non-ESG funds in the quartiles than ESG funds. On average, only 14% of the ESG funds are in the fourth quartile, but 24% of the Non-ESG funds. According to the one-sample *t*-test, the differences are all significant at the 1% level, with the exception of the third quartile. In conclusion, Non-ESG funds are more or less equally distributed across the four quartiles, whereas ESG-oriented funds are more distributed across the first two quartiles, which suggests that they perform better on average.

Independent Variables:

- **Vintage Year:** The vintage year is the year in which the fund conducts its first investment. It is included in the analysis as an independent variable because the fund's performance depends, among others, on the economic conditions that prevailed during the period in which the fund was active. The expected returns during a boom differ from the returns expected during a recession (Kaplan & Schoar, 2005; Sommer, 2013). So, the vintage year of a fund can indirectly take the business cycle into account.
  Appendix 5 shows that the sample contains funds whose vintage years are lying between 1982 and 2018. However, almost 50% of the Non-ESG funds have their vintage year between 1995 and 2001, and the distribution of the ESG-oriented funds peaks also around the years 1997 to 2000, suggesting an increased investment activity during this time period. It is also worth noting that there are no ESG funds in this sample for the vintage years 2017 and 2018.
- **Fund Size:** The fund size is also included as an independent variable in the analysis. It is assumed that the size of a fund positively impacts its performance, even if the marginal returns might have a decreasing tendency (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009). In order to account for this concavity, the squared fund size is also included as a control variable into this analysis. This allows us to check whether the decreasing marginal size effect also applies to this sample.
  The fund size is expressed in million (MN) USD. The fund sizes included in the sample range from 0.40 MN USD to 17,708.40 MN USD and the average fund size of this

sample is 383 MN USD (see Appendix 2). However, 50% of the funds have a fund size lower than 148 MN USD, implying that most of the sample funds are rather small funds. When comparing the fund size of ESG and Non-ESG funds (Appendix 4), it can be observed that ESG-oriented funds are on average much larger (514.51 MN USD), than Non-ESG-oriented funds (289.87 MN USD). Based on the one-sample *t*-test, this difference in average fund size is significant at the 1% level (see Appendix 4). Therefore, it is important to control for the fund size in order to make sure that the overperformance of ESG-oriented funds is not due to an on average higher fund size.

- **Fund Manager:** It seems that the skills of the fund managers play a major role for the heterogeneity of the returns between different funds, and at the same time for the persistence in the performance of funds of the same GP (Kaplan & Schoar, 2005; Ghai et al., 2014). Therefore, the fund managers are included in the analyses via ten dummy variables, in order to control for their impact on the performance. As mentioned above, the fund managers are allocated to the dummy variables based on the PEI 300 ranking. Out of the 1,918 sample funds, 507 funds are raised by GPs included in the ranking, which represents a share of 26%. While having a look on the share of ESG and Non-ESG funds per dummy variable, it can be observed that 87% of the funds raised by the top ninety fund managers (GPtopten, GPsecondgroup, GPthirdgroup, and GPfourthgroup) are ESG funds.

  88% of the Non-ESG funds in this sample are launched by fund managers who are not included in the top 300 ranking and which are therefore included in one of the "not ranked" dummy variables. With regard to ESG-oriented funds, only 51% of the funds are raised by GPs that are not ranked (see Appendix 4).

  As the PEI 300 ranks the fund managers based on the capital they have raised in the last five years (Private Equity International, 2021b), the distribution of the ESG funds across the fund manager dummy variables could mean that the ESG funds have on average a larger fund size than the Non-ESG funds, as their fund managers raise on average larger amounts of capital. This is consistent with the statistics of the fund size variable. Moreover, it could also be assumed that fund managers with a good past performance can more easily raise larger amounts of capital for subsequent funds. This is because the track record often serves as an indicator of future performance (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009). Consequently, this distribution could also indicate that many ESG funds have a good performance, because they are launched by GPs which have a promising track record, and which were therefore able to raise a lot of capital.

- **Fund Number (Series):** This variable reflects the fund manager's experience with respect to a particular strategy, as it indicates how many of the GP's funds, prior to the fund under observation, have already followed the same strategy. It is assumed that the performance is increasing with the fund manager's experience and thus with the fund number (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009). Therefore, the fund number (series) will be integrated as control variable in the analysis.

  The sample contains funds whose fund number, for a specific series, ranges from 1 to 11 with the average fund number being 2.51 (see Appendix 2). This means that the funds have on average 1 to 2 predecessor funds. Accordingly, funds with a high fund number are rather rare.

  These findings remain true, while considering both ESG-oriented and Non-ESG-oriented funds in isolation (see Appendix 4). Consequently, fund series with an ESG focus do on average not achieve higher fund numbers. Instead the distribution of fund numbers follows the same tendency as for other strategies.
- **Fund Number (Overall):** This variable can also be understood as an indicator of the GP's experience. It specifies how many funds have been launched already by the same GP before the current fund, regardless of the funds' strategies. As the fund manager's experience is supposed to have a positive impact on the performance (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009), we include also the fund number (overall) as an independent variable in our analysis.

  In our sample, the maximum fund number (overall) is 51, representing a wider range than for the fund number (series) (see Appendix 2). However, this is quite logical, because for the overall fund number, the constraint that the previous funds must follow the same strategy has been removed. The average fund number is also higher with a value of 3.65, suggesting that the funds have on average 2 to 3 predecessor funds (see Appendix 2). This signifies that the funds are again concentrated at low fund number levels, with 80% of the funds being first-time, second-time, third-time or forth-time funds, and with a decreasing tendency the higher the fund number gets (see Appendix 6).

  If we look at funds with and without an ESG orientation in isolation (see Appendix 4), we can observe differences between the two distributions this time. For funds without an ESG orientation, 98.5% of the funds have fund numbers lower or equal to 10 (see Appendix 6). This results in an average fund number of 2.86, indicating that on average Non-ESG funds have 1 to 2 predecessor funds.

For the ESG funds in our sample, the range is smaller, with a maximum fund number of 40, but on the other hand, the distribution is more dispersed. 89% of the ESG funds are distribute, within the 1 to 10 range, and another 9% are included within the range 11 to 20. ESG-funds with a fund number higher than 20 are exceptions (see Appendix 6). Accordingly, the average fund number for the ESG-oriented funds is also higher at 4.75, which indicates that ESG-oriented funds have on average 3 to 4 predecessor funds. The difference between these two average fund numbers is according to the one-sample *t*-test significant at the 1% level (see Appendix 4).

These results suggest that, on average, ESG-oriented funds are launched by GPs, which have already launched several funds before, implying that they are already more experienced. Therefore, in the following performance analysis, we must control for this variable, in order to ensure that the performance of ESG funds is not driven by their higher average fund number (overall).

- **Asset Class:** This variable categorises the funds into three groups, namely VC, private equity (PE) and multi. However, the multi category includes only two funds. Therefore, no separate dummy variable is created for this category and the two observations are dropped during the data processing. Consequently, two dummy variables are created and included in the analysis. It is important to control for the asset class, because VC funds are supposed to earn better returns than other private equity funds, such as LBO funds (Kaplan & Schoar, 2005).

  37% of the sample funds are included in the VC category and 63% are included in the PE category. While considering ESG and Non-ESG funds in isolation (see Appendix 4), one can observe that for Non-ESG funds the split between both categories is more or less equal. 48% of the Non-ESG funds belong to the VC asset class and 52% to the PE asset class. However, the distribution of ESG funds differs significantly (1% level) from that of Non-ESG funds. 78% of the ESG funds are concentrated in the PE category, and only 22% are part of the VC asset class.

  Under the assumption that VC funds achieve a better performance, the distribution of the ESG-oriented funds across both asset classes would imply that the ESG-oriented fund performance is downward biased. Therefore, it is important to control for this potential asset class effect.

- **Strategy:** This variable enables a more detailed breakdown of the different strategies, compared to the asset class variable. After completion of the data processing part, the strategy variable is composed of twelve different strategy types, which are represented by nine dummy variables. These dummy variables are included in the analysis, in order to control for differences in the performance which can be attributed to different strategies. Besides the assumption that VC funds outperform LBO funds, it is further assumed that the life stage of the investment targets also has an impact on performance (Kaplan & Schoar, 2005).

  In this sample, the three most applied strategies are buyout strategies (40%), venture strategies (23%) and early stage strategies (11%).

  Appendix 4 shows that most ESG and Non-ESG funds adopt buyout strategies (45% of the ESG and 37% of the Non-ESG funds) and venture strategies (14% of the ESG and 29% of the Non-ESG funds). The third most used strategy for Non-ESG funds is the early stage investment strategy (16%), which is less frequently used by ESG funds (5%). Conversely, ESG-oriented funds often take the form of a fund of funds (14%), which is rarely the case for Non-ESG-oriented funds (2%). For a more detailed distribution of ESG funds and Non-ESG funds across the other strategy types, please refer to Appendix 4.
- **Core Industries:** This variable indicates in which industries the funds are primarily investing. The core industry variable consists of fifteen core industry categories, which are grouped together into eight dummy variables. It is likely that funds investing in different core industries will achieve different returns, which may be due to the fact that some industries are booming while others are in recession, or that some industries are just more profitable than others. Therefore, the core industry dummy variables are included as control variables in the analysis, in order to remove the industry effect from the ESG effect.

  While having a look at the distribution of the ESG-oriented and Non-ESG-oriented funds across the different industries (Appendix 4), it can be observed that for both the distribution is concentrated in the same three industries. 74% of the ESG funds and 47% of the Non-ESG funds are diversifying their portfolios by investing in different industries. Additionally, most funds invest in the Information Technology (IT) industry (10% of the ESG and 18% of the Non-ESG funds) and in the Healthcare industry (6% of the ESG and 17% of the Non-ESG funds). Please refer to Appendix 4, in order to have a look at the distribution of the funds across the other industries.

- **Primary Region Focus:** In their investment decisions, GPs often decide to focus on certain regions, which in turn can have an impact on the performance. There exists, for example, the assumption that US-focused funds perform better than EU-focused funds (Phalippou & Gottschalg, 2009; Sommer, 2013). The primary region focus variable covers eight regions, represented by six dummy variables that are included in the analysis as control variables.

  In this sample, 66% of the funds have their investment focus on North-America, 21% on Europe and 8% on Asia. This region ranking remains the same if ESG-oriented and Non-ESG-oriented funds are considered in isolation (Appendix 4), only the shares per region change. 81% of the Non-ESG funds are investing in North America and only 8% in Europe. For ESG-oriented funds, however, the distribution between North America and Europe is more balanced. 44% of the ESG funds invest mainly in North American targets and 39% in European targets (see Appendix 4).

  Consequently, 77% of the funds primarily investing in Europe, are ESG-oriented funds. This might be due to the fact that the trend towards sustainability is already more advanced in Europe.

- **Home Region:** In the following performance analysis, the home region of the fund will also be considered as control variable. This ensures that the potential over- or underperformance of ESG-funds is not due to the region in which the fund was launched. The variable is classified into seven regions, which in turn are grouped into five dummy variables.

  For the sample under consideration, 67% of the funds are launched in North America, 22% are European funds, and 6% are Asian funds. It can be observed that the distribution of the home region variable is more or less the same as for the primary region focus, especially for the Non-ESG-oriented funds. For ESG funds, the distribution is also very similar, but the share of ESG funds launched in Europe is slightly higher compared to the share of ESG funds primarily investing in Europe (see Appendix 4). This can again be explained by the fact that Europe was to some extent a pioneer for the integration of ESG factors.

  While taking a closer look at the sample, it can be observed that most of the funds invest primarily in their home region, explaining the similar distribution of the home region variable and the primary region focus variable.

- **Fund Currency:** This variable indicates the currency in which the fund is expressed. There are nineteen different currencies in this sample. These are integrated into the analysis as control variables using six dummy variables. The main reason for including them in the analysis is to account for macroeconomic tendencies, which translate into exchange rate fluctuations of specific currencies, which in turn can affect the fund performance. Moreover, the fund currency can also be perceived as a region indicator.
  In this sample, 75% of the funds are expressed in USD, 12% are denominated in Euro and 5% are expressed in Pound Sterling. If the ESG and Non-ESG-oriented funds are considered in isolation (Appendix 4), one can observe that 88% of the Non-ESG funds are expressed in USD. For the ESG funds, the distribution is again more balanced with 57% of the ESG funds being expressed in USD and 24% in Euro. Again, this distribution is similar to the one of the home region and the primary region focus variable, suggesting that the fund currency is also an indicator for the region.
- **Called (%):** This variable indicates how much of the committed capital is called and invested by the GP. It could be interpreted in such a way that if not all the committed capital is called, the GP is not able to identify enough investment opportunities, which could potentially have a negative impact on the performance. Therefore, it is included as a control variable in the performance analysis.
  For this sample, on average 97% of the committed capital is called, suggesting that most of the GPs are able to identify investment opportunities and use the capital committed by the investors (see Appendix 2). While considering ESG-oriented and Non-ESG-oriented funds in isolation, no significant difference is observable neither between the two types of funds, nor in the respective comparisons with the average of the entire sample (see Appendix 4).
  896 funds, representing almost half of the sample, have called exactly 100% of the committed capital. 14% of the funds have called even more than the initially committed amount, and only 4% of the funds have called less than 75% of the committed capital. In the following analyses, we will observe whether the proportion of capital called is positively or negatively correlated to the performance of a fund.

3.3.2 Limitations

It is only since 2010 that the literature has increasingly addressed the implementation of sustainable development and ESG factors in the investment industry, and even later with regard to the private equity industry (Zaccone & Pedrini, 2020). Therefore, it should be kept in mind that the existing records on ESG factor integration and impact investing strategies are limited, especially with regard to their implications on private equity fund performance.

One important limitation represents the self-selection bias. Lambert (2020) explains that private equity firms can decide whether they want to disclose the fund returns to non-investors or not. Therefore, this sample might not be completely representative, which limits the possibility of drawing conclusions from the sample results that allow for generalisations concerning private equity funds (Lambert, 2020). Poorly performing funds are more likely to not report their returns, whereas well-performing private equity funds are likely to disclose return data, as this helps the GPs to attract new capital for the following funds (Kaplan & Schoar, 2005). Therefore, it can be assumed that the underlying sample consists to a large part of well performing funds and therefore the conclusions are especially applicable to these funds.

