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**Exploring The Environmental Impact of Innovation Through Technology-Driven
Mergers and Acquisitions:**
Assessing The Influence Of Technology-driven M&As On The CSR Performance Of Public US
Firms In The Energy Sector

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

This study investigates how technology-driven mergers and acquisitions (M&As) affect the Corporate Social Responsibility (CSR) performance of publicly traded US companies, focusing on Environmental, Social, and Governance (ESG) scores, from 2002 to 2022. The analysis particularly emphasizes the energy sector. Fixed effects and OLS regressions are used to explore the hypothesized relationships. The results show that technology-driven M&As improve acquiring companies' ESG scores a year after the merger, though this relationship is complex and varies by sector. In the energy sector, common M&As tend to improve ESG performance, whereas technology-driven M&As have a negative impact on ESG scores, emphasizing the challenge of integrating new technologies into existing systems. These findings indicate that, while adopting new technologies poses significant obstacles, particularly in the highly regulated energy industry, such innovations have the potential to improve ESG performance in other sectors over time. This demonstrates the strategic importance of emphasizing high-quality technological advancements to achieve long-term sustainability goals.

Keywords: Technological innovation, Green Innovation, Patents, ESG, CSR, M&A, Energy Sector

JEL Classification: G11, G30, G34, M14, O31, O32, O34, Q50, Q55,

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Chapter 1

Introduction

The energy sector is currently at an important moment, facing increasing worldwide pressure for sustainable and environmentally friendly operational practices. This trend is being driven by an intensifying focus on Environmental, Social, and Governance (ESG) standards. There is a growing consensus among experts and industry professionals that it is important to incorporate innovative technologies in companies to boost environmental sustainability, improve social accountability and establish strong governance frameworks (Kendpal et al., 2024). According to Ebrahim (2020), using these technologies is seen as more and more important for companies to match their strategies with the wider sustainability goals. This improves their Corporate Social Responsibility (CSR) performance. At the same time, the role of technology-driven mergers and acquisitions (M&As) becomes more important in the sector's transformation, boosting the adoption of innovative and sustainable technologies (Sue et al., 2022). Although technology-driven M&As have the potential to accelerate positive CSR performance, research on this topic is still in its early stages, especially in the energy sector. This thesis seeks to close this gap by investigating how technology-driven M&As affect the CSR performance of energy firms, with an emphasis on technology integration and operationalization, as well as their impact on ESG performance. This research also aims to contribute to the debate on sustainable development by exploring the strategic value of technology-driven M&A in promoting sustainability in the energy sector.

In the constantly evolving mergers and acquisitions landscape, technology-driven M&As stand out as important to fostering corporate innovation and increasing companies' competitive advantage in an era of rapid technological evolution and industrial transformation. Integrating insights from the literature on CSR and M&As, it is important to recognize that M&As involving companies with good CSR practices are perceived favorably by the market as less risky, resulting in higher long-term profitability and success rates (Barros et al., 2022). The technology-driven transactions allow companies to quickly acquire external technologies and innovative capabilities, thereby reducing the innovation cycle and potentially increasing market valuation and CSR performance after the transaction (Suo et al., 2023; Tampakoudins & Anagnostopoulou, 2020). The literature emphasizes the strategic importance of technology-driven M&As in enhancing a firm's innovation output, such as increased patent outputs and citation frequencies, especially from firms with previously weaker technological capabilities. Combining CSR efforts with technology-driven M&As provides therefore a robust strategy for business growth. One of the main reasons for blending innovation with CSR and ESG principles globally is the ongoing fight against climate change. The energy industry has a large impact on climate change, accounting for almost two-thirds of total CO₂ emissions (Global Energy Review 2019, 2019).

With global energy demand predicted to rise by 50% between 2018 and 2050 (International Energy Outlook 2019, 2019), the sector is under high pressure to adopt cleaner, renewable energy sources. As a result, studying how strategic decisions, like conducting in an M&A, can affect CSR performance of energy firms is important in order to be able to improve environmental practices.

The existing research on the relationship between M&A performance and CSR performance frequently focuses on how the target’s pre-merger CSR performance affects the acquirer’s post-merger financial performance (Feng, 2021; Teti & Spiga, 2023; Rahman & Wu, 2024). This study, however, takes a somewhat reversed approach by investigating the influence of a specific type of M&A, technology-driven M&As, on the CSR performance of energy companies. This reverse investigation provides new insights into the strategic considerations that drive M&As, as well as the larger implications for sustainability. It can also demonstrate how much technological improvements contribute to sustainable company operations, which is becoming increasingly important regarding global environmental issues. Furthermore, while current research illustrates the role of technology-driven M&As in contributing to corporate innovation and maintaining competitive advantage in rapidly evolving technological landscapes, there is a significant gap in understanding how these technology-driven M&As affect CSR performance, particularly in the energy sector. This link to the energy industry holds significance for research because of the sector’s significant contribution to global CO2 emissions and the urgent need to switch to sustainable energy alternatives. Technology-driven M&As can help to accelerate this transformation by boosting innovation. Therefore, the research question of this study is as follows:

“Is pursuing a technology-driven M&A a successful strategy for an acquiring company in the energy sector to enhance its CSR performance?”

The starting point of this analysis are the studies by Tampakoudins & Anagnostopoulou (2020) “The effect of mergers and acquisitions on environmental, social and governance performance and market value: Evidence from EU acquirers” and Barros et al. (2022) “M&A activity as a driver for better ESG performance”, which are one of the few to study the effect of M&As on ESG performance. This research shares similarities with the core of both studies, but focuses specifically on technology-driven M&As in the energy sector. In the existing literature, a technology-driven M&A is defined as such when the target company has pursued at least one patent publication in the five years preceding the transaction (Ahuja & Katila, 2001). In this study, a transaction is considered as technology-driven if the target company has published a patent related to technological development (Y-patent) within the same timeframe. The patent portfolio size of the target company is assessed based on the number of patent publications between 1997 and 2022, retrieved from The Lens patent database, who sources its patent information from several prominent global patent offices, such as the United States Patent and Trademark Office (USPTO), the World Intellectual Property Organization (WIPO) and the European Patent Office (EPO). Furthermore, the CSR performance of companies is measured by its Environmental, Social, and Governance (ESG) score. Certified rating agencies derive these ESG scores by combining the scores for the three components using a specific weighting criteria. This weighting varies per industry (Giese et al., 2020). The ESG data is retrieved from the Thomson Reuters Refinitiv ESG database, formally ASSET4. This database provides ESG scores of US companies between zero and 100. The M&A data spans from 2002-2022 and is extracted from Eikon, using the Refinitiv database. From the Refinitiv database, the Sector Identification Classification (SIC) codes of the

companies are also retrieved. The SIC codes provide identification codes for all industry sectors where the companies operate in. Incorporating these codes into the dataset allows for targeted research across both the energy sector and other industries. The financial information of the acquiring companies for the control variables is sourced from Compustat.

The findings of this study indicate that while technology-driven M&As generally boost the ESG scores of acquiring companies one year after the M&A, they face sector-specific integration challenges. The effect on the ESG scores is, contrary to the hypothesis, negative in the energy sector. The study also highlights that the quality of technological innovation, measured by patent citations, positively influences ESG scores over time. The research shows that a larger ESG score gap between the target and the acquiring companies in the year before the merger can initially hinder ESG performance. However, improvements are expected as integration progresses. Additionally, general M&As in the energy sector tend to improve ESG performance, indicating that while integrating new technologies presents difficulties, it holds significant potential for long-term ESG gains.

This paper is organized in the following manner. Section 2 offers an overview of relevant literature and previous studies on (technology-driven) M&As, alongside theories related to M&A, CSR and innovation. It also outlines the hypotheses developed from the literature review. Section 3 describes the data collection process, sample construction and the variables employed for hypothesis testing. Section 4 explains the empirical methodologies applied in the analysis. Section 5 presents the results of the empirical study, and finally, Section 6 contains the conclusion and discussion of this research.

Chapter 2

Theoretical Framework

In recent years, there has been a surge in consumer preference towards products produced by companies emphasizing sustainability in their operations (Yuen et al., 2016; Renneboog et al., 2008). Additionally, there is a growing trend towards investing in companies with superior environmental practices (Riedl & Smeets, 2017). Despite the increased awareness of social responsibility, only a limited number of studies have attempted to illuminate the direct impact of M&As on CSR performance. The following section provides an overview of CSR literature and its association with technology-driven M&As and innovation, encompassing an examination of their effects on CSR performance.

2.1 Technology-driven M&As

2.1.1 Background

Corporate restructuring, such as M&As, has become an international trend used by firms to achieve strategic objectives. In the dynamic landscape of business, M&As can help companies to expand into new markets, increase profitability and strengthen economic efficiency by reallocating resources (Jiang, 2022). With globalization and rapid technological advancements, M&A has become a popular growth strategy for enterprises (Kumar, 2018). One way for a company to accelerate (green) innovation, is by conducting a technology-driven M&A. Technology-driven M&As refer to strategic transactions wherein a company acquires technology-related assets from another entity. These assets may include the target company's technology (patents), research and development (R&D) staff, and products. The objective is to enhance the acquiring company's R&D endeavors by incorporating additional technological resources (Ruckman, 2009).

2.1.2 Theories on M&As

The resource-based theory states that businesses leverage various unique and strategic resources to maximize their value and gain a competitive advantage. These resources are characterized as unique, strategic and hard to replicate, thereby serving as the foundation for establishing and sustaining a competitive advantage within enterprises (Wernerfelt, 1984). By acquiring advanced technology through M&As, companies can quickly enhance their competitiveness by integrating the acquired firm's technological advantages (Suo et al., 2023).

The synergy theory states that M&As enable enterprises to achieve resource sharing in technology, management, and capabilities, leading to improved performance and value for both parties

involved. This collaboration results in synergies that go beyond the individual capabilities of each company, as outlined by Ansoff (1965). These synergies are the strongest in management, operational, and financial aspects. The primary motivation for most companies to engage in M&A activities is to enhance management efficiency and pursue synergistic benefits, as highlighted by Jensen and Ruback (1965).

2.1.3 Technology as the motivation for M&As

When a company is acquired for its technological knowledge or capabilities, it constitutes a technology-driven acquisition (Arthur & Khindanova, 2023). These technology-driven acquisitions are important for gaining and sustaining competitive advantages (Ahn, 2020). In line with the resourced-based theory, these acquisitions afford companies economies of scale and competitive edge, enhancing their capacity to absorb, develop, and integrate knowledge in innovative ways, thereby enhancing both short-term performance and long-term competitiveness (McCarthy & Aalbers, 2016). Ahuja and Katilla (2001) discovered a positive relationship between the quantity of the knowledge base acquired through technology-driven acquisitions and output. By combining target companies' technology skills, acquiring companies can improve their technological knowledge, setting the stage for innovative restructuring (Arthur & Khindanova, 2023).

In today's business landscape, the demand for innovation has increased the significance of acquiring external technology through M&As. According to the open innovation theory, such moves provide firms with a quick route to more knowledge pools, including technologies that are not widely available in the market. Companies can close the innovation gap faster than industry leaders by exploiting mergers and acquisitions. Furthermore, in the dynamic landscape of mergers and acquisitions, technology-driven M&As stand out as important for nurturing corporate innovation, enhancing firms' competitive edge in an era marked by rapid technological evolution and advancements in the industry (Suo et al., 2023). These transactions offer an opportunity for companies to rapidly acquire external technologies and innovative capabilities, thereby reducing the innovation cycle and potentially enhancing market valuation and CSR performance post-transaction (Bena & Li, 2014; Suo et al., 2023; Tampakoudins & Anagnostopoulou, 2020).

Moreover, as firms navigate the complexities of technological advancements and sustainability goals, technology-driven M&As emerge as a strategic tool for not only enhancing innovation, but also to align their strategies with broader sustainability objectives, ultimately strengthening their performance in CSR initiatives (Ebrahim, 2020).

However, the negative inhibition theory suggests that M&As can actually reduce R&D expenses. It claims M&As can increase the complexity of organizational structures and also financial limitations may contribute to decreased R&D expenditure, reducing innovation. Furthermore, managers may change their focus from internal innovation to external technology acquisition, after which the focus on R&D activity after a merger declines, which can ultimately lower the company's innovation (Suo et al., 2023).

2.2 Corporate Social Responsibility and ESG

Habermas (1976) discusses how new social forces formed in Europe throughout the 1960s. These groups sought to address problems such as regional autonomy, homosexual rights, and women's liberation, which differed from classic Marxist class conflicts. More recently, there has been an increase

in movements promoting issues including recycling (Lounsbury et al., 2003), shareholder activism (Davis & Thompson, 1994), and civil society organizations (Sjostrom, 2007). These movements are categorized as Corporate Social Responsibility (CSR) movements (Gendron & Turcotte, 2007). According to Zald and Berger (1978), CSR movements are similar to new social movements in that they develop collective identities, pool resources for common aims, modify existing institutions, and strive for broader societal change.

Davis (1973) defined CSR as corporations addressing social and environmental challenges in addition to their core economic and legal responsibilities, to achieve broader societal advantages as well as financial goals. The European Commission built on this concept in 2001, describing CSR as enterprises that actively incorporate social and environmental issues into their operations and relationships with stakeholders. This concept was refined in 2010 and 2011, reflecting ongoing changes in how CSR is perceived and handled in contemporary business situations.

Despite a lot of research (Crane et al., 2008; Lockett et al., 2006), defining CSR remains challenging due to its controversial nature, internal complexities, and flexibility. CSR frequently crosses with other business-society relationship models (Matten & Crane, 2005), it is dynamic and ever-changing (Carroll, 1999), making it difficult to define it exactly.

CSR is really about corporations realizing their societal responsibility and the consequences of their conduct. Practically, CSR consists of explicit policies and actions intended at improving society, but the specifics of these duties vary every organization. It differs between firms' primary profit-making objectives and governments' involvement in social welfare (Friedman, 1970).

Dahlsrud (2008) believes that the existence of many definitions of CSR is not particularly problematic because they all have five fundamental dimensions: environmental, economic, social, stakeholder, and voluntariness, which serve as the foundation for practically all definitions of CSR. Despite the multiple definitions, the essential principles of CSR converge greatly, minimizing the need for a universal definition. Dahlsrud underlines that the true problem for corporations is not defining CSR, but rather understanding its social construction in specific situations and incorporating this knowledge into strategic planning.

ESG scores constitute a component of the broader concept of CSR. In 2022, ESG investing encompassed more than 20 trillion US dollars in Assets Under Management (AUM) representing approximately one-quarter of all professionally managed assets globally. Moreover, ESG data constitutes a distinct category in financial analysis, centering on a company's environmental (E), social (S) and governance (G) practices, in addition to traditional financial metrics (Li et al., 2021). It prioritizes and examines the enterprises' contributions to environmental conservation and fulfillment of social responsibilities while advancing sustainable economic development. In detail, "E" refers to the enterprise's resource needs, energy consumption and management, waste management, and the environmental impact of its business operations and investments. "S" shows the enterprise's interactions with internal and external stakeholders such as employees, shareholders, and customers, evaluating its capacity to maintain harmonious relationships. Meanwhile, "G" analyzes internal processes such as corporate structure, risk management tools, management compensation practices, and compliance with ethical business norms (Amel-Zadeh & Serafeim, 2018).

2.3 ESG, M&As and technological innovation

2.3.1 The shareholder and stakeholder theory

Two contrasting perspectives exist concerning CSR: the shareholder perspective and the stakeholder perspective. The shareholder perspective originates from neoclassical economic theory, stating that managers' primary obligation is to maximize profit (Friedman, 1970). Under this view, social and environmental concerns are expected to be addressed by the market within the confines of regulatory frameworks, and if necessary, by government intervention (Arouri et al., 2019). As per this perspective, as the implementation of CSR initiatives can incur significant costs and compete for a company's limited financial resources alongside essential marketing activities such as new product development and advertising, CSR activities could not yield the optimal effect on profit maximization. Consequently, firms prioritize assessing the financial implications of CSR activities (Bhardwaj et al., 2018). However, despite their potential strategic advantages, empirical research yields inconclusive findings regarding the effects of CSR on firms' financial performance (Margolis and Walsh, 2003; Margolis et al., 2009). From the shareholders' perspective, the benefits accruing to other stakeholders from CSR activities come at the cost of shareholder wealth, leading to a transfer of wealth from shareholders to other stakeholders (McWilliams & Siegel, 2001).

Given the fundamental link between business and ethics, this includes taking into account the interests of all stakeholders involved in their company operations and effectively controlling the influence of their activities on these parties (Freeman, 1994). The purpose is to maximize the creation of shared value that benefits owners/shareholders, stakeholders, and society as a whole (Fernández-Guadaño & Sarria-Pedroza, 2018). Porter and Kramer (2006) contend that corporate success and social welfare are not mutually exclusive, but can instead complement one another. Therefore, CSR-related initiatives enhance stakeholders' endorsement of a company's undertakings, thereby ultimately serving the interests of the shareholders (Arouri et al., 2019). As a result, CSR initiatives are frequently linked with enhanced reputation (Martinez-Ferrero et al., 2016). This stronger reputation can subsequently enhance the ability to attract financial investments by fostering greater trust, thereby potentially boosting financial performance (Cheng et al., 2014).

Although both of these opposing theories are supported by existing literature, there has been relatively little research conducted on what the role of M&As is in these theories. This paper aligns with the stakeholder view, which regards CSR as a signal of value enhancement through the maximization of total stakeholder value.

2.3.2 ESG transparency and innovation

Existing research in the field of ESG and sustainability reveals that businesses that apply ESG practices may gain a range of benefits, including competitive advantages. These advantages include improved reputation (Dash & Mohanty, 2023), improved financial performance (Ghardallou, 2022), increased market value (Pulino et al., 2022), better access to equity financing (Cheng et al., 2014), and risk reduction (Benlemlih & Girerd-Potin, 2017; Jo & Na, 2012).

Comparison of ESG scores across companies requires the implementation of independent audits on sustainability reports. Del Giudice and Rigamonti (2020) found that companies with third-party audited ESG reports maintain consistent scores, even after a scandal, unlike those without audited reports, which often see a significant decline. This indicates that independent auditing can significantly enhance the reliability and credibility of ESG scores by ensuring that they accurately reflect

the company's actual sustainability practices. Also, in March 2022, the Securities and Exchange Commission (SEC) proposed rule changes mandating climate-related disclosures in registration statements and periodic reports. These disclosures cover climate risks' impact on business, operations, and financial statements, as well as greenhouse gas emissions. The rules are intended to improve transparency and reliability in climate-related reporting, what will minimize ESG uncertainty, making sustainable investing less risky and promoting greater investor engagement, resulting in higher economic wellbeing (Avramov et al., 2022).

As the quality and reliability of ESG ratings improve with the introduction of audited reports and enhanced transparency, improvements in environmental, social, and governance activities will have an impact on the value of the ESG score. Among these activities, firm innovation contributes significantly. Research by McWilliams and Siegel (2001) and Fishman et al., (2006) suggests a positive correlation between firm innovation and ESG performance. This implies that a company's ESG performance is impacted by the quality and quantity of its successful innovations (Mishra, 2015). Furthermore, according to Tempakoudins and Anagnostopoulou (2020) and Suo, Yang, and Li (2023), technology-driven mergers and acquisitions have the potential to accelerate innovation. This, in turn, can potentially improve ESG performance, resulting in a positive result for the study's core research question.

2.3.3 Technological innovation and CSR

As more companies realize how technology can help them fulfill their social and environmental responsibilities, they are integrating it into their corporate social responsibility (CSR) programs. Businesses are focusing on this sector since the majority of governments have made the development of green technologies a top priority to address resource restrictions and environmental challenges. Companies can maximize and advance the goal of sustainable development by using green technologies. They not only get more efficient, but they also satisfy consumer demand for more environmentally friendly products and more strict environmental laws while also improving social, environmental, and economic factors (Li & Zhou, 2022).

Particularly in environmental management, technology significantly improves CSR performance. By optimizing procedures and closely observing activities, cutting down on their negative effects on the environment and society, cutting-edge techniques like AI and big data analytics enhance sustainability (Al-Sharafi et al., 2023; Hassoun et al., 2022; Chrishty, 2023).

Technology not only improves processes but also increases the transparency of CSR initiatives. Real-time reporting and thorough disclosures are now possible with digital tools, and these are necessary for meeting legal requirements and interacting with stakeholders. Stakeholder demands for more accountability and more transparent information regarding CSR operations make this improved transparency necessary (Yu et al., 2018). Blockchain technology, for instance, improves supply chain transparency by offering safe records of CSR initiatives (Varma et al., 2024). According to Teoh et al. (2019), these developments enhance report accuracy and help forecast CSR outcomes, enabling more informed strategic choices and long-term sustainability planning. It is anticipated that increased CSR transparency will reduce ESG uncertainties, reduce investment risks associated with sustainable projects, and increase investor participation, all of which can improve economic well-being (Avramov et al., 2022).

2.3.4 Hypothesis 1

The purpose of this study is to research how technology-driven M&As affect the CSR performance of US public companies. Sue et al. (2023) claim that because these M&As allow businesses to acquire and use cutting-edge technology resources, they can stimulate innovation. They support organizations in integrating multiple technological assets to improve their ability to innovate. Technology-driven M&As also bring in new data and technology, which improves R&D operations' efficacy.

Innovation helps companies use new technologies like AI, IoT, and blockchain to better manage their environmental impact and use resources more efficiently. These tools help reduce waste, save energy, and monitor CSR activities more accurately (Chrishty, 2023; Hassoun et al., 2022). They also make it easier for companies to meet the increasing demands for transparency and accountability in their CSR efforts (Varma et al., 2024; Yu et al., 2018).

M&As in general are increasingly recognized for their potential to improve corporate sustainability, which positively impacts the ESG score of companies. (For example, the paper by Barros et al. (2022) states that the improved ESG performance after an M&A is not reflected in the ESG score immediately, but becomes significant in the year following the transaction. This highlights that the integration and operational efficiencies positively influence the ESG practices. The paper by Tempakoudins and Anagnostopoulou (2020) also confirm that M&As, especially those driven by strategic motivations to acquire innovative capabilities, significantly improve the ESG practices of the acquir-

ing companies. This is due to the integration of advanced technologies and operations that align with global sustainability goals, thereby improving CSR performance across multiple dimensions. The mentioned studies highlight both the financial and ethical drivers behind M&As, showing that while the relationship is complex, it significantly leads to better CSR results. On the other hand, occasionally, research show that technology-driven acquisitions result in negative correlations with innovation and ESG practices, because of integration challenges after the acquisition (Desyllas & Hughes, 2010; Graebner et al., 2010). Based on the mostly positive impact of (technology-driven) M&As discussed in the papers in this paragraph, Hypothesis 1 predicts that:

H1: Technology-driven M&As lead to an improvement in the ESG scores of acquiring companies in the year after the merger

2.3.5 Hypothesis 2

Wang et al. (2023) look into how ESG ratings affect a company's green innovation efforts. They suggest that higher ESG ratings, which indicate better environmental and social practices, tend to boost a company's focus on green innovation. The idea is that companies with strong ESG ratings are seen as more responsible and sustainable, attracting investors who are willing to support long-term, innovative projects. These investors are often more patient and interested in quality, which can lead to increased investment in green technologies and processes. Higher ESG ratings also enhance a company's reputation, which can lower capital costs and open up new funding opportunities for sustainable projects. These benefits can strongly encourage and support a company's investment in green innovation.

The opposite has been studied by Zheng et al (2022), who examined the effect of green innovation on ESG ratings and financial performance. Technologies, especially those associated with green patents, are important for improving ESG metrics because they introduce new methods of environmental management and energy efficiency that align with global sustainability goals. The study further emphasizes that the effectiveness of these technologies in enhancing ESG scores can often be derived from the innovation quality of the target firms, which can be assessed through the number of patent publications and citations. Firms with a high number of technological patent publications are likely to be leaders in innovation, possessing technologies that can directly contribute to better environmental and social outcomes after conducting an M&A. Moreover, patents with a higher number of citations reflect technologies where the quality has been recognized by the market and academia. This suggests that the quality of those patents is higher, which makes them potentially more effective at enhancing ESG outcomes. When these technologies of the target company are combined with those of the acquiring company through an M&A, they can help the acquiring company manage its environmental impact more effectively. As Zheng et al. (2022) suggest, the technology brought by these patents play an important role in improving the environmental performance of acquiring companies. Due to the influence of innovation on ESG performance, Hypothesis 2a posits the following prediction:

H2a: Technological innovation, measured by the number of Y-patent publications from the target company, exhibits a positive relationship with the ESG score of the acquirer in the year following a technology-driven M&A.

