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How Sustainable Is Private Equity? Unlocking the Impact of Private Equity on Asset-Level Sustainability: An Empirical Investigation

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Abstract

The debate over the broader impact of the private equity industry has been a contentious topic in the academic literature. While recently, private equity investors have endorsed sustainability in their investment strategies, little is known whether the industry promotes sustainable transformation. This research uses data from the U.S. Environmental Protection Agency on the emission and handling of toxic chemicals in U.S. factories from 1991 to 2021 as a proxy for facility sustainability. The study reveals that, compared to the overall peer group facilities involved in a private equity takeover reduce pollution by 1.55 %-points less and reduce production waste by 1.1 %-points more in the two years after takeover. Further analysis indicates, that with a higher environmental hazard of the underlying chemicals, both the increase in pollution and the decrease in production waste become more pronounced. The study reveals that private equity ownership does not result in enhanced ecological sustainability. Further, the concurrence of the found trends with generally rising costs of both pollution control and raw materials of higher hazards suggest that the private equity business model is only effective in achieving sustainability goals if those are well aligned with financial objectives.

Keywords: impact of private equity; private equity; SRI; sustainability; sustainable finance

1. Introduction

The following chapter first gives an overview of the topic and the motivation for its selection is provided. Then, the significance of the topic to the scientific community is highlighted and a clear objective for the thesis is formulated. Lastly, a brief outline of the thesis is presented, laying out the structure of the upcoming chapters.

1.1. Background and motivation

At the forefront of modern finance, Modern Portfolio Theory[1] has evolved from a purely financial optimization framework to a comprehensive approach that integrates considering environmental, social and governance (ESG) factors into investment decisions, recognizing the importance of investing for both financial and non-financial outcomes. Sustainability goals such as the United Nations Sustainable Development Goals (SDGs) have created significant public and political pressure on the financial industry to steer investment flows towards projects that promote a sustainable future.[2] The ensuant behavior spurred the development of Socially

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[1] For the evolution of Modern Portfolio Theory see Elton and Gruber (1997, pp. 1750–1758).

[2] See United Nations (2023); A comprehensive synopsis of the Sustainable Development Goals (SDGs), which commonly serve as the basis for many investors' ESG strategies, can be found on the official United Nations website.

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Responsible Investment (SRI), an investment methodology that assimilates social, environmental and governance considerations to the process of making investment decisions.[3] As for the public capital market, economic uncertainty and financial crises are leading individual and institutional investors to express a preference for companies with better ESG ratings.[4] Not least, ESG has also permeated the private markets, and private equity (PE) market participants have begun to incorporate ESG concerns into their investment strategies and are playing an increasingly significant role in the socially responsible investing space.[5] The private equity industry has a unique opportunity to foster transformation of portfolio companies yet an unambiguous perception whether it has capitalized on this potential remains elusive.[6] A frequent challenge for research on this topic is the dearth of available data from private companies immanent due to their private status. Additionally, readily available data on ESG performance is often not useful for academic research. For example, ESG ratings have been identified as highly biased metrics that do not provide a true picture of a company's true impact on its environing economy.[7] The general data scarcity problem results in academic research often limiting the research to special cases, such as public to private deals or reverse buyouts where the data situation is more affluent. However, it has been demonstrated that such narrow analyses faintly generalize to the entire population of PE deals.[8]

Recently, academia has taken an interest in publicly available pollution data from the United States Environmental Protection Agency (EPA) to examine the impact of private equity ownership on environmental pollution. Emanating evidence provides mixed results regarding the impact of private equity ownership on pollution. Most notably, Abraham et al. (2022) find that average pollution is generally reduced after private equity takeover but is already lower before takeover when the PE investor advocates ESG on its website.[9] Findings from Bellon (2020) infer that a positive effect on environmental impact is the case only in the presence of significant liability risks.[10] On the other hand, Shive and Forster (2020) found that private equity is associated with no effect on greenhouse gas releases when controlling for industry, time and location of the portfolio firms, respectively.[11] In light of this uncertainty, this thesis is motivated by the critical value a thorough understanding of the broader economic implications of the private equity business model has. The findings are critical for both the scientific community and policymakers, as well as for targeting in environmental decision-making and the efforts of environmentalists.

To build on the existing findings and to clarify uncertainties within this empirical domain, this study examines the impact of private equity acquisitions on the sustainability of target firms at the asset level. Subsequently, the motivated research question that this thesis aims to address is: *Does PE-takeover lead to an improved level of environmental pollution management in target companies at the facility-level?*

1.2. Relevance of the research within this work

This thesis contributes to the existing body of literature by exploring a relatively new area of environmental impact assessment, that uses raw granular data about industrial processes of facilities and chemical properties of pollutants to link private equity ownership and environmental outcomes. To operationalize the ESG performance of PE-backed assets, a metric using changes in the amount of toxic chemicals as a proxy for asset-level environmental sustainability is drawn from the data of the Toxics Release Inventory (TRI) of the EPA. Prior studies utilizing the TRI have mainly considered pollution quantities without exploiting the granularity of the TRI's environmental impact measurements as it has been done for other areas of economic research.[12] By proceeding with the toxicological data of the chemicals associated with these pollutions the environmental ramifications of a pollution can be derived. The toxicological study of the nature and quantity of pollution emanating from a PE-backed asset thus allows an unequivocal indication of its environmental impact, yet has not been involved in the research of the impact of private equity.

Conclusively, this unveils a clear gap in the current research on the matter of asset-level sustainability within the private equity asset class that this thesis tries to fill from a toxicological point of view.

1.3. Outline of the thesis

The remainder of this thesis is organized as follows: Chapter 2 presents a review of recent literature on ESG and its adoption in the private equity industry. This is followed by a summary of current research that links the business of private equity to the environmental impacts of portfolio companies. The chapter concludes with the development of hypotheses upon which the research in this thesis is presumed. The third section describes the data sources for the research and the methods used. The fourth section examines the results of the empirical analysis, while the fifth section provides a detailed discussion of the results and the limitations of the study. In addition, this last section provides recommendations for further research on the topic.

For this study, it is important to discriminate between the terms ESG and CSR, as they are not used interchangeably. Specifically, ESG pertains to environmental, social and governance issues, which encompass a broad range of social and economic topics. In contrast, CSR specifically refers to a company's actions with respect to ESG issues, which are usually

[3] See Renneboog et al. (2008, p. 1724).
[4] See Bauer et al. (2021, p. 3977).
[5] See Zaccone and Pedrini (2020, p. 5727).
[6] See Crifo and Forget (2013, pp. 22–23).
[7] See Berg et al. (2022, p. 1316).
[8] See Cohn et al. (2014, pp. 469–490).
[9] See Abraham et al. (2022, p. 29).
[10] See Bellon (2020, pp. 28–29).
[11] See Shive and Forster (2020, p. 1315).
[12] See for example Mastromonaco (2015, pp. 54–55) or Bradley C. Karkkainen (2019, p. 116).

(but not necessarily) hardly quantifiable in financial terms.[13] In essence, the degree to which a company considers ESG issues in its strategic decision-making process can determine its level of CSR. Likewise, an investor's approach to integrating environmental, social and governance considerations into his investment framework defines his strategy as socially responsible investment (SRI).[14]

2. Literature review

A growing body of literature comprises the adoption of ESG in finance and private equity. The following sections provide an overview of the topics underlying this research and introduce the context of the subsequent empirical analysis. First, a discussion on the comprehension of ESG in Finance and private equity is given. Then, recent literature on the broader consequence of PE on the economy is reviewed and lastly the hypotheses are elaborated.

2.1. Risk, value and business opportunity: ESG in finance

Environmental, social and governance, short ESG, factors have gained unprecedented importance in today's business landscape and are more salient than ever in investors' decision-making. Within this connotation, the environmental (E) pillar is concerned with mitigating climate change, reducing pollution, and preserving the natural world.[15] The social (S) pillar refers to social equality, human rights protection, and advocating for consumer rights[16] and the governance (G) pillar addresses corporate governance, tax issues, employee rights, and the promotion of fair compensation. Although non-financial in the nature of its objective, ESG may have direct financial implications. For example, regarding the governance component, empirical evidence suggests that employee representation on supervisory boards has a positive impact on firm efficiency and market valuation.[17] The bundle of ESG criteria incorporated as non-financial objectives into strategic considerations determines the aim of the corporate social responsibility, short CSR of a company. Conclusively, actively allocating capital towards firms with *high* CSR qualifies an investment as socially responsible investment, short SRI, which prioritizes social and environmental outcomes alongside financial returns.

In practice, ESG comprises factors that pose potential risks present within an economy (e.g., the risk of rising sea levels due to climate change), where the risks are innately distributed unevenly across market agents in the economy (e.g., a company located on the coast is at much risk due to rising sea levels). Yet the materialization of these risks must be assumed to be transmittable upon economic interaction of the market agents (e.g., the coastal company may be a supplier to companies located inland), to an unknown degree (e.g., the coastal company supplies a special good which might not be easily substituted). In this notion, a firm maximizing its own shareholder value, can decide, whether to consider only business risks that directly jeopardize the company's business model or also to reduce uncertain risks associated with the company's operations. Following the distinction of Knight (1921), ESG at the market agent level thus reflects a confrontation with risks (i.e., the direct ESG risks) and uncertainties (i.e., the uncertain ESG-risks).[18] A CSR strategy, as a risk management strategy that embodies stewardship in addressing both risks and uncertainties, aims to implement operational measures that not only address immediate risk factors for the company, but also mitigate risk factors for other stakeholders. Due to the antiegalitarian distribution of direct ESG risks, a firm executing a such a strategy will generate non-financial utility that benefit the other stakeholders in managing their direct risks. By implementing CSR strategies, organizations can proactively manage their resilience not only to known risks, but also to unknown uncertainties whose occurrence, timing, and impact are unclear but known to exist.[19] As such, ESG considerations can be regarded as an economic solution to internalize the risks of other stakeholders in order to maximize long-term shareholder value. Thus, the implementation of CSR can be viewed as a Coasian solution to problems associated with social costs, that relies on the principle of internalizing externalities.[20] This is critical in developing an effective CSR strategy for companies, as the costs determine the extent to which the strategy can be implemented.