Another limitation is that the underlying sample does not allow to determine which sustainable investment strategy has been adopted by the funds. The sample description shows that the distribution of the ESG funds is mainly concentrated in the years 1997 to 2000. Given that many private equity funds initially used negative screening (Zaccone & Pedrini, 2020) this could indicate that many ESG sample funds apply this strategy. However, negative screening tends to lead to returns, which lie below the market averages (Kotsantonis et al., 2016), which could imply that the performance of the ESG-oriented sample funds is downward biased.

Moreover, from the literature review on the performance of private equity funds, it was evident that performance can be influenced by many fund characteristics. One example is the fund size. As shown by the descriptive statistics, the distribution of the fund size indicates that most of the funds in the sample are small funds. Based on the findings of the literature review, this could represent a downward bias, as larger funds are assumed to perform better than small funds (Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009). Other influencing factors can be the fund characteristics described above in the independent variables section. However, in the following analyses, we attempt to adjust the effects of these fund characteristics and to isolate them from the ESG effect.

4 METHODOLOGY

4.1 Basic Assumptions

We have already compared the average TVPIs and Net IRRs of the ESG and Non-ESG funds. Thereby, it could be observed that the ESG-oriented funds have a higher average TVPI and Net IRR than the Non-ESG-oriented funds. Moreover, the distribution of the sample funds across the four quartiles shows that funds integrating ESG factors in their investment strategy are rather concentrated in the first and second quartile, which is also an indicator for good performance.

However, as shown in the literature review and in the sample description, this overperformance can also be driven by other fund characteristics, which raises the need for a more detailed analysis. Two different types of analyses are carried out to determine the ESG effect. First, the OLS approach is used to estimate the coefficients of the ESG variable and of the other control variables. Then, the second analysis is based on PSM, whereby the funds are matched based on their characteristics. Both approaches are described in more detail in the next subsection.

The fund characteristic (dummy) variables are divided into groups that are successively included into the analyses. The first variable group contains the vintage year, the fund size and the fund size squared. In the second variable group, the effects of the GP, of the fund number series and of the fund number overall are additionally taken into consideration. The third variable group also includes the asset class and strategy dummy variables, and through the fourth variable group the effect of the core industries is added. The fifth group includes the dummy variables of the primary region focus, of the home region and of the fund currency. Finally, with the last group the variable Called is added to the analysis. Thanks to this technique, it can be observed how the ESG effect changes when these characteristics are gradually added to the analysis. This enables at the same time to better understand the effects of the fund characteristics on performance.

Moreover, the two types of analysis are performed for both the TVPI and the Net IRR. This allows a comparison between the effects that the ESG orientation has on the TVPI and the effects that it has on the Net IRR.

4.2 Ordinary Least Squares Regression

4.2.1 Simple Regression Model with OLS Estimates

The aim of a simple regression model, which is also called two-variable linear regression model, is to study "[…] how y varies with changes in x" (Wooldridge, 2013, p. 22). However, it should be kept in mind that it is unrealistic to assume that there is an exact relationship between those variables. The simple regression model simply ignores that there are other factors, which have an impact on the dependant variable y (Wooldridge, 2013).

The simple regression model can be represented by the following equation:

$$y = \beta_0 + \beta_1 x + u$$

where y is the dependant variable, x is the explanatory variable, β_0 is the intercept parameter, β_1 is the slope parameter, and u is the error term, which includes the ignored, or so-called unobserved, factors.

The functional relationship between the two variables is, under the assumption that the error term u is constant, given by β_1 (Wooldridge, 2013). It measures the linear effect that the explanatory variable has on the dependant variable (Wooldridge, 2013). With other words, to determine which effect a change in x has on y, the change in x needs only to be multiplied with its parameter β_1, while keeping the unobserved factors constant (Wooldridge, 2013). However, this relationship does generally not allow drawing ceteris paribus conclusions and thus gaining inference on the causal effects, as the other factors are ignored and in addition assumed to be constant (Wooldridge, 2013). Moreover, in most cases at least one of the ignored factors is correlated with x (Wooldridge, 2013).

Therefore, two important assumptions of this simple regression model are that, under consideration of the entire population, the expected value of the error term u is zero and that the explanatory variable x and the error term u have zero covariance (Wooldridge, 2013).

In order to determine the estimates of the two parameters (β_0, β_1) the OLS approach is used (Wooldridge, 2013). The OLS regression line of a simple regression model is given by the following equation:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

In the following, it is assumed that the sample is composed of n observations, such that $\{(x_i, y_i): i = 1, 2, \dots, n\}$ (Wooldridge, 2013).

The aim of this method is to determine the estimates $\hat{\beta}_0, \hat{\beta}_1$ in such a way that the sum of the squared residuals is minimised (Wooldridge, 2013), which corresponds to minimising the following expression:

$$\sum_{i=1}^{n}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

Therefore, the first order conditions must be fulfilled (Wooldridge, 2013), which are:

$\sum_{i=1}^{n}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$

$\sum_{i=1}^{n} x_i(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$

This then results in the following solutions for $\hat{\beta}_0, \hat{\beta}_1$:

$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$, under the condition that $\sum_{i=1}^{n}(x_i - \bar{x})^2$ is strictly larger than 0;

$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$, where $\bar{x}$ and $\bar{y}$ are the sample averages of the x_i and y_i, respectively.

The two estimated parameters can be interpreted as follow: The parameter $\hat{\beta}_0$ is the estimated intercept of the OLS regression line with the Y-axis (Wooldridge, 2013). Consequently, it predicts the value of y in the scenario that $x = 0$. The parameter $\hat{\beta}_1$ represents the estimated slope of the OLS regression line and predicts how a change in the explanatory variable x translates into the dependant variable y (Wooldridge, 2013).

In the context of the topic at hand, the simple regression model with OLS estimates is applied, to analyse how the TVPI and the Net IRR vary if a fund applies an ESG orientation. Therefore, two simple regression analyses are carried out in Stata[4], using the command *regress*. The sample comprises 1,918 observations ($n = 1{,}918$). The TVPI and the Net IRR are the respective dependant variables y and the ESG orientation is the explanatory variable x. For these two regression analyses the other fund characteristics are ignored. Therefore, they are probably contained in the error term u. The objective is to obtain $\hat{\beta}_1$in order to assess how the TVPI and the Net IRR change if a fund is ESG-oriented. The intercept parameter $\hat{\beta}_0$ is of no special interest in this context.

[4] https://www.stata.com/

4.2.2 Multiple Regression Model with OLS Estimates

The multiple regression model "[…] allows us to explicitly control for many other factors that simultaneously affect the dependant variable" (Wooldridge, 2013, p. 68). This should generally make it easier to draw conclusions on the casual effects. Moreover, through the integration of a larger number of explanatory variables, the variance of the dependant variable can be better explained, which allows for a more accurate prediction of the dependant variable (Wooldridge, 2013). The multiple regression model can be described by the following equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + u\,,$$

where y is the dependant variable, x_j $(with\, j = 1, \dots, k)$ is the jth explanatory variable, β_0 is the intercept parameter, β_j $(with\, j = 1, \dots, k)$ is parameters of the jth explanatory variable. Thereby, β_j indicates how y changes with respect to changes in x_j, while keeping other factors fixed (Wooldridge, 2013). The u of the equation represents again the error term, because regardless of how many factors we integrate in the model, there are always some factors that we cannot include or that are unobservable (Wooldridge, 2013). Furthermore, it is possible that measurement errors occur when the effects of a particular factor can only be analysed by integrating another imperfect factor in the analysis, since only the latter is observable (Wooldridge, 2002). This makes it very likely that the estimator is also only an approximation, leading to measurement errors (Wooldridge, 2002).

The key assumption for this type of model is similar to the one of the simple regression model, and is given by:

$$E(u|x_1, x_2, \dots, x_k) = 0$$

This assumption ensures that the functional relationship between y and x has been correctly captured and that the explanatory variables are not correlated with the factors from the error term (Wooldridge, 2013). This assumption is also central in the following part on the OLS estimates, as it ensures that the OLS is free of any bias and that no important factor is left unobserved (Wooldridge, 2013).

As for the simple regression model, the OLS approach is also used for the estimation of the $k + 1$ parameters of the multiple regression model (Wooldridge, 2013).

The estimated OLS equation, with k explanatory variables, is defined as follows:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_k x_k ,$$

where $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k$ are the estimates of the respective parameters. The sample under consideration comprises n observations for y and for the k explanatory variables, thus $\{(x_{i1}, \ldots, x_{ik}, y_i): i = 1, 2, \ldots, n\}$.

The objective of the OLS approach is to determine the parameter estimates $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k$ such that the sum of the squared residuals is as low as possible (Wooldridge, 2013). In other words, it aims at minimizing the following expression:

$$\sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \cdots - \hat{\beta}_k x_{ik})^2$$

However, solving this minimisation problem means solving an equation system with $k + 1$ linear equations, and $k + 1$ unknowns (Wooldridge, 2013). Solving such a system of equations by hand can quickly turn out to be very difficult, especially if the sample includes a large number of observations. Therefore, statistical programs are generally used to solve such an optimisation problem.

The estimated parameters $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k$ can be interpreted similarly to the ones of the simple regression model. The $\hat{\beta}_0$ represents the estimate of the OLS intercept, which predicts y in the case that $x_j = 0 \;\; (with\, j = 1, \ldots, k)$ (Wooldridge, 2013). The other estimated parameters $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_k$ are the OLS slope estimates, which represent the partial effects of the corresponding explanatory variables (Wooldridge, 2013). This means $\hat{\beta}_j$ measures the effect that an increase in x_j, by one unit, has on the $\hat{y}$, while controlling for the other explanatory variables by keeping them constant (Wooldridge, 2013).

The effect of an ESG orientation on the fund performance is additionally analysed using the multiple regression model. This allows the fund characteristics, which are included in the error term of the simple regression model, to be introduced in the analysis as explanatory variables. The ESG orientation is one of the explanatory variables $x_j \; (with\, j = 1, \ldots, 53)$. The dependant variable y is either the TVPI or the Net IRR. As the sample is the same as for the simple regression model, $n = 1{,}918.$ In order to be able to observe the evolution of the ESG effect on performance, the OLS regression is set up for each of the six variable groups. With each group the number of explanatory variables increases and the error term u decreases.

Moreover, it is assumed that the sixth variable group contains all the important influencing factors, and that the error term u is therefore almost nil. This enables to better understand the causal relationships and to draw conclusions that are more accurate. Consequently, twelve minimisation problems are solved, each being a system of 54 equations, in order to determine the 54 parameter estimates $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_{53}$. For this purpose, we again use Stata[5] and the command *regress*. The OLS slope estimates $\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_{53}$ indicate each the partial effect that the respective explanatory variable has on the TVPI or on the Net IRR, while keeping the other explanatory variables fixed. The OLS intercept estimate $\hat{\beta}_0$ has, as was the case for the simple regression model, no specific meaning in this context.

4.2.3 Limitations of the OLS Regression Models

In the simple and multiple OLS regression model, the relationship between the explanatory variable(s) and the dependant variable is assumed to be linear (Imbens, 2015). In reality, however, it is rare to observe that an outcome is linearly related to the predictors, especially if the outcome is a continuous variable. The linearity also implies that outliers, which should generally not be given any weight, can strongly affect the results (Imbens, 2015).

Moreover, "[…] regression methods are fundamentally not robust to the substantial differences between treatment and control groups" (Imbens, 2015, p. 382).

This means that the OLS regression models assume that the fund characteristics are all linearly related to fund performance, which is obviously not the case, as can already be observed based on the fund size. Moreover these regressions do not take into account if the ESG-oriented funds and the Non-ESG-oriented funds differ in terms of their fund characteristics.

Matching methods, such as PSM, represent a good alternative. No assumptions are made with regard to the relationship between the covariates and the treatment outcome. Moreover, the treatment group and the control group are very similar in terms of fund characteristics and outliers are not included. Finally, the PSM method calculates a weighted average instead of a simple average (Lambert, 2014).

[5] https://www.stata.com/

4.3 Propensity Score Matching

4.3.1 Theoretical Background

The basic idea behind the propensity score matching approach is to estimate an average treatment effect (ATE): "[…] An ATE is an average partial effect for a binary explanatory variable" (Wooldridge, 2002, p. 603). It is also worth mentioning, that this measure "[…] averages across the entire population […]" (Wooldridge, 2002, p. 604).

In the context of this topic, this approach is used to estimate the ATE of an ESG orientation on private equity fund performance. Thereby, the ESG orientation can be understood as the binary treatment variable. A fund is either ESG-oriented or Non-ESG-oriented. Consequently, there is one sub-population consisting of ESG-oriented funds representing the treated observations ($w = 1$), and one sub-population consisting of Non-ESG-oriented funds representing the control observations ($w = 0$).

This poses the fundamental problem that for each observation only one of the two potential treatment outcomes (y_0, y_1) can be observed. Consequently, there is always one unobserved outcome, which is referred to as counterfactual outcome (Caliendo & Kopeinig, 2008; Wooldridge, 2002). However, to gain inference on the causal effects of a treatment, both treatment outcomes are needed in order to compare them (Rosenbaum & Rubin, 1983). This is because the ATE is defined as follows:

$$ATE \equiv E(y_1 - y_0)$$

The ATE indicates the expected average effect of a specific treatment on an observation, which is randomly selected from the population (Wooldridge, 2002).

Moreover, there exists another measure, similar to the ATE, which estimates the average effect of a specific treatment but only for those observations, which are already participating in the treatment (Wooldridge, 2002). This measure is called average treatment effect on the treated (ATET) and is obtained by averaging only across the treatment sub-population (Wooldridge, 2002). The ATET is defined as follows:

$$ATET \equiv E(y_1 - y_0 \mid w = 1)$$

Important assumptions in the context of the estimation of the ATE and the ATET are:

- *Stable unit treatment value assumption* (SUTVA), which states that "[…] treatment of unit i affects only the outcome of unit i […]" (Wooldridge, 2002, p. 604);
- *Self-selection*, which states that observations can generally decide to a certain extent if they want to participate in the treatment. This decision may be driven by the effect of the treatment, represented by $y_1 - y_0$ (Wooldridge, 2002);
- *Ignorability of treatment* (given a vector x of observed covariates), which states that "conditional on x, w and (y_0, y_1) are independent" (Wooldridge, 2002, p. 607). This means that in a randomized experiment, every observation has the possibility to participate in the treatment ($w = 1$) or not ($w = 0$), given its covariates (Rosenbaum & Rubin, 1983). It should be noted that this assumption allows for the possibility that treatment w depends on unobserved covariates, but these unobserved random covariates must be independent of (x, y_0, y_1) (Wooldridge, 2002).