The number of patents is an accurate measure of a company's innovation activities, and how often those patents are cited shows their broader influence and practical value (Atanassov, 2013). (Zhang and Xu (2019) found that patents with more citations are not only recognized by others but are widely used in practice. This indicates that patents with a lot of citations have a big impact on their associated industry. This leads to the idea that acquiring companies with acquired highly cited patents are likely to see greater improvements in their ESG scores. These companies provide technologies that are validated and widely recognized, which could boost ESG performance more than fewer recognized technologies. Based on this, Hypothesis 2b investigates whether the acquirer's ESG performance can be improved by the quality of technological innovation that has been purchased:

H2b: The quality of technological innovation, as indicated by the number of patent citations pre-M&A, is positively correlated with the ESG scores of the acquiring company post-merger.

2.3.6 Hypothesis 3

According to the research by Hong et al. (2022) and Deng et al. (2022), the success rate of M&A deals can be higher if the ESG scores of both the target and acquiring companies are relatively high before a merger. The scores of the acquiring companies have a particularly large impact on the success rate of the deals. Barros et al. (2022) examined the impact of M&As on the global ESG performance of acquiring companies in the year after the merger, where they also researched the effect on the separate environmental, social, and governance pillar scores of acquiring companies. According to their findings, there was a general improvement in the environmental and social scores following the merger, but the governance pillar outcomes were less evident. This is most likely a result of the public and regulatory focus on companies' impact on the environment and society, which has led to the growing focus on ESG practices in the first place.

Barros et al. (2022) did not separate ESG performance before the merger from ESG performance after the merger. The papers by Tempakoudis and Anagnostopoulou (2020) and Aktas et al. (2011), did. The issue with acquiring companies with large differences in innovation or ESG performance-levels is that it can negatively affect firm operations because of agency problems and informational asymmetries (Scharfstein & Stein, 2000). Conversely, the paper by Aktas et al. (2011) found that acquiring companies who acquired high-rated ESG targets were better at learning and improving their sustainability practices. This effect got more significant when there was a bigger difference in ESG scores between the target and the acquiring firm before the merger. The paper by Tempakoudis and Anagnostopoulou (2020) came to the same conclusion that the ESG score of the acquirer is improved by the acquisition of a target company with a superior ESG performance score. Based on these findings, Hypothesis 3 is proposed:

H3: When the gap in pre-merger ESG scores between the target and acquirer widens, the acquirer's post-merger ESG score tends to be higher

2.4 Green innovation: the case of the energy sector

2.4.1 Green technological innovators

Attention must be directed towards the CSR and sustainability efforts of energy companies, given that they operate in an environmentally sensitive sector. In today's landscape, the energy sector has to deal with environmental and social challenges during a growing preference towards renewable energy sources.

Making sure that there is a sustainable and reliable long-term energy supply that meets the demand, which is driven by today's modern lifestyle and improved quality of life, creates a big challenge for energy companies. Meanwhile, adding to these challenges, firms in other industries are prioritizing CSR initiatives, reducing their energy consumption to protect the environment and bringing down manufacturing costs, which negatively influences the revenue of energy companies (Gigauri & Vasilev, 2022).

Because of the increasing pressure on all companies to switch to renewable energy sources, the demand for such energy is rising. Energy companies are therefore forced to look for new energy sources that can satisfy this demand. Consuming energy has a growing role in modern society, as technological innovations are improving the quality of life with products that can't exist without energy and is therefore irreplaceable for fueling economies worldwide (Smill, 2017). Energy companies will have to manage proper societal expectations, fit into local and international regulatory requirements, and respect global commitments such as the Sustainable Development Goals (SDG's) if they are to maintain their social legitimacy (Agudelo et al., 2020). This means that they have to safeguard their reputations, stay competitive, and attract and keep highly skilled personnel by creating a modern, positive corporate culture (Raman, 2018).

By implementing green innovation strategies, energy businesses can reduce the harmful effects of their production processes. Green innovation includes the use of innovative problem-solving methods and environmentally friendly procedures that emphasize negative environmental impacts (Chen, 2008). Studies by Chan (2005) and Zhang and Zhang (2014) highlight the potential competitive advantages and improved performance because of green innovation in energy companies.

Because companies in the energy sector are often involved in fossil fuels activities, they generally have lower ESG scores and are therefore excluded from investment initiatives with an ESG focus, but they stand out as leaders in green technology innovation. Not only are the energy companies highly productive in generating green patents but they also produce innovations that have substantial quality and impact in the sector, for example in the important field of carbon capture (Cohen et al., 2020). These companies have been in the forefront of innovating technologies that establish the foundation for more extensive green technology breakthroughs, and with that shaping later breakthroughs in the industry. The fact that energy firms lead in green technologies, while they usually have lower ESG scores, emphasizes their important role in innovating sustainable solutions within the industry.

2.4.2 Hypothesis 4

The paper by Cohen et al. (2020) provides a contradictory analysis of the role that energy sector companies play in green technology innovation, despite having generally lower ESG scores. The study demonstrates how these companies are at the forefront in the development of innovating important green technology but still get frequently left out of ESG investment funds because of their lower environmental performance ratings. Firms in the oil, gas, and energy production sectors have not

only embraced innovation but have become drivers in the field of green patent production in the United States. These firms consistently produce a significant volume of green patents, which are of high quality and have a big influence in the sector. The paper by Cohen et al. (2020) highlights the significant role of these firms in green technology, particularly in areas like carbon capture and renewable energy solutions, where their innovations serve as a foundation for further research and development.

Cohen et al. (2020) identified a negative correlation between ESG ratings and green innovation in the US energy industry. However, contrasting findings suggesting a positive correlation between ESG ratings and green innovation have been found in other studies (Mneimneh et al., 2023; Wang et al., 2023; Zhang et al., 2020). As a result, Hypothesis 4a will be explored:

H4a: The correlation between ESG scores and technological innovation diverges between energy sector firms and others, with the former often displaying a weaker or inverse relationship.

Based on the insights of Hypothesis 4a about how sectors can impact the relationship between green innovation and ESG performance, it is important to look closer at how these sectorial differences can impact the effect of technology-driven M&As. Technology-driven M&As usually bring changes in technology and innovation. The energy industry is subject to strict regulations and significant operational demands. Therefore, gaining helpful new technology through conducting an M&A can have a greater impact there. To better understand why there is a shift in ESG scores following an M&A, Hypothesis 4b seeks to investigate how these effects on ESG performance vary across different industries. The results of this hypothesis will provide better strategic insights for companies that consider an M&A as a way to improve their ESG performance. Because the typically lower ESG scores of companies in the energy sector, it would suggest that there is greater room for improvement (Clement et al., 2022), which could potentially result in a more substantial increase in ESG scores following technology-driven M&As in the energy sector compared to other sectors where the average ESG scores might be higher. Hypothesis 4b:

H4b: Technology-driven M&As in the energy sector lead to more substantial improvements in ESG performance compared to M&As in sectors with higher initial ESG ratings.

Chapter 3

Data

This section outlines the procedures used in the collection of datasets from different data sources, the construction of the sample, and the selection of variables necessary for testing the hypotheses of this study. It details the sources of the data, the criteria for data inclusion, and the reasons for choosing particular variables.

3.1 Data collection

To effectively investigate the hypothesis concerning the influence of technology-driven M&As on the ESG performance of US firms, particularly within the energy sector, it is necessary to gather a thorough panel dataset including M&A transactions, along with relevant information regarding the acquiring and target entities. This information includes the number of patents and citations for the target companies, to label M&As as technology-driven. Financial metrics are also necessary for the acquiring firms to be able to construct control variables. Moreover, access to ESG scores for both acquiring and target companies, both pre- and post-M&A is needed. Furthermore, Sector Identification Classification (SIC) codes are required to distinguish results within the energy sector from other sectors. The dataset for this study spans from 2002 to 2022 and exclusively includes publicly listed companies in the United States. Detailed elaboration of the specific data requirements for the hypotheses will be discussed below.

3.1.1 Patent data

Previous studies related to innovation often use R&D expenditures as a proxy for the level of innovation (Chen et al, 2022; Pegkas et al, 2019; Savrul & Incekara, 2015). However, these expenditures alone do not capture the quality of innovation, as they are just one of several inputs needed for successful innovation. Other inputs include physical and human capital, managerial and employee efforts, and creativity. Over-reliance on R&D spending without effectively leveraging these other inputs can actually decline innovation (Atanassov, 2013). The paper by Attanasov suggests that using output measures, such as the number of patent publications and the number of patent citations provides a clear assessment of the innovation quality of a firm.

In this research, M&As are categorized as technology-driven if the acquired company shows a positive shift in its technology patent portfolio within the preceding five years prior to the acquisition (Ahuja & Katila, 2001). M&As are labeled non-technology-driven if the acquired company has not pursued any technology patent publication in the previous five years leading up to the deal. Since the

first M&A in the dataset happened in 2002 and the last in 2022, the size of the target company's patent portfolio is assessed by counting the number of technological development (Y) patent publications between 1997 and 2022. The evaluation of the acquired company's patent portfolio size is determined based on the number of technological development (Y) patent publications between 1997 and 2022.

The first step in gathering data for this study involved collecting information on patents, which is used for testing hypotheses 1, 2a, 4a and 4b. Additionally, data on patent citations is used for Hypothesis 2b. There are various sources for patent data that contain characteristics of patents, though many of these sources are not freely accessible. Prominent patent offices such as the European Patent Office (EPO) provide extensive information on patents registered in Europe. Similarly, the United States Patent and Trademark Office (USPTO) offers comprehensive data for patents registered in the US. While both databases offer detailed records on individual patents, they do not provide aggregated data at the level of patent owner. For the purposes of this study, essential patent details required include publication year, publisher and citation counts. Furthermore, while a substantial amount of existing literature on innovation employs the NBER patent dataset introduced by Hall et al. (2005), demonstrating that innovations enhance firm value, it is worth noting that this dataset spans only the period from 1975 to 2000, making it unsuitable for this study's timeframe.

This paper uses The Lens (www.lens.org) patent dataset. The Lens serves as a worldwide, freely accessible platform, created to enhance the transparency and accessibility of innovation. It combines patent data with scholarly and technical literature to offer a comprehensive understanding of the innovation ecosystem. Operated by Cambia, a non-profit organization, The Lens is dedicated to empowering researchers, entrepreneurs, and policy makers with easily accessible, premium-grade information to aid their initiatives. The dataset offers comprehensive data at the firm level. It encompasses approximately 156 million patents, which have 58 million citations, originating from 17.6 million applicants (The Lens, 2024). The Lens sources its patent information from several prominent global patent offices, such as the USPTO, the World Intellectual Property Organization (WIPO) and the EPO.

To distinguish between patent applications, the Lens offers two classification systems: the Cooperative Patent Classification (CPC) and the International Patent Classification (IPC). While both systems are used, CPC is primarily employed by the USPTO and is favored in this research, due to its inclusion of a filter for newly developed technologies, known as Y-patents. This filter allows for more precise identification of patents related to recent technological advancements (USPTO, 2024).

The initial criterion for extracting patent and patent citation records involves selecting the appropriate date range. For the purposes of this study, the relevant period is set between 1997 and 2022. The Lens platform offers various options regarding the date of patents, including filing date, earliest priority date, published date, anticipated termination date, and granted date. The filing date denotes when a patent application is initially submitted to a patent office, while the priority date signifies the first filing date of a patent application globally, typically in the applicant's domestic patent office. The publication date marks the moment when patent application information becomes publicly available, usually occurring 18 months after the priority date. Anticipated termination date refers to the expiration date of the patent, typically 20 years from the earliest filing date for US patents. Finally, the granted date is when the patent office officially issues a patent to the applicant. On average, the process of patent approval at the USPTO takes approximately three years (USPTO, 2023; The Lens, 2023).

Since inventions don't spread right away after being applied for, there's a delay between apply-

ing and actually using them. Depending only on when applications are made can be biased because not all patents end up getting published. Another concern arises from the fact that the uniqueness of the patent can only be determined after its publication. Using publication dates of patents makes it easier to compare and analyze different patents and innovations. In this study, where M&A activity is considered technology-driven if the target company has had patents published within the five years before the M&A, it's important that the patents of the target are public knowledge and have been published. That's why, for this study, the dates when patents are made public are used.

The data extraction process began by applying specific filters to construct the patent dataset necessary for hypothesis testing. Initially, the "Published Date" filter was applied, covering the time-frame from January 1997 to December 2022, to capture the relevant patent data within the designated period. Subsequently, only the "has Owner" flag was selected to ensure inclusion of patents attributed to an owner in the dataset. Given the focus of this study on M&A activity involving US acquirers and target companies, jurisdiction was restricted to the United States. Finally, for the "Document Type" filter, both "Patent Application" and "Granted Patent" documents were chosen. These filtered criteria resulted in a comprehensive patent dataset comprising 1,704,778 patents and 1,389,007 "Citations by Patents", representing the number of citations received by the patents.

One limitation of The Lens database, for this research, is its restriction to downloading a maximum of 50,000 rows per session. Therefore, in order to obtain the complete patent dataset, manual downloads and extraction to a CSV document was necessary. A total of 1,704,778 patents were acquired through 35 separate downloads, each time with only several months at a time. Excel has a maximum row limit of around one million, resulting in the dataset exceeding the capacity of a single Excel sheet. After finishing the downloading process, a CSV sheet was constructed with different columns for the publication year, applicants, owners and citations by patents.

A challenge faced because of the way the patent data of The Lens database is constructed is the inability to also download a unique company code for the applicants, like a Cusip, Datastream or ISIN code. Because these company identification codes are not available, it is a challenge to integrate different datasets using a shared identifier. The methodology for addressing this limitation will be discussed further in Section 3.2.

3.1.2 M&A data

The main focus of this paper revolves around investigating the impact of technology-driven M&As. To achieve this, the M&A dataset served as the core, from which the relevant company ID codes were extracted that were used in the data collection process of relevant variables. The relevant M&A data is obtained through the use of the Deal Screener function within Refinitiv Eikon. Based on existing research (Aktas et al., 2010; Deng et al., 2013), specific deal criteria were selected.

For inclusion in the dataset each deal had to meet certain requirements. These included the criteria that only completed transactions were considered, with the acquiring entity obtaining a stake of over 50% of the equity after the deal. Additionally, the deal value had to exceed 5 million US dollars, and both the acquiring and target companies had to be publicly listed entities. Moreover, additional filters were applied, to align with the research objectives.

The dataset includes M&A transactions announced between January 2002 and December 2022, involving exclusively US-based acquirers and targets. Following the application of these additional criteria, a total of 5,139 deals were identified within the Eikon dataset.

3.1.3 Company data

To enable the testing of hypotheses, it was necessary to gather additional information for each deal. This included the full names of both acquiring and target companies for the merging with the patent dataset. Moreover, the SIC codes for both entities needed to be included, in order to distinguish M&As within the energy sector from those in other sectors.

Furthermore, to access and retain ESG scores from the Thomson Reuters Refinitiv database, the unique CUSIP code for each company was required. The use of CUSIP codes allows for the retention of financial data from Compustat as well. These codes were generated using the Workspace function within Refinitiv, using the Datastream codes.

3.1.4 CSR/ESG data

In this study, the ESG scores of firms have been selected to measure the CSR performance of companies. This method of assessing CSR performance is commonly used, including in high-quality journal research (Arouri et al, 2019; Bae et al., 2021; Liang & Renneboog, 2017).

The evaluation of sustainability-related data poses a challenge due to its qualitative nature, leading to varied outcomes. According to Eccles et al. (2019), the market is flooded with approximately hundreds of ESG rankings and disclosure standards. This lack of standardized metrics has resulted in varying ways in how ESG metrics are measured and assessed by different data providers. Berg et al. (2022) found significant differences in sustainability ratings among six prominent ESG rating agencies, with correlations ranging from 0.38 to 0.71, contrasting with the near-perfect correlation in credit ratings. Despite insights from academic research, differences in scoring models persist, complicating ESG performance assessment and leading to underinvestment in sustainability. Moreover, investors typically pay for ESG scores, adding complexity to rating variances, as ESG rating agencies base their scores primarily on data provided by companies (Zumente & Lāce, 2021).

Another problem arises from the limited availability of data and the slow integration of ESG scoring in the market. The OECD notes that ESG rating availability is higher in terms of market capitalization, indicating a preference for awarding ESG scores to larger companies. This potentially sidelines smaller peers lacking the capacity for extensive sustainability implementation and reporting (Boffo & Patalano, 2020).

To mitigate the primary issues associated with ESG ratings, this research incorporates information sourced from Thomson Reuters Refinitiv database, formally ASSET4. The ESG database provided by Thomson Reuters is widely recognized as a frontrunner in the market, enjoys acknowledgment and is used often within academic circles (Yunus et al., 2020; Burritt et al., 2020; Jeriji & Louhichi, 2021). The ESG scores provide an evaluation of companies' relative environmental, social and governance performance, based on publicly-available data. These scores are built upon a framework that integrates over 630 company-level ESG measures. From this pool, a selected group of 186 measures, chosen for their comparability and significance across industries, influences the overall evaluation process. Factors such as data availability, industry relevance and impact guide the selection of these measures, which are grouped into 10 key categories. The final ESG score reflects a company's commitment and effectiveness in ESG matters, given in percentile rank ratings, compared to the Refinitiv Business Classifications (TRBV) industries. This evaluation offers a transparent and data-driven insight into companies' relative ESG performance (Refinitiv, 2024).

The Datastream codes of the acquiring and target companies, retrieved from the M&A dataset,

served as input for the Refinitiv ESG database. Upon exploiting the data to Excel, it was organized in a multi-row per item format, with various metrics distributed across several rows and columns for each company. Through steps in the Power Query function of Excel like unpivoting and pivoting, filtering, cleaning and adjusting data types, a transformed dataset was constructed. In the transformed dataset, the scores for each company across different categories, such as the individual pillars scores of the ESG ratings and the overall ESG score, were consolidated into a panel data structure. Each company is represented by a single row per year, with columns designated for E-, S-, G- and the comprehensive ESG score. This adjustment streamlines the data structure, making it more suited to compare different metrics and analyze trends over time.

3.1.5 Financial data

Lastly, firm-level financial data for the acquirers was retrieved from Compustat. Compustat Fundamentals offers standardized annual financial statement and market data for over 80,000 publicly traded companies, both active and inactive, spanning over 50 years (WRDS, 2024). This financial data will serve to construct control variables across all hypotheses. The following ratios and variables were sourced from Compustat using the companies' CUSIP codes from the M&A dataset: book-to-market ratio, leverage, return on assets, R&D intensity and total assets. These variables will be elaborated on further in Section 3.3.3: Control variables.

3.2 Sample construction

As previously stated, five separate datasets required merging to form a comprehensive final panel dataset. The main dataset incorporates mergers and acquisitions data, providing details on both acquiring and target companies, including SIC codes and the complete names of the entities involved. It enables the identification of the acquiring and target companies through unique Datastream and Cusip codes. Following this, the patent dataset contains Y-patents alongside publisher names, publication years, and citation numbers, lacking unique company identification codes. Additionally, there are two ESG datasets, featuring ESG scores of acquiring companies and target companies per year, also identifiable by Datastream and Cusip code. Finally, the financial dataset for control variables includes acquiring companies' financial data identified by unique Cusip codes.

The first step is to merge the patent data into the main M&A dataset. Once this process is completed, the ESG scores of both acquiring and target companies are merged into the M&A-patents dataset. After that, the financial data is integrated into the main dataset, creating a panel dataset with all the relevant information for testing the hypotheses per company per year.

Due to the absence of a unique company identification code in the patent dataset, the merging process posed challenges. Integration between the patent and M&A data required dependence on company names. However, differences existed between the company names in the patent and M&A datasets. Various techniques were employed in order to maximize the number of successful merges.

The variation in company names between the datasets posed a significant challenge for the merging process, as the company names are the only possible matching criteria. Differences arise when one dataset employs capitalization or includes specific abbreviations like 'corp.', 'inc.', or 'ltd.', whereas the other dataset spells them out fully or excludes these abbreviations entirely. This is the case for the ESG dataset, which excludes all the abbreviations, while the patent dataset often contains additional descriptors added to the company names. Consequently, the merging process may

result in failed matches between identical companies. In contrast, the use of fuzzy matching leads to matched results between companies with comparable names that are in fact, separate entities. This can significantly impact the study's result.

Ultimately, a solution has been found to ensure the merging of as many patents as possible into the M&A dataset. To ensure that the names in both datasets are exactly the same, all punctuation such as commas, periods, hyphens, and quotation marks has been replaced with spaces. Furthermore, all company names in the M&A dataset and all applicant names in the patent dataset have been converted to lowercase. Then, because there was no unique company identification code present, one was created. The merging process was based on the first two words of the company's name.

By using the first two words of the "applicants" string in the patent dataset and the initial two words of the "company names" from the ESG data file, a company ID was created. Matching between both datasets was primarily based on the year of publication/merger and the company ID. Attempts at matching focused solely on the first word in both the patent and the ESG companies' IDs. If no match was found, the second word was also taken into account. This method was effective in filtering out words that did not provide significant identity information about the firm, such as "abbvie Incorporated", which often followed the firm's name. In the dataset with the ESG scores, only the initial words that appeared once were retained to prevent multiple ESG firms from mistakenly matching with the same patent firms. The recurrence of words in the ESG dataset highlights their limited utility in identifying companies. For example, when comparing "abbott lab" and "abbott malcolm" for similarity, the term "abbott" would be disregarded, and only the subsequent word evaluated, potentially resulting that there was no match. Conversely, within the Patent dataset, initial words that appeared more than once were preserved, as various versions of a company's name could exist. For instance, in the patent dataset, there are more than 130 distinct company names that begin with "mitsubishi," representing various entities within different contexts, such as the car manufacturing part, but also the electrical part, the software part and a chemical part. It is important to note that patents are often transferred to or published by various subsidiaries from the same holding company.

Unfortunately, despite thorough efforts, there is a chance that some firms involved in M&A activity may not have been matched with the patents they published. This disparity arises from the less accurate nature of merging based on company names compared to using a unique company identification code like Cusip of Datastream. This is the case because various sources use different full names, unfortunately for this study, and, a Cusip of Datastream code remains unique to each company. However, there is no indication that a missing match occurred systematically, so they are unlikely to significantly impact the results.

In this study, a technology-driven M&A is defined as an acquisition involving a target company that has published a Y-patent within five years preceding the M&A event. Consequently, the patent dataset required aggregation to represent the cumulative count of patents and citations by each company for each year. Afterward, the aggregated patent data is merged into the M&A dataset five times based on the year and company ID. Each time, the year in the M&A dataset is adjusted to a year further from the merger year. This adjustment enables the merging of patent data from the target company dating back five years prior to the M&A.

After merging the patent data into the M&A dataset, the acquirer's ESG dataset and financial data were also integrated into the main dataset using Cusip code and year variables. However, when attempting to merge the target ESG scores, numerous duplicates arose for Cusip-Year combinations

due to the presence of many missing target Cusip values. To address this issue and to enable merging of the target ESG dataset into the main dataset, a unique merger key was established. Because the target ESG score was only needed for the ESG gap variable, the target company’s ESG score was taken from the year before the merger. This was achieved by creating a merger key variable comprising the (year-1) appended to the associated CUSIP code. For instance, if there was data for a company with Cusip code "00089C107" in the year 2006, the merger key variable would be assigned a value of "00089C1072005". For observations where Cusip values were absent, a merger key was generated with a value of "NOMATCH+observation number" to ensure uniqueness of the merger key variable. The same unique merger key was created in the target ESG scores excel dataset, so the both datasets could be merged on the merger key code. Subsequently, all observations where the acquirer’s ESG score was unavailable were removed from the dataset, given that the primary research focus of this paper pertains to the impact of technology-driven M&As on the acquirer’s ESG score. Additionally, M&As involving either the acquiring or target company having a SIC code for the financial sector (≥ 6000 and ≤ 6999) (Kahle & Walking, 1996) were excluded from the analysis (Moeller et al., 2004). Following the completion of the merging processes, a final sample comprising 6,793 company-year observations remained. Within this final sample, there were 509 different companies, who conducted 860 distinct mergers, including 265 technology-driven ones. Of these 860 M&As, 121 occurred in the energy sector and of these 121, 17 M&As were technology-driven ones in the energy sector.