Likewise for an investor, developing an SRI strategy translates to the question of whether to base investment decisions solely on the idiosyncratic risk-return characteristics of potential investments or to tolerate suboptimal financial performance in order to align with his philosophy of impact related to social responsibility.[21] This requires determining his own willingness-to-pay for the implementation of sustainability in the portfolio; if non-financial utility is to be derived from investing in socially responsible companies, then inferior financial performance to non-SRI investments will be accepted. In cases of refractory underperformance, such investors may consider whether adhering to Friedman, who argued that socially responsible investing is less efficient than investing in better performing conventional funds and using some of the returns to support personal beliefs through charitable giving, represents a more efficient way to achieve positive social impact.[22] This trade-off is especially pertinent in the light of numerous examples where SRI funds underperform ethical

[13] See Gillan et al. (2021, p. 101889) for a detailed elaboration of the terminology.
[14] See Renneboog et al. (2008, p. 1724).
[15] See Goodland (1995, pp. 2–8).
[16] See Littig and Griessler (2005, p. 65).
[17] See Fauver and Fuerst (2006, p. 677).
[18] See Jochen Runde (1998, pp. 539–546); For the original discussion on the meaning of risk and uncertainty see Knight (1921).
[19] See Galbreath (2009, pp. 120–122) for an investigation of strategical objectives of CSR strategies.
[20] See Heal (2005, pp. 387–409) for the application of the Coase theorem on CSR in finance.
[21] See Renneboog et al. (2008, p. 1723).
[22] See Friedman (2007, pp. 173–178); The so called Friedman Doctrine is a common objection to the recent trend of CSR. The approach has created

agnostic funds on a risk adjusted basis but at the same time attract greater capital inflows than traditional funds, resulting in increased profits for the fund manager.[23] Here, limited partners of an investment model also face increased agency costs, since the naturally highly heterogeneous objectives of SRI destabilize a fund managers' obligation to pursue high risk adjusted returns.[24] Hence, for an investor embracing SRI, substantial information about the CSR of a company is essential to mitigate information asymmetry and assess the SRI potential. This is especially crucial, since the quality of CSR is not easily observable and investors can be taken for a ride by managers who endorse responsible investment to pander to investor preferences. The relevance of proper information about sustainability aspects of investees has led to the development of various frameworks aimed at promoting sustainable finance. Alongside the United Nations' Sustainable Development Goals, the European Union's Sustainable Finance Disclosure Regulation (SFDR) is a prominent example of such a framework, designed to increase transparency and standardization of ESG reporting requirements for financial market participants.[25] Similarly, initiatives such as the UN Principles for Responsible Investment (PRI) are driving the creation of new guidelines and values for sustainable investing globally.[26]

The increasing market demand for ESG data is frequently supplied with ESG ratings, which aim at providing investment professionals with ESG data and typically focus on relative performance, providing a broad view of the market with comparisons across industries, peers, and companies. Yet Berg et al. (2022) find a questionable correlation between rating methodologies from different ESG-data vendors that was as low as 0.38. According to their research, ratings diverge due to three aspects: scope divergence, which can be seen as a selection bias in the type of data used for the rating; measurement divergence, where indicators are measured differently (i.e., a subjective application of different scientific methodologies); and finally weight divergences, where emphasis is placed on different issues to assess CSR (i.e. the preferential selection of certain ESG factors over others).[27] Overall, this emphasizes the importance of granular, objective data, obtained through reliable methods when assessing a company's interaction with the environment and society.

To summarize, the internalization of social costs associated with externalities related to ESG factors as well as investors' willingness-to-pay for non-financial utility effectively implement sustainability in economy. However, both fail when stakeholders have diverging perceptions of what constitutes ESG. This underscores the imperative of a collective *theory of impact*, in which all stakeholders in an economy are committed to conjointly pursuing non-financial goals.[28]

2.2. The role of ESG in the private equity industry

With the surge of SRI as investment theme in the last decade, limited partners of private equity firms adopted significant non-financial objectives, that the private equity general partner must deliver with its investment case. As a result, general partners are under increasing pressure from limited partners to allocate funds to projects that meet environmental, social and governance (ESG) objectives.[29] An increasing number of private equity firms have thus expanded their corporate missions to engaging all key stakeholders as response to the heightened focus on topics such as climate change, social issues or technology disruption. During the latest renaissance of private equity, proficient management of ESG risks and the pursuit of ESG as a value opportunity have emerged as a singular investment theme utilized by GPs to uncover novel value drivers.[30]

According to Crifo and Forget (2013), SRI renders two main approaches for private equity firms.[31] First, similar to impact investing strategies in the public capital market, private equity investors can use ESG criteria as a risk screening tool, either negatively to exclude companies, particularly in certain industry sectors for ethical or moral reasons, or positively, to actively seek out specific investment opportunities that align with their ESG principles. Indeed, many private equity investors have been using environmental, social, and governance metrics primarily as a risk management tool, with ESG issues integrated mostly as incumbent risk factors – in a 2020 survey, only 40 % of private equity managers consider ESG as a value opportunity.[32] The second approach private equity investors take to SRI according to Crifo and Forget (2013) is an engagement approach. Other than atomistic public financial market participants, PE has the potential to actively promote objectives such as CSR in a portfolio company. By virtue of their controlling stake in the company, PE investors can disrupt managerial entrenchment and thereby mitigate the tendency to maximize short-term value at the expense of long-term value.[33] As elaborated in the previous chapter, long-term financial value demands preparing for ESG-factors. Thus, PE firms will entail ESG considerations because the private equity business model itself fosters CSR as a side product by linking incentives to the long-term profitability (i.e., considering ESG-risks *and* uncertainties) of the firm.[34] In that sense, the shareholder centric rationale of private equity aligns SRI in the pursuit of the maximization of a

an increasing market for charitable giving, where companies offset the environmental damage of their operations by donating a part of their profits, for example with voluntary carbon offset certificates. This is not to be confused with the market for externalities due to Pigouvian taxes such as pollution permits.

[23] See Liang et al. (2022, pp. 1585–1590)

[24] See Renneboog et al. (2008, pp. 1724–1725).

[25] See EUROSIF (2019).

[26] See UN PRI (2019).

[27] See Berg et al. (2022, pp. 1316–1317).

[28] This highlights the importance of well-defined sustainability objectives to work in an economy, such as the science-based targets, COP15 or the Paris Climate Agreement.

[29] See Bian et al. (2022, pp. 3–5).

[30] See Indahl and Jacobsen (2019, pp. 34–36).

[31] See Crifo and Forget (2013, pp. 22–23).

[32] See Zaccone and Pedrini (2020, p. 5730).

[33] See Shleifer and Vishny (1986, pp. 463–472).

[34] See Sørensen and Yasuda (2022, pp. 16–17).

single objective where the internalization of social costs can be assumed to be compensated by the reduction of agency costs manifested in efficiency gains. It is interesting to contend that, along these lines, stricter ESG regulations, which append higher external costs to social and environmental factors, can be expected to act as Pigouvian taxes that further tighten the alignment of SRI goals with the financial objective of the private equity management model.

The adoption of ESG as value creation opportunity requires the general partners to evaluate an additional set of non-financial data to measure their progress toward SRI goals. This necessitates a shift in the governance model private equity firms apply to their portfolio companies, from traditional financial metrics towards soft information about CSR. The existing ambiguity in ESG data as well as the lack of clear standards can be a significant barrier to pursuing SRI strategies.[35] Essentially, the issue centers on the measurement of the externalities produced by portfolio companies and the allocation of those externalities at the fund level.

2.3. The impact of private equity

A private equity firm is typically structured as a partnership in which general partners, on behalf of limited partners, control and actively monitor the board of directors of their portfolio companies. With that, the private equity firm acts as an intermediary between a large, mostly institutional investor base and the private market, thereby occupying a pivotal role in the financing of unlisted, mostly small to medium-sized companies.[36] These companies require significant capital investment to implement ESG considerations operationally, and their inherent risks and information asymmetries make traditional credit funding difficult to obtain.[37] Even in the presence of legal and regulatory frameworks that mandates a firm to internalize a considerable portion of the social costs linked to ESG factors, the expenses associated with environmental protection and social responsibility can elicit insurmountable illiquidity barriers for private companies. Private equity-backed firms are less constrained financially, in principle enabling them to invest more freely in abatement technologies. Consequently, it is argued that such firms exhibit stronger incentives than other privately held firms to reduce pollution levels when facing increased ESG risks. As such, the PE business models is considered as crucial to facilitating the transition to a more sustainable economy.

However, the empirical evidence whether private equity generates non-financial for the broader economy is inconclusive, as prior research has yielded conflicting findings. While at the time of the first private equity boom, Shleifer and Summers (1988) argued that buyouts create shareholder value at the expense of other stakeholders of the firm,[38] this cannot be directly inferred from current research. However, one conjecture from the extant literature is that for the impact on employer welfare pre-deal ownership status plays a crucial role. Workers in private-to-private targets face increased employment due to transferable skillset growth in addition to a better wage growth in the long run,[39] whereas in public-to-private targets, workers performing automatable tasks face a higher risk of unemployment,[40] with older male workers being significantly worse off than their younger counterparts.[41] Also, research has provided evidence of private equity takeovers leading to a reduction of work hazards for employees, thus contributing to improving the governance pillar of ESG by increasing workplace safety.[42] Lastly, for the government, the immanent debt structure of leveraged buyouts in private equity transactions creates negative spillover effects due to interest tax shields,[43] although evidence suggests that targets typically already have high levels of leverage at the time of a buyout, and increases in debt associated with the buyout only tend to be marginally relevant.[44]

In addition, the impact of private equity on the ESG performance of a portfolio company has been shown to be conditional on the industry of the portfolio company and the regulatory regimes under which the business operates. Examples for the positive asset-level effects of private equity takeover can be found in the food industry for example, where private equity buyouts have been shown to improve the quality of customer service and experience. Restaurants are reported to be better maintained after private equity takeover, especially when the private equity GPs have prior industry experience.[45] On the contrary, private equity ownership has been shown to be detrimental to consumers in sectors where intensive government subsidy and economic moats of incumbents can lead to financial incentives being misaligned with the social utility of the business. This is evidenced in the healthcare industry where the impact of private equity ownership results in negative consequences for other stakeholders, particularly in terms of social factors such as affordable, high-quality health care.[46] A recurring observation in the literature is that the impact of private equity on the wider economy and the environment depends on the regulatory and market framework in which private equity portfolio companies operate. Accordingly, in competitive industries where incentives are aligned between stakeholders, private equity buyouts of companies create value for both consumers of the company and its shareholders. Conversely, in more concentrated industries and those reliant on government as a customer base, private equity ownership often leads to the pursuit of profit maximization at the expense of other stakeholders. This di-

[35] See Eccles et al. (2017, pp. 128–132).
[36] See Kaplan and Strömberg (2009, pp. 122–124).
[37] See Kim and Xu (2022, pp. 576–578).
[38] See Shleifer and Summers (1988, pp. 33–68).
[39] See Agrawal and Tambe (2016, pp. 2455–2460).
[40] See Olsson and Tåg (2017, pp. 697–702).
[41] See Antoni et al. (2019, pp. 634–657).
[42] See Cohn et al. (2021, p. 4835).
[43] See Kaplan (1989, pp. 611–623).
[44] See Cohn et al. (2022, p. 284).
[45] See Bernstein and Sheen (2016, p. 2388).
[46] See Atul Gupta et al. (2021, pp. 2–3).

vergence in incentives between investors and consumers can have long-term negative effects on the society, as evidenced by the impact of PE ownership in higher education, where private equity takeovers resulted in a decline of the quality of education while tuition fees increased.[47] As such, it is critical for policymakers to gain a deep understanding of the inherent structures of the private equity model in order to align the outcomes of the business model with desired societal and environmental objectives. Conversely, the presence of misalignments in this investor model tends to be magnified by the incentive power of the private equity management model to maximize financial objectives.[48]

Generally, discerning the impact of PE firms on asset-level operations is difficult, primarily due to the private status of PE-backed companies, which exempts them from mandatory disclosure of financial and non-financial information. In that light, disclosure laws, which are designed to provide the public with information that is not typically included in the normal exchange of goods and services are valuable sources of unbiased information on private companies. These laws, in the US often referred to as "right-to-know" laws, have been deemed necessary in various sectors of the economy. As for the scientific community, right-to-know laws are thus crucial for conducting research. The Toxic Release Inventory from the US Environmental Protection Agency provides such a data source and is one of the most extensive longitudinal data series on facility environmental performance in the United States. EPA's TRI data, with its comprehensive coverage and facility-level information dating back to 1988, offers a valuable tool for examining the connection between economic activities and their environmental impact. A detailed elaboration of the scope and limitations of the TRI database can be found in chapter 3.1 of this work.