  A weaker form of this assumption is the *ignorability in the sense of conditional mean independence* (Wooldridge, 2002), given by:

  (a) $E(y_0 \mid x, w) = E(y_0 \mid x)$;
  (b) $E(y_1 \mid x, w) = E(y_1 \mid x)$

  This version implies that if the vector x does contain a sufficiently large number of covariates determining the treatment, then, conditional on vector x, the treatment outcomes (y_0, y_1) and the treatment w might be mean independent (Wooldridge, 2002; Rosenbaum & Rubin, 1983). Moreover, it allows for the variances of the treatment outcomes y_0, y_1 (given x and w) to depend on the treatment w (Wooldridge, 2002).

However, in order to be able to estimate the ATE and the ATET, it is necessary to overcome the missing data problem, and to construct the counterfactual outcome (Rosenbaum & Rubin, 1983). Therefore, the PSM is a suitable approach. It is a statistical method that matches treated observations and control observations, based on observable characteristics, so-called covariates that the matching partners have in common (Caliendo & Kopeinig, 2008). This matching process is carried out based on the estimated propensity score (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008). "The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum & Rubin, 1983, p. 41).

This may be denoted by:

$$p(x) \equiv P(w = 1 \mid x)$$

Thereby $p(x)$ represents the propensity score, which is a function of x, the vector of observed covariates. An additional assumption of the PSM approach is that $0 < p(x) < 1$, for all x (Wooldridge, 2002).

Given this assumption and the ignorability of treatment assumption (together the *strong ignorability of treatment* assumption), if two observations are matched based on their propensity score $p(x)$, then the expected difference between the two observed treatment outcomes, conditional on $p(x)$, is equal to the ATE, conditional on $p(x)$ (Rosenbaum & Rubin, 1983; Wooldridge, 2002). This translates to:

$$E[y \mid w = 1, p(x)] - E[y \mid w = 0, p(x)] = E[y_1 - y_0 \mid p(x)]$$

It should be noted that the PSM approach is a two-stage estimation process. First the propensity scores have to be estimated, because they are needed to match the observations (Wooldridge, 2002). Then, the outcome differences must be estimated for each pair matched, and finally the average of all these outcome differences need to be calculated (Wooldridge, 2002).

Generally, two observations having the same observable characteristics, have the same probability of receiving treatment and thus have the same propensity score (Caliendo & Kopeinig, 2008). However, in practice, it is not always possible to find treated and control observations which have identical estimated propensity scores, as it is often unlikely to get identical probabilities. Therefore, treated and control observations, having similar propensity scores, are also considered a match (Wooldridge, 2002).

In order to implement PSM, first, the probability model needs to be selected. For the binary treatment case, it can be chosen between logit and probit models (Caliendo & Kopeinig, 2008). However, Caliendo and Kopeinig (2008) explain that both models lead to very similar results. Afterwards, the variables need to be selected. Furthermore, a matching algorithm should be selected. It can be differentiated between Nearest Neighbour (NN) Matching, Caliper and Radius, Stratification and Interval Matching, Kernel and Local Linear Matching and Weighting on Propensity Score (Caliendo & Kopeinig, 2008).

4.3.2 Practical Implementation

The practical implementation to the topic at hand makes it possible, to estimate the ATE of an ESG orientation ($w = 1$) on fund performance y (represented by the TVPI and the Net IRR) and to avoid biased results due to the selection problem. The other fund characteristics are successively added to the vector x of observable covariates. ESG funds and Non-ESG funds are only matched if they have similar propensity scores, which implies that the funds are very similar with regard to the observable fund characteristics contained in vector x. Thereby, it is assumed that funds, which are matched based on the sixth variable group, only differ in terms of their ESG orientation and that there are no unobserved characteristics.

The software Stata[6] is used to carry out the PSM. Therefore, the command *teffects psmatch* is used. The probability model chosen is the logit model. The default settings are the estimation of the ATE, by matching ESG- and Non-ESG funds, with their nearest neighbour of the opposite treatment group. Moreover, the ATET is also estimated. Therefore, each of the 795 ESG-oriented funds is matched to its nearest neighbour from the Non-ESG sub-population. It allows to assess how the average ESG effect on the performance of ESG-oriented funds (ATET) differs from the average ESG effect on the performance of a randomly selected fund (ATE).

In addition to these two standard versions, oversampling is used to estimate the ATE and the ATET. This means the ESG- and Non-ESG funds can be matched with more than just one nearest neighbour of the opposite treatment group. Therefore, the variance of the estimator is lower, because a larger number of matches enables to collect more information, which in turn improves the generation of the counterfactual outcome. However, the average quality of the matches is worse, which results in a larger bias. Therefore, a caliper is additionally used. This ensures that ESG- and Non-ESG funds are only matched if the absolute difference between their propensity scores does not exceed a specified value (Caliendo & Kopeinig, 2008). Consequently, this rises the matching quality again. In order to obtain the best variance-bias-trade-off, we try to keep the number of allowed nearest neighbours as large as possible, while keeping the caliper as small as possible. Using this method, we end up with five nearest neighbours and a caliper of 0.165.

These four different treatment effects are estimated for both, the TVPI and the Net IRR, in order to be able to compare the effects of an ESG orientation on the respective performance measure.

[6] https://www.stata.com/

5 EMPIRICAL RESULTS

5.1 Results: OLS Regression Analysis

5.1.1 ESG Effect on the TVPI

First, the OLS regression analysis is performed without any control variables (see Appendix 7, column (1)). It can be observed that the ESG effect is positive and significant at the 1% level. A fund that is ESG-oriented, relative to a Non-ESG-oriented fund, earns on average 0.27 USD more per USD invested, which is in line with the result of the TVPI mean comparison between ESG and Non-ESG funds.

By adding the vintage year, the fund size and the fund size squared to the regression (see Appendix 7, column (2)), the ESG coefficient becomes even larger, indicating that ESG funds earn on average 0.34 USD more per USD invested, than Non-ESG funds. This ESG effect is significant at the 1% level. However, the vintage year and the fund size seem to have both a negative effect on the TVPI. The fund size squared indicates that this negative fund size effect becomes marginally weaker. However, tests have shown that the effect of the fund size does not turn into a positive effect, but always remains negative. This signifies that more recent funds and/or larger funds tend to have on average a worse TVPI than older and/or smaller funds. For all of them the effect is significant at the 1% level. Concerning the fund size, this negative relation to the TVPI is surprising, as it stands in contrast to the findings of Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009)

Thereafter, the fund manager dummy variables are added to the regression, as well as the two types of fund number variables (series and overall) (see Appendix 7, column (3)). By adding these control variables to the analysis, the ESG effect becomes smaller, but remains positive. Funds with an ESG orientation earn now on average only 0.17 USD more per USD invested than Non-ESG-oriented funds. However, the ESG effect is now only significant at the 10% level. While observing the GP dummy variables, it turns out that fund managers of the ranks 61 to 90 (d_GPfourthgroup) launch funds that achieve on average higher TVPIs than the other GPs in the sample, although this positive effect is not significant.[7] The only effects that are significant (5-10% level), are the negative effects of the fund managers from the seventh group

[7] As a reminder, the dummy variables that belong to one main variable are always expressed relative to a reference category. For this and subsequent interpretations, comparisons between dummy variables are always made following this logic.

(ranks 231 to 300) and of the fund managers that are not ranked. This shows us that the GPs that are not ranked achieve worse TVPIs compared to the ranked fund managers. This worse performance could be a reason why these fund managers are not able to raise large amounts of capital. As Kaplan and Schoar (2005) have stated, the past performance plays an important role in fund raising and is a good predictor for future performance. While having a look at the fund number, regarding a specific series of funds, it can be noticed that the coefficient is positive, indicating that the more predecessor funds a fund has with regard to a specific strategy, the higher the TVPI. For the overall fund number the coefficient is also positive but almost nil. This positive relation between fund number and performance is again in line with the observations made by Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009). However, for both types of fund numbers the effect is insignificant.

In a next step, the asset class and strategy dummy variables are also included into the regression (see Appendix 7, column (4)). As a result, the ESG coefficient rises again to 0.28 and gains significance (back at the 1% level). Based on the asset class dummy variables, it can be observed that funds contained in the VC asset class have on average a higher TVPI, than the funds from the more general PE asset class, although this effect is not significant. By looking at the strategy dummy variables, it can be noticed that funds applying growth strategies or buyout strategies reach on average the highest TVPIs. Conversely, secondaries and fund of funds are generally the strategies which achieve on average the lowest TVPIs, compared to funds that apply other strategies. However, the effects are not significant for any of the strategy dummy variables.

Additionally, considering the core industries in which the funds mainly invest leads to a slight decrease in the ESG effect, however it remains significant at the 1% level (see Appendix 7, column (5)). According to this regression result, ESG funds earn on average 0.27 USD more per USD invested, than funds without an ESG orientation. Regarding the individual core industries, the IT industry and the Consumer Discretionary industry achieve on average better TVPIs compared to the other industries. Moreover, the “Other Industries” dummy variable, consisting of Raw Materials & Natural Resources, Real Estate, Financial & Insurance Services, Business Services and Business Services & Healthcare, also has a positive coefficient. The worst performing core industry is the Telecoms & Media industry. Again, all the effects are insignificant.

The isolation of the potential regional and currency effects leads to a further decrease in the ESG coefficient to 0.25, which is, however, still significant at a 5% level (see Appendix 7, column (6)). While considering the coefficients of the primary region focus dummy variables, it can be concluded that funds mainly investing in North America achieve higher TVPIs than funds that primarily invest in one of the other regions (in line with the observations made by Phalippou & Gottschalg, 2009). Contrarily, investing primarily in Australasia, compared to other regions, has a negative effect on the TVPI, which is significant at the 5% level. All the other effects are insignificant. However, regarding the home regions, an opposite observation can be made. Funds set up in Australasia, Africa, Latin America and in the Middle East reach on average higher TVPIs than funds set up in Asia, Europe or even North America. Again, all the effects are insignificant, except the one for Australasia (10% level). Regarding the fund currencies, it can be observed that all the currencies achieve lower TVPIs compared to the Australian Dollar. Again, almost all currencies have insignificant effects, with the exception of the Pound Sterling (5% significance level).

Finally, the variable Called is included in the regression (see Appendix 7, column (7)). The consideration of this variable leads to a slight increase in the ESG coefficient, indicating that ESG funds earn on average 0.27 USD more per USD invested, relative to funds without ESG orientation. Comparing this coefficient with the one from the first regression, without control variables, no difference can be noticed. The only thing that has changed is the significance level, which is now at 5% instead of 1%. The proportion of capital called, contrary to the initial expectations, correlates negatively with the TVPI, and this suggests that the more capital is called the smaller the TVPI. This negative effect is significant at the 1% level.

5.1.2 ESG Effect on the Net IRR

The effect of an ESG orientation, without the consideration of control variables, is also positive with regard to the Net IRR as a performance measure and significant at the 1% level (Appendix 8, column (1)). The coefficient indicates that ESG-oriented funds have on average a Net IRR which is 4.04 percentage points higher, relative to funds, which are not including ESG factors in their investment decisions. As expected, this corresponds to the result from the mean comparison of the Net IRR between ESG- and Non-ESG-oriented funds.

By adding the vintage year, the fund size and the fund size squared as control variables, the ESG coefficient increases to 4.94 and is significant at the 1% level (see Appendix 8, column (2)).

The vintage year and the fund size have both a negative coefficient and the fund size squared has a positive coefficient. Moreover, the effects of these control variables are all significant at a 1% level. This is consistent with the findings regarding the TVPI.

Then, the fund manager and his experience are included in the analysis through the fund manager dummy variables, the fund number of a specific series and the overall fund number (see Appendix 8, column (3)). As a result, the ESG coefficient falls sharply and loses its significance. The Net IRR of ESG funds is on average only 1.67 percentage points higher than the Net IRR of Non-ESG funds. With regard to the fund manager dummy variables, it can be observed that not only the GPs of the ranks 61 to 90 (d_GPfourthgroup), but also of the ranks 91 to 160 (d_GPfifthgroup) have positive, although insignificant, coefficients. The other fund managers have all negative and significant coefficients, indicating that they all achieve on average worse Net IRRs than the fund managers of the ranks 61 to 160. If we have a look at the fund numbers, it is stunning that the fund number (series) is negatively related to the Net IRR, even if the coefficient is small and not significant. This is also in contrast to the observations made by Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009). Nonetheless, the effect of the overall fund number on the Net IRR remains positive and insignificant, as in the analysis of the TVPI.

By taking into account the fund's asset class and its strategy, the ESG coefficient rises again to 2.68, which signifies that ESG funds achieve an on average 2.68 percentage points higher Net IRR compared to Non-ESG-oriented funds (see Appendix 8, column (4)). This effect is, however, not significant. Regarding the asset classes, it can be stated that funds of the VC asset class achieve a worse Net IRR, than funds from the PE asset class. This negative effect of the VC orientation is significant at the 10% level. While looking at the individual strategies, one can observe that the three best performing strategies are the venture strategy, the late-stage strategy and the growth strategy. Thereby, the coefficient of the venture strategy is significant at the 1% level. This implies that venture strategies lead to a higher Net IRR than buyout strategies, which is again consistent with the observations of Kaplan and Schoar (2005). However, it is quite contradictory that funds from the VC asset class seem to achieve lower Net IRRs, than funds from the PE asset class. Nevertheless, the venture strategies are the best-performing strategies. The strategy that achieves the lowest Net IRR compared to the other strategies, is the fund of funds strategy (10% significance level).

Next, the core industry dummy variables are added as control variables, leading to a slight decrease in the ESG effect (see Appendix 8, column (5)). Thereby, the ESG effect is insignificant. The result of this regression analysis indicates that ESG funds have on average a Net IRR which is 2.60 percentage points higher relative to Non-ESG funds. Regarding the different core industries, it can be observed that the IT industry seems to outperform the other industries contained in this sample, which is consistent with the observations made with regard to the TVPI. The positive effects of this industry as well as the effects of the other industries are, however, not significant.