3.3 Variables

3.3.1 Dependent variables

The study employs the ESG scores of acquiring companies and their adaptations as dependent variables. As discussed before, the ESG scores are percentile rank ratings compared to industry peers. The variable *ESGscore* represents the combined value derived from weighted environmental (E), social (S), and governance (G) metrics, reflecting the company’s commitment and effectiveness in addressing ESG matters. Additionally, *F.ESGscore* serves as a derived metric from the *ESGscore*, indicating its value in the subsequent year following the merger. This specific dependent variable is relevant for the hypotheses.

3.3.2 Independent variables

This study incorporates several independent variables. Hypothesis 1 includes a dummy variable for technology-driven M&As. For Hypotheses 2a and 2b there is a variable for innovation and one for innovation quality, respectively. For Hypothesis 3, the independent variable is a different version of the ESG score variables, focusing on the gap between the acquiring and target company’s ESG scores. In Hypothesis 4a, an interaction variable between the innovation variable and the energy sector variable is constructed. Lastly, the final hypothesis includes an interaction variable between technology-driven M&As and the energy sector. All continuous variables are winsorized at the 1st and 99th percentiles to remove the influence of extreme outliers.

Hypothesis 1 examines the impact of technology-driven M&As on the ESG scores of acquiring companies compared to non-technology-driven M&As in the year following the merger. This is evaluated using the dummy variable *TechnologyDrivenM&A*, which takes a value of 1 if the target company has issued at least one Y-patent within the five years leading up to the deal, and 0 otherwise.

Hypothesis 2a explores innovation by assessing the number of patent publication from the target company in the five years prior to the deal. The *Patents* variable is derived by dividing the total number of patents published by a company in the five years prior to the M&A by the mean number of patents per two-digit SIC code of the target company. This adjustment accounts for any truncation bias in patent grants (Atanasov, 2013). In Hypothesis 2b, innovation quality is evaluated by examining the total number of citations received by all patents published by the target company in the five years leading up to the M&A. This value is then divided by the total number of patents published by the target company during the same period, resulting in the *InnovationQuality* variable. By dividing the number of citations by the number of patents over time, the *InnovationQuality* variable corrects for year fixed effects (Atanasov, 2013).

In Hypothesis 3, the central focus is the *ESGgap* variable, which is derived by subtracting the *acquirerESG* score variable from the *targetESGscore* variable. This analysis explores how this gap impacts the acquiring companies' ESG score one year after the merger.

The correlation between ESG scores and innovation for firms active within and outside the energy sector is studied in Hypothesis 4a. In order to investigate this, the analysis includes an interaction variable between the *Innovation* variable and a dummy variable named *EnergySector*. This dummy variable takes a value of 1 if the acquiring company operates within the energy sector, and 0 otherwise. The energy sector classification follows the approach outlined in Cohen et al. (2020), where specific industries are categorized under the energy sector based on the first two digits of their Standard Industrial Classification (SIC) codes. These sectors comprise 10 for "Metal and Mining", 12 for "Coal Mining", 13 for "Oil & Gas Extraction", 14 for "Non-metallic Minerals excluding Fuels", 29 for "Petroleum and Coal Products", and 49 for "Electric, Gas, and Sanitary Services".

In the final hypothesis, 4b, the focus shifts to investigating the impact of technology-driven M&As within the energy sector on the enhancement of ESG scores among acquiring companies, relative to other industries. To explore this aspect, an interaction variable is created. This variable, calculated as the product of *TechnologyDrivenM&A* and *EnergySector*, highlights the specific effect of technology-driven M&As within the energy sector.

3.3.3 Control variables

Control variables are important in research because they allow for the adjustment of potential confounding factors, helping to isolate and clarify the specific effects of the main variables of interest, enhancing the credibility of the results. Including control variables helps in generalizing findings to other populations by addressing external factors not central to the study. They are particularly important in studies involving group comparisons, where they help manage individual differences among participants, ensuring that comparisons accurately reflect true differences rather than participant variability (Schjoedt & Sangboon, 2015).

Previous studies examining the effects of M&As on ESG scores or innovation have identified several variables that potentially influence these outcomes. Therefore, firm size, leverage, profitability, book-to-market ratio and R&D intensity are included as control variables in the regression (Beronne et al., 2013; Wang et al., 2023). Firm fixed and year fixed effects are also controlled for in the analysis. A detailed overview of the variables used in the regressions are displayed in Table 3.1.

Firm size

Size significantly influences ESG scores, with larger firms generally exhibiting higher scores due to economies of scale, enhanced efficiency, and increased pressure for sustainability reporting (Barros et al., 2022; Liang & Renneboog, 2016). Additionally, larger firms have greater availability of data and resources for ESG disclosures (Drempetic et al., 2019). To improve the statistical properties of the model and ensure comparability across firms of varying sizes, the natural logarithm of the book value of total assets, denoted as $\ln(TotalAssets)$, is included as a control variable. This adjustment not only enhances the interpretability of the model but also provides a more robust framework for analysis. $\ln(TotalAssets)$ represents firm size, with smaller firms often leveraging accessible resources more effectively for green innovation, while larger companies possess more favorable conditions for successful innovation (Lin et al., 2019). Smaller firms encounter limitations in resources and intensified competition, potentially hindering investments in sustainability innovation (Anderson et al., 2019). Therefore, it is anticipated that there will be a positive correlation between company size and ESG performance.

Book-to-market ratio

The book-to-market (BTM) ratio contrasts a company's book value of its equity to the market value of the equity (market capitalization), as represented in formula 3.1. It is an effective control variable for financial analyses focusing on a firm's intrinsic worth versus its market valuation. This ratio is significant in M&A studies due to its ability to capture key drivers of M&As such as growth opportunities, overvaluation and asset complementary (Bena & Li, 2014; Rhodes-Kropf & Viswanathan, 2004). A higher BTM ratio typically indicates undervaluation, potentially signaling lower market expectations for future profitability and ESG initiatives. Consequently, higher BTM ratios may negatively impact ESG scores as they could suggest a lack of market confidence in firms' ability to invest in and benefit from ESG activities.

$$BTM = \frac{\text{Book Value of Equity}}{\text{Market Value of Equity}} = \frac{\text{Common Shareholders' Equity}}{\text{Market Capitalization}} \quad (3.1)$$

Leverage ratio

In this study, the leverage ratio is defined as the ratio of the firm's book value of total debt relative to the book value of total assets at the end of the year, as given in formula 3.2 (Wang et al., 2023). The *Leverage* variable represents the percentage of a company's assets financed with debt. As debt increases, interest expenses rise, which can mean that there is limiting cash flow available for R&D activities. Leverage measures a company's financial health and debt flexibility, influencing its investment potential (Arugaslan & Miller, 2006). A lower leverage ratio often signals better governance and ESG performance, which aligns managerial incentives with shareholder concerns (Dalal & Thaker, 2019). On the other hand, financially leveraged firms are under increased scrutiny for their ESG reporting due to the risks associated with higher debt levels (Ghosh, 2013).

$$\text{Leverage ratio} = \frac{\text{Total Debt}}{\text{Total Equity}} \quad (3.2)$$

Profitability

Return on assets (ROA) is a financial term used to assess a company's profitability by expressing net income as a proportion of total assets, as shown in formula 3.3. ROA will be employed to assess the profitability of the acquiring firm (Eccles et al., 2014; Yu et al., 2018). Higher profitability can provide firms with the necessary resources to invest in sustainable practices, which could lead to higher ESG scores. These investments may enhance corporate reputation, attract socially conscious investors and potentially reduce costs through improved efficiencies and risk management. Furthermore, Di Simone et al. (2022), Wang et al. (2023), and Tempakoudis & Anagnostopoulou (2020) included ROA as a control variable in their studies on innovation, M&As, and ESG ratings, and all found it to have a significant positive impact. This consistent finding implies that more profitable enterprises are more likely to have higher ESG scores, supporting the theory that profitability may directly benefit or reflect a firm's ability to implement effective ESG measures.

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}} \quad (3.3)$$

R&D intensity ratio

In this study, R&D intensity is calculated by dividing research and development (R&D) expenses of the company by their total sales, as indicated in formula 3.4, with the goal of capturing the proportion of total sales dedicated to R&D operations. This technique relates to Wang et al.'s (2023) study, which constructed and used R&D intensity as a control variable. Wu and Reuer (2014) argue that R&D expertise is critical for effective technology integration and encouraging innovation following technology-driven M&As. Similarly, Benitez and Ray (2012) argue that organizations with strong R&D skills are more likely to gain better technological synergy following such M&As. This capability not only encourages operational savings and new product creation, but it may also improve a company's practices in environmental sustainability and social responsibility, thereby increasing its ESG scores.

$$\text{R\&D Intensity} = \frac{\text{R\&D Expenses}}{\text{Total Revenue}} \quad (3.4)$$

Year fixed effects

Including year fixed effects in regressions analyzing technology-driven M&As and their impact on ESG scores is important for addressing variations in the volume and nature of M&As over different years. Some years may experience higher activity in technology-driven M&As, which can differently influence ESG scores. Also, the increasing significance of ESG practices reflects the rising societal and regulatory focus on these factors year over year. This growing emphasis can significantly influence the outcomes of mergers and acquisitions in terms of ESG performance. By incorporating year fixed effects in the analysis researchers can effectively isolate the impact of M&As from the broader trends in ESG focus, which vary every year. This structure ensures that the analysis provides a more precise understanding of how M&A specifically influence ESG scores, independent of general annual shifts in ESG priorities.

Table 3.1: Overview of Hypotheses Variables

Variable	Description	Formula
<i>F.ESGscore</i>	ESG score of the acquiring company in the year following the merger	
<i>ESGscore</i>	Combined ESG score from environmental, social and governance metrics	
<i>TechnologyDrivenM&A</i>	Dummy variable indicating if the M&A is technology-driven, based on the recent technology patent activity of the target company	
<i>Ln(TotalAssets)</i>	Natural logarithm of the book value of total assets, representing firm size of the acquiring company	$\ln(\text{Total Assets})$
<i>BTM</i>	Book-to-market ratio compares a company's book value of equity to its market value of equity	$\frac{\text{Book Value of Equity}}{\text{Market Value of Equity}}$
<i>Leverage</i>	The proportion of a firm's total debt relative to its total assets' book value at the end of a specific year for the acquiring company	$\frac{\text{Total Debt}}{\text{Total Equity}}$
<i>ROA</i>	Return on assets, profitability measure for the acquiring company	$\frac{\text{Net Income}}{\text{Total Assets}}$
<i>R&DIntensity</i>	Proportion of revenue spent on R&D	$\frac{\text{RDIntensity}}{\text{Total Revenue}}$
<i>Innovation</i>	Measures the innovation output of the target company via the number of Y-patent publications	$\frac{\text{Totalnumberofpatentspublished}}{\text{Industryaverageofpatentspublished}}$
<i>InnovationQuality</i>	Measures the quality of innovation via the number of citations per patent	$\frac{\text{Totalpatentcitations}}{\text{Numberofpatentspublished}}$
<i>ESGgap</i>	The gap between the ESG score of the target and acquiring company in the year before the merger	$(\text{TargetESG} - \text{AcquirerESG})$
<i>Innovation * EnergySector</i>	Interaction variable between the number of patents published and the energy sector	
<i>TechnologyDrivenM&A * EnergySector</i>	Interaction variable between a technology-driven M&A and the energy sector	
<i>YearFixedEffects</i>	Controls for time-specific effects	

3.4 Descriptive statistics

This section will delve into the descriptive statistics of the dataset variables. First, the summary statistics of the variables in Table 3.2 will be reviewed and after that, the correlation statistics between the variables from Table 3.3 will be discussed.

3.4.1 Summary statistics

In the following section, the summary statistics of the dataset variables will be discussed. Table 3.2 presents the summary statistics of the variables used in hypotheses 1 to 3, which are the regressions at the firm level. These variables play an important role in exploring the relationships between technology-driven M&As, innovation, innovation quality and ESG scores of acquiring companies. For the industry-level hypotheses, 4a and 4b, Tables 2 and 3 are included in Appendix A to compare companies inside the energy sector to those outside of it. Table 2 shows the summary statistics of all the variables used in the hypotheses of the companies active in sectors outside of the energy sector. Table 3 shows the summary statistics of the companies in the dataset that are active in the energy sector. Furthermore, Table 4 shows the summary statistics of the aggregated dataset, which is the basis for hypotheses 4a and 4b. Table 5 and 6 both use Table 4 as a basis, but the statistics are separated based on the industries the companies are active in. Both tables are constructed by aggregating the dataset based on the two-digit SIC code of the acquiring company and the year variables to compute industry-year averages. This comparison aims to determine the impact of the energy industry on the ESG scores of acquiring firms.

ESG scores

The acquiring companies' ESG score in the year after the merger, referred to as *F.ESG score*, shows an average value of 48.16 with a standard deviation of 20.39. The forward ESG scores have a very broad range, from 2.20 to 95.16, which indicates significant variation in ESG performance among organizations. The median value is 47.19, meaning that half of the organizations have ESG scores that are lower than this value, which is close to the average. The low skewness of 0.08 implies a nearly symmetric distribution around the mean, while the kurtosis of 1.96 suggests a flatter distribution than a normal distribution, with fewer extreme values in the tails.

The acquiring companies' overall ESG scores in the merger year have a similar mean of 46.66 and a standard deviation of 20.65. These ratings similarly range from 1.67 to 95.16, demonstrating a wide variety of ESG practices and performance among the sample firms. The median ESG score is 45.12, slightly lower than the mean, which could suggest a slight skew towards lower scores. The skewness score of 0.15 is quite low, indicating minimal asymmetry. With a kurtosis of 1.97, the distribution again has flatter tails than a normal distribution, indicating a wide range of ESG scores throughout the sample.

The ESG gap is the difference in ESG scores between the target and acquiring firms in the year preceding the merger. Due to a shortage of Datastream codes for the target company in the M&A dataset, there are only 239 observations. The average ESG gap is -15.69 with a standard deviation of 24.24, indicating that on average target companies tend to have lower ESG scores than their acquirers before the merger. The range is relatively wide, from -74.02 to 60.25, indicating wide variations in ESG performance relative to the target companies. The negative skewness of -0.25 and the higher

kurtosis of 3.01 indicate a peakier distribution with fewer extreme values in the tails, implying that the majority of the ESG gaps cluster closer to the mean, though on the negative side.

M&As and Innovation

The M&A variable is a dummy that indicates if the acquiring company engaged in an M&A. The variable has a mean of 0.13 and an SD of 0.33. This means that a merger or acquisition occurred in 13% of the firm-year observations, which are 860 M&As. The range is from 0 to 1, with a skewness of 2.25, confirming that most firm-year observations showed no M&A activity. The kurtosis of 6.04 reveals that the distribution is more peaked and has fatter tails than a normal distribution, this is due to the relatively low number of M&As relative to the number of firm-year observations.

Technology-Driven M&A is a dummy variable that shows if M&A transactions involve a target firm that has published technology-driven (Y) patents in the five years before the year of purchase. The variable's average value is 0.04, with a standard deviation of 0.19, indicating that technology-driven M&As account for 4% of the firm-year observations in the dataset, or 265 in total. The skewness score is positive at 4.76, indicating that the majority of the samples' M&As are not driven by technology. The high kurtosis value of 23.68 suggests a peakier distribution, which is concentrated around the mode of zero. This is probably because it is a dummy variable with more values of zero, than of ones. This is explained by the relatively small number of technology-driven M&As when compared to the other firm-year data.

Innovation is defined as the total number of patents published by target companies in the five years before a technology-driven M&A and is normalized against the industry average in the database. The variable has a mean of 2.96 and a standard deviation of 5.24 based on 265 observations. This illustrates a wide range in patent output among target firms, from 0.05 to 36.30. The distribution is skewed (3.62) and has a very high kurtosis of 18.58, indicating that while the majority of target organizations have few patents, a small number have very high output, which skews the distribution significantly. This is mainly due to the excessive number of zeros in the sample.

Innovation Quality is defined as the number of citations per patent for patents published by target companies in technology-driven M&As and has an average of 2.94 with a standard deviation of 9.00 based on 263 observations. The values of the Innovation Quality variable span from 0 (patents with no citations) to 111.29 (highly cited patents). The skewness of 8.06 and kurtosis of 86.94 indicate a distribution with many low values and a few extremely high values, emphasizing a few patents with outstanding significance. The high kurtosis value is primarily due to the high number of zeros in the sample as well.

Financial variables

$\ln(\text{TotalAssets})$ is the natural logarithm of total assets measured in US billion dollars. This variable is a proxy for the size of a firm. The summary statistics show that firm size varies widely between the companies. The average company size in our sample is 9.14 with a standard deviation of 1.40. The size of the company should be taken into account since companies of larger size usually have more resources and therefore greater capacity for involvement in ESG initiatives.

The Book-to-Market Ratio (BTM) variable has a quite varied distribution of values clustered around a mean of 0.42 with a standard deviation of 0.35. BTM values vary between -0.29 to 1.94, indicating that some companies' BTM values are negative. This can occur when the equity book value is negative because accumulated losses exceed total assets. The positive skewness of 1.55 suggests that

the majority of companies in the data set have a higher book value than market value, which tends to drive BTM ratios up (Jan & Ou, 2012). This skewness could be driven by sectors in which the market undervalues companies or where low investor confidence prevails, such as traditional manufacturing or utilities. To limit extreme values, the variable is adjusted by using winsorization. Unfortunately, the kurtosis value is still high at 7.06, which indicates the presence of outliers.

The dataset's leverage ratio ranges from 0 to 3.94 and has a mean of 0.95. The winsorization approach for this variable was chosen to account for the wide distribution and strong skewness in the original data. Despite the winsorization at the 5th and 95th percentile, the skewness value of 1.74 and the kurtosis value of 5.28 indicate a distribution with a tail skewed towards higher values, suggesting that some companies in the dataset have unusually high debt/equity ratios.

The mean Return On Assets (ROA) in this sample is 0.04 and has a standard deviation of 0.1, which indicates that there is significant diversity in profitability among the firms in the dataset. The median value of 0.05 is slightly above the mean, which indicates that the distribution is slightly skewed with most of the companies producing returns that are above the average. The minimum ROA is -0.47, which means that some firms are generating big losses, relative to their assets. This could be due to inefficient operations, or large investments that have not yet provided positive returns. In comparison, a maximum ROA of 0.27 means that there are companies in the sample that are efficient at creating profits from their assets. The skewness of -2.20 and kurtosis of 11.78 confirm a left-skewed and leptokurtic distribution.

The dataset's R&D intensity, which measures the percentage of revenue dedicated to research and development, has an average of 0.10 with a standard deviation of 0.21, showing that R&D expenses are relatively low for a lot of companies, while a few companies have a very high ratio. This could be related to the fact that around 13% of companies reported zero R&D spending in relation to sales, while approximately 26% dedicated less than 1% of revenue to R&D. The skewness of 6.24 and a kurtosis of 50.71 confirm this variability in R&D spending. The sample includes industries such as real estate, construction, wholesale trade, retail, and transportation, which usually have relatively low R&D spending. These industries value for example operational efficiency and customer service over technology innovation. Discrepancies in financial statement reporting of R&D spending may potentially lead to similar trends in Compustat results.

Table 3.2: Summary Statistics of Sample

Variables	N	Mean	SD	Min	p25	Median	p75	p95	Max	Skewness	kurtosis
F.ESG score	6285	48.16	20.39	2.20	31.04	47.19	65.29	80.75	95.16	.08	1.96
ESGscore	6794	46.66	20.65	1.67	29.32	45.12	64.09	80.25	95.16	.15	1.97
ESGgap	239	-15.69	24.24	-74.02	-31.47	-12.67	.45	19.59	60.25	-.25	3.01
M&A	6794	.13	.33	0	0	0	0	1	1	2.25	6.04
Technology-Driven M&A	6794	.04	.19	0	0	0	0	0	1	4.76	23.68
Innovation	265	2.96	5.24	.05	.43	2.89	12.89	36.30	36.30	3.62	18.58
Innovation-Quality	262	2.94	9.00	0	0	.36	13.00	111.29	111.29	8.06	86.94
Ln(Total Assets)	6792	9.14	1.40	5.20	8.21	9.10	10.07	11.46	13.53	.006	3.11
BTM	6756	.42	.35	-.29	.20	.36	.56	1.06	1.94	1.55	7.06
Leverage	6079	.95	1.03	0	.29	.60	1.15	3.94	3.94	1.74	5.28
ROA	6742	.04	.10	-.47	.02	.05	.09	.17	.27	-2.20	11.78
R&D Intensity	4247	.10	.21	0	.01	.04	.13	.31	1.94	6.24	50.71

Note: This table presents the descriptive statistics of firm-year observations for dependent, independent, and control variables spanning from 2002 to 2022. F.ESGscore, ESGscore, and ESGgap are straightforward interpretations of the ESG scores: F.ESGscore represents the ESG score in the year following the merger, ESGscore denotes the ESG score in the merger year, and ESGgap indicates the ESG score difference between the target and acquiring companies in the year preceding the merger. ESG scores range between 0 and 100. TechnologyDrivenM&A and M&A are dummy variables set to 1 for technology-driven and general M&As in respective years. Innovation reflects the number of patents published by the target in the five years before a technology-driven M&A, normalized by the average. InnovationQuality measures patent citations per published patent. Ln(Assets) denotes the natural logarithm of total assets in billions. Leverage, return on assets by sales (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales are ratios requiring appropriate interpretation.

3.4.2 Correlation statistics

Table 3.3 displays the correlation statistics between all the variables included in the hypotheses regressions. According to Pallant (2005), correlations above -0.5 or 0.5 indicate moderate multicollinearity, while correlations exceeding -0.7 or 0.7 indicate high correlation. Testing for multicollinearity will be further discussed in section 4.2, Assumption tests.

The high correlation statistic of 0.933 ($p < 0.01$) between ESG score and F.ESG score is of course logical, as the F.ESG score is the ESG score of the same company, but then one year after the merger. The same situation occurs for the Technology-driven M&A variable and the M&A variable, as the M&A variable will always be 1 if the technology-driven M&A is 1. The correlation statistics are all put in one table, but a lot of the variables will not occur in the same regression, so their correlation will not influence the results.

Other relatively large correlation statistics in this study are the negative correlation statistics of -0.550 ($p < 0.01$) and -0.611 ($p < 0.01$) between the ESG gap and the F.ESGscore and ESG score in the year of the merger, respectively. This suggests that a wider gap in ESG scores between the target and the acquiring company in the year before the merger correlates with lower (forward) ESG scores.

The correlation between Technology-Driven M&A and both F. ESG score (0.054, ($p < 0.01$)) and ESG score (0.030, ($p < 0.10$)) suggests a modest positive relationship, indicating that M&As focused on technology may have a small favorable impact on a firm's ESG performance in the year of the merger and the subsequent year. This implies that technology initiatives can contribute to enhancing ESG

metrics.

The missing value for the correlation between the M&A variable and the ESG gap is because ESG gap only has a value when the M&A dummy variable equals one. Therefore, there is no variability in the values of ESG gap, when the M&A variable equals zero. The same situation occurs between innovation and innovation quality and the correlation with the M&A and technology-driven M&A variables. Innovation and innovation quality are constructed by counting the number of patent publications and patent citations, which only occur in this dataset when there was a technology-driven M&A. Consequently, the M&A variable is then also set to one.

The correlation between Year and F.ESG score is 0.357 ($p < 0.01$), indicating a moderate positive trend over time. This suggests that the forward ESG scores of firms tend to improve as the years progress, possibly due to increased regulatory pressures, better ESG reporting practices, or evolving CSR norms.

The same goes for the correlation between Year and the ESG score. The correlation statistic is even higher with 0.368 ($p < 0.01$), strengthening the idea that ESG scores are improving over time. This consistent improvement across different ESG metrics over the years may reflect a growing emphasis on sustainable practices within the corporate sector and a broader market response to ESG issues.

Furthermore, the correlation between company size ($\ln(\text{Total Assets})$) and both F. ESG score and ESG score stand at 0.510 ($p < 0.01$) and 0.515 ($p < 0.01$), respectively, indicating that larger firms tend to have higher ESG ratings. This strong positive correlation can be attributed to larger enterprises' ability to invest more heavily in sustainability activities. Larger companies can usually attribute more resources to ESG initiatives and can maintain transparency in ESG reporting, which can result in higher ESG scores. The high correlation value emphasizes the importance of scale in creating and maintaining high levels of corporate sustainability.