2.4. Hypotheses development

As explained above, based on the shareholder theory, ESG considerations are a valuable resource that private equity managers are incentivized to exploit. The conjecture in this thesis is that after a private equity takeover, regardless of the type of deal, the private equity management will seek to identify and address inefficiencies that generate negative externalities in order to curtail the internalized social costs of the asset. In the pollution data captured by the EPA, this should manifest as a discernible decline in the amount of pollution released commencing from the year of the deal.

The observable outcome as lower pollution has been researched by Shive and Forster (2020), in the context of greenhouse gas emissions of US facilities. They find that independent private facilities have lower greenhouse gas emissions than public firms and that this is possibly a result of concentrated ownership. In their research the private equity ownership, in contrast to the private independent ownership, does not result in lower emissions.[49] A more detailed view was taken by Bellon (2020) in the context of the oil and gas industry, who finds that location-specific environmental liability risk is a key driver of differences in the impact of PE ownership on pollution abatement at PE-owned facilities. The absence of such risks results in private equity negatively influencing pollution at the target facility level (inferring that private equity fails to internalize social costs and liability risks and Pigouvian taxes are required to correct the market failure).[50] An industry-agnostic view is taken by Abraham et al. (2022), who use a staggered difference-in-differences design to find that pollution reduction is less likely for portfolio companies of private equity firms with high ESG disclosure than it is for private equity firms with low or no ESG disclosure. In their study, this is due to the fact that such PE firms select already clean firms in the investment process.[51]

To further this research, the question arises as to whether the reduction in pollution following the acquisition by a private equity firm is a) generally an effect of private equity takeover or only present in certain industries and b) significantly increased at PE owned facilities in an all-else-equal scenario. The corresponding null hypothesis is, that the reduced pollution is a reflection of the baseline decline in pollution among TRI facilities over time. Hence, based on the internalization of social costs in a shareholder value theory and in accordance with the previous literature findings, the following statement is hypothesized:

> *Hypothesis 1a: Private equity takeover leads to a decrease in pollution post deal year*

As mentioned above, CSR can include the consideration of both imminent ESG-related risks and uncertainties related to ESG factors. This is particularly relevant for private equity investors who seek to maximize long-term value over short-term gains. To mitigate such risks, private equity management aims to minimize the potential impact of known potentialities for the occurrence of unknown social costs (i.e., "known unknowns"). Given that the amount of hazardous substance handled at a facility is a significant source of environmental pollution, a private equity acquisition should result in a reduction in the amount of hazardous waste generated by the facility. Thus, the following hypothesis is constituted:

> *Hypothesis 1b: Private equity takeover leads to a decrease in production waste post deal year*

Private equity firms can leverage their expertise and overcome information asymmetries to gain a comprehensive understanding of the assets they acquire. With this knowledge,

[47] See Eaton et al. (2020, pp. 4032–4035).
[48] See Sørensen and Yasuda (2022, p. 41).
[49] See Shive and Forster (2020, pp. 1296–1330); Alternatively to the TRI database, EPA's Greenhouse Gas Reporting Program (GHGRP) has captured CO2-emission equivalents since 2010 and was used in their study.
[50] See Bellon (2020, pp. 28–29).
[51] See Abraham et al. (2022, p. 29).

they can identify and mitigate risks and implement measures to address potentially costly issues. As a result, there should be a discernible divergence between pollution associated with highly hazardous substances and those with minimal environmental or social impact. Along these lines, the following hypothesis is constituted:

> *Hypothesis 2a: Private equity ownership results in a greater reduction of highly dangerous pollution compared to less dangerous pollution.*

Similarly, the assessment of materialization risks related to unknown social costs should result in a discernible difference in the amount of production-related waste generated by highly hazardous versus less hazardous substances, resulting in a reduced environmental hazard from the asset. Hence, the following hypothesis is constituted:

> *Hypothesis 2b: Private equity ownership results in a greater reduction of highly dangerous production waste compared to less dangerous production waste.*

3. Methodology

The following section details the methodology used in this thesis. First, the chapter highlights the data sources used to compile the necessary data to construct the sample. Next, the variables of interest and control variables used in the analysis are outlined. Finally, this section elaborates on the empirical models and examines the methods applied in the analysis.

3.1. Data collection and sample reparation

A database of PE transaction data, facility-specific data, and data on environmental pollution is needed to analyse whether the acquisition of a facility's parent company results in a change in its environmental impact. This subsection first explains the deal data source and the resources used to obtain the environmental pollution data. Finally, the procedure used to assemble the final data sample is presented.

3.1.1. Deal data source

The sample of private equity owned firms is drawn from Preqin's Private Equity Database. The Preqin Private Equity Database contains information on PE firms, their funds, portfolio companies linked to the funds and relevant fund performance metrics such as deal date, financial performance indicators, fundraising amounts and exits. Preqin's data is compiled by extracting information from regulatory filings, press releases, the business press and website content.[52] A challenge encountered in utilizing the Preqin database is the prevalence of inaccuracies in the company names of the target companies. This is because Preqin also captures information on real asset deals or acquisitions of businesses units and spin-offs or carve outs. In addition, the target company identifier provided by Preqin is not compatible with other data platforms used for this research. To obtain accurate company identifications, a manual matching process was performed against the Orbis company database of Bureau van Dijk, a comprehensive business data resource on public and private companies.[53] The Orbis BvD IDs were added as company identifier to the Preqin data sample, which was necessary to achieve a consistent match with the parent companies listed by the EPA. The information used from Preqin and Orbis is as of March 2022 and October 2022, respectively.

3.1.2. Facility-level sustainability data source – the TRI program

To measure the asset-level sustainability of private equity transactions, this study utilizes the Toxic Release Inventory from the Environmental Protection Agency of the United States as data source for environmental pollution. The Toxic Release Inventory is a database maintained by the EPA which contains information on the use of certain toxic chemicals by industrial facilities in the United States. Importantly, the TRI also includes relevant facility information, such as location, including exact address and industry sector, as well as the name of the parent company. The database is open to the public under www.epa.gov and can be downloaded or accessed via an API. The jurisdictional basis for the TRI is founded by the Emergency Planning and Community Right-to-Know Act (EPCRA)[54] enacted in 1986 as a response to a severe incident at a chemical facility in West Virginia.[55] Under the Section 313 - EPCRA, all industrial facilities in the US are required to report to the TRI when they meet the following minimum criteria: (i) their operations include the handling, manufacturing, processing or otherwise use of a listed chemical in quantities greater than a threshold during a calendar year (usually 25,000 pounds; 11.34 metric tons of an individual substance), (ii) more than ten full-time workers are employed and (iii) it is classified under a relevant industry sector.[56] At the time of this research, 770 individually listed chemicals and 33 chemical categories were covered by the TRI; the full list is available on the EPA website.[57] The TRI database includes information on the release of these chemicals to the environment (such as through air emissions, water discharges, and land releases), as well as the use, disposal, and treatment of these chemicals. Figure 1 provides an il-

[52] See Preqin (2023).

[53] See Bureau van Dijk Electronic Publishing Ltd (2023).

[54] See "Toxic Chemical Release Reporting: Community Right-To-Know - PART 372" (1988).

[55] See Franklin (1985); The incident occurred at the same type of chemical plant and just eight months after the Bhopal disaster in India, where a cloud of highly toxic methyl isocyanate gas leaked from a Union Carbide chemical plant in Bhopal, India, on Dec. 4th. Thousands of local people died in which is considered as one of the worst industrial disasters in history.

[56] See EPA (2023); For a full list of all covered industry sectors see appendix B.

[57] See EPA (2022a).

lustration of the TRI's tracking of toxic chemicals.[58] For the research in this thesis, information on two reported quantities of toxic chemicals is taken from the TRI database for each facility:

a) The quantities of on-site releases and off-site releases are combined to give the total releases of toxic chemicals associated with a facility's operations which are indicative of a facility's direct environmental impact;
b) The production waste as the amount of toxic chemicals in all non-product outputs generated by the facility which is indicative of the potential of the facility to cause a hazard to the environment. Notably, the total releases are part of the production waste.

Emissions of environmental pollution of a particular facility can be analyzed both as total annual amounts (in pounds) of hazardous chemicals (using the pristine data from the TRI) and as total annual toxic loads using the Risk Screening Environmental Indicators (RSEI) program from the EPA. RSEI processes TRI data to account for the toxicity of a chemical release based on its environmental implications. This is especially relevant when comparing various chemical releases with respect to their environmental hazards.[59] In this thesis, the full RSEI model itself is not used as it is only available for a subset of a few large facilities in the TRI, but the following information from the RSEI program about the total releases and the production waste is obtained:

1) Carcionogen: This boolean variable indicates whether the chemical associated with a reported quantity is considered as carcinogen by the EPA;[60]
2) Persistent Bioaccumulative Toxics (PBT): This boolean variable indicates whether the chemical exhibits a low or no biodegradability and accumulates in living organisms, persistently in adipose tissues of long-living animals i.e., humans.[61]

This research in this thesis innovates and introduces a modified variable based on these indicators to define the *environmental hazard* of a chemical. The *environmental hazard model* (EHM) developed in this thesis is a primitive measure to assess the severity of the pollution when a chemical is released to the environment. The environmental hazard levels are used as pollution-specific control variables which allow a more detailed assessment of the environmental impact of a facility (i.e., a PE-owed asset) on an ordinary scale from 1 to 4. Figure 2 shows the interpretation of the environmental hazard used for the research in this thesis.[62]

The TRI data used for this research included reporting forms processed by the EPA as of October 19, 2022. The data was retrieved on the facility-chemical-year level, meaning that individual quantities for each specific chemical handled at a facility in a reporting year were obtained. As the focus of this study is the impact of private equity takeover on the environmental impact of a facility, the observation of interest is the change in the environmental impact of a facility ocurring in the year of the acquisition. In this context, the relative changes in the amounts of toxic chemicals present in production waste and total releases, respectively are needed. To facilitate this, the total data sample was grouped by year, facility, and hazard level and aggregated by the hazard level. For each facility-hazard-year observation, the difference d_t for a given reporting year t is obtained as shown in Formula 1 by comparing the mean quantities (Y) two years before (*ante*) and two years after (*post*) the reporting year, relative to the mean quantities from the two years preceding (*ante*) the reporting year. This difference is calculated as

$$d_t = \frac{Y_{t+1} + Y_{t+2} - Y_{t-1} - Y_{t-2}}{Y_{t-1} + Y_{t-2}} \quad \text{if } \forall\ Y_{t+z};\ z = \{-2, -1, 1, 2\} \text{ are non-missing} \tag{1}$$

where Y_t denotes the sum of all quantities of toxic chemicals with the same hazard class handled in the facility in the reporting year, normalized to the facility's productivity level for the reporting year under consideration.[63] Normalization allowed controlling for variations in pollution levels attributable to fluctuations in production output, which is necessary to eliminate the effects of increases or decreases in the facility's productivity on the change in quantities handled at the facility. The difference is calculated for the quantities of total releases and for the quantities of production waste individually, henceforth called *Difference Total Releases* and *Difference Production Waste*, respectively. Each difference is calculated only for those reporting years in a facility-hazard group that exist within conjunction of five consecutive reporting years, encompassing two preceding and two subsequent reporting years.