Thereafter, the regions in which the funds primarily invest, as well as the home regions and fund currencies, are included in the analysis (see Appendix 8, column (6)). As a result, the Net IRR of ESG funds is on average only about 1.02 percentage point higher than the one of Non-ESG funds. This effect is insignificant. When looking at the different regions, the same observations can be made as for the TVPI. North America is the best-performing primary investment region (5% significance level), and Australasia is the worst-performing primary investment region (1% significance level). For the different home regions, the opposite tendency can be observed. This time, the effects of the home regions Australasia and North America are both significant at the 5% level. With regard to the fund currencies, the coefficients indicate that all the currencies have a worse effect on the Net IRR than the Australian Dollar currency. All fund currency effects are significant, except the effect of the Japanese Yen currency.

Finally, the proportion of capital called is added to the regression analysis (see Appendix 8, column (7)). This has a positive effect on the ESG coefficient, which indicates that ESG-oriented funds have an on average 1.21 percentage points higher Net IRR than Non-ESG-oriented funds. However, the ESG effect remains insignificant. Concerning the variable Called the same observations can be made as for the TVPI. The proportion of capital called is negatively related to the Net IRR, which means that the more capital is called the worse the Net IRR. This effect is significant at the 5% level.

5.1.3 Implications

Probably the most important conclusion of these two analyses is that the ESG orientation has on average a positive effect on the performance of private equity funds, measured by the TVPI and Net IRR. For each of the individual regressions, the ESG coefficient was positive, suggesting that the ESG-oriented funds achieve on average higher TVPIs and Net IRRs, compared to Non-ESG-oriented funds.

However, the matter of the significance of the ESG effect cannot be solved by these two analyses. Under consideration of the TVPI as performance measure, the effect of the ESG orientation is always significant (at least 10% level), indicating that the coefficients are significantly different from 0. Thus the Null Hypothesis can be rejected. If, however, the Net IRR is used as performance measure, the positive effect of the ESG orientation is only significant for the first two regressions, considering only a few control variables. Therefore, only for these two regressions, the Null Hypothesis that the coefficient is equal to zero can be rejected.

While comparing the TVPI-based analysis with the analysis based on the Net IRR, the same tendency can be observed (Table 2). The ESG effect increases and decreases with respect to the same control variables.

Introduction of the…	TVPI	Net IRR
1st variable group	↗	↗
2nd variable group	↘	↘
3rd variable group	↗	↗
4th variable group	↘	↘
5th variable group	↘	↘
6th variable group	↗	↗

Table 2: Summary of the variable groups' effects on the ESG coefficients

The consideration of the vintage year and the fund size leads to an increase in the ESG coefficient in both analyses. This means that the positive ESG effect is not attributable to a time or size effect. On the contrary, as the fund size and the vintage year have both a negative effect, the isolated consideration of these fund characteristics leads to an increase in the ESG effect. Thus, the hypothesis can be rejected that ESG-oriented funds have a better performance because of their higher average fund size.

When the fund managers and their experience (represented by the two types of fund number) are included as control variables, the ESG effect is only half as large, which shows that part of the initial ESG effect is due to the skills and experience of the GP. This observation is consistent with the assumptions from the literature review that fund managers' skills and their experience are positively related to the fund's performance (Kaplan & Schoar, 2005; Ghai et al., 2014).

However, if we look at the individual fund manager groups, we notice that the top ten fund managers, who raise today the most capital, are not the ones achieving the best TVPIs and Net IRRs, but primarily the fund managers of the ranks 61 to 90. And since these GPs set up in 70% of the cases ESG-oriented funds, these ESG funds benefit to a large extent from the skills of these GPs. Therefore, isolating the GP effects also leads to a reduction of the actual ESG effect. The GPs that are not ranked, are the ones achieving the worst performance. However, these unranked fund managers only set up 29% ESG-oriented funds, but 71% Non-ESG-oriented funds. Therefore, ESG funds are not as strongly affected by the poor skills of these GPs, as Non-ESG-oriented funds. Regarding the fund numbers, it can be observed that the overall fund number has a positive effect, but that this effect is very small, so that the isolation of the effect of the overall fund number should not have a strong impact on the ESG effect. The fund number related to a specific series, nevertheless, has a larger effect on performance, which is positive, except for the OLS regression analysis with regard to the Net IRR, which is based on the second variable group. However, ESG and Non-ESG funds have the same average series fund number. Therefore, there should not be any major differences in performance due to this variable.

In both cases, the integration of the asset class and the fund's strategy has led to an increase in the ESG effect. This could be explained by the fact that the ESG funds in this sample often operate in the form of a fund of funds. However, the coefficient of the fund of funds strategy indicates in both cases a strong negative effect on performance, relative to the other strategies. By isolating this effect, the actual ESG effect becomes stronger again.

The incorporation of the core industries has led to a reduction in the ESG coefficient. This can be explained by the fact that in addition to the 74% that invest in diversified industries, 10% of the ESG funds set their investment focus on the IT industry. As the IT industry is the best performing industry, the isolation of its positive effect leads to a decrease of the actual ESG effect.

If the effect of the primary region focus, the home region and the fund currency is isolated, it can be seen that the positive effect of the ESG orientation further decreases. This is because North-America-focused funds achieve a better performance, compared to the other primary investment regions. And because 44% of the ESG-oriented funds invest primarily in North America, the isolation of this positive regional effect leads to a reduction in the ESG effect. Surprisingly, when looking at the different home regions, North American funds perform the worst relative to other home regions, closely followed by European funds. However, as the sample description shows that most funds invest primarily in their home region, this result is quite surprising.

By considering the variable Called in isolation, the ESG coefficient becomes somewhat larger again. This new increase is due to the fact that the proportion of capital called is negatively related to the two performance measures and by separating this negative effect from the ESG effect, the latter increases.

Even though the same tendency can be observed for both analyses, the implications are different. Table 3 displays the ESG coefficients with regard to the TVPI and the Net IRR for the simple regression without control variables and for the regression including all available fund characteristics.

	TVPI	Net IRR
ESG Coefficient (without control variables)	0.27***	4.04***
ESG Coefficient (based on the 6^{th} variable group)	0.27**	1.21

Table 3: Overview of the ESG coefficients with and without control variables

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

For the TVPI-based analysis, it can be concluded that the integration of the control variables has no major impact on the ESG coefficient. It can be assumed that ESG-oriented funds earn on average 0.27 USD more per USD invested, relative to funds without ESG orientation. The only thing that changes, through the introduction of the control variables, is the level of significance. The ESG effect is only significant at the 5% level, instead of the 1% level. In the Net IRR-based analysis, on the other hand, the introduction of the control variables, leads to a sharp decrease in the ESG coefficient from 4.04 to 1.21. This indicates that the initially assumed ESG effect is not solely attributable to the ESG orientation itself but includes effects of other fund characteristics. According to this analysis, ESG-oriented funds earn on average a 1.21 percentage points higher Net IRR compared to Non-ESG-oriented funds. Moreover, the ESG effect is no longer significant, thus the Null Hypothesis, stating that the coefficient is equal to zero, cannot be rejected.

5.2 Results: Propensity Score Matching

5.2.1 ESG Effect on the TVPI

Estimation of the ATE (NN = 1)

First the PSM is performed using the default settings. This means that each of the 1,918 sample funds is matched to its nearest neighbour fund of the opposite treatment group regarding the propensity score.

The first match is based on the first variable group, consisting of the vintage year, the fund size and the fund size squared (see Appendix 9, column (1)). If the funds are matched based on these three characteristics, the ATE is positive and significant at the 5% level, indicating that if one fund is randomly selected from the entire sample, an ESG orientation would on average lead to an increase in its TVPI multiple by 0.34.

The next match is established based on the vintage year, the fund size, the fund size squared, the fund manager, the overall fund number and the fund number related to a specific series (see Appendix 9, column(2)). Thereby, the ESG coefficient is strongly reduced and loses its significance. This is because the match is based on more fund characteristics, which helps to isolate the ESG treatment effect. The resulting ATE of an ESG orientation is an increase in the TVPI by on average 0.14 for a fund randomly selected from the sample.

If matching is based on the third variable group, the asset class category and the investment strategy applied by the fund are also taken into consideration for the matching (see Appendix 9, column (3)). As a result, the ATE increases again and suggests that if any fund from the sample (ESG-oriented or not) decides to apply ESG factors, it will on average earn 0.30 USD more per USD invested. Moreover, this ESG treatment effect is again significant at the 5% level.

Appendix 9, column (4) shows that with the introduction of the core industries into the matching process, the ESG coefficient continues to rise and reaches a level of 0.39. This indicates that a randomly selected funds (ESG-oriented or not), which decides to consider ESG factors, will on average earn 0.39 USD more per USD invested. The resulting ATE is significant at the 1% level.

Additionally, matching the funds based on their regional investment focus, their home region and their currency, strongly decreases the ESG coefficient and renders the ATE insignificant (see Appendix 9, column (5)). Consequently, if a sample fund (ESG-oriented or not) decides to integrate ESG factors in its investment decisions, this fund earns on average only 0.04 USD more per USD invested.

Finally, the proportion of capital called relative to the capital committed is included in the list of fund characteristics, which is used as a basis for matching (see Appendix 9, column (6)). As a result, the average ESG treatment effect increases slightly. The ESG coefficient indicates that if a randomly selected fund (ESG-oriented or not) adopts an ESG orientation, its TVPI multiple would on average only increase by 0.06. However, the ATE remains insignificant.

In summary, it can be concluded that the ATE of the ESG treatment on the TVPI has strongly decreased throughout the different PSMs. This decrease can be traced back to a more accurate matching, based on more fund characteristics, which in turn helps to isolate the ATE of an ESG orientation from the effects of other fund characteristics. Taking all control variables into account, the ESG effect is still positive but not significant.

Estimation of the ATE using Oversampling

In a next step, the average ESG treatment effect is estimated based on the five nearest neighbours of the respective opposite treatment group, lying within a caliper of 0.165. The ATE is again estimated for each of the six variable groups in order to observe the impact of the successive inclusion of the fund characteristics in the matching, and thus of the increasing isolation of the ESG effect. The results of these six PSMs (see Appendix 10) are compared with those of the default version (see Appendix 9) in order to determine how oversampling affects the ATE on the TVPI.

It can be observed that for the first PSM, which is based on the vintage year, the fund size and the fund size squared, the oversampling results in a slightly higher ESG coefficient of 0.37, which is significant at the 1% level (see Appendix 10, column (1)). However, in the following PSMs, which are based on more and more fund characteristics, the same tendency can be observed as in the default version. The only exception is the PSM that additionally matches the funds based on their core industries (see Appendix 10, column (4)). In this case the ATE is slightly decreasing, whereas in the default version the integration of the core industries leads to an increase in the ATE (Appendix 9, column (4)).

Moreover, for each of these four PSMs, the ATE is somewhat lower and less significant than the ATE in the default version. Only in the last PSM, which is based on the sixth variable group (see Appendix 10, column (6)), the ATE based on the five nearest neighbours is slightly higher, than the ATE which is only based on the nearest neighbour. According to this ATE, a randomly selected fund that decides to consider ESG factors earns on average 0.08 USD more per USD invested. This means that the larger amount of information, obtained through a higher number of matching partners, results in a slightly higher ATE, compared to the default scenario where only the nearest neighbour information is used to estimate the ATE.

Estimation of the ATET (NN = 1)

For the estimation of the ATET, each one of the 795 ESG-oriented funds is matched to its nearest neighbour from the subgroup of Non-ESG-oriented funds. Six successive PSMs, which are based on an increasing number of fund characteristics, are carried out.

For the first PSM, the matching is only based on the vintage year, the fund size and the fund size squared (see Appendix 11, column (1)). The resulting ESG coefficient indicates that for ESG-oriented funds the ESG orientation leads on average to an increase in the TVPI multiple by 0.43. In other words, the decision to incorporate ESG factors into the investment decisions results in ESG-oriented funds earning on average 0.43 USD more per USD invested. This ATET is significant at the 1% level.

However, if the funds are additionally matched based on their fund manager and their fund numbers (overall and series), then the ATET drops sharply and loses its significance (see Appendix 11, column (2)). On average, ESG funds earn only 0.07 USD more per USD invested due to their ESG orientation.

By matching the funds also based on their asset class category and their main investment strategy (see Appendix 11, column (3)), the ESG coefficient increases again to a level of 0.26, indicating that the average ESG effect for the ESG-oriented funds is an increase in the TVPI multiple by 0.26. Moreover, the ATET is again significant at the 5% level.

If the matching is, however, based on the fourth variable group, the industry focus of the funds is also included in the matching process (see Appendix 11, column (4)). As a consequence, the ESG coefficient decreases, and loses its significance. The ATET indicates that the ESG funds earn on average only 0.21 USD more per USD invested, because of their ESG orientation. This stands in contrast to the results from the estimation of the ATE (NN = 1), where the isolation of the industry effects leads to an increase in the ESG coefficient, which was then significant at the 1% level (see Appendix 9, column (4)).

Subsequently, the funds are also matched based on their primary investment region, their home region and their currency, leading to a decrease in the ESG coefficient, which is statistically insignificant (see Appendix 11, column (5)). The resulting ATET indicates that the TVPI multiple of ESG funds increases by 0.19 because of the consideration of ESG factors.

Finally, Appendix 11, column (6) shows that the introduction of the variable Called into the matching process leads to a further reduction in the ATET, which indicates that, on average, ESG-oriented funds earn only 0.17 USD more per USD invested due to their ESG orientation. This is less than half of the initial ATET, suggesting that the initial ATET incorporates effects of the other characteristics. Moreover, this ATET is not significant, whereas the initial ATET is significant at the 1% level.

With regard to the ATET, the same conclusion can be drawn as for the ATE (NN = 1). The average effect of an ESG orientation on the TVPI is positive, but not significant. However, it can be observed that the final ATET (NN = 1) is larger than the final ATE (NN = 1).

Estimation of the ATET using Oversampling

In order to assess how oversampling affects the ATET, the six PSMs are repeated. However, each ESG-oriented fund will be matched to its five nearest neighbours of the Non-ESG sub-population by respecting a caliper of 0.165. The results from those six PSMs (see Appendix 12) are then compared to the above-described results (see Appendix 11).