Table 3.3: Correlation Statistics of Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) F.ESG score	1.000												
(2) ESG score	0.933***	1.000											
(3) ESG gap	-0.550***	-0.688***	1.000										
(4) M&A	0.008	-0.017	.	1.000									
(5) Technology-Driven M&A	0.054***	0.030**	0.042	0.529***	1.000								
(6) Innovation	0.092	0.098	0.160	.	.	1.000							
(7) Innovation Quality	0.016	-0.018	0.159	.	.	0.384***	1.000						
(8) Ln(Total Assets)	0.510***	0.515***	-0.343***	0.034***	0.067***	0.211***	0.118*	1.000					
(9) BTM	-0.126***	-0.124***	0.239***	-0.011	-0.029**	0.016	-0.000	0.006	1.000				
(10) Leverage	0.085***	0.061***	-0.070	-0.010	-0.050***	0.229***	0.000	0.125***	-0.120***	1.000			
(11) ROA	0.165***	0.177***	-0.135***	-0.006	0.034**	-0.006	0.044	0.216***	-0.214***	-0.107***	1.000		
(12) R&D Intensity	-0.127***	-0.139***	0.116	0.058***	0.043***	0.012	-0.013	-0.288***	-0.088***	-0.081***	-0.470***	1.000	
(13) Year	0.357***	0.368***	-0.117	-0.030*	-0.041***	0.010	-0.154	0.032***	-0.012	0.185***	-0.107***	0.097***	1.000

Note: The table above presents pairwise correlations computed using the Pearson test. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 4

Methodology

4.1 Fixed Effects model

Panel data regression techniques are employed in this study, due to the longitudinal structure of the data, in order to investigate the effects of technology-driven M&As and innovations on corporate ESG scores. With statistical analysis of panel data the choice for analysis usually has to be made between the Fixed Effects (FE) model and the Random Effects (RE) model. Both the FE and RE model account for unobserved group-specific effects (μ) in the disturbance term, which indicates differences across groups. The distinction between both models lies in how each model treats this group heterogeneity: the RE model assumes these effects are unrelated to the independent variables, maintaining mean independence of the error term. The FE model assumes a relationship between group heterogeneity and the independent variables, and therefore violates the mean independence assumption (Borenstein et al., 2010). Also, with FE models, it is assumed that the unobserved effects correlated with the independent variables remain constant over time and are therefore fixed (Hedges, 1994). The FE model in this study thereby captures variations within Cusip codes over time rather than across different Cusip codes.

In order to find out if the RE or FE model fits your study's data better, the Hausman test can be conducted. The Hausman test plays an important role in model selection, as it assesses whether the differences between the coefficients estimated in a FE model and a RE model are systematic. If the Hausman test results a significant p-value (<0.01), the null-hypothesis can be rejected, making the FE model more appropriate (Amini et al., 2012).

Based on the significant p-value that resulted from the Hausman test in this study, the FE model is the most appropriate model to use for the regressions of hypotheses 1, 2a, 2b, 4a and 4b. This approach is particularly suitable for examining how specific events, such as (technology-driven) M&As impact ESG scores over time.

4.2 Regression models

4.2.1 Regressions at firm level

Each regression model incorporates control variables for firm size, financial metrics, and fixed effects to ensure that any observed relationships accurately reflect the unique impact of the technological changes, while accounting for other potential influences. By adjusting for these factors, the aim is to provide a clear and precise understanding of how technological initiatives within firms affect their

sustainability practices across various industries and time periods. For Hypothesis 1 (regression 4.1), the regression model examines the impact of technology-driven M&As on the ESG scores of companies in the year following the merger. The dependent variable is the forward ESG score ($F.ESGscore$), which is the ESG score of the acquiring company in the year after the merger. It is predicted by the independent variable $TechnologyDrivenM\&A$, along with the control variables and $YearFixedEffects$.

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot TechnologyDrivenM\&A + \beta_2 \cdot \ln(TotalAssets) + \\
& \beta_3 \cdot BTM + \beta_4 \cdot ROA + \beta_5 \cdot R\&DIntensity \\
& + YearFixedEffects + \epsilon
\end{aligned} \tag{4.1}$$

For Hypothesis 2a (regression 4.2), the regression model investigates the impact of technological innovation on forwarded ESG scores, specifically measuring innovation through the number of Y-patent publications by the target company. The coefficient β_1 for the $Innovation$ variable will reveal whether a higher frequency of Y-patent outputs correlates with positive or negative changes in the ESG scores in the year following the acquisition activities.

In Hypothesis 2b (regression 4.3), the focus shifts to the quality of technological innovation, assessed through the number of patent citations ($InnovationQuality$). This model assesses if higher-quality innovations, as signified by more patent citations, are associated with better ESG outcomes compared to just the quantity of innovations.

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot Innovation + \beta_2 \cdot \ln(TotalAssets) + \\
& \beta_3 \cdot BTM + \beta_4 \cdot Leverage + \beta_5 \cdot ROA + \beta_6 \cdot R\&DIntensity \\
& + YearFixedEffects + \epsilon
\end{aligned} \tag{4.2}$$

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot InnovationQuality + \beta_2 \cdot \ln(TotalAssets) + \beta_3 \cdot BTM \\
& + \beta_4 \cdot leverage + \beta_5 \cdot ROA + \beta_6 \cdot R\&DIntensity \\
& + YearFixedEffects + \epsilon
\end{aligned} \tag{4.3}$$

In Hypothesis 3 (regression 4.4), an Ordinary Least Squares (OLS) regression model is employed to examine the relationship between the ESG gap, which is defined as the difference between the ESG score of the target company and the acquiring company in the year before the merger, and the ESG score in the year after the merger. In this regression, an OLS regression is employed instead of a FE regression model, due to the absence of multi-year ESG gap data for companies. The OLS regression model is chosen due to its simplicity and effectiveness in estimating linear relationships between variables, making it suitable for analyzing how these factors collectively influence the ESG score of the acquirer the year after the merger. Additionally, the model includes the variable $Year$, to control for time-specific effects.

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot ESGgap + \beta_2 \cdot \ln(TotalAssets) + \\
& \beta_3 \cdot BTM + \beta_4 \cdot Leverage + \beta_5 \cdot ROA + \beta_6 \cdot R\&DIntensity \\
& + YearFixedEffects + \epsilon
\end{aligned} \tag{4.4}$$

In hypotheses 1 through 3, the primary focus is on the coefficient β_1 , which evaluates the direct impact

of *TechnologyDrivenM&A*, *Innovation*, *InnovationQuality* or the *ESGgap* on the ESG performance of the acquiring company. This coefficient is important for understanding how these variables of interest influence ESG scores post M&A. The analysis controls for various factors to isolate the specific contributions of these technological and strategic inputs to corporate sustainability outcomes, highlighting how different interventions uniquely affect ESG within firms.

4.2.2 Regressions at industry level

In the analysis for Hypotheses 4a and 4b, the impact of technology-driven M&As on ESG scores are assessed, with a specific focus on the energy sector. Hypothesis 4a (regression 4.5) examines whether the association between technological innovation and the ESG scores of the acquirer is less strong or even negative in energy sector firms, by integrating innovation metrics with an energy sector indicator. Hypothesis 4b (regression 4.6) explores whether technology-driven M&As in the energy sector lead to greater enhancements in ESG performance compared to sectors with initially higher ESG scores, using interaction terms to reveal these complex effects.

In order to be able to compare the effect of innovation and technology driven M&As on the ESG performance of companies in the energy sector with companies outside of the energy sector, an aggregated dataset is constructed, aggregated on the 2-digit SIC codes and Year variable. As a result, the mean values of all the variable used in the following regressions per 2-digit SIC code and Year were calculated. The distribution of the ESG scores over the different 2-digit SIC codes are shown in Table 1. The regression controls for both industry-specific and time-specific factors, enhancing comparability and statistical stability.

Both models include logarithmic transformations to address outliers and capture non-linear dynamics as well, while also integrating controls for firm size, financial metrics, and year fixed effects to clarify these relationships.

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot AverageInnovation + \beta_2 \cdot (Innovation * EnergySector) \\
& + \beta_3 \cdot \ln(AverageTotalAssets) + \beta_4 \cdot AverageBTM \\
& + \beta_5 \cdot AverageLeverage + \beta_6 \cdot AverageROA \\
& + \beta_7 \cdot AverageR\&DIntensity + YearFixedEffects + \epsilon
\end{aligned} \tag{4.5}$$

$$\begin{aligned}
F.ESGscore = & \beta_1 \cdot TechnologyDrivenM\&A \\
& + \beta_2 \cdot (TechnologyDrivenM\&A * EnergySector) \\
& + \beta_3 \cdot Average(\ln(TotalAssets)) + \beta_4 \cdot AverageBTM \\
& + \beta_5 \cdot AverageLeverage + \beta_6 \cdot AverageROA \\
& + \beta_7 \cdot AverageR\&DIntensity + YearFixedEffects + \epsilon
\end{aligned} \tag{4.6}$$

For Hypotheses 4a and 4b, the focus is on the coefficient β_2 of the interaction variable between *Innovation*, *TechnologyDrivenM&A* and the *EnergySector*. The significance of this coefficient was assessed using a z-test based on the normal distribution. The null hypothesis (H_0) posits that β_2 is smaller than or equal to 0, indicating no positive effect of being in the energy sector on innovation and M&As influencing ESG scores. This suggests that industries with lower ESG ratings, such as the

energy sector, do not produce more Y-patents compared to sectors with higher ESG ratings initially, and that M&As in the energy sector do not significantly enhance ESG scores compared to more sustainable sectors. Conversely, the alternative hypothesis (H_a) proposes $H_a: \beta_2$ is greater than 0, asserting that, on average, the energy sector shows higher Y-patent publication rates (Hypothesis 4a) and that M&As in the energy sector exert greater influence on ESG scores than those in more sustainable industries. Rejection of the null hypothesis occurs if β_2 is statistically significant and greater than 0, supporting the alternative hypothesis.

4.3 Assumption tests

In this section, the results of the assumption tests conducted to identify potential violations in the regression models are discussed.

4.3.1 Heteroscedasticity

A common concern in panel data analysis is heteroscedasticity. Especially when using fixed effects regression models. Heteroscedasticity occurs when the variance of error terms varies across observations. This can lead to biased estimates of standard errors and unreliable statistical inferences. In order to ensure the robustness of regression results, it is important to detect heteroscedasticity.

Detecting groupwise heteroscedasticity can be done by performing the Modified Wald test. The test evaluates whether error variance differ across the different groups typical of panel data. The null hypothesis (H_0) of the test assumes equal error variances across panels, which is called homoscedasticity. Rejection of H_0 indicates heteroscedasticity, implying that error variances differ between groups and standard errors may be not be estimated accurately.

In this study, the Modified Wald Test is used to check for heteroscedasticity in panel data, verifying assumptions within the fixed effects model. The Chi^2 statistic of the Modified Wald test for the hypotheses 1, 2a, 2b, 4a, and 4b in this study are extremely high, and very significant, indicating the presence of heteroscedasticity. This means that robust standard errors are needed in the regression to ensure accurate estimation and reliable statistical conclusions from the fixed effects regression analysis.

For Hypothesis 3, a different test is used to check for heteroscedasticity since panel data is not used, and instead, a standard OLS regression is performed. In order to test for heteroscedasticity the Breusch-Pegan Test is performed. The Breusch-Pegan Test checks whether the variance of the errors from a regression is dependent on the values of the independent variables (Halunga et al., 2017). The test resulted in a Chi^2 statistic of 0.19 with a p-value of 0.6656, which means that there is not enough statistical evidence to reject the H_0 , indicating that the variance of the residuals is constant across levels of the independent variables.

4.3.2 Autocorrelation

To test for autocorrelation in panel data, the Wooldridge test is performed. This statistical test specifically checks for first-order autocorrelation in the residuals of fixed effects panel regression models. Autocorrelation in panel data occurs when the error from one observation correlates with the error from the preceding observation. Violating the assumption can result in inefficient estimates and potentially misleading conclusions, particularly regarding the significance of variables (Born & Breitung, 2016).

The null hypothesis (H_0) of the Wooldridge test posits that there is no first-order autocorrelation in the panel data residuals. For hypothesis 1, the test statistic F has a value of 419.968 with a highly significant p-value of 0.0000, leading to the rejection of the null hypothesis. This indicates the presence of significant first-order autocorrelation in the residuals of the model. The presence of this first-order autocorrelation suggests that the estimations from the fixed effects model may be biased, particularly in the estimated standard errors. This can lead to incorrect conclusions about the significance of the predictors in the model.

Hypothesis 2a also showed significant autocorrelation with an F-statistic of 34.845 and a p-value of 0.0041. Hypothesis 2b, however, resulted in a lower F-statistic, namely 2.655, with a p-value of 0.1786, indicating that the null hypothesis should not be rejected. This suggests that no significant autocorrelation was found in the residuals of the fixed effects model that was used to test Hypothesis 2b.

For Hypothesis 3, the panel-specific Wooldridge test would not be appropriate as the data lacks a panel structure. In this hypothesis, the dataset contains only information needed to calculate the ESG gap, for the years of a merger. Each observation represents a company-year combination without consecutive yearly data for any single company. This means that there are no repeated measures over time for the same entities, which are necessary to assess autocorrelation. Therefore, the dataset for Hypothesis 3 lacks the conditions needed to detect time-based patterns that autocorrelation typically examines.

Hypotheses 4a and 4b also exhibited significant autocorrelation, with F-statistics of 199.254 and 17.986, respectively. Both autocorrelation tests yielded p-values of 0.000. These results indicate pronounced autocorrelation in the residuals of these models, emphasizing the need for robust standard errors, which control for heteroskedasticity and autocorrelation across panels.

4.3.3 Multicollinearity

Multicollinearity occurs when there are strong correlations among the variables in a regression model. It can lead to biased or misleading results when attempting to determine how effectively each variable predicts or explains the response variable in the model (Young, 2017). Specifically, multicollinearity tends to widen confidence intervals and reduce the reliability of probability estimates for predictors. Therefore, findings from a model affected by multicollinearity may lack reliability (Hosmer et al., 2013).

One of the main methods used to detect multicollinearity is the Variance Inflation Factor (VIF). The variance inflation factor quantifies the degree to which the variance of an estimated regression coefficient increases due to correlations among the independent variables. VIF is computed as follows:

$$\text{VIF} = \frac{1}{(1 - R^2)} = \frac{1}{\text{Tolerance}} \quad (4.7)$$

The Tolerance is essentially the inverse of the VIF. A lower Tolerance indicates a higher likelihood of multicollinearity between the variables. A VIF value of 1 indicates that the independent variables are uncorrelated. If the VIF ranges between 1 and 5, it suggests substantial correlation between the variables. Values between 5 and 10 indicate significant correlation, posing challenges due to multicollinearity. VIF values exceeding 10 indicate pronounced multicollinearity, leading to poorly estimate regression coefficients (Shrestha, 2020).

To calculate the VIF in this study, the fixed effects model needs to be transformed into an OLS

regression. After estimating the fixed effect model, residuals are calculated to capture the portion of the dependent variable's variance that is not explained by observed factors and fixed effects. In order to transform the regression as accurately as possible and to isolate the effects of independent variables from fixed effects in panel data, variables are adjusted by subtracting their means over time from their original values. An Ordinary Least Squares (OLS) regression is then conducted using these adjusted variables and the predicted residuals.

Following the OLS regressions for each hypothesis, the mean VIFs were calculated. For Hypothesis 1, the average VIF was found to be 1.18. Similarly, for Hypotheses 2a and 2b, the mean VIFs were both 1.12. Hypothesis 3, Hypotheses 4a and 4b exhibited mean VIFs of 1.16, 1.12 and 1.16 respectively. These results indicate low levels of multicollinearity among the independent variables across all hypotheses, supporting the robustness of the regression models.

Chapter 5

Results

In Chapter 5, the empirical findings from the regression analyses of the hypotheses will be presented. Hypotheses 1, 2a, 2b, 4a, and 4b are analyzed using the fixed effect model. Hypothesis 3, however, employs an OLS regression due to the absence of multi-year data for companies. Additionally, robust standard errors are applied to address potential issues such as autocorrelation and heteroscedasticity.

5.1 Technology-driven M&As on forward ESG scores

The regression study in Table 5.1 investigates the impact of different types of M&As on the ESG scores of acquiring corporations (model (1)) and on the ESG scores one year after the merger (model (2), (3) and (4)). The study spans the years 2002 to 2022 and uses a fixed effects model to examine Hypothesis 1: *Technology-Driven M&As lead to an improvement in the ESG scores of acquiring companies in the year after the merger.* The results are interpreted in the text below.

Model (1) estimates the regression coefficient of technology-driven M&As on its relation to ESG scores in the year when the acquisition occurred. The regression coefficient of technology-driven M&As is 0.201, meaning that the relationship is positive, though it is statistically insignificant.

In Model (2), the estimation focuses on the effect of technology-driven M&As concerning ESG scores one year after the acquisition occurred. It has a positive coefficient with a value of 1.209 and is statistically significant at the 10% level. This suggests a lagged positive impact of technology-driven M&As on ESG performance.

Model (3) researches non-technology-driven M&As and their impact on forward-looking ESG scores. Again, the coefficient is positive but not statistically significant. The coefficient equals 0.786, which means that there is a positive relationship between the variables, but the non-technology-driven M&As do not significantly influence the forward ESG scores.

Model (4)'s main variable of interest is the M&A variable. The M&A variable has a positive influence (coefficient of 1.036) on the acquiring businesses' forward ESG score, statistically significant at the 5% level, confirming the results of the studies Barros et al. (2023) and Tempakoudis and Anagnostopoulou (2020). The M&A variable is a dummy variable with a value of one in the event of any M&A, whether technology-focused or non-technology-focused. This suggests that, regardless of their focus, M&As have a beneficial impact on acquiring companies' ESG performance.

The control variables provide additional insight into the elements that influence forward ESG scores. Firm size consistently correlates positively with ESG performance, demonstrating that larger enterprises outperform in sustainability efforts, with the relationship proving statistically significant at the 1% and 5% levels across all models. The book-to-market ratio (BTM) has a negative influence

(statistically significant at the 1% and 5% level), indicating that enterprises with higher book values relative to market values will have a lower ESG performance. The return on assets (ROA) has a positive influence on the ESG score in the year after the merger, however, this correlation is also not statistically significant. R&D intensity has the same result, having all positive but statistically insignificant results. The R^2 values, which indicate the extent to which the independent variables explain the variability in the ESG scores, show with coefficients of over 57% a relatively high level of explanatory power for the models.

In summary, there is enough evidence to support the first hypothesis that technology-driven M&As positively influence the ESG scores of acquiring companies in the year after the merger and not in the year of the merger, which is also the case for the results of general M&As in the paper by Barros et al. (2023). While significance at the 10% level is less strict than the 5% level, it still provides evidence to support the hypothesis that there is a relationship between the technology-driven M&A and the forward ESG score.

Table 5.1: Empirical Results Hypothesis 1

Hypothesis Model Variables	H1			
	(1) ESGscore	(2) F.ESGscore	(3) F.ESGscore	(4) F.ESGscore
Technology-Driven M&A	.201 (.713)	1.209* (.729)		
Non-tech-drivenM&A			.786 (.616)	
M&A				1.036** (.512)
ln(Total Assets)	3.149*** (.715)	3.659*** (.764)	3.670*** (.763)	3.638*** (.512)
BTM	-3.198** (1.315)	-3.685*** (1.415)	-3.627** (1.412)	-3.648** (2.889)
ROA	.763 (2.710)	3.359 (2.892)	3.496 (2.891)	3.421 (2.889)
R&D Intensity	.192 (2.675)	.642 (3.065)	.647 (3.058)	.599 (3.065)
Constant	-2.787 (6.449)	-6.764 (6.333)	-6.920 (6.325)	-6.703 (6.319)
YearFE	controlled	controlled	controlled	controlled
N	4,232	3,921	3,921	3,921
P	0.000	0.000	0.000	0.000
R^2	.591	.573	.573	.574
Number of companies	335	334	334	334

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022. In model (1), the influence of technology-driven M&As on the ESG score in the year of the merger is investigated and in Model (2) is the relationship between technology-driven M&As on the forward ESG score researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset

for their respective years. The control variables consist of $\ln(\text{TotalAssets})$, which denotes the natural logarithm of total assets in billions US dollars, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Technological innovation and innovation quality on ESG scores

Table 5.2 shows the regression results for hypothesis 2a and 2b. In Hypothesis 2a, model (1) investigates how innovation, as defined by the number of patents published compared to the industry average, affects the forward ESG score. Similarly, model (2) looks into the impact of innovation on the ESG score in the year of the merger. For Hypothesis 2b, model (3) investigates the impact of innovation quality, as measured by the number of patent citations relative to the industry average, on the forward ESG score. Model (4) examines the effect of innovation quality on the ESG score in the year of the merger. The study spans the years 2002-2022 and uses a fixed effects model. Hypothesis 2a posits that technological innovation, measured by the number of Y-patent publications from the target company, exhibits a positive relationship with the ESG score of the acquirer following an M&A. Hypothesis 2b states that the quality of technological innovation, as indicated by the number of patent citations pre-M&A, is positively correlated with improvements in ESG scores of the acquiring company post-merger.

In model (1), the coefficient of the innovation variable is marginally positive at 0.044, indicating a possible positive relationship between the number of patents published by target companies and the ESG score of acquirers, though this relationship is not statistically significant. In contrast, in model (2), the innovation variable appears to have a negative but statistically insignificant connection with the ESG score of acquiring companies in the year of merger.

Hypothesis 2b investigates the impact of innovation quality on both the forward and the ESG scores. Model (3) demonstrates a positive and statistically significant coefficient for innovation quality at the 10% significance level, demonstrating that more patent citations from target companies have a positive impact on acquiring firms' forward ESG scores. However, in model (4), the coefficient of innovation quality in relation to the ESG score in the year of the merger exhibits a modest negative trend but is statistically insignificant.

For the control variables, firm size consistently notes a positive coefficient, with a minimum of 2.474, indicating that larger firms have higher ESG scores, but the results consistently lacks significance. BTM consistently exhibits a negative correlation with both forward and ESG scores in the year of the merger, meaning that firms with a higher book value relative to their market value have lower ESG scores. The coefficients for leverage are statistically significant at the 1% and 5% levels and positive in all the four models, indicating that firms with higher levels of debt are more likely to have better ESG ratings in both the longer and short term. ROA is positively related to forward ESG ratings, but negatively linked to ESG scores in the year of the merger. Lastly, the R&D intensity coefficients for the forward ESG scores in models (1) and (3) are highly positive and significant at the 1% and a 5% level, with a minimum value of 68.942, indicating that firms with high R&D expenses relative to their sales, potentially have higher ESG scores in the year after the merger. The R^2 values show with coefficients over 68% a relatively high level of explanatory power for the models.

In summary, the regression analysis for Hypothesis 2a does not provide evidence to support the hypothesis, but the data does provide evidence that leverage and R&D intensity positively influence the forward ESG score and merger-year ESG score. For Hypothesis 2b, there is evidence to support

the hypothesis that innovation quality impacts the post-merger ESG score.

Table 5.2: Empirical Results Hypothesis 2

Hypothesis Model Variables	H2a		H2b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Innovation	.044 (.156)	-.242 (.168)		
Innovation Quality			.119* (.071)	-.021 (.121)
ln(Total Assets)	2.474 (2.444)	3.002 (2.407)	2.679 (2.249)	2.847 (2.392)
BTM	-9.957 (10.837)	-9.767 (11.483)	-8.384 (11.100)	-8.908 (11.104)
Leverage	6.616** (3.259)	11.349*** (3.082)	6.366** (3.082)	10.713*** (2.969)
ROA	27.695 (19.007)	-22.186 (21.891)	28.832 (18.668)	-15.034 (20.559)
R&D Intensity	72.695*** (27.182)	33.811 (30.354)	68.942** (27.897)	39.003 (29.498)
Constant	-17.510 (26.151)	-17.651 (28.088)	-19.832 (24.665)	-16.648 (27.930)
YearFE	controlled	controlled	controlled	controlled
N	194	212	194	211
P	0.000	0.000	0.000	0.000
R^2	.686	.716	.697	.712
Number of companies	114	124	114	123

Note: This table shows the result of the fixed effects model, studying the relationship between innovation and innovation quality and the ESG performance of acquiring companies over the period 2002-2022. For Hypothesis 2a, in model (1) and (2), the influence of innovation on the forward ESG score and ESG score, respectively, is investigated. For Hypothesis 2b, in model (3) and (4) the relationship between innovation quality on the forward ESG score and ESG score in the year of the merger is researched, respectively. Innovation is the variable that represents the number of published patents by the target company, compared to the average per industry and Innovation quality is the number of patent citations, also compared to the industry average. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 ESG gap on ESG scores

Table 5.3 shows the regression results for Hypothesis 3, which looks at the relationship between the width of the ESG gap and both the forward ESG score (model 1) and the merger-year ESG score (model 2) over the period 2002-2022 and uses an OLS regression model. The ESG gap is defined as the difference in ESG scores between the target company and the acquiring company in the year preceding the merger. Hypothesis 3 states that the width of the ESG gap positively influences the

ESG scores of the acquiring companies.