3.1.3. Data preparation and sample construction

The data was prepared in a staged approach, where the deal data sample was first assembled from the Preqin database and then merged with the TRI database to produce the final sample. The initial Preqin deal data sample consisted of 48,232 private equity acquisitions for which Preqin provides transaction information, involving 38,694 unique companies. Of these, 29,652 unique target companies involved in 37,308 transactions were successfully matched manually to their record in the Orbis database. All records with missing information on the year of the transaction were then removed, resulting in 36,082 deals involving 28,945 unique companies. The initial TRI contains data from 18,526 facilities belonging to 4,887 companies. This pristine database was also matched against the Orbis database on

[58] A detailed explanation of the TRI data model can be viewed in appendix C pp. 3–6.
[59] See EPA (2022b).
[60] See EPA (2022b).
[61] See EPA (2022d).
[62] See p. 7 in appendix C for a more detailed explanation of the EHM.
[63] See p. 19 in appendix C for a schematic explanation how the normalized difference was retrieved.

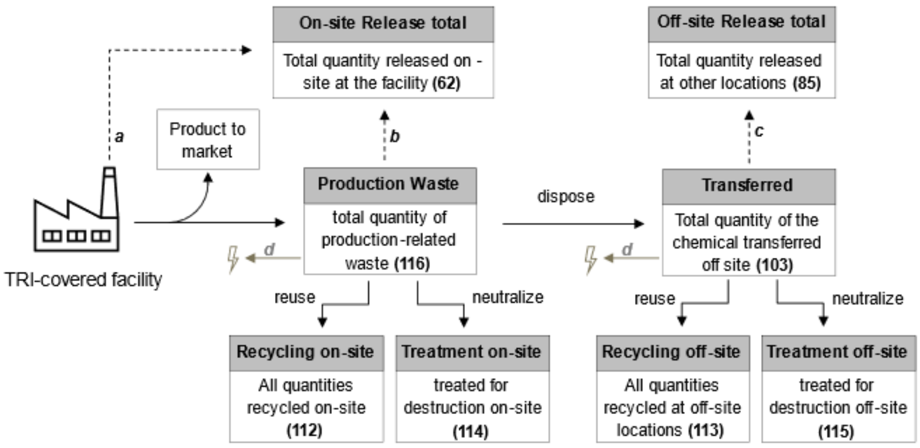

Figure 1: TRI data scope. The figure shows a simplified version of the data notation of the TRI-data points that a facility has to report for any section-313 EPCRA chemical. Numbers in brackets represent data field number in the TRI basic datafile and are used to annotate data for a facility in this thesis too. Dashed errors denote releases to the environment, solid arrows denote transport processes. Sources for pollution are (a) e.g., fugitive or stack air, or (b) e.g., dust or leaching to groundwater while storing, additionally (c) e.g., loss during transportation. While not used in this research, TRI also captures utilization of substance for energy production (d). Also, for (a), (b) and (c): loss of containment as one-time release is covered by the TRI under No. 117, though rarely reported in general. Source: authors own illustration according to EPA (2022c).

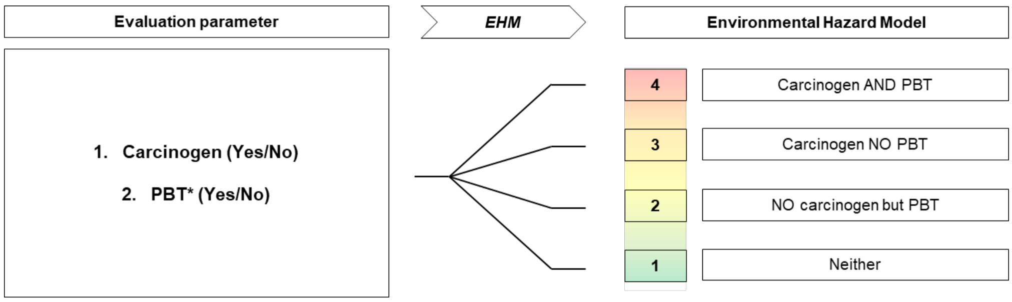

Figure 2: Environmental Hazard Model. The figure shows the interpretation of the environmental hazard of pollution based on RSEI indicators "Carcinogen" and "PBT".

the standardized parent company name[64] using the Orbis search engine, to generate registries with Orbis IDs. To obtain the final sample for the analysis, the TRI sample was then merged to the deal data sample on the Orbis ID which resulted in 330 deals with 219 target companies. A total of 709 TRI-covered facilities were associated with these companies. For all of the 219 TRI-covered target companies, the matched Orbis record was verified manually to prevent false matches of PE-backed companies.

From the final datasample, the following information is obtained: the name of the facility, the verified Orbis ID of the parent company, its location at the state level, its classification in one of 23 industries, the name of the chemical, the amount of production waste and total releases for each chemical used at a facility in a reporting year, respectively, the productivity ratio as the change in productivity from a previous year to the reporting year, and additionally Boolean indicators of whether the chemical is classified as a carcinogen or a persistent bioaccumulative toxic, respectively, and whether the facilities parent company was involved in a transaction during the reporting year. Before assemling the final data sample, all registries corresponding to less than 5 reporting years of a facility as well as registries with missing productivity ratio and or missing quantity for production waste were excluded. The composition of the final sample is summarized in Table 1. The final sample contains data from 1991 to 2021, which resulted in 357,366 facility-year observations in total and thereof 1,054 facility-year observations for facilities associated with an acquired parent company. Since the quantities of toxic chemicals used by a facility in a reporting year are recorded separately for each chemical, the final data sample consisted of 1.45 million facility-chemical-year observations, of which 3,970 observations belonged to facilities involved in a PE transaction. The quantities for production waste and

[64] To enable consolidation of facility-level TRI data with the corresponding parent company, EPA maintains consistent referencing of each company by using the name EPA manually verified. This eliminates typos and variations in names that complicate data aggregation on the parent company level. It also enabled automatic matching by the Orbis search engine with high accuracy.

total releases, respectively, were then aggregated at the facility level by substituting the variables "carcinogen" and "PBT" with the environmental hazard as a model variable. After this, the final sample consisted of 609,916 total and thereof 1,746 deal-related facility-hazard-year observations.

3.2. Variables and empirical models

In this section first, the classification for the independent variable is derived, which is followed by the definition of the dependent variables. Lastly, control variables are established. The chapter then elaborates the construction of the empirical model of this thesis.

3.2.1. Independent variable

A dichotomous independent variable PE is constructed which indicates treatment of an observation (involvement of a facility in a private equity takeover) in a reporting year t. Formula 2 gives the mathematical definition of the independent variable. It is defined as

$$PE = \begin{cases} 1, & \text{the reporting year is a deal year} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

This study assumes that the Preqin database contains all US private equity deals between 1991 and 2021. All observations which exhibit the value PE = 0 constitute the group of untreated observations (= the control group).

3.2.2. Dependent variable

In order to test the hypotheses that private equity takeover leads to a reduction in environmental pollution through reduced total releases and to decreased quantities of toxic chemicals in production waste, the dependent variables are defined as follows:

a) For hypotheses 1a and 2a, the difference d is defined according to Formula 1 for the amount of total releases, distinguishing between hazard levels 1 to 4 for hypothesis 2a.
b) For hypotheses 1b and 2b, the difference d is defined according to Formula 1 for the amount of production waste, distinguishing between hazard levels 1 to 4 for hypothesis 2b.

Importantly, the quantity of toxic chemicals in a reporting year itself is not part of the dependent variable. As shown in Formula 1, the dependent variable considers the quantities of toxic chemical *before* and *after* a reporting year, not *in* a reporting year. This exclusion is critical, as it allows the quantity of toxic chemicals in production waste during year t to be employed as a potential control variable without introducing a logical fallacy into the analysis.

3.2.3. Control variables

Alongside the primary variables of interest, additional control variables are incorporated into the analyses to account for potential confounding factors. Confounding factors are related to facility-fixed effects and pollution-fixed effects. Consequently, the control variables are categorized into the facility-specific control variables and pollution-specific control variables. For the latter, the environmental hazard level h is used. This categorical variable takes into account all effects arising from the potential harm of the chemical when it is released into the environment. This can be exogenous effects, such as tighter regulations for substances exhibiting hazards of highest concern (carcinogenicity, mutagenicity, reproductive toxicity) but also endogenous effects as the cost of precautionary measures increases with higher toxicity of the substances used.

The firm-specific control variables are the facility location on the U.S. state level, the industry sector of the facility, the deal year and the quantity of production waste in the reporting year.

a) The categorical variable facility location k with the 52 U.S. states as categories was included in the model because the sample exhibits significant heterogeneity in geographical distribution and private equity investors exhibit a selection bias for some states.[65] The differences in geographical distribution are highly relevant to the measurement of pollution levels, as state laws regarding environmental protection vary greatly. Previous studies have shown that increased environmental liability risk in a state positively correlates with a better ESG-impact of private equity.[66]
b) The categorical variable industry sector i was included in the model because technological implications due to industry specific processes might potentially influence pollution abatement capabilities in facilities. Additionally, the treatment and control group differed significantly in their distribution of facilities across the industry sectors.[67] For the purposes of this study, facilities were categorized into 23 industries based on their primary NAICS codes.[68]
c) The reporting year t presents an important control variable related to several external effects on the pollution at a facility. External effects include the enactment of environmental protection laws which can greatly distort the treatment effect on pollution change, especially in the location-year combination. Also changes in the TRI reporting requirements from one year to another greatly influence reported quantities and imposes a significant imbalance on comparing assets' inter-year absolute pollution levels.[69]

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65 See p. 12 of appendix C for e graphical representation on the distribution of the facilities and differences thereof between the $PE = 0$ and the $PE = 1$ sample.

66 See Bellon (2020, p. 2).

67 See appendix C, pp. 16-17 for all the industrial sectors by their North American Industry Classification System (NAICS) codes present in the sample and a graphical representation of the distribution among industries.

68 See United States Census Bureau (2022) for the classification of industry sectors on NAICS codes.

69 See appendix C, pp. 8-11 for the effect of changes in the TRI reporting framework on the reported quantities.

Table 1: Composition of the final data sample. a: The term "in-deal" refers to the count of cases that are associated with parent companies engaged in private equity transactions.

	Total sample	**Thereof in-deal**[a]
Number of facilities	18,526	709
Number of Facility-year observations	357,366	1,054
Number of facility-chemical-year observations	1,445,609	3,970
Number of facility-hazard-year observations	609,916	1,746

d) The size of the facility is an important confounder, yet difficult to exactly assess. The implication of facility size is that large facilities can implement measures more easily, and facilities with high initial pollution can reduce pollution easier. On the other hand, large facilities have a large absolute reduction in pollution, even if the reduction is only a few percentage points. To account for this production waste in the reporting year is used as a proxy for industry size to omit influences of pollution-scale distortions. The measure is imperfect as the ideal measure would be units of production output, but this data is not present. As a compromise, the control variable for the plant size $s = Y(t)$ is introduced as the amount of production waste in year t.

Taken together, the pollution specific and facility-specific control variables constitute a multidimensional vector of characteristics $X_n = \langle f\ (h,k,i,t,s) \rangle$ for each facility-hazard-year observation. In the research design of this thesis, this control vector absorbs salient differences between assets from PE-backed and non-PE-backed facilities.