It can be noticed that, apart from one exception, all ESG coefficients are smaller, compared to the ATETs based on their nearest neighbour matching. This indicates that through the oversampling, more information can be gained resulting in a smaller, but still positive, average ESG Effect for the ESG-oriented funds. These different ATETs are all insignificant except the one for the first PSM, which is significant at the 1% level.

If the changes between the six PSMs are considered, it can be observed that the tendencies are the same as in the nearest neighbour scenario, except for the PSMs based on the third variable group and the last variable group (see Appendix 12, column (3) and (6)). The integration of the asset class categories and the strategies leads to a reduction in the ESG coefficient. Furthermore, the integration of the variable Called leads to a slight increase of the ESG coefficient. That the effects of these variables change may be due to the fact that each ESG fund is matched with five Non-ESG funds. This provides more information for the construction of the counterfactual outcome, but it also gives additional insight regarding the other characteristics. The final PSM, which matches ESG funds based on all control variables, shows that ESG-oriented funds earn on average 0.07 USD more per USD invested due to their ESG orientation. This is 0.10 USD less per USD invested than for the ATET, which is based on the nearest neighbour.

In summary, the results of the oversampling version show that the average ESG effect, for funds which have already included ESG factors in their decisions, is even smaller and not significant.

5.2.2 ESG Effect on the Net IRR

Estimation of the ATE (NN = 1)

The basis for this analysis is again the default PSM, which matches each ESG-oriented fund to its nearest neighbour from the Non-ESG sub-population, and vice versa. Consequently, each of the 1,918 sample funds is matched.

If the matching is based on the first variable group, the ESG coefficient is positive and significant at the 5% level (see Appendix 13, column (1)). According to this coefficient, the average effect of an ESG orientation for a randomly selected fund is an increase in the fund's Net IRR by 4.28 percentage points.

Additionally, the fund manager and the two different types of fund numbers are integrated in the matching process (see Appendix 13, column (2)). Consequently, the ESG coefficient decreases strongly, indicating that a randomly selected fund, which decides to implement an ESG-oriented investment strategy, has on average only a 0.61 percentage points higher Net IRR. However, this effect is insignificant.

If the funds are matched additionally based on the funds' asset class and investment strategy, the ESG coefficient rises again to a level of 1.58, which is still insignificant (see Appendix 13, column (3)). This ESG coefficient suggests that if a randomly selected fund decides to integrate ESG factors in its strategy, this leads to an on average 1.58 percentage points higher Net IRR.

When funds are matched based on their industry focus in addition to the above-mentioned characteristics, the ESG coefficient rises again (see Appendix 13, column (4)). It indicates that, on average, the effect of being ESG-oriented is an increase in the Net IRR of 3.96 percentage points. This ATE applies both to funds that are already ESG-oriented and to funds for which this is not yet the case. For the latter, the ATE can be understood as an indicator of the potential of such an orientation. This ATE is significant at the 5% level.

If the matching is based on the fund characteristics of the fifth variable group, this leads to a negative, although not significant, ESG coefficient (see Appendix 13, column (5)). Thus, the ATE of an ESG orientation is a decrease in the Net IRR by 0.54 percentage points.

Through the introduction of the variable Called in the matching process, the average ESG effect remains negative and is even further decreasing (see Appendix 13, column (6)). If a randomly selected fund (ESG-oriented or not) would decide to base its investment decisions on the ESG factors, this would lead to an on average 0.85 percentage points lower Net IRR. However, this ATE is not significant.

The conclusion of these six PSMs is that the initial positive ATE is due to positive effects of other fund characteristics. The last PSM shows that if funds are matched based on all available fund characteristics, the average effect of an ESG orientation on the Net IRR is negative, even though it is not significant.

<u>Estimation of the ATE using Oversampling</u>

Another six PSMs are carried out, in order to evaluate how oversampling impacts the ATE of an ESG orientation on the Net IRR. Again, each fund (ESG-oriented or not) is matched to its five nearest neighbours of the opposite treatment group within a caliper of 0.165. Appendix 14 represents the six resulting ATEs, which are compared to those of the nearest neighbour scenario (see Appendix 13).

The ATE resulting from the first PSM, which matches funds based on their vintage year, their fund size and their fund size squared, is larger compared to the one of the default version (ATE, NN = 1). It suggests that if a fund (ESG-oriented or not) decides to integrate ESG factors in its investment decisions, this results in an on average 4.75 percentage points higher Net IRR. This effect is significant at the 1% level (see Appendix 14, column (1)). With regard to the PSMs, which are based on the variable groups two to five, the same tendency can be observed as in the above-described default version. However, due to the oversampling, the ESG coefficients are each time smaller. Only for the last PSM the tendency differs. Appendix 14, column (6) shows that if the variable Called is included in the matching process, the ESG coefficient increases to a level of -0.33, which is higher than the nearest neighbour ESG coefficient (see Appendix 13, column (6)), but still insignificant. It indicates that a randomly selected fund that decides to apply ESG factors has on average a 0.33 percentage points lower Net IRR.

Consequently, the oversampling leads to the result that the ESG orientation still has an on average negative effect on the Net IRR, but that this negative effect is now weaker.

<u>Estimation of the ATET (NN = 1)</u>

Again six PSMs are carried out, whereby each of the 795 ESG-oriented funds is matched with its nearest neighbour from the subgroup of Non-ESG funds.

When the matches are established based on the funds' vintage year, their fund size and their fund size squared (see Appendix 15, column (1)), the ATET indicates that ESG funds have on average a 5.71 percentage points higher Net IRR resulting from their ESG orientation. This average ESG treatment effect is significant at the 1% level.

If the fund characteristics of the second variable group are used to perform the matching, the ESG coefficient gets slightly negative and insignificant (see Appendix 15, column (2)). Consequently, this signifies that the ESG treatment leads on average to a decrease in the ESG funds' Net IRR by 0.71 percentage points. This is consistent with the tendency from the estimation of the ATE (NN = 1). However, the ATET gets negative, whereas the ATE remains positive (see Appendix 13, column (2)).

The exact same tendency is observable if the matching process includes the asset class and the investment strategies of the fund as well (see Appendix 15, column (3)). The ATET further decreases to a level of -2.81, which is however insignificant.

Matching the funds additionally based on their industry focus, results in an increase in the ESG coefficient, which gets positive again (see Appendix 15, column (4)). ESG-oriented funds earn on average a 0.39 percentage points higher Net IRR thanks to the integration of ESG factors in their investment decisions. Still, this ATET remains insignificant.

In a next step, the funds are additionally matched based on their primary region focus, their home region and their currency (see Appendix 15, column (5)). Due to this more accurate matching, a new drop in the ESG coefficient can be observed, which is now back at a level of -2.72. Nevertheless, the ATET is not significant.

Finally, the ESG funds are also matched based on the proportion of capital they have called, relative to the committed capital. This further decreases the ESG coefficient (see Appendix 15, column (6)). The final ATET is at -2.82, which implies that, on average, ESG-oriented funds have a 2.82 percentage points lower Net IRR, which can be traced back to their ESG orientation. However, this effect is still insignificant.

It can be concluded that for ESG funds, the ESG orientation leads on average to a decrease in the Net IRR, which is however not significant. Moreover, it can be observed that the ATET suggests an even more negative ESG effect on the Net IRR than the ATE.

Estimation of the ATET using Oversampling

The goal is to find out how oversampling affects the average effect of an ESG orientation on the Net IRR of already ESG-oriented funds. As already mentioned, all 795 ESG funds are matched with their five nearest neighbours from the Non-ESG subgroup, which lie within a caliper of 0.165. These results (see Appendix 16) are then compared with the ATETs specified above (see Appendix 15).

The comparison shows that in 4 out of 6 cases, oversampling leads to lower ATETs. In three cases, the already negative effect is further reinforced, indicating that the integration of ESG factors leads on average to an even greater decline in the Net IRR of ESG funds. Thereby, all ATETs are insignificant except for the one of the first PSM, where the ATET is significant at the 1% level.

Regarding the tendencies across the different PSMs, it can be observed that there is only a change for the last PSM (see Appendix 16, column (6)). Because of the additional information obtained from the oversampling, the insolation of the variable Called now leads to an increase in the ESG coefficient. The resulting final ATET indicates that ESG-oriented funds will on average earn a 3.78 percentage points lower Net IRR, because of their decision to consider ESG factors.

The conclusion of this comparison is that the additionally gained information from the four new matching partners, leads in most cases to a lower ESG coefficient. Consequently, the ATETs, which are based on oversampling, are more pessimistic, even if they are not significant.

5.2.3 Implications

The question of whether or not the ESG orientation of private equity funds leads to a better performance cannot be answered unanimously on the basis of these PSMs.

With regard to the TVPI as a performance measure, the average effect of an ESG orientation is always positive, although in 67% of the PSMs not significant. The lowest ESG coefficient out of the twenty-four PSMs is 0.04 and the highest is 0.43. However, these ESG coefficients are not all representing pure ESG effects, because they partially contain the effects of other fund characteristics. Therefore, if only the four PSMs, for which the matching process is based on all available fund characteristics, are considered, the lowest ESG coefficient is 0.06 and the highest is 0.17. Thus, the isolation of the effects of other fund characteristics leads to a smaller range of the calculated ESG coefficients. In conclusion, it can be stated that, on average, the ESG orientation leads to an increase in the TVPI, although only a small one.

Nonetheless, if the Net IRR is considered as performance measure, the average effect of an ESG orientation is not always positive. For 12 PSMs the result indicates that the ESG orientation has a negative effect on the Net IRR and for the other 12 PSMs the result suggests that the ESG orientation positively affects the Net IRR. When looking at the significance level, it can be observed that for 79% of the PSMs the ESG effect, whether positive or negative, is not significant. The lowest ESG coefficient is -4.44, and the highest one amounts to 5.71. However, if only the four PSMs which are based on the sixth variable group are considered, then the lowest ESG coefficient is -3.78 and the highest lies at -0.33. So, if we assume that the funds, matched on the basis of the sixth variable group only differ on the basis of their ESG orientation, this means that the pure ESG effect on the Net IRR is on average negative.

Consequently, the conclusions regarding the two performance measures lead to different results. If the TVPI is used as performance measure, the ESG effect is on average positive and if the Net IRR is used, the ESG effect is on average negative. However, for both performance measures most ESG effects are insignificant, which means that the coefficients are not significantly different from 0 and all contain 0 in their confidence interval.

If we now compare the ATE variants with the ATET variants, it can be seen that for 71% of the PSMs the resulting ATET is smaller than the resulting ATE. This tendency is particularly strong when the Net IRR is used as a performance measure, because in that case for 10 out of 12 PSMs the average ESG effect for ESG funds is smaller than the average ESG effect for any given fund, ESG-oriented or not. However, if the TVPI is chosen as performance measure, this tendency is somewhat weaker, with only 7 out of 12 PSMs. Moreover, if only the four PSMs for which the ESG effect is completely isolated are taken into account, it can again be observed that in 3 out of 4 cases the ATET is smaller than the ATE. Consequently, it can be concluded that the average ESG effect on performance is most of the time more positive for a randomly selected fund than for an already ESG-oriented fund, especially if the Net IRR is the performance measure.

Through oversampling, more information can be obtained, because 5 matches are established instead of just one. To ensure that this oversampling does not affect the matching quality too much, a caliper of 0.165 is implemented. Comparing the PSMs based on the nearest neighbour with the PSMs based on the five nearest neighbours, it can be observed that for 71 % of the PSMs this additional information leads to a decrease in the ESG coefficient. If we have a closer look at the ATE and ATET variants, it becomes apparent that for 9 out of the 12 ATET-PSMs and for 8 out of the 12 ATE-PSMs, the oversampling has led to a reduction in the ESG effects. Moreover, in 9 out of the 12 TVPI-PSMs and in 8 out of the 12 Net IRR-PSMs, the ESG coefficients are reduced due to this additionally considered information. Consequently, it can be said that oversampling mostly leads to a weakening of the average ESG effect on private equity fund performance, and this is especially the case for already ESG-oriented funds and particularly for the TVPI. Conversely, if only the four PSMs for which we assume that matching ensures that the funds only differ on the basis of their ESG orientation are considered, we can clearly see that oversampling leads twice to a higher and twice to a lower ESG coefficient. The two decreases in the ESG coefficient occur for the ATET variants. In summary, this means that on the one hand the additional information shows that for randomly selected funds the average effect of an ESG orientation on performance is even more positive than assumed based on the nearest neighbour. On the other hand, it can be observed that for already ESG-oriented funds the average ESG effect on performance is lower than estimated based on the nearest neighbour.

Table 4 summarises how the average ESG treatment effect changes in the different scenarios, when matching is based on an increasing number of fund characteristics.

	TVPI				Net IRR			
Matching based on the:	ATE, NN = 1	ATE, NN = 5	ATET, NN = 1	ATET, NN = 5	ATE, NN = 1	ATE, NN = 5	ATET, NN = 1	ATET, NN = 5
2nd variable group	↘	↘	↘	↘	↘	↘	↘	↘
3rd variable group	↗	↗	↗	↘	↗	↗	↘	↘
4th variable group	↗	↘	↘	↘	↗	↗	↗	↗
5th variable group	↘	↘	↘	↘	↘	↘	↘	↘
6th variable group	↗	↗	↘	↗	↘	↗	↘	↗

Table 4: Summary of the variable groups' impacts on the different average ESG treatment effects

With regard to the effects of the different fund characteristics, it can be observed that when the funds are matched based on their fund manager and the two types of fund numbers (2nd variable group), this leads to a decrease in the ESG coefficient in all eight PSMs. For the primary region focus, the home region and the fund currency (5th variable group), the same observation can be made. This is consistent with the tendencies that can be observed in the two OLS regression analyses.

Regarding the other fund characteristics, it gets more difficult to draw clear conclusions, as the effects change across the eight variants.

The Table 5 below summarises the most saturated results (considering all control variables) from the eight different scenarios.