In model (1), the ESG gap variable has a highly significant coefficient of -0.298 ($p < 0.01$). Contrary to the hypothesis, this shows that the forward ESG score of acquiring companies drops as the target company's ESG score exceeds that of the acquiring company. Model (2) shows a negative correlation of -0.409, which is also statistically significant at the 1% level. This suggests that a larger ESG difference has a greater negative impact on merger-year ESG scores.

Firm size is still highly significant and positive, with a minimum value of 5.211, demonstrating that larger firms have higher ESG scores in both the forward and merger periods. ROA shows positive values of 27.465 and 30.931, significant at the 5% and 10% levels, indicating that increased profitability corresponds to higher forward and merger-year ESG ratings. The R^2 values (63% and 72%) show a relatively high level of explanatory power for the models.

In summary, while the coefficients of the variable of interest are highly significant, the direction of the magnitude contradicts Hypothesis 3. Therefore, there is sufficient evidence to reject hypothesis 3. Firm size and ROA have a positive influence on the forward and merger-year ESG score.

Table 5.3: Empirical Results Hypothesis 3

Hypothesis Model Variables	H3	
	(1) F.ESGscore	(2) ESGscore
ESG gap	-.298*** (.048)	-.409*** (.046)
ln(Total Assets)	5.211*** (.683)	5.245*** (.628)
BTM	3.476 (4.426)	7.170 (3.960)
Leverage	1.617 (1.097)	.582 (1.021)
ROA	27.465** (13.831)	30.931** (12.039)
R&D Intensity	-1.956 (5.518)	.160 (4.389)
Constant	-21.574 (12.771)	-30.213 (12.433)
YearFE	controlled	controlled
N	144	164
P	0.000	0.000
R^2	.694	.761

Note: This table shows the result of the OLS regression model, studying the relationship between the width of the ESG gap and the ESG performance of acquiring companies over the period 2002-2022. In model (1), the influence of the width of the ESG gap on the forward ESG score is investigated and in Model (2) the relationship between the ESG gap on the ESG score in the year of the merger is researched. ESG gap is the variable representing the difference between the ESG score of the target company and of the acquiring company in the year prior to the merger. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Technological innovation and M&As on ESG scores in the energy sector

Table 5.4 shows the regression results for the relationship between innovation, different forms of M&As, and ESG scores in the energy sector from 2002 to 2022. The dataset contains mean values of regression variables aggregated by two-digit SIC code and year. Models (1) and (2) explore the effect of aggregated average innovation and innovation particular in the energy sector (Innovation * Energy Sector) on acquiring businesses' ESG scores. Models (3) and (4) include various M&A variables: the general M&A variable, which covers all types of M&As, M&A * Energy Sector, which indicates the additional effect of general M&As within the energy sector on ESG scores, technology-driven M&As, and technology-driven M&A * energy sector, which shows the additional effect of technology-driven M&As specifically within the energy sector on ESG scores.

Through the use of a fixed effects regression model, the regression examines the influence of innovation and technology-driven M&As in the energy sector on ESG scores of acquiring companies, as hypothesized in Hypothesis 4a: *"The relationship between ESG scores and technological innovation differs between energy sector firms and others, often displaying a weaker or inverse relationship"* and Hypothesis 4b: *"Technology-driven M&As in the energy sector lead to more substantial improvements in ESG performance compared to M&As in sectors with higher initial ESG ratings."*

In model (1), a positive coefficient for average innovation in the aggregated dataset suggests a positive correlation between innovation and the forward ESG score of acquiring companies on average. Consistent with the hypothesis, the coefficient for innovation within the energy sector specifically is negative (-0.106), though statistically insignificant. In model (2), a similar pattern occurs where the innovation variable within the energy sector shows an opposite direction of magnitude (-0.054) compared to innovation in the aggregated dataset (0.126).

In model (3), all the sorts of M&As have a small negative connection with the forward ESG score (-0.026), which is not statistically significant. M&A transactions, specifically in the energy industry, considerably increase ESG scores after acquisition, with a statistically significant correlation of 0.859. Technology-driven M&As have a positive coefficient of 0.232 but are not statistically significant, whereas technology-driven M&As in the energy sector considerably drop ESG scores post-merger (-1.750 at 10%).

Model (4) indicates positive but statistically insignificant coefficients for regular M&As and energy sector M&As (0.120 and 0.511, respectively). Technology-driven M&As and those within the energy sector show negative coefficients of -0.145 and -0.821, respectively, without statistical significance.

Average firm size consistently shows a positive and statistically significant effect (1% and 5% levels), starting at 5.193 in model (1). Average BTM ratios are consistently negative and insignificant. Average leverage is negative and significant at the 1% and 5% levels in models (1) and (2) (-6.087 and -5.717, respectively), indicating that higher debt to equity levels lead to lower ESG scores post-merger. In models (3) and (4), average leverage coefficients are 2.023 and 1.688, respectively, and not statistically significant.

The average ROA is significant in the first two models (30.666 and 23.253, respectively), indicating that better profitability correlates with higher forward ESG and merger-year ESG scores. R&D intensity becomes significant at the 1% and 5% levels in models (3) and (4) (2.200 and 2.137, respectively), demonstrating that more R&D spending relative to sales improves ESG scores after the merger.

The R^2 values show with coefficients above 90% (model 1 and 2) and above 70% (model 3 and 4), a relatively high level of explanatory power for the models.

In summary, while the average innovation coefficient in the energy sector is in the opposite direction of that of innovation in the whole sample, these findings are statistically insignificant and do not support Hypothesis 4A. Average company size, leverage, and ROA have significant effects on both the merger-year and forward ESG ratings.

The variable of interest for Hypothesis 4b, Technology-driven M&A * Energy Sector, is negative and statistically significant, therefore it can be concluded that a technology-driven M&A in the energy sector negatively influences the ESG score in the year after the merger. Because the result does not follow the hypothesized direction, Hypothesis 4b is still rejected. The average firm size and R&D intensity have a significant and positive influence on both merger-year and forward ESG scores.

Table 5.4: Empirical Results Hypothesis 4

Hypothesis Model Variables	H4a		H4b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Average Innovation	.096 (.129)	.126 (.105)		
Innovation * Energy Sector	-.106 (.154)	-.054 (.139)		
Merger & Acquisition			-.026 (.176)	.120 (.198)
M&A * Energy Sector			.859** (.414)	.511 (.307)
Technology Driven M&A			.232 (.287)	-.145 (.299)
Technology Driven M&A * Energy Sector			-1.750* (.952)	-.821 (.930)
Ln(Average Total Assets)	5.193*** (1.727)	5.490** (2.074)	7.582*** (1.776)	7.599*** (1.758)
Average BTM	-2.162 (2.836)	-.378 (2.967)	-2.773 (2.764)	-3.141 (3.130)
Average Leverage	-6.087** (2.429)	-5.717*** (1.997)	2.023 (1.406)	1.688 (1.391)
Average ROA	30.666* (16.410)	23.253** (12.881)	1.560 (6.632)	2.709 (6.551)
Average R&D Intensity	-4.159 (3.999)	-5.211 (4.658)	2.200** (1.070)	2.137*** (.792)
Constant	-13.447 (15.329)	-15.584 (19.257)	-39.475** (15.538)	-40.951** (15.237)
Year Fixed Effects	controlled	controlled	controlled	controlled
N	129	133	632	663
P	0.000	0.000	0.000	0.000
R^2	.911	.924	.712	.731
Number of groups	26	26	39	39

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022. In model (1), the influence of technology-driven M&As on the forward ESG score is investigated and in Model (2) is the relationship between technology-driven M&As on the ESG score in the year of the merger researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets by sales (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.5 Robustness checks

Robustness checks in empirical research studies are important to ensure the stability and validity of the results. This study will conduct four robustness checks. First, the years of the credit crisis (2007-2011) and the COVID-19 crisis (2020-2022) will be removed from the dataset, to reduce the potential biases caused by economic turbulence and interruptions. Secondly, Delta ESG is used as a different dependent variable, like in the study by Tampakoudis & Anagnostopoulou (2020). Delta ESG represents the difference between the ESG score of the acquiring company in the year before and after the merger. This will help provide a dynamic view of the implications of M&As with regard to sustainability outcomes. Thirdly, lagged independent variables will be used to solve potential endogeneity issues and therefore improve the robustness of causal inferences from the models. Lastly, propensity score matching is used in order to balance the measured variables across firms that have engaged in a technology-driven acquisition and firms who did not. The key findings are considered robust and validated results when the coefficients maintain their directions and achieve comparable statistical significance in the different described situations.

5.5.1 Excluding the years of the financial and COVID-19 crisis

In the initial analysis of all the hypotheses, data was used for the years 2002 to 2022. Both the financial credit crisis (2007-2011) and the COVID-19 crisis (2020-2022) occurred in that timeframe. These crises have made a large impact on the global economy, financial markets, and the behaviors of firms and could therefore also have impacted the effects of technology-driven M&As on the ESG scores of acquiring companies. Firms doing business during the credit crisis were under very tight financial considerations, increased risk aversion and stakeholder pressure that may have affected strategic priorities in ESG investment decision-making. Similarly, the COVID-19 crisis caused exceptional commotion and forced companies to adopt survival strategies that might have affected long-term ESG promises. These events potentially introduced noise and volatility in the results. Excluding these crisis years from the sample can ensure that the findings are not affected by these exceptional economic and operational conditions and provide a clearer and more accurate assessment of the relationships studied in this study.

For Hypothesis 1, in model (1) from Table 7, the variable of interest, Technology-Driven M&A, remains negative and insignificant in their influence on the merger-year ESG score. In model (2), the impact of Technology-Driven M&A on the forward ESG score is researched and it remains positive and

significant at the 10% level. Model (3) points out that when removing the crisis years from the dataset, the effect of non-tech-driven M&As on forward ESG scores stays positive, and becomes statistically significant at the 1% level, contrasting with its lack of significance in the primary regression. The (significant) coefficient also shows that in this dataset, non-tech-driven M&A has the biggest impact on the ESG score in the year after the merger. In the last model, (4), the variable M&A stays positive and statistically significant, showing no notable changes, which confirms the research of Barros et al. (2023) and Tempakoudis and Anagnostopoulou (2020). The results of the robustness check regressions indicate that economic conditions influence the impact of non-tech-driven M&As on the forward ESG scores of acquiring companies, which is in line with the paper by Battisti et al. (2024). So, for Hypothesis 1, excluding the crisis years from the dataset did not affect the sufficient support to accept the first hypothesis.

In the regressions for Hypothesis 2a, the first model studies the impact of innovation on the forward ESG score of acquiring companies, as can be seen in Table 8. The variable Innovation maintains the positive direction and the insignificance level. Contrasting with the main regression, the influence of Innovation on the merger-year ESG score in model (2) becomes significant at the 1% level. The direction of the variable stays positive. In model (3), which is part of Hypothesis 2b, the variable Innovation Quality maintains its positive direction and significance level of 1%. The direction and level of statistical significance of the variable Innovation Quality do not change in the regression of model (4), which investigates the impact of innovation quality on the merger-year ESG scores of acquiring companies.

Excluding the specified crises from the regression dataset does not change the conclusion that there is still insufficient evidence to support Hypothesis 2a. However, the evidence continues to give substantial support for hypothesis 2b, which states that innovation quality has a favorable impact on ESG scores in the year following the merger.

Model (1) and (2) from the regressions of Hypothesis 3 in Table 9, show the same level of significance ($p < 0.01$) and negative direction of the influence of the ESG gap on both the forward ESG score as the merger-year ESG score. Therefore, after excluding crisis data from the sample, there is still enough evidence to reject Hypothesis 3, which states that the ESG gap positively influences the ESG scores of acquiring companies.

The coefficient of the variable of interest in model (1) and (2) of Hypothesis 4a in Table 10, Innovation * Energy Sector, stays negative like in the main dataset regression, but becomes statistically significant at the 1% level for the influence of innovation in the energy sector on forward ESG scores. This contradicts the result of the regression in the main dataset, which has an insignificant coefficient. The Average Innovation variable stays positive, but also becomes statistically significant ($p < 0.05$). In model (2), The Innovation variable stays positive as well, but becomes statistically significant ($p < 0.05$) again. For Innovation * Energy Sector, the coefficient becomes negative, but stays insignificant. These results indicate that innovation in the energy sector is dependent on economic conditions, which is in line with the paper of Griliches (1998), who states that the number of patent applications was lower during the Great Depression and also during World War 2.

In model (3) of the regression of Hypothesis 4b, the Merger & Acquisition variable coefficient changes to a positive number, but remains insignificant. The variable for M&As in the energy sector remains positive, but becomes statistically insignificant, in contradiction to the positive and significant coefficient of the regression in the main dataset. The coefficient of Technology-Driven M&As stays positive and insignificant. For the variable of interest, Technology-Driven M&As * Energy Sector, the

coefficient loses its statistical significance after excluding the crisis years. This indicates again that M&As are influenced by economic conditions (Battisti et al., 2024). In model (4), the coefficient of the variable Technology-Driven M&A becomes positive, but it is still insignificant. The rest of the coefficients do not change direction or significance.

After excluding the crisis years from the main dataset, the coefficient of Innovation * Energy Sector becomes statistically significant at the 1% level, indicating that hypothesis 4a can be accepted, but with the important qualification that this effect is primarily observed during non-crisis periods. The change in significance for the variable Technology-Driven M&A * Energy Sector in model (3) of Hypothesis 4b indicates that the impact of the variable is influenced by changing economic conditions. This does not necessarily mean that the acceptance of the hypothesis cannot happen, but it does mean that the effect is likely context-dependent, particularly influenced by the crisis periods.

5.5.2 Different dependent variable

In the main hypotheses regressions, the variables of the ESG score in the merger-year and the forward ESG score are used as dependent variables. To ensure that the findings are not an artifact of a specific measure or time frame and to help capture the true nature of the relationship between the M&As and the different types of ESG scores, a different dependent variable is used in the robustness check regressions. For this specific robustness check, the variable Delta ESG is used as the dependent variable. Delta ESG is the difference between the acquirer's ESG score in the year after the merger and the ESG score in the year before the merger. By using Delta ESG, the changes in the ESG score over time, and therefore the dynamic nature of the ESG performance can be researched (Tampakoudis & Anagnostopoulou, 2020).

For Hypothesis 1, in model (1) from Table 11, the variable of interest, Technology-Driven M&A, has a positive (0.152) and statistically significant ($p < 0.01$) impact on the Delta ESG score. In model (2), the coefficient of the Non-tech-M&A variable is also positive (0.110) and statistically significant, but at the 10% level. The M&A variable in model (3) is also positive (0.138) and statistically significant ($p < 0.01$), indicating that all the types of M&As have a positive influence on the difference of the acquirer's ESG score in the year after and before the merger. Because the variable of interest remains positive and statistically significant, there is enough support to conclude that technology-driven M&As have a positive impact on the acquirer's ESG scores, which is in line with Hypothesis 1. The M&A variable is also positive and significant, which is in line with the results of Barros et al. (2023) and Tampakoudis and Anagnostopoulou (2020).

In model (1) of the regression for Hypothesis 2a in Table 12, the Innovation variable is the variable of interest. The coefficient of the variable is slightly positive (0.014) and significant at the 1% level, indicating that the number of patents published by the target company, relative to the industry average, has a positive impact on the change in the acquirer's ESG scores over time. This contradicts the rejection of Hypothesis 2a in the main regressions. The variation could be attributed to the fact that innovation effects may take time to materialize and be reflected in ESG scores. The Delta ESG reflects this by comparing two distinct time points, suggesting an overall improvement, whereas the forward ESG score may be influenced by immediate post-merger integration challenges or short-term disruptions. In model (2), the Innovation Quality variable is positive (0.008) and statistically significant at the 1% level, indicating that the number of patent citations also positively impacts the change in ESG scores over time. Hypothesis 2b can therefore again be accepted.

Model (3) shows the results of the variables for Hypothesis 3. The coefficient of the ESG

Gap is, in contrast to the result of the main Hypothesis 3 regression, positive (0.005) and significant at the 1% level. This result provides confirmation of Hypothesis 3, which states that the width of the ESG gap has a positive impact on the ESG scores of the acquiring companies. The difference in the direction of the ESG Gap coefficient can be due to the challenging initial integration of differing ESG practices, but substantial improvements can be achieved over time. With adding the Delta ESG variable as a robustness check, both short-term and long-term effects of the impact of the variables of interest on ESG performance can be evaluated.

In Table 13, the results of Hypotheses 4a and 4b are shown. In model (1), the variable of interest in Innovation * Energy Sector. The coefficient of the 'regular' Innovation variable is positive (0.027) and significant at the 5% level. The coefficient of innovation in the energy sector is negative and significant at the 1% level. The direction of the coefficient is the same as in the main regression and in the regression where the crisis years were excluded, but the result is only significant in both robustness check regressions, not in the main regression. Hypothesis 4a can be accepted with Delta ESG as the dependent variable. In model (2), all the coefficients of the different types of M&As are insignificant. Because the technology-driven M&A variable is insignificant, there is not enough support to accept or reject Hypothesis 4b.

After changing the dependent variable to Delta ESG, almost all the hypotheses can be accepted. The coefficient of Innovation * Energy Sector becomes statistically significant at the 1% level, indicating that hypothesis 4a can be accepted under the Delta ESG dependent variable. That the coefficient of Technology-Driven M&A * Energy Sector stays negative, but becomes statistically insignificant with this dependent variable, could mean that the initial negative impact in the main regression, does not result in a significant net change, indicating that the acquiring companies may overcome early setbacks and stabilize their ESG performance. The R^2 coefficients are all lower in the models where Delta ESG is the dependent variable, than the R^2 values of the main regression models.

5.5.3 Lagged independent variables

According to the results of the Wooldridge tests in Section 4.3.2, the regressions of hypotheses 1, 2a, 2b, 4a and 4b showed signs of potential autocorrelation. Consequently, this section employs a robustness check to address this issue by incorporating lagged independent variables. This can help reducing autocorrelation in the residuals by accounting for the influence of past values, leading to more reliable standard errors and test statistics.

The results of using the lagged independent variables for Hypothesis 1 are shown in Table 14. The coefficient of the effect of the variable Technology-Driven M&A on the forward ESG score is again positive (1.773) and statistically significant ($p < 0.05$). Hypothesis 1 can therefore be accepted, again. This means that the variable not only has a positive and significant effect in the main regression, but also in the three robustness check regressions. The M&A variable is also positive (0.894) and significant, which is in line with the results of Barros et al. (2023) and Tempakoudis and Anagnostopoulou (2020).

In models (1) and (2) of Table 15, the coefficients of Innovation are positive (0.129 and 0.011, respectively), but insignificant. This means that there is not enough support to accept or reject hypothesis 2a, when using lagged independent variables in the regression. Innovation Quality, on the other hand, is positive and significant in model (3) (0.220, $p < 0.01$) and in model (4) (0.158, $p < 0.10$). This indicates that Innovation Quality has the most impact on the forward ESG score (model (3)), but also has a positive impact on the merger-year ESG score (model (4)). Hypothesis 2b can therefore

be accepted when using lagged independent variables.

The results of Hypothesis 3 are shown in models (1) and (2) of Table 16. In model 1, the coefficient of the variable of interest, ESG Gap, is negative (-0.262) and statistically significant at the 1% level. This indicates that the larger the difference between the target company's and the acquiring company's ESG score in the year prior to the merger is, the lower the forward ESG score of the acquiring company will be. This is the same result as in the main regression for Hypothesis 3 and in the robustness check regression with the dataset where the crisis years were excluded. In model (2), the coefficient of the effect of the ESG Gap on the merger-year ESG score is also negative (-0.390) and statistically significant at the 1% level. Therefore, there is enough support to be able to reject Hypothesis 3, which states that the magnitude of the ESG gap, positively impacts the ESG scores of the acquiring companies.

For Hypotheses 4a and 4b, the results are displayed in model (1)-(4) of Table 17. In model (1), the coefficient of the variable for innovation in the energy sector does have a negative direction (-0.004) when displaying the effect on the forward ESG score of acquiring companies, but is statistically insignificant. Model (2) shows a positive coefficient for the Innovation * Energy Sector variable, but is also insignificant. This means that there is not enough support to accept or reject Hypothesis 4a when using lagged independent variables. Models (3) and (4) show a positive and significant effect (0.856, $p < 0.05$ and 0.633, $p < 0.10$) on both the forward ESG score and the merger-year ESG score, respectively. Model (3) also shows a negative (-2.017) and statistically significant ($p < 0.10$) coefficient of the variable for the effect of a technology-driven M&A in the energy sector on the forward ESG score. This result aligns with the result for Hypothesis 4b in the main regression and indicates that a technology-driven M&A has a negative impact on the forward ESG score of the acquiring company. Therefore, there is sufficient support to reject Hypothesis 4b, which states that a technology-driven M&A in the energy sector has a positive impact on ESG performance of the acquiring companies.

After using lagged independent variables, the results of the regressions for the six hypotheses align with the results of the six main regressions. This indicates that these results can reduce the likelihood of autocorrelation, omitted variable bias and reverse causality. This strengthens the causal interpretation of the findings.

5.5.4 Using propensity score matching

Propensity Score Matching (PSM) is a research technique for creating a comparison group that is as close to the treatment group as possible. This is accomplished by pairing each company in the treatment group with a company in the control group that shares similar features. By comparing the results of these matched combinations, researchers can evaluate the intervention's effects (Croce et al., 2013). The results of the PSM regressions are displayed in Tables 18 - 21 in Appendix E.

In this study, the propensity score represents the conditional probability of engaging in a technology-driven acquisition as opposed to a non-tech-driven acquisition, given the confounding variables Firm Size, BTM, Leverage, ROA, and R&D intensity. This method helps to balance these measured variables across firms that have undergone technology-driven acquisitions and those that have not, thereby providing a more accurate estimate of what would have happened to the firms had they not been involved in a technology-driven acquisition.

The variable of interest in the used model for hypotheses 1 and 4b is a dummy variable for technology-driven acquisitions, set to 1 if the acquired company published Y patents in the five years preceding the merger, and 0 otherwise. Therefore, logistic regression is used to estimate propensity

scores based on the independent variables and radius caliper matching. For the other hypotheses, the variables of interest were continuous variables, so generalized propensity scores were estimated using regression with generated weights, creating a matched sample. Following the estimation of the propensity scores, it is determined whether the balancing property is met, which means that the distributions of covariates in the treated (technology-driven acquisitions) and control (non-technology-driven acquisitions) groups should be comparable. This involves determining the ideal number of matching blocks and performing balance checks within each block by comparing the distribution of variables graphically. This approach guarantees that the propensity scores are spread evenly among the groups within each block and that the model is properly stated (Imbens, 2004). Most variables are balanced within a 5% margin of error, which is considered acceptable given the model's complexity and the number of blocks used.

The results of the regressions of Hypothesis 1 are displayed in Table 18. The variable for technology-driven M&As in model (2) is statistically significant, with a positive coefficient of 1.234 ($p < 0.10$), indicating that propensity score matching does not influence the direction or the significance of the coefficient, as they do not change compared to the results of Hypothesis 1 from the main regression. Technology-driven M&As have a positive influence on the ESG score of the acquiring company in the year after the merger. The M&A variable in model (4) is also positive and statistically significant (1.023, $p < 0.05$), indicating that an M&A, technology-driven or not, also has a positive influence on the forward ESG score. Hypothesis 1 can therefore still be accepted.

The innovation variable in model (1) and (2) of Table 19 is negative and statistically insignificant, indicating that also with propensity score matching, Hypothesis 2a can not be accepted. The coefficient for innovation quality in model (3) is positive (0.095) and statistically significant ($p < 0.10$), indicating that the number of patent citations has a positive influence on the forward ESG score. Hypothesis 2b can therefore also be accepted after using propensity score matching. These decisions to accept or reject the hypotheses do not differ from the decisions for Hypotheses 2a and 2b of the main dataset regressions.