3.2.4. Empirical models

This thesis follows an adapted notation of Imbens (2004) to develop the model for the estimation of the treatment effect (i.e., the impact of private equity takeover).[70] To begin with, all facility-hazard-year observations are denoted as N cases indexed by n. For each of this case, the differences d_n are observed as dependent variables. Each observed difference for a case n comprises the sum of two components, a population constant baseline difference C_p multiplied by the case-specific vector of characteristics X_n and the effect size E of the treatment effect multiplied by the independent variable PE_n which is 1 if the case has received treatment and 0 otherwise. Formula 3 gives the composition of the observed difference as

$$d_n = E * PE_n + C_p * X_n \tag{3}$$

As the independent variable PE is binary, each case has a pair of potential outcomes for the difference. Accordingly, Formula 4 describes the realized outcome as

$$d_n \equiv d_n(PE_n) = \begin{cases} d_n(1), & if\, PE_n = 1 \\ d_n(0), & if\, PE_n = 0 \end{cases} \tag{4}$$

[70] See Imbens (2004, pp. 5–6).

Substituting $d_n(PE)$ in Formula 4 with Formula 3, the effect size of the treatment can simply be calculated by subtracting the difference $d_n(0)$ from the difference $d_n(1)$. However, as $d_n(0)$ and $d_n(1)$ are never observed for the same case, the effect size must be calculated by subtracting the difference between a treated case n and an untreated case n'. Accordingly, Formula 5 calculates the difference as

$$d_n(PE=1) - d_{n'}(PE=0) = E + C_p * X_n - C_p * X_{n'} \tag{5}$$

Since C_p is not known, for the effect size to be calculated the condition $X_{n'} = X_n$must fulfil. As elaborated in chapter 3.2.3 the vector $X_n$is defined as $X_n = \langle f\ (h,k,i,t,s) \rangle$ and for

$$\begin{gathered} X_{n'} = X_n \Longleftrightarrow X_{h,k,i,t,s} = X_{h',k',i',t',s'} \\ \text{and thus for } \{h = h', k = k', i = i', t = t',\ s\ = s'\} \\ \Longrightarrow n \overset{\text{def}}{=} n'; \forall n, n' \in N \end{gathered} \tag{6}$$

Under the condition of Formula 6 formula 5 can be written as shown in Formula 7 with

$$\begin{aligned} & d_{h,k,i,t,s}(PE=1) - d_{h,k,i,t,s}(PE=0) \\ & = E + C_p * (X_{h,k,i,t,s} - X_{h,k,i,t,s}) \equiv E \end{aligned} \tag{7}$$

Conclusively, as shown in Formula 6 the effect size of the treatment (the impact of private equity takeover) on the change in quantities of toxic chemicals can be estimated by the difference between two cases (facilities) which are similar in terms of their control variables. The estimation is done for the amount of toxic chemicals production waste and the amount of toxic chemical as total releases separately.

3.3. Empirical methods

To estimate the effect size of the treatment effect on the treated under the aforementioned empirical model, it is necessary to identify an untreated control observation for each treated observation that is similar in terms of confounding factors (i.e., control variables). Subsequently, the difference between the treated and control observations can be calculated. Otherwise, the difference in outcomes could simply be the result of the continuation of pre-existing different trends in the facilities, where the trends are caused or at least related to the confounding factors. To facilitate this, two different methods have been used for matching to fulfil the condition in Formula 6, i.e., to find pairs of cases which are balanced in terms of their vectors of characteristics. In the following, first the propensity score matching method is explained. Since the matching with the propensity scores was of poor quality, a second matching method was developed which is specifically tailored to the data types present in the sample used for this research.

3.3.1. Probabilistic matching: Propensity Score Matching

In the first approach to investigate whether firms undergoing private equity buyouts achieve lower pollution levels *after* takeover, the Propensity Score Matching (PSM) was employed to create a group of control firms. The propensity score of a subject is the calculated probability of this subject for receiving the treatment conditional on a set of characteristics other than the one being tested for (i.e., the control variables).[71] The selected control variables on which a propensity score for each subject is calculated on must effectively characterize idiosyncratic properties of the subject to avoid overfitting of the propensity score matching.[72] The selection process should be grounded in sound reasoning and take into consideration the extent to which treated and untreated groups differ with respect to each control variable. For the latter, the identification of confounders for the matching was based on the difference between the treated and the untreated group in the context of the respective confounder. Austin (2011b) introduces a measure for the difference for continuous variables as shown in Formula 7.[73] This standardized difference is calculated as

$$d_{st} = \frac{\overline{x}_{treated} - \overline{x}_{untreated}}{\sqrt{\frac{s^2_{treated} + s^2_{untreated}}{2}}} \tag{8}$$

where $\overline{x}$ denotes the mean of treated and untreated samples, respectively, and $s^2_{treated}$ and $s^2_{untreated}$ are the corresponding variances of the treated and untreated sample, respectively. For the categorical variables industry, location and hazard level, the absolute difference in proportions was estimated based on an adapted approach from Austin (2010) as shown in Formula 6.[74] Consequently, in this thesis the difference is calculated as

$$d_{abs} = \frac{1}{2}\sum_{i=1}^{C}\left|p_{treated,c} - p_{control,c}\right| c \in C \tag{9}$$

where $p_{treated,c}$ and $p_{control,c}$ are the proportions of category c in the treatment and control group, respectively and C is the set of categories a categorical variable can take. The results for the differences are shown in Table 2, the interpretation of the values is given in chapter 4.2.

By and large, the results for the difference reinforce the assumptions for the relevance of the control variables made in chapter 3.2.3. Only the facility size (proxied by the quantity of production waste in the reporting year), was highly similar for both groups. Hence, the propensity score was calculated based on deal year, the location, hazard, and industry. To deal with the multilevel categorical variables location and industry in propensity score matching, binary indicator variables were introduced via one-hot encoding. Thus, in the propensity score model the condition of Formula 6 was adapted as shown in Formula 10 with

$$\begin{gathered} X_{n'} = X_n \Longleftrightarrow X_{h,k,i,t} = X_{h',k',i',t'} \\ \text{with } P(PE_n = 1|X_n) \cong P(PE_{n'} = 1|X_{n'}) \\ \forall n \in N, \forall n' \in N \end{gathered} \tag{10}$$

Here, the PSM matches a pair of cases that have approximately the same probability P of receiving treatment conditional on their vectors of characteristics. In the PSM model used in this study, the propensity score was estimated using logistic regression and is used to match observations with a similar balance of control variables with a k-nearest neighbour algorithm. The matching was conducted using a Python programming environment.[75]

3.3.2. Deterministic matchig: Blocking and Matching

Due to the high relevance of categorical variables as confounders in this research, an adapted blocking and matching (BaM) method was developed and employed on the dataset.[76] Blocking is a method in big data analytics where records are grouped that share the same confounding variables.[77] In the case of the TRI dataset, first blocks based on exact record linkage of industry, state, hazard and year were created. Then for each treated facility in a block the closest untreated facility based on the quantity of production waste was found. The resulting pairs resemble tuples of a treated and an untreated facilities with similar (theoretically identical) control vectors. Thus for the blocking and matching the condition in Formula 6 was adapted as shown in Formula 11 with

$$\begin{gathered} X_{n'} = X_n \Longleftrightarrow X_{h,k,i,t,s} = X_{h',k',i',t',s'} \\ where\ n \overset{\text{def}}{=} n\ \forall n \in N, n' \in N \\ \Longleftrightarrow \left\{h = h', k = k', i = i', t = t',\ s\ \approx s'\right\} \end{gathered} \tag{11}$$

The blocking approach for this research used deterministic blocking based on logical conjunction of year (deal year

[71] See Austin (2011b, pp. 399–424).
[72] See Cepeda et al. (2003, pp. 280–287).
[73] See Austin (2011b, pp. 410–411).
[74] See Austin (2010, p. 2140); The formula is adjusted by using a factor of 0.5 instead of 1/k, as the latter would give values too small for meaningful interpretation. Because the absolute difference in proportion was only needed to be informative for relative comparisons between groups or before and after matching, this adjustment was not detrimental.

[75] See Kline and Luo (2022, pp. 1354–1357); See appendix A p. 1 for the code used for PSM in this research.
[76] This was inspired by the generalized randomized block design according to Addelman (1969, p. 35) where blocking maximizes the covariance between treated and untreated samples based on their control variables, resulting in a minimum variance in the difference between treated and untreated samples. Essentially, this method aims to isolate any observed difference in treatment effect and attribute it solely to the effect of the treatment itself.
[77] See IBM Corporation (2021); Blocking and matching is commonly used in big data analysis to reduce computing power when examining data connections. Although the data structure of the TRI lends itself well to this methodological approach, it does not appear to have been used in research on the TRI.

Table 2: Balance of the covariates in treated and untreated group. a: Absolute quantities of toxic chemical in deal year in pounds.

Covariates	**Difference**
Continuous Variables[d_{st}]	
Year	0.4637
Total Releases[a]	-0.0314
Production Waste[a]	-0.0053
Categorical Variables [d_{abs}]	
Location	0.1446
Industry	0.2428
Chemical hazard	0.0175

= record year) and the categorical variables industry, state and hazard level. The blocking proceeded as follows: Two datasets were separated from the original database based on the status $PE = 1$ and $PE = 0$. Then, for each case in the $PE = 1$ sample, all cases from the $PE = 0$ sample were found via exact record linkage (i.e., with exactly the same combination) on year, industry, state and hazard level.[78] Within each block for the $PE = 1$ constituent the PE = 0 case which was closest on quantity of toxic chemical in production waste was found with the pandas *merge_asof* function to account for the proxied facility size.[79] The blocking and matching method proved to be a computationally intensive process, requiring approximately 2 hours to complete the matching.[80]

4. Empirical results

In the following, first the descriptive statistics of the final sample are shown. Then, the efficiency and quality of the matching methods are elaborated and lastly, the results of the matching for the estimated effect size of private equity takeover are presented.

4.1. Descriptive statistics

In Table 3 the summary statistics on the variables are shown. The control group is shown in Panel A and the treatment group in Panel B. It presents the number of observations, the mean, the standard deviation, the minimum, the 25 %, 50 %, 75 % quartiles and the maximum. From the final sample which consisted of 609,916 total and 1,746 deal-related facility-hazard-year observations, the dependent variables according to Formula 1 could be calcuated for approximatly two thirds of the cases (see column *N* in Table 3). As the dependent variables represent relative changes, these are highly sensitive to outliers in the underlaying data.[81] This manifests in the dataset by exaggeratedly great erroneous values (see column *Max* in Table 3) which significantly distort descriptive statistics (see the column *Mean* in Table 3). On the other hand, the minimum (see column *Min* in Table 3) of *-1* in the total releases indicates, that a facility completely stopped emitting any quantities associated with the chemical in the measured timeframe. Likewise, the minimum of *-1* in the production waste indicates that the facility no longer produces any waste containing the chemical. Especially for small facilities, it is also possible that the amount of the chemical handled has fallen below the reporting threshold. In addition to the presence of errors, high levels of disproportionality characterize quantities of toxic chemicals at the facility level in the TRI dataset.[82] Both, errors and disproportionalities suggest that the descriptive statistics fundamentally mischaracterize the environmental performance of facilities.[83] A skewness of 30 and a kurtosis of roughly 900 for the distribution of the dependent variables in Panel A, strongly disfavor the case of normality and reinforce this conjecture. To introduce robust statistical analysis which is less sensitive to the outliers, the median and the median absolute deviation (MAD) were used instead of the mean and the standard deviation.[84] To deal with outliers, the approach of Leys et al. (2013) was followed and subsequently cases greater than 2.5*MAD +- median were removed from the analysis.[85]

The trimming was done for the difference in total releases and production waste individually. The percentile value of the cut-off value was calculated as a measure for the proportion of data not being classified as outliers. A cut-off value of 2.6471 means that any observation inferring that a facility increased its pollution by more than 264.71% was excluded from the subsequent analysis. Table 4 shows the robust descriptive statistics for the dependent variables after the trimming step.[86] The median is again used as the better suited measure for ratios. The number of observations was reduced by the trimming, but more than 90 % of the data remained in the analysis. The values for skewness and kurtosis of below 2 are considered as acceptable to assume normal univariate

[78] See Fellegi and Sunter (1969, pp. 1183–1210) for a detailed explanation of record linkage.