	TVPI				Net IRR			
Matching is based on the 6th variable group	ATE, NN = 1	ATE, NN = 5	ATET, NN = 1	ATET, NN = 5	ATE, NN = 1	ATE, NN = 5	ATET, NN = 1	ATET, NN = 5
ESG Coefficient	0.06	0.08	0.17	0.07	-0.85	-0.33	-2.82	-3.78

Table 5: Overview of the different average ESG treatment effects under the consideration of all control variables

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Looking only at the actual ESG effects, adjusted for the effects of other fund characteristics, the following conclusions can be drawn. A fund's ESG orientation has on average a positive effect on its TVPI, but a negative effect on its Net IRR, which is quite contradictory, as both are measures of performance. However, none of the eight average ESG effects are significantly different from zero, therefore the Null Hypothesis, stating that the ESG coefficient is equal to zero, cannot be rejected. Furthermore, the average effect of an ESG orientation on performance is generally higher (less negative) for randomly selected funds (ATE) rather than for already ESG-oriented funds (ATET). The only exception is the scenario based on the nearest neighbour and the TVPI as a performance measure. Moreover, the information obtained from the four additional matching partners leads to an increase in the average ESG effect for randomly selected funds (ATE), while the average ESG effect decreases for funds that have already adopted an ESG orientation (ATET).

Comparing these eight results with the two of the OLS regression analyses, it becomes clear that the estimated average ESG effect of the OLS regression is strongly upward biased for both the TVPI and the Net IRR. Under the consideration of all control variables, the OLS ESG coefficient amounts to 0.27 with regard to the TVPI and to 1.22 with regard to the Net IRR, which is higher than each of the eight PSM ESG coefficients.

6 CONCLUSION

Even though the finance literature has not yet been dealing with sustainable investment strategies for an extended period of time, it is clear that this topic is becoming increasingly relevant and will probably be firmly embedded in due diligence and investment processes in the future. This is due to the fact that current circumstances, especially environmental ones, urgently necessitate it. In particular, companies are required to adapt their business practices and take ESG factors into account. However, this can have a positive impact on the company's operational and financial performance and increase its market valuation.

In the investment industry, the implementation of an ESG orientation is expected by various stakeholders. Furthermore, it is also encouraged by regulations, principles and standards. Private equity plays an important role in this context as it is particularly well suited for the integration of sustainable investment strategies. This is partly due to its long investment horizon. In addition to negative or positive screening strategies, the integration of ESG factors and active ownership strategies, it is possible for private equity fund managers to intervene directly in the management of portfolio companies. This allows them to have a positive impact in terms of ESG factors and other moral or ethical aspects.

To answer the question of whether or not private equity funds can achieve better performance through an ESG orientation, a data set consisting of 1,918 liquidated private equity funds was used. Of these, 795 funds are ESG-oriented.

Using the simple OLS regression model, it can be concluded that the ESG orientation leads to a better performance with respect to both performance measures (TVPI and Net IRR). ESG-oriented private equity funds earn on average 0.27*** USD more per USD invested, and have an on average 4.04*** percentage points higher Net IRR than Non-ESG-oriented private equity funds. However, since the performance of private equity funds is influenced by various fund characteristics, the results of the simple regression model are biased due to the selection problem.

To solve this selection problem, the multiple OLS regression model is applied. The fund characteristics are successively inserted as explanatory variables in the regression analysis.

Taking all fund characteristics into account, the same conclusion can be drawn as for the simple regression model, namely that the ESG orientation of a private equity fund has a positive effect on its performance. While the estimated ESG coefficient regarding the TVPI remains at 0.27**, the estimated ESG coefficient regarding the Net IRR drops to 1.21.

However, because of the limitations of the OLS regression models, PSM is applied to estimate the average effect of an ESG orientation on private equity fund performance. Based on the nearest neighbour matching, the estimated ATE with regard to the TVPI is positive and suggests that if a randomly selected fund integrates ESG factors this will lead to an increase in the TVPI multiple by on average 0.06. With regard to the Net IRR, however, the ATE is negative, indicating that if a randomly selected fund decides to consider ESG factors in its strategy, this leads to an on average 0.85 percentage points lower Net IRR.

For the estimation of the ATET, similar results can be observed, except that the ATET is generally lower than the ATE. On the one hand, ESG-oriented funds earn on average 0.17 USD more per USD invested due to their ESG orientation. But on the other hand, the ESG coefficient with regard to the Net IRR suggests that ESG-oriented funds have an on average 2.82 percentage points lower Net IRR, which can be traced back to their ESG orientation.

If the matching is carried out based on the five-nearest neighbours, it can be observed that the oversampling leads to an increase in the ATEs and to a decrease in the ATETs. According to these results the average effect of an ESG orientation for a randomly selected fund is an increase in the TVPI multiple by 0.08 and a decrease in the Net IRR by 0.33 percentage points. The average ESG treatment effect for an already ESG-oriented fund is an increase in the TVPI multiple by 0.07 and a decrease in the Net IRR by 3.78 percentage points.

In summary, while the results of the OLS regression analyses suggest that ESG-oriented private equity funds outperform other Non-ESG-oriented private equity funds, the PSM results challenge these findings. This positive ESG effect on performance can only be observed in terms of TVPI. If the Net IRR is taken as performance measure, the PSM results show that the ESG orientation of private equity funds leads on average to worse performance. Moreover, the eight ESG coefficients of the PSMs are all insignificant, which means that the coefficients are not significantly different from 0 and all contain 0 in their confidence interval.

Since the PSM method is the most accurate and least biased method and because the TVPI is a more reliable performance measure than the Net IRR (due to the reinvestment assumption and the potential for manipulation by the GP), it can be concluded that the ESG orientation has on average a positive but insignificant effect on the performance of private equity funds.

An avenue for future research could be to conduct another performance analysis with more recent funds, as the distribution of ESG funds in this sample is concentrated around the vintage years 1997 to 2000. And since most private equity funds primarily used SRI and negative screening strategies in the beginning, this could imply a potential downward bias in performance, as the returns of these strategies are often below the market average. In addition, ESG investing and impact investing have only become more widespread during the last few years. Thus, most private equity funds applying these strategies are probably not yet liquidated. Following on from this, it might also be interesting to conduct a performance analysis to identify the most promising sustainable investment strategies in the private equity industry.

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APPENDIX

Data Processing

Appendix 1: Variable Overview

Variable Name	Reason for omission/ Reason for including the variable
Fund ID	Fund Identification
Firm ID	Not relevant
Name	Not relevant
Vintage/Inception Year	Control Variable
Strategy	Control Variable
Called (%)	Control Variable
DPI (%)	Performance Measure
RVPI (%)	Performance Measure
Net IRR (%)	Dependant Variable/Performance Measure
Net Multiple (X) *Has been renamed to TVPIX*	Dependant Variable/Performance Measure
Quartile	Performance Measure
Date Reported	Not relevant
Asset Class	Control Variable
Primary Region Focus	Control Variable
Status	The same for all funds >> liquidated (one of the initial conditions)
Fund Size (USD MN)	Control Variable
Fund Manager	Control Variable
Fund Structure	Control Variable *(after the data processing not included anymore)*
Domicile	Less than 1,000 observations
Fund Legal Structure	Less than 1,000 observations
Fund Number (Overall)	Control Variable
Fund Number (Series)	Control Variable
Single Deal Fund	Control Variable *(after the data processing not included anymore)*
Lifespan (Years)	Less than 1,000 observations
Lifespan Extension	Less than 1,000 observations
Solely Financed By	Less than 1,000 observations
Target IRR – Net Min	Less than 1,000 observations
Target IRR – Net Max	Less than 1,000 observations
Target IRR – Gross Min	Less than 1,000 observations
Target IRR – Gross Max	Less than 1,000 observations
Fund Currency	Control Variable
Target Size (Curr. MN)	Less than 1,000 observations
Target Size (USD MN)	Less than 1,000 observations
Target Size (EUR MN)	Less than 1,000 observations

Initial Target (Curr. MN)	Less than 1,000 observations
Initial Target (USD MN)	Less than 1,000 observations
Initial Target (EUR MN)	Less than 1,000 observations
Hard Cap. (Curr. MN)	Less than 1,000 observations
Hard Cap. (USD MN)	Less than 1,000 observations
Hard Cap. (EUR MN)	Less than 1,000 observations
Fund Raising Launch Date	Less than 1,000 observations
Latest Interim Close Date	No observations
Latest Interim Close Size (Curr. MN)	No observations
Latest Interim Close Size (USD MN)	No observations
Latest Interim Close Size (EUR MN)	No observations
Final Close Date	Not relevant
Final Close Size (Curr. MN)	Equivalent to "Fund Size"
Final Close Size (USD MN)	Equivalent to "Fund Size"
Final Close Size (EUR MN)	Equivalent to "Fund Size"
Offer Co-Investment Opportunities to LPs?	Less than 1,000 observations
Co-Investment Capital Amount (Curr. MN)	Less than 1,000 observations
Co-Investment Capital Amount (USD MN)	Less than 1,000 observations
Co-Investment Capital Amount (EUR MN)	Less than 1,000 observations
Months to First Close	Less than 1,000 observations
Months in Market	Less than 1,000 observations
Core Industries	Control Variable
Industries	The variable "Core Industries" is sufficient
Industry Verticals	Less than 1,000 observations
PE: Buyout Fund Leverage (%)	No observations
PE: Buyout Fund Size	Less than 1,000 observations
PE: Investment Size per Portfolio Company (Min)	Less than 1,000 observations
PE: Investment Size per Portfolio Company (Max)	Less than 1,000 observations
Placement Agents	Less than 1,000 observations
Law Firms	Less than 1,000 observations
Administrator	Less than 1,000 observations
Auditor	No observations
Prime Broker	No observations
Custoian	No observations
Mgmt Fee Rate (%) during Inv Period	Less than 1,000 observations
Charge Frequency	Less than 1,000 observations
Investment Period (YRS)	Less than 1,000 observations
Mechanism for Mgmt Fee Reductions - Post-Investment Period	Less than 1,000 observations
Mgmt Fee Rate (%) - Post-Investment Period	Less than 1,000 observations
Special Provision for Larger LPs	Less than 1,000 observations
Carried Interest (%)	Less than 1,000 observations
Carried Interest Basis	Less than 1,000 observations
GP Catch-Up Rate (%)	Less than 1,000 observations
Hurdle Rate (%)	Less than 1,000 observations
Key Man Clause	Less than 1,000 observations
Share of Transaction Fees Rebated to LP (%)	Less than 1,000 observations
No-Fault Divorce Clause?	Less than 1,000 observations
LP Majority Required (%)	No observations

Fund Formation Costs (MN)	Less than 1,000 observations
Advisory Board LP Representation	Less than 1,000 observations
Advisory Board LP Representation (Notes)	No observations
GP Committments to Fund (% of Total)	Less than 1,000 observations
Number of LPs (Min)	Less than 1,000 observations
Number of LPs (Max)	Less than 1,000 observations
Percentage of Returning LPs	Less than 1,000 observations
Region *Has been renamed to Home Region*	Control Variable
Address	Not relevant
City	The variable "Region" is sufficient
State/County	The variable "Region" is sufficient
ZIP Code	Not relevant
Country	The variable "Region" is sufficient
Website	Not relevant
Email	Not relevant
Tel	Not relevant
Fax	Not relevant
Benchmark Name	Not relevant
Median Benchmark Net IRR (%)	Not relevant
Median Benchmark Called (%)	Not relevant
Median Benchmark Distributed (%) DPI	Not relevant
Median Benchmark Net Multiple (X)	Not relevant
Median Benchmark RVPI (%)	Not relevant
Average Benchmark Net IRR (%)	Not relevant
Average Benchmark Called (%)	Not relevant
Average Benchmark Distributed (%) DPI	Not relevant
Average Benchmark Net Multiple (X)	Not relevant
Average Benchmark RVPI (%)	Not relevant
Weighted Benchmark Net IRR (%)	Not relevant
Weighted Benchmark Called (%)	Not relevant
Weighted Benchmark Distributed (%)DPI	Not relevant
Weighted Benchmark Net Multiple (X)	Not relevant
Weighted Benchmark RVPI (%)	Not relevant
Pooled Benchmark Net IRR (%)	Not relevant
S&P 500 LN-PME	Less than 1,000 observations
S&P 500 KS-PME	Less than 1,000 observations
S&P 500 PME+	Less than 1,000 observations
Russell 2000 LN-PME	Less than 1,000 observations
Russell 2000 KS-PME	Less than 1,000 observations
Russell 2000 PME+	Less than 1,000 observations
Russell 3000 LN-PME	Less than 1,000 observations
Russell 3000 KS-PME	Less than 1,000 observations
Russell 3000 PME+	Less than 1,000 observations
MSCI Emerging Markets LN-PME	Less than 1,000 observations
MSCI Emerging Markets KS-PME	Less than 1,000 observations
MSCI Emerging Markets PME+	Less than 1,000 observations
MSCI Europe Standard LN-PME	Less than 1,000 observations
MSCI Europe Standard KS-PME	Less than 1,000 observations

MSCI Europe Standard PME+	Less than 1,000 observations
MSCI US REIT LN-PME	Less than 1,000 observations
MSCI US REIT KS-PME	Less than 1,000 observations
MSCI US REIT PME+	Less than 1,000 observations
MSCI World LN-PME	Less than 1,000 observations
MSCI World KS-PME	Less than 1,000 observations
MSCI World PME+	Less than 1,000 observations
Estimated Launch	No observations
Subscription Credit Facility	Less than 1,000 observations
Geographic Exposure	The variable "Primary Region Focus" is sufficient
Geographic Focus	The variable "Primary Region Focus" is sufficient
Other Geographies	Less than 1,000 observations
AUM (Curr. MN)	Less than 1,000 observations
AUM (USD MN)	Less than 1,000 observations
AUM (EUR MN)	Less than 1,000 observations
Dry Powder (Curr. MN)	Less than 1,000 observations
Dry Powder (USD MN)	Less than 1,000 observations
Dry Powder (EUR MN)	Less than 1,000 observations
Unrealized Value (Curr. MN)	Less than 1,000 observations
Unrealized Value (USD MN)	Less than 1,000 observations
Unrealized Value (EUR MN)	Less than 1,000 observations
S&P 500 Direct Alpha	Less than 1,000 observations
Russell 2000 - Direct Alpha	Less than 1,000 observations
Russell 3000 - Direct Alpha	Less than 1,000 observations
MSCI Emerging Markets - Direct Alpha	Less than 1,000 observations
MSCI Europe Standard - Direct Alpha	Less than 1,000 observations
MSCI US REIT - Direct Alpha	Less than 1,000 observations
MSCI World - Direct Alpha	Less than 1,000 observations
ESG (created manually)	Treatment Variable