For hypothesis 3, the results of the propensity score matching technique regressions are displayed in Table 20. In both model (1) and (2), the coefficient of ESG gap is negative (-0.352 and -0.325, respectively) and statistically significant at the 1% level. This indicates that also after using propensity score matching, the ESG gap has a negative impact on both the forward and merger-year ESG score. Hypothesis 3 can therefore be rejected, similar to Hypothesis 3 in the main dataset regressions.

The results for the regressions of hypotheses 4a and 4b, are displayed in Table 21. The innovation variable in the energy sector is negative and statistically insignificant in both model (1) and (2). This means that there is not enough support to accept Hypothesis 4a, which is the same conclusion as the one for Hypothesis 4a of the main dataset. The technology-driven M&A variable in the energy sector in model (3) is negative (-1.569) and statistically significant ($p < 0.10$), indicating that a technology-driven M&A has a negative impact on the forward ESG score of the acquirer. This contradicts Hypothesis 4b. The coefficients of M&A * Energy Sector in model (3) and (4) are positive (0.742 and 0.520, respectively) and statistically significant at the 5% level. This indicates that conducting an M&A in the energy sector in general, has a positive impact on both the forward and the merger-year ESG score. Still, similarly to the conclusion for Hypothesis 4b in the main dataset, Hypothesis 4b can also be rejected.

Chapter 6

Conclusion and Discussion

While there is extensive research on M&As and ESG subjects separately, as well as on the impact of ESG practices on M&A performance, there is a significant gap in research that focuses on ESG as the dependent variable in the context of M&As. Tempakoudis and Anagnostopoulou (2020) explored how M&As affect the difference in ESG scores between acquirers pre- and post-merger, discovering that acquiring corporations tend to enhance their ESG performance after acquiring targets with higher initial ESG scores.

Barros et al (2023) examined the overall impact of global M&As on both ESG pillars and scores. The authors concluded that M&As have a positive impact on the ESG scores of acquiring companies, but only in the year after the merger. Other research examined the effects of mergers and acquisitions on corporate innovation, proxied with R&D intensity (Denzi et al., 2018; Suo et al., 2023). These papers both found a favorable relationship between the two factors.

This study adds to the existing literature by combining three distinct areas of research: mergers and acquisitions, ESG performance, and (technological) innovation. It introduces technological innovation through technology-driven M&As, by using metrics as the count of technological (Y) patents and patent citations. Unlike previous studies, which used R&D intensity as a proxy for innovation (Chen et al, 2022; Pegkas et al, 2019; Savrul & Incekara, 2015). R&D expenses do not capture the output of innovation, whereas patents and patent citations effectively measure innovation outputs (Atanassov, 2013). Moreover, what also adds to the current literature is the fact that the focus in this study is on the energy sector, because of the large environmental footprint that it leaves and the ongoing shift toward renewable energy sources across the globe to mitigate the environmental impact of the sector. The emphasis on this sector increases the importance and urgency of the results in ensuring the development of solutions to fight climate change by reaching the innovative potential of the sector. By combining these aspects, this study provides a comprehensive view of how M&A transactions might improve ESG performance by acquiring innovative technologies. This empirical research highlights the strategic advantages of such initiatives for good company sustainability efforts. The main research question is *"Is pursuing a technology-driven M&A a successful strategy for an acquiring company in the energy sector to enhance its CSR performance?"*

Hypothesis 1 focuses on the potential improvements in the ESG scores of acquiring companies in the year after conducting a technology-driven M&A. Both the main dataset regression results and the regressions from the robustness checks consistently showed positive and statistically significant outcomes, reinforcing the reliability and validity of the findings. Therefore, Hypothesis 1 can be accepted, indicating that technology-driven M&As positively impact the forward ESG score of

acquiring companies. This result underscores the potential of integrating innovative technologies to enhance corporate sustainability practices and emphasizes the strategic benefits of technology-driven acquisitions.

Hypotheses 2a and 2b test the relation between the quantity and quality of technological innovation and the ESG scores of acquiring firms one year following a technology-driven M&A. Hypothesis 2a is only partially supported because the regression result was only positive and statistically significant when Delta ESG was used as the dependent variable. In both the main dataset regression and the other robustness checks regressions, the coefficient was positive but insignificant. The variable results for Hypothesis 2a indicate that technical innovation and ESG performance have a complex relationship. The statistically significant coefficient for the Delta ESG dependent variable suggests that technical innovation may boost ESG performance more over time. These findings indicate that more improvements in sustainability can be expected when innovative technologies become fully integrated. This emphasizes the importance of taking a long-term view when considering the sustainability benefits of technology innovation.

In Hypothesis 2b, the effect of innovation quality on the forward ESG score of acquiring companies is researched. The Innovation Quality variable consistently shows positive and statistically significant coefficients for all the regressions in the different datasets. Both in the main dataset regression and in the robustness checks regressions. Therefore it can be concluded that Hypothesis 2b can be accepted, indicating that innovation quality, measured by the number of patent citations relative to the industry average, positively influences the forward ESG score of acquiring companies.

Hypothesis 3 examines the effect of the difference in the ESG score of the target company and the acquiring company in the year before the merger on the ESG performance of the acquiring company. The hypothesis can only partially be accepted, because contrary to the hypothesis, the results for the regression in the main dataset, the dataset where the crisis years were excluded, in the regression where the lagged independent variables were used and the results of the propensity score matching regressions, all had a negative but statistically significant coefficient. This indicates that companies who acquired a target company with a higher ESG score in the year before the merger would have a lower ESG performance score in the merger year and the year after. When the Delta ESG dependent variable was used like in the paper of Tempakoudis and Anagnostopoulou (2020), the results were positive and statistically significant, which is in line with the mentioned paper. These findings indicate that initially, a larger ESG gap can negatively influence the acquiring firm's ESG performance, possibly due to the challenges of integration or a mismatch in ESG practices, but that over time acquirers can benefit from the acquisition of the superior ESG practices of their targets.

Hypotheses 4a focuses on the difference in the effect of innovation on the ESG performance of acquiring companies in the energy sector, compared to companies outside of it. It suggests that the link between technological innovation and ESG scores in the energy sector is likely to be weaker or negative than that of other sectors. The coefficients of the Innovation variable in all the regressions were consistently positive, except for the propensity score matching, where the coefficient was negative. In line with the hypothesis, the coefficients of the Innovation * Energy Sector were negative in all the regressions in the different situations, but not all of the coefficients were statistically significant. Therefore, the hypothesis can only partially be accepted. In the dataset where the crisis years were excluded and when Delta ESG was the dependent variable, the results were statistically significant. These results indicate that the sector-specific factors of the energy sector can complicate the relationship between Innovation and ESG performance. This can be because companies in the energy sector

usually have lower ESG scores because of the pollution of their products, but they hold a substantial portfolio of innovative patents for various green technologies in carbon capture or renewable energy solutions (Cohen et al., 2020). Over time, however, these innovations might gradually be integrated, but the initial impact seems to be negative.

Hypothesis 4b examines the influence that the energy sector has on the effect of technology-driven M&As on the ESG performance of acquiring companies. The hypothesis is that the M&As in the energy sector will have a positive influence on ESG performance, as companies in the energy sector have relatively low ESG scores, suggesting greater room for improvement (Clement et al., 2022). The results were negative and statistically significant for the main dataset regression, the regression with the lagged independent variables and the propensity score matching regressions, indicating that contrary to the hypothesis, technology-driven M&As in the energy sector are associated with a decrease in ESG performance. Hypothesis 4b can therefore be rejected. The high regulatory and operational complexities involved in integrating new technologies into an industry heavily scrutinized for environmental impact could be the reason for the negative impact on the ESG performance of the energy sector. The fact that a 'regular' M&A in the energy sector has a positive influence on the (forward) ESG score in some of the regressions, underscores the challenge of integrating new technology within an organization, due to significant disruptions, effort and resources needed to smoothly integrate new technological innovations into existing systems. In other industries, the effect of technology-driven M&As is positive, as they have less regulatory resistance and can leverage the technological advancement more quickly in a way that improves their ESG practices. Given that the robustness checks where the crisis years were excluded and where Delta ESG is used as the dependent variable showed negative but statistically insignificant results, the observed negative impact may not be robust against different economic conditions and over time. The long-term effects are less clear and could lead to less negative, even positive effects on ESG performance.

The impact of the financial control variables in the regressions will now be discussed. The coefficients of the total assets of the acquiring company, which is the proxy for firm size, are in almost all the regressions positive and highly significant. This indicates that larger companies will generally exhibit higher ESG scores, because of economies of scale and enhanced efficiency, which is in line with the paper by Barros et al. (2023). When comparing the effect of firm size on ESG performance in the energy sector with those outside of it, the coefficients remain positive and significant, indicating that sector-specific characteristics do not influence the effect of firm size. The book-to-market (BTM) ratio frequently shows negative coefficients, which is consistent with the work by Bena and Li (2014), but it also has positive coefficients when the Delta ESG variable is utilized. The negative BTM coefficients indicate a lack of market confidence in the companies' ability to invest in and benefit from ESG operations. The leverage variable has different effects on company ESG performance, but the most statistically significant coefficients are negative, consistent with the findings of Barros et al. (2023). A lower leverage ratio typically indicates better governance and ESG performance (Dalal & Thaker, 2019). The higher the debt-equity ratio a company has, the lower the ESG performance will be. The profit proxy variable, ROA, has usually a positive coefficient, but is not often significant. The last control variable that influences the ESG performance of acquiring companies is R&D intensity. R&D intensity usually has positive and significant coefficients, indicating that the ratio of R&D expenses to sales positively impacts the company's practices in environmental sustainability and social responsibility, thereby increasing its ESG scores.

The findings of this thesis add significantly to the literature, because of the combination of

M&A, ESG, and technological innovation, particularly in the energy sector. The findings show that technology-driven mergers and acquisitions generally increase ESG scores, but they have a negative influence on ESG performance in the energy industry, contrary to early predictions, which answers the main research question. This negative connection is statistically significant in both the main regression and the lagged independent variables regression, indicating sector-specific integration difficulties. The positive and significant effect of patent citations on forward ESG scores underscores the value of high-quality innovations, while the positive relationship between technical innovation and Delta ESG speaks to long-term ESG payoffs. The negative effect of the width of the ESG gap on the ESG performance of acquiring companies indicate initial integration challenges. The finding that general M&As in the energy business increase acquiring firms' ESG performance in the year following the acquisition is an entirely new finding beyond previous results. These findings underscore the complexity of technological improvements in the energy sector, highlighting their potential to drive long-term ESG gains, along with significant recommendations for policymakers and corporate managers.

6.1 Limitations and avenues for further research

This study empirically examines the relationship between technology-driven mergers and acquisitions and acquiring companies' ESG performance, focusing on the energy sector. While the findings suggest a potential correlation between these factors, there are certain limitations that have to be considered.

The first limitation is that the findings depend on database limitations, sample characteristics, and biases in CSR reporting. As mentioned in 2.2, multiple CSR rating agencies rate companies on ESG criteria. The KLD database has the limitation that it only assigns CSR scores to the top 3000 biggest US-based companies, based on market capitalization. This limits the comparability of the different ESG scores across all companies. The IVA database covers over 5000 companies around the globe and evaluates the CSR practices based on the core business of the firm and the key industry-specific CSR issues. The CSR database that is used in this study, the Refinitiv database, is the biggest database and rates its CSR score on about 9000 global firms, while using 400 standardized ESG criteria, making sure that the scores are comparable across the entire sample instead of only being comparable within industries. Not all the ESG rating agencies use the same criteria for sample selection or for ESG score construction. For example, Berg et al. (2022) found significant differences in ESG ratings among six prominent ESG rating agencies, with correlations ranging from 0.38 to 0.71. Therefore, because different databases apply different criteria for which companies to include in their database and also differ in the standardized ESG criteria to construct the ESG scores, the outcome of this study cannot directly be compared to the results of studies where different ESG databases were used. An interesting avenue for further research would therefore be to use different ESG rating agency's databases, in order to be able to conclude if the results of this study can be compared to those results.

A second limitation is that this study only focuses on a relatively small sample of public companies due to the lack of availability of all sorts of financial data. The Thomson Reuters Refinitiv ESG database includes firms of varying sizes and industries globally, but it only covers publicly listed companies, which have different regulations than private firms. That is why the results of this study cannot be generalized for all companies.

A third limitation of this study is the potential bias that exists in CSR scores due to voluntary reporting practices by firms. When a rating does not find all the right information for the ESG score

criteria in the publicly available reports, the firm will score a zero for the associated criteria. This would imply that firms who have the resources to report all the rated items, often the firms with more resources and capacity for disclosing more CSR metrics, would inherently score higher, therefore creating potential bias in the results for larger and more capital-intensive firms. This negatively influences the generalizability of the results again.

A fourth limitation of this study is that the merging process involving M&A information and patent data was conducted based on company names instead of using unique company identifiers like Cysip of Datastream. Therefore, there is a possibility that not all patent applicants were merged into the M&A dataset. Future research using patent dataset with unique company identifiers could help verify if the results remain consistent with this study's findings.

Another limitation of the results is the fact that not all the companies and industries publish patents for their innovations. Sometimes because the invention does not meet the criteria for the publishing of a patent and sometimes this can be the case because the inventor rely on secrecy or alternative methods to protect their innovation (Atanassov, 2013). Industries like software development uses copyrights or trademarks to protect their innovations for example. Furthermore, industries with sectors like pharmaceuticals and biotechnology often prefer to keep the innovation confidential for competitive reasons. When not all firms from these industries are included in the patent dataset, the results of this study can't be applied for all the the different companies. An interesting recommendation for further research would therefore be to classify a technology-driven M&A in a different way, to be able to include more companies in different industries. A different way would be for example to use the number of new product launches, instead of patent output, or to evaluate the technological expertise and skills of the target company's personnel. Firms with a high proportion of employees in the fields of science, technology, engineering and mathematics.

The last limitation of this study is about the linear rise in average ESG scores of the companies in the dataset in the last 20 years. Figure 6.1 in Appendix F illustrates the rising trend. Between 2002 and 2022, the average ESG score per year increased almost linearly from 29 to 59. This indicates that in 20 years, the average annual ESG score has risen to 59. So, in 20 years, average ESG scores have increased to twice as high. Even after accounting for fixed-year effects, the overall increase in ESG scores suggests an industry-wide improvement in business sustainability policies, affected by changing rules, public expectations, and market trends. This increasing improvement can make it difficult to determine the specific impact of technology-driven M&As on ESG performance, as some observed increases in ESG scores may be due to broader developments rather than the M&As themselves. As a result, this trend may overestimate the impact of technology-driven mergers and acquisitions, mistaking generic industry developments for specific corporate initiatives. While fixed-year effects help to manage some temporal changes, they do not completely separate the overall rising trend in ESG scores from the benefits of technology innovations obtained through M&As. This emphasizes the need for more advanced analytical methodologies that can clearly distinguish the effects of broad industry improvements from those caused by technology-driven M&As, allowing for a more exact understanding of ESG performance improvements. Using other techniques like difference-in-differences, synthetic control methods, or time-series analysis could be used to distinguish the effects of M&As from general improvements in business sustainability practices driven by regulatory changes, market trends, and evolving public expectations. This avenue of further research addresses the limitation of distinguishing the specific impacts of M&As from broader industry trends, providing a clearer understanding of how technology-driven M&As contribute to ESG performance.

REFERENCES

- Agudelo, M. A. L., Johannsdottir, L., & Davidsdottir, B. (2020). Drivers that motivate energy companies to be responsible. A systematic literature review of Corporate Social Responsibility in the energy sector. *Journal of cleaner production*, *247*, 119094.
- Ahn, H.S. (2020). Sustaining the family business through open innovation: The role of technological acquisitions in shareholder value creation. *Sustainability*, *12*(18), 1-17. doi: 10.3390/su12187819]
- Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic management journal*, *22*(3), 197-220.
- Aktas, N., De Bodt, E., & Cousin, J. (2011). Do Financial Markets Care About SRI? Evidence From Mergers and Acquisitions. *Journal of Banking & Finance*, *35*(7), 1753-1761.
- Al-Sharafi, M. A., Al-Emran, M., Arpaci, I., Iahad, N. A., AlQudah, A. A., Iranmanesh, M., & Al-Qaysi, N. (2023). Generation Z use of artificial intelligence products and its impact on environmental sustainability: A cross-cultural comparison. *Computers in Human Behavior*, *143*, 107708. <https://doi.org/10.1016/J.CHB.2023.107708>
- Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial analysts journal*, *74*(3), 87-103.
- Andersén, J., Jansson, C., & Ljungkvist, T. (2020). Can environmentally oriented CEOs and environmentally friendly suppliers boost the growth of small firms?. *Business Strategy and the Environment*, *29*(2), 325-334.
- Arouri, M., Gomes, M., & Pukthuanthong, K. (2019). Corporate social responsibility and M&A uncertainty. *Journal of Corporate Finance*, *56*, 176-198.
- Arthur, C., & Khindanova, I. (2023). Technological Acquisitions: The Impact of Innovation on Stock Performance. *The Journal of Applied Business and Economics*, *25*(4), 252-274.
- Avramov, D., Cheng, S., Lioui, A., & Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, *145*(2), 642-664. <https://doi.org10.1016/j.jfineco.2021.09.009>
- Bae, K. H., El Ghouli, S., Gong, Z. J., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. *Journal of Corporate Finance*, *67*, 101876.
- Barros, V., Matos, P. V., Sarmiento, J. M., & Vieira, P. R. (2022). M&A activity as a driver for better ESG performance. *Technological Forecasting and Social Change*, *175*, 121338.
- Battisti, E., Nirino, N., Leonidou, E., Thrassou, A., & Vrontis, D. (2024). Mergers and acquisitions and environmental conditions: a systematic literature review to investigate their linkage. *Management Research Review*, *47*(2), 226-244.
- Benitez-Amado, J., & Ray, G. (2012). Introducing IT-enabled business flexibility and IT integration in the acquirer's M&A performance equation.
- Benlemlih, M., & Girerd-Potin, I. (2017). Corporate social responsibility and firm financial risk reduction: On the moderating role of the legal environment. *Journal of Business Finance & Accounting*, *44*(7-8), 1137-1166.
- Berg, F., Kölbel, J. F., & Rigobón, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance*, *26*(6), 1315-1344.
- Bhardwaj, P., Chatterjee, P., Demir, K. D., & Turut, O. (2018). When and how is corporate social responsibility profitable?. *Journal of Business Research*, *84*, 206-219.
- Boffo, R., & Patalano, R. (2020). ESG investing: practices, progress and challenges. *Éditions OCDE, Paris*.

- Born, B., & Breitung, J. (2016). Testing for serial correlation in fixed-effects panel data models. *Econometric Reviews*, 35(7), 1290-1316.
- Broadstock, D. C., Matousek, R., Meyer, M., & Tzeremes, N. G. (2020). Does corporate social responsibility impact firms' innovation capacity? The indirect link between environmental & social governance implementation and innovation performance. *Journal of Business Research*, 119, 99-110
- Carnini Pulino, S., Ciaburri, M., Magnanelli, B. S., & Nasta, L. (2022). Does ESG disclosure influence firm performance?. *Sustainability*, 14(13), 7595.
- Carroll, A. B. (1979). A three-dimensional model of corporate social performance. *Academy of Management Review*, 4: 497-505.
- Carroll, A. B. (1991). The pyramid of corporate social responsibility: Toward the moral management of organizational stakeholders. *Business Horizons*, 34(4): 39-48.
- Chan, R. Y. (2005). Does the natural-resource-based view of the firm apply in an emerging economy? A survey of foreign invested enterprises in China. *Journal of management studies*, 42(3), 625-672
- Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic management journal*, 35(1), 1-23.
- Chen, C., Gu, J., & Luo, R. (2022). Corporate innovation and R&D expenditure disclosures. *Technological Forecasting and Social Change*, 174, 121230.
- Chen, Y.S. (2008). The driver of green innovation and green image—green core competence. *Journal of Business Ethics*, 81, 531–543.
- Chishty, S. K. (2023). Economic and Environmental Efficiencies of Organizations: Role of Technological Advancements and Circular Economy Practices. *Sustainability*, 15(22), 15935.
- Clément, A., Robinot, É., & Trespeuch, L. (2022). Improving ESG scores with sustainability concepts. *Sustainability*, 14(20), 13154.
- Cohen, L., Gurun, U. G., & Nguyen, Q. H. (2020). *The ESG-innovation disconnect: Evidence from green patenting* (No. w27990). National Bureau of Economic Research.
- COMMISSION OF THE EUROPEAN COMMUNITIES. (2001a). GREEN PAPER Promoting a European framework for Corporate Social Responsibility. In *COM(2001) 366 Final*. https://www.europarl.europa.eu/meetdocs/committees/deve/20020122/com%282001%29366_en.pdf
- Crane, A., McWilliams, A., Matten, D., Moon, J., & Siegel, D. (2008). *The Oxford handbook of CSR*. Oxford: Oxford University Press
- Dahlsrud, A. (2008). How corporate social responsibility is defined: an analysis of 37 definitions. *Corporate social responsibility and environmental management*, 15(1), 1-13.
- Dalal, K., & Thaker, N. (2019). ESG and Corporate Financial Performance: A Panel Study of Indian Companies. *IUP Journal of Corporate Governance*, 18(1), 44-59
- Dash, A., & Mohanty, S. K. (2023). The mediating effect of a firm's corporate reputation and sustainability practices in translating CSR into competitive performance in Indian ESG companies. *Society and Business Review*, 18(4), 691-709.
- Davis, G. F., & Thompson, T. A. (1994). A social movement perspective on corporate control. *Administrative science quarterly*, 141-173.
- Davis, K. (1973). The case for and against business assumption of social responsibilities. *Academy of Management journal*, 16(2), 312-322.
- Del Giudice, A., & Rigamonti, S. (2020). Does Audit Improve the Quality of ESG Scores? Evidence

- from Corporate Misconduct. *Sustainability*, 12(14), 5670. <https://doi.org/10.3390/su12145670>
- Deng, X., Kang, J., & Low, B. (2013). Corporate Social Responsibility and Stakeholder Value Maximization: Evidence from Mergers. *Journal of Financial Economics*, 87-109.
- Drempetic, S., Klein, C., & Zwergel, B. (2019). The Influence of Firm Size on the ESG Score: Corporate Sustainability Ratings Under Review. *Journal of Business Ethics*, 167, 333-360.
- Ebrahim, T. Y. (2020). Clean and sustainable technology innovation. *Current Opinion in Environmental Sustainability*, 45, 113-117.
- Eccles, R. G., Lee, L. E., & Strohle, J. C. (2020). The social origins of ESG: An analysis of Innovest and KLD. *Organization & Environment*, 33(4), 575-596.
- European Commission. (2010). *Corporate Social Responsibility (CSR)*. Retrieved from http://ec.europa.eu/enterprise/policies/sustainable-business/corporate-social-responsibility/index_en.htm
- European Commission. (2011). *Corporate Social Responsibility: a new definition, a new agenda for action*. Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/MEMO_11_730
- Feng, X. (2021). The role of ESG in acquirers' performance change after M&A deals. *Green finance*, 3(3), 287-318.
- Fernández-Guadaño, J., & Sarria-Pedroza, J. H. (2018). Impact of corporate social responsibility on value creation from a stakeholder perspective. *Sustainability*, 10(6), 2062.
- Fishman, R., Heal, G., & Nair, V. (2006). *A model of corporate philanthropy*. University of Pennsylvania Working Paper.
- Friedman, M. (1970). The social responsibility of business is to increase its profits. *New York Times Magazine*, September 13: 32-33, 122-126.
- Gendron, C., & Turcotte, M. F. (2007). Les nouveaux mouvements sociaux économiques au cœur d'une nouvelle gouvernance. [*The New Economic Social Movements at the Heart of a New Governance*]. *Revue Organisations & territoires*, 16(1), 23-32.
- Ghardallou, W. (2022). Corporate sustainability and firm performance: The moderating role of CEO education and tenure. *Sustainability*, 14(6), 3513.
- Giese, G., Nagy, Z., & Lee, L. E. (2020). Deconstructing ESG ratings performance: Risk and return for E, S, and G by time horizon, sector, and weighting. *The Journal of Portfolio Management*.
- Gigauri, I., & Vasilev, V. (2022). Corporate social responsibility in the energy sector: towards sustainability. In *Energy Transition: Economic, Social and Environmental Dimensions* (pp. 267-288). Singapore: Springer Nature Singapore.
- Global Energy Review 2019: *The latest trends in energy and emissions*. (2019). International Energy Agency. <https://www.iea.org/reports/global-energy-review-2019/co2-emissions>.
- Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence* (pp. 287-343). University of Chicago Press.
- Habermas, J. (1975). *Legitimation crisis*. (Vol.519). Beacon Press.
- Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 32, 101-128.
- Halunga, A. G., Orme, C. D., & Yamagata, T. (2017). A heteroskedasticity robust Breusch-Pagan test for Contemporaneous correlation in dynamic panel data models. *Journal of econometrics*, 198(2), 209-230.
- Hassoun, A., Prieto, M. A., Carpena, M., Bouzembrak, Y., Marvin, H. J. P., Pallarés, N., Barba, F. J., Punia Bangar, S., Chaudhary, V., Ibrahim, S., & Bono, G. (2022). Exploring the role of green and industry 4.0 technologies in achieving sustainable development goals in food sectors.