[79] See Petrou (2017, pp. 338–386); See appendix A p. 3 for the code used for BaM in this research.

[80] The code was executed using parallelized threads according to Python Software Foundation (2023).

[81] See Miller (1993, pp. 457–459).

[82] See Collins et al. (2020, p. 2).

[83] See pp. 14-15 of appendix C for a graphical representation of the distribution of pollution in the TRI data.

[84] See Huber (2011, pp. 1248–1251).

[85] See Leys et al. (2013, pp. 764–766).

[86] See p. 20 in appendix C for graphical representation of the dependent variables of the trimmed sample.

Table 3: Summary of the descriptive statistics. This table summarizes the descriptive statistics of the unmatched data sample. Additionally, it presents the firm-specific and pollution-specific control variables. The unmatched sample is segmented according to whether a parent company of a facility was involved in a private equity takeover during a reporting year. a: Facility size is in quantities of toxic chemicals in pounds. * Statistics for the deal year other than Min and Max were omitted as not reasonably meaningful.

Panel A: Descriptive statistics PE = 0

Variable	N	Mean	SD	Min	25 %	Median	75 %	Max
Dependent Variables								
Difference Total Release	360,123	$6.44*10^8$	$2.28*10^{11}$	-1	-0.3931	-0.0422	0.3427	$9.98*10^{13}$
Difference Production Waste	389,902	$5.95*10^8$	$2.19*10^{11}$	-1	-0.3208	-0.0197	0.3211	$9.98*10^{13}$
Independent Variable								
PE	608,170	0	0	0	0	0	0	0
Firm-specific Control Variables								
Facility Location	608,170	-	-	-	-	-	-	-
Reporting Year	608,170	-*	-	1991	-	-	-	2021
Facility Size^a	608,170	$1.11*10^6$	$1.79*10^7$	0	548.23	15,350	121,500	$3.75*10^9$
Industry	608,170	-	-	-	-	-	-	-
Pollution-specific Control Variable								
Environmental Hazard	608,170	2.0607	1.1516	1	1	2	3	4

Panel B: Descriptive statistics PE = 1

Variable	N	Mean	SD	Min	25 %	Median	75 %	Max
Dependent Variables								
Difference Total Release	1,142	35.66	711.45	-0.9999	-0.3584	-0.0194	0.3961	22,750
Difference Production Waste	1,241	25.47	659.74	-0.9939	-0.2825	-0.0148	0.3043	22,272
Independent Variable								
PE	1,746	1	0	1	1	1	1	1
Firm-specific Control Variables								
Facility Location	1,746	-	-	-	-	-	-	-
Reporting Year	1,746	-*	-	1991	-	-	-	2021
Facility Size^a	1,746	$1.03*10^6$	$1.10*10^7$	0	984.87	20,345	117,932	$4.27*10^8$
Industry	1,746	-	-	-	-	-	-	-
Pollution-specific control Variable								
Environmental Hazard	1,746	2.0710	1.1489	1	1	2	3	4

distribution.[87] To summarize, eliminating outliers to obtain robust statistics improved data quality, but it also introduced an omitted measurement bias by excluding roughly 10 % of the data.

The median is slightly different between the treated and untreated groups but the differences should not be further interpretated because of the different number of observations. However, the difference for total releases and production waste in the PE = 0 sample can be taken as the median baseline reduction of quantities in any given reporting year, which is -8.6 % for total releases and -5 % for production waste. To summarize, while trimming effectively induced normality required for univariate data analysis, the differences are not suited to estimate impact effect of private equity takeover both on the change in quantities in total releases and production waste, respectively.

[87] A general convention is that a skewness less than 3 refers to a degree of symmetry of the normal distribution. See Burdenski (2002, p. 16) for further information.

4.2. Matching evaluation

For matching, from the original final sample with 609,916 facility-hazard-year observations, all cases with insufficient data for the difference in production waste data field were removed to reduce computing time, resulting in 391,143 observations subjected to the matching. The result of the matching is given in Table 5. PSM was able to match 100 % of the treatment group with facilities similar on their propensity logits from the control group since no caliper width was used. BaM was able to match 94 % of treated facilities to untreated facilities in the same year, state, and industry and on similar amount of production waste.

Before estimating the treatment effect, the matched sample is evaluated based on the quality of the matching. This assessment is critical to determine whether the imbalance of control variables has been adequately reduced, ensuring the reliability of the subsequent analysis. Thus, the standardized difference (Formula 8) and the absolute difference in proportions (Formula 9) were calculated for the matched sample. The results are shown in Table 6.

Table 4: Robust statistics for the dependant variables after trimming. Cut-Off at 2.5 x median absolute deviation (MAD) ± median (for trimming the cut-off is value is calculated based on the MAD and the median of the untrimmed distribution).

Variable	N	Median	MAD	Upper Cut-Off	Cut-Off Percentile	Skewness	Kurtosis
PE = 0							
Difference Total Release	331,719	-0.0863	0.3106	2.6471	92.11 %	1.3088	2.5973
Difference Production Waste	362.581	-0.0505	0.2742	2.4436	93.05 %	1.2181	2.4887
PE = 1							
Difference Total Release	1.029	-0.0760	0.2960	2.2837	90.11 %	1.0236	1.4907
Difference Production Waste	1.161	-0.0429	0.2480	2.3499	93.52 %	1.1996	2.1494

Table 5: Matching results. a: Each case presents a facility-hazard-year observation which has a value for the difference in for the production waste.

	PSM	BaM
Before matching		
Treated cases[a]	1,241	
Untreated cases[a]	391,143	
After matching		
Matched cases	1,241 (100 %)	1,169 (94.20 %)

Table 6: Standardized differences before and after matching.

	Unmatched	PSM	BaM
Continuous Variables $[d_{st}]$			
Year	0.4637	0.3419	-0.0207
Total Releases[a]	-0.0314	-0.1767	-0.0234
Production Waste[a]	-0.0053	0.0847	0.0005
Categorical Variables $[d_{abs}]$			
Location	0.1446	0.4214	0.0278
Industry	0.2428	0.4891	0.0306
Chemical hazard	0.0175	0.1708	0.0136
Imbalance reduction			
d_{st}	-	-20.56 %	91.09 %
d_{abs}	-	-167.05 %	82.21 %

The values for continuous variables before matching suggest that the groups exhibit considerable differences in terms of reporting years. The positive value indicates that treated sample possesses a higher average reporting year than the control sample, implying that private equity deals tend to be more prevalent in more recent reporting years.[88] The negative values for the quantities of production waste and total releases respectively indicate, that treated facilities have on average slightly lower amounts of toxic chemicals in those respective data fields. The values for the categorical variables show that, in the unmatched sample, the groups differ considerably in the proportions of facilities belonging to the respective industries. Although to a lesser extent, the distribution of facilities across states also differs between the groups. The groups show less variation in the levels of hazards present in the facilities. The propensity score matching provided a slightly better match rate and reduced imbalance for reporting year, but the value of 0.3419 still suggests high imbalance. PSM reduced imbalance between samples in terms of reporting years, but at the expense of imbalance in other control variables, ultimately resulting in 20 % and 167 % higher imbalance for continuous and categorical control variables, respectively. This is explained by the categorical nature of 3 of the 5 covariates, which necessitated their implementation through one-hot coding, resulting in a large number of binary covariates for which PSM has been shown to be generally weak to generate model dependence.[89] To summarize the values in Table 6 show that the PSM method was unsuccessful in achieving balance be-

[88] See p. 13 in appendix C for the number of reporting facilities per reporting year in the respective groups.

[89] See King and Nielsen (2019, pp. 435–454).

tween the treatment and control groups. Additionally, the findings support the strategy of treating the year as a categorical variable and subject it to exact record linkage matching, as opposed to considering it as a continuous variable in the propensity score calculation. This approach is especially crucial because comparisons across facilities may be significantly skewed by alterations in the TRI reporting framework in certain years, particularly in the case of lower reporting thresholds for specific chemical types.[90] Therefore, this study relied on blocking based on categorical covariates in the second matching method to ensure balance between treatment and control groups. Indeed, the BaM method successfully reduced the imbalance by over 80% across all control variables. Furthermore, all continuous control variables were balanced to a value for the difference of less than 0.1, which is generally considered to represent a negligible difference between the samples in the mean of control variables.[91]

It is crucial to note that the standardized difference and the absolute difference in proportions reflect the overall similarity between the two samples. Although these measures reveal improvements resulting from the matching methods employed, they do not allow an evaluation of the similarity of individual 1:1 matched pairs. To further assess the quality of the matching, the propensity scores as the probability of being assigned to one treatment, given an observation's measured baseline covariates was calculated for both matched samples. The resulting propensity score distribution is shown in Figure 3 for both methods.

The distribution in Figure 3a shows that both, the treated and control group exhibit similar propensity scores after the blocking and matching method. This indicates that the matching has been effective in balancing the covariates between the treatment and control groups. The peak at ~ 0.5 suggests that many of the matched samples have roughly equal probabilities of being in either the treatment or control group based on their covariates.

The Gaussian curves of the propensity scores depicted in Figure 3b for the treatment and control groups after the Propensity Score Matching reveal substantial non-overlapping distributions. This observation suggests that the propensity scores of a considerable number of samples differ, and matches have been paired that exhibit variations in their probability of receiving treatment based on their control variables. Overall, after the PSM the covariate distributions between the treatment and control groups still differ dramatically. A maximum caliper width was not used in this analysis as this would have resulted in a limited number of matches.[92]

4.3. Estimation of treatment effects

In order to test hypotheses 1a and 1b, which constitute that the impact of private equity on target companies manifests in a reduced amount of toxic chemicals emitted or wasted, for each matched pair, the effect size for production waste and total releases was calculated according to Formula 7. Since the effect size is no longer a ratio, trimming was not necessary for the resulting data and the median was used as an immanent robust measure. Hence the sample median treatment effect on the treated was estimated.[93] Table 7 summarizes results obtained for the effect of private equity ownership on the facilities. It compares the two matching methods employed and presents the number of pairs, the sample median treatment effect for the treated and the median absolute deviation. The unit of the effect size is in percentage points.

The estimated effect sizes from both methods are similar; however, the values derived from the blocking and matching approach are considered more reliable due to the poor quality of the propensity score matching. The value for the median effect size for total releases obtained through the BaM method suggests that the average quantities released at a facility two years after a private equity takeover of its parent company, exhibit a median increase of 1.5535 %-points relative to a similar facility that did not experience a change in ownership. Conversely, the quantity of production waste in the PE-backed facility is on median 1.1090 %-points lower following the private equity takeover of its parent company relative to non-acquired peers.

To differentiate between severity of the released and wasted quantities and to test hypotheses 2a and 2b, the matches were grouped by environmental hazard h to distinguish between hazard levels of toxic chemicals according to the developed environmental hazard level. The sample median treatment effect on the treated can thereby be observed for different hazard levels. The results are shown in Table 8.