Table 6: Overview of all variables and the reasons why some of them are excluded

Sample Description

Appendix 2: Descriptive Statistics

Descriptive Statistics	Mean	SD	Min	Max
TVPI (X)	2.10	2.00	0.00	32.42
TVPI_PERCENTAGE	209.67	200.25	0.00	3241.52
DPI (%)	209.39	200.37	0.00	3241.52
RVPI (%)	0.28	4.60	0.00	104.47
NET IRR (%)	18.37	34.29	-100.00	514.33
d_firstquartile	0.27	0.45	0.00	1.00
d_secondquartile	0.27	0.45	0.00	1.00
d_thirdquartile	0.25	0.43	0.00	1.00
d_fourthquartile	0.20	0.40	0.00	1.00
ESG (1 vs. 0)	0.41	0.49	0.00	1.00
VINTAGE YEAR	1998.35	6.29	1982.00	2018.00
FUND SIZE (MN USD)	382.98	866.67	0.40	17708.40
FUND SIZE SQUARED	897399.14	8669535.14	0.16	3.14e+08
d_GPtopten	0.03	0.17	0.00	1.00
d_GPsecondgroup	0.05	0.21	0.00	1.00
d_GPthirdgroup	0.05	0.22	0.00	1.00
d_GPfourthgroup	0.03	0.18	0.00	1.00
d_GPfifthgroup	0.04	0.20	0.00	1.00
d_GPsixthgroup	0.03	0.18	0.00	1.00
d_GPseventhgroup	0.03	0.17	0.00	1.00
d_GPnotrankedone	0.26	0.44	0.00	1.00
d_GPnotrankedtwo	0.23	0.42	0.00	1.00
d_GPnotrankedthree	0.24	0.43	0.00	1.00
FUND NUMBER (SERIES)	2.51	1.82	1.00	11.00
FUND NUMBER (OVERALL)	3.65	4.70	1.00	51.00
d_classPE	0.63	0.48	0.00	1.00
d_classVC	0.37	0.48	0.00	1.00
d_venture	0.23	0.42	0.00	1.00
d_buyout	0.40	0.49	0.00	1.00
d_earlystage	0.11	0.32	0.00	1.00
d_latestage	0.03	0.18	0.00	1.00
d_growth	0.07	0.25	0.00	1.00
d_balanced	0.04	0.19	0.00	1.00

d_fundoffunds	0.07	0.26	0.00	1.00
d_secondaries	0.04	0.20	0.00	1.00
d_others	0.01	0.09	0.00	1.00
d_diversifiedindustries	0.58	0.49	0.00	1.00
d_informationtechnology	0.15	0.35	0.00	1.00
d_healthcare	0.12	0.33	0.00	1.00
d_energyutilities	0.01	0.12	0.00	1.00
d_telecomsmedia	0.03	0.17	0.00	1.00
d_consumerdiscretionary	0.03	0.18	0.00	1.00
d_industrials	0.04	0.20	0.00	1.00
d_otherindustries	0.03	0.16	0.00	1.00
d_northamerica	0.66	0.47	0.00	1.00
d_europe	0.21	0.41	0.00	1.00
d_asia	0.08	0.27	0.00	1.00
d_americas	0.01	0.12	0.00	1.00
d_australasia	0.02	0.13	0.00	1.00
d_rest	0.03	0.16	0.00	1.00
d_homenorthamerica	0.67	0.47	0.00	1.00
d_homeeurope	0.22	0.42	0.00	1.00
d_homeasia	0.06	0.23	0.00	1.00
d_homeaustralasia	0.02	0.13	0.00	1.00
d_homerest	0.03	0.18	0.00	1.00
d_USD	0.75	0.43	0.00	1.00
d_EUR	0.12	0.32	0.00	1.00
d_JPY	0.02	0.14	0.00	1.00
d_GBP	0.05	0.22	0.00	1.00
d_AUD	0.01	0.12	0.00	1.00
d_otherCURR	0.05	0.21	0.00	1.00
CALLED (%)	97.22	10.56	7.60	162.14
N	1918.00	.	.	.

Table 7: Overview of the variables' descriptive statistics

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 3: Statistical Distribution of the Variable RVPI

RVPI (%)	Frequency	Percent
0.00	1,887	98.38
0.01	2	0.10
0.08	1	0.05
0.20	1	0.05
0.21	1	0.05
0.42	1	0.05
0.50	1	0.05
0.53	1	0.05
0.66	1	0.05
0.67	1	0.05
1.40	1	0.05
2.00	2	0.10
2.02	1	0.05
2.80	1	0.05
3.01	1	0.05
3.66	1	0.05
4.14	1	0.05
4.24	1	0.05
4.75	1	0.05
5.24	1	0.05
6.15	1	0.05
9.40	1	0.05
9.50	1	0.05
18.00	1	0.05
20.00	1	0.05
42.55	1	0.05
83.49	1	0.05
100.00	2	0.10
104.47	1	0.05
Total	1,918	100.00

Table 8: Statistical distribution of the variable RVPI

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 4: Descriptive Statistics for ESG funds and Non-ESG funds

Descriptive Statistics (Mean)	Non-ESG Funds	ESG Funds	Difference
TVPI (X)	1.98	2.26	2.94
NET IRR (%)	16.69	20.73	2.55
d_firstquartile	0.25	0.31	3.18
d_secondquartile	0.25	0.31	2.91
d_thirdquartile	0.26	0.24	-1.02
d_fourthquartile	0.24	0.14	-5.71
ESG (1 vs. 0)	0.00	1.00	.
VINTAGE YEAR	1998.15	1998.63	1.63
FUND SIZE (MN USD)	289.87	514.51	5.64
FUND SIZE SQUARED	425602.59	1563848.86	2.84
d_GPtopten	0.00	0.07	8.45
d_GPsecondgroup	0.00	0.11	10.68
d_GPthirdgroup	0.01	0.11	9.64
d_GPfourthgroup	0.02	0.05	4.56
d_GPfifthgroup	0.03	0.05	1.80
d_GPsixthgroup	0.02	0.06	5.54
d_GPseventhgroup	0.02	0.04	2.30
d_GPnotrankedone	0.30	0.21	-4.62
d_GPnotrankedtwo	0.28	0.15	-6.92
d_GPnotrankedthree	0.30	0.15	-7.68
FUND NUMBER (SERIES)	2.51	2.52	0.15
FUND NUMBER (OVERALL)	2.86	4.75	8.85
d_classPE	0.52	0.78	11.82
d_classVC	0.48	0.22	-11.82
d_venture	0.29	0.14	-7.76
d_buyout	0.37	0.45	3.68
d_earlystage	0.16	0.05	-7.51
d_latestage	0.03	0.03	0.19
d_growth	0.08	0.05	-2.48
d_balanced	0.03	0.06	3.33
d_fundoffunds	0.02	0.14	9.93
d_secondaries	0.02	0.07	6.04
d_others	0.01	0.01	0.11
d_diversifiedindustries	0.47	0.74	12.00
d_informationtechnology	0.18	0.10	-5.44

d_healthcare	0.17	0.06	-7.11
d_energyutilities	0.02	0.01	-0.86
d_telecomsmedia	0.04	0.02	-2.54
d_consumerdiscretionary	0.03	0.04	1.04
d_industrials	0.05	0.03	-2.75
d_otherindustries	0.04	0.01	-3.63
d_northamerica	0.81	0.44	-18.57
d_europe	0.08	0.39	17.66
d_asia	0.06	0.10	3.77
d_americas	0.02	0.01	-0.23
d_australasia	0.01	0.03	2.44
d_rest	0.02	0.03	1.08
d_homenorthamerica	0.82	0.45	-18.65
d_homeeurope	0.08	0.42	19.07
d_homeasia	0.05	0.08	2.69
d_homeaustralasia	0.01	0.03	2.26
d_homerest	0.03	0.03	-0.71
d_USD	0.88	0.57	-16.21
d_EUR	0.03	0.24	14.29
d_JPY	0.00	0.04	6.47
d_GBP	0.02	0.09	6.30
d_AUD	0.01	0.02	3.08
d_otherCURR	0.05	0.03	-2.10
CALLED (%)	97.42	96.95	-0.96
N	1123.00	795.00	.

Table 9: Descriptive statistics with a distinction between ESG funds and Non-ESG funds

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 5: Statistical Distribution of the Variable Vintage Year

Vintage Year	Non-ESG Funds	ESG Funds	Total
1982	3	6	9
1983	10	6	16
1984	13	9	22
1985	13	6	19
1986	16	8	24
1987	20	12	32
1988	20	13	33
1989	30	12	42
1990	26	20	46
1991	11	15	26
1992	39	16	55
1993	35	28	63
1994	43	31	74
1995	55	29	84
1996	53	30	83
1997	82	50	132
1998	91	67	158
1999	85	65	150
2000	129	66	195
2001	64	45	109
2002	39	40	79
2003	27	43	70
2004	41	38	79
2005	43	47	90
2006	35	32	67
2007	31	25	56
2008	24	16	40
2009	8	3	11
2010	5	4	9
2011	5	4	9
2012	8	4	12
2013	5	1	6
2014	4	1	5
2015	4	2	6
2016	1	1	2
2017	2	0	2
2018	3	0	3
Total	1,123	795	1,918

Table 10:Statistical distribution of the variable Vintage Year with a distinction between ESG funds and Non-ESG funds

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 6: Statistical Distribution of the Variable Fund Number (Overall)

Fund Number (Overall)	Non-ESG Funds	ESG Funds	Total
1	415	204	619
2	258	156	414
3	186	112	298
4	115	78	193
5	63	44	107
6	37	36	73
7	17	26	43
8	9	22	31
9	3	19	22
10	3	10	13
11	1	9	10
12	2	9	11
13	1	8	9
14	1	7	8
15	0	10	10
16	0	7	7
17	0	5	5
18	0	5	5
19	0	4	4
20	1	5	6
21	0	1	1
22	0	1	1
23	0	2	2
24	0	1	1
25	1	2	3
26	1	1	2
27	0	4	4
28	1	1	2
29	0	1	1
30	0	1	1
32	0	1	1
33	1	0	1
34	1	0	1
35	1	1	2
37	1	1	2
38	1	0	1
40	0	1	1
46	1	0	1
47	1	0	1
51	1	0	1
Total	1,123	795	1,918

Table 11: Statistical distribution of the variable Fund Number (Overall) with a distinction between ESG funds and Non-ESG funds

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Results: OLS Regression Analysis

Appendix 7: OLS Regression Table Based on the TVPI

TVPI (X)	(1) Without control variables	(2) 1^{st} variable group	(3) 2^{nd} variable group	(4) 3^{rd} variable group	(5) 4^{th} variable group	(6) 5^{th} variable group	(7) 6^{th} variable group
ESG (1 vs. 0)	0.27***	0.34***	0.17*	0.28***	0.27***	0.25**	0.27**
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.13)	(0.13)
VINTAGE YEAR		-0.07***	-0.06***	-0.07***	-0.07***	-0.07***	-0.08***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FUND SIZE (USD MN)		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FUND SIZE SQUARED		0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
d_GPtopten			-0.50	-0.53	-0.54	-0.46	-0.24
			(0.64)	(0.64)	(0.64)	(0.64)	(0.46)
d_GPsecondgroup			-0.88	-0.94	-0.93	-0.86	-0.66
			(0.62)	(0.63)	(0.63)	(0.63)	(0.43)
d_GPthirdgroup			-0.95	-0.98	-0.98	-0.94	-0.77*
			(0.62)	(0.62)	(0.62)	(0.62)	(0.41)
d_GPfourthgroup			0.31	0.18	0.20	0.19	0.26
			(0.79)	(0.80)	(0.80)	(0.80)	(0.66)
d_GPfifthgroup			-0.34	-0.42	-0.49	-0.42	-0.17
			(0.70)	(0.70)	(0.69)	(0.69)	(0.53)
d_GPsixthgroup			-0.59	-0.69	-0.64	-0.59	-0.42
			(0.74)	(0.73)	(0.75)	(0.77)	(0.64)
d_GPseventhgroup			-1.03*	-1.10*	-1.12*	-1.21*	-0.99**
			(0.62)	(0.63)	(0.63)	(0.63)	(0.44)
d_GPnotrankedone			-1.09*	-1.11*	-1.12*	-1.12*	-0.91**
			(0.60)	(0.60)	(0.61)	(0.61)	(0.41)
d_GPnotrankedtwo			-1.24**	-1.25**	-1.26**	-1.26**	-1.05***
			(0.60)	(0.60)	(0.60)	(0.61)	(0.40)
d_GPnotrankedthree			-1.20**	-1.20**	-1.20**	-1.20**	-1.01**
			(0.60)	(0.61)	(0.61)	(0.61)	(0.40)
FUND NUMBER (SERIES)			0.04	0.05	0.04	0.05	0.06*
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
FUND NUMBER (OVERALL)			0.00	0.00	0.00	0.00	0.01
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
d_classPE				-	-	-	0.28
							(0.41)
d_classVC				0.08	-0.01	-0.07	-
				(0.39)	(0.40)	(0.40)	
d_venture				-0.11	-0.10	-0.06	-0.08
				(0.23)	(0.23)	(0.24)	(0.24)
d_buyout				0.03	-0.01	0.00	-0.24
				(0.34)	(0.34)	(0.35)	(0.36)
d_earlystage (omitted)				-	-	-	-
d_latestage				-0.31	-0.28	-0.35	-0.37
				(0.25)	(0.25)	(0.26)	(0.26)
d_growth				0.42	0.36	0.28	-0.01
				(0.37)	(0.37)	(0.38)	(0.39)
d_balanced				-0.28	-0.33	-0.33	-0.57
				(0.36)	(0.37)	(0.37)	(0.38)
d_fundoffunds				-0.36	-0.39	-0.39	-0.68*
				(0.35)	(0.36)	(0.37)	(0.39)

d_secondaries	-0.38	-0.42	-0.41	-0.63*
	(0.35)	(0.35)	(0.36)	(0.37)
d_others (omitted)	-	-	-	-
d_diversifiedindustries		-0.06	-0.03	-0.02
		(0.26)	(0.27)	(0.26)
d_informationtechnology		0.29	0.31	0.35
		(0.30)	(0.31)	(0.30)
d_healthcare		-0.22	-0.18	-0.14
		(0.30)	(0.31)	(0.30)
d_energyutilities (omitted)		-	-	-
d_telecomsmedia		-0.40	-0.37	-0.36
		(0.29)	(0.30)	(0.29)
d_consumerdiscretionary		0.26	0.27	0.29
		(0.37)	(0.36)	(0.35)
d_industrials		-0.25	-0.22	-0.20
		(0.28)	(0.29)	(0.28)
d_otherindustries		0.10	0.07	0.11
		(0.30)	(0.32)	(0.31)
d_northamerica			0.32	0.38
			(0.51)	(0.49)
d_europe			-0.09	-0.05
			(0.54)	(0.52)
d_asia			-0.06	-0.00
			(0.57)	(0.55)
d_americas (omitted)			-	-
d_australasia			-1.56**	-1.59**
			(0.72)	(0.70)
d_rest			-0.29	-0.28
			(0.64)	(0.62)
d_homenorthamerica			-0.46	-0.50
			(0.33)	(0.34)
d_homeeurope			-0.18	-0.26
			(0.30)	(0.32)
d_homeasia (omitted)			-	-
d_homeaustralasia			0.91*	0.96*
			(0.51)	(0.50)
d_homerest			0.49	0.49
			(0.39)	(0.39)
d_USD			-0.41	-0.36
			(0.36)	(0.35)
d_EUR			-0.17	-0.07
			(0.35)	(0.35)
d_JPY			-0.11	-0.23
			(0.45)	(0.44)
d_GBP			-0.68**	-0.68**
			(0.34)	(0.32)
d_AUD (omitted)			-	-
d_otherCURR			-0.15	-0.10
			(0.32)	(0.31)