- Food Research International, 162, 112068. <https://doi.org/10.1016/J.FOODRES.2022.112068>
- Heinkel, R., Kraus, A., & Zechner, J. (2001). The Effect of Green Investment on Corporate Behavior. *Journal Of Financial And Quantitative Analysis*, 36(4), 431. <https://doi.org/10.2307/2676219>
- Hong, X., Lin, X., Fang, L., Gao, Y., & Li, R. (2022). Application of Machine Learning Models for Predictions on Cross-Border Merger and Acquisition Decisions with ESG Characteristics from an Ecosystem and Sustainable Development Perspective. *Sustainability*, 14(5), 2838.
- International Energy Outlook 2019*. (2019). U.S. Energy Information Administration. <https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf>.
- Jan, C. L., & Ou, J. A. (2012). Negative-book-value firms and their valuation. *Accounting horizons*, 26(1), 91-110.
- Jeriji, M., & Louhichi, W. (2021). The relationship between poor CSR performance and hard, negative CSR information disclosures. *Sustainability Accounting, Management and Policy Journal*, 12(2), 410–436. <https://doi.org/10.1108/SAMPJ-04-2020-0094>
- Jiang, G. H. (2022). How M&A effect the performance of acquired firms: Based on the perspective of merge and acquisition of Chinese industrial firms. *Management World*, 38(07), 196-212.
- Jo, H., & Na, H. (2012). Does CSR reduce firm risk? Evidence from controversial industry sectors. *Journal of business ethics*, 110, 441-456.
- Kahle, K. M., & Walkling, R. A. (1996). The impact of industry classifications on financial research. *Journal of financial and quantitative analysis*, 31(3), 309-335.
- Kandpal, V., Jaswal, A., Santibanez Gonzalez, E. D., & Agarwal, N. (2024). Sustainable Energy Transition, Circular Economy, and ESG Practices. In *Sustainable Energy Transition: Circular Economy and Sustainable Financing for Environmental, Social and Governance (ESG) Practices* (pp. 1-51). Cham: Springer Nature Switzerland.
- Kell, G. (2022, 12 october). The remarkable rise of ESG. *Forbes*. <https://www.forbes.com/sites/georgkell/2018/07/11/the-remarkable-rise-of-esg/?sh=54e411821695>
- Kumar, B. R., & Kumar, B. R. (2019). *Mergers and Acquisitions* (pp. 1-15). Springer International Publishing.
- Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, 72(2), 853-910.
- Lin, W. L., Cheah, J. H., Azali, M., Ho, J. A., & Yip, N. (2019). Does firm size matter? Evidence on the impact of the green innovation strategy on corporate financial performance in the automotive sector. *Journal of Cleaner Production*, 229, 974-988.
- Li, T.T.; Wang, K.; Sueyoshi, T.; Wang, D.D. (2021). ESG: Research progress and future prospects. *Sustainability*, 13, 11663.
- Li, T., & Zhou, X. (2022). Research on the mechanism of government–industry–university–institute collaborative innovation in green technology based on game–based cellular automata. *International Journal of Environmental Research and Public Health*, 19(5), 3046.
- Lockett, A., Moon, J., & Visser, W. 2006. Corporate social responsibility in management research: Focus, nature, salience and sources of influence. *Journal of Management Studies*, 43: 115-136.
- Lounsbury, M., Ventresca, M., & Hirsch, P. M. (2003). Social movements, field frames and industry emergence: A cultural–political perspective on US recycling. *Socio-economic review*, 1(1), 71-104
- Margolis, J. D., Elfenbein, H. A., & Walsh, J. P. (2009). *Does it pay to be good and does it matter? Meta analysis of the relationship between corporate social and financial performance*. Working

Paper.

- Margolis, J. D., & Walsh, J. P. (2003). Misery loves companies: Rethinking social initiatives by business. *Administrative Science Quarterly*, 48(2), 268-305.
- Martínez-Ferrero, J., Banerjee, S., & García-Sánchez, I.M., (2016). Corporate social responsibility as a strategic shield against costs of earnings management practices. *Journal of Business Ethics* 133, 305–324.
- Matten, D., & Crane, A. 2005. Corporate citizenship: Toward an extended theoretical conceptualization. *Academy of Management Review*, 30: 166-179.
- Matten, D., & Moon, J. (2008). “Implicit” and “Explicit” CSR: A Conceptual Framework for a Comparative Understanding of Corporate Social Responsibility. *Academy Of Management Review*, 33(2), 404–424. <https://doi.org/10.5465/amr.2008.31193458>
- McCarthy, K.J., & Aalbers, H.L. (2016). Technological acquisitions: The impact of geography on post-acquisition innovative performance. *Research Policy*, 45(9), 1818–1832
- McWilliams, A., & Siegel, D. (2001). Corporate social responsibility: A theory of the firm perspective. *Academy of Management Review*, 28, 117–127.
- Mishra, D.R. (2015). Post-innovation CSR Performance and Firm Value. *Journal Of Business Ethics*, 140(2), 285–306. <https://doi.org/10.1007/s10551-015-2676-3>
- Mneimneh, F., Al Kodsi, M., Chamoun, M., Basharoush, M., & Ramakrishna, S. (2023). How can green energy technology innovations improve the carbon-related environmental dimension of ESG rating?. *Circular Economy and Sustainability*, 1-17.
- Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of financial economics*, 73(2), 201-228.
- Moon, J., Crane, A., & Matten, D. (2005). Can corporations be citizens? Corporate citizenship as a metaphor for business participation in society. *Business Ethics Quarterly*, 15: 427-451
- Pegkas, P., Staikouras, C., & Tsamadias, C. (2019). Does research and development expenditure impact innovation? Evidence from the European Union countries. *Journal of Policy Modeling*, 41(5), 1005-1025
- Pri. (2024). *About the PRI*. <https://www.unpri.org/about-us-about-the-pri>
- Rahman, J., & Wu, J. (2024). M&A activity and ESG performance: evidence from China. *Managerial Finance*, 50(1), 179-197.
- Raman, S. (2018). Managing employees perception on organizational practices-a contextual study on retention of Indian mining professionals. *Sankalpa*, 8(1), 85-93.
- Renneboog, L., Ter Horst, J., and Zhan g, C. (2008), “Socially responsible investments: Institutional aspects, performance, and investor behavior”, *Journal of Banking and Finance* 32, 9, pp.1723-1742.
- Riedl, A. & Smeets, P. (2017), “Why Do Investors Hold Socially Responsible Mutual Funds?,” *Journal of Finance* 72(6), 2505–2550.
- Refinitiv. (2024). *ESG scores*. <https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores>
- Rhodes-Kropf, Matthew, and S. Viswanathan, 2004, Market valuation and merger waves, *Journal of Finance* 59, 2685–2718.
- Ruckman, K. (2009). Technology sourcing acquisitions: What they mean for innovation potential. *Journal of Strategy and Management*, 2(1), 56-75).
- Schjoedt, L., & Sangboon, K. (2015). Control variables: problematic issues and best practices. In

- The Palgrave Handbook of Research Design in Business and Management* (pp. 239-261). New York: Palgrave Macmillan US.
- SEC.gov — SEC Proposes Rules to Enhance and Standardize Climate-Related Disclosures for Investors. (2022, 21 maart). <https://www.sec.gov/news/press-release/2022-46>
- Di Simone, L., Petracchi, B., & Piva, M. (2022). Economic sustainability, innovation, and the ESG factors: An empirical investigation. *Sustainability*, 14(4), 2270.
- Sjostrom, E. (2007). Translating ideologically based concerns: How civil society organisations use the financial market to protect human rights. *International journal of environment and sustainable development*, 6(2), 157-173.
- Song, M. L., Fisher, R., Wang, J. L., & Cui, L. B. (2018). Environmental performance evaluation with big data: Theories and methods. *Annals of Operations Research*, 270, 459-472.
- Suo, L., Yang, K., & Ji, H. (2023). The Impact of Technological Mergers and Acquisitions on Enterprise Innovation: A Review. *Sustainability*, 15(17), 12883.
- Tampakoudis, I., & Anagnostopoulou, E. (2020). The effect of mergers and acquisitions on environmental, social and governance performance and market value: Evidence from EU acquirers. *Business Strategy and the Environment*, 29(5), 1865-1875.
- Teoh, T. T., Heng, Q. K., Chia, J. J., Shie, J. M., Liaw, S. W., Yang, M., & Nguwi, Y. Y. (2019, November). Machine learning-based corporate social responsibility prediction. In *2019 IEEE International conference on cybernetics and intelligent systems (CIS) and IEEE conference on robotics, automation and mechatronics (RAM)* (pp. 501-505). IEEE.
- Teti, E., & Spiga, L. (2023). The effect of environmental, social and governance score on operating performance after mergers and acquisitions. *Business Strategy and the Environment*, 32(6), 3165-3177.
- Varma, A., Dixit, N., Ray, S., & Kaur, J. (2024). Blockchain technology for sustainable supply chains: A comprehensive review and future prospects. *World Journal of Advanced Research and Reviews*, 21(3), 980-994.
- Wang, J., Ma, M., Dong, T., & Zhang, Z. (2023). Do ESG ratings promote corporate green innovation? A quasi-natural experiment based on SynTao Green Finance's ESG ratings. *International Review of Financial Analysis*, 87, 102623.
- Wernerfelt, B. (1984). A resource based view of the firm. *Strategic Management Journal*, 5, 171-180
- Yuen, K. F., Thai, V. V., & Wong, Y. D.. (2016) Are customers willing to pay for corporate social responsibility? A study of individual-specific mediators, *Total Quality Management & Business Excellence*, 27(7-8), 912-926
- Yu, E. P. Y., Guo, C. Q., & Luu, B. V. (2018). Environmental, social and governance transparency and firm value. *Business Strategy and the Environment*, 27(7), 987-1004.
- Yunus, S., Elijido-Ten, E. O., & Abhayawansa, S. (2020). Impact of stakeholder pressure on the adoption of carbon management strategies: Evidence from Australia. *Sustainability Accounting, Management and Policy Journal*, 11(7), 1189–1212. <https://doi.org/10.1108/SAMPJ-04-2019-0135>
- Zald, M. N., & Berger, M. A. (1978). Social movements in organizations: Coup d'état, insurgency, and mass movements. *American journal of sociology*, 83(4), 823-861.
- Zhang, F., Qin, X., & Liu, L. (2020). The interaction effect between ESG and green innovation and its impact on firm value from the perspective of information disclosure. *Sustainability*, 12(5), 1866

- Zhang, X.; Xu, B. (2019). R&D Internationalization and Green Innovation? Evidence from Chinese Resource Enterprises and Environmental Enterprises. *Sustainability*, *11*, 7225.
- Zhang, G., & Zhang, X. J. (2014). Driving factors of green innovation strategy: Multiple case study. *Journal of Zhejiang University (Humanities and Social Sciences)*, *44*(1), 113-124.
- Zheng, J., Khurram, M. U., & Chen, L. (2022). Can green innovation affect ESG ratings and financial performance? Evidence from Chinese GEM listed companies. *Sustainability*, *14*(14), 8677.
- Zumente, I., & Lāce, N. (2021). ESG Rating—Necessity for the Investor or the Company? *Sustainability*, *13*(16), 8940. <https://doi.org/10.3390/su13168940>

A APPENDIX A

Table 1: Summary statistics of sample by 2-digit SIC

SIC2	N	Mean	SD
7	9	18.25	3.81
8	18	81.46	5.39
10	21	51.90	16.41
12	8	45.75	6.30
13	21	37.96	7.29
14	21	33.90	10.31
15	21	30.01	8.94
16	8	37.55	11.94
20	21	54.95	12.59
21	19	37.76	16.11
23	21	52.40	17.19
24	17	38.28	14.71
25	16	55.26	13.20
26	21	55.09	14.21
27	21	42.41	10.90
28	21	48.03	7.74
29	21	55.49	9.50
30	21	40.79	12.89
31	21	44.06	16.84
33	21	40.30	13.03
34	21	38.45	19.68
35	21	49.61	10.14
36	21	47.00	10.76
37	21	47.30	10.31
38	21	45.58	9.63
40	4	21.44	3.96
42	21	63.94	9.81
44	15	36.37	8.74
45	21	50.19	17.60
47	18	24.84	16.41
48	21	35.37	8.72
49	21	48.34	9.89
50	21	35.87	10.94
51	21	44.11	13.57
52	21	55.36	10.40
53	21	49.11	11.20
54	21	53.59	20.64
55	15	33.95	6.07
57	21	54.94	19.54
58	21	60.79	10.70
59	21	47.46	11.89
61	19	34.11	13.11
70	21	46.35	13.47
72	15	24.71	10.14
73	21	42.53	7.54
75	19	34.16	8.77
78	21	37.82	10.29
79	15	26.59	4.44
80	21	47.00	9.94
82	21	23.37	6.42
87	19	41.96	11.84

Note: This table shows the distribution of the ESG scores over the different 2-digit SIC codes in the aggregated dataset. N is the number of companies in the associated 2-digit SIC code, Mean is the mean ESG score of companies in the corresponding sector, indicated by the 2-digit SIC codes and SD is the standard error. The energy sector comprise the 2-digit SIC codes 10, 12, 13, 14, 29, and 49 (Cohen et al., 2020).

Table 2: Summary statistics of non-energy sector companies

Variables, EnergySector = 0	N	Mean	SD	Min	Max
F.ESG score	5210	48.11	20.38	2.2	95.16
ESG score	5636	46.61	20.64	1.67	95.16
ESG gap	196	-15.55	25.04	-74.02	60.25
M&A	5636	0.13	0.34	0	1
Technology- Driven M&A	5636	0.04	0.21	0	1
Innovation	248	2.68	4.84	0.05	36.30
Innovation Quality	245	2.632	8.681	0	111.29
Ln(Total Assets)	5634	9.03	1.39	5.20	13.53
BTM	5601	0.39	0.32	-0.29	1.94
Leverage	5309	0.98	1.07	0	3.94
ROA	5584	0.04	0.10	-0.47	0.27
R&D Intensity	4068	0.11	0.21	0	1.94

Note: This table shows the summary statistics of the companies that are active outside of the energy sector. The N is the number of observations per variable, the mean is the mean value of the associated variable, the SD is the standard deviation, and the Min and Max are the minimum and maximum values of the variables.

Table 3: Summary statistics of energy sector companies

Variables, EnergySector = 1	N	Mean	SD	Min	Max
F.ESG score	1075	48.42	20.45	7.53	91.32
ESG score	1157	46.95	20.73	7.13	91.32
ESG gap	43	-16.32	20.41	-62.94	26.90
M&A	1157	0.10	0.31	0	1
Technology- Driven M&A	1157	0.01	0.12	0	1
Innovation	17	7.15	8.41	0.83	35.36
Innovation Quality	17	7.36	12.22	0	46.10
Ln(Total Assets)	1157	9.70	1.32	5.20	12.80
BTM	1154	0.60	0.40	-0.29	1.94
Leverage	769	0.77	0.75	0	3.94
ROA	1157	0.02	0.10	-0.47	0.27
R&D Intensity	179	0.01	0.01	0	0.05

Note: This table shows the summary statistics of the companies that operate in the energy sector. The N is the number of observations per variable, the mean is the mean value of the associated variable, the SD is the standard deviation, and the Min and Max are the minimum and maximum values of the variables.

Table 4: Aggregated summary statistics

Variables	N	Mean	SD	Min	Max
(mean) F.ESG score	918	45.65	16.07	3.21	88.82
(mean) ESG score	969	44.21	16.22	3.21	88.82
(mean) ESG gap	143	-13.47	23.20	-74.02	60.25
(mean) M&A	969	0.89	1.76	0	10
(mean) Technology- Driven M&A	969	0.27	0.82	0	10
M&A Energy	969	0.12	0.66	0	8
Technology-Driven M&A Energy	969	0.02	0.13	0	1
(mean) Innovation	142	3.29	4.82	0.05	35.36
(mean) Innovation Quality	139	3.14	6.70	0	46.10
Innovation Energy	142	0.86	3.67	0	35.36
(mean) Ln(Total Assets)	969	9.10	0.89	5.64	11.42
(mean) BTM	962	0.44	0.30	-0.29	1.94
(mean) Leverage	955	1.05	0.83	0	3.94
(mean) ROA	961	0.05	0.07	-0.47	0.27
(mean) R&D Intensity	666	0.05	0.14	0	1.94

Note: This table shows the summary statistics of the aggregated dataset, used for hypotheses 4a and 4b. The dataset is constructed by aggregating all the mean values of the variables by the 2-digit SIC code and corresponding Year. The N is the number of observations per variable, the mean is the mean value of the associated variable, the SD is the standard deviation, and the Min and Max are the minimum and maximum values of the variables.

Table 5: Aggregated summary statistics of non-energy sector companies

Variables, EnergySector = 0	N	Mean	SD	Min	Max
(mean) F.ESG score	810	45.45	16.40	3.21	88.82
(mean) ESG score	856	44.04	16.57	3.21	88.82
(mean) ESG gap	113	-12.46	24.38	-74.02	60.25
(mean) M&A	856	0.86	1.77	0	10
(mean) Technology- Driven M&A	856	0.29	0.86	0	10
(mean) Innovation	125	2.77	3.87	0.05	22.06
(mean) Innovation Quality	122	2.55	5.36	0	37.84
(mean) Ln(Total Assets)	856	9.06	0.88	5.64	11.42
(mean) BTM	849	0.43	0.29	-0.29	1.94
(mean) Leverage	844	1.09	0.86	0	3.94
(mean) ROA	848	0.05	0.07	-0.47	0.27
(mean) R&D Intensity	597	0.05	0.15	0	1.94

Note: This table shows the summary statistics of the aggregated dataset, used for hypotheses 4a and 4b, for the companies who are not active in the energy sector. The dataset is constructed by aggregating all the mean values of the variables by the 2-digit SIC codes for companies outside of the energy sector and the corresponding Year. The N is the number of observations per variable, the mean is the mean value of the associated variable, the SD is the standard deviation, and the Min and Max are the minimum and maximum values of the variables.

Table 6: Aggregated summary statistics of energy sector companies

Variables, EnergySector = 1	N	Mean	SD	Min	Max
(mean) F.ESG score	108	47.12	13.25	12.44	78.47
(mean) ESG score	113	45.53	13.28	11.33	72.43
(mean) ESG gap	30	-17.29	17.90	-62.94	16.92
(mean) M&A	113	1.07	1.64	0	9
(mean) Technology- Driven M&A	113	0.15	0.36	0	1
(mean) M&A Energy	113	1.07	1.64	0	9
(mean) Technology-Driven M&A Energy	113	0.15	0.36	0	1
(mean) Innovation	17	7.15	8.41	0.83	35.36
(mean) Innovation Quality	17	7.36	12.22	0	46.10
(mean) Innovation Energy	17	7.15	8.41	0.83	35.36
(mean) Ln(Total Assets)	113	9.41	0.89	7.10	10.98
(mean) BTM	113	0.59	0.33	-0.03	1.94
(mean) Leverage	111	0.79	0.55	0.22	2.87
(mean) ROA	113	0.03	0.08	-0.27	0.27
R&D Intensity	69	0.01	0.01	0	0.03

Note: This table shows the summary statistics of the aggregated dataset, used for hypotheses 4a and 4b, for the companies who are active in the energy sector. The dataset is constructed by aggregating all the mean values of the variables by the 2-digit SIC codes for companies active in the energy sector and the corresponding Year. The N is the number of observations per variable, the mean is the mean value of the associated variable, the SD is the standard deviation, and the Min and Max are the minimum and maximum values of the variables.

B APPENDIX B

Table 7: Years of financial crisis and COVID-19 excluded H1

Hypothesis	H1			
Model	(1)	(2)	(3)	(4)
Variables	ESGscore	F.ESGscore	F.ESGscore	F.ESGscore
Technology-Driven M&A	-0.459 (0.894)	1.154* (0.729)		
Non-tech-driven M&A			2.176*** (0.741)	
M&A				1.942*** (0.595)
ln(Total Assets)	1.167 (0.873)	3.783*** (0.901)	2.684*** (0.889)	2.632*** (0.889)
BTM	-2.879* (1.698)	-3.629** (1.843)	-3.403* (1.838)	-3.503* (1.840)
ROA	1.216 (3.535)	4.237 (3.351)	4.163 (3.391)	3.948 (3.379)
R&D Intensity	2.904 (3.579)	2.983 (2.971)	2.772 (2.990)	2.658 (3.065)
Constant	13.396 (7.343)	0.951 (7.427)	1.004 (7.379)	1.448 (7.380)
YearFE	controlled	controlled	controlled	controlled
N	2,565	2,520	2,520	2,520
P	0.000	0.000	0.000	0.000
R^2	0.633	0.621	0.622	0.623
Number of companies	323	322	322	322

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2006 and 2012-2019, excluding the years of the financial credit and COVID-19 crisis. In model (1), the influence of technology-driven M&As on the ESG score in the year of the merger is investigated and in Model (2) is the relationship between technology-driven M&As on the forward ESG score researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Years of financial crisis and COVID-19 excluded H2

Hypothesis Model Variables	H2a		H2b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Innovation	.133 (.182)	-.372*** (.112)		
Innovation Quality			.161** (.064)	.050 (.067)
ln(Total Assets)	-.107 (2.813)	-3.932* (2.214)	-.051 (2.940)	-2.893 (2.513)
BTM	-11.982 (28.654)	11.427 (30.599)	-3.213 (31.381)	4.972 (32.356)
Leverage	-9.465 (6.184)	6.911 (5.948)	-7.685 (5.691)	1.731 (6.231)
ROA	-37.002 (38.305)	-76.163 (47.758)	-25.912 (38.896)	-67.717 (50.942)
R&D Intensity	-44.318 (50.198)	-128.140** (61.124)	-50.081 (44.548)	-122.864 (62.942)
Constant	14.737 (24.302)	42.329** (18.842)	10.807 (22.952)	41.343** (17.411)
YearFE	controlled	controlled	controlled	controlled
N	121	127	121	127
P	0.000	0.000	0.000	0.000
R^2	.779	.815	.806	.802
Number of companies	82	87	82	87

Note: This table shows the result of the fixed effects model, studying the relationship between innovation and innovation quality and the ESG performance of acquiring companies over the period 2002-2006 and 2012-2019, excluding the years of the financial credit and COVID-19 crisis. For Hypothesis 2a, in model (1) and (2), the influence of innovation on the forward ESG score and ESG score, respectively, is investigated. For Hypothesis 2b, in model (3) and (4) the relationship between innovation quality on the forward ESG score and ESG score in the year of the merger is researched, respectively. Innovation is the variable that represents the number of published patents by the target company, compared to the average per industry and Innovation quality is the number of patent citations, also compared to the industry average. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Years of financial crisis and COVID-19 excluded H3

Hypothesis	H3	H3
Model	(1)	(2)
Variables	F.ESGscore	ESGscore
ESG Gap	-0.309*** (0.057)	-0.433*** (0.057)
ln(Total Assets)	5.354*** (0.836)	5.615*** (0.841)
ROA	39.318* (22.231)	32.226 (22.296)
BTM	8.323 (5.961)	10.701* (5.983)
Leverage	1.379 (1.436)	1.034 (1.449)
R&D Intensity	0.515 (8.819)	0.712 (8.812)
Constant	-25.373 (14.057)	-35.320 (14.161)
YearFE	controlled	controlled
N	94	95
P	0.000	0.000
R^2	0.672	0.732