When differentiating between hazard levels, the discrepancies between the matching methods become more apparent and as before, the values obtained from the blocking and matching approaches are considered more reliable. The number of observations varies between the hazard scores (see column N in Table 8), and a majority of chemicals used pose minimal hazards and releases are of low severity according to the environmental hazard model of this thesis. The number of observations for PBT-only substances (hazard score 2) is even lower than for carcinogen-only substances (hazard score 3). The median values for total releases of hazard score 2 and hazard score 4 quantities, with differences of 5.4541 and 11.4158 %-points, respectively, indicate that private equity-backed facilities significantly increase pollution with these chemicals after takeover. The situation is different for production waste. There, all hazard levels except hazard level 2 show a decrease in quantities compared to facilities that have not undergone a private equity takeover. Figure 4 provides a graphical representation that, although only informative, highlights the overarching patterns regarding the impact of private equity acquisitions contingent upon the environmental hazard. Interestingly, the trend direction for the

[90] See for example EPA (1999).
[91] See Normand et al. (2001, pp. 388–398).
[92] See Austin (2011a, pp. 151–161); The caliper width is the distance by which the propensity scores of a matched pair is allowed to differ by at most which avoids matching of highly dispersed propensity logits.
[93] Adapted from Imbens (2004, pp. 5–6).

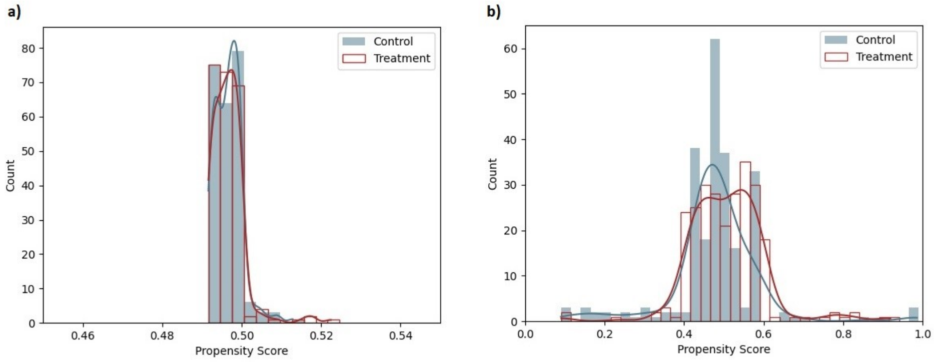

Figure 3: Calculated propensity score distribution of the matched samples. a) Matching based on BaM. b) Matching based on PSM. The two graphs are not to scale as the x-axis is zoomed in in Figure 3a.

Table 7: Estimated treatment effect on the treated. PSM stands for propensity score matching, BaM stands for blocking and matching. MAD stands for median absolute deviation from the median.

	Method: PSM			**Method: BaM**		
Variable	N	Median	MAD	N	Median	MAD
Effect size Total Release	1,227	1.0392	1.0444	1,080	1.5535	0.9168
Effect size Production Waste	1,241	-1.9657	1.0461	1,169	-1.1090	0.9746

Table 8: Estimated treatment effect on the treated distinguishing between hazard levels 1 to 4. PSM stands for propensity score matching, BaM stands for blocking and matching. MAD stands for median absolute deviation from the median.

	Method: PSM			**Method: BaM**		
Variable	N	Median	MAD	N	Median	MAD
Effect size Total Release						
Hazard level 1	596	-1.3920	0.0212	526	0.0130	0.0177
Hazard level 2	146	-4.9290	0.0646	126	5.4541	0.0572
Hazard level 3	314	-0.5266	0.0127	284	0.6299	0.0110
Hazard level 4	171	13.0623	0.1601	144	11.4158	0.1484
Effect size Production Waste						
Hazard level 1	602	-3.6206	0.0821	583	-0.9953	0.0217
Hazard level 2	147	1.9211	0.0215	131	4.0495	0.0482
Hazard level 3	316	-3.9517	0.0649	297	-1.9834	0.0430
Hazard level 4	176	1.9850	0.0393	158	-3.6917	0.0775

difference in production waste and total releases is diametrically opposed. As the hazard scores are derived from an ordinal scale, the ranking depends on the interpretation of the underlying severity of a hazard. In general, for both production waste and total releases, the effect size is greater for substances that are both carcinogenic and a PBT (hazard level 4) compared to substances that are either carcinogenic (hazard level 3) or PBTs (hazard level 2). Yet, private equity-backed facilities appear to be less concerned about substances that are PBTs (hazard level 2) compared to chemicals that are neither PBTs nor carcinogens (hazard level 1).

By and large, these trends suggest a hazard-dependent treatment effect for the treated facilities, where higher hazard is directly correlated with increased total releases and inversely correlated with decreased production waste.

5. Conclusion

The following section first draws the main conclusions from the findings. Then the chapter continues with a reflection on the limitations of the research imposed by the data and methodology. Finally, conjectures and ideas offer possible further research questions.

5.1. Discussion

This thesis investigates the evolution of environmental pollution emanating from facilities operated by companies that have experienced private equity takeovers in the United States between 1991 and 2021. It is one of the few academic papers to use the Toxic Release Inventory to assess ESG issues in the context of private equity and among those, it is

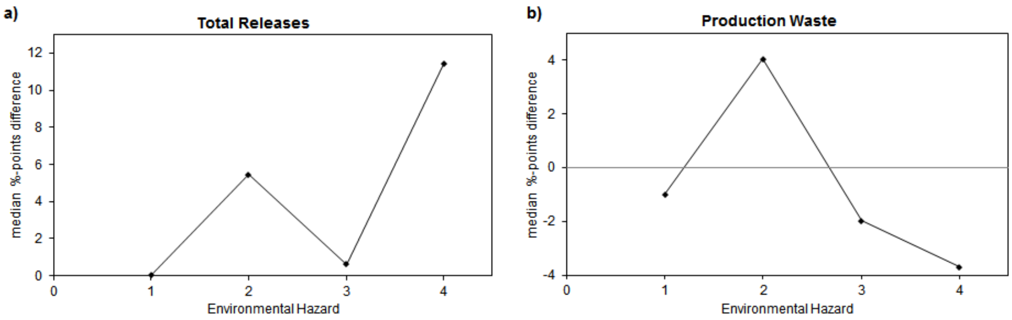

Figure 4: Graphical representation of the difference in %-points discriminating between environmental hazard level 1 to 4. The graphs show the difference in %-points obtained by the BaM method.

the first[94] to a) cover an extensive 30-year period, providing a comprehensive longitudinal perspective on the issue and b) utilize data on pollution and production waste as well as information about the environmental hazards of the chemicals thereof, thereby employing the TRI's extensive scope of information provided. The plethora of data available in the TRI allowed examining a period of two years before and after the deal for each facility. Therefore, this study effectively captures a five-year timeframe to evaluate the impact of private equity ownership on environmental performance which reduces influence of possible fluctuations in the environmental pollution due to one-time releases or other incidents. In addition, by excluding the environmental performance in the deal year itself from the analysis, the study avoids potential concerns of facilities deceiving sustainability by transiently reducing emissions in the deal year in order to pander private equity investors' ESG-due-diligence frameworks. For the research on asset-level sustainability two key aspects of the TRI-program append a unique value to the database: First, the database exhibits a comprehensive scope of data dating back to a time when ESG was far from established as an investment theme, thereby representing a remarkable standard of unconfoundness and data quality, which is ensured by capturing objective, granular information on various forms of releases through quantitative chemical analysis methods. Secondly, the TRI program only monitors, and does not impose restrictions on the use of chemicals. Although compulsory disclosure of information regarding the handling of toxic chemicals by industries to the public generates an incentive to enhance environmental performance,[95] this feature is crucial in the context of the research design in this thesis as the lack of legal pressure to reduce pollution from the program itself leaves the causality for the change in pollution level of a TRI-covered facility solely to the implication of universal factors, for example state laws and regulations as well as technological advances, organizational structure or both of the latter.[96] Setting aside such external effects, a main rationale in this thesis was, that when controlling for financial or judicial pressure, a decrease in pollution can be interpreted as a reflection of the investors (i.e., facilities owners) willingness to adopt sustainable practices. By using the TRI, this thesis also successfully overcomes the challenge of data scarcity, which is a pertinent problem in studying the private equity industry, especially when analyzing non-financial information about target firms. Yet, this challenge becomes apparent in the light of the sample construction: Out of 1.45 million observations in the TRI, less than 0.3% were attributable to firms involved in a private equity deal between 1991 and 2021. Half of these transactions in the datasample were buyouts according to Preqin and the majority took place after the year 2000.[97]

The methodological approach employed in this thesis utilizes robust methods to estimate the effect size of private equity takeovers and developes a novel matching method based on blocking and matching that significantly outperforms the alternative probabilistic matching based on propensity scores by up to over 200%. Matching is essential for studying the influence of private equity ownership on environmental performance, as it helps mitigate problems of selection bias arising from the tendency of private equity firms to favor certain industries. For instance, PBTs are chemicals that are typically used for very technology specific purposes, with electronics and computer products being a major application. In this industry, PE showed a positive selection bias, with 3.64 % of facilities in this sector in the full sample compared to 6.91 % of facilities in this sector in the PE=1 subset. The exact record linkage based on industry and hazard score in the BaM method used in this thesis avoided influence of such confounding factors. The novel matching process effectively reduces omitted variable bias that arises from facility- and pollution-fixed effects by comparing pairs of facilities that share both, idiosyncratic characteristics, and the environmental ramifications of their operations. This allowed controlling for facility size, industry, changes in productivity, as well as legal and other externalities which are due to location, environmental hazard of pollution and time. Additionally, the blocking and matching method developed in this study employes matching on similar quantities of production

[94] To the best of the author's knowledge.

[95] See for example Konar and Cohen (1997, pp. 109-124) or Saha and Mohr (2013, pp. 284-291).

[96] See for example Prechel and Zheng (2012, p. 950) or Mary L Streitwieser (1994, p. 2).

[97] For summary information on the transactions, see appendix C, p. 2.

waste, which addresses a potential selection bias exhibited by private equity investors who use ESG as a risk framework to select facilities that are already clean and do not require an investor to implement further pollution or waste reduction. As for the innovated blocking and matching approach greater accuracy and reliability in the analysis is ensured, the results obtained from BaM are considered for further interpretation.