CALLED (%)							-0.02***
							(0.01)
Observations	1,918	1,918	1,918	1,918	1,918	1,918	1,918
R-squared	0.00	0.06	0.08	0.09	0.10	0.10	0.12

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

Table 12: OLS regression table with the TVPI as dependant variable
Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 8: OLS Regression Table Based on the Net IRR

NET IRR (%)	(1) Without control variables	(2) 1st variable group	(3) 2nd variable group	(4) 3rd variable group	(5) 4th variable group	(6) 5th variable group	(7) 6th variable group
ESG (1 vs. 0)	4.04***	4.94***	1.67	2.68	2.60	1.02	1.21
	(1.48)	(1.46)	(1.62)	(1.67)	(1.69)	(1.80)	(1.80)
VINTAGE YEAR		-0.51***	-0.40***	-0.47***	-0.49***	-0.59***	-0.66***
		(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)
FUND SIZE (MN USD)		-0.00***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FUND SIZE SQUARED		0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
d_GPtopten			-10.13**	-10.06**	-10.32**	-9.49*	-7.29*
			(5.09)	(5.02)	(5.03)	(4.95)	(3.94)
d_GPsecondgroup			-9.46*	-10.14**	-9.95**	-10.20**	-8.27**
			(5.05)	(4.99)	(4.95)	(4.80)	(3.65)
d_GPthirdgroup			-9.20*	-9.41**	-9.53**	-10.10**	-8.49**
			(4.86)	(4.78)	(4.79)	(4.63)	(3.39)
d_GPfourthgroup			3.38	3.94	3.93	3.03	3.73
			(7.11)	(7.12)	(7.18)	(7.11)	(6.35)
d_GPfifthgroup			0.82	0.07	-1.15	-1.03	1.47
			(8.73)	(8.53)	(8.26)	(8.16)	(7.66)
d_GPsixthgroup			-10.65**	-11.79**	-11.18**	-12.91***	-11.30***
			(4.97)	(4.93)	(4.97)	(4.90)	(3.75)
d_GPseventhgroup			-15.39***	-16.64***	-17.20***	-20.40***	-18.28***
			(5.17)	(5.22)	(5.24)	(5.66)	(4.81)
d_GPnotrankedone			-15.67***	-14.84***	-15.04***	-16.91***	-14.84***
			(4.47)	(4.45)	(4.48)	(4.43)	(3.23)
d_GPnotrankedtwo			-16.59***	-15.73***	-15.77***	-17.57***	-15.55***
			(4.45)	(4.48)	(4.49)	(4.28)	(3.01)
d_GPnotrankedthree			-18.64***	-18.14***	-18.05***	-20.09***	-18.20***
			(4.35)	(4.39)	(4.43)	(4.36)	(3.07)
FUND NUMBER (SERIES)			-0.10	0.07	0.00	0.19	0.24
			(0.52)	(0.51)	(0.50)	(0.51)	(0.50)
FUND NUMBER (OVERALL)			0.17	0.16	0.19	0.04	0.08
			(0.16)	(0.15)	(0.15)	(0.17)	(0.17)
d_classPE				-	-	-	17.03***
							(6.38)
d_classVC				-10.75*	-14.35**	-14.94**	-
				(5.92)	(6.15)	(6.17)	
d_venture				8.83***	9.48***	10.64***	10.47***
				(3.23)	(3.24)	(3.35)	(3.35)
d_buyout				-2.75	-3.64	-3.26	-5.63
				(5.67)	(5.60)	(5.57)	(5.79)
d_earlystage (omitted)				-	-	-	-
d_latestage				5.92	6.96*	6.25	6.02
				(4.27)	(4.21)	(4.50)	(4.52)
d_growth				3.23	1.92	0.19	-2.67
				(6.45)	(6.34)	(6.95)	(7.27)
d_balanced				-7.00	-8.10	-7.41	-9.74
				(6.06)	(6.02)	(6.03)	(6.26)
d_fundoffunds				-10.98*	-12.28**	-9.87*	-12.67**
				(5.70)	(5.68)	(5.70)	(6.02)
d_secondaries				-1.90	-3.14	-1.24	-3.38
				(5.91)	(5.88)	(5.85)	(6.07)
d_others (omitted)				-	-	-	-

d_diversifiedindustries					-2.86	0.69	0.79
					(8.11)	(8.35)	(8.26)
d_informationtechnology					4.86	9.22	9.58
					(8.48)	(8.98)	(8.90)
d_healthcare					-3.42	1.16	1.48
					(8.53)	(8.86)	(8.77)
d_energyutilities (omitted)					-	-	-
d_telecomsmedia					-4.75	-0.00	0.10
					(8.84)	(9.16)	(9.06)
d_consumerdiscretionary					-0.53	2.95	3.19
					(8.76)	(8.97)	(8.89)
d_industrials					-7.56	-3.86	-3.68
					(8.40)	(8.54)	(8.45)
d_otherindustries					-1.34	2.13	2.52
					(8.56)	(8.85)	(8.79)
d_northamerica						17.09**	17.64**
						(7.85)	(7.79)
d_europe						9.54	9.96
						(8.36)	(8.32)
d_asia						10.71	11.27
						(7.90)	(7.88)
d_americas (omitted)						-	-
d_australasia						-27.65***	-27.93***
						(10.43)	(10.35)
d_rest						3.47	3.61
						(6.37)	(6.34)
d_homenorthamerica						-11.30**	-11.66**
						(5.16)	(5.21)
d_homeeurope						-7.20	-8.01
						(5.26)	(5.31)
d_homeasia (omitted)						-	-
d_homeaustralasia						15.35**	15.86**
						(7.27)	(7.30)
d_homerest						1.54	1.49
						(7.46)	(7.51)
d_USD						-25.83***	-25.35***
						(8.50)	(8.36)
d_EUR						-16.44**	-15.41**
						(7.65)	(7.48)
d_JPY						-20.81	-21.98
						(13.69)	(13.75)
d_GBP						-23.32***	-23.30***
						(7.70)	(7.51)
d_AUD (omitted)						-	-
d_otherCURR						-10.12*	-9.58*
						(5.76)	(5.57)
CALLED (%)							-0.20**
							(0.09)
Observations	1,918	1,918	1,918	1,918	1,918	1,918	1,918
R-squared	0.00	0.02	0.04	0.05	0.06	0.07	0.08

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

Table 13: OLS regression table with the Net IRR as dependant variable
Source: This table is based on author's calculations run in Stata using data from Preqin Pro
(data was retrieved on 18.05.2021).

Results: Propensity Score Matching

Appendix 9: PSM Regression Table Based on the TVPI (ATE, NN = 1)

TVPI (X) ATE, NN = 1	(1) 1st variable group	(2) 2nd variable group	(3) 3rd variable group	(4) 4th variable group	(5) 5th variable group	(6) 6th variable group
ESG (1 vs. 0)	0.34**	0.14	0.30**	0.39***	0.04	0.06
	(0.14)	(0.11)	(0.12)	(0.13)	(0.14)	(0.14)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 14: PSM regression table with the TVPI as dependant variable (ATE, NN = 1)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 10: PSM Regression Table Based on the TVPI (ATE, NN = 5)

TVPI (X) ATE, NN = 5	(1) 1st variable group	(2) 2nd variable group	(3) 3rd variable group	(4) 4th variable group	(5) 5th variable group	(6) 6th variable group
ESG (1 vs. 0)	0.37***	0.10	0.19*	0.17	0.04	0.08
	(0.11)	(0.08)	(0.11)	(0.10)	(0.13)	(0.15)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 15: PSM regression table with the TVPI as dependant variable (ATE, NN = 5)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 11: PSM Regression Table Based on the TVPI (ATET, NN = 1)

TVPI (X) ATET, NN = 1	(1) 1st variable group	(2) 2nd variable group	(3) 3rd variable group	(4) 4th variable group	(5) 5th variable group	(6) 6th variable group
ESG (1 vs. 0)	0.43***	0.07	0.26**	0.21	0.19	0.17
	(0.12)	(0.15)	(0.11)	(0.15)	(0.13)	(0.15)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 16: PSM regression table with the TVPI as dependant variable (ATET, NN = 1)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 12: PSM Regression Table Based on the TVPI (ATET, NN = 5)

TVPI (X) ATET, NN = 5	(1) 1st variable group	(2) 2nd variable group	(3) 3rd variable group	(4) 4th variable group	(5) 5th variable group	(6) 6th variable group
ESG (1 vs. 0)	0.33***	0.12	0.10	0.09	0.05	0.07
	(0.10)	(0.11)	(0.14)	(0.16)	(0.19)	(0.19)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 17: PSM regression table with the TVPI as dependant variable (ATET, NN = 5)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 13: PSM Regression Table Based on the Net IRR (ATE, NN = 1)

NET IRR (%)	(1)	(2)	(3)	(4)	(5)	(6)
ATE, NN = 1	1st variable group	2nd variable group	3rd variable group	4th variable group	5th variable group	6th variable group
ESG (1 vs. 0)	4.28**	0.61	1.58	3.96**	-0.54	-0.85
	(1.76)	(1.81)	(2.40)	(1.72)	(2.95)	(4.40)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 18: PSM regression table with the Net IRR as dependant variable (ATE, NN = 1)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 14: PSM Regression Table Based on the Net IRR (ATE, NN = 5)

NET IRR (%)	(1)	(2)	(3)	(4)	(5)	(6)
ATE, NN = 5	1st variable group	2nd variable group	3rd variable group	4th variable group	5th variable group	6th variable group
ESG (1 vs. 0)	4.75***	0.06	0.84	2.14	-1.42	-0.33
	(1.50)	(1.57)	(1.63)	(1.51)	(2.02)	(2.32)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 19: PSM regression table with the Net IRR as dependant variable (ATE, NN = 5)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 15: PSM Regression Table Based on the Net IRR (ATET, NN = 1)

NET IRR (%)	(1)	(2)	(3)	(4)	(5)	(6)
ATET, NN = 1	1st variable group	2nd variable group	3rd variable group	4th variable group	5th variable group	6th variable group
ESG (1 vs. 0)	5.71***	-0.71	-2.81	0.39	-2.72	-2.82
	(2.10)	(2.42)	(3.00)	(1.96)	(2.51)	(3.51)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 20: PSM regression table with the Net IRR as dependant variable (ATET, NN = 1)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

Appendix 16: PSM Regression Table Based on the Net IRR (ATET, NN = 5)

NET IRR (%)	(1)	(2)	(3)	(4)	(5)	(6)
ATET, NN = 5	1st variable group	2nd variable group	3rd variable group	4th variable group	5th variable group	6th variable group
ESG (1 vs. 0)	4.85***	-0.82	-1.09	0.93	-4.44	-3.78
	(1.48)	(1.91)	(1.09)	(1.55)	(3.86)	(3.89)
Observations	1,918	1,918	1,918	1,918	1,918	1,918

Standard errors in parentheses

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

Table 21: PSM regression table with the Net IRR as dependant variable (ATET, NN = 5)

Source: This table is based on author's calculations run in Stata using data from Preqin Pro (data was retrieved on 18.05.2021).

EXECUTIVE SUMMARY

Sustainable development and environmental, social and governance (ESG) factors are playing an increasingly important role both in the corporate sector and in the investment industry. Based on the existing literature, it can be stated that the consideration of ESG factors is expected by various stakeholders, such as consumers, investors, workers, regulators, the media, etc. In addition, this tendency is further encouraged by an increasing number of regulations, initiatives and standards.

With regard to the investment industry, various ways exist to integrate sustainability and ESG factors into the investment process. The potential of private equity funds in this context is very large due to the characteristics of this asset class. However, the question that might interest many of its institutional investors is whether these strategies lead to good financial performance in addition to their contribution to sustainable development.

Therefore, this master thesis aims at answering the question of whether or not the ESG orientation of private equity funds can lead to a better performance. To answer this question, a data set consisting of 1,918 liquidated private equity funds is used, of which 795 are ESG-oriented. Three methods are used to investigate the effect of an ESG orientation on two different performance measures (TVPI, net IRR). The first method is based on a simple OLS regression analysis. Due to the selection bias in this first method, a multiple OLS regression analysis is applied in a second step. Thereby, the fund characteristics, also impacting the performance of private equity funds, are integrated as control variables. However, due to the limitations of the OLS regression models, propensity score matching (PSM) is applied as a third method. Based on the formed matches, the average effect of an ESG orientation is then estimated. However, on the basis of the different methodologies and performance measures, different results can be found. The result that is considered as being the most reliable, suggests that the ESG orientation of private equity funds has a positive but not significant impact on performance.

Keywords: ESG Factors, Private Equity Performance, Propensity Score Matching, OLS Regression Analysis