Note: This table shows the result of the OLS regression model, studying the relationship between the width of the ESG gap and the ESG performance of acquiring companies over the period 2002-2006 and 2012-2019, excluding the years of the financial credit and COVID-19 crisis. In model (1), the influence of the width of the ESG gap on the forward ESG score is investigated and in Model (2) the relationship between the ESG gap on the ESG score in the year of the merger is researched. ESG gap is the variable representing the difference between the ESG score of the target company and of the acquiring company in the year prior to the merger. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Years of financial crisis and COVID-19 excluded H4

Hypothesis Model Variables	H4a		H4b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Average Innovation	.136** (.061)	.209** (.076)		
Innovation * Energy Sector	-.695*** (.239)	-.409 (.275)		
Merger & Acquisition			.042 (.259)	.202 (.328)
M&A * Energy Sector			.433 (.426)	.332 (.597)
Technology Driven M&A			.441 (.437)	.104 (.452)
Technology Driven M&A * Energy Sector			-1.159 (2.878)	-1.555 (4.055)
Ln(Average Total Assets)	7.138*** (1.354)	7.498*** (1.572)	8.531*** (1.374)	8.374*** (1.418)
Average BTM	-23.846* (2.836)	-12.077 (12.622)	-.650 (3.186)	-1.508 (3.387)
Average Leverage	-9.487*** (1.703)	-7.874*** (1.729)	.685 (.755)	.191 (.579)
Average ROA	33.763 (20.503)	40.684** (19.956)	7.392 (7.262)	1.728 (6.481)
Average R&D Intensity	-5.058 (3.709)	-3.995 (4.631)	1.324 (.912)	1.757 (1.191)
Constant	-18.534 (12.558)	-26.869 (14.980)	-48.229*** (.912)	-47.808*** (12.677)
Year Fixed Effects	controlled	controlled	controlled	controlled
N	83	83	404	405
P	0.000	0.000	0.000	0.000
R^2	.959	.9483	.776	.797
Number of groups	21	21	39	39

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2006 and 2012-2019, excluding the years of the financial credit and COVID-19 crisis. In model (1), the influence of technology-driven M&As on the forward ESG score is investigated and in Model (2) is the relationship between technology-driven M&As on the ESG score in the year of the merger researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets by sales (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C APPENDIX C

Table 11: Using a different dependent variable H1

Hypothesis	H1		
Model	(1)	(2)	(3)
Variables	Delta ESG	Delta ESG	Delta ESG
Technology-Driven M&A	.152*** (.048)		
Non-tech M&A		.110* (.060)	
M&A			.138*** (.042)
ln(Total Assets)	.047** (.021)	.047** (.022)	.044** (.021)
BTM	.027 (.039)	.033 (.039)	.030 (.038)
ROA	.196 (.120)	.216* (.117)	.198* (.120)
R&D Intensity	.154 (.137)	.150 (.146)	.141 (.142)
Constant	-1.734 (.192)	-1.791 (.194)	-1.607 (.193)
YearFE	controlled	controlled	controlled
N	3,616	3,616	3,616
P	.000	.000	.000
R^2	.058	.058	.062
Number of companies	324	324	324

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the Difference in ESG performance of acquiring companies between the year before and the year after the merger, indicated by the Delta ESG variable, over the period 2002-2022. In model (1), the influence of technology-driven M&As on the ESG score in the year of the merger is investigated and in Model (2) is the relationship between technology-driven M&As on the forward ESG score researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Using a different dependent variable H2 & H3

Hypothesis	H2		H3
Model	(1) Fixed Effects	(2) Fixed Effects	(2) OLS Regression
Variables	Delta ESG Score	Delta ESG score	Delta ESG Score
Innovation	.014*** (.004)		
Innovation Quality		.008*** (.001)	
ESG Gap			.005*** (.001)
ln(Total Assets)	-.201** (.089)	-.180* (.097)	-.023** (.012)
BTM	.761** (.373)	.812** (.384)	-.174 (.112)
Leverage	-.211* (.122)	-.170 (.123)	.046 (.039)
ROA	2.165* (1.155)	1.964* (1.121)	-.378 (.414)
R&D Intensity	1.493** (.672)	1.026 (.628)	.219* (.132)
Constant	1.342* (.747)	1.229 (.808)	.188 (.119)
YearFE	controlled	controlled	controlled
N	184	183	144
P	0.000	0.000	0.000
R^2	.537	.563	.428
Number of companies	109	108	144

Note: This table shows the result of the fixed effects model, studying the relationship between innovation and innovation quality and the difference in ESG performance of acquiring companies between the year before and the year after the merger indicated by the Delta ESG variable, over the period 2002-2022. For Hypothesis 2a, in model (1), the influence of innovation on the Delta ESG variable is investigated. For Hypothesis 2b, in model (2) the relationship between innovation quality on the Delta ESG variable is researched. Innovation is the variable that represents the number of published patents by the target company, compared to the average per industry and Innovation quality is the number of patent citations, also compared to the industry average. The results of the regression of Hypothesis 3 is shown in model (3), where the influence of the width of the ESG gap on the Delta ESG variable is investigated. The ESG gap is the variable representing the difference between the ESG score of the target company and of the acquiring company in the year prior to the merger. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Using a different dependent variable H4

Hypothesis	H4a	H4b
Model	(1)	(2)
Variables	Delta ESG	Delta ESG
Innovation	0.027** (0.012)	
Innovation * Energy Sector	-0.033*** (0.012)	
Merger&Acquisition		0.010 (0.008)
M&A * Energy Sector		-0.004 (0.012)
Technology-Driven M&A		-0.001 (0.013)
Technology-Driven M&A * Energy Sector		-0.040 (0.048)
ln(Total Assets)	.046 (.079)	-0.027 (0.059)
BTM	.132 (.248)	0.174 (0.134)
Leverage	.004 (.125)	-0.006 (0.024)
ROA	.093 (.459)	0.061 (0.206)
R&D Intensity	.268 (.239)	0.024 (0.074)
Constant	-.309 (.822)	0.426 (0.405)
YearFE	controlled	controlled
N	125	599
P	0.000	0.000
R ²	0.443	0.154
Number of groups	26	39

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the difference in ESG performance of acquiring companies between the year before and the year after the merger indicated by the Delta ESG variable, over the period 2002-2022. In model (1), the influence of technology-driven M&As on the forward ESG score is investigated and in Model (2) is the relationship between technology-driven M&As on the ESG score in the year of the merger researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets by sales (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * p<0.10, ** p<0.05, *** p<0.01.

D APPENDIX D

Table 14: Using lagged independent variables H1

Hypothesis	H1			
Model	(1)	(2)	(3)	(4)
Variables	ESGscore	F.ESG score	F.ESG score	F.ESG score
Technology-Driven M&A	.110 (.726)	1.773** (.715)		
Non-tech M&A M&A			.194 (.622)	.894* (.500)
Lag ln(Total Assets)	3.638*** (.761)	4.083*** (.836)	4.056*** (.841)	4.093*** (.841)
Lag BTM	-3.672*** (1.420)	-3.241** (1.488)	-3.239** (1.485)	-3.211** (1.484)
Lag ROA	3.298 (2.891)	3.061 (2.838)	3.206 (2.840)	3.094 (2.843)
Lag R&D Intensity	.755 (3.052)	-.048 (3.033)	-.187 (3.033)	-.163 (3.038)
Constant	-6.567 (6.315)	-5.698 (6.890)	-5.354 (6.969)	-5.770 (6.961)
YearFE	controlled	controlled	controlled	controlled
N	3,915	3,605	3,605	3,605
P	0.000	0.000	0.000	0.000
R^2	.573	.543	.541	.543
Number of companies	334	324	324	324

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022, using lagged control variables. In model (1), the influence of technology-driven M&As on the ESG score in the year of the merger is investigated and in Model (2) is the relationship between technology-driven M&As on the forward ESG score researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The lagged control variables consist of the lagged Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars in the year before the observation, lagged return on assets (Lag ROA), Lagged book-to-market ratio, and Lagged research & development (Lag R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Using lagged independent variables H2

Hypothesis Model Variables	H2a		H2b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Innovation	.129 (.187)	.011 (.195)		
Innovation Quality			.220*** (.048)	.158* (.095)
Lag ln(Total Assets)	1.697 (3.431)	5.541* (2.948)	4.575** (1.926)	9.419*** (1.688)
Lag BTM	-.939 (14.008)	9.581 (10.331)	.187 (8.173)	-4.312 (6.332)
Lag leverage	1.367 (5.176)	4.661 (3.039)	.166 (1.345)	-.059 (1.165)
Lag ROA	30.882 (23.461)	54.316 (34.194)	14.052 (11.728)	14.980 (16.484)
Lag R&D Intensity	79.034 (57.062)	88.940* (52.758)	23.283 (33.177)	44.511 (27.632)
Constant	-60.921 (28.077)	-43.142 (22.829)	-14.491 (18.730)	-61.021 (15.349)
YearFE	controlled	controlled	controlled	controlled
N	179	197	414	452
P	0.000	0.000	0.000	0.000
R^2	.180	.181	.296	.364
Number of companies	108	118	223	242

Note: This table shows the result of the fixed effects model, studying the relationship between innovation and innovation quality and the ESG performance of acquiring companies over the period 2002-2022, using lagged control variables. For Hypothesis 2a, in model (1) and (2), the influence of innovation on the forward ESG score and ESG score, respectively, is investigated. For Hypothesis 2b, in model (3) and (4) the relationship between innovation quality on the forward ESG score and ESG score in the year of the merger is researched, respectively. Innovation is the variable that represents the number of published patents by the target company, compared to the average per industry and Innovation quality is the number of patent citations, also compared to the industry average. The lagged control variables consist of the lagged Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars in the year before the observation, lagged return on assets (Lag ROA), Lagged book-to-market ratio, lagged leverage and Lagged research & development (Lag R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Using lagged independent variables H3

Hypothesis Model	H3	
	(1)	(2)
Variables	F.ESGscore	ESGscore
ESG Gap	-.262*** (.055)	-.390*** (.048)
Lag ln(Total Assets)	5.375*** (.613)	5.314*** (.552)
Lag BTM	1.757 (4.653)	5.302 (4.499)
Lag leverage	.382 (1.284)	-.461 (1.103)
Lag ROA	3.441 (10.277)	9.543 (13.410)
Lag R&D Intensity	-6.241 (3.842)	-3.006 (4.453)
Constant	-19.033*** (5.462)	-27.630 (4.794)
Year	controlled	controlled
N	142	161
P	0.000	0.000
R^2	.650	.739

Note: This table shows the result of the OLS regression model, studying the relationship between the width of the ESG gap and the ESG performance of acquiring companies over the period 2002-2022. In model (1), the influence of the width of the ESG gap on the forward ESG score is investigated and in Model (2) the relationship between the ESG gap on the ESG score in the year of the merger is researched. ESG gap is the variable representing the difference between the ESG score of the target company and of the acquiring company in the year prior to the merger. The lagged control variables consist of the lagged Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars in the year before the observation, lagged return on assets (Lag ROA), Lagged book-to-market ratio, lagged leverage and Lagged research & development (Lag R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Using lagged independent variables H4

Hypothesis Model Variables	H4a		H4b	
	(1) F.ESGscore	(2) ESGscore	(3) F.ESGscore	(4) ESGscore
Innovation	.103 (.121)	.098 (.134)		
Innovation * Energy Sector	-.004 (.143)	.130 (.160)		
Merger&Acquisition			.065 (.157)	.093 (.190)
M&A * Energy Sector			.856** (.367)	.633* (.358)
Technology-Driven M&A			.185 (.326)	-.013 (.286)
Technology-Driven M&A * Energy Sector			-2.017* (1.128)	-1.030 (1.196)
Lag ln(Total Assets)	2.337 (1.739)	2.987 (2.239)	6.815*** (1.613)	6.964*** (1.736)
Lag BTM	2.285 (3.141)	3.542 (3.286)	-1.322 (2.237)	-3.641 (2.644)
Lag leverage	-8.558*** (2.042)	-7.799*** (1.737)	.455 (1.428)	-.292 (1.403)
Lag ROA	22.565* (11.945)	20.366* (12.293)	.932 (6.838)	-.820 (7.074)
Lag R&D Intensity	-16.641* (9.564)	-18.663* (12.050)	2.884** (1.217)	1.834* (1.065)
YearFE	controlled	controlled	controlled	controlled
N	124	129	598	629
P	0.000	0.000	0.000	0.000
R ²	.897	.926	.677	.705
Number of companies	25	25	39	39

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022, using lagged control variables. In model (1), the influence of technology-driven M&As on the forward ESG score is investigated and in Model (2) is the relationship between technology-driven M&As on the ESG score in the year of the merger researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The lagged control variables consist of the lagged Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars in the year before the observation, lagged return on assets (Lag ROA), Lagged book-to-market ratio, lagged leverage and Lagged research & development (Lag R&D) expenses relative to sales. Significance levels are indicated by asterisks: * p<0,10, ** p<0.05, *** p<0.01.

E APPENDIX E

Table 18: Using propensity score matching Hypothesis 1

Hypothesis	H1			
Model	(1)	(2)	(3)	(4)
Variables	ESGscore	F.ESG score	F.ESG score	F.ESG score
Technology-Driven M&A	-0.332 (0.698)	1.234* (0.726)		
Non-tech M&A			0.725 (0.619)	
M&A				1.023** (0.513)
ln(Total Assets)	3.157*** (0.718)	3.676*** (0.764)	3.668*** (0.771)	3.629*** (0.763)
BTM	-3.208** (1.320)	-3.701*** (1.417)	-3.685*** (1.413)	-3.648*** (1.414)
ROA	1.200 (2.757)	3.464 (2.912)	3.521 (2.930)	3.450 (2.894)
R&D Intensity	1.269 (2.918)	0.847 (3.138)	2.043 (3.662)	0.709 (3.240)
Constant	-2.912 (6.038)	-6.862 (6.335)	-6.951 (6.405)	-6.608 (6.328)
YearFE	controlled	controlled	controlled	controlled
N	4,222	3,915	3,909	3,916
P	0.000	0.000	0.000	0.000
R ²	0.590	0.573	0.573	0.573
Number of companies	335	334	334	334

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022 using the propensity matched sample. Propensity Score Matching (PSM) pairs each company in the treatment group with a similar company in the control group to assess the effects of different acquisition types. This study uses PSM to compare technology-driven versus non-tech-driven acquisitions by matching firms based on factors such as Firm Size, BTM, Leverage, ROA, and R&D intensity. This method helps balance these variables across the two groups, providing a more accurate estimate of the impact of technology-driven acquisitions. In model (1), the influence of technology-driven M&As on the ESG score in the year of the merger is investigated and in Model (2) is the relationship between technology-driven M&As on the forward ESG score researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions US dollars, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * p<0,10, ** p<0.05, *** p<0.01.

Table 19: Using generalized propensity score matching Hypothesis 2

Hypothesis Model	H2a		H2b	
	(1)	(2)	(3)	(4)
Variables	F.ESGscore	ESGscore	F.ESGscore	ESGscore
Innovation	-.186 (.202)	-.081 (.229)		
Innovation Quality			.095* (.061)	-.048 (.104)
ln(Total Assets)	7.943*** (.157)	7.890*** (.163)	7.838*** (.160)	7.903*** (.155)
BTM	-5.748*** (.943)	-5.478*** (1.001)	-5.380*** (1.001)	-5.687*** (.945)
Leverage	-.236 (.259)	-.347 (.276)	-.293 (.274)	-.200 (.257)
ROA	20.687*** (2.644)	22.208*** (2.866)	22.215*** (2.867)	20.657*** (2.651)
R&D Intensity	3.302*** (1.250)	4.515*** (1.329)	4.322*** (1.322)	3.147** (1.245)
Constant	-36.302*** (2.205)	-36.570*** (2.247)	-36.165*** (2.234)	-35.992*** (2.198)
YearFE	controlled	controlled	controlled	controlled
N	4,006	3,702	4,006	4,006
P	0.000	0.000	0.000	0.000
R ²	.478	.465	.461	.475
Number of companies	334	320	334	334

Note: This table shows the result of the fixed effects model, studying the relationship between innovation and innovation quality and the ESG performance of acquiring companies over the period 2002-2022 using the propensity matching score. Propensity Score Matching (PSM) pairs each company in the treatment group with a similar company in the control group to assess the effects of different acquisition types or continuous variables. In this case, the propensity score matching (PSM) compares the F.ESG score and ESG score across different levels of Innovation and Innovation Quality, controlling for covariates to isolate the effect of Innovation and Innovation Quality. It does so by weighting observations based on a generalized propensity score derived from the predicted values of Innovation and Innovation Quality from a regression on factors such as Firm Size, BTM, Leverage, ROA, and R&D intensity. For Hypothesis 2a, in model (1) and (2), the influence of innovation on the forward ESG score and ESG score, respectively, is investigated. For Hypothesis 2b, in model (3) and (4) the relationship between innovation quality on the forward ESG score and ESG score in the year of the merger is researched, respectively. Innovation is the variable that represents the number of published patents by the target company, compared to the average per industry and Innovation quality is the number of patent citations, also compared to the industry average. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * p<0.10, ** p<0.05, *** p<0.01.

Table 20: Using generalized propensity score matching Hypothesis 3

Hypothesis Model	H3	
	(1)	(2)
Variables	F.ESGscore	ESGscore
ESG gap	-.352*** (.037)	-.325*** (.036)
ln(Total Assets)	4.950 (4.093)	4.481*** (.916)
BTM	-69.376*** (7.915)	-15.923*** (3.260)
Leverage	-8.473*** (2.158)	-2.321*** (.377)
ROA	-34.833 (68.617)	72.407*** (7.818)
R&D Intensity	-96.455*** (21.432)	-32.493*** (2.749)
Constant	18.503 (38.329)	15.807 (14.767)
YearFE	controlled	controlled
N	144	164
P	0.000	0.000
R^2	.998	.999

Note: This table shows the result of the OLS regression model, studying the relationship between the width of the ESG gap and the ESG performance of acquiring companies over the period 2002-2022 using propensity score matching. Propensity Score Matching (PSM) pairs each company in the treatment group with a similar company in the control group to assess the effects of different acquisition types. For this hypothesis, because of the continuous nature of the variables of interest, the PSM methodology uses a generalized propensity score to weight observations based on the predicted values of ESG gap from a regression on factors such as Firm Size, BTM, Leverage, ROA, and R&D intensity. It compares the F.ESG and ESG variable across different levels of ESG gaps, controlling for covariates to isolate the effect of ESG gap. In model (1), the influence of the width of the ESG gap on the forward ESG score is investigated and in Model (2) the relationship between the ESG gap on the ESG score in the year of the merger is researched. ESG gap is the variable representing the difference between the ESG score of the target company and of the acquiring company in the year prior to the merger. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Using propensity score matching Hypothesis 4

Hypothesis Model Variables	H4a		H4b	
	(1)	(2)	(3)	(4)
	F.ESGscore	ESGscore	F.ESGscore	ESGscore
Average Innovation	-.164 (.154)	-.012 (.141)		
Innovation * Energy Sector	-.044 (.160)	-.072 (.155)		
Merger & Acquisition			-.018 (.186)	.093 (.221)
M&A * Energy Sector			.742** (.341)	.520** (.249)
Technology Driven M&A			.223 (.309)	-.045 (.322)
Technology Driven M&A * Energy Sector			-1.569* (.782)	-.749 (1.056)
Ln(Average Total Assets)	5.803*** (1.150)	5.894*** (1.148)	6.392*** (1.725)	7.351*** (1.560)
Average BTM	-7.559* (3.957)	-11.734** (4.211)	-1.711 (2.622)	-2.159 (3.117)
Average Leverage	-1.316 (2.916)	-1.130 (2.152)	3.040* (1.698)	1.413 (1.267)
Average ROA	52.384*** (19.619)	39.742** (18.585)	.837 (8.448)	-2.565 (6.957)
Average R&D Intensity	1.931 (5.664)	1.643 (5.243)	-1.280 (5.505)	-2.515 (5.274)
Constant	-18.424* (10.225)	-15.975 (9.889)	-29.511 (15.334)	-38.224 (13.957)
Year Fixed Effects	controlled	controlled	controlled	controlled
N	128	133	552	558
P	0.000	0.000	0.000	0.000
R ²	.748	.786	.705	.747

Note: This table shows the result of the fixed effects model, studying the relationship between technology-driven M&As and the ESG performance of acquiring companies over the period 2002-2022 using propensity score matching. Propensity Score Matching (PSM) pairs each company in the treatment group with a similar company in the control group to assess the effects of different acquisition types. This study uses PSM to compare technology-driven versus non-tech-driven acquisitions in the energy sector by matching firms based on factors such as Firm Size, BTM, Leverage, ROA, and R&D intensity. This method helps balance these variables across the two groups, providing a more accurate estimate of the impact of technology-driven acquisitions. In model (1), the influence of technology-driven M&As on the forward ESG score is investigated and in Model (2) is the relationship between technology-driven M&As on the ESG score in the year of the merger researched. In Model (3) is the impact of non-technology-driven M&As on the forward ESG scores studied. Model (4) contains the results of the regression that examined the correlation between all M&As and the forward ESG score. TechnologyDrivenM&A, Non-TechDrivenM&A and M&A are dummy variables set to 1 to indicate the presence of technology-driven, non-technology driven and all M&As within the dataset for their respective years. The control variables consist of Ln(TotalAssets), which denotes the natural logarithm of total assets in billions of US dollars, Leverage, return on assets by sales (ROA), book-to-market ratio, and research & development (R&D) expenses relative to sales. Significance levels are indicated by asterisks: * p<0,10, ** p<0,05, *** p<0,01.

F APPENDIX F

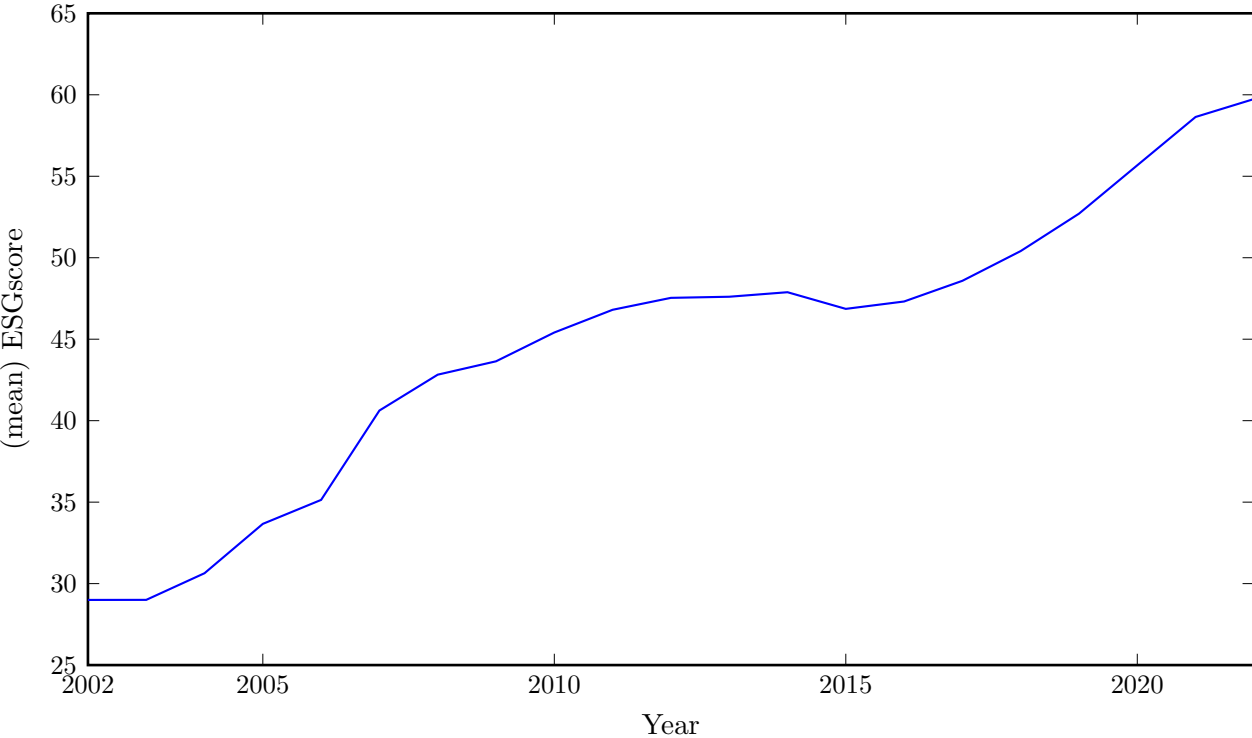


Figure 1: Mean ESG Scores Over Time