The findings of this thesis reveal a general trend in which facilities reduce their pollution in terms of total releases by about 8.6 % per year and the amount of toxic chemicals as production waste by about 5.1 % per year over the period from 1991 to 2021.This baseline reduction aligns with observed trends in existing literature.[98] In the context of the impact of private equity on pollution, this study finds that the annual pollution reduction rate is 1.55 %-points lower if a facility's parent company is acquired by a private equity investor in the same year (i.e., a facility indirectly involved in a PE deal reduces pollution by about 7.05 % in the deal year). Conversely, the research finds that the reduction in production waste is 1.11 %-points higher in a year when a facility is indirectly involved in a PE deal (i.e., a facility reduces the amount of production waste by approximately 6.21 % in that year). In examining whether PE investors discriminate between different levels of environmental risk, the thesis further finds that higher chemical hazard is directly correlated with increased total releases and inversely correlated with decreased production waste. Conclusively, while the hypotheses theorized under the rationale of the private equity business model more effectively internalizing the social costs of pollution to maximize shareholder value suggest that private equity takeover leads to better overall pollution management in the target company, the implications drawn from the data of this thesis reveal a contrary image. First, it appears that the average private equity investor does not leverage its controlling stake in a company to encourage cleaner facilities and instead results in worse sustainability of the facilities. Thus, under the general view applied in the research of this thesis, the private equity business model clearly fails to internalize the social costs of environmental pollution. The findings infer that private equity investors instead have an incentive to avoid internalizing social costs of pollution, and this inclination becomes more salient in situations where associated costs are higher, i.e., in the case of pollution with a substance exhibiting high environmental hazard. Echoing the environmental hazard model interpretation, a general positive correlation of increased environmental pollution with increasing hazard is indeed observed. Interestingly, as PBTs persist in the environment for long periods of time and generally exhibit constant time-dependent degradation, they can be easily traced back to specific times and quantities of their releases. As a result, private equity investors may still remain liable even after divestiture of the asset, which is especially relevant for substances classified as environmental hazard class 4 (both PBT and carcinogenic), as they can cause severe damage long after their release and therefore have a high potential for lingering liability. Although this potential liability risk aligns with future social costs it is not internalized in the overall view of this research. The higher increase for substances with higher hazards may be attributed to the fact that pollution abatement measures for chemicals of high hazards are typically already using the best available technology (as typically required by law) and the increase in productivity after private equity takeover resulting in higher tonnage of toxic chemicals handled cannot be offset by these measures because they are already operating at their limits. This might elucidate the measurable increase despite controlling for changes in productivity and suggests a scenario where PE investors, yet aware of liability risks, still favor generating present profits over preparing for future penalties. This reality is supported by the work of Shive and Forster, who found significantly more judicial actions and higher penalties for PE-backed facilities compared to private independent backed facilities.[99]

The implications of production waste can be divided into two distinct, yet entangled narratives. The first narrative, the ESG-narrative, considers quantities of toxic chemicals in the production waste as risk factor for possible future occurrence of social costs which may arise from pollution or the imposition of Pigouvian taxes (see chapter 2.2). The other narrative considers quantities of toxic chemicals in production waste as an opportunity for value creation due to operational improvement, as waste represents wasted resources and financial losses. Since operational improvements at the target company level have been identified as a key driver of private equity sponsors' return,[100] in the quantity of toxic chemical in production waste, environmental and financial objectives are tied together where reduction of toxic (and expensive) chemicals results in cheaper (and cleaner) operations. As more hazardous substances are typically more expensive (both costs of the chemical itself and associated safety measures as well as allowances for the workers handling such substances), the incentive to reduce production waste increases with potential threat coming from the production waste. In the light of the results of this research, that a) the quantity of toxic chemical in production waste is reduced after private equity takeover and b) this reduction is more pronounced for substances that pose greater hazards, this finding reinforces the deduction that the private equity business model is only effective in achieving non-financial goals when these are well aligned with the financial ones.

Notwithstanding the first key finding of this thesis, which indicates that private equity ownership has a negative impact on the pollution levels of U.S. facilities, the theoretical foundations of the impact of capital deployed – which unequivocally show that a policy of engagement is superior to simply impact divesting[101] – highlight the realization for LPs pursuing socially responsible impact of their investments that the

[98] See for example Collins et al. (2020, p. 4).

[99] See Shive and Forster (2020, p. 1320).

[100] See Achleitner et al. (2011, pp. 155–156).

[101] See Berk and van Binsbergen (2021, p. 26).

private equity asset class is a viable instrument for achieving their objectives – if LPs reconcile this realization by the second key finding of this thesis that these objectives must be well aligned with incumbent financial objectives.

5.2. Limitations of the research

Databases such as the TRI are essential for measuring the relationship between economic activity and environmental pollution in the United States.[102] The employment of the TRI in academic research has led to various insights into the effects and the broader economic impact of pollution and polluting businesses, respectively.[103] More specific to the research on the effect of private equity ownership on environmental pollution, the TRI database has been used to uncover factors influencing asset-level sustainability, for example liability risks imposed by geographic location.[104] Nevertheless, it must be noted that the TRI database incurs several limitations with respect to the data availability for a single facility or a company holding such facilities. First, the TRI only refers to facility level sustainability and not portfolio company level sustainability. Besides that, another major impingement on the utilization of the data is the threshold for the quantity of substances at which a facility must begin monitoring the substance for a given calendar year. The ramification is, that facilities that are required to report are typically larger ones owned by publicly traded companies, while small- and medium-sized facilities (i.e., parent companies), which are typically targets of private equity deals in the US, are less extensively covered by the TRI database. In addition, a facility does not report for a calendar year if the amount of substance handled in that year is below the threshold, which hampers a year-to-year comparisons to a certain extent, but more so for small and medium-sized facilities. Another important caveat, especially for longitudinal use of TRI data, is that reporting standards and regulations (e.g., chemicals listed, thresholds, industries covered) have changed over time. This was especially true in the early years after 1987, and data prior to 1991 are generally considered to be of limited quality,[105] especially because the reporting threshold was 75.000 pounds in 1987, 50.000 pounds in 1988 and was set to 25.000 pounds in 1989.[106] For this reason, the panel data in this paper starts with the reporting year 1991 to analyze the pollution level of facilities. To facilitate data analysis, the EPA periodically updates the database from previous reporting years to reflect updates and mitigate disproportionality; however, the presence of minor inconsistencies in reporting standards must be considered as an inevitable limitation when interpreting the results of this thesis. Other limitations of the TRI are that it does not cover all industry sectors, not every facility within covered sectors is mandated to report to TRI, and from an environmental perspective, the TRI chemical list does not encompass all toxic chemicals utilized in the United States.

Regarding the environmental hazard model, the findings of this thesis infer a hazard-dependent treatment effect. It is important to note that this influence may be largely attributable to the ordinal hazard score developed in the study, which may exhibit significant model dependence. Specifically, the fluctuations observed in the trends may be a result of the interpretation inherent in the environmental hazard model created for this research. Hence, the implications from considering different hazard scores are only considered to be informative. Yet, disentangling nuanced trends with such intricate dependencies has not been previously explored in the literature.

In the methodological approach, the research in this thesis faced the pertinent limitations that are frequently incurred by the propensity score matching method. A major reason for the deficient performance of the propensity score model in this research is that the categorical variables *Industry* (23 industries) and *Location* (52 states) were implemented as binary variables via one-hot encoding which resulted in 75 binary variables in the matching process (additionally to the year, facility size and environmental hazard variables). Coarsened Exact Matching (CEM) has been shown to be superior to propensity score matching for samples with imbalances due to higher order interactions,[107] and the CEM approach has been used to study the environmental performance of companies in similar contexts.[108] However, the method could not be successfully applied in the setting of this thesis because data formatting issues in the TRI database. As an alternative to CEM, principal component analysis in the propensity score matching model was tested as this has been shown to be expedient in economic research when addressing a large set of confounders in PSM.[109] However, the approach did not succeed and subsequently, efforts were guided towards developing the novel blocking and matching method.

The blocking and matching method has the limitation that the algorithm used in this research performes 1:many matching. Since the preceding exact blocking on 4 variables created a large number of small blocks compromised of subsets of facilities within which matching was performed, 1:many matching was beneficial in this case as it ensured reduced bias due to missing matches. The preceding exact blocking also immanently limits overestimation of the treatment effect due to multiple pairing of a control case, as it constraints the maximum number of control cases which can be matched to a treatment case. It must be noted however,

[102] See Bradley C. Karkkainen (2019).
[103] For a comprehensive review on research including the TRI, see Young et al. (2022).
[104] See Bellon (2020, p. 2).
[105] See Scott de Marchi and James T. Hamilton (2006, pp. 60–61).
[106] See "Toxic Chemical Release Reporting: Community Right-To-Know - PART 372" (1988)
[107] For a detailed elaboration on the advantages of CEM over traditional matching methods, especially propensity score matching, the reader should refer to Iacus et al. (2012, p. 2).
[108] For research using CEM as a matching method in the context of environmental performance in the US, see Hora and Subramanian (2019, p. 6), and in Europe see Kube et al. (2019, pp. 104558–104570).
[109] See for example Griffin et al. (2020, pp. 5537–5549).

that in case of less stringent blocking, greedy 1:1 matching should be performed.

5.3. Further research

The findings of this thesis offer intriguing research questions that could reveal relevant ramifications for policymakers as well as for market participants in the private equity industry. As elaborated above, ESG-considerations can protect future revenues from exposure to threats when these eventually become substantial. Thus ESG-performance equivalates possible financial outperformance in a more distant future. According to the results of this thesis, this possible financial return is not harvested through internalization of present social costs related to environmental pollution. In this context, current research revealed that the timeframes of asset managers are often too short to evaluate ESG-performance of assets.[110] Hence, further research could focus on determining whether a) private equity firms exhibit inability to accurately evaluate ESG risks and thus fail to address relevant topics at the portfolio company level or b) the private equity business model exhibits an investment period that is too short to internalize long-term social costs. To address this question, the overall impact of private equity, as measured in this thesis, could be disaggregated by investor characteristics to identify factors that foster an ESG-friendly phenotype among PE investors. In this context, Abraham et al. (2022) discovered that PE investors who emphasize ESG as a value driver on their website contribute to a decrease in pollution after takeover, relative to investors who do not adhere to SRI principles.[111] In addition, the research could explore the "skill or luck" question[112] to determine whether the ESG performance of these investors is due to their ability to drive sustainable change or merely the result of serendipity.

In the context of the relative decrease of the amount of production waste, it would be intriguing to investigate whether the reduction is a directly aspired outcome of the operational engineering that private equity firms undertake to enhance efficiency after takeover, or attributable to the alleviation of financial constraints that enable technology investment and thereby indirectly reduce hazard potentiality as a byproduct. To address this question, hypothetical differences between facilities supported by industry-agnostic PE investors and those with industry expertise could be explored. Both of the above research questions have important implications for policymakers in determining how to effectively regulate the private equity business model to position it as a catalyst for transforming the manufacturing sector toward better sustainability, while ensuring that private equity continues to play a constructive role in delivering financial value to limited partners.

Echoing the hazard score interpretation, the model in this thesis relied on an ordinal scale and exhibited significant model dependance. This might explain, why private equity takeover appears to induce an increase in the total releases and production waste of substances classified as PBTs (environmental hazard level 2) compared to substances classified as neither PBT nor carcinogen (environmental hazard level 3). While for the production waste this increase might be due to aforementioned model dependance, the general positive correlation of increased environmental pollution with increasing hazard suggests a tendency of PE investors to care less about the environment. Further research is needed to distinguish between hazard scores and could for example employ the full RSEI model from the EPA.

Along these lines, a potential further research question could focus on deal characteristics and how they relate to ESG-performance of target facilities. Arguably, certain deal types, such as those involving LPs investing through funds of funds, could serve to mask investments in environmentally detrimental assets. Such investments could then be used to offset lower returns from environmentally sustainable ventures. This thesis did not delve into the intricacies of deal structures; therefore, future studies could focus on addressing the limitations of missing data from the Preqin data source and further investigate the potential impact of deal characteristics on ESG performance.

Lastly, to engender a holistic view on the ESG performance of the PE-backed facilities examined in this thesis, the S and the G pillar are eminent topics of further research. In this thesis the focus is on the “E” (i.e., environmental) component of ESG and it would be interesting to reveal the S pillar of ESG in the same context to give a detailed picture.[113]

[110] See Eccles et al. (2017, p. 128).

[111] See Abraham et al. (2022, p. 13).

[112] See Korteweg and Sorensen (2017, pp. 535–562) for the question of skill and luck in private equity performance.

[113] For example the National Establishment Time-Series database would provide the S component and can be used well together with the data from the TRI (Technische Universität München (2023)).